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Environmental Sensitivity Index (ESI) Feasibility Study of All-Hazards Indices Expansion

Research Planning, Inc

Environmental Sensitivity Index (ESI) Feasibility Study of All-Hazards Indices Expansion

Final Report

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Introduction

Environmental Sensitivity Index (ESI) products are developed by the National Oceanic and Atmospheric Administration (NOAA) to support planning for and responding to coastal oil and chemical spills. ESI data describe a variety of coastal resources that are at risk from oil spills that include sensitive shorelines (e.g., marshes, tidal flats), biological resources (e.g., birds, shellfish beds), and human-use resources (e.g., public beaches, water intakes). ESI maps and datasets include shoreline types that are ranked according to their sensitivity to oil and chemical spills. This index was the original focus of ESI maps and has been a standard for industry and responders since the late 1970s. ESI products also include extensive data describing the distribution of other biological and human-use resources at risk in a coastal area, typically displayed along with the ranked shoreline types in map products.

The NOAA Office of Response and Restoration (NOAA ORR) is interested in expanding the content and application of ESIs by incorporating additional, specific sensitivity scales that enhance their utility as planning tools for a broader suite of coastal hazards than oil and chemical spills. Expanding the content and applicability of ESI products will enhance the tool as a "one-stop shop" for coastal planners and emergency responders. The goal is that NOAA ESI data will be useful for broader coastal hazard planning and response by federal, state, tribal, and municipal agencies as well as industry and the public at large.

To this end, Research Planning, Inc. (RPI) undertook the project *Environmental Sensitivity Index (ESI) Feasibility Study of All-Hazards Indices Expansion* in response to a grant issued by the University of New Hampshire Coastal Response Research Center (CRRC) and NOAA ORR. This project investigates the feasibility of expanding the applicability of ESI products to include additional hazards. To accomplish this, new indices were developed to rank the relative sensitivity of selected natural and human population resources or "receptors" to an expanded suite of coastal hazards or "stressors." The methods and concepts that were developed were applied to a pilot area consisting of two ESI atlases in southern Florida by comparing the distribution of the receptors of interest with the stressor/hazard occurrence rates to evaluate exposure, then spatially analyzing where exposures of sensitive receptors to likely stressors occur. This report summarizes methods and data sources used, pilot results, and preliminary findings.

Methodology Overview

For the *ESI Feasibility Study of All-Hazards Indices Expansion* study, the terms of risk assessment are used as a conceptual framework and to describe methodology. The language used to define concepts such as risk, stressor, hazard, vulnerability, sensitivity, receptors, and similar concepts often differ by discipline, so it is useful to explicitly define terms and concepts proposed for use. In this context, risk is considered as the probability of an adverse outcome to a receptor of interest or concern due to the exposure of a given stressor or hazard. The terms "stressor" and "hazard" are equivalent in this document. Risk is both stressor- and receptor-specific and is considered as a function of the exposure to a stressor or hazard and the sensitivity of that receptor to that stressor. A risk assessment thus includes:

- A description of the probability and/or intensity of past, and future, hazards or stressors affecting a location;
- An inventory of assets or receptors (e.g., natural resources, population, etc.) at a location;
- A determination of exposure where these overlap;
- An evaluation of the relative sensitivity of a given asset or receptor to that stressor/hazard, and;
- Evaluation of the severity of consequences, and overall risk over all locations.

The core of this work is the development of new indices, or ways of ranking both the natural resource receptors described by the ESI data and the human population receptors as described by social vulnerability variables, based upon their sensitivity to a list of coastal stressors or hazards. In the existing ESI data, the shorelines are ranked by relative sensitivity to oil spills. Shorelines are not ranked by relative sensitivity to other stressors or hazards. Other biological and human-use resources are inventoried, but are not ranked by sensitivity to any hazards. This work expands this sensitivity index ranking concept to include a pilot suite of additional resources or receptors and additional hazards or stressors. A unique index is required for each receptor and each stressor. These unique indices were developed primarily by a comprehensive literature review.

The stressors or hazards included here for analysis were determined in consultation with NOAA and are:

- Acute coastal or storm surge flooding
- Tropical cyclone or convective storm wind events
- Chronic inundation
- Marine debris events
- Shoreline erosion
- Contaminants from spill events

Study Area

As part of this work, a pilot-scale analysis was undertaken to develop an example set of multi-hazard risk indices and analysis products for a multicounty-scale geographic area in southern Florida (Figure 1) using existing ESI data. This area is large enough to enable a robust evaluation of a diverse set of natural resource receptors and to provide a wide range of exposures to most of the identified stressors/hazards. Further, a pilot-scale analysis in this area, consisting of the spatial extents of the adjacent South Florida and Southwest Peninsular Florida ESI atlases (NOAA ORR, 2013; 2016a) will allow a robust evaluation of potential data gaps or issues that arise from assessing adjoining ESI datasets and ESI datasets of different vintages.

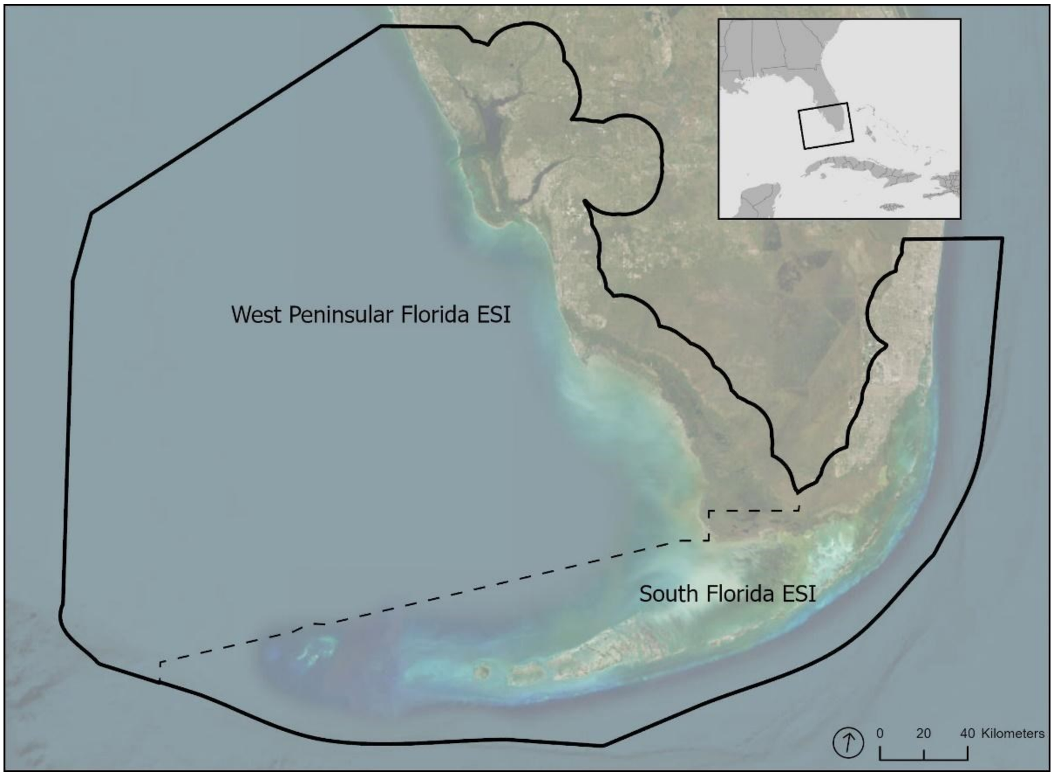

Figure 1. Study area in southern Florida representing the combined extents of the South Florida and Southwest Peninsular Florida ESI atlases. Dashed line indicates ESI atlas boundary.

Grid System

Binning spatial data into a grid system is a simple way of conducting visualization and analysis of complex and variably referenced spatial data. This process simplifies visual communication, allows more accurate visual estimates of count or density data, and facilitates smoothing and aggregation of data using consistent spatial framework across spatial scales. H3 (Uber 2020) is a discrete global grid system (Sahr et al. 2003) consisting of a multi-precision hexagonal tiling of the sphere with hierarchical indexes. Hexagonal gridding or tiling systems have advantages in that all neighbors are equidistant, which simplifies aggregation, flow modeling, etc. and scales from global to fine spatial scales without distortion. H3 is available both in ArcGIS (ESRI 2024) as well as other free and open-source software libraries, and it has been used in a variety of recent coastal (Bousquin 2021) and risk-assessment applications (Aini et al. 2023) that require spatial gridding.

The H3 system is hierarchical such that hexagonal grids at a given resolution nest within and can be programmatically related to grid cells at a coarser resolution (Figure 2). Given the scale of features represented in ESI atlases and the scale of stressor variability, the recommended scale range for visualizing and analyzing the data here is between levels 5 and 8 (Table 1), representing phenomena that vary over scales over hundreds of meters (m) to tens of kilometers (km).

Table 1. Size statistics for subset of H3 hexagonal grid system resolution levels. Note that area and dimension statistics will vary slightly at different areas on the earth surface.

H3 Scale Level	Average Area (km^2)	Average Edge Length (km)	Average Diameter (km)
5	234.1	9.59	18.79
6	33.46	3.72	6.94
7	4.78	1.41	2.68
8	0.74	0.52	1.00

In the sections that follow, visualizations are generally made using H3 grid cells at scale level 7 where each hexagon in the study area is approximately 4.78 square kilometers (km^2) in area. Accompanying digital deliverables include four different resolution grids, each with the same attributes, as discussed and visualized in this report.

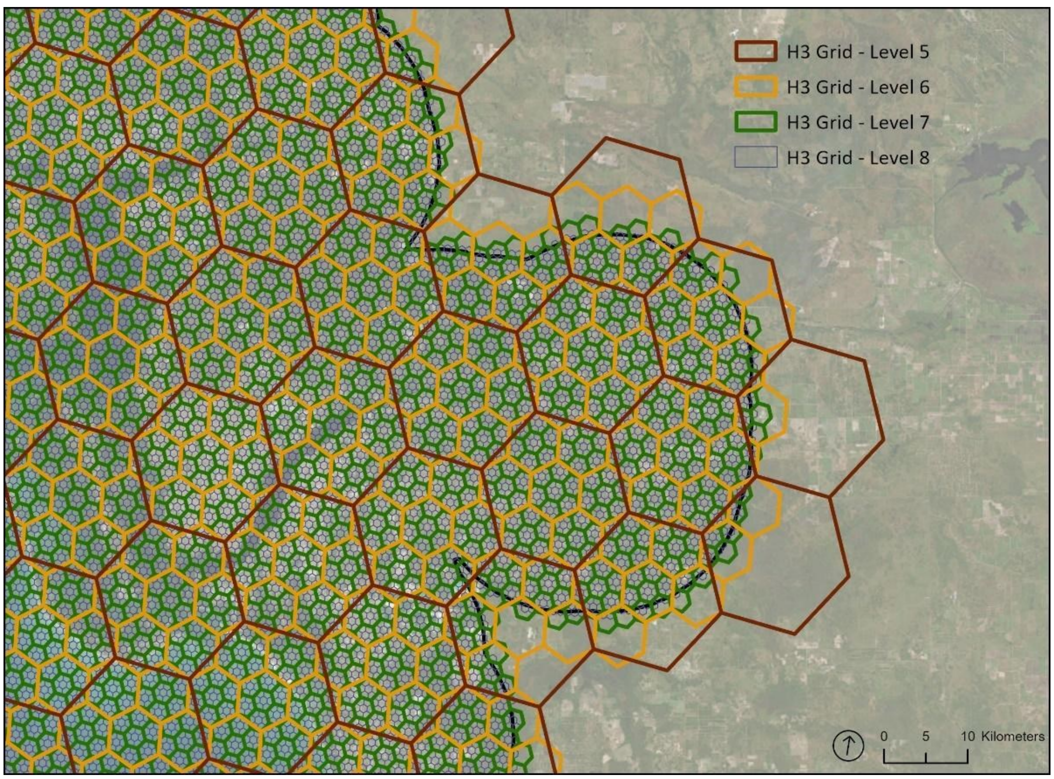

Figure 2. Examples of H3 hexagonal grids at four different scales over a portion of the study area in the Ft. Meyers area. Study area boundary is in black.

Ranking Methods

For this project, a variety of relative ranks of hazard intensity, resource exposure, and resulting risk are presented at different spatial grid cell resolutions. In each case, a unique categorization is performed for each visualization to standardize values into a 5-category system: High, Medium-High, Medium, Medium-Low, and Low. This is performed in each case using a Jenks natural breaks optimization method (Jenks 1967) which optimizes class categories based on numeric attributes by minimizing variance within classes and maximizing variance between classes. These categories are computed for each visualization or index calculation and stored as a numeric integer ranging from 1 (Low) to 5 (High).

Evaluated Stressors

For the *ESI Feasibility Study of All-Hazards Indices Expansion* study, a set of additional coastal hazards or stressors was selected via discussion with NOAA and other stakeholders. Stressors or hazards were selected to prioritize events or phenomena that fall under NOAA's interests for scientific investigation or emergency response, and for which there may be significant differences in the distribution and intensity of hazards or stressors across the U.S. Spatial maps describing the distribution of each evaluated stressor or hazard were compiled using nationally standard datasets. Methods and data sources used for each stressor or hazard are described in the following sections.

Acute Coastal or Storm Surge Flooding

Acute coastal or storm surge flooding is defined as flooding of coastal areas due to the vertical rise above normal water level caused by a cyclonic storm (e.g., hurricane, typhoon, or tropical storm) or other meteorological event that generates strong, persistent onshore wind and/or low atmospheric pressure. In coastal regions, life and property are at greatest risk from coastal or storm flooding (e.g., storm surge and coastal flooding; NOAA NHC 2024a).

To estimate the distribution of hazards posed by coastal and storm surge flooding over the study area, national storm surge hazard maps derived from the NOAA Sea, Lake, and Overland Surges from Hurricanes (SLOSH) data (NOAA NHC 2024a; Zachry et al. 2015) were used. These data map modeled storm surge inundation depth from a large ensemble of simulated tropical cyclones with varying storm intensity, angle of approach to the coastline, and other hydrodynamic variables. Initially, a weighted average of expected storm surge flooding depth reflected in the Maximum of Maximum Envelope of Water (MOM) product was computed as the mean of all categorical flooding depths, weighted by the relative historical frequency of landfalling hurricane category in continental US (Knapp et al. 2010a,b).

Hazard intensity categories were computed for individual grid cells by summing the storm surge flooding depth raster pixels in each cell and multiplying this value by the total area of all raster pixels in each cell to yield a value of volume of storm surge per cell and ranking these values using the natural breaks method. Figure 3 depicts the weighted average of storm surge flooding depth and resulting gridded hazard intensity categories.

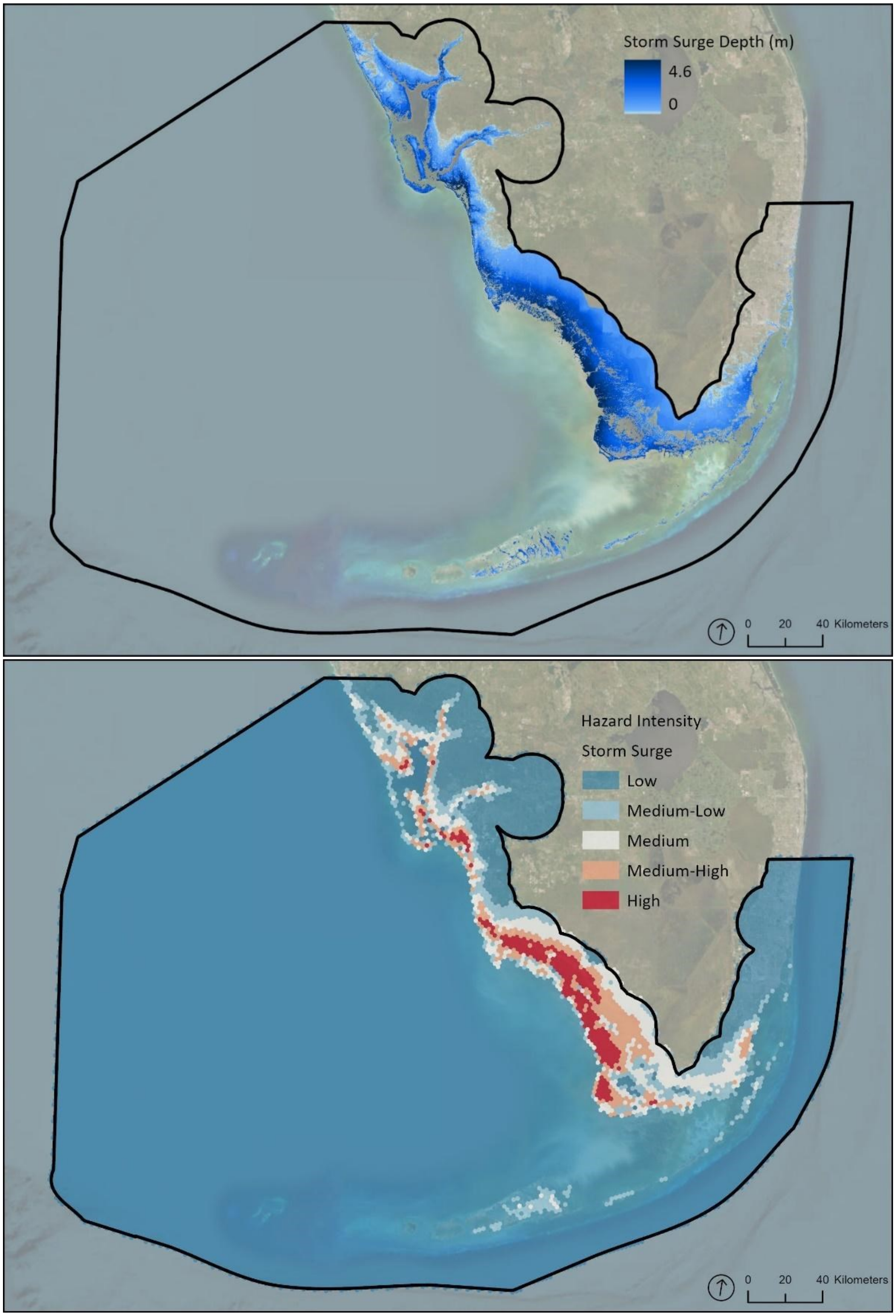

Figure 3. Weighted average of Maximum of Maximum Envelope of Water (MOM) storm surge flooding depth in meters from NOAA SLOSH model output (top) and resulting gridded hazard intensity categories (bottom).

Tropical Cyclone or Convective Storm Wind Events

Damaging winds from tropical storms and convective storms (thunderstorms) are significant hazards. Tropical storm winds are one of many natural hazards caused by tropical cyclones. When winds exceed 64 knots (kt), cyclones in the Atlantic Ocean are classified as hurricanes, while tropical storms and tropical depression are terms used to describe weaker cyclones. The damaging impacts of tropical storm winds occur in conjunction with the other natural hazards caused by tropical cyclones, so that it is often difficult to assess the damage caused by a specific hazard (Blake et al. 2011). Tropical storm winds differ from convective storm winds and tornadoes because of their size, which can be hundreds of kilometers in diameter, and the relative infrequency with which they occur. Though associated wind speeds are often less intense, convective storms are much more common than tropical storms. Convective storms are most frequent during the summer months (June-August), having a near-daily occurrence in the afternoon. Nationally, non-tornadic convective storm winds are responsible for approximately one in three wind-related deaths (Black and Ashley 2010).

To estimate the distribution of hazards associated with tropical storm winds, analysis of the NOAA IBTrACS database (Knapp et al. 2010a,b) for the period from 1851 to 2023 was carried out after the methods described in Emrich et al. (2022b) and Demuth et al. (2006). Briefly, asymmetrical wind swaths were generated for all North Atlantic tropical cyclones making landfall in the study area during 1851-2023 by implementing the multi-distance asymmetrical buffer for wind radii at 34 and 64 knots using methods similar to those described in Demuth et al. (2006). After generating these wind swath polygons for all tropical storms in the vicinity of the study area, the resulting vector polygonal swaths were intersected. For each resulting unique overlapping polygon, the count of unique occurrences in each speed category was determined. The count attributes of these polygons were converted to a raster at 1-km cell size, and the raster was smoothed using a moving-window median calculation with a 10-km radius. The average annual occurrence rate of tropical cyclone winds greater than 64 kt for each raster cell was computed by dividing the total number of occurrences by the 172-year evaluation period (1851-2023).

To estimate the distribution of hazards posed by convective storm high-wind events, point data on the occurrence of severe (>64 kt) thunderstorm and other winds were obtained from the NOAA National Weather Service Storm Prediction Center Severe Weather Geographic Information Systems Database (SVGIS; NOAA SPC 2023). Hart and Janish (1999) provide additional details. As per the methods referenced in the NOAA SPC 30-year Severe Weather Climatology data sets (NOAA SPC 2024), a kernel density of these point events within a 120-km radius was computed using a subset of points from 1993 to 2023 (ESRI 2024; Silverman 1986). The average annual occurrence rate of convective storm winds >64 kt for each raster cell was computed by dividing the total number of occurrences by the 30-year evaluation period (1993-2023). Figure 4 depicts the annual empirical occurrence rate of tropical cyclone winds >64 kt and annual empirical occurrence rate of severe convective storm winds >64 kt.

The expected count per year of all winds >64 kt for each raster cell was computed as the sum of the annual occurrence probability of both winds >64 kt from tropical cyclones and the annual

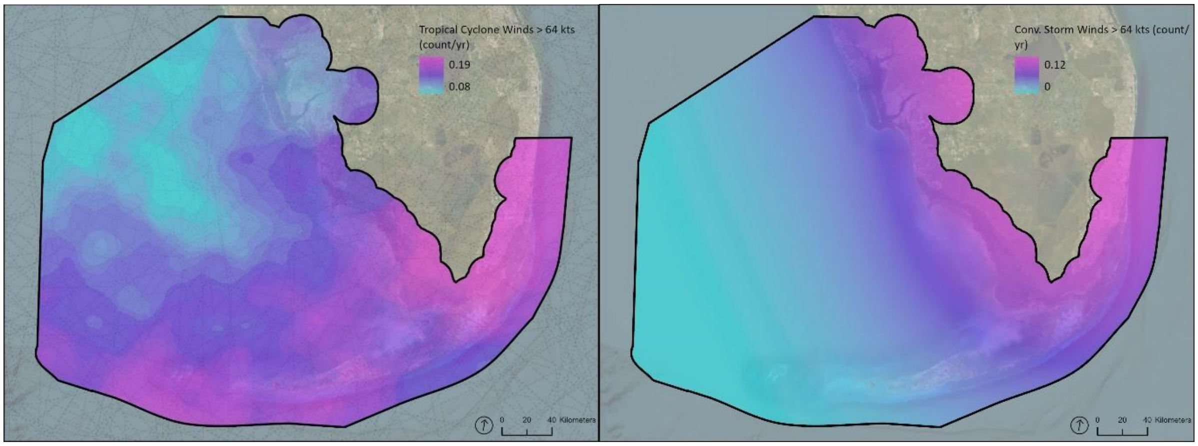

Figure 4. Annual empirical occurrence rate of tropical cyclone winds >64 kt (1851-2023; left) and annual empirical occurrence rate of severe convective storm winds (>64-kt) from NOAA Storm Prediction Center SVGIS data (1993-2023; right).

occurrence probability of winds >64 kt from convective storms. Hazard intensity categories were computed for individual grid cells by taking the mean of the expected occurrence rate for all winds >64 kt for raster pixels in each cell and ranking these values using the natural breaks method. Figure 5 depicts the weighted average of storm surge flooding depth and resulting gridded hazard intensity categories.

Chronic Inundation

High tide flooding (HTF), often referred to as “king tides,” “nuisance,” or “sunny day” flooding, occurs when sea level rise combines with local factors to push water levels above the normal high tide mark. Changes in winds or currents, and normal tidally driven water level elevation changes can all cause high tide flooding, inundating upland areas even during fair weather. High tide flooding frequency is accelerating and is more than twice as likely now as it was in 2000 (Sweet et al. 2018).

To estimate the distribution of hazards posed by chronic flooding, the extensive spatial data presented as part of the multi-agency analysis described in the 2022 Sea Level Rise Technical Report (Sweet et al. 2022) to characterize the extent and predicted frequency of chronic inundation events were used (see Sweet et al. 2018 for additional details). The Coastal Flood Threshold Inundation Extent data were obtained (NOAA OCM 2024b) describing the current extent of modeled HTF areas nationally. Additionally, HTF days per year were obtained from NOAA CO-OPS for all tide stations where available (NOAA CO-OPS 2024) from the available data period (2019-2023). The counts of HTF days were interpolated over the study area where HTF flooding extents were present using a spline interpolation method with a coarse upland boundary barrier (ESRI 2024) to a raster with a 1-km cell size, apportioned to each cell in the HFT extent rasters (3 m rasters), and resampled to 30-m cell size. The average annual HTF day occurrence rate for each raster cell was computed by dividing the interpolated value in all cells by the 5-year evaluation period (2019-2023).

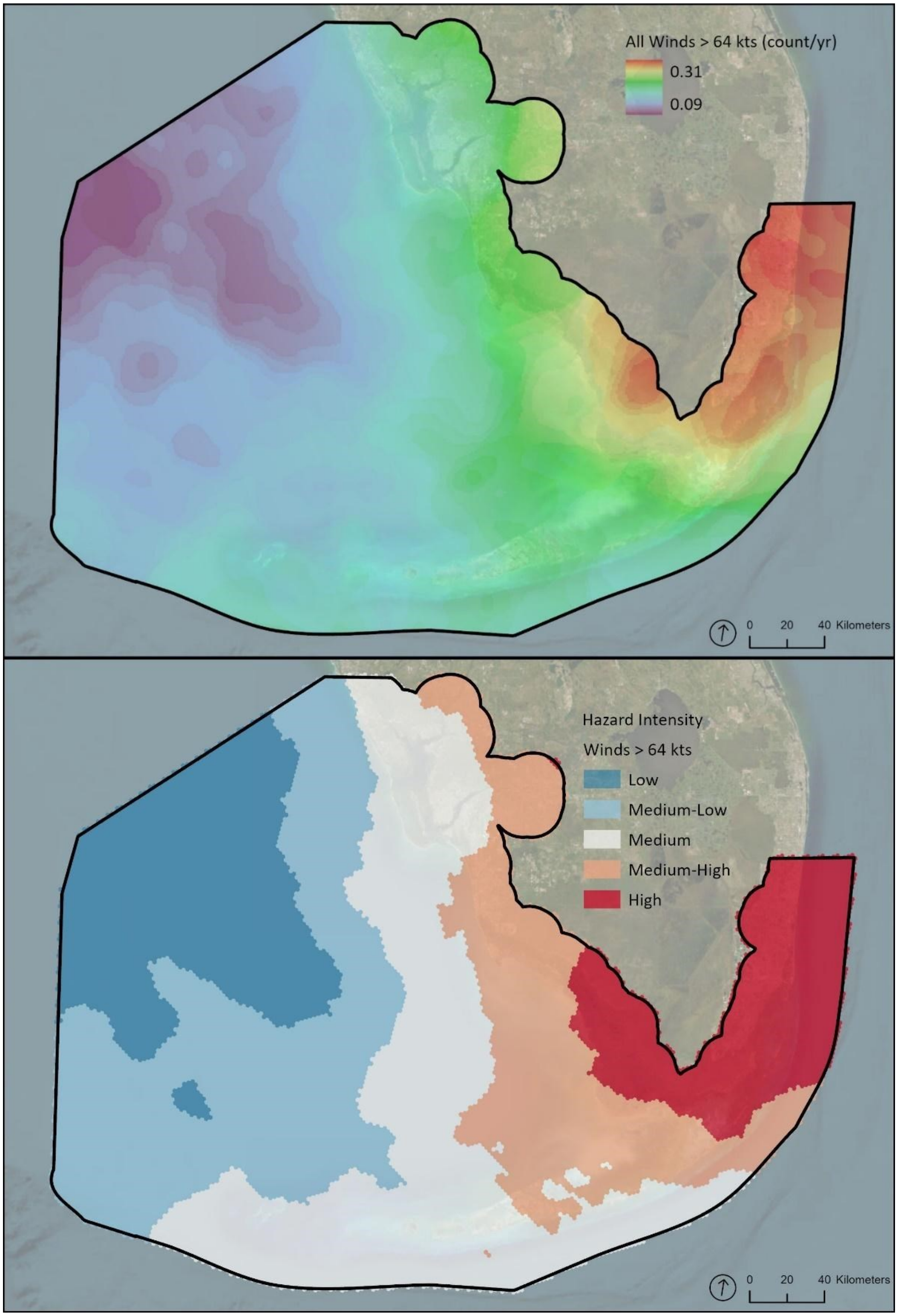

Figure 5. Annual empirical occurrence rate of all wind events >64-knots (tropical storms and severe convective storms; top) and resulting gridded hazard intensity categories (bottom).

Hazard intensity categories were computed for individual grid cells by summing the values of annual HTF day occurrence rate for all raster pixels in each cell and multiplying this value by the total area of all raster pixels in each cell, to yield a value of the expected area of HTF per year per cell and ranking these values using the natural breaks method. Figure 6 depicts the weighted average of storm surge flooding depth and resulting gridded hazard intensity categories.

Marine Debris Events

Hurricanes and tropical storms, tsunamis, floods, and landslides that impact U.S. coasts can be a notable acute source of marine debris, distinct from chronic sources of marine debris . High winds, storm surges, and heavy rains transport household products, hazardous waste, and construction debris into the surrounding waters. Natural disasters can also create Abandoned and Derelict Vessels (ADVs) and other items of concern. This debris can be a hazard to navigation, damage habitat, and pose pollution threats.

Few data exist that are suitable for nationwide estimation of hazards posed by acute accumulations of large marine debris generated by tropical storms and tsunamis. To estimate this hazard, a statistical model was developed to predict the relative likelihood of occurrence of event-generated marine debris. Training data for this model was compiled from internal data sets from recent Emergency Support Function (ESF)-10 and ESF-3 responses identifying ADVs and other debris items of concern for Hurricanes Irma, Maria, Florence, Michael, Laura, Sally, and Ida. For these hurricanes, 10,099 items were identified in NC, FL, AL, LA, PR, and the USVI primarily via interpretation of post-storm imagery. A raster was created covering the entirety of the searched extent for each debris mapping project/storm at 1-km cell size, and the count of ADVs and other targets per raster pixel was computed.

A set of spatial rasters at 1-km cell size was developed for a suite of predictive variables over this same raster extent. Predictive variable rasters were generated as follows. Distance to shorelines was extracted from the Global Self-consistent, Hierarchical, High-resolution Geography database (GSHHG; Wessel and Smith 1996). A raster representing land was also derived from the GSHHG, and focal mean values representing proportion of land area were computed at 2- and 10-km radii. Focal mean values of population density extracted from the Gridded Population of the World, Version 4 (GPWv4; CIESIN 2018) were computed at 2- and 10-km radii. Finally, a database of marina locations was compiled from ESI atlases (NOAA ORR 2000a; 2000b; 2007; 2010; 2014) and supplemental state datasets (FWC 2024b; LA GOHSEP 2024) for all states with mapped debris items. Kernel density surfaces in units of marinas per km^2 were generated using a 2-km and 10-km search radii. Finally, the maximum categorical wind speed for each storm was extracted for all locations from NOAA National Hurricane Center best track wind swath data (NOAA NHC 2024b). All locations in the raster extent had wind speeds above 34 kt (tropical storm force), but only some locations had wind speeds above 64 kt (hurricane force). A Poisson regression model was developed using the counts of ADVs and other targets per 1 km^2 as the independent variable and the values of the variables discussed above as predictor variables.

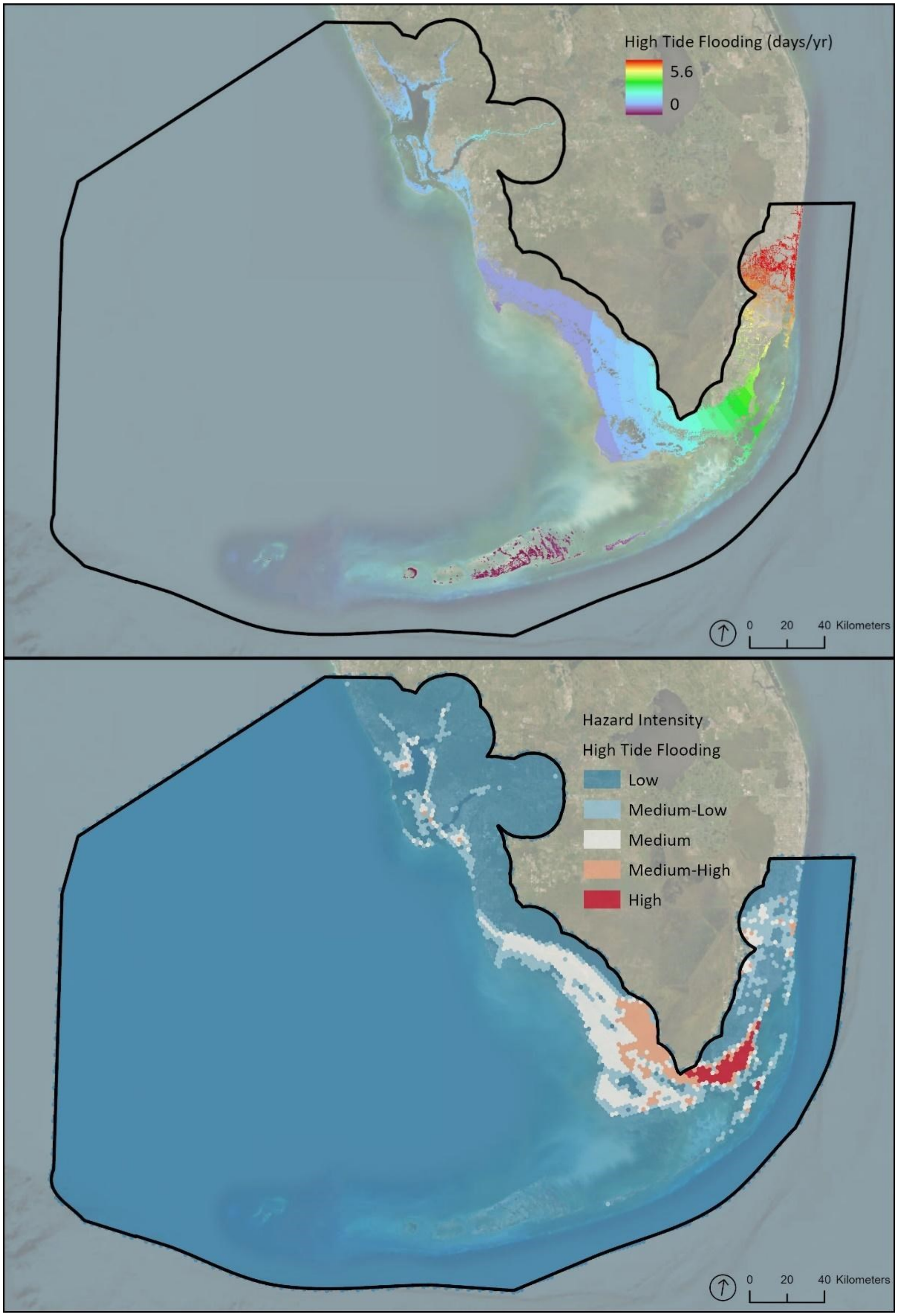

Figure 6. Extent and annual empirical occurrence rate of high tide flooding (HTF) derived from NOAA Coastal Flood Threshold Inundation Extent and CO-OPS data (top) and resulting gridded hazard intensity categories (bottom).

The final model selected was highly significant (Wald Statistic=29816.7, df=8, Prob > chi-squared < 0.0001), used all predictor variables, and explained 39% of the variability in ADV/debris counts as evaluated by deviance. Model parameters are given in Table 2.

Table 2. Model parameters for Poisson regression relating count of event-generated ADVs and other targets per 1 km^2 on multiple predictor variables.

Variable	Coefficient	Significance
Intercept	-1.778735	< 0.000001
Distance to shoreline (m)	-0.002060	< 0.000001
Mean population density within 2 km (count/km^2)	0.000096	< 0.000001
Mean population density within 10 km (count/km^2)	0.000164	< 0.000001
Marina density within 2 km (count/km^2)	0.769921	< 0.000001
Marina density within 10 km (count/km^2)	1.368407	< 0.000001
Land to water ratio within 2 km	1.229009	< 0.000001
Land to water ratio within 10 km	-0.496450	< 0.000001
Wind speed greater than 64 knots	1.185371	< 0.000001

This model was used to make predictions for the entirety of the study area for both conditions with and without winds greater than 64 kt. Each resulting predicted raster surface was multiplied by the rasters describing the average annual occurrence rate of tropical cyclone winds greater than 34 and 64 kt, respectively (as described in the section on tropical cyclone wind events above). These two rasters were then summed to yield a raster with the predicted annual count of event-generated ADVs and other targets per km^2.

Hazard intensity categories were computed for individual grid cells by taking the mean of the predicted annual count of event-generated ADVs and other targets per km^2 and ranking these values using the natural breaks method. Figure 7 depicts the predicted annual count of event-generated ADVs and other targets per km^2 and resulting gridded hazard intensity categories.

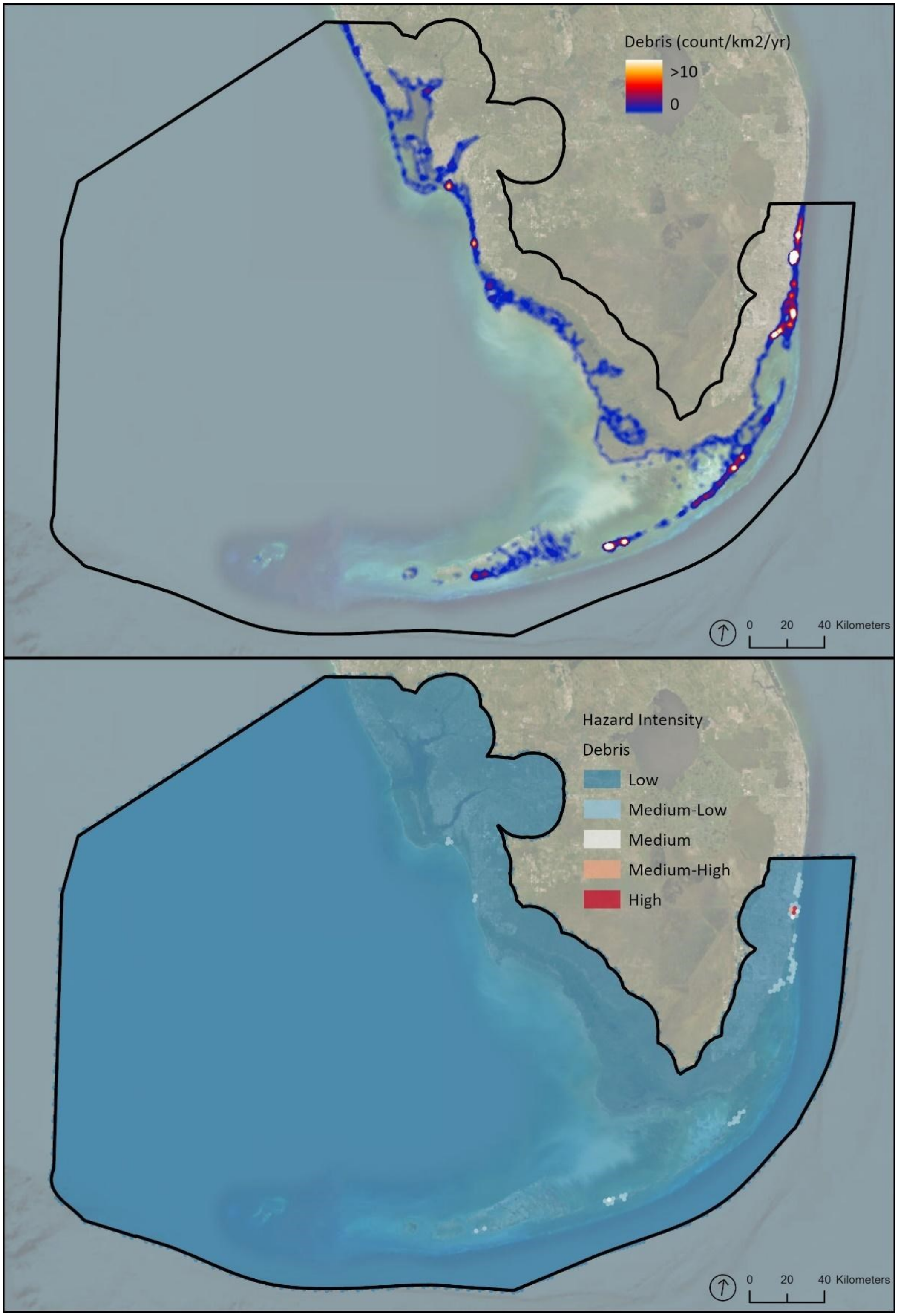

Figure 7. Predicted annual count of emergency generated debris items per km2 (top) and resulting gridded hazard intensity categories (bottom).

Shoreline Erosion

Shoreline erosion is a widespread process along most open-ocean shores of the United States that affects both developed and natural coastlines. Erosion can cause a variety of impacts to coastal communities, habitats, and the physical characteristics of the coast, including beach erosion, shoreline retreat, land loss, and damage to infrastructure.

To estimate the hazards posed by shoreline erosion, data were integrated from several sources. For outer sand beach shorelines, the U.S. Geological Survey (USGS) National Assessment of Shoreline Change (USGS 2023; Kratzmann et al. 2021) data were used. This national dataset measures long- and short-term shoreline change rates at multiple transects along the open coasts of the U.S., primarily along exposed beach shoreline. The long-term annualized linear retreat rate computed at each transect was assigned to a point location at the intersection of that transect with the most recent shoreline. These data were filtered to retain only locations with shoreline retreat rates that were positive (erosional). Finally, an average annual areal land loss rate was computed at each location by multiplying the long-term annualized linear retreat rate at each location by 50 m (the alongshore spacing of the USGS transects). To evaluate erosion and coastal land loss in areas not covered by the USGS shoreline change data, NOAA Coastal Change Analysis Program (C-CAP) Regional Land Cover 30-m data (NOAA OCM 2024a) were used. These data were processed at native resolution to extract pixels with change from upland or wetland (excluding unconsolidated shore and barren areas) to water between 1996 and 2016. The resulting locations were filtered to remove areas of change inland and along outer coasts where the USGS data were considered to supersede the NOAA data. The average annual areal land loss rate for each pixel was computed by dividing the area of each pixel (900 m^2) by the 20-year evaluation period (1996-2016). These two datasets were merged together.

Hazard intensity categories were computed for individual grid cells by summing the annual estimated areal rate of shoreline erosion of all points in each cell to yield a value of total area lost per year per cell and ranking these values using the natural breaks method. Figure 8 depicts the annual estimated areal rate of shoreline erosion and coastal land loss and resulting gridded hazard intensity categories.

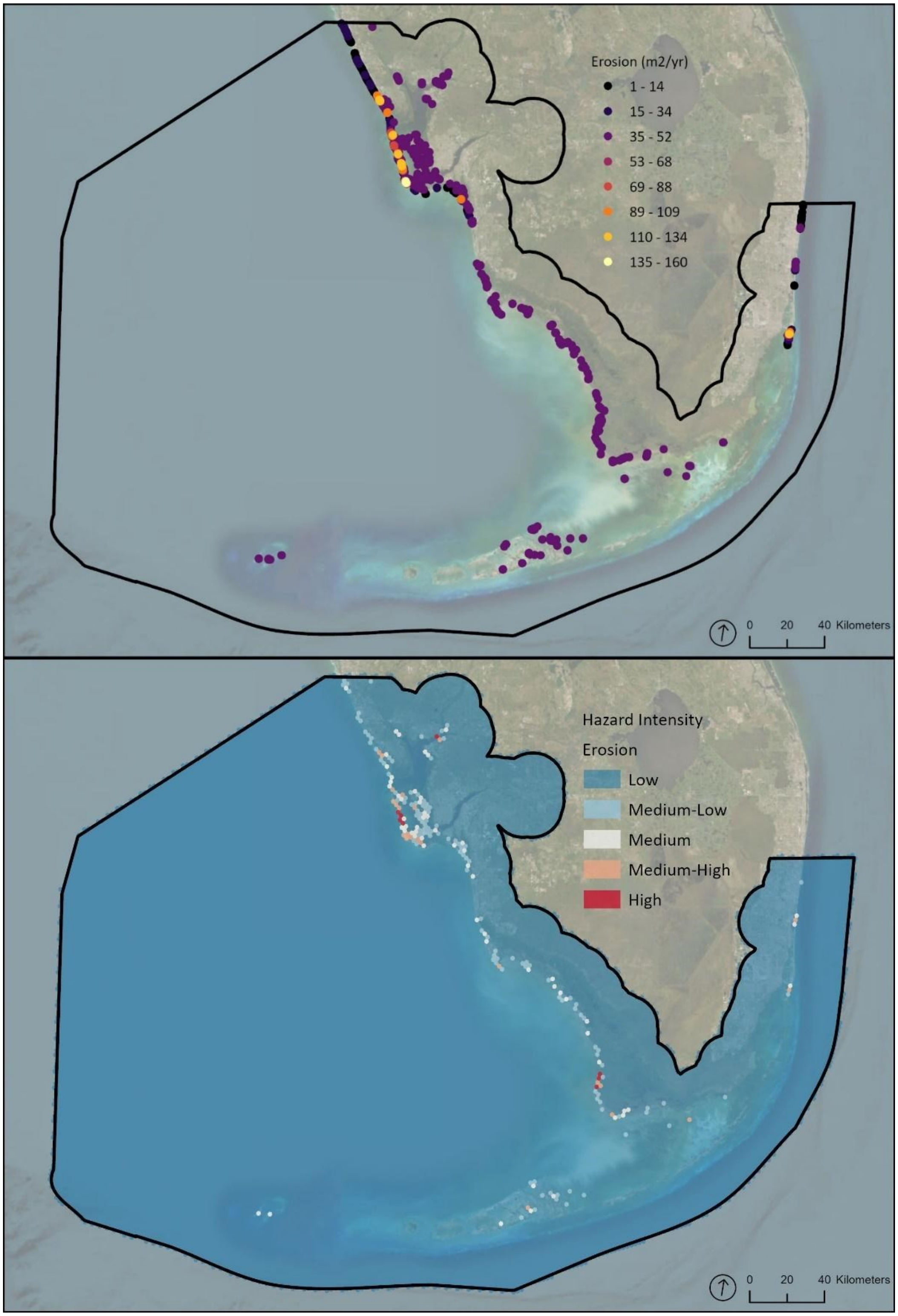

Figure 8. Location and annual estimated areal rate of shoreline erosion and coastal land loss derived from USGS National Assessment of Shoreline Change and NOAA Coastal Change Analysis Program data (top) and resulting gridded hazard intensity categories (bottom).

Contaminants from Spill Events

A wide range of chemicals can contaminate coastal areas. Most contaminants enter the environment from industrial and commercial facilities, oil and chemical spills, or non-point sources. Many hazardous waste sites and industrial facilities have been contaminated for decades and continue to affect the environment. To estimate hazards posed by contaminants in coastal areas, an empirical analysis was carried out using the USCG/USEPA National Response Center (NRC 2024) data describing spill reports between 2003 and 2023. These data were compiled, and records with explicit spatial coordinates were mapped. Records without explicit coordinates were tabulated at the zip code or county level, as available. Background spill counts were computed for each zip code and county polygon in the study area in units of spills per km^2. The count attributes of these polygons were converted to rasters at 1-km cell size. A kernel density surface in units of spills per km^2 was generated for records with explicit coordinates using a 10-km kernel in ArcGIS Pro (ESRI 2024; Silverman 1986) and stored as a raster at 1-km cell size. Finally, both background spill count rasters and the kernel density raster were summed to yield a total spill count raster. and the raster was smoothed using a moving window median calculation with a 10-km radius. The average annual spill occurrence rate per km^2 for each raster cell was computed by dividing the total value in all cells by the 20-year evaluation period (2003-2023).

Hazard intensity categories were computed for individual grid cells by taking the mean annual spill occurrence rate per km^2 in each cell and ranking these values using the natural breaks method. Figure 9 depicts the mean annual spill occurrence rate per km^2 and resulting gridded hazard intensity categories.

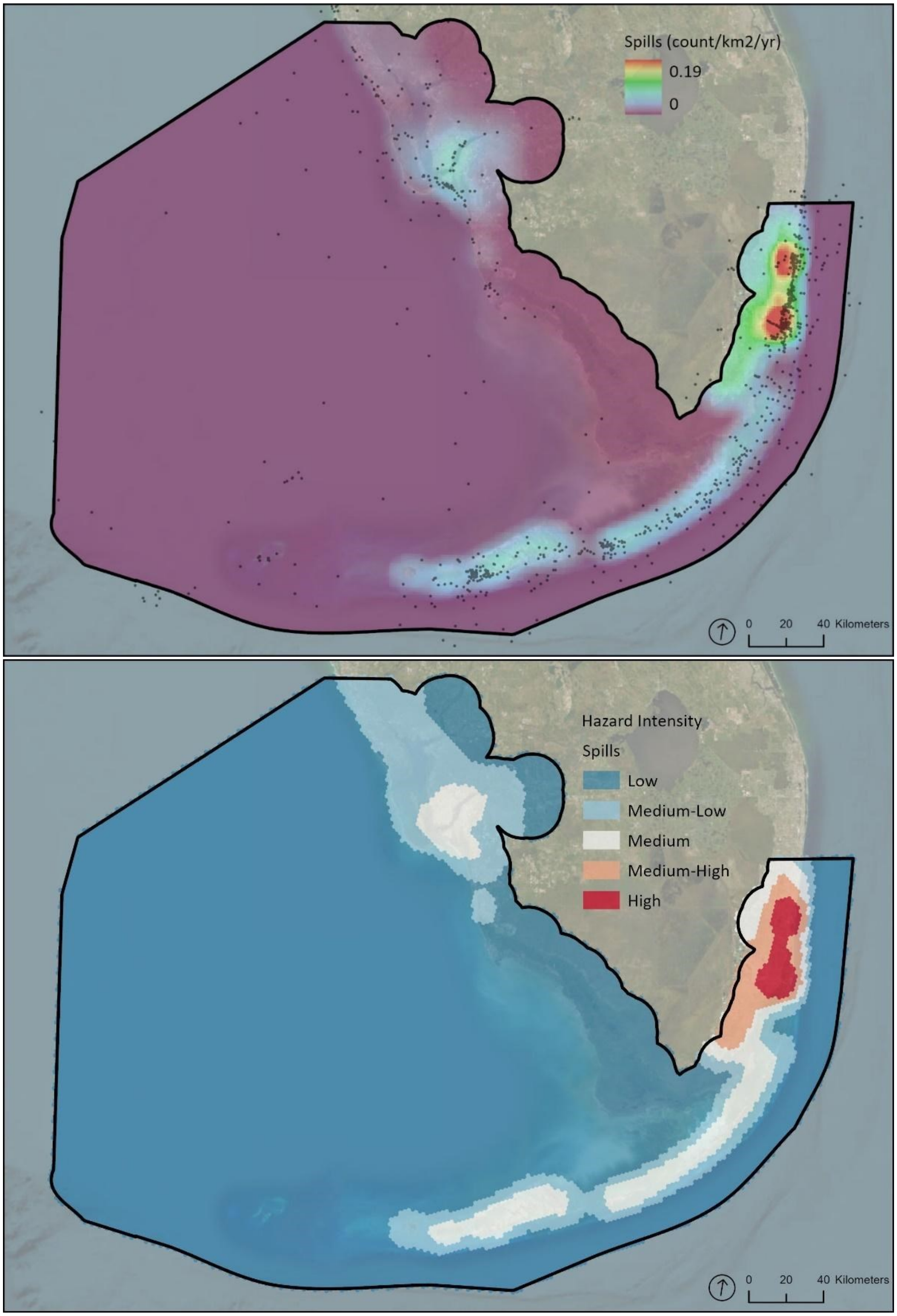

Figure 9. Annual empirical occurrence rate of oil and chemical spill derived from USCG/USEPA National Response Center data (2003 to 2023; top) and resulting gridded hazard intensity categories (bottom).

Natural Resource Receptors

The primary utility of ESI atlases is that they collect, compile, and communicate information on biology, human-use, and shoreline resources that may be at risk from oil spills in a standard way across all coastal areas. ESI data inherently describe a set of natural resource receptors, ranked according to sensitivity to oil spills, a primary coastal stressor such as those described above.

The core of this project involves the development of new sensitivity indices for natural resource receptors contained in ESI atlases. While all ESI data are collected and compiled according to a common standard, their contents vary according to regional priorities and by the age of the atlas, as the ESI standard has evolved over time. In general, it is expected that sensitivity index development would take place primarily for Threatened and Endangered Species (including their Critical Habitats and other important habitats) and wetlands, coral reef, seagrass, and other sensitive benthic habitats. These habitats provide protection of adjacent lands, people, and resources during extreme storms such as hurricanes, but they are also at risk of damage from hurricane-generated waves, coastal erosion, sedimentation, and marine debris. Because there is a large number of potential species, habitats, and other natural resources contained in ESI atlases, a subset of resources present in the study was specifically selected for sensitivity index development as part of this project via discussion with NOAA and other stakeholders. These resources include one species or guild from each biological element mapped as part of ESI atlases. The resources selected for inclusion from the two ESI atlases in the study area are:

- Terrestrial Mammal (Key deer)
- Marine Mammals (West Indian manatee)
- Shorebirds (Nesting and Wintering)
- Wading Birds
- Fish (Smalltooth sawfish)
- Invertebrate (Queen conch)
- Reptiles (Sea turtles)
- Wetlands (Mangroves)
- Wetlands (Seagrass)
- Hardbottom Habitat (Coral reefs)

Key deer (*Odocoileus virginianus clavium*) are listed as endangered under both federal and state regulations. They are the smallest subspecies of the North American white-tailed deer. They are the only large herbivore in the Florida Keys and can be found in every habitat, where they feed on dozens of native plant species. They travel through all of the Florida Keys habitats, and can walk, wade or swim from island to island. The 2024 Key deer population is estimated to be 700 to 800 deer, with the greatest concentrations on Big Pine Key and No Name Key (FWC 2024a). Key deer were selected to represent terrestrial mammals that are listed under the Federal Endangered Species Act (ESA) and intimately associated with coastal habitats.

West Indian manatees (*Trichechus manatus*) are listed as threatened under both federal and state regulations, as well as under the Marine Mammal Protection Act. The subspecies Florida manatee (*Trichechus manatus latirostris*) primarily inhabit Florida's coastal waters, rivers and springs. During the warmer months, some manatees travel up the eastern coastline into Georgia and the Carolinas, with a few animals traveling as far north as Massachusetts. In the Gulf, manatees can be found west through coastal Louisiana and occasionally as far west as Texas. The statewide abundance in Florida for the 2021-2022 period is 8,350-11,730 manatees (Gowan et al. 2023). Manatees live in marine, brackish, and freshwater systems in coastal and riverine areas throughout their range. They are aquatic herbivores, preferring habitats near the shore featuring submerged aquatic vegetation like seagrass and eelgrass. They cannot tolerate temperatures below 68°F for extended periods of time; during the winter months, cold temperatures keep the population concentrated mostly in peninsular Florida. Manatees were selected to represent marine mammals that are ESA-listed and intimately associated with coastal habitats.

Nesting and wintering shorebirds are a sub-element for birds in the ESI data in the study area, with 23 species mapped. Shorebirds are closely associated with coastal habitats for nesting, feeding, and loafing. Piping plover and rufa red knot are ESA-listed as threatened; American oystercatcher, black skimmer, least tern, and snowy plover are state listed as threatened. Some species nest in dense mixed-species colonies (e.g., terns, gulls), whereas some species are solitary nesters (e.g., plovers, oystercatchers). Shorebirds represent a guild of coastal birds that are highly susceptible to disturbances that could lead to reduced nesting success, particularly from human disturbance and predation.

Wading birds are a sub-element for birds in the ESI data for the study area. They include herons (little blue and tricolored herons are state listed as threatened), egrets, American flamingo, roseate spoonbill (state listed as threatened), ibis, limpkin, Florida sandhill crane (state listed as threatened), and wood stork (ESA-listed as threatened). Many nesting species establish nests in shrubs or trees over or adjacent to wetlands in colonies of tens to hundreds of nests, often with at least two species nesting in the colony. Nesting colonies also need to be near aquatic feeding areas. Wading birds represent a guild of coastal birds that are susceptible to disturbances that could lead to reduced nesting success and/or colony abandonment, particularly from degradation of feeding areas and physical damage to the colony vegetation.

Smalltooth sawfish (*Pristis pectinata*) is listed as endangered under both federal and state regulations due to their dramatic decline in population and range due to habitat loss and accidental capture in fisheries. Critical habitat has been designated along the southwest coast of Florida, from Florida Bay to Marco Island and parts of Estero Bay, San Carlos Bay, and Charlotte Harbor. Juveniles are associated with mangrove and seagrass habitats in areas such as estuaries, river mouths, and bays year-round, preferring water salinities between 18 and 30 parts per thousand. Adults are typically found in open-water habitats, but have been encountered near coral reefs and occur inshore during the spring when females give birth and mating is thought to occur. They are representative of marine fish that are highly dependent on shallow coastal habitats and are listed under ESA.

Queen conch (*Aliger gigas*) was federally listed as threatened in 2024 due to overfishing and poaching. This long-lived (up to 30 years) invertebrate species occurs in sandy and hard bottoms, coral rubble, and occasionally in seagrass beds. Queen conch was selected as representative of invertebrates that are reliant on nearshore coastal habitats and are ESA-listed.

Sea turtles are marine reptiles, with all five species in Florida listed as either threatened or endangered under both federal and state regulations. Adult females lay eggs at their natal beaches in Florida between April and October. Loggerhead sea turtles (*Caretta caretta*) are the most common nester, and all life stages may be present in nearshore waters of south and central Florida throughout the year. Adult green sea turtles (*Chelonia mydas*) are the second most common nester, and may be present in waters near nesting beaches during time periods surrounding the nesting season. Non-adult green sea turtles may be present in inshore seagrass habitats and nearshore hardbottom habitats throughout the year. Leatherback sea turtles (*Dermochelys coriacea*) nest in small numbers between March and July, and may be encountered in offshore waters throughout the year. Hawksbill sea turtles (*Eretmochelys imbricata*) are rare nesters in Florida, but all life stages are present throughout the year in nearshore reef and hardbottom habitat. Non-adult Kemp's ridley sea turtles (*Lepidochelys kempii*) are rare nesters in Florida, but may be present throughout south Florida waters during all months.

Mangroves are the dominant intertidal wetland habitat in southern Florida. They maintain water quality by trapping sediment and taking up excess nutrients from the water. There is increasing appreciation for their value in sequestering carbon. They play an important role in shoreline protection and stabilization, and they provide important habitat for a wide variety of species of commercial, recreational, subsistence, and conservation interest. They are one of the most sensitive shoreline habitats in Florida (ESI rank of 10).

Seagrass beds are highly productive habitats. They serve as important carbon and nutrient sinks and produce substantial amounts of oxygen for sediments and the overlying water column. They are a food source for many animals including sea urchins, sea turtles, manatees, and some fish and crustaceans. They are nursery habitat that provides structure for various life stages of commercially and economically important fish and invertebrates. They also stabilize the sediment around coastal areas, protecting coastlines from tropical storms that threaten beaches and infrastructure. Seagrass beds can be both intertidal and subtidal in Florida.

Coral reefs create specialized habitats that provide shelter, food, and breeding sites for numerous plants and animals. Coral reefs lay the foundation of a dynamic ecosystem with tremendous biodiversity. Coral reefs act like submerged breakwaters by breaking waves and dissipating their energy offshore before they flood coastal properties and communities. Annually, reefs in Florida provide flood protection benefits to more than 5,600 people and $675 million in averted damages to property and economic activity (Storlazzi et al. 2019). Coral reefs in Florida have experienced declines due to a combination of global and local factors, including high ocean temperatures resulting in more frequent coral bleaching events, coral disease, poor water quality associated with land-based sources of pollution, and other human impacts. In 2006, elkhorn and staghorn coral were listed as threatened species under the ESA; in 2014 boulder star coral, mountainous star coral, lobed star coral, rough cactus coral and pillar coral were also ESA-listed as threatened. Critical habitat for elkhorn and staghorn coral in Florida extends offshore from Boynton Beach to Key West and around the Dry Tortugas.

Polygons and points representing each of these species, habitats or sub-elements were extracted from both ESI atlases and merged together by species. For species or sub-element with data describing both wide general distribution and more spatially constrained areas of importance, a subset of points and polygons were extracted for areas representing areas of importance only. For the West Indian manatee, smalltooth sawfish, queen conch, and sea turtles, polygons with high concentrations, or that were identified as breeding, nursery, or other significant locations were considered as important areas. For shorebirds and wading birds, points indicating nesting colonies were considered as important areas. No specific important areas were extracted for Key deer, mangroves, seagrass, and coral reefs. Figures 10 through 19 depict the distribution of data representing these resources extracted from ESI atlases.

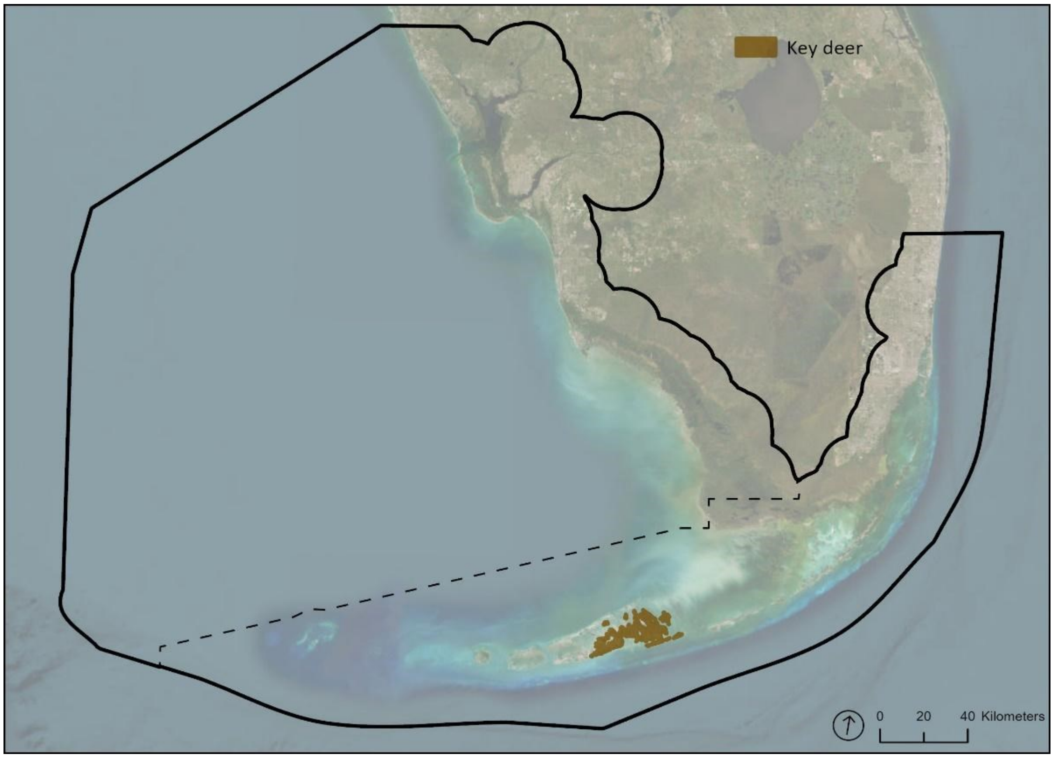

Figure 10. Florida key deer location data extracted from ESI atlases. Dashed line indicates ESI atlas boundary.

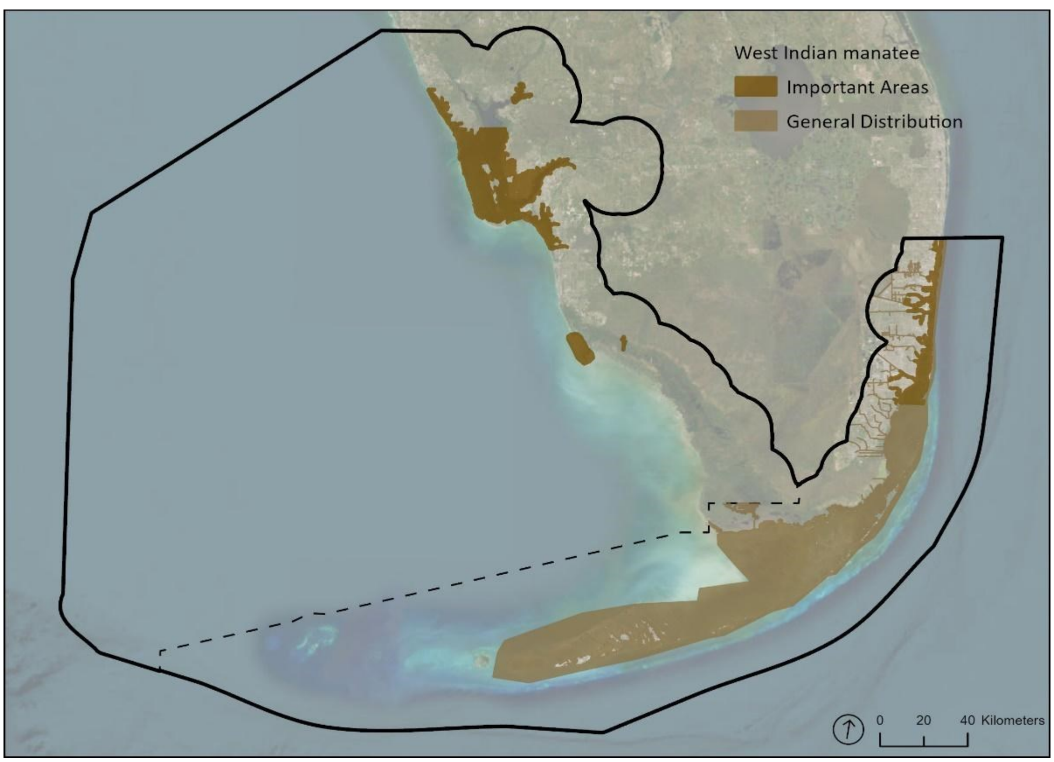

Figure 11. West Indian manatee location data (general distribution and important areas) as extracted from ESI atlases. Dashed line indicates ESI atlas boundary.

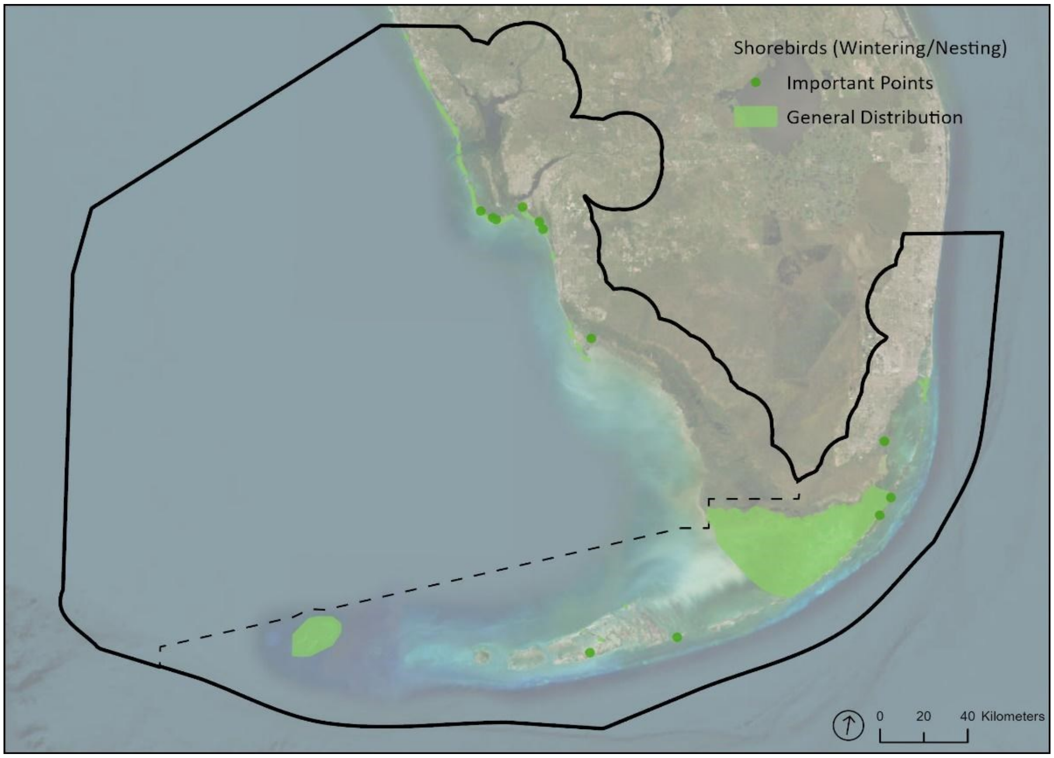

Figure 12. Wintering and nesting shorebird data (general distribution and important areas) as extracted from ESI atlases. Dashed line indicates ESI atlas boundary.

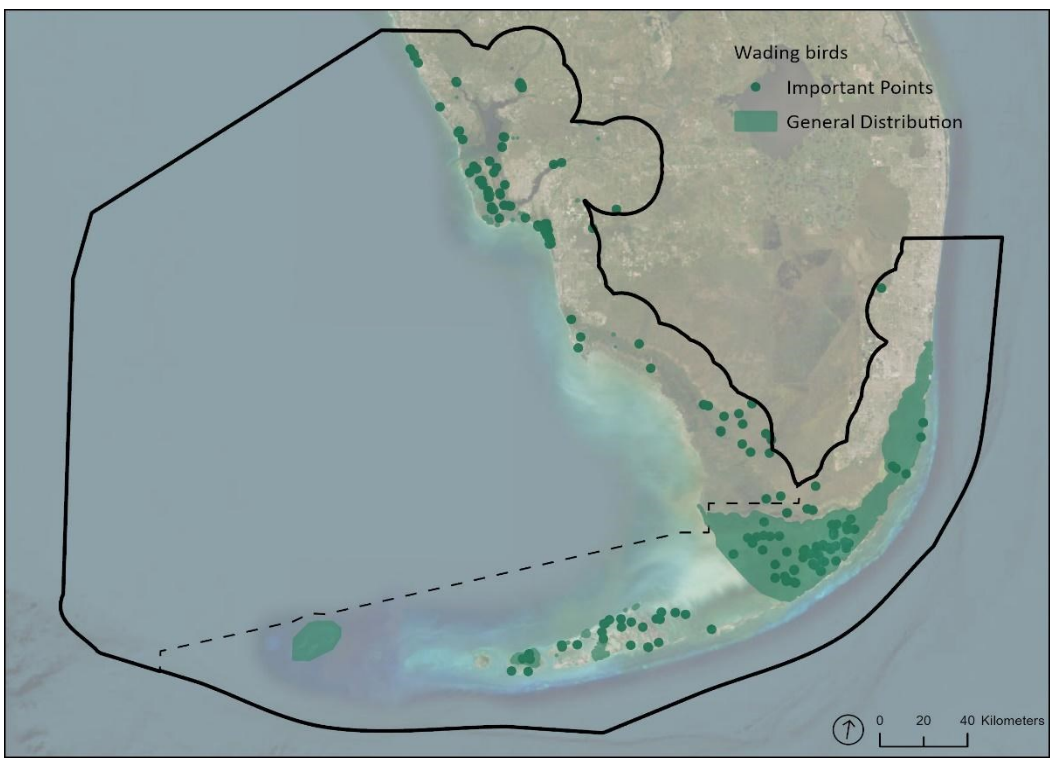

Figure 13. Wading bird data (general distribution and important areas) as extracted from ESI atlases. Dashed line indicates ESI atlas boundary.

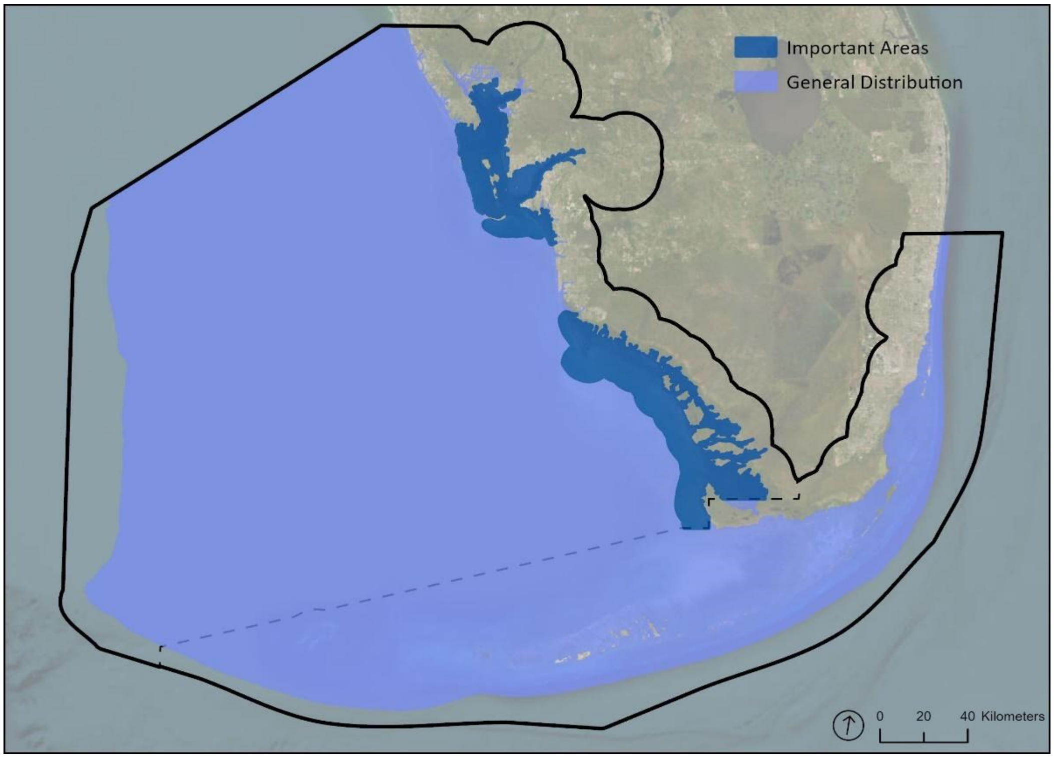

Figure 14. Smalltooth sawfish location data (general distribution and important areas) as extracted from ESI atlases. Dashed line indicates ESI atlas boundary.

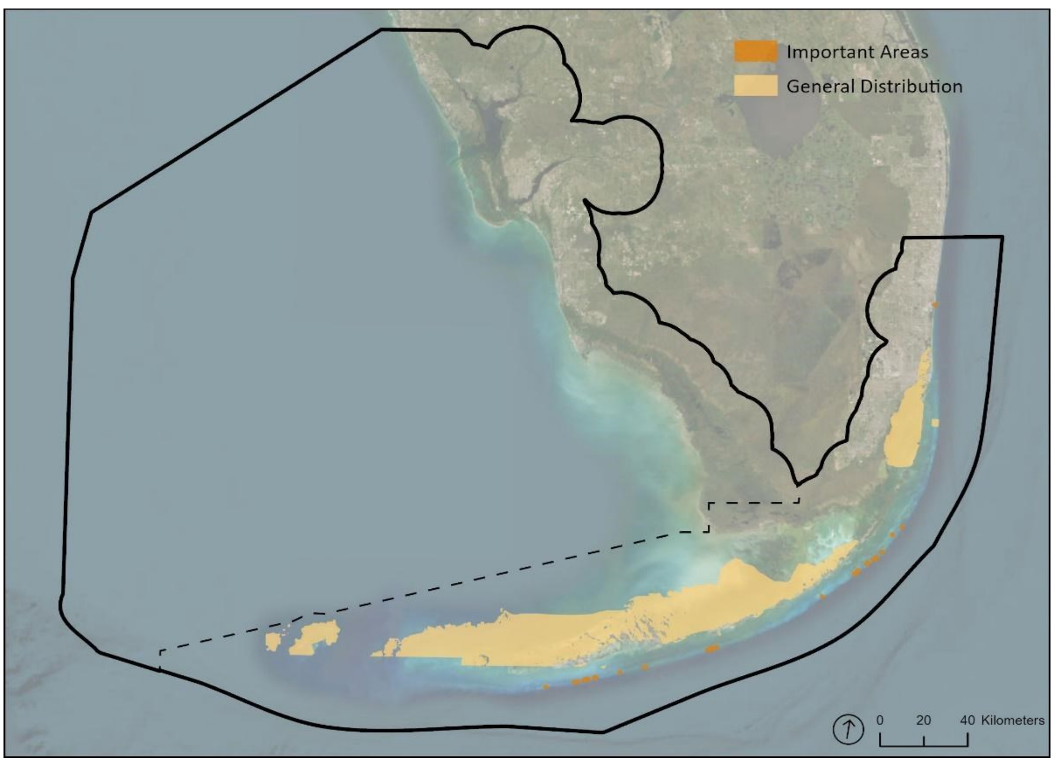

Figure 15. Queen conch location data (general distribution and important areas) as extracted from ESI atlases. Dashed line indicates ESI atlas boundary.

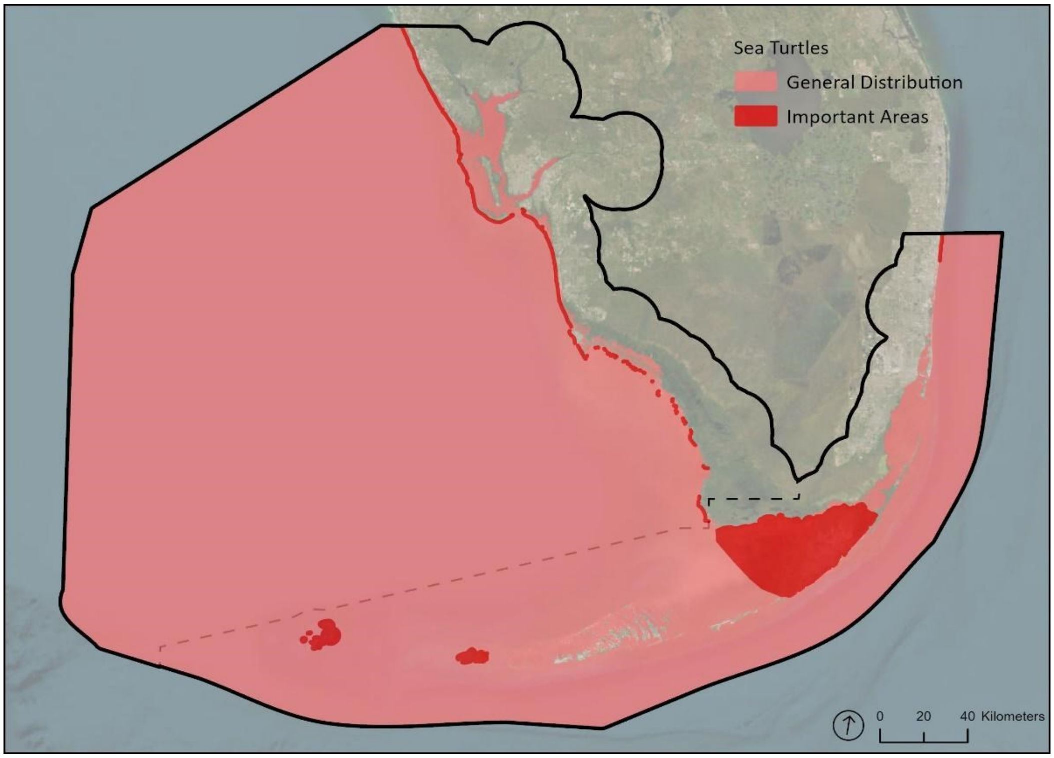

Figure 16. Sea turtle location data (general distribution and important areas) as extracted from ESI atlases. Dashed line indicates ESI atlas boundary.

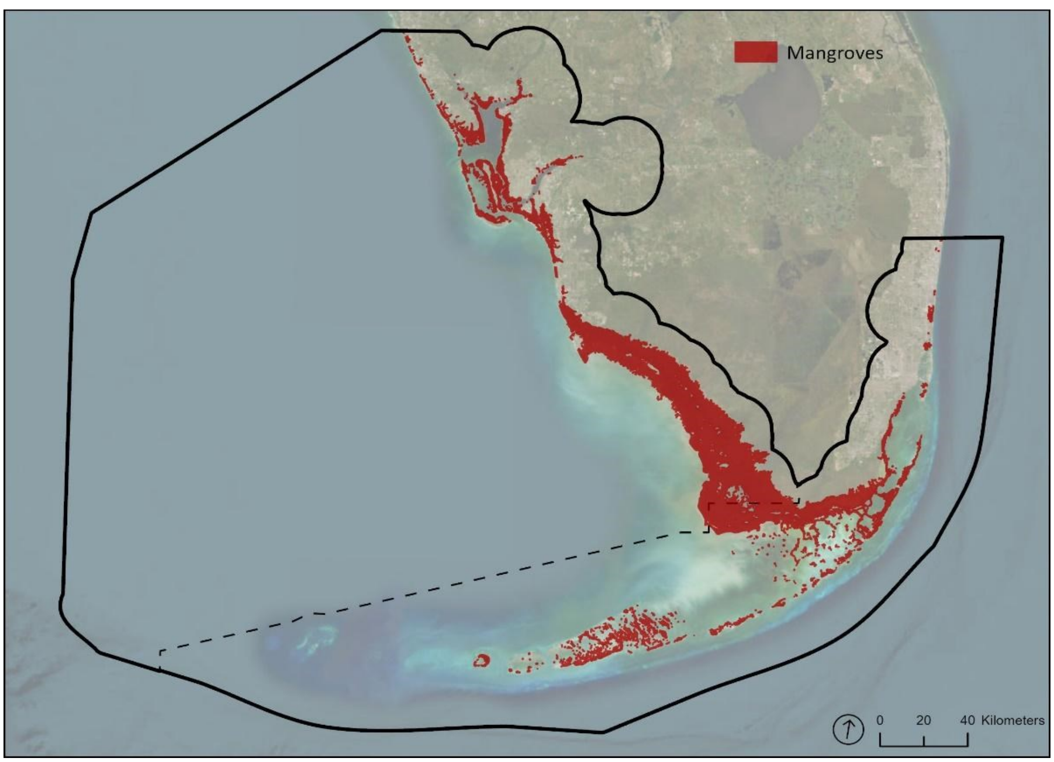

Figure 17. Mangrove location data as extracted from ESI atlases. Dashed line indicates ESI atlas boundary.

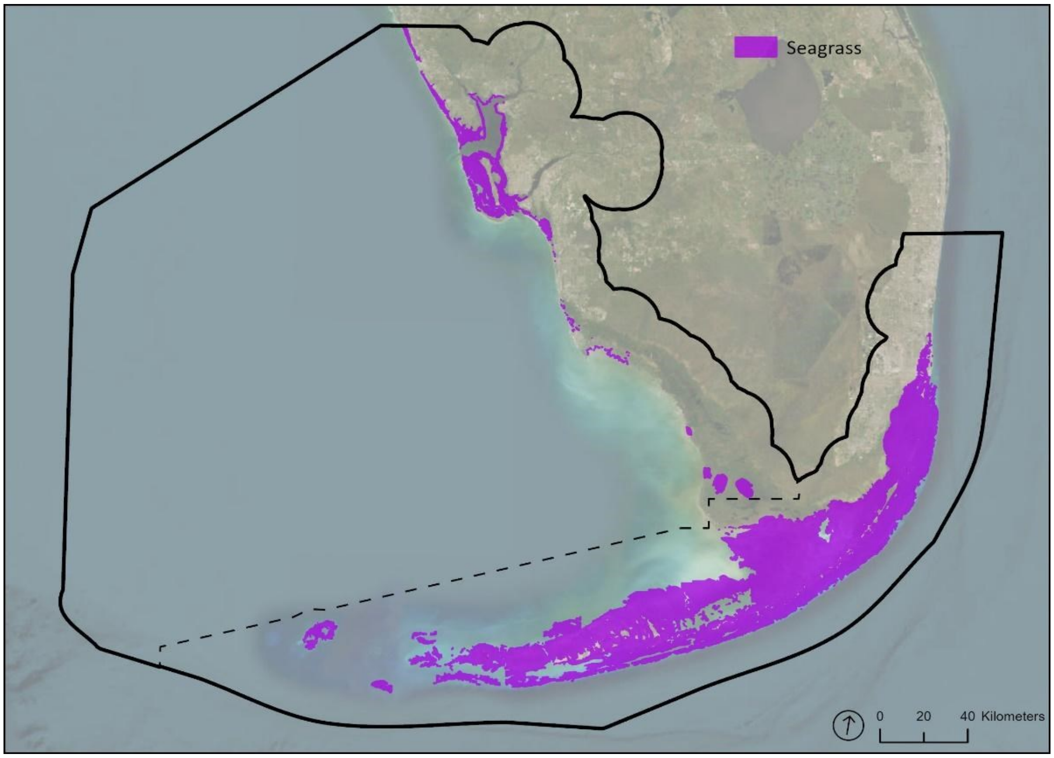

Figure 18. Seagrass location data as extracted from ESI atlases. Dashed line indicates ESI atlas boundary.

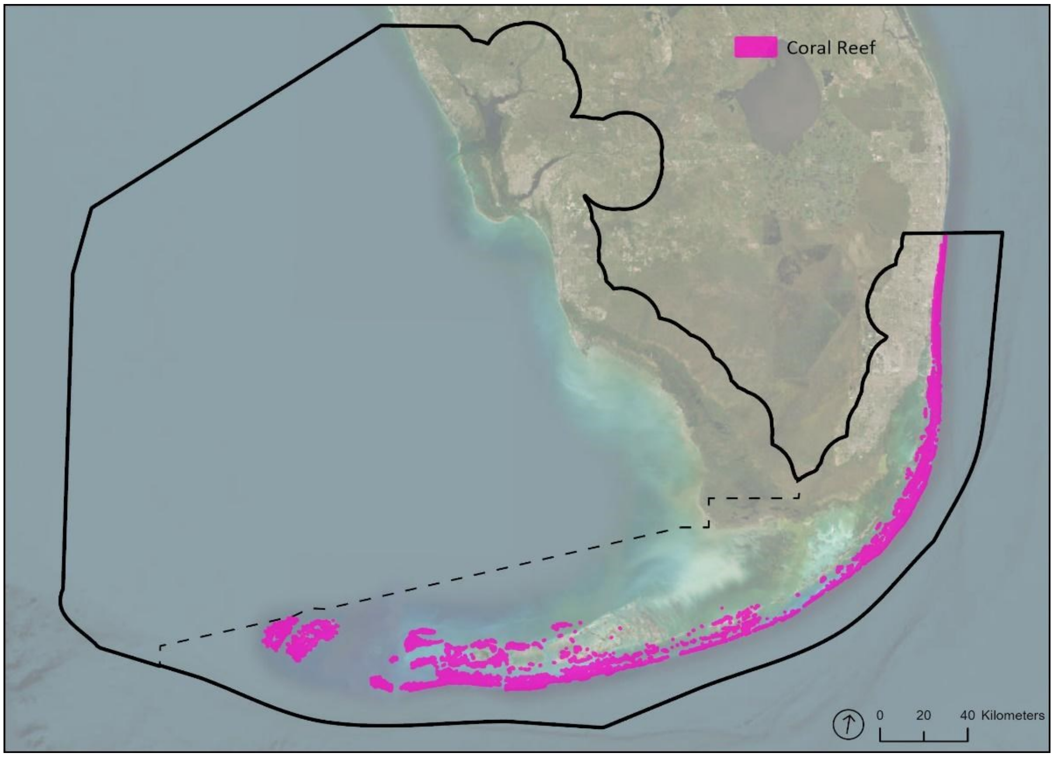

Figure 19. Coral reef location data as extracted from ESI atlases. Dashed line indicates ESI atlas boundary.

Human Population Receptors

In addition to the information on the distribution of natural resource receptors contained in the ESI atlases already, it was of interest to examine the feasibility of integrating information on the distribution of vulnerable human populations in the investigation. A number of different existing indices exist that quantify the distribution of vulnerable human populations. For this analysis, the Social Vulnerability Index (SoVI), developed by researchers at the University of South Carolina and University of Central Florida (Emrich et al. 2022a; Emrich and Cutter 2011), was adopted. SoVI is a model that measures vulnerability to the environment which synthesizes a total of 29 variables extracted from U.S. Census and American Community Survey (ACS) data. Other such indices exist and were comparatively evaluated (Appendix A). The variables are grouped into six pillars of vulnerability that include employment structure, housing, population structure, race and ethnicity, socioeconomic status, and special needs. SoVI is derived via a latent variable and using principal component analysis approach and yields an index representing the level of vulnerability in an area (Burton and Cutter 2008; Tate et al. 2010). Figure 20 depicts the 5-class categorization of the SoVI index for the study area.

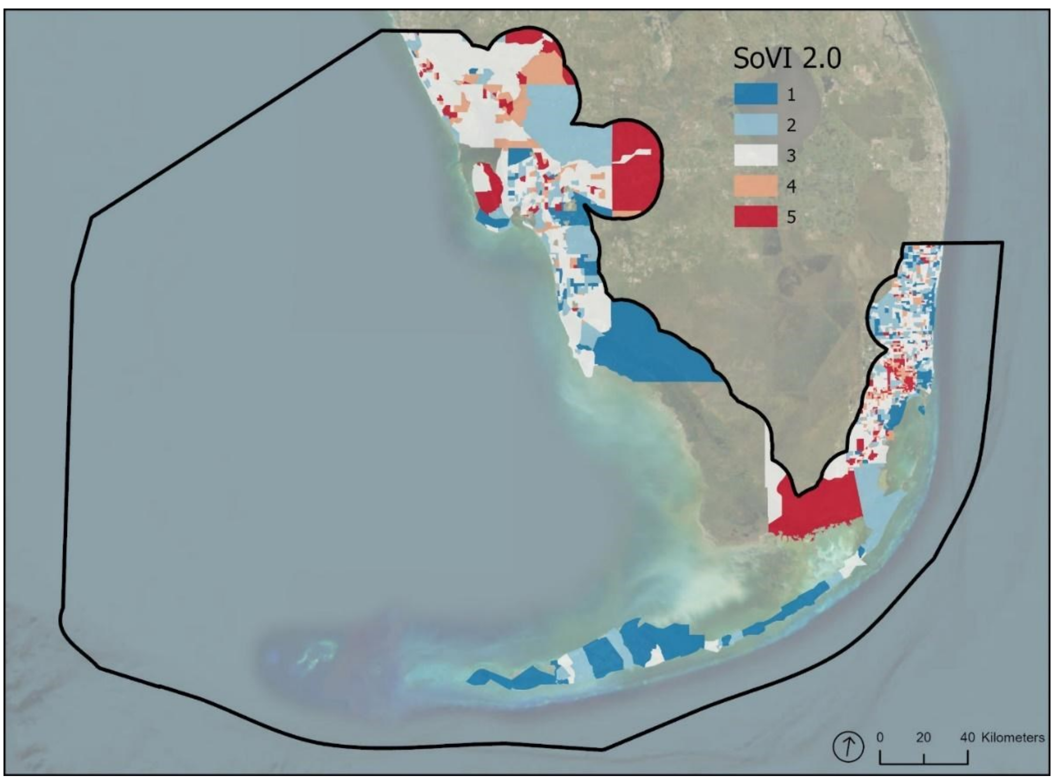

Figure 20. The 5-class categorical ranking of Social Vulnerability Index (SoVI), by census tract polygon, summarizing the distribution of socially vulnerable human populations as part of the ESI All-Hazards Expansion derived from compiled ESI data.

Sensitivity of Natural Resource Receptors to Stressors

Ten natural resources were selected to represent the range of sensitive biological resources and habitats for use in the pilot of the All-Hazards Indices Expansion of the Environmental Sensitivity Index (ESI) mapping products. A comprehensive literature search was conducted to assess the sensitivity of the ten identified natural resource receptors to each stressor/hazard type. Figure 21 summarizes the natural resources and shows the sensitivity rankings for each of the six stressors. The basis for the effects ranking is provided in the following tables, ordered by the listing of natural resources.

Resource / Receptor	Stressor / Hazard					
	Acute Coastal/ Storm Surge Flooding	Chronic Inundation	Marine Debris Events	High Wind Events	Shoreline Erosion	Contaminants from Spill Events
1. Terrestrial Mammals: Key deer	-	- -	-[a]	-	-[a]	-[a]
2. Marine Mammals: West Indian manatee	-	-	-	0[a]	-[a]	-
3. Shorebirds: Nesting and wintering	+[b]	-	-	0	- -	- -
4. Wading Birds	-[c]	-	-	-	- -	-
5. Fish: Smalltooth sawfish	0	-	0	0	0	-
6. Invertebrates: Queen conch	--	-[a]	-	0	-[a]	-
7. Reptile: Sea turtles	-	-	-	0	-	-
8. Wetlands: Mangroves	- -	-[d]	-	- -	- -	- -
9. Wetlands: Seagrass	-	- -	-	-	-	-
10. Hardbottom Habitat: Coral Reef	- -	- -	-	-	0	-

Sensitivity Ranking Key

- -	Large negative effect
-	Small negative effect, short term
0	No effect
+	Small positive effect

Footnotes:

[a] No literature found. Effect ranking is based on best professional judgment.

[b] See caveat for hurricane effect ranking following hurricane impacts literature summary.

[c] Most effects are negative, but some species under certain circumstances may benefit from post-hurricane conditions. See hurricane impacts literature summary.

[d] See caveat for chronic inundation effect ranking following inundation impacts literature summary.

Figure 21. Matrix of sensitivity rankings of stressors and natural resources used in the All Hazards Indices Expansion of the ESI.

Terrestrial Mammal (Key Deer)

Table 3. Summary of hurricane (acute coastal/storm surge flooding) impacts to Key deer.

Effect	Literature Summary
Drowning	• Lopez et al. (2003) documented the drowning of one radiomarked Key deer during the landing of Hurricane Georges (Category 2, 1998) in the Florida Keys. • Study of white-tailed deer (*Odocoileus virginianus seminolus*) movements in southwestern Florida during Hurricane Irma's landfall (Category 4, 2017) revealed behavioral responses to the hurricane. Deer selected higher elevation pine and hardwood forests and avoided marshes during the storm. Most deer left their home ranges, and no mortality was attributed to the hurricane (Abernathy et al. 2019). The limited habitat sizes on the small islands that Key deer inhabit may include little or no higher elevation refuge area, which may negatively affect their survival during a hurricane. Many small islands that

Effect	Literature Summary
	support small Key deer populations were completely inundated by storm surge from Hurricane Georges (Lopez et al. 2003).
Habitat degradation	• Storm surge due to Hurricane Wilma (Category 3, 2005) resulted in the mortality of trees in pine forests on Sugarloaf Key and Big Pine Key, which support most (approximately 75%; Lopez et al. 2003) of the Key deer population. At low elevations (<1 m), survival of pine trees on Big Pine Key was less than 20%; whereas, at elevations >1 m, two-thirds or more of pine trees survived. On Sugarloaf Key, live pine seedlings were completely absent following the storm (Ross et al. 2009). • Following Hurricane Irma, total mortality of pine trees in slash pine forests on Big Pine Key was 32%, with mortality concentrated in the largest trees (52% mortality for trees ≥ 25 cm DBH). Mortality was attributed to extensive salt water flooding throughout the island due to storm surge, and sea level rise (see following section on chronic inundation impacts) exacerbated storm surge mortality by allowing more of the land surface to be flooded by salt water (Ross et al. 2019).
Increased Key deer productivity (fawn:adult doe ratio)	• On Big Pine Key and No Name Key, Key deer productivity, measured as fawn:adult doe ratios, significantly increased following hurricane years (0.31 for non-hurricane years and 0.64 in post-hurricane years; Lopez et al. 2003). This difference may be explained by higher post-hurricane food availability. Following Hurricane Georges, overstory on Big Pine Key and No Name Key was reduced by approximately 50% due to strong winds and windthrown trees. This reduction in overstory may have resulted in increased understory forage for Key deer in the short term from downed trees and branches and in the long term due to regrowth and sprouting, which in turn may have resulted in increased fitness for female Key deer (Lopez et al. 2003).
Salinization of water holes	• Following Hurricane Wilma, salinity in sinkholes that normally contained fresh water on Big Pine Key became brackish and remained brackish through June 2006 (Ross et al. 2009). • Following Hurricane Georges, 27% of freshwater sinkholes monitored on islands that Key deer inhabit were found to be no longer suitable for deer use (salinity >15 ppt) due to encroachment by storm surge. Impacted water holes remained at unsuitable elevated salinities for weeks or months after the storm (Lopez et al. 2003).
Deposition of hurricane-related debris	• Parker et al. (2020) reported "ubiquitous hurricane-related debris" in Key deer habitat following Hurricane Irma.

Note: Hurricane impacts on Key deer populations may be mixed (both + and -). Negative effects from direct mortality, degradation of habitat, and decreased availability of drinking water may be somewhat offset by positive effects on Key deer productivity.

Table 4. Summary of chronic inundation impacts to Key deer.

Effect	Literature Summary
Change and loss of habitat due to saltwater intrusion of the root zone and freshwater lens	• Key deer prefer upland habitats (>1 m above mean sea level; pineland, hammock, developed) and avoid tidal or lower-elevation areas (<1 m above mean sea level; freshwater marsh, buttonwood, mangrove) (Lopez et al. 2004). These upland habitats are dependent on fresh groundwater to support the vegetation, particularly the salt-intolerant slash pine forests (Ross et al. 2009). In the Florida Keys, this groundwater exists as a shallow freshwater lens that lies below a shallow soil layer and a layer of oolitic limestone. This freshwater lens floats on top of the underlying salt water and reaches up into the limestone layer where it provides fresh water to root zones and terrestrial species. The areal extent and depth of the freshwater lens are affected by tides, rainfall, evapotransporation, and pumpage from local wells, and the lens can be shrunk or displaced by sea level rise (SLR). By shrinking and salination the freshwater lens, SLR can lead to vegetation and habitat change from the Key deer's preferred pine forest and hammock habitats to mangrove and estuary habitats (Miller and Harwell 2022). Ross et al. (2009) attribute a transition of pine forest to more salt-tolerant vegetation types on Sugarloaf Key to a shrinking freshwater lens because of SLR. Their data show a decline of pine forest from 88 ha before 1935 to 30 ha in 1991. Using SLR model projections on islands inhabited by Key deer, Miller and Harwell (2022) calculated reductions of dry land habitat (developed and undeveloped, respectively) of 10.6% and 18.5% with 0.3 m of SLR, 35.2% and 51.3% with 0.6 m of SLR, 70.3% and 78.8% with 0.9 m of SLR, and 87.2% and 90.2% with 1.2 m of SLR. Thus, dry land will be replaced by mangroves, which Key deer

Effect	Literature Summary
	avoid. The authors conclude that beyond 0.9 m of SLR, Key deer have few adaptation options other than relocation outside of the Florida Keys. • Chronic inundation will be punctuated by short-term, stochastic, and extreme events (e.g., king tides and storm surge), which will cause the elevation of root zone to be inundated with seawater well before projections of mean sea level reach that elevation (Miller and Harwell 2022). These events could accelerate habitat change. • In a standardized vulnerability assessment conducted on species in Florida, Reece et al. (2013a) found that Key deer had "exceedingly high extinction risk", with SLR as one of the primary threats influencing their extinction risk (along with other barriers to dispersal and genetic swamping or competition with mainland deer if Key deer are relocated).
Loss of fresh drinking water	• Miller and Harwell (2022) note that along with the loss of habitat with SLR, fresh drinking water sources for Key deer will also be reduced.

Table 5. Summary of marine debris impacts to Key deer.

Effect	Literature Summary
Entanglement	• Water deer (*Hydropotes inermis*) are a coastal deer species found in Korea. Hong et al. (2013) reported an incidence of a water deer getting entangled in a derelict gill net in the Han River estuary. Its legs were entangled in the net, which led to its drowning during a flood tide.

Note: No literature was found on impacts of marine debris on Key deer, but one study was found on marine debris impacts on another coastal deer species found in Korea. Impacts to Key deer would likely be similar to those observed on coastal deer in Korea.

Table 6. Summary of convective storm wind event impacts to Key deer.

Effect	Literature Summary
Reduced feeding	• Hardin (1974) found no statistically significant correlation of wind on Key deer feeding in summer, but found that high wind was associated with reduced feeding activities in winter. Additionally, Barrett and Stiling (2006) noted that Key deer were "apprehensive to feed" on days with strong wind.
Reduced activity	• Hardin (1974) found that Key deer activity (movement) decreased with increasing wind speeds. Key deer also bedded more in strong winds.
Change in habitat use	• Hardin (1974) observed that Key deer were "cautious and stayed in heavy cover" on days with very strong winds (30 mph or more).

Note: No specific studies were found of convective storm high wind event impacts on Key deer. The one study found that integrated impacts of wind on Key deer examined wind as a continuous (binned) variable rather than an event. Storm event impact studies on Key deer focused on hurricanes (see hurricane section above).

Table 7. Summary of shoreline erosion impacts to Key deer.

Effect	Literature Summary
Potential habitat loss	• Key deer generally prefer upland habitats (>1 m above mean sea level) and avoid tidal or lower-elevation areas (<1 m above mean sea level) (Lopez et al. 2004), but as shoreline habitats erode and migrate landward, available upland habitat on the islands inhabited by Key deer may decrease in area. Habitat loss due to urban development and sea level rise is a major threat to Key deer persistence and recovery (Lopez et al. 2004; Miller and Harwell 2022; Reece et al. 2013a), and shoreline erosion may indirectly impact Key deer populations by causing further upland habitat loss.

Note: No literature was found on shoreline erosion impacts on Key deer, so impacts discussed are considered "potential" and are based on best professional judgment.

Table 8. Summary of contaminant/spill event impacts to Key deer.

Effect	Literature Summary
Direct exposure to oil	• While mammals that feed on shoreline habitats may be exposed to oil through inhalation, fur contact, or ingestion while grazing (Bergeon Burns et al. 2014), Key deer prefer upland habitats (>1 m above mean sea level; pineland, hammock, developed) and avoid tidal or lower-elevation areas (<1 m above mean sea level; freshwater marsh, buttonwood, mangrove) (Lopez et al. 2004). Therefore, direct marine spill impacts on Key deer, while possible, are considered to be minimal.
Habitat disturbance due to response activities	• Upland terrestrial habitats that are adjacent to oiled shorelines are often used for spill response staging areas, access corridors, or decontamination sites (Michel et al. 2017), which could disturb or degrade Key deer habitat.

Note: No literature was found on spill impacts to Key deer, so impacts discussed are considered "potential" and are based on best professional judgment.

Marine Mammals (West Indian Manatee)

Table 9. Summary of hurricane (acute coastal/storm surge flooding) impacts to manatees.

Effect	Literature Summary
Lower survival probability	• Using mark-resighting statistical models and 19 years of photoidentification data, Langtimm and Beck (2003) found significant annual variation in adult survival of Florida manatees in northwest Florida. Variation coincided with years with strong hurricanes (Category 3 or greater), and analysis suggested a cause-effect relationship. Mean survival probability during years without strong hurricanes was 0.972. Survival probability dropped to 0.936 in 1985 with Hurricanes Elena, Kate, and Juan; and to 0.817 in 1995 with Hurricanes Opal, Erin, and Allison. Proposed mechanisms for the lower survival probabilities during hurricane years include: stranding from storm surge, blunt injury from debris, being swept out to sea, and death from cold stress in colder waters following hurricanes if storms occurred in late fall. • In 2004 and 2005, years with several major hurricanes impacting Florida, tagged manatees were observed to stay in their pre- and post-storm home ranges during the storms, rather than making lateral movements or moving either further inland or offshore to deeper water for greater protection (Langtimm et al. 2006). Thus, Langtimm et al. (2006) suggest that hurricane effects on manatee survival will be confined to the manatees inhabiting areas within the track line of the storm.
Emigration and/or starvation when food base (seagrass) is degraded or destroyed*	• On the coast of Queensland, Australia, increased movements of dugongs occurred following extensive damage to seagrass beds caused by the tropical cyclone Althea in 1971. A dietary change in dugongs occurred along with their increased movements, with large amounts of macroalgae in addition to seagrass found in stomach contents of 9 out of 12 dugongs after the storm, compared to only 2 out of 16 dugongs prior to and immediately after the storm. This dietary shift suggests that dugongs had to move greater distances in search of food (Heinsohn and Spain 1974). • In Hervey Bay, Australia, the dugong population dropped precipitously following the loss of seagrass habitat. In 1988, southern Hervey Bay contained an estimated 1753 (±388 s.e.) dugongs. Following two floods and a cyclone in 1992 that resulted in the loss of 1000 km^2 of seagrass from Hervey Bay, the southern bay population of dugongs numbered only 71 (±40) individuals. Ninety-nine dugong carcasses were recovered following the loss of seagrass, with most dying 6-8 months later and emaciated from starvation. Many dugongs left Hervey Bay after the loss of seagrass, and some travelled upwards of 900 km before they died. Some did successfully relocate to other areas, temporarily boosting the abundances of other populations (Preen and Marsh 1995).
Decreased proportion of calves in the population*	• Following the 1992 die-off of seagrass in Hervey Bay, Australia, the proportion of dugong calves in the regional (Hervey Bay plus Great Sandy Strait) population declined, from 22% in 1988 to only 2.2% in 1993 (Preen and Marsh 1995).

Note: No literature was found on these effects in Florida manatees, but these effects are well-documented in Australia in dugongs, another Sirenia species.

Table 10. Summary of chronic inundation impacts to manatees.

Effect	Literature Summary
Loss or degradation of warm-water refuges	• Most Florida manatees rely on localized warm-water refuges to survive winter, including areas of warm water discharge (natural springs and power plant outfalls; Laist and Reynolds III 2005; Laist and Reynolds 2005). Sea level rise may result in the flooding and disruption of coastal power plants whose outfalls create warm-water refuges (Hardy et al. 2019; Martin et al. 2011). Additionally, inundation and saltwater intrusion will reduce the amount of freshwater available for human consumption in Florida and cause greater demands for groundwater removal, which in turn will reduce natural warm-water spring flow that creates manatee thermal refuges. Monitoring and hydrological modeling indicate that certain minimum flow levels at natural springs are required to maintain manatee thermal refuges (Martin et al. 2011).

Table 11. Summary of marine debris impacts to manatees.

Effect	Literature Summary
Lethal and sublethal effects due to debris ingestion	• From 1978 to 1986, marine debris was found in the gastrointestinal tracts of 14.4% of examined salvaged dead Florida manatees, and four manatees died as a direct result of debris ingestion (Beck and Barros 1991). • From 1993 to 2012, in the Florida Fish and Wildlife Research Institute (FWRI) manatee mortality database, there were 37 cases of ingestion of marine debris as the probable cause of death. An additional 598 manatees had marine debris in their gastrointestinal tracts (non-lethal ingestion). Overall, 9.7% of all manatee carcasses examined during this period had ingested marine debris (Reinert et al. 2017). • Ingestion of marine debris by manatees can cause impaction, peritonitis, intussusception of the small intestine, obstruction, and perforation of the gastrointestinal tract (Beck and Barros 1991; Reinert et al. 2017). • Necropsies of 26 dead manatees from Tampa Bay revealed macroplastic pieces in the gastrointestinal tracts of seven (26.9%) individuals and microplastic pieces in the gastrointestinal contents of 19 (73.1%) individuals. Five individuals contained both macro- and microplastic pieces, so the overall frequency of plastic ingestion was 76.9%. The physiological effects of microplastic ingestion on sirenians are unknown (Gowans and Siuda 2023). • Adimey et al. (2014) suggested that manatees incidentally ingest marine debris due to their feeding behavior of indiscriminate foraging in shallow habitats.
Entanglement	• Entanglement in marine debris (lines and nets) killed 11 Florida manatees from 1974 to 1986, and numerous living manatees at the time had missing or scarred flippers from past entanglements or flippers that were currently still entangled (Beck and Barros 1991). • From 1997 to 2009, 380 of the total 4,962 manatee strandings reported in Florida were identified as fishery gear interactions, and the number of reported fishery gear interaction cases increased over time (Adimey et al. 2014). • From 1993 to 2012, in the FWRI manatee mortality database, there were 13 cases of entanglement as the probable cause of death. Of these 13 cases, six manatees died as a result of a secondary infection related to the entanglement. An additional 101 manatee carcasses had external evidence of entanglement. Overall, 1.7% of all manatee carcasses examined during this period had evidence of external entanglement in marine debris (e.g., attached line, scars, amputations; Reinert et al. 2017). • From 1993 to 2012, 21.8% of the reported 1244 manatee rescues in the FWRI database were classified as entanglements, making entanglement the second leading cause for rescue. Several rescued manatees exhibited signs of multiple entanglements, including healed entanglement wounds (Reinert et al. 2017). • Manatee entanglements in fishery gear most commonly occurred on the flippers (Adimey et al. 2014; Reinert et al. 2017). • Entanglement observations were less common in calves than in juvenile and adult manatees. This trend may be due to juveniles and adults spending most of their day feeding, when they are likely to encounter debris; whereas, calves nurse rather than forage, which may reduce their chances of debris interaction (Adimey et al. 2014).

Table 12. Summary of convective storm wind event impacts to manatees.

Effect	Literature Summary
Potential decrease in survival probability	• While wind speed was not reported, Langtimm and Beck (2003) observed a decrease in survival probability of manatees in northwest Florida following a strong winter storm in March 1993 (survival probability of 0.972 during years with no or low intensity storms and 0.909 in 1993). Winter storms generally are not rated on the Saffir-Simpson Hurricane Scale, but comparisons of barometric pressure and storm surge heights during this winter "Storm of the Century" with the scale indicated that the storm was analogous to a Category 3 hurricane. This comparison suggests that this storm brought strong winds to the area; however, conclusions on impacts of wind during this storm event at the exclusion of other variables are not possible with the available data.
Reduced winter counts of manatees with increased wind speeds	• Manatee counts from aerial surveys in Tampa Bay from 1987 to 1994 were significantly reduced in the cold season as wind speeds increased; however, wind speed was not significantly related to year-round or warm season counts (Wright et al. 2006). Wright et al. (2006) note that higher winds disturb the water surface and can make aerial observations difficult, but no discussion of the seasonal differences in the relationship between manatee counts and wind speed is presented.

Note: No specific studies were found of convective storm high wind event impacts on manatees. Langtimm and Beck (2003) suggest potential impacts from a storm event, but effects of wind specifically are not presented and cannot be disentangled from other storm variables. The only study found that investigated impacts of wind on manatees (Wright et al. 2006) examined wind as a continuous variable rather than an event.

Table 13. Summary of shoreline erosion impacts to manatees.

Effect	Literature Summary
Potential declines in seagrass habitat due to erosion	• Seagrass habitats are declining worldwide and are projected to continue to decline with negative effects of erosion (e.g., Cabaço et al. 2008; Duarte 2002). Seagrasses are manatee's principal food resource (e.g., Lefebvre et al. 2017), so impacts to seagrass habitat will likely have cascading impacts on manatee populations.

Note: No literature was found on shoreline erosion impacts on manatees, so indirect impacts are assumed from degradation of manatee's seagrass habitat and based on best professional judgment. See Seagrass literature summary for details of shoreline erosion impacts to that resource.

Table 14. Summary of contaminant/spill event impacts to manatees.

Effect	Literature Summary
Direct effects of oil exposure	• Manatees can be exposed directly through inhalation, ingestion, and dermal exposure. For most marine mammals, the most serious threats may be from severe damage to the respiratory system through inhalation of toxic aromatic oil components and damage to internal organs due to ingestion of oil (Helm et al. 2014), but specific impacts of oil exposure on manatees are largely unknown (Wilkin et al. 2017). Other expected effects of oil exposure based on studies of other marine mammals include short-term irritation of the eyes and mucus membranes (Helm et al. 2014). Oil likely would not cause much harm to the thick epidermis of manatees (St Aubin and Lounsbury 1990), but sensory hairs that may have a function in orientation could be negatively affected if oiled (Helm et al. 2014). • Only anecdotal reports exist on impacts of oil spills on sirenians: o During the Iran-Iraq War in 1983, 53 dugong carcasses were recovered in the Arabian Gulf approximately 5 months after the spill, but no necropsy data were gathered (St Aubin and Lounsbury 1990). o In 1991, 14 dead dugongs were observed in the impact area of the Gulf War oil spill (Helm et al. 2014). o No manatee deaths due to oil or dispersants were confirmed during the *Deepwater Horizon* spill (Helm et al. 2014).
Indirect effects of oil exposure*	• Manatees can be indirectly impacted by an oil spill if the abundance and quality of their food (seagrass) has been reduced as a result of the spill (Helm et al. 2014).
Impacts of spill response activities*	• Manatees can be susceptible to impacts from spill response activities, including collisions with boats and entanglement in ropes and lines (Helm et al. 2014).

*These effects are considered “potential”, as no case studies of these effects were found in the literature search.

Shorebirds (Nesting and Wintering)

Table 15. Summary of hurricane (acute coastal/storm surge flooding) impacts to nesting and wintering shorebirds.

Effect	Literature Summary
Nesting habitat creation from overwash	• Convertino et al. (2011) reported that along the Gulf coast of Florida, favorable snowy plover (a resident shorebird) nesting areas are located in regions impacted more frequently by tropical cyclones. The odds of snowy plover nesting in these areas the spring following a tropical cyclone was seven times higher than the odds in the spring following a season without a cyclone. Furthermore, they found that the occurrence of snowy plover nesting grounds is 8.5 times more likely in the spring following a tropical cyclone compared to years without a cyclone. • Hurricane Isabel (2003) resulted in an increase of open sand flat area (nesting habitat for American oystercatchers and other shorebirds) from 31 to 110% at sites in North Carolina. American oystercatcher nest survival at one site increased from 0.170 during baseline years to 0.772 in the year immediately following the hurricane (2004); whereas, the other site exhibited no effect of the hurricane on nest survival (Schulte and Simons 2016). • Hurricane Sandy (2012) resulted in the overwash of Fire Island and Westhampton Island (NY) and flattened dunes, buried vegetation, and breached the barrier islands. Prior to the hurricane, piping plovers selected nest sites farther from the ocean and bay than would be expected with random nest site selection. After the hurricane, piping plovers selected nest sites closer to the ocean and bay, predominantly in or near storm overwash habitat and newly created bayside foraging habitats. Piping plover breeding pair abundance increased 93% by 2018 from pre-Hurricane Sandy levels, with most pairs nesting in new, hurricane-created habitats (Walker et al. 2019). American oystercatchers, willets, and killdeer were also observed nesting in Hurricane Sandy-created habitats in this study (Walker et al. 2019). Zeigler et al. (2019) found that Hurricane Sandy increased piping plover habitat by 9 to 300% at sites in New York and New Jersey and decreased habitat by 27% at a site in Virginia (the Virginia site may have been too far from the epicenter of the storm to create new early successional habitat). At these study sites, 14 to 57% of all piping plover nests were located in newly created habitat in the 2013 breeding season. (While piping plovers do not nest in Florida, they are often used as an “umbrella conservation species” for co-occurring nesting shorebirds (Maslo et al. 2016).)
Reduction in nest depredation	• During non-hurricane years on North Core Banks (NC), 58% of American oystercatcher nests laid were lost to mammalian depredation. In the first year after Hurricane Isabel (2003), nests lost to mammalian predation dropped to 20%, and signs of predators (tracks and sightings) disappeared almost entirely. On nearby South Core Banks (NC), no reduction of mammalian predation on nests was observed (Schulte and Simons 2016).
Loss of foraging habitat	• Johnson and Baldassarre (1988) reported the destruction of piping plover feeding sites at Dauphin Island and Little Dauphin Island (Alabama) during Hurricane Elena in September 1985. Increased piping plover foraging was observed at a nearby alternate feeding site following the hurricane.
Nest washout	• Shorebird nests can be washed out with storm surges (see Denmon et al. 2013; Jodice et al. 2014; Schulte and Simons 2015; Schulte and Simons 2016; and Chronic Inundation section below). However, shorebird nesting season for many species in Florida ends before hurricane season becomes most active (South Florida ESI 2013; Southwest Florida ESI 2016).

Note: Temporal and spatial aspects of storm events (when and where they occur) influence their impacts on shorebirds. Whether effects are + or – would largely be determined by timing of storm during nesting season (negative or net neutral effects if storm occurs during nesting season; positive effects on shorebird populations in subsequent year(s) if storm occurs after nesting season). Also, similar nearby sites impacted by a single hurricane can have different storm effects on shorebird populations (Schulte and Simons 2016).

Table 16. Summary of chronic inundation impacts to nesting and wintering shorebirds.

Effect	Literature Summary

Reduced foraging and nesting habitat	• Galbraith et al. (2002) projected major losses (up to 70%) of intertidal foraging habitat for shorebirds due to inundation from sea level rise. Sites studied were either categorized by the Ramsar Convention or by the Western Hemisphere Shorebird Reserve Network (WHSRN) as at least hemispheric importance for migratory or wintering shorebirds, and included sites in Willapa Bay (Washington), Humboldt and San Francisco Bays (California), Bolivar Flats (Texas), and Delaware Bay (New Jersey and Delaware). Losses were projected to be most severe at sites where the topography prevents movement of the tidal zone inland or at sites with human structures such as seawalls. • Von Holle et al. (2019) projected that 51% of coastal nesting habitat for Wilson's plover, 44% of nesting habitat for American oystercatcher, and 50% of wintering habitat for piping plover would be more vulnerable to sea level rise, compared to its 2000 vulnerability, in the South Atlantic Bight (Cape Hatteras, NC to Sebastian Inlet, FL).
Nest washout/ flooding	• Jodice et al. (2014) reported that overwash (flooding) accounted for up to 89% of American oystercatcher nest loss in the Cape Romain region of South Carolina. Maximum tide height has a strong effect on daily survival rate of nests, and flooding is the most common cause of American oystercatcher nest loss in the region. Overwash from storms and spring tides was also a major source of American oystercatcher nest failure in the Outer Banks of North Carolina (Schulte and Simons 2015) and in Fisherman Island National Wildlife Refuge in Virginia (Denmon et al. 2013).
High tide roost inundation	• Increased risk of inundation of American oystercatcher roosts (measured by increased duration of extreme high tides) on the Florida coast was associated with a 7.3% decline in annual survival, from 0.96 to 0.89, over a 12-year study period (2007-2018; Griffin et al. 2023).

Table 17. Summary of marine debris impacts to nesting and wintering shorebirds.

Effect	Literature Summary
Lethal and sublethal effects due to debris ingestion	• Ingested debris can accumulate in a bird's digestive tract, which can block the digestive tract, reduce digestive capacity, reduce appetite and food intake, and lead to starvation (e.g., Pierce et al. 2004). Also, chemical contaminants from debris can be released in the digestive tract, or birds may ingest contaminated prey (e.g., Tanaka et al. 2013). • A review of shorebird plastic ingestion by Flemming et al. (2022) found that 53% of shorebird individuals sampled from 26 species within 16 studies contained some form of plastics pollution. Species that foraged at sea, on mudflats, or on beaches had a higher frequency of occurrence of plastic ingestion than species that foraged in upland or freshwater habitats. Also, species that used a sweeping foraging technique had a higher probability of ingesting plastics than those that used visual or tactile techniques.
Entanglement	• A global review of bird interactions with anthropogenic litter reported several studies with evidence of entanglement of shorebird species (Battisti et al. 2019). • Winter storm surges continuously supply litter to beaches in Italy, increasing the density of entangling litter (fishing lines, hooks, and nets) throughout the season. At the study site, two plover species were recorded to be entangled in litter from 2018-2022 (Battisti et al. 2023).

Note: General impacts of marine debris on shorebirds are reported here. No papers were found on impacts of storm-specific marine debris events on shorebirds.

Table 18. Summary of convective storm wind event impacts to nesting and wintering shorebirds.

Effect	Literature Summary
Change in habitat use	• Jech and Forys (2023) surveyed piping plover, snowy plover, and Wilson's plover on tidal mudflat and adjacent beach habitats in Southwest Florida outside their breeding season (surveys conducted September to March 2022) to examine the influence of wind and tide on their abundance and foraging. Abundances of piping and Wilson's plovers increased on mudflats with decreased tide, and this increase was greatest when wind was low. The abundances of both species increased on the beach with increasing tide and wind. Snowy plover abundance increased on mudflats with decreased tide but was not affected by wind speed on mudflats. Snowy plover abundance on the beach increased with increasing wind and tide. All three species appeared to seek refuge on the beach during high winds and tides. Piping and snowy plovers were only observed foraging on mudflats, and Wilson's plovers were not

Effect	Literature Summary
	observed foraging during the study. Peck rates of piping and snowy plovers were not affected by tide or wind.

*No specific studies were found of convective storm high wind event impacts on shorebirds. The only study found that investigated impacts of wind on Florida shorebirds examined wind as a continuous variable rather than an event. Storm event impact studies on shorebirds focused on hurricanes (see hurricane section above).

Table 19. Summary of shoreline erosion impacts to nesting and wintering shorebirds.

Effect	Literature Summary
Habitat loss	• On Fire Island, New York, Zeigler et al. (2022) predicted reductions in piping plover nesting habitat area from 5.1 km^2 observed in 2014-2015 to 4.3 km^2, 3.6 km^2, or 2.8 km^2 by 2050 under three different shoreline change scenarios. (While piping plovers do not nest in Florida, they are often used as an “umbrella conservation species” for co-occurring nesting shorebirds (Maslo et al. 2016).)
Increased habitat usage around breakwaters built to counteract shoreline erosion	• Shoreline behind breakwaters built to counteract shoreline erosion off the coast of Louisiana supported higher piping plover densities (12.4 piping plovers per km) than unprotected shoreline (0.49 piping plovers per km). Possible explanations for this trend include: 1) breakwaters decrease wave energy and increase sediment accretion; 2) more macroinvertebrate may exist on protected shoreline; and 3) piping plovers may congregate along protected shorelines to be more secure from predators because other waterbirds are also attracted to these sites (Selman and Collins 2018).
Decreased shorebird species richness and abundance	• Dugan et al. (2008) reported decreased shorebird species richness and abundance on armored shorelines, which experience greater erosion than unarmored shorelines. Mean species richness was two times greater on unarmored shoreline segments (2.2 species) than on armored segments (1.1 species), and mean abundance was more than three times greater for unarmored segments (19.3 birds per km) than for armored segments (5.6 birds per km). These differences were attributed to habitat loss, reductions in macroinvertebrate prey availability, and decreased accessibility during high tide. (Coastal armoring accelerates shoreline erosion, so armored shorelines are considered here as a treatment proxy for high erosion conditions, in the absence of other literature.) • Menn (2002) reported higher sanderling abundance on an accreting sandy shore in the North Sea relative to an adjacent eroding sandy shore, likely due to differences in invertebrate prey communities that were supported by the two habitat types.

Note: No literature was found on shoreline erosion impacts on shorebirds in Florida, so studies from other regions are discussed. Additional studies that examined impacts to shorebirds of structures built to counteract shoreline erosion are included.

Table 20. Summary of contaminant/spill event impacts to nesting and wintering shorebirds.

Effect	Literature Summary
Impaired pre-migratory fueling/ Delayed migration	• Bianchini and Morrissey (2018b) captively dosed sanderling with polycyclic aromatic hydrocarbons (PAH) during a simulated pre-migratory fueling period, resulting in reduced body mass gain in dosed birds relative to controls. Changes in fat load, biochemical profiles, liver mass, and lipid content following dosing suggest that PAH exposure can interfere with lipid transport and metabolism, cause muscle damage, and result in reduced overall fat loads, which in turn can impact migratory success. • Inadequate premigratory fattening can result in delayed departure for breeding grounds (Henkel et al. 2012). A field study following the *Deepwater Horizon* spill measured body mass, morphometrics, and plasma metabolites in sanderling and red knots captured during their northward migrations from sites in Louisiana (heavily impacted, high sediment PAH concentrations) and Texas (lower sediment PAH concentrations). Fueling rates for sanderling were lower in Louisiana than in Texas, and both species departed later for continued migration from Louisiana (Bianchini and Morrissey 2018a). Earlier arrival on breeding grounds is associated with increased clutch size and offspring survival (Harrison et al. 2011). • Shorebirds following the *Deepwater Horizon* spill were likely exposed to indirect effects of the spill, including reduced foraging time due to oiling of foraging habitat or disturbance by spill cleanup

Effect	Literature Summary
	activities. Dunlin fuel stores and fattening rates during spring migration were not influenced by site oiling level, but were influenced by the level of disturbance from cleanup activity at study sites, with lower energy reserves at sites with the highest level of disturbance. This suggests that dunlin stopping over in the northern Gulf of Mexico during migration may have had difficulty reaching necessary fuel stores due to disturbance from spill cleanup activities (Henkel et al. 2014). Burger (1997) observed nearly 50% of foraging time of shorebirds on beaches was interrupted by cleanup personnel and vehicles following the *Anitra* spill in New Jersey. Additionally, time spent preening oiled plumage (i.e., time not spent foraging) was positively correlated with the percent of the bird that was oiled.
Physiological effects of oil exposure	• Physiological effects of oil exposure on shorebirds can be lethal or sublethal, and occur through several pathways: o Loss of waterproofing and insulating capabilities of feathers, leading to death from hypothermia (Leighton 1993). o Oil ingestion through preening of oiled feathers and/or foraging in contaminated habitats, leading to dehydration, starvation, infections, pneumonia, arthritis, gastrointestinal problems, and cloacal impaction. Oil ingestion can cause mortality primarily through acute toxic effects to the liver, kidney, and gastrointestinal tract (Briggs et al. 1996; Leighton 1993). o Sublethal toxicological effects can also result from ingested oil, including hemolytic anemia, reduced reproduction, and immunosuppression (Henkel et al. 2012). o Eye irritation from oil contact (Briggs et al. 1996).
Prey and habitat switching	• Shorebirds have been documented to switch to non-preferred prey and alternative habitats if the intertidal zone cannot fulfill their energy requirements. Lower quality prey and habitats could result in decreased fitness and reproductive success. Though prey switching has not been documented in shorebirds following an oil spill, this is a potential impact of oil spills on these species (Henkel et al. 2012).
Reduced flight performance	• Small amounts of crude oil on the wings and tail of western sandpipers reduced takeoff flight performance by reducing distance traveled in the first 0.4 s after takeoff (29%) and decreasing takeoff angle (10°) relative to unoiled birds. Slower and lower takeoff would increase the probability of oiled birds being captured by predators, which would reduce survival and facilitate exposure of predators to oil (Maggini et al. 2017a). • Western sandpipers exposed to weathered MC252 crude oil experienced increased cost of transport (energy expenditure) of 22% for lightly oil birds (<20% of body surface oiled) and 45% for moderately oiled birds (~30% of body surface oiled) relative to unoiled controls. Oiling also resulted in larger wingbeat amplitudes than controls and greater wingbeat frequencies. Oiling therefore causes sublethal effects by increasing the difficulty and energy costs of locomotion, which could impact several aspects of life history (Maggini et al. 2017b).

Wading Birds

Table 21. Summary of hurricane (acute coastal/storm surge flooding) impacts to wading birds.

Effect	Literature Summary
Changes in nesting effort due to habitat loss and degradation	• Following Hurricane Hugo (1989), the numbers of nesting great egrets, tricolored herons, and white ibises declined substantially (44%, 19%, and 100%, respectively) on Pumpkinseed Island, South Carolina, in the nesting season after the storm (1990). The greatest decline was observed in white ibises, whose numbers plunged from >10,000 pairs in 1989 to 0 pairs in 1990. Conversely, numbers of nesting pairs of snowy egrets and glossy ibises increased (36% and 3%, respectively) in the year following the storm. The decline in great egret nesting effort may be explained by hurricane damage to their nesting habitat of woody marsh elder vegetation. The hurricane damaged an estimated 60-75% of aboveground woody marsh elder vegetation at this site. Snowy egrets nest directly on the ground under marsh elder, so their nesting habitat was not impacted as much as that of the great egret, and this may explain the increase in nesting numbers of snowy egrets following the storm. However, most snowy egret nests (86%) in 1990 were abandoned due to tidal inundation, so the increased nesting effort did not translate to increased nesting success. Nesting ibises are heavily dependent on freshwater prey, especially crayfishes, and hurricane

Effect	Literature Summary
	disturbance of freshwater feeding sites may explain the complete nesting failure of white ibises at Pumpkinseed Island and the nearly flat nesting of glossy ibises following the storm (Shepherd et al. 1991). • Following Hurricanes Gustav and Ike (both in 2008), which impacted the northern coast of the Gulf of Mexico, nearly all wading bird species experienced declines in breeding pairs on Isles Dernieres Barrier Island Refuge of Louisiana in the two breeding seasons after the storms (2009 and 2010). Numbers of great egret, snowy egret, tricolored heron, reddish egret, green heron, black-crowned night-heron, and white ibis breeding pairs decreased in the years following the storms; whereas, roseate spoonbill breeding pairs increased in 2009 and decreased in 2010. These overall declines in wading birds nesting were attributed to loss of nesting habitat due to the storms (Raynor et al. 2013). • Leberg et al. (2007) conducted a regionwide study across southern Louisiana in which they compared numbers of nesting colonial wading birds in years before Hurricanes Rita and Katrina (both in 2005) and numbers of nesters during and after the year with the storms. They found that one-third of the surveyed colonies became inactive following the storms, and others experienced large shifts in numbers of nesting pairs. Despite these changes, region-wide, the total numbers of nesting birds of most species increased following the hurricanes. The authors hypothesize that birds shifting from damaged from active colonies could explain the increase in total numbers of nesting birds regionally, and that monitoring colonies across broad geographic scales, rather than individual sites, is necessary to fully understand hurricane impacts (Leberg et al. 2007).
Increased adult mortality	• A satellite telemetry study of reddish egrets in coastal Louisiana from 2016-2021 revealed that 9 of 25 (36%) transmitted reddish egrets experienced direct mortality immediately on or around (within 1 day of) the arrival of tropical cyclones (including hurricanes) in the area. Mortality was assumed to be due to storm-related impacts. The observed mortality rate indicates that reddish egret populations may decline substantially due to direct mortality from tropical cyclones, and this species may be particularly vulnerable to these impacts because it is a coastal specialist that is restricted to island habitats for nesting (Vasseur et al. 2023).
Brood failure/chick mortality	• Collins et al. (2021) reported failure of three reddish egret broods with young chicks in southwestern Louisiana following Tropical Storm Cindy (2017). Chicks were found drowned in their nests following the passage of the storm.
Irruptive breeding due to increased prey availability	• The flooding of freshwater wetlands in the Everglades following Hurricane Irma (2017) promoted crayfish production, and crayfish are important prey for breeding white ibises. Crayfish biomass in the wet season prior to the 2018 breeding season (post-hurricane) was 6.7x higher than in the wet season prior to the 2017 breeding season (pre-hurricane). The higher crayfish abundances initiated irruptive, extraordinarily high white ibis breeding in 2018 (30,420 nests in 2018, compared to an average of 913±956 nests from 1999 to 2016; Cocoves et al. 2021).

Table 22. Summary of chronic inundation impacts to wading birds.

Effect	Literature Summary
Reduced foraging and nesting habitat	• Calle et al. (2018) modeled time-integrated intertidal habitat availability for little blue herons and great white herons in the Florida Keys and found that this attribute had the greatest effect size of all resource attributes (including traditional attributes such as substrate type, water depth, and proximity to mangroves) on probability of habitat use. Both species were two to three times more likely to use foraging locations with greater (7 h) time-integrated habitat availability than nearby sites with lower (1 h) availability. Calle et al. therefore suggest that habitat loss with long-term sea level rise is both temporal and spatial, as the negative effects of spatial habitat loss are compounded by a loss in duration of access. • Using a tidal inundation model to examine the availability of the range of water depths needed for little blue heron foraging habitat in Florida Bay and the Florida Keys, Martinez et al. (2022) found short-term gains and losses in foraging habitat that resulted from slight differences in annual tidal cycles. These results highlight how sensitive this foraging habitat is to sea level fluctuations. More study is needed to elucidate how little blue heron shallow-water foraging habitat use may change with sea level rise. • Cox et al. (2018) observed that sites in Florida with a greater amount of foraging habitat within a 5-km radius had a greater number of nesting reddish egrets. The authors therefore highlight the need to understand the effects of sea level rise (inundation) on availability of foraging habitat and note that reddish

Effect	Literature Summary
	egrets may be particularly vulnerable to sea level rise because they are coastal specialists, while other species are also found in freshwater environments. • Wood stork and great egret nesting colonies in the Everglades and Florida Bay collapsed in the second half of the 20th century, and these collapses were accompanied by decreases in roseate spoonbill nesting in northeast Florida Bay. These declines in wading bird nesting corresponded with reduction of freshwater flow to the estuary and associated sparse populations of the birds' marsh fish prey. Thus, hydrological changes associated with sea level rise can have cascading effects on wading bird nesting (Davis et al. 2005).
Nest washout/ flooding	• From 2016 to 2018, overwash (flooding) from extreme high tides was the primary cause of known nest and brood loss of reddish egrets in southwestern Louisiana, accounting for 49% of all nest failures and 28% of all brood failures. Following overwash, pairs appeared to construct higher nests, though nest heights before and after overwash were not significantly different. Increased occurrence of overwash events is expected with sea level rise (Collins et al. 2021). • Ritenour et al. (2021) found that timing of inundation events impacted wading bird nest survival on Rabbit Island, Louisiana. Nest failure occurred when high water depths were ~0.4 m at a monitoring station, and from 2006 to 2018, water level records showed 29 individual inundation events. These events were usually associated with storms and occurred during every month of the breeding season (March through June). Inundation was the primary known cause for nest failure of roseate spoonbills and was responsible for 39% of failed nests from 2017 to 2018.
Reductions in prey resources	• Pearlstine et al. (2010) note that roseate spoonbills in the Everglades, Florida, are experiencing food resource stress as their demersal fish prey in freshwater wetlands are impacted by water management changes, and they suggest that sea level rise will exacerbate this problem. • Romañach et al. (2019) sampled fish communities that are prey resources for wading birds in the southwest portion of the Everglades, Florida. In this system, sea level rise and reduction of freshwater flow have converted freshwater marsh into estuarine mangrove habitats. The authors found that salinity changes altered fish production and community composition, and they hypothesize that these changes in prey may have cascading effects on wading birds. • Wading bird prey abundance changes dramatically with water level and duration of inundation (Beerens et al. 2011; Beerens et al. 2015; Lorenz 2013). Lorenz 2013 quantified the relationship between water level and roseate spoonbill prey abundance in Florida Bay and found that a series of thresholds in water level resulted in concentrated prey. He also found that spoonbills rely on water level-induced prey concentrations to have enough food to raise young. Thus, water management strategies, sea level rise, and/or chronic inundation may impact prey availability for wading birds.

Table 23. Summary of marine debris impacts to wading birds.

Effect	Literature Summary
Lethal and sublethal effects due to debris ingestion	• Ingested debris can accumulate in a bird's digestive tract, which can block the digestive tract, reduce digestive capacity, damage gastric tissue, reduce appetite and food intake, and lead to starvation (e.g., Browne et al. 2015; Pierce et al. 2004). Also, chemical contaminants from debris can be released in the digestive tract, or birds may ingest contaminated prey (e.g., Tanaka et al. 2013). • Browne et al. (2015) hypothesize that sublethal effects on birds due to ingesting plastic debris may cascade to population-level impacts as the compromised physiological conditions of birds that have ingested debris may feed and grow at slower rates and produce smaller and fewer offspring. Lethal effects may lead to population-level impacts as fewer individuals are available for reproduction and rearing young (Browne et al. 2015). • Vanstreels et al. (2021) documented ingestion of marine debris in 50% of great egrets sampled on the southeastern coast of Brazil. Ingested debris consisted of plastic fragments/pellets, filaments, and films. • A global review of bird interactions with anthropogenic litter reported several studies with evidence of debris ingestion by wading bird species (Battisti et al. 2019).
Entanglement	• Hong et al. (2013) documented black-faced spoonbills entangled in plastic strings, using plastic materials in nests, and with hooks impaled in their bodies. Overall, they observed great egret, black-faced spoonbill, night heron, and grey heron individuals impacted by marine debris in coastal Korea.

Effect	Literature Summary
	• A global review of bird interactions with anthropogenic litter reported several studies with evidence of entanglement of wading bird species (Battisti et al. 2019).

Note: No literature was found on marine debris impacts on wading birds in Florida, so studies from other regions are discussed.

Table 24. Summary of convective storm wind event impacts to wading birds.

Effect	Literature Summary
Significant correlation between wind speed and nest failure	• Frederick and Loftus (1993) monitored 198 great egret nests during the nesting seasons of 1986 and 1987 in the Everglades, Florida. They found a significant correlation between nest failure and maximum daily wind speed during the 14 days prior to nest success or failure. The authors suggest that egrets abandon their nests under high winds (and under low temperatures) due to reduced ability to forage.
Influence on foraging success	• Bates and Ballard (2014) detected an interaction between wind speed and light intensity on foraging strike efficiency (the proportion of successful strikes) of reddish egrets in Laguna Madre, Texas. Under low light conditions, strike efficiency decreased with increasing wind speed, but as ambient light increased, strike efficiency increased with increasing wind speed. The authors hypothesized that bright ambient light and high wind speeds may result in increased prey vulnerability due to a decreased ability to detect predators. • Rodgers (1983) observed that wind increased wave action, which decreased foraging success of herons in Tampa Bay, Florida. • Rodgers (1983) also observed that reddish egrets ran into the wind with open wings (the “openwing” foraging method), which allowed them to have increased lift for sustained running and improved maneuverability while foraging. • During a 3-day windy winter storm in February 1987 in coastal Louisiana, five species of wading birds (herons and egrets) suspended foraging and remained sheltered from the wind. Simulation modeling predicted 6-12% decreases in body mass over 3 days of fasting, with smaller species losing proportionally more mass (DuBowy 1996).
Potential mortality	• After the passage of the 3-day winter storm in coastal Louisiana mentioned above, DuBowy (1996) observed fewer wading birds and suggested that mortality of wading bird species had occurred with the storm.

Note: The only study found of convective storm high wind event impacts on wading birds did not quantify wind as a variable, but only described the winter storm as “a period of very cold (<10°C), windy weather” (DuBowy 1996). The other studies found impacts of wind on wading birds examined wind as a continuous variable rather than an event.

Table 25. Summary of shoreline erosion impacts to wading birds.

Effect	Literature Summary
Habitat loss	• In Tangier Sound, Chesapeake Bay, Virginia, a group of 15 islands experienced erosion and habitat loss via washovers that resulted in reduction of their area by 21% from 1993/1994 to 2007/2008. Concurrently, nesting wading birds (herons and egrets) declined by 51%. Watts Island, the island with the vast majority of observed nesting wading birds and part of a national wildlife refuge, eroded by 35% (36.3 ha to 25.4 ha). On Watts Island, cattle egrets declined from 375 pairs in 1993 to zero in 2008, snowy egrets declined from 425 pairs to 85, tricolored herons declined from 48 pairs to 10, little blue herons declined from 34 pairs to 7, and glossy ibis declined from 209 pairs to 68 over the same time period. Small numbers of wading birds (less than 200 pairs) likely moved from Watts to nearby Lower Bernard Island (Erwin et al. 2011). • A 2016 analysis of 61 colonial waterbird rookery island units within 2.5 km of the Gulf Intracoastal Waterway in coastal Texas revealed that 15 island groups are at risk of disappearing completely within 50 years, and 31 are predicted to experience at least “medium” erosion (25-50% of area lost) within 10 years. These islands host 7 species of colonial waterbirds, including roseate spoonbill and snowy egret. Though wading birds may find alternative rookery sites, the erosion of these rookery islands puts these species at risk of decline (Hackney et al. 2016).

Effect	Literature Summary
	• Erwin et al. (1995) observed that great white herons (a race of great blue herons) in the Florida Keys had greatest nest density on islands in the 2 to 10 ha size range and lowest for islands larger than 100 ha. These preferred smaller islands are more vulnerable to erosion, and the authors emphasize the importance of protection of these islands from erosion to conserve the great white heron metapopulation.
Increased habitat usage in terraced marsh ponds built to counteract marsh erosion	• Terraced marsh ponds built to counteract marsh erosion on the Chenier Plain, Louisiana, supported 77% higher wintering wading bird (great blue heron, tricolored heron, great egret, snowy egret, and white ibis) abundances than unterraced ponds. Possible explanations for this trend include: 1) terracing increases the proportion of marsh edge and habitat complexity, which is preferred by wading birds; and 2) terracing increases habitat interspersion of cover and open water, which increases macroinvertebrate prey densities. Thus, pond terracing may reduce erosion, whereby improving multiple ecological services, which may in turn benefit wading birds (O'Connell and Nyman 2011).

Note: Only one study was found that addressed shoreline erosion impacts on wading birds in Florida, so studies from other regions are also discussed. An additional study that examined impacts to wading birds of structures built to counteract shoreline erosion are included.

Table 26. Summary of contaminant/spill event impacts to wading birds.

Effect	Literature Summary
Direct oil exposure	• Following the *Deepwater Horizon* spill (2010), Johnson et al. (2017) monitored the frequency and extent of oiling of coastal waterbirds from Louisiana to the Florida panhandle. Across all sites throughout the study period (May through November 2010), wading birds (including herons, egrets, and ibis) were the most frequently oiled guild (10.3 for dark waders; 10.9% for light waders). During the peak of the oil spill (June and July 2010), oiling encounter rates were higher at 16.7% for dark wading birds and 16.5% for light wading birds. The authors suggested that the higher rates of oiling observed in wading birds than in other guilds may be explained by the habitat of wading birds being along the land-water interface where oil can accumulate, thereby increasing their risk of exposure relative to birds who spend more time in, on, or above the water. • Despite the documented oiling of wading birds following the *Deepwater Horizon* spill, Burger (2018) found that in 2011 there were no significant differences in the number of species nesting in waterbird colonies (including egrets, herons, roseate spoonbills, and others) as a function of shoreline oiling category; no differences in colony phenology as a function of shoreline oiling category; no differences in the mean number of chicks per nest as a function of shoreline oiling category (or the “no oil” category had similar or smaller numbers); and average chick sizes in nests in the “no oil” category were similar to or lower than chick sizes in the “light oil” and “moderate/heavy oil” categories. Thus, Burger concluded that there were no differences in waterbird reproductive success in the year following the spill, but both chronic and episodic spills in the Gulf of Mexico make it difficult to examine the effects of any single oil spill.
Physiological effects of oil exposure	• Physiological effects of oil exposure on wading birds can be lethal or sublethal, and occur through several pathways: o Loss of waterproofing and insulating capabilities of feathers, leading to death from hypothermia (Leighton 1993). o Oil ingestion through preening of oiled feathers and/or foraging in contaminated habitats, leading to dehydration, starvation, infections, pneumonia, arthritis, gastrointestinal problems, and cloacal impaction. Oil ingestion can cause mortality primarily through acute toxic effects to the liver, kidney, and gastrointestinal tract (Briggs et al. 1996; Leighton 1993). Sublethal toxicological effects can also result from ingested oil, including hemolytic anemia, reduced reproduction, and immunosuppression (Leighton 1993). o Eye irritation from oil contact (Briggs et al. 1996).
Foraging habitat switching	• Following a series of oil spills in 1990 into the Arthur Kill estuary (New York and New Jersey), in some cases, wading birds shifted to foraging at freshwater sites rather than in tidal estuaries (Maccarone and Brzorad 1995). Seven years after the spills, some freshwater sites had again become less heavily used, but numbers of wading birds in estuaries had still not returned to pre-spill levels. By 1997, estuaries were more productive as prey capture rates and foraging strike success increased compared to 1990, but

Effect	Literature Summary
	feeding success had still not returned to pre-spill patterns (Maccarone and Brzorad 1998). By 1999, wading birds had returned to once-contaminated estuaries to forage, and feeding success had returned to pre-spill levels (Maccarone and Brzorad 2000).

Fish (Smalltooth Sawfish)

Table 27. Summary of hurricane (acute coastal/storm surge flooding) impacts to smalltooth sawfish.

Effect	Literature Summary
Population effects	• In a study comparing number, size, and movement patterns of smalltooth sawfish using data collected 2 years prior to and 2 years after Hurricane Charley (Category 4) in Charlotte Harbor, FL, Simpfendorfer and Wiley (2006) concluded that smalltooth sawfish continued to occur in habitats affected by Hurricane Charley. Analysis of encounter data showed that there was no detectable difference in the number of smalltooth sawfish occurring in areas affected by Hurricane Charley. Movement and habitat use patterns of juvenile sawfish did not appear to be affected by habitat damage to the nursery area. There were no consistent differences in the behavior and habitat use patterns of juvenile sawfish between the impact and control sites. This included no differences in swimming speeds, cumulative linearity of tracks or depth distributions between the sites.

Table 28. Summary of chronic inundation impacts to smalltooth sawfish.

Effect	Literature Summary
Habitat quality	• In a study from 2010 to 2013, juvenile sawfish in the Caloosahatchee River (a highly human-altered nursery) moved between four nursery hotspots, depending on water salinity, moving downriver as salinity approached zero. In the Peace River (a more natural nursery), sawfish generally stayed within 2-5 km of one nursery hotspot (Scharer et al. 2017). Both rivers are designated as Critical Habitat (in 2009) for smalltooth sawfish, which was listed as endangered on April 1, 2003. • In a study between 2007 and 2009, Poulakis et al. (2012) found that juvenile sawfish remained in the Caloosahatchee River under a wide range of environmental conditions, but moved upstream as salinity increased. • In a study between 2005 and 2007, Simpfendorfer et al. (2011) found that juvenile sawfish in the Caloosahatchee River estuary preferred salinities between 18 and at least 24 psu. Thus, freshwater flow from Lake Okeechobee and its effect on salinity affects the location of individuals within the estuary. • Smalltooth sawfish are piscivorous and shift from shallow estuarine waters as small juveniles to a broader array of coastal habitats as large juveniles and adults. The species is physiologically resilient to anthropogenic stressors (Brame et al. 2019). • These studies show that juvenile smalltooth sawfish can and will move to their preferred salinity ranges in response to short-term (months) changes in salinity due to variations in water quality. • However, forced landward progression of the preferred shallow-water mangrove habitat for juveniles poses the greatest threat in areas where there is limited or no room for landward or lateral migration due to shoreline armoring and coastal development. Reductions in the availability of shallow water or mangroves could have numerous ecological effects on sawfish, including increased sawfish predation, higher metabolic stress, and decreased body condition (Brame et al. 2019).

Table 29. Summary of marine debris impacts to smalltooth sawfish.

Effect	Literature Summary
Hurricane debris	• Simpfendorfer et al. (2005) surveyed mangrove areas in Charlotte Harbor damaged during Hurricane Charley (Category 4) several months after the storm. They found that the storm generated a large amount of death or complete defoliation of red mangroves, but they did not find a significant amount of trash accumulated in the shoreline mangrove habitats. Most sites had less than 10 items (bigger than an aluminum can) per 100 m segment.

Effect	Literature Summary
	• Seitz and Poulakis (2006) interviewed 989 individuals who reported some type of encounter with smalltooth sawfish in south Florida. They reported 15 incidents with entanglement in various forms of marine debris, including a PVC pipe, an elastic band, and monofilament, non-monofilament, and braided fishing lines.

Table 30. Summary of convective storm wind event impacts to smalltooth sawfish.

Effect	Literature Summary
Habitat degradation	• In an acoustic study of nursery habitat use in the Everglades National Park, Hollensead et al. (2018) found that juvenile sawfish had an increased probability of being encountered in narrow tidal creeks and shallow tidally influenced mangroves with high prop root density. Thus, impacts to mangroves in these areas could affect the habitat quality, though most studies after hurricanes showed mangrove damage was limited to areas of highest wind. Thus, it is not likely that a single convective storm could affect a large nursery area.

Table 31. Summary of shoreline erosion impacts to smalltooth sawfish.

Effect	Literature Summary
Habitat quality	• Sawfish spend their first few years within nurseries and eventually move into a broader range of coastal habitats. The greatest impacts have resulted from replacement of mangrove-lined shorelines with man-made structures (Poulakis and Grubbs 2019). However, in southwest Florida, Critical Habitat designations in their most important nursery areas (Charlotte Harbor and the Everglades) will minimize this stressor. In these areas, shoreline erosion is less of a concern.

Table 32. Summary of contaminant/spill event impacts to smalltooth sawfish.

Effect	Literature Summary
Direct effects of oil exposure	• Juvenile fish that rely on estuarine nursery habitats, in general, are more sensitive to oil spills because of the risk of increased exposure in shallow or narrow waterbodies and because they often have smaller ranges, where a spill could affect more of their preferred habitat.
Indirect effects of oil exposure	• Spills can cause tree mortality and dieback of prop roots along tidal channels (Garrity and Levings 1993; 1994), which is the preferred habitat in Florida for juvenile sawfish.

Invertebrate (Queen Conch)

Table 33. Summary of hurricane (acute coastal/storm surge flooding) impacts to queen conch.

Effect	Literature Summary
Reduced adult density, leading to depensation	• Adult queen conch densities declined in the Florida Keys by over 80% immediately following the passage of Hurricane Irma (2017) and by ~45% following the passage of Hurricane Ian (2022). The mobilization of sand during passage of the storms likely buried conch and caused mortality. Following both hurricanes, adult queen conch populations declined below the minimum mating threshold for the Florida Keys, indicating depensation triggered by the hurricanes. Long-term annual monitoring revealed a lack of recovery 5 years after Hurricane Irma, which was attributed to queen conch's density-dependent reproduction and age at sexual maturity of ~4 years (Voss et al. 2024). • Following Hurricane Maria (2017), Agar et al. (2020) reported that fishers in Puerto Rico had to dive in deeper waters for queen conch due to damage to inshore habitats. Fishers also reported lower queen conch catches.
Hypothesized effects on larval transport and survival	• Stoner et al. (2023) suggested likely impacts of hurricanes on queen conch veliger larva transport and survival due to the disruption of the mixing layer over a large scale. Disruption of benthic habitats with hurricanes may impact settlement and post-settlement survival; whereas, faster storm currents may enhance distant transport.

Table 34. Summary of chronic inundation impacts to queen conch.

Effect	Literature Summary
Potential declines in seagrass and coral reef habitats with sea level rise	• Seagrass and coral reef habitats are declining worldwide and are projected to continue to decline with increasing inundation due to sea level rise (e.g., Saunders et al. 2014; Scalpone et al. 2020). Queen conch primarily occurs in seagrass beds, coral reefs, and sand plains (Horn et al. 2022), so impacts to those habitats will likely have cascading impacts on queen conch populations.

Note: No literature was found on direct inundation impacts on queen conch, so potential indirect impacts are assumed from degradation of queen conch's seagrass and coral reef habitats and based on best professional judgment. See Seagrass and Coral Reef literature summaries for details of chronic inundation impacts to those resources.

Table 35. Summary of marine debris impacts to queen conch.

Effect	Literature Summary
Microplastic ingestion	• Queen conch fecal analyses from 11 sites around the wider Caribbean, including a site in the Florida Keys, revealed that microplastics were present in all 175 conch sampled. No geographic pattern was found across the Caribbean, and mean number of microplastic pieces per queen conch ranged from 42 to 270. Microplastic fibers were the most frequent particle type at every site (99% of particles at the Florida Keys site); other microplastic types found were films and spheres. These results highlight the relatively high levels of microplastic pollution in the Caribbean Sea compared with global averages, the ability of queen conch to ingest microplastics, and the ubiquity of microplastic contamination in queen conch throughout its distribution (Aranda et al. 2022). Horn et al. (2022) suggest that high levels of microplastic ingestion in queen conch may negatively affect reproduction.

Table 36. Summary of convective storm wind event impacts to queen conch.

Effect	Literature Summary
Altered vertical distribution of larvae	• While multiple interacting environmental conditions can impact vertical distribution of queen conch veliger larvae, turbulence in surface waters can drive larvae lower in the water column (Stoner et al. 2023). Stoner and Davis (1997) found that density of queen conch veligers in the top meter of the water column was inversely related to sea height, and that modal veliger depth was directly related to wind speed. Wind-caused surface turbulence overwhelmed veligers' weak vertical swimming ability. Because queen conch veliger larvae have diel vertical migration (Stoner and Davis 1997), it is unclear whether any population-level impacts would occur as a result of a convective storm wind event.
Altered horizontal larval transport	• As queen conch veligers typically inhabit the upper several meters of the water column, wind forcing affects their horizontal transport. In a study at Lee Stocking Island in the Bahamas, Stoner and Smith (1998) found that across-shelf distribution of queen conch veliger larvae was affected by wind forcing. Seaward transport, which is unfavorable to recruitment, was driven by prevailing offshore winds, which suggests that recruitment of conch larvae to nursery grounds occurs during anomalous summer wind conditions at this site. Additionally, Stoner and Smith suggested that short-term (6-8 h) changes in wind stress may significantly affect across-shelf larval transport.

Note: No specific studies were found of convective storm high wind event impacts on queen conch. The studies presented examined general wind conditions and wind forcing as a continuous variable, but they did not specifically examine wind events.

Table 37. Summary of shoreline erosion impacts to queen conch.

Effect	Literature Summary
Potential declines in seagrass and coral reef habitats due to erosion	• Seagrass and coral reef habitats are declining worldwide and are projected to continue to decline with negative effects of erosion (e.g., Cabaço et al. 2008; Duarte 2002; Morris et al. 2022; Toth et al. 2022). Queen conch primarily occurs in seagrass beds, coral reefs, and sand plains (Horn et al. 2022), so impacts to those habitats will likely have cascading impacts on queen conch populations.

Note: No literature was found on shoreline erosion impacts on queen conch, so potential indirect impacts are assumed from degradation of queen conch's seagrass and coral reef habitats and based on best professional judgment. See Seagrass and Coral Reef literature summaries for details of shoreline erosion impacts to those resources.

Table 38. Summary of contaminant/spill event impacts to queen conch.

Effect	Literature Summary
Direct effects of oil exposure	• Little information on direct effects of oil exposure exists for queen conch; however, Nadeau and Bergquist (1977) observed that large numbers of conch were washed ashore on the third day following the *Zoe Colocotronis* spill in Puerto Rico. Additionally, many invertebrate species were observed dying and decomposing in nearby seagrass beds. • Static acute toxicity tests on queen conch veliger larvae with artificially weathered crude oil, dispersant (Corexit 9500), and dispersed oil revealed that dispersed oil was more toxic than crude oil for all larval stages, survival decreased with increased exposure time, and younger larval stages were more sensitive than older stages (Laramore et al. 2012). • Studies of other effects on other gastropod species have shown that exposure to petroleum hydrocarbons can impair gastropod mobility and foraging behavior at sublethal doses (Hyland and Miller 1979; MacFarlane et al. 2004), and acute exposure after oil spills can cause high levels of mortality (Blackburn et al. 2014).
Indirect effects of oil exposure*	• Spill impacts to queen conch habitat (including substrate destruction or modification) may have cascading impacts on queen conch populations. The effects of degraded habitat following a spill may be of greatest concern in shallow waters (Horn et al. 2022).

*Potential indirect impacts are assumed from degradation of queen conch's seagrass and coral reef habitats and based on best professional judgment. See Seagrass and Coral Reef literature summaries for details of spill impacts to those resources.

Reptiles (Sea Turtles)

Table 39. Summary of hurricane (acute coastal/storm surge flooding) impacts to sea turtles.

Effect	Literature Summary
Nesting success	• Hurricane Andrew affected turtle nests over a total of 90 miles of beaches on the east and west coasts of Florida. The storm surge associated with the hurricane produced the greatest mortality through nest flooding. The greatest surge effect was felt on beaches closest to the "eye" of the hurricane, where egg mortality was 100%. Further mortality occurred when surviving turtles suffocated in nests situated in the beach zone where sand had accreted (Milton et al. 1994). • In a study of 7 km of beaches along central east Florida, Lindborg et al. (2016) showed that hatching and emergence success over the period 2004-2014 were lowest during tropical cyclones, which corresponded with an increased number of complete nest wash-outs. • As reported by Edmiston et al. (2008), along the beaches of Apalachicola Bay, two tropical storms and a tropical depression in 1994 washed out nests and nest markers, and inundated most remaining nests with as much as 0.4-0.6 m of tightly packed sand. Three hurricanes, Allison, Erin, and Opal, impacted area beaches in 1995 causing severe beach erosion, leveling the entire primary dune system, and eliminating more than 40% of the nests on two islands. In 1998, Hurricane Earl destroyed 54% of the nests on St. George Island and 45% of nests on Cape St. George Island.

Effect	Literature Summary
	• Ware et al. (2021) used wave runup models for 40 nesting beaches in the Florida Panhandle to show that, on average, approximately 50% of the available beach area and 34% of nesting locations per nesting beach face a significant risk of wave exposure, particularly during tropical storms. Field data showed that 42.3% of all nest locations reported wave exposure, which resulted in a 45% and 46% decline in hatching and emergence success, respectively.
Population impacts	• In an analysis of historical hurricane paths from 1970 to 2007, Dewald et al. (2013) showed that hurricanes affected 97% of sea turtle beaches, seasonally overlapping with nesting and egg incubation periods. However, females lay 2-7 clutches at 2 week intervals; thus, impacts on sea turtle populations may be limited because only a portion of adult females are reproducing and only those eggs incubating at the time of the storm are directly impacted. • In spite of ten catastrophic hurricanes from 1988 to 2004 that affected a barrier island off the southern Florida coast, 72% of clutches produced by nesting females were undisturbed—median hatching success for these clutches was an astonishing 92% (Cassill 2021). The author concluded that diversified maternal investments over time and space by nesting females are reproductive adaptations that have successfully offset clutch losses, thus enabling populations of loggerhead females to meet or exceed their reproductive goal of replacement fitness.

Table 40. Summary of chronic inundation impacts to sea turtles.

Effect	Literature Summary
Reduced hatching success	• Fuentes et al. (2020) modelled the geographic distribution of climatically suitable nesting habitat for marine turtles in the USA under future climate scenarios, and identified potential range shifts by 2050, determined impacts from sea-level rise, and explored changes in exposure to coastal development as a result of range shifts. Sea-level rise is projected to inundate 78-81% of current habitat predicted to be climatically suitable in the future, depending on species and scenario. Nevertheless, new beaches will also form, and suitable nesting habitat could be gained, with leatherback turtles potentially experiencing the biggest percentage gain in suitable habitat. • Loggerhead hatching success decreased as inundation, water content, and salinity increased on low-lying mangrove islands in the Ten Thousand Islands region of Florida. However, the researchers noted that clutches can tolerate a certain amount of inundation (Foley et al. 2006). • Using a dataset of over 9,000 nest inventories from five nesting areas that span the latitudinal extent of primary nesting locations in the United States, Lyons et al. (2022) found that nesting distance from the high waterline was important in determining the probability of inundation and depredation disturbance events, as well as clutch failure. Nests that experienced at least one inundation event were more likely to have no emergence than nests that experienced at least one depredation event. • Pike et al. (2015) showed that saltwater inundation directly lowers the viability of green turtle eggs collected from the world's largest green turtle nesting rookery at Raine Island, Australia, which is undergoing enigmatic decline. Inundation for 1 or 3 h reduced egg viability by less than 10%; whereas, inundation for 6 h reduced viability by approximately 30%.

Table 41. Summary of marine debris impacts to sea turtles.

Effect	Literature Summary
Lethal and sublethal effects due to debris ingestion	• In a study of gastrointestinal tracts of 42 post-hatchling loggerhead sea turtles stranded in Northeast Florida, abundant numbers of plastic fragments (hard and sheet plastic) ranging from 0.36 to 12.39 mm were found in 93% of the animals. The authors suggested that there were significant negative health consequences from ingestion in animals at this life stage (Eastman et al. 2020). • Of 20 juvenile loggerhead sea turtles from the North Atlantic Tropical Gyre, off the Azores, 83% were found to have ingested plastic items (primarily polyethylene and polypropylene), with an average of 15.83 ± 6.09 particles per animal (Pham et al. 2017). • In a quantitative analysis of hundreds of records, Wilcox et al. (2018) found a 50% probability of mortality once a sea turtle had 14 pieces of plastic in its gut.

Effect	Literature Summary
	• Garrison and Fuentes (2019) found anthropogenic marine debris at all of the ten highest density nesting beaches on Florida's Gulf coast, ranging from 16-363 items/km, with plastic and foam accounting for 92% (n= 13,566). • In a field study in NW Florida, Fujisaki and Lamont (2016) found that the number of turtle nests increased 200% and false crawls increased by 55% on a segment of shoreline where natural and anthropogenic debris was removed, compared to two other segments without removal, indicating that large debris may have an adverse impact on sea turtle nesting behavior. • Debris was found in 25 of 51 sea turtle carcasses from the east and west coasts of Florida, consisting of plastic, monofilament line, fish hooks, rubber, aluminum foil, and tar. For the two turtles who died as a result of debris ingestion, the debris represented 4.6% and 5.8% of wet mass and 3.2% and 9.8% of volume of the gut contents, which affected gut function (Bjorndal et al. 1994). • In a controlled experiment with 15 captive-reared juvenile loggerhead sea turtles, Pfaller et al. (2020) found that the sea turtles responded to airborne odorants emanating from biofouled plastic in the same way that they responded to food odorants, making them at higher risk of ingestion. • For 54 loggerhead sea turtles from the Mediterranean Sea, 43 contained marine debris with plastic the most common (75.9%) but also tar, paper, Styrofoam, wood, reed, feathers, hooks, lines, and net fragments. The volume of debris increased proportionally to the size of the turtles (Tomás et al. 2002). • Of 380 neonatal sea turtles that washed ashore the Florida east coast, 78.7% had ingested plastic and 45.3% had ingested tar. Ingested plastics included microplastics (<5 mm) and larger sizes up to 25% of carapace length (Rice et al. 2021). • In a study of 52 dead post-hatchling sea turtles from the Florida east coast, White et al. (2018) determined that ingestion of micronizing plastic by post-hatchling sea turtles is likely a substantial risk to survival of these endangered and threatened species.
Entanglement	• In a study of sea turtle strandings (n=17,763) in Florida during 1997–2009, Adimey et al. (2014) reported that 1,070 sea turtle cases (5%) were identified as fishery gear interactions, consisting of 75.2% hook and line, 16.6% trap pot gear, 6.2% fishing net, and 2.0% multiple gear. Interactions were higher in summer/fall and increased over time.

Table 42. Summary of convective storm wind event impacts to sea turtles.

Effect	Literature Summary
Dispersal of turtles at sea	• Monzon-Arguello et al. (2012) used multidisciplinary oceanographic, atmospheric and genetic mixed stock analyses to show that juvenile turtles are encountered 'downstream' at sites predicted by currents. However, in some cases, unusual occurrences of juveniles are more readily explained by storm events, and the researchers showed that juvenile turtles may be displaced thousands of kilometers from their expected dispersal based on prevailing ocean currents. • DuBois et al. (2020) used an ocean circulation model to explore seasonal and annual variation in the dispersal of post-hatchling Kemp's ridley sea turtles from nesting beaches in the western Gulf of Mexico. High numbers of hurricanes corresponded to shorter dispersal distances and less variance within the first 6 months. Their findings suggest that differences in dispersal among sites and the impact of hurricane frequency and intensity could influence the survivorship and somatic growth rates of turtles from different nesting sites and hatching cohorts, either improving survival by encouraging retention in optimal pelagic habitat or decreasing survival by pushing hatchlings into dangerous shallow habitats.

Table 43. Summary of shoreline erosion impacts to sea turtles.

Effect	Literature Summary
Nesting success	• In a seven-year study along Vero Beach, Florida, Rizkalla and Savage (2011) found that fewer loggerhead sea turtles attempted to nest on beaches with passive erosion due to nearshore placement of seawalls compared with unarmored beaches. Nests placed in front of seawalls were more likely to be washed away in storms. • Reece et al. (2013b) used a multiple regression model based on climate change, sea-level rise and land use that described 47% of the spatial variation in loggerhead nesting on the largest loggerhead rookery in the Atlantic Ocean, at Melbourne Beach, Florida from 1986 to 2006. Nests have shifted northward (likely

Effect	Literature Summary
	in response to warming temperatures), away from intensive coastal development, and, surprisingly, toward areas of increased erosion. • Studies have shown that sea turtles nest denser and closer to the vegetation line on eroding beaches (Fujisaki et al. 2018; Lamont and Houser 2014). • Along the southeastern coast of Brazil, a study of 731 loggerhead sea turtle nests found only 6% were found on beach sectors with severe and extreme erosion, compared to 50% that were found on low-urbanized beaches (Costa et al. 2023). • Lyons et al. (2020) predicted the future location of nesting areas within four barrier island National Seashores in the southeastern United States based on a sea level rise scenario for 2100 and quantified how impervious surfaces will inhibit future beach movement, which will impact both the total available nesting area and the percentage of nesting area predicted to flood following a hurricane-related storm surge. Contrary to their expectations, those barrier islands with the greatest levels of human infrastructure were not projected to experience the greatest percentage of sea turtle nesting area loss due to sea level rise or storm surge events. Notably, loss of nesting beach areas will not have equal impacts across the four Seashores; the Seashore projected to have the least amount of total nesting area lost and percentage nesting area lost currently has the highest nesting densities of the two study species, suggesting that even low levels of beach loss could have substantial impacts on future nesting densities and disproportionate impacts on the population growth of these species.

Table 44. Summary of contaminant/spill event impacts to sea turtles.

Effect	Literature Summary
Direct oil exposure	• Physical fouling by oil is the most frequently reported effect of oil exposure on sea turtles (Wallace et al. 2020; Shigenaka et al. 2010). Coating of oil on sea turtles at any life stage can have similar effects caused by smothering, clogging the mouth and nose, or creating an inability to maneuver. • Oil contact can cause acute toxicity in hatchlings and impair their movements and normal bodily functions if coated (Shigenaka et al. 2010). • At sea, juvenile and adult sea turtles can be weighed down by oil, obstructing their ability to surface for air, reducing their ability to dive for feeding, avoid predators or vessel strikes, and regulate body temperature. Ingesting oil either directly (i.e., eating tar balls) or indirectly (i.e., consuming contaminated foods) can cause acute toxicity or, in terms of tar balls, can lead to blockage of their mouths or esophageal pathways. • Loehefener et al. (1989) found tar balls in the mouths, esophagi, and stomachs of 65 out of 103 post-hatchling loggerhead turtles off the east coast of Florida in a convergence zone. • The *Deepwater Horizon* oil spill was shown to negatively affect sea turtle nesting on oiled beaches in NW Florida, with a reduction of 43.7% relative to expected nesting rates in the absence of DWH oil and cleanup efforts (Lauritsen et al. 2017).
Indirect effects of oil exposure	• Witherington (1994) studied post-hatchlings in convergence zones, or weed lines, off the coast of Florida and found that 34% of individuals had tar in their mouths or esophagi, with over half with tar in their jaws. Hatchlings, juveniles, and adults can experience difficulty eating if their beaks and esophagi are blocked, which could lead to starvation. • Ingested oil can also cause gut blockage, decreased absorption efficiency, absorption of toxins, effects of general intestinal blockage (i.e., local necrosis or ulceration), interference with fat metabolism, and buoyancy control problems caused by buildup of fermentation gases (Shigenaka et al. 2010). Buoyancy control allows sea turtles to surface or dive to depth freely; without this ability, they are especially vulnerable to predators, vessel strikes, and disruption of normal feeding behavior.
Spill risk	• According to Wallace et al. (2020), of 2,316 oil spills of all sizes worldwide over the past 60 years, 1,432 spills occurred within subtropical waters where sea turtles occur. However, only 22 spills reported impacts to sea turtles. The distribution was heavily favored toward North America (13 spills). Effects involving nesting females and/or hatchlings were reported more frequently than oceanic involvement of sea turtles, other than the occasional observational report of dead sea turtles in the waters near a spill. The potential for sea turtles to be impacted by oil spills is very high; however, these incidents are few in number either by chance occurrence or by limited reporting.

Note: Included limited studies on oil effects on sea turtles following the *Deepwater Horizon* spill because its magnitude is not representative of the degree and extent of oil exposure considered in this assessment.

Wetlands (Mangroves)

Table 45. Summary of hurricane (acute coastal/storm surge flooding) impacts to mangroves.

Effect	Literature Summary
Forest dieback	• Hurricane Donna (1960) caused 30-100% mortality, with higher mortality at interior sites (Craighead and Gilbert 1962). Delayed mortality was noted 10 years later (Craighead 1971). • Hurricane Andrew (1992) impacts to the Everglades National Park, Ten Thousand Islands NWR, and Rookery Bay NERR were 20-94% reduction in basal area in the eyepath, 1-51% in the right quadrant, and 2-24% in the left quadrant. Taller dominant trees and stands incurred greater damage from windthrow, whereas subcanopy trees were affected by felled and topped canopy trees. There was large-scale defoliation in all areas (Doyle et al. 1995). • Recovery monitored for 7 years after Hurricane Andrew involved different pathways depending on resprouting capability, seedling survival, post-hurricane seedling recruitment, and colonization by herbaceous vegetation. Sites with surviving red mangrove seedling grew a dense single-species canopy. Sites with low survival of red mangrove seedlings were colonized by mixed species and herbaceous vegetation in open patches (Baldwin et al. 2001). • Hurricane Wilma (2005) damaged 1,250 ha of mangroves, mainly as a narrow band averaging 250 m wide and extending for 50 km adjacent to the Gulf of Mexico. Basin forests had higher basal area losses (mean 75%), compared to riverine (18%) and island (20%) forests (Smith et al. 2009). • As a result of Hurricane Irma (2017), 10,760 ha of mangroves in southwest Florida suffered complete mortality within 15 months post-storm (based on airborne and satellite imagery), with largest impacts in tall forests (>10 m) and in forests dominated by red mangroves that were also areas with low elevation where the storm surge exceeded 1.4 m. Mangroves on well-drained sites (83%) resprouted new leaves within 1 year after the storm. By contrast, poorly drained inland sites experienced the highest mortalities due to hypersalinization (accounting for 75% of the total dieback) (Lagomasino et al. 2021). • Using satellite imagery from 1985-2017, Han et al. (2018) showed large-scale damage to mangrove forests in the Everglades National Park after Hurricanes Floyd (1987), Andrew (1992). Charley (2004). Wilma (2005), and Irma (2017). However, these large mangrove die-off areas gradually recovered to pre-hurricane levels within 3-4 years.
Sediment and nutrient addition	• Hurricane Irma resulted in storm deposits extending 2-5 km from the mouth of estuaries in the southwestern Everglades, resulting in vertical accretion that was 6.7 to 14.4 times greater than the long-term (100 y) annual accretion rate (0.27 ± 0.04 cm y^{-1}). Total P (TP) inputs were highest at the mouth of estuaries, with P concentration double that of underlying surface (top 10 cm) soils. This P deposition contributed 49 to 98% to the soil nutrient pool. As a result, all mangrove species showed a significant increase in litter foliar TP and soil porewater inorganic P concentrations in early 2018, 3 months after Irma's impact (Castaneda-Moya et al. 2020). • Feher et al. (2020) reported abrupt increases in elevation due to sediment inputs and subsurface expansion along the Shark River Estuary in the Everglades during Hurricane Wilma that were followed by: (1) an initial post-hurricane period of elevation loss due to erosion of hurricane sediments and subsurface contraction; (2) a secondary period of elevation gain due primarily to accretion; and (3) an abrupt elevation gain due to new sediment inputs during Hurricane Irma. They suggested that storm-induced deposition of marine sediments may be critical to the establishment and continued persistence of mangrove ecosystems in non-deltaic areas that receive minimal terrigenous sediment inputs and also have a disturbance regime of reoccurring storms.
Peat collapse	• The 1935 Labor Day hurricane caused extensive mangrove forest mortality and a reduction in the soil elevation of 58.2 cm and the permanent conversion of mangrove forest to mudflat over the period 1930-1998 due to peat collapse, compared to the accretion of 15.2 in areas where mangrove forests persisted (Osland et al. 2020).

Table 46. Summary of chronic inundation impacts to mangroves.

Effect	Literature Summary
Drowning of mangroves/ retreat/ transition to open water	• Carbon sequestration and trapping of sediment in mangroves can offset sea level rise to a point. In a global analysis, Saintilan et al. (2023) found that mangroves' ability to vertically adjust to sea level rise is very likely to be exceeded (i.e., elevation deficit) at relative sea level rise between 7 and 8 mm/yr. Under a global warming scenario of 3°C, Florida will experience relative sea level rise >7 mm/yr, and retreat of mangrove habitats will be very likely. • However, in a local study at sites in the Everglades in South Florida, steady-state soil accretion rates were 0.9 to 2.4 mm/yr and recent (2001 to 2016) estimated sea level rise was 7.7 mm/yr. Despite this accretion deficit, mangrove "drowning" has not been observed at those sites, which suggests that short-term environmental disturbance (e.g., storms) may contribute to non-steady state accretion and make up the accretion deficit (Chambers et al. 2021). • A model by Parkinson and Wdowinski (2022) of mangrove resilience in South Florida as a function of sea level rise and vertical sediment accumulation indicates that by 2040 to 2050, mangroves will begin a widespread conversion to intertidal and subtidal environments, which will result in plant destabilization and a transition to mudflats or formation of inundation ponds. By 2100, most mangrove forested areas in South Florida will be submerged.
Peat collapse feedback loop	• Constant inundation and burial by sediment cause stress or mortality of mangroves because gas exchange by aerial root structures is reduced. Subsequent loss of belowground roots and increased decomposition result in loss of surface elevation through peat collapse, which in turn increases the degree of inundation (Radabaugh et al. 2021). • In a mesocosm experiment, Chambers et al. (2014) found a significant decrease in mangrove soil bulk density with increased inundation, which could lead to peat collapse.
Landward expansion of mangroves	• Remote sensing analysis of 15 islands in Florida Bay that were dominated by mangroves on the coastal fringe showed that from 1953 to 2014, all islands had significant mangrove expansion and the landward expansion of mangroves replaced inland non-mangrove habitats (brackish or freshwater plants; Zhai et al. 2019). • Using a sea level and elevation model, Doyle et al. (2010) found that mangrove forests in South Florida are expected to replace retreating freshwater forests over the next century. • Sklar et al. (2021) used land cover data in coastal South Florida along with sea level rise scenarios to estimate sea level rise impacts on mangroves. Under a low sea level rise scenario of 0.27 m by 2070 with mangrove accretion included in the model, mangroves were able to migrate inland while maintaining the current coastline. However, under a high sea level rise scenario (1.13 m by 2070), accretion could not compensate for inundation and mangrove coastline was lost. • Long-term data from the Everglades show that a 10 cm rise in sea level over the previous 50 years, along with reduced freshwater delivery during that time, led to landward migration of mangroves of ~1.5 km over 54 years (Rivera-Monroy et al. 2011). • Sea level rise-driven mangrove encroachment of marshes in Ten Thousands Island National Wildlife Refuge in Florida resulted in a 35% increase in mangrove coverage from 1927 to 2005 (Krauss et al. 2011).
Altered mangrove growth and physiology	• Ellison and Farnsworth (1997) conducted a 2.5-year greenhouse study of *Rhizophora mangle* with simulated tides and an inundation level expected to occur in the Caribbean by 2050 to 2100 to assess mangrove physiological and growth responses to sea level rise. By the end of the experiment, mangroves exposed to the increased sea level treatment were 10 to 20% smaller than the plants exposed to current sea level conditions. Additionally, relative to the current sea level plants, the increased sea level plants had lower maximum photosynthetic rates and lower relative growth rates.

Note: Degree of chronic inundation (i.e., sea level rise) will determine whether effects on mangroves are net positive or negative. Under lower inundation levels, mangroves can accrete sediment to vertically adjust to sea level rise and can expand landward. However, under higher inundation levels, mangrove vertical adjustment cannot keep up with rising sea level and mangroves retreat/drown.

Table 47. Summary of marine debris impacts to mangroves.

Effect	Literature Summary
Relative amounts	Microplastics: • Microplastics have been shown to occur in mangrove surface waters and mangrove sediments at many locations worldwide, and different shapes of microplastics found in mangrove habitats include fibers, fragments, films, pellets, and granules. Microplastics are mainly created from the breakdown of microplastic debris (Deng et al. 2021). • Zhou et al. (2020) observed that, in China, sediments in mangrove areas contained more abundant microplastics than sediments in neighboring non-mangrove beach areas by a factor of 1.1 to 8.5. Additionally, the site with highest microplastic abundance was in a heavily touristed area near a mariculture area, and the lowest microplastic abundance was found at a site in a mangrove nature reserve. • Zhang et al. (2020) found between 5 and 10 times more microplastics in the landward zones compared to the seaward zones in mangroves along the Beibu Gulf in China. Microplastic abundance in the different zones of the mangrove forest was strongly linearly related to tidal current velocity. Macrodebris: • In Java, Indonesia, van Bijsterveldt et al. (2021) found significantly higher numbers of microplastic items in the landward mangrove fringe than in the seaward fringe or in the mangrove basin. An average of 17% of the mangrove forest floor was covered by plastic, and plastic was found up to at least 35 cm deep in the sediment. • In Papua New Guinea, Smith (2012) found mean debris loads (number of macrodebris items per m^2) ranging from 1.2 to 78.3 at mangrove sites, and width of the debris bands ranging from 0.5 to 10 m. The vast majority (89.7%) of items were made of plastic. Other materials were glass, metal, paper, rubber, textile, and wood. • Gajanur and Jaafar (2022) counted 6,239 abandoned, lost, or discarded fishing gear items at mangrove sites around Singapore. Nets were by far the most abundant type of debris (3,260 items) in mangroves, followed by fishing lines (1,505 items), traps (584 items), floats and buoys (556 items), and lures, sinker, hooks, and rods (329 items). • In a literature review of mangrove macrodebris studies through 2020, Luo et al. (2021) summarized studies that showed average number of items per m^2 ranging from 0.054 (in Colombia) to 21.23 (in Papua New Guinea).
Physiological stress of mangrove trees	• In a field experiment in Indonesia that covered the root zone of mangrove trees with plastic, van Bijsterveldt et al. (2021) found that prolonged suffocation by plastic created anoxic conditions that caused immediate pneumatophore growth and potential leaf loss. Leaf area was maintained in the treatment with 50% of the root zone covered by plastic, but significantly decreased leaf area and survival were observed when 100% of root zone was covered by plastic. • Marine debris can potentially mask mangroves from solar radiation if the whole tree is entangled, or it can cover the pneumatophores and lead to oxygen deprivation (Kesavan et al. 2021). • Damage from marine debris colliding with mangrove trunks was strongly associated with crown dieback in Thailand (Pranchai et al. 2019). • Smothering of planted seedlings by marine debris has caused the failure of efforts to rehabilitate mangrove habitats (Smith 2012).
Impacts on mangrove fauna	• Anthropogenic marine debris may provide additional, transient habitat that may protect fauna from physical stress in mangroves. Riascos et al. (2019) reported that a variety of species, including periwinkles, mussels, crab, and shrimps, utilized mangrove marine debris as habitat in Colombia. • Gajanur and Jaafar (2022) documented the entrapment of organisms in abandoned, lost, or discarded fishing gear in coastal habitats, including mangroves, around Singapore. They found that plastic polymer nets trapped the highest diversity and abundance of organisms, and the most frequently entrapped taxa were horseshoe crabs, ray-finned fishes, and crustaceans. • Sandilyan and Kandasamy (2012) reported that the sound of rustling plastic bags in the mangrove canopy in India deter waterbirds that are dependent on mangrove habitats. • In an experiment in a mangrove forest in Brazil, Clemente et al. (2022) examined the impact of plastic bags on macroinvertebrate fauna. After 2 months, the plastic bag treatment (substrate covered with

Effect	Literature Summary
	plastic bags) macrofauna abundance decreased from 1,350 to 167 individuals; whereas, in the control treatment, macrofauna abundance increased from 1,004 to 5,162 individuals. • In a literature review of microplastics in mangrove ecosystems, Deng et al. (2021) report that microplastics can be taken up by and accumulate in mangrove biota, including crabs, snails, clams, and fishes. Ingestion is the main pathway of microplastic intake by mangrove biota.

Note: No literature was found on impacts of marine debris on mangroves in Florida, but several studies were found on marine debris impacts on mangroves in other regions, particularly southeast Asia. Impacts to mangroves in Florida would likely be similar to those observed in other regions.

Table 48. Summary of convective storm wind event impacts to mangroves.

Effect	Literature Summary
Loss of vegetation and leaf area	• After a strong storm with a maximum wind gust of 58 km/hr and hail in 2019, mangrove areas in southeastern Brazil had reduced vegetation and leaf area indices (normalized difference vegetation index [NDVI] reduced from 0.72 to 0.35 and leaf area indices [LAI] reduced from 4.25 to 0.63) and drastically reduced proportion of live trunks (93.2% pre-storm to 5.8% post-storm). Natural recovery had not occurred 3 years after the storm (Lima et al. 2023).
Fruit abortion / premature detachment	• *Rhizophora mangle* propagule detachment in part depends on mechanical force, which can be aided by wind. However, strong winds can cause either the abortion or detachment of immature fruit. Peel et al. (2019) observed a significant correlation between fruit shedding and maximum wind speeds at three mangrove sites on the Yucatan Peninsula, Mexico. Most fruits caught in traps during the study were immature.
Gap creation	• Duke (2001) reported that forest gaps in mangroves may be created by wind storms. This process was outlined in a conceptual forest development and regeneration model that Duke developed based on field observations in *Rhizophora* mangrove stands in Panama. Gap closure (recovery) occurs through reproductive and vegetative processes and may take decades. • In a black mangrove (*Avicennia germinans*) forest in Costa Rica, Putz et al. (1984) found that the width of crown gaps was positively correlated to the distance trees adjacent to the gap swayed in the wind. Buds, leaves, and branches knocking into each other due to wind appeared to create and maintain gaps around tree crowns.
Changes in hydrodynamics	• Davis et al. (2004) recounted multiple windstorm events in the Everglades (including winter storms lasting up to 10 days) that altered mangrove creek discharge (reversals of flow), salinity (changes up to 20 psu), and stage (increase of nearly 3 m). These storms can account for a substantial proportion of annual flux of freshwater between mangroves and the adjacent Florida Bay.

Table 49. Summary of shoreline erosion impacts to mangroves.

Effect	Literature Summary
Mangrove loss	• A global land use change analysis of remotely sensed images revealed that shoreline erosion was the greatest driver of natural mangrove loss, responsible for 27% (912 ± 41 km^2) of global mangrove loss from 2000 to 2016 (Goldberg et al. 2020). • Manual interpretation of remotely sensed images from 1996 to 2010 showed that erosion-driven mangrove loss was widespread globally and was most commonly observed in high-energy environments (e.g., exposed coastlines and at river mouths; Thomas et al. 2017).
Reduced seedling retention	• In a study of mangrove seedling retention in Florida estuaries, Kibler et al. (2022) found that dislodgement of established mangrove seedlings by hydrodynamic force can occur as sediment erodes around the roots. Erosion of sediments can lead to uprooting at both small (around individual seedling roots) and large scales (through bed degradation).

Note: Many studies have shown that mangroves protect shorelines from erosion. Studies presented here focus on impacts of shoreline erosion to mangroves, rather than vice versa.

Table 50. Summary of contaminant/spill event impacts to mangroves.

Effect	Literature Summary

Impacts of oil exposure to mangrove trees	Acute impacts:
	• Mangroves are highly vulnerable to oil spills because oil deposits on sensitive plant surfaces exposed during the ebb and flow of tides (Duke 2016). Oiling can kill mangroves within a few weeks to several months (Hoff and Michel 2014). Symptoms of acute impacts to mangroves include (as summarized by Hoff and Michel (2014)):
	  o Seedling death
	  o Leaf yellowing (chlorosis)
	  o Defoliation
	  o Tree death
	Chronic impacts:
	• Oil can be retained in mangrove sediments for years and can be re-released and cause chronic oiling. Following the Bahia Las Minas spill in Panama, oil persisted in mangrove sediments and leached out of sediments for at least 5 years (Burns and Yelle-Simmons 1994).
	• Additionally, chronic impacts may occur from the initial oiling event and may continue for years to decades and result in permanent habitat loss (Hoff and Michel 2014).
	• In a literature review, Duke (2016) summarized the chronic impacts of oiling on mangroves. Symptoms include:
	  o Death of trees with seedling regeneration
	  o Defoliation and canopy thinning
	  o Leaf yellowing
	  o Reduced growth of surviving trees
	  o Poor seedling establishment
	  o Toxic response deformities and morphological changes (e.g., pneumatophore branching; root abnormalities, fewer lenticels; and mutated, variegated leaves)
	• In a field experiment in Panama using Prudhoe Bay crude oil, defoliation had begun by 4 months post-exposure and continued through 20 months post-exposure, when defoliation was observed in 78% of surviving trees and average estimated defoliation was 47.5%. Propagule sprouting success was also reduced at the oiled site. Tree death continued through 10 years post-exposure. The number of live mature trees and the number of seedlings in the oiled site increased at 20 years post-exposure (Renegar et al. 2022).
	• The magnitude of impacts to mangroves is related to oil type and concentration, duration of exposure, sensitivity of individual mangrove species, physical factors that control oil persistence (e.g., wave exposure, currents), and presence and density of burrowing animals that can allow oil penetration of substrate via burrows (Duke 2016; Hoff and Michel 2014).

Impacts on mangrove fauna	• Following the Bahia Las Minas oil spill in Panama, a wide range of mangrove-associated fauna were examined for impacts:
	  o Pre- and post-spill comparisons of percent cover of four bivalve species and one barnacle species that live on mangrove roots in low wave energy habitats revealed direct mortality that varied among species and over time. Population reductions were greatest in brackish streams and showed no sign of recovery 1 year post-spill (Garrity and Levings 1993).
	  o In open coast habitats, sessile invertebrates that grew on submerged prop roots included sponges, corals, anemones, tunicates, bryozoans, vermetids, and hydroids. In the first year after the spill, sessile invertebrate cover dropped to less than 5%, compared to 10% at unoiled sites (Garrity et al. 1993).
	  o Levings and Garrity (1994) observed that mangrove epibiota (algae, hydroids, and bryozoans) that serve as juvenile habitat for spiny lobsters were reduced by 40 to 50% for at least 5 years after oiling.
	• In mangroves in the Panama field experiment, immediate (4 days post-exposure) mortality of crabs and tree snails was observed, and population impacts persisted for over a year. Mangrove oysters were minimally impacted (Renegar et al. 2022).

Wetlands (Seagrass)

Table 51. Summary of hurricane (acute coastal/storm surge flooding) impacts to seagrass.

Effect	Literature Summary
Burial by storm-generated sediments	• In a meta-analysis of 51 studies of cyclone/hurricane damage to seagrass, Correia and Smee (2022) found that sediment shift/burial caused damage in 9 out of 12 studies. The degree and duration of damage depended on the amount of burial: most studies reported short-term impacts. • Steward et al. (2006) reported no scour and limited effects from burial resulting from the four 2004 hurricanes that crossed the Indian River Lagoon. No impacts were observed 1 year post-storms.
Plant damage	• Tilmant et al. (1994) reported minor effects on seagrass (blade density) in Biscayne Bay and Florida Bay after Hurricane Andrew, with some blowouts enlarged toward the shelf margin. • Rodríguez et al. (1994) reported 10 km^2 of seagrass meadows destroyed by Hurricane Hugo (winds >150 mph) along the eastern shore of Puerto Rico, mostly by scour but also by burial by sand. • Hammerstrom et al. (2006) reported minimal impact from Hurricane Irene on seagrass on the West Florida Shelf, hypothesizing that the storm exposed buried seed banks that supported biomass recovery 1 year post storm. • Following Hurricane Georges (Category 2), *Syringodium filiforme* coverage was reduced by 19%; whereas, the strong, deep root network of *Thalassia testudinum* only experienced a 3% loss in the leaf biomass (Fourqurean and Rutten 2004). • Pu et al. (2014) used Landsat TM imagery to compare seagrass cover in the year before and after the passage of 3 hurricanes in 2004, showing a slight increase (6%) in estuaries along the central west FL coast. • Patrick et al. (2020) reported 30-100% loss of seagrass cover in areas that experienced winds of Category 3 or 4. Damage included both complete removal (roots/rhizomes ripped from the sediment) and partial removal (aboveground biomass sheared off). Where rhizomes remained intact, regrowth occurred within 1-3 months. • Wilson et al. (2019) used long-term monitoring data for Florida Bay and the Florida Keys NMS to find that impacts from Hurricane Irma were limited in spatial extent.
Water quality changes	• In a meta-analysis of 51 studies of cyclone/hurricane damage to seagrass, Correia and Smee (2022) found that changes in water quality (reduced salinity, temperature, and dissolved oxygen, and increased turbidity, phosphorous, and chlorophyll a), negatively influenced seagrass cover in 10 out of 11 (91%) studies. • Following the 2005 hurricane season, Cole et al. (2018) found that water quality impacts persisted for >1 year. The duration of water quality impacts were highly variable and depend on water retention times in the affected bay or estuary. • Hurricanes can improve water quality with increased fresh water inflows, particularly in areas affected by very high salinity resulting from long-term droughts (Zink et al. 2020).
Changes in fish and macro-invertebrate communities	• Following Irma, the Category 4 hurricane that affected Florida Bay, there were fish kills, reduced dissolved oxygen and increased turbidity and chlorophyll a that resulted in loss of seagrass-associated faunal species with an increase in water column species (e.g., bay anchovy) that had a rapid response to increased phytoplankton (Zink et al. 2020).

Table 52. Summary of chronic inundation impacts to seagrass.

Effect	Literature Summary
Changes in extent of seagrass due to SLR	• Models have been used to predict the changes in seagrass cover and distribution for different SLR scenarios. Most studies predict large reductions in seagrass habitat extent, particularly where landward migration is constrained by coastal development (Nicastro et al. 2012; Saunders et al. 2013; Scalpone et al. 2020). Davis et al. (2016) predicted substantial seagrass losses in deeper estuarine areas and a net shoreward movement of seagrass beds, as long as there are new sites available for colonization. • In contrast, Dumbauld et al. (2022) predicted as much as 34% more eelgrass in Willapa Bay by 2100.

Effect	Literature Summary
	• Chen and Lin (2022) described four different mechanisms by which the species composition in shallow seagrass beds could respond to increased sea levels, considering increased flushing and nutrients, and reduction in the effects of droughts. • For seagrasses that are sheltered from wave action by offshore coral reefs, it is not likely that vertical accretion on the coral reefs will be sufficient to maintain suitable conditions for reef lagoon seagrass (Saunders et al. 2014). • McHenry et al. (2021) used models to predict that SLR could result in significant losses of current seagrass beds and potential restoration areas, causing contracted distributions and lower seagrass cover along the Florida Gulf coast.
Changes in water quality	• High temperatures and indirect impacts on water quality (high suspended sediments, eutrophication and hypoxia) can result in reduced seagrass extent (Short et al. 2016) and have cumulative negative impacts (Losciale et al. 2024).
Changes to benthic macrofauna	• Nicastro and Bishop (2013) ran a manipulative field experiment that indicated changes to tidal inundation regime will reduce seagrass-dwelling macroinvertebrates through a combination of direct and indirect effects.
Carbon sequestration	• Long-term sea-level rise effects such as tidal inundation and increased porewater salinity will likely decrease ecosystem carbon stocks in the absence of upslope wetland migration buffer zones (Kauffman et al. 2020).

Table 53. Summary of tropical storm marine debris events and chronic plastic impacts to seagrass.

Effect	Literature Summary
Relative amounts	Microplastics: • Seagrass habitats in the Florida Keys had slightly more microplastic (fibers and fragments) compared to adjacent sand flats (Plee and Pomory 2020). • Microplastics were more abundant in seagrass sediments compared to bare sediments, were adhered to every sample of seagrass blade, and in biota associated with seagrass in a field study of *Zostera marina* in Scotland (Jones et al. 2020). • No differences in total microplastic counts were found in *Zostera capensis* meadows compared with adjacent bare sediments in a very small-scale study in South Africa (Boshoff et al. 2023). • In a study of *Zostera marina* in Estonia, surface water in seagrass beds had microplastic counts similar to other areas of the Baltic Sea; whereas, sediments had much higher microplastic counts than previously recorded from adjacent unvegetated and offshore sediments, thereby suggesting a strong ability of the sediments in seagrass beds to retain microplastics (Kreitsberg et al. 2021). • Seng et al. (2020) found significantly higher microplastic densities on seagrasses compared to macroalgae in Singapore but no relationships between microplastic density and epibiont cover in both. • Goss et al. (2018) found that 75% of *Thalassia* blades in a study in Belize had encrusted microplastics, with microfibers the more dominant type. They identified potential mechanisms for microplastic accumulation as entrapment by epibionts, or attachment via biofilms, suggesting that macro-herbivory is a viable pathway for microplastic pollution to enter marine food webs. • In a study of two bays in China, Huang et al. (2020) found that seagrass sediments were enriched in microplastics by a factor of 2.1 to 2.9, and the trap effect of seagrass was non-selective regarding the shape, color and size of microplastics. • In a mesocosm study, Menicagli et al. (2021) found that both HDPE and biodegradable starch-based macroplastics, if deposited on marine bottoms, could make seagrasses vulnerable to sedimentation and reduce plant cover within meadows. • In a study of eight *Zostera marina* beds and adjacent unvegetated sites in the UK, Unsworth et al. (2021) found elevated counts of microplastics in all sediments, reflecting general build-up of microplastics in the wider environment rather than becoming concentrated within seagrass as an enhanced sink. • In a study of a lagoon in Portugal, Cozzolino et al. (2020) found that macroplastics (all fibers) accumulated in all vegetated habitat but not in nearby unvegetated areas. However, they cautioned that generalizations in the trapping effect of coastal vegetated areas should be done with caution, since it be highly variable and may depend on the plastic size, habitat and tidal position.

Effect	Literature Summary
	• In a study of ephemeral seagrass (*Halophila ovalis*) beds in the Swan-Canning Estuary, Western Australia, Wright et al. (2023) found microplastics attached to seagrass blades and in sediments; however, they could not support the hypothesis that this seagrass species acts as a sink for microplastic particles in sediments. • In a study of microplastic counts in sediment cores from two sites in Spain with different adjacent land-use patterns, Dahl et al. (2021) found that an increase in microplastics in the seagrass soil was associated with land-use change following the intensification of the agricultural industry in the area, with a clear relationship between the development of the greenhouse industry and the concentration of microplastics in the historical soil record. • In a mesocosm study using *Zostera marina*, Molin et al. (2023) observed a decrease in photosynthetic activity and respiration, which they speculated was caused by leachates from microplastics. • In a review of 112 studies on plastic pollution, Ouyang et al. 2022 reported that plastics are more abundant in mangrove forests and tidal marshes than in tidal flats and seagrass meadows, and that microplastics (dominated by fibers) are much more common (reported in 88.3% of the studies). Macro-litter: ● In a study of two sites with two seagrass species, salt marsh, sandy beach, bare sediment and rocky bottom in Spain, Egea et al. (2023) found that vegetated habitats showed the highest macroplastic accumulation in autumn-winter seasons, especially in medium-lower tidal-elevation zones. Seagrasses accumulated most of the degraded macroplastics. ● In a study in Spain across six *Posidonia oceanica* meadows, Navarrete-Fernández et al. (2022) found that macro-litter items consisted of 80% plastic and 20% non-plastic items. Non-plastic materials included glass, metal, wood and paper (40%, 30%, 20% and 10%, respectively). Macro-litter accumulated mostly along the landward edge of the seagrass. ● In a seasonal study across multiple habitats in Singapore, Fong et al. (2023) found that litter density in terms of count was generally lower in seagrass meadows and coral reefs compared to mangroves and beaches. Macroplastics in seagrass were dominated by glass, plastic, fishing gear, and cloth.
Food web risks	• Remy et al. (2015) found ingested artificial fibers of various sizes and colors were found in 27.6% of the digestive tracts of nine dominant species that feed on dead seagrass blades in Corsica, regardless of their trophic level or taxon. There were no seasonal, spatial, size, or species-specific significant differences, suggesting a constant rate of ingestion. In the gut contents of invertebrates, varying by trophic level, and across trophic levels, the overall ingestion of artificial fibers was low (approximately 1 fiber per organism). • Tahir et al. (2020) found microplastics in sediment, water, fish, and benthic species in a seagrass area in Indonesia, showing a wide dispersion of microplastics contamination in the marine food web. • In a review of the literature, Bonanno and Orlando-Bonaca (2020) concluded that the impact of microplastics on seagrass ecosystems remains largely unknown.
Nutrient processing	• In mesocosm studies, Litchfield et al. (2020) reported that high levels of plastic pollution (low-density polyethylene shopping bags) significantly reduced the decomposition rate of eelgrass by 36% in comparison to controls, and significantly slowed nitrogen liberation from seagrass detritus. • In mesocosm studies, Balestri et al. (2017) suggested that biodegradable bags altering sediment geochemistry could promote the spatial segregation of seagrass clones and influence species coexistence.

Note: Impacts of macro- and microplastics on seagrass are reported here. No papers were found on impacts of storm-specific marine debris events on seagrass.

Table 54. Summary of convective storm wind event impacts to seagrass.

Effect	Literature Summary
Habitat damage	• In shallow beds of *Zostera marina* in the Baltic Sea, the experimental removal of the eelgrass canopy strongly increased the risk of mussel dislodgement during a moderate storm with a median return time of 6.5 months. In contrast, no protection of mussels by eelgrass was found during a series of three intense storms, each of which had a median return time of > 11.5 yr (Reusch and Chapman 1995). • Following an intense storm (winds up to 140 km/h) along the Iberian Peninsula, Spain, up to 40 cm of sediment was eroded over 50% of 42 meadows of *Posidonia oceanica*. There was 10–80 % of meadow

Effect	Literature Summary
	cover buried under 7 cm of sediment—a survival threshold for *P. oceanica*. Exposed and patchy meadows were much more vulnerable to the overall impact than sheltered or continuous meadows (Marco-Mendez et al. 2024).
Water quality	• In the Florida Keys, turbidity was maximal during winter due to seasonally maximum wind conditions, which resulted in higher water column concentrations of particulate N and P (Lapointe and Clark 1992). • Strong storms caused high freshwater flows from a creek into Florida Bay, impacting water quality, scouring seagrass beds, and depositing a layer of 5 cm layer of mud (Davis et al. 2004). • After a storm event in Chesapeake Bay, Gurbisz et al. (2016) documented physical removal of plants around the edge of seagrass beds by high flows, followed by subsequent wind-driven resuspension of newly deposited sediment and attendant light-limiting conditions that were detrimental to the bed.

Table 55. Summary of shoreline erosion impacts to seagrass.

Effect	Literature Summary
Habitat degradation	• In Morro Bay, CA, following massive eelgrass loss since 2010, over 90% of locations that previously had eelgrass experienced erosion. Elevation losses (erosion) reached 0.50 m in some places (mean loss of 0.10 m) with as much as a 50% decrease (median decrease of 13.6%) in elevation (i.e., increase in depth) compared to pre-decline levels (Walter et al. 2020). • In Italy, in an area of a sediment-starved beach and a change to finer-grained sediment in the nearshore, the seagrass *Posidonia oceanica*, which requires stable environmental conditions and has a preference for coarse-grained sandy substrate, was being replaced by the pioneering and opportunistic *Cymodocea nodosa* (Cavazza et al. 2000).
Shoreline stabilization	• *In situ* comparisons of SAV beds adjacent to both natural and hardened shorelines in 24 sub-estuaries throughout the Chesapeake and Mid-Atlantic Coastal Bays indicated that shoreline hardening does impact adjacent SAV beds. Species diversity, evenness, and percent cover were significantly reduced in the presence of riprap revetment (Landry and Golden 2017).

Note: Many studies have shown that seagrasses protect shorelines from erosion. Only one study was found that documented impacts to seagrasses along eroding shorelines.

Table 56. Summary of contaminant/spill event impacts to seagrass.

Effect	Literature Summary
Vegetation damage	• Following the M/V *Cosco Busan* spill of a heavy fuel oil in San Francisco Bay, many eelgrass beds were exposed to oil, but there was little evidence to suggest serious injuries. Response vessels impacted shallow subtidal eelgrass beds, documented through side scan sonar surveys (Fonseca et al. 2017). • In a field experiment in Panama using Prudhoe Bay crude oil, initial short-term effects in the first 2 years indicated reduced seagrass growth rates within the oiled site as there were effects on leaf blade area and densities that continued for 10 years. 20-years post spill: an increasing trend of *Thalassia testudinum* growth rate at the oil treatment sites (Renegar et al. 2022). • In a review of the literature, Fonseca et al. (2017) determined that effects of oil spills on seagrass beds were dependent on many factors: proximity of the site to the point of oil release; oil type; tidal stage, range, and circulation patterns; and the location of the seagrass beds in the tidal frame. SAV are rooted vascular plants that cannot actively avoid contact with submerged oil that is transported in the water column or deposited on the substrate. Lighter oils are generally more acutely toxic and heavier oils can result in fouling and smothering effects. Longer-term impacts may be expected where sediments are contaminated, and roots and rhizomes are exposed to heavy or chronic oiling.

Hardbottom Habitat (Coral Reefs)

Table 57. Summary of hurricane (acute coastal/storm surge flooding) impacts to coral reefs.

Effect	Literature Summary
Physical damage	• Category 5 Hurricanes Irma and María during 2017 caused unprecedented damage to coral reef ecosystems across northeastern Puerto Rico. Hurricanes inflicted significant site-, depth-, and life history trait-specific impacts to endangered corals, with substantial and widespread mechanical damage to branching species and moderate mechanical damage to foliose species (Hernández-Delgado et al. 2024). • Fong and Lirman (2008) monitored a patch reef of the branching coral *Acropora palmata* damaged by Hurricane Andrew, leading them to conclude that *A. palmata* is adapted to disturbances of both low intensity and high frequency (conditions typical of reef flat zones) and episodic high intensity and low frequency events (hurricanes and tropical storms). • Following Hurricane Andrew, Lirman and Fong (1997) monitored *A. palmata* damaged along the Florida Keys, finding that more than 50% of the *A. palmata* fragments were alive and that stabilization was related to proximity to a patch of mature colonies and substrate, with higher survival in hard substrates. • In a detailed study of 15 fore-reef plots in the Florida Keys, Williams and Miller (2011) found that between 2004 and 2010, the study population showed more than 50% decline in live area, with half this decline occurring the 2005 hurricane season, from which recovery was minimal by 2010. • Study of the impacts from Hurricane Andrew off Dade County, FL, showed: greatest damage to the offshore reefs compared to middle and inner reefs; the algal community had 40->90% loss of benthic cover; the sponge community was slightly (0-25%) to heavily impacted (50-75%); soft corals had 25-50% loss and 0-25% on the offshore and inshore reefs, respectively; and hard corals were least affected with a moderate loss of benthic cover (38%) on the offshore reef and slight loss (23%) on the other inner two reefs (Blair et al. 1994). • Gleason et al. (2007) monitored the combined impacts of Hurricanes Dennis, Katrina, Rita, and Wilma in 2005 on a population of *A. palmata* at Molasses Reef, FL. They found 2 of 18 colonies were lost, and a large section of the reef framework was dislodged and transported to the bottom of the reef spur. • The 2005 hurricane season (four storms) resulted in substantial loss of *A. palmata* from the upper Florida Keys fore-reef from a combination of physical removal and subsequent disease-like tissue mortality, and yielded few recruits of either sexual or asexual origin (Williams and Miller 2011). • In a meta-analysis of data for 286 coral reef sites in the Caribbean between 1980 and 2001, Gardner et al. (2005) found that coral cover at sites impacted by a hurricane declined at a significantly faster rate (6% per annum) than nonimpacted sites (2% per annum), due almost exclusively to higher rates of loss in the year after impact in the 1980s. There is no evidence of recovery to a pre-storm state for at least 8 years after impact. • After Hurricane Hugo passed over Buck Island, U.S. Virgin Islands in 1989, Bythell et al. (2000) reported that by 1996, strong coral recruitment had occurred in shallow, exposed areas that showed the greatest hurricane impacts, and these areas are now more species rich than in 1988, although coral cover has not reached pre-hurricane levels.
Burial by storm-generated sediments	• Category 5 Hurricanes Irma and María during 2017 in Puerto Rico caused coral reef damage from localized sediment bedload (horizontal sediment transport and abrasion), and burial by hurricane-generated rubble fields, with moderate to high localized damage to small-sized encrusting and massive morphotypes due to sediment bedload and burial by rubble (Hernández-Delgado et al. 2024). • After Hurricane Irma in the Florida Keys, there was a correlation between the magnitude of decline in *Diadema antillarum* density (a keystone grazer) and the magnitude of sediment deposition on reefs, suggesting that abrasion or burial from sediment transport may have contributed to *D. antillarum* mortality (Kobelt et al. 2019).
Water quality changes	• Manzello et al. (2007) found that hurricane-induced cooling was responsible for the documented differences in the extent and recovery time of coral bleaching between the Florida Reef Tract and the U.S. Virgin Islands during the Caribbean-wide 2005 bleaching event.
Changes in associated communities	• Simmons et al. (2021) monitored soundscapes at two sites in the Florida Keys for effects from Hurricane Irma and they reported that on short time scales, temporal patterns in the coral reef soundscape were relatively resilient to acoustic energy exposure during the storm, as well as changes in the benthic habitat and environmental conditions resulting from hurricane damage.

Effect	Literature Summary
	• After Hurricanes Irma and Maria, Gochfeld et al. (2020) studied impacts to coral reef sponge communities, noting 24.9% reduction after the storms, but recruitment and/or regrowth was observed within 10 weeks post-hurricanes, indicating potential resilience in Caribbean sponge communities. • Following Hurricane Irma, a long-standing sacoglossan sea slug population, which historically numbered in the thousands, was completely eliminated from its habitat off a site in the Florida Keys, even though its habitat recovered (Middlebrooks et al. 2020). • Hurricanes Frances and Jeanne removed virtually all of an invasive macroalgae that covered 90% of the reefs off southeast Florida; however, the relief was only temporary (Lapointe et al. 2006). • Segura-Garcia et al. (2024) found that populations of clonal marine species with low pelagic dispersion, such as the sponge, *Aplysina cauliformis*, may benefit from increased frequency and magnitude of hurricanes for the maintenance of genetic diversity and to combat inbreeding, enhancing the resilience of Caribbean sponge communities to extreme storm events.

Table 58. Summary of chronic inundation impacts to coral reefs.

Effect	Literature Summary
Ability of coral reefs to keep up with SLR	• Modeling the ability of coral reefs in Florida and the Caribbean to maintain their elevation under different sea level rise scenarios using carbonate budgets shows that most reefs will only be able to keep pace with future sea-level rise if anthropogenic CO_2 emissions are reduced (Webb et al. 2023; Rodriguez-Ruano et al. 2023; Kuffner et al. 2019; Toth et al. 2022; Morris et al. 2022). • In a study of vertical growth potential of more than 200 tropical western Atlantic and Indian Ocean reefs, Perry et al. (2018) found that, though many reefs retain accretion rates close to recent SLR trends, few will have the capacity to track SLR projections under RCP4.5 scenarios without sustained ecological recovery, and under RCP8.5 scenarios most reefs are predicted to experience mean water depth increases of more than 0.5 m by 2100. • Models by Cacciapaglia and van Woesik (2020) predict that only 4% of Indo-Pacific coral reefs are projected to keep up with SLR by the year 2100, of which most will be located near the Equator.

Table 59. Summary of tropical storm marine debris events and chronic plastic impacts to coral reefs.

Effect	Literature Summary
Physical impacts	• In a study in Thailand, Ying et al. (2021) showed that, after 4 weeks of being covered by transparent and opaque plastic bags and fishing nets, some coral species had reduced photosynthetic performance, symbiont density, and calcification rate, particularly for the materials that were opaque. • In a field study of nearly 3,000 m^2 in Indonesia, Mueller et al. (2022) found that branching corals, especially *Porites cylindrica*, were most affected by litter entanglement. Field experiments with *P. cylindrica* showed that attached plastic induced bleaching, necrosis, and algal overgrowth within 5 months.
Invasive species/ disease introduction	• Parsons et al. (2023) documented the occurrence of nonindigenous sun corals (*Tubastraea* spp.) settled on polypropylene rope debris in the Florida Keys, which they say is highly abundant and widely distributed along the Florida Keys. • Applying a numerical modeling approach, Soares et al. (2023) demonstrated that rafting invasive corals (*Tubastraea* spp.) can be transported over long distances and reach the wider Caribbean in <100 days. They hypothesized a high risk of bioinvasion. • Lamb et al. (2018) assessed the influence of plastic waste on disease risk in 124,000 reef-building corals from 159 reefs in the Asia-Pacific region. The likelihood of disease increased from 4% to 89% when corals were in contact with plastic.
Ghost fishing	• Ghost traps in Florida Bay and Atlantic inshore killed 6.8±1.0 and 6.3±0.88 lobsters per trap annually, while Atlantic offshore traps killed fewer (3.0±0.69) lobsters, likely as a result of lower lobster abundance in traps. The combined effects of greater lobster mortality and greater abundance of lost traps in inshore areas account for the majority of the estimated 637,622±74,367 lobsters that die in ghost traps annually (Butler and Matthews 2015).

Effect	Literature Summary
	• In a 2007 study by Uhrin et al. (2014), they reported that coral habitats had the greatest density of lobster trap debris despite trap fishers' reported avoidance of coral reefs while fishing in the Florida Keys National Marine Sanctuary. The accumulation of trap debris on coral emphasizes the role of wind in redistributing traps and trap debris in the sanctuary. They estimated that 85,548±23,387 ghost traps and 1,056,127±124,919 nonfishing traps or remnants of traps were present in the study area. • In a study where lobster traps were placed in hardbottom and reef habitats in the Florida Keys and monitored over three winters and 26 wind events, Lewis et al. (2009) found that injuries caused by trap movement included scraped, fragmented, and dislodged sessile fauna, resulting in significant damage to stony coral, octocoral, and sponges. Overall, sessile fauna cover along the trap movement path was reduced from 45% to 31%, 51% to 41%, and 41% to 35% at the 4-m, 8-m, and 12-m sites, respectively.

Table 60. Summary of convective storm wind event impacts to coral reefs.

Effect	Literature Summary
Habitat damage	• Madden et al. (2023) developed a model to quantify the impact of hurricane-force winds on coral reef fragility, by species and damage metrics.
Invasive species transport	• Johnston and Purkis (2015) showed that perturbations to the Florida Current caused by hurricanes are relevant to the spread of invasive lionfish from Florida to the Bahamas.

Table 61. Summary of shoreline erosion impacts to coral reefs.

Effect	Literature Summary
Shoreline stabilization	● Toth et al. (2023) proposed that restoration of *Acropora palmata* at Buck Island, U.S. Virgin Islands, if successful, could mitigate the most extreme impacts of coastal flooding by reversing projected trajectories of reef erosion and allowing reefs to keep pace with the ~0.5 m of sea-level rise expected by 2100 with moderate carbon emissions reductions.

Note: Many studies show that coral reefs serve as natural barriers that protect adjacent shorelines from erosion during storms. Protection and restoration of coral reefs have been proposed to slow coastal erosion. No studies were identified that evaluated the effect of erosion of adjacent shorelines on coral reef health.

Table 62. Summary of contaminant/spill event impacts to coral reefs.

Effect	Literature Summary
Reef impacts	● There are relatively few case studies of oil spills on coral reefs, and, in some cases, oil exposure may have been limited. However, when coral reefs are exposed to spills, the effects can be severe and last for years, with intertidal and very shallow subtidal reefs particularly at risk. Corals had the longest time to recovery, at 3.5 to 10 years, followed by algae (1.5 to >3 years), sea urchins (0.7 to >3 years), and mollusks (>2 years). No impacts were detected in reef fish in the studies that examined them (Szathmary et al. 2024).

Sensitivity of Human Resource Receptors to Stressors

Vulnerable human resources are summarized by the SoVI. The relative sensitivity of vulnerable human populations to each stressor/hazard type was assessed using a qualitative assessment of results in FEMA's National Risk Assessment (Zuzek et al. 2022; 2023). Stressor event occurrences expected to cause large economic losses to property, buildings or agriculture, and/or likely to result in injuries or fatalities, are assumed to have a large negative effect on vulnerable human populations. Stressor event occurrences expected to cause lesser economic losses to property, buildings or agriculture, and less likely to cause injuries or fatalities, are assumed to have a small negative effect on vulnerable human populations. Stressor event occurrences expected to cause only minimal economic losses to property, buildings or agriculture, and that are unlikely to cause injuries or fatalities, are assumed to have no net effect on vulnerable human populations. Figure 22 shows the sensitivity rankings for vulnerable human populations to each of the six stressors.

Resource / Receptor	Stressor / Hazard					
	Acute Coastal/ Storm Surge Flooding	Chronic Inundation	Marine Debris Events	High Wind Events	Shoreline Erosion	Contaminants from Spill Events
1. Socially Vulnerable Population	- -	-	0	- -	-	-

Sensitivity Ranking Key

- -	Large negative effect
-	Small negative effect, short term
0	No effect
+	Small positive effect

Figure 22. Matrix of sensitivity rankings of stressors and human resources used in the All-Hazards Indices Expansion of the ESI.

Exposure of Receptors to Stressors

After compiling all hazard/stressors and receptors/resources as described above, an obvious initial analysis and visualization is to evaluate exposure of receptors/resources to hazard/stressors. To this end, the location and relative hazard rank of each receptor/resource from each hazard are depicted in Figures 23 through 32. These results may be used to evaluate the spatial distribution of exposure of a given resource to a given hazard. Results are depicted only for natural resource receptors. Exposure of human populations to each stressor may be generally assessed via inspection of hazard intensities in land areas of the figures in the Evaluated Stressors section above.

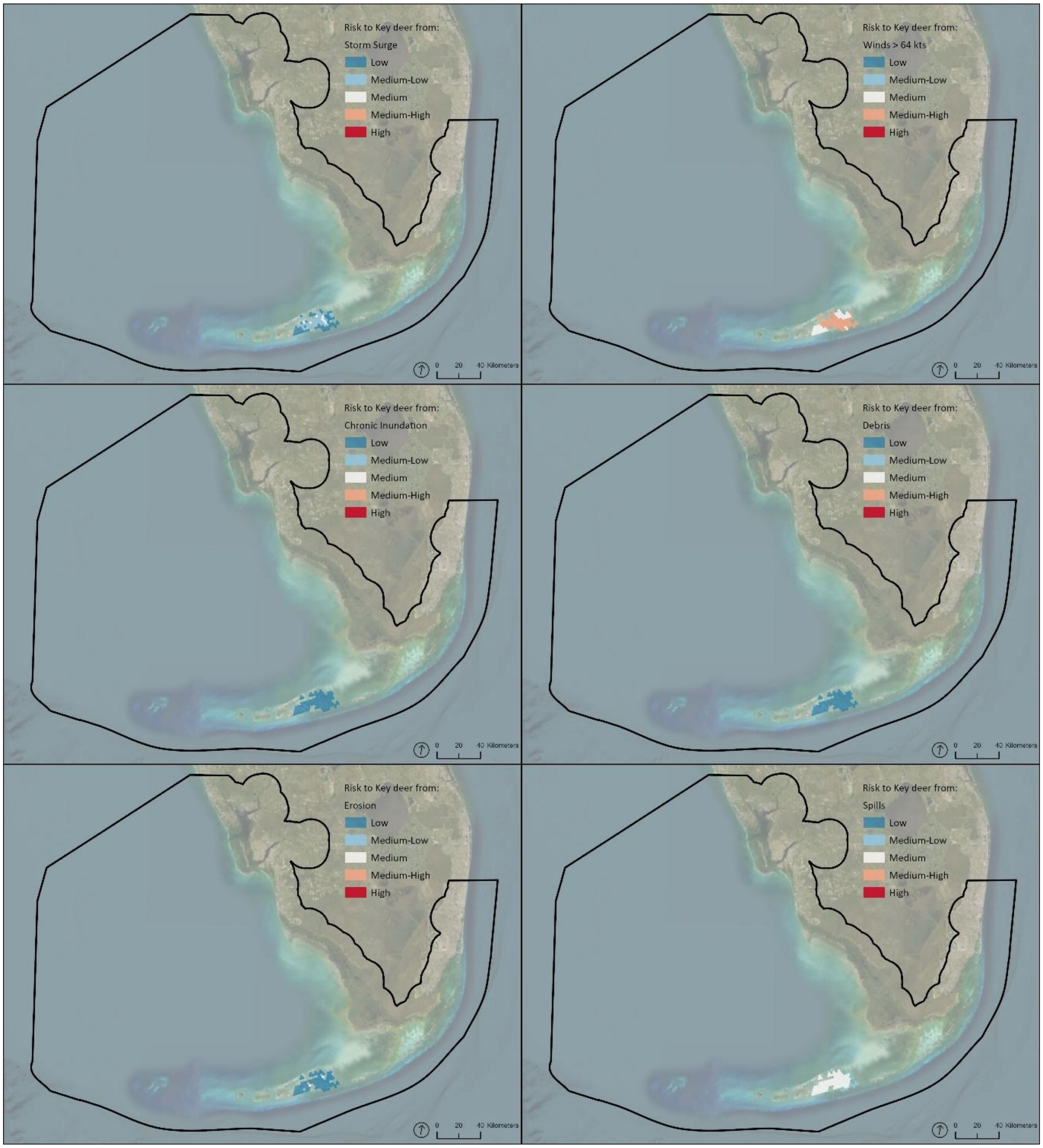

Figure 23. Exposure summary of Key deer to each evaluated stressor.

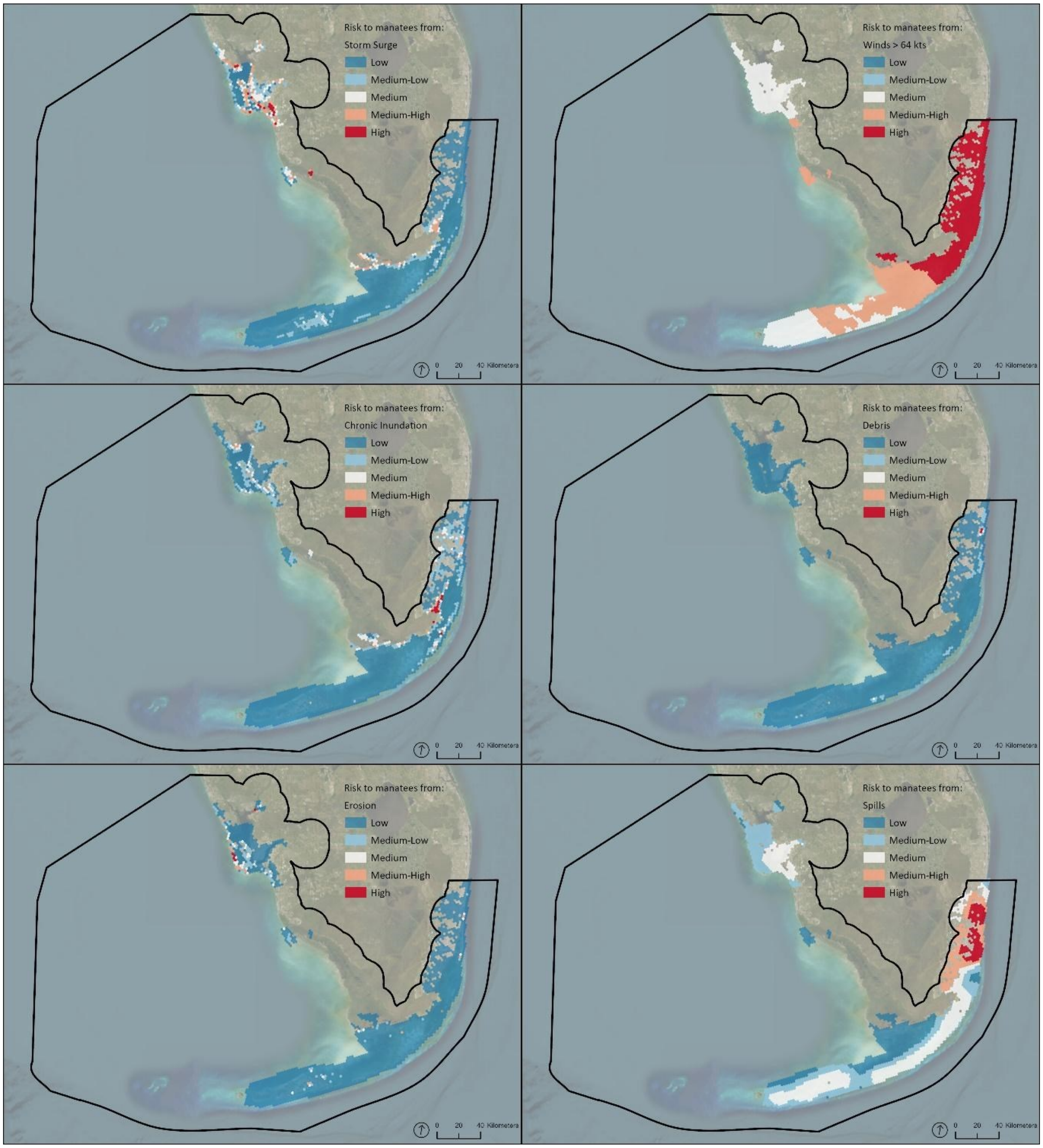

Figure 24. Exposure summary of West Indian manatee to each evaluated stressor.

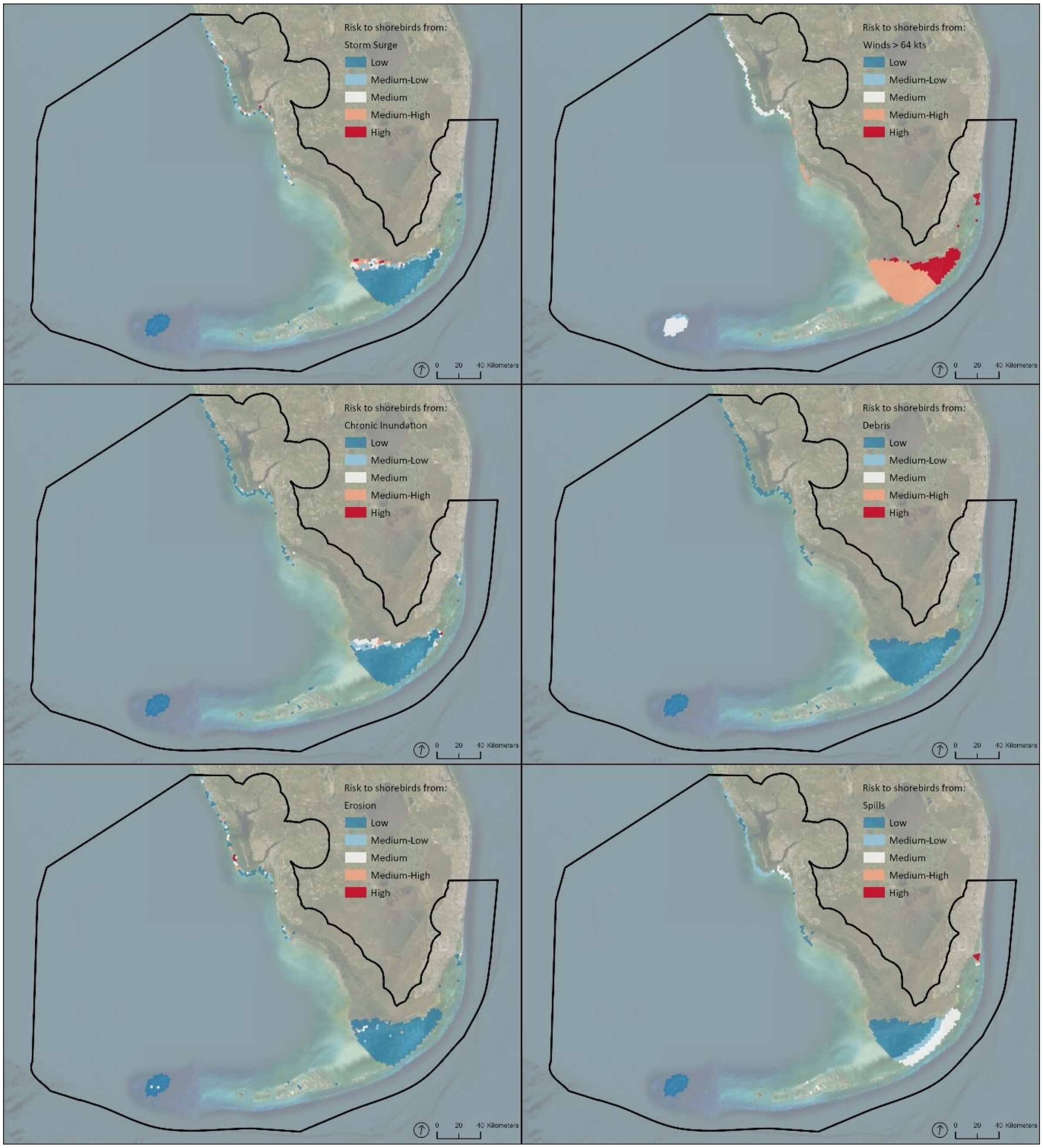

Figure 25. Exposure summary of shorebirds to each evaluated stressor.

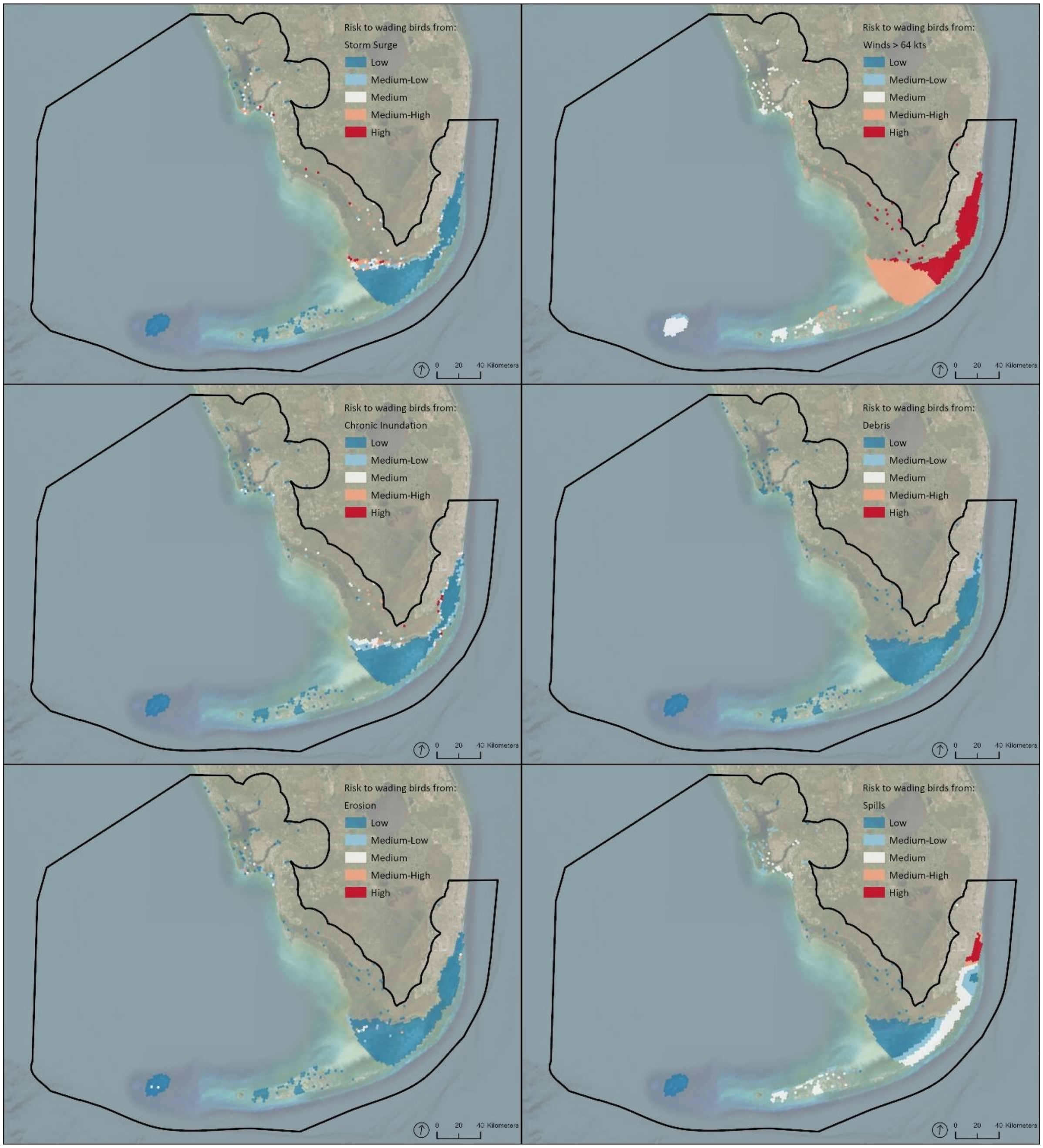

Figure 26. Exposure summary of wading birds to each evaluated stressor.

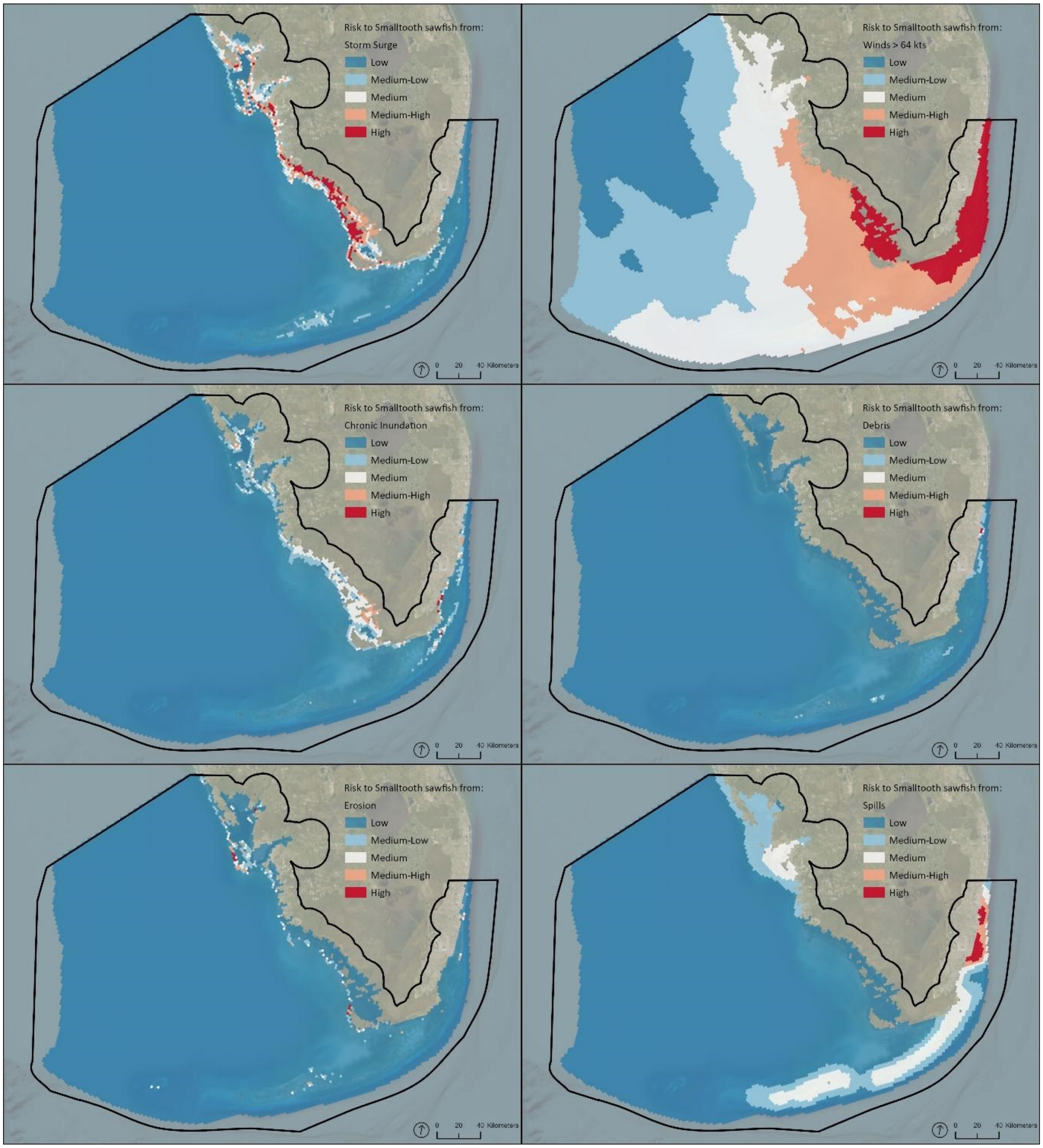

Figure 27. Exposure summary of Smalltooth sawfish to each evaluated stressor.

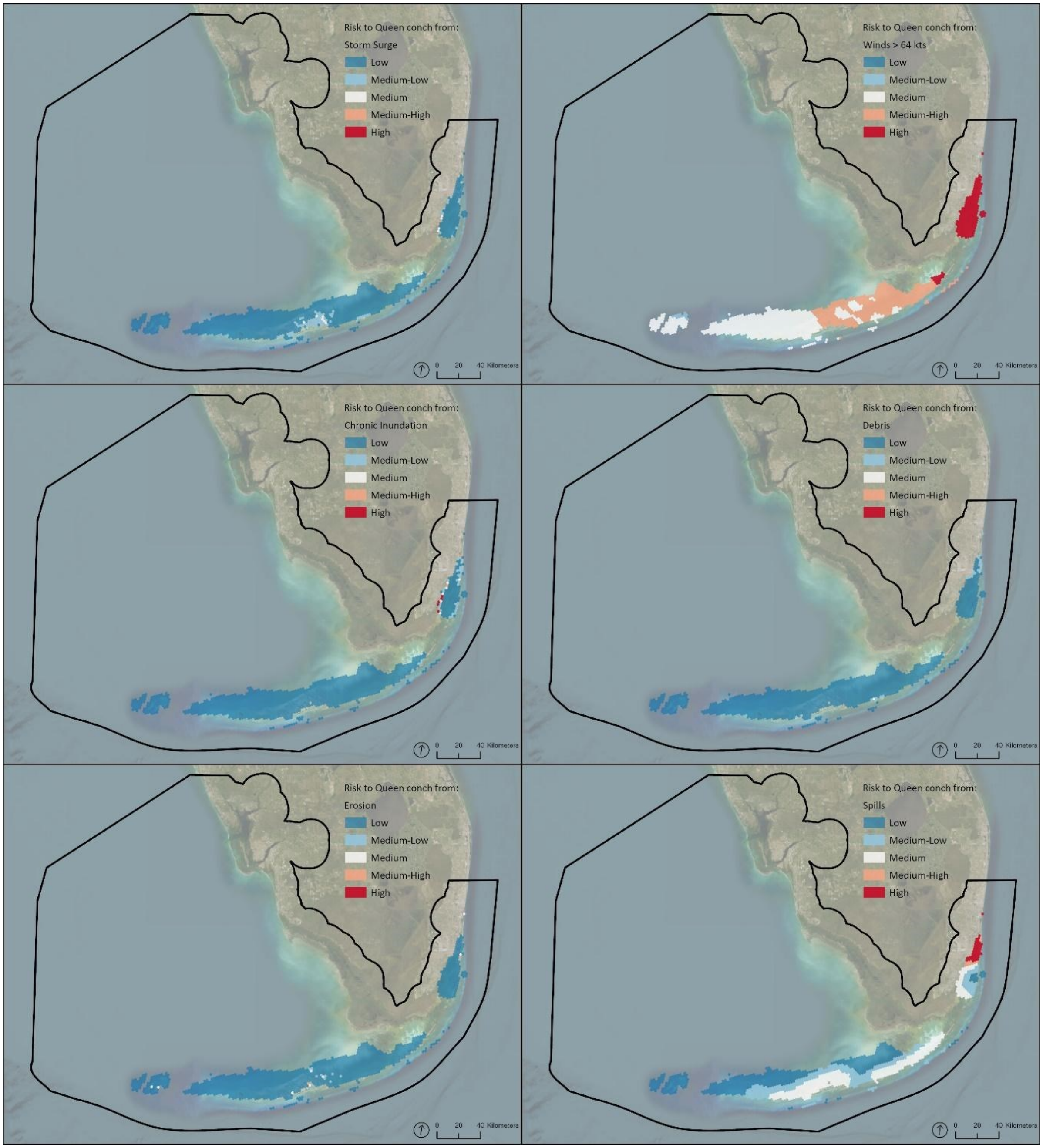

Figure 28. Exposure summary of Queen conch to each evaluated stressor.

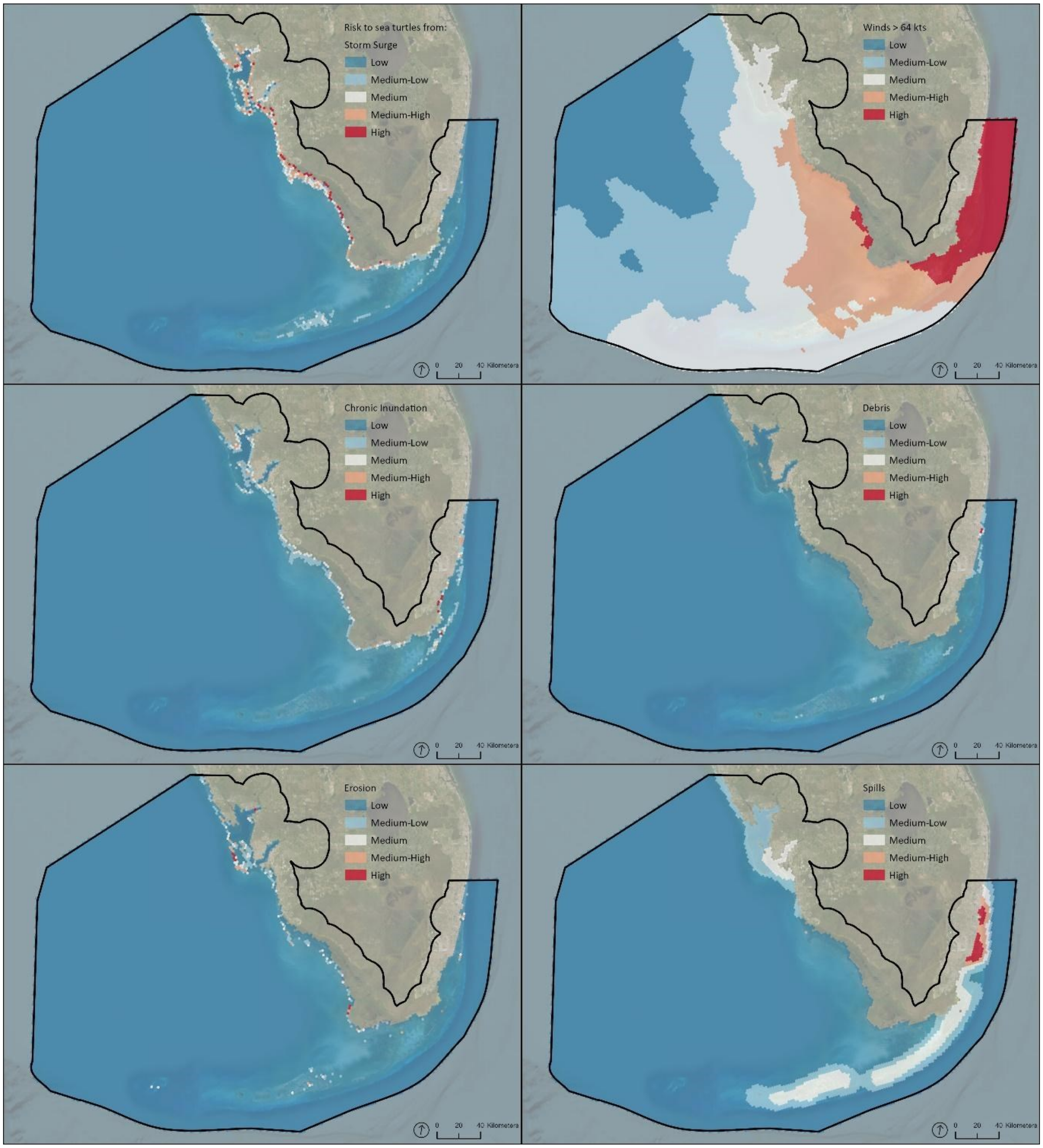

Figure 29. Exposure summary of sea turtles to each evaluated stressor.

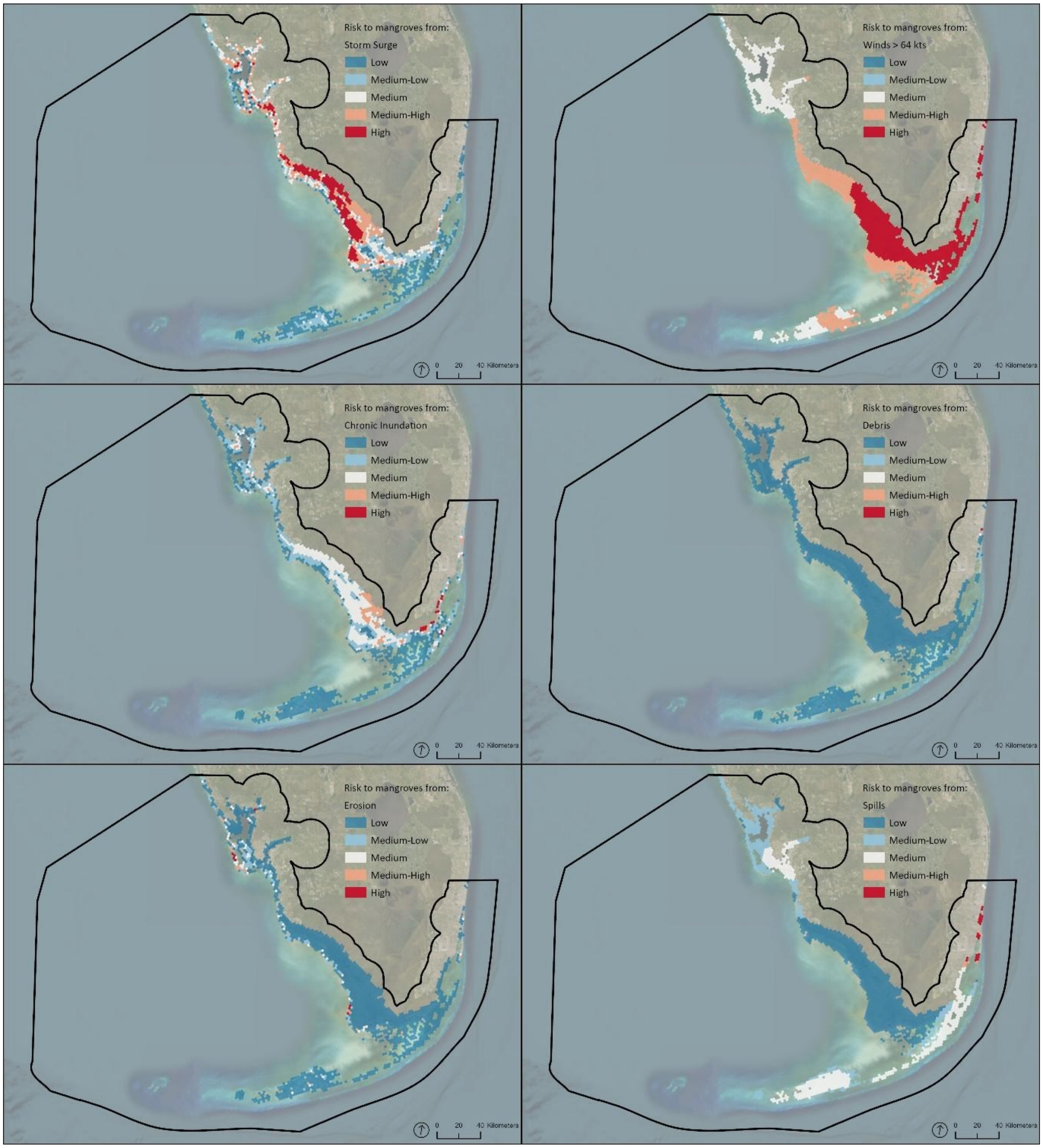

Figure 30. Exposure summary of mangroves to each evaluated stressor.

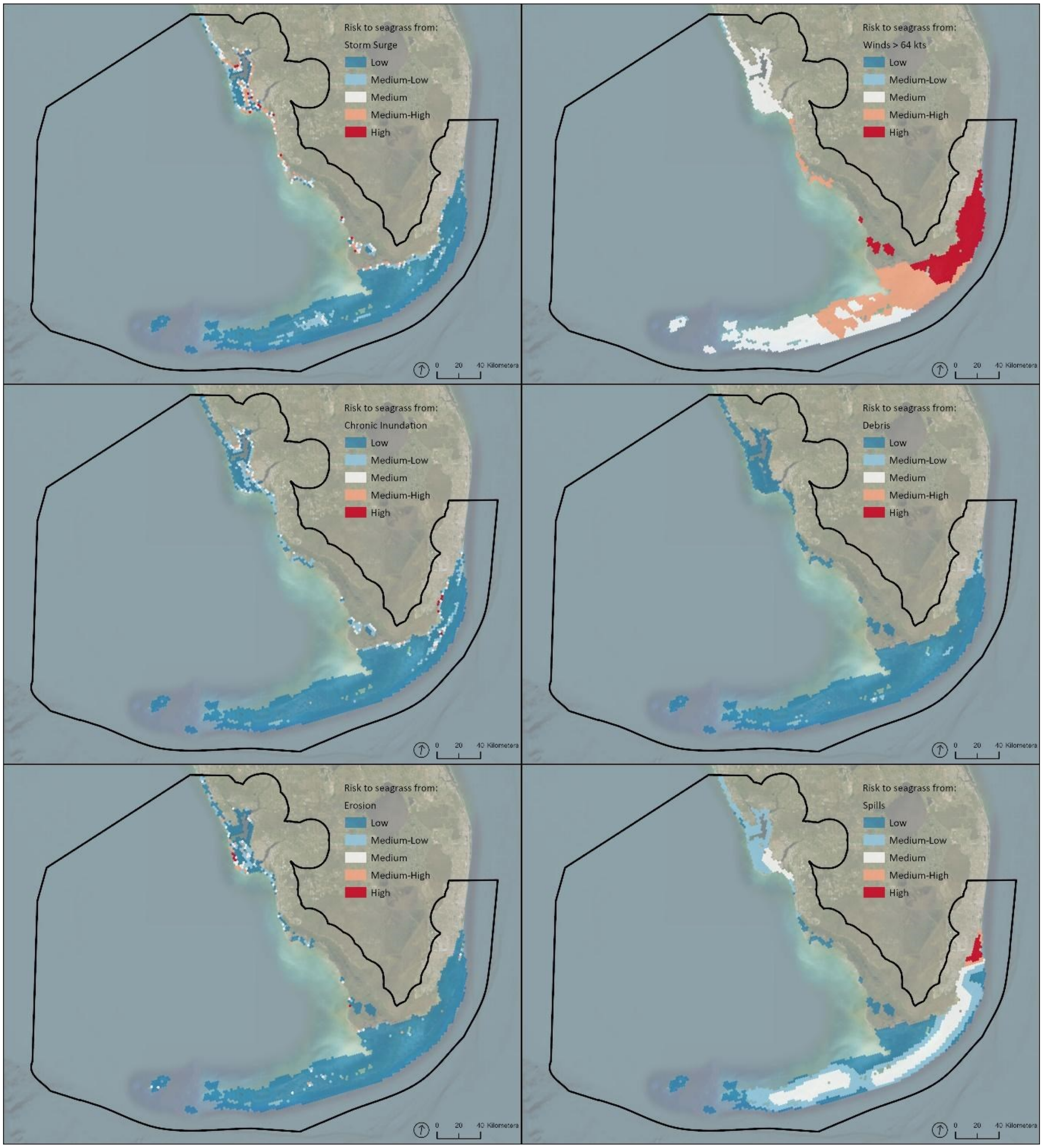

Figure 31. Exposure summary of seagrass to each evaluated stressor.

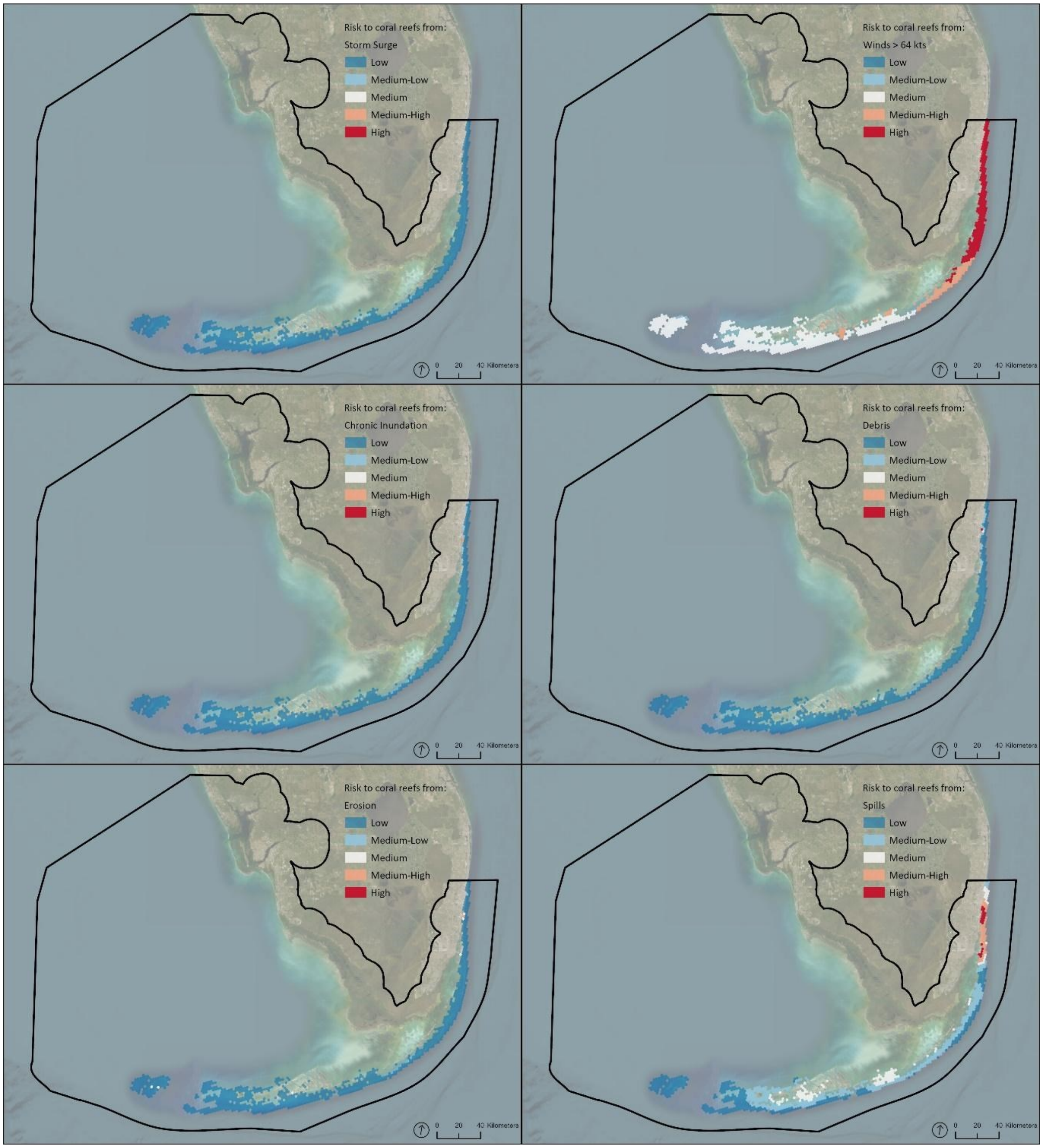

Figure 32. Exposure summary of coral reefs to each evaluated stressor.

Cumulative Risk

A more useful analysis, which makes use of the sensitivity indices developed and described above, is to evaluate the cumulative risk to each receptor/resource ***from all evaluated hazards/stressors***. These results may be used to evaluate the spatial distribution of risk to a specific receptor/resource from *all* evaluated hazards. For natural resources, this may be useful for assessing the most threatened populations or habitats. For human resources, this may be used to assess the location where vulnerable populations are most at-risk. This concept incorporates:

- The distribution of the density of receptor/resource
- The distribution of the categorical intensity of the stressors/hazards, and
- The specific sensitivity of that receptor/resource to each of the stressors/hazards.

To accomplish this, a cumulative risk score was developed as follows:

$$CR_i = R_i \sum_{j=1}^{n} (S_{ij} H_j)$$

where CR_i is the cumulative risk score for resource i, n is the number of evaluated stressors (here, 6), S_{ij} is the sensitivity score for resource i to stressor j (from -1 for small positive effect to 2 for large negative effect), H_j is the integer value of the hazard intensity category (from 1 to 5) for hazard/stressor j, and R_i is the integer value of the resource density category of receptor/resource i. The resource density category value for natural resources is considered as 1 for general distribution areas, and 2 for important areas. For human resources, the resource density category value is considered as the integer representing the categorical SoVI rank (from 1 to 5).

The cumulative risk score is computed for each receptor/resource for all grid cells, and these values are reranked from 1 (Low) to 5 (High) using the Jenks natural breaks method. Resulting values for natural resource receptors are depicted in Figure 33 through 42. Values for vulnerable human populations are depicted in Figure 43.

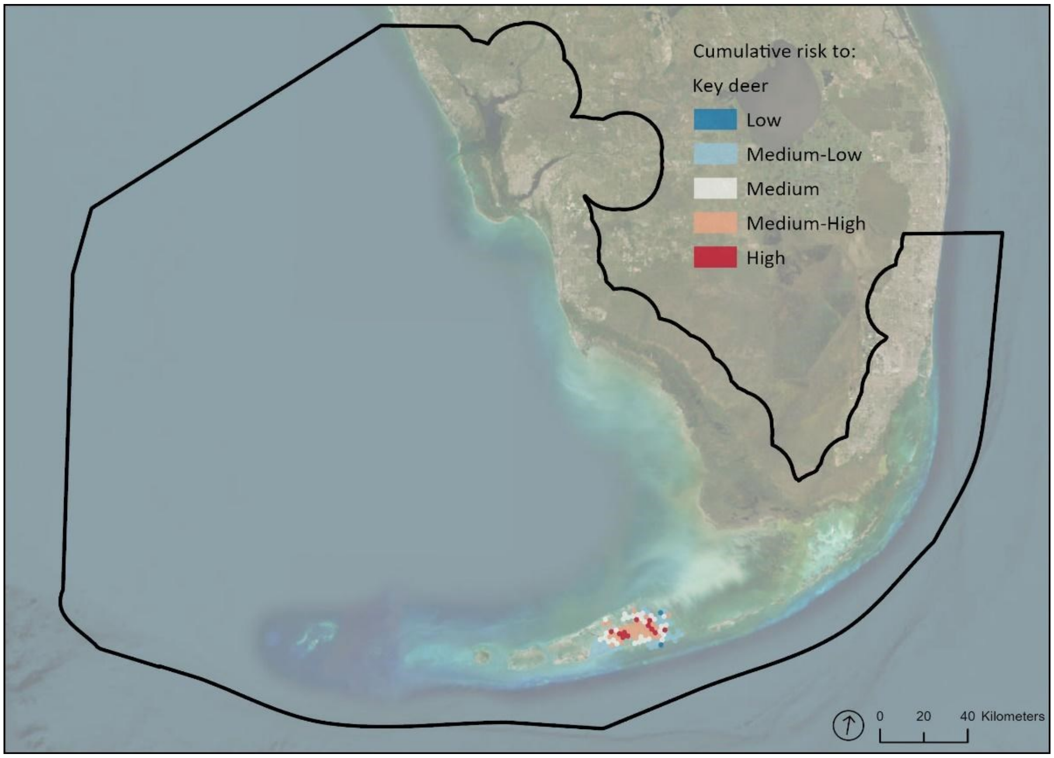

Figure 33. Cumulative risk to Key deer from all evaluated stressors.

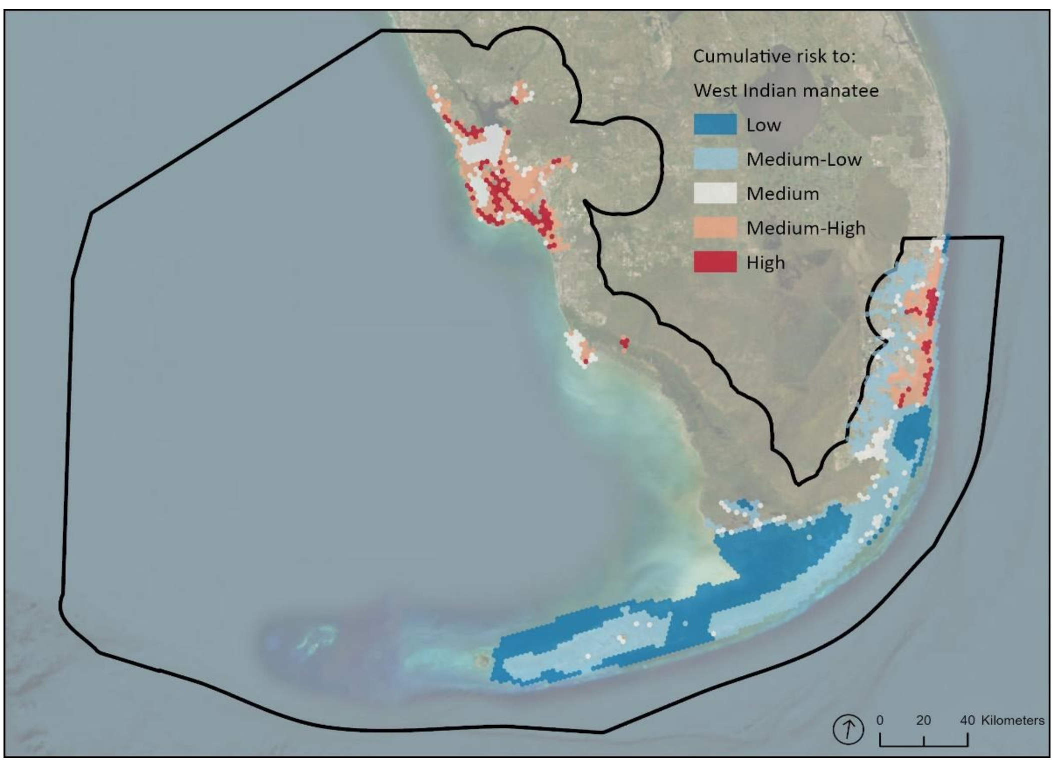

Figure 34. Cumulative risk to West Indian manatee from all evaluated stressors.

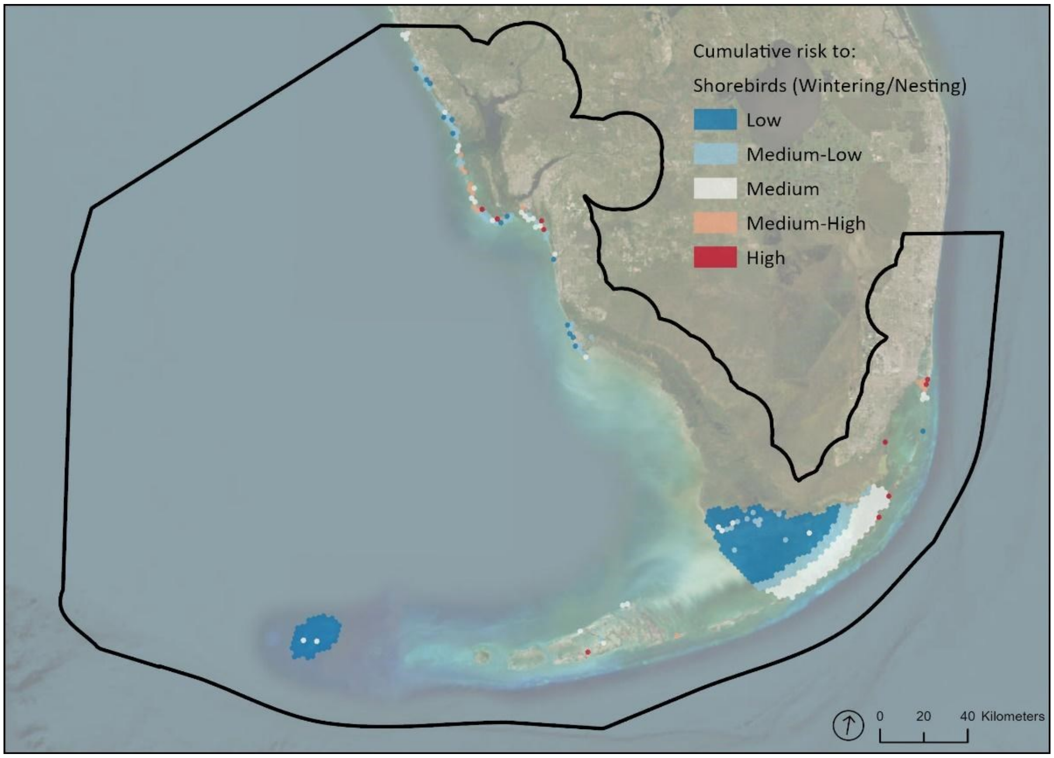

Figure 35. Cumulative risk to wintering and nesting shorebirds from all evaluated stressors.

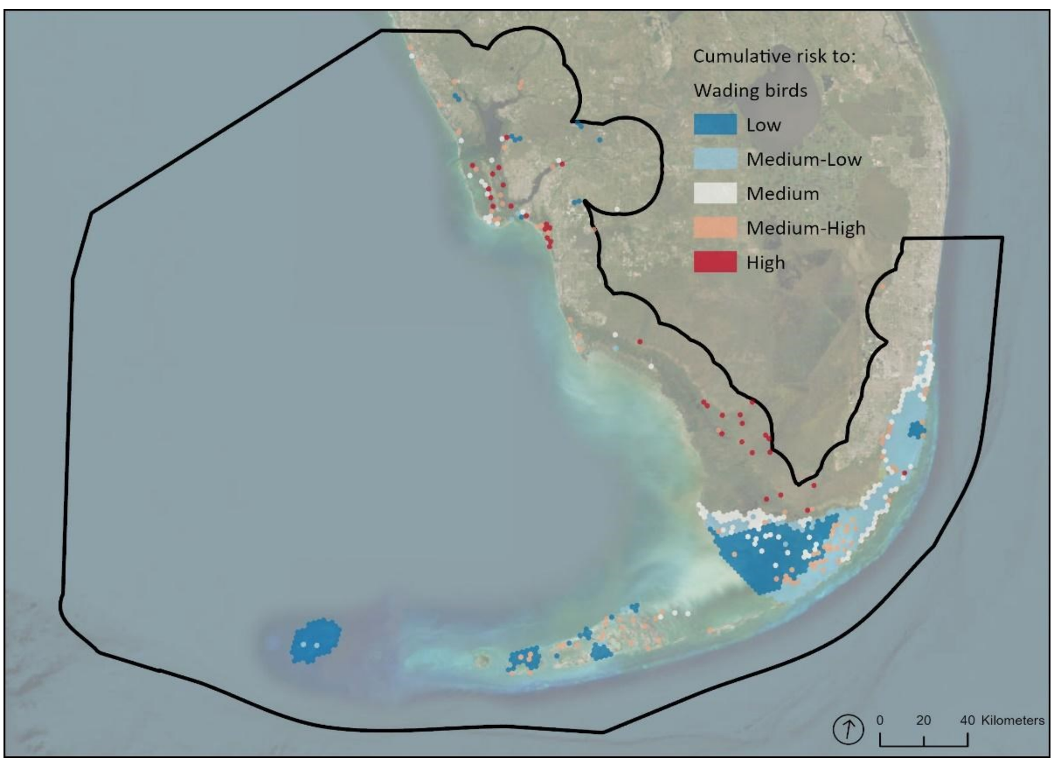

Figure 36. Cumulative risk to wading birds from all evaluated stressors.

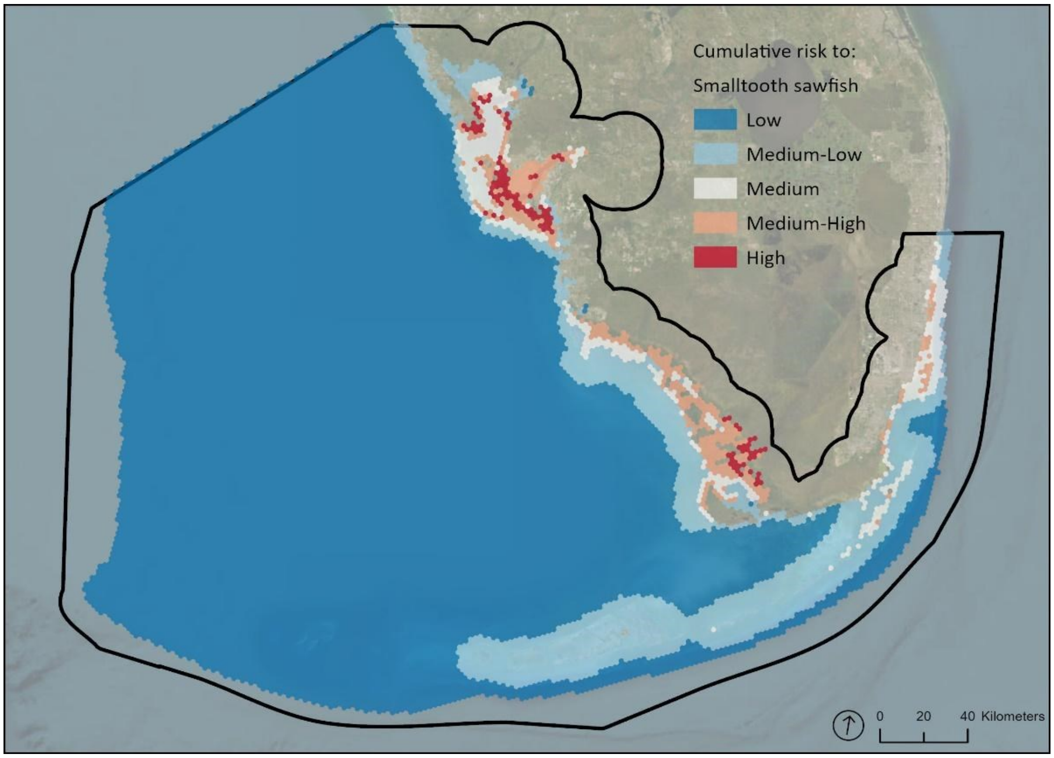

Figure 37. Cumulative risk to Smalltooth sawfish from all evaluated stressors.

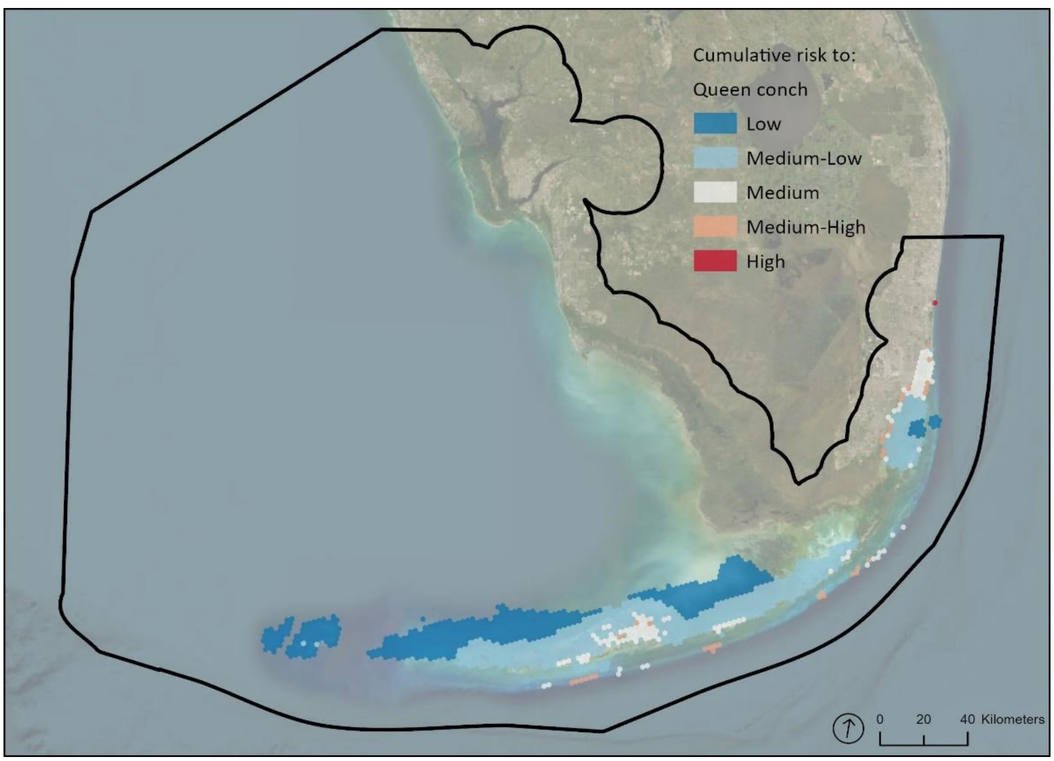

Figure 38. Cumulative risk to Queen conch from all evaluated stressors.

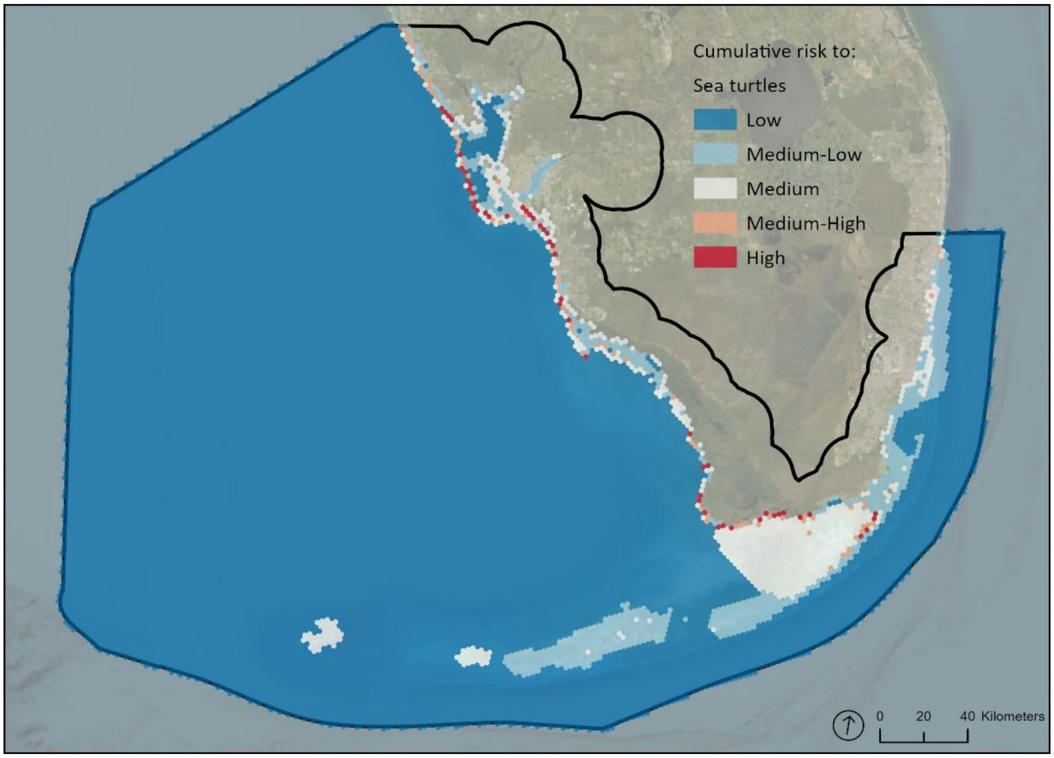

Figure 39. Cumulative risk to sea turtles from all evaluated stressors.

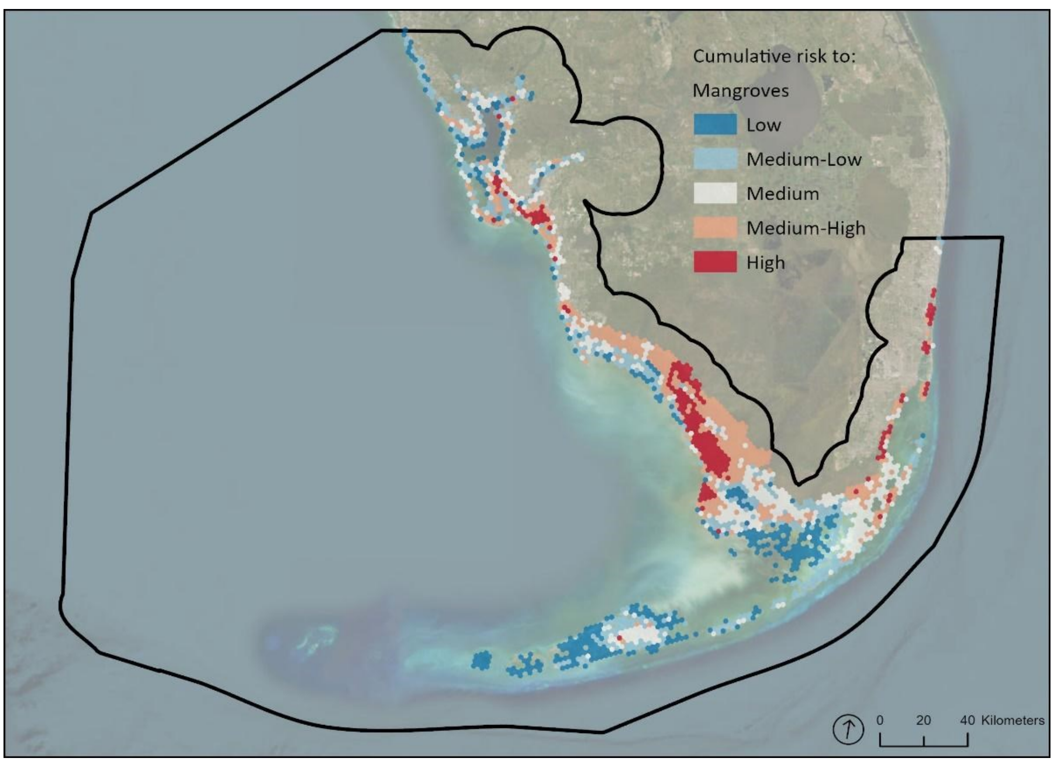

Figure 40. Cumulative risk to mangroves from all evaluated stressors.

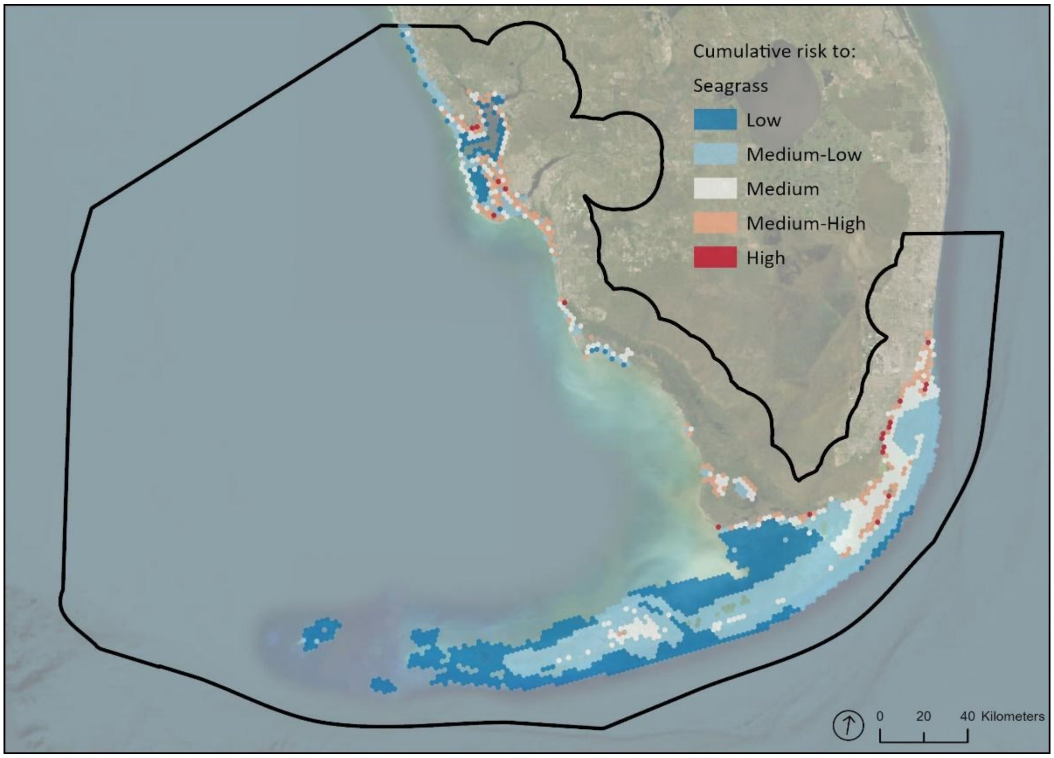

Figure 41. Cumulative risk to seagrass from all evaluated stressors.

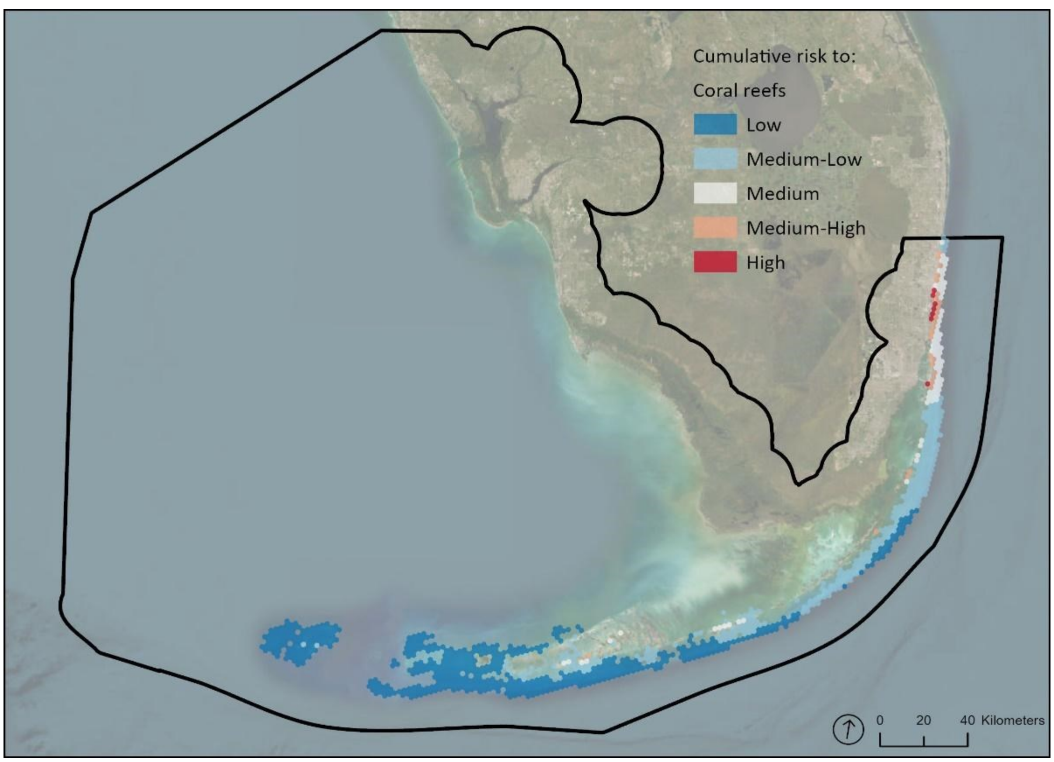

Figure 42. Cumulative risk to coral reefs from all evaluated stressors.

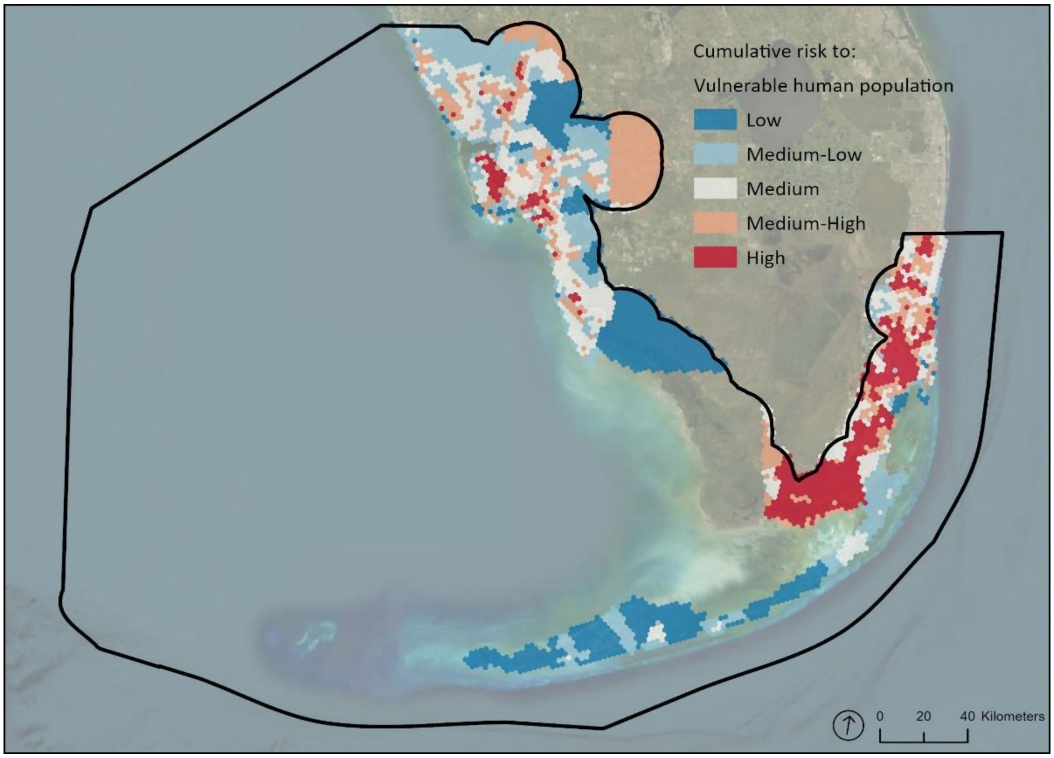

Figure 43. Cumulative risk to vulnerable human populations from all evaluated stressors.

Aggregate Hazard

Another useful analysis is evaluation of the aggregate hazard posed by each hazard/stressor ***to all included receptors/resources***. As with cumulative risk, this analysis also integrates the distribution of the density of receptors/resources, the distribution of the categorical intensity of the stressor/hazard, and the specific sensitivity of each receptor/resource to that specific stressor/hazard. For both natural and human resources, this may be useful for assessing where hazard mitigation measures or resilience enhancements may be most useful. To accomplish this, an aggregate hazard score was developed as follows:

$$AH_j = H_j \sum_{i=1}^{n} (S_{ij} R_i)$$

where AH_j is the aggregate hazard score for hazard j, n is the number of evaluated resources (here, 10), S_{ij} is the sensitivity score for resource i to stressor j (from -1 for small positive effect to 2 for large negative effect), H_j is the integer value of the hazard intensity category (from 1 to 5) for hazard/stressor j, and R_i is the integer value of the resource density category (1 for general distribution and 2 for importance area) of receptor/resource i. The aggregate hazard score is computed for each hazard/stressor for all grid cells, and these values are reranked from 1 (Low) to 5 (High) using the Jenks natural breaks method. Resulting values are depicted in Figure 44 through 49 below.

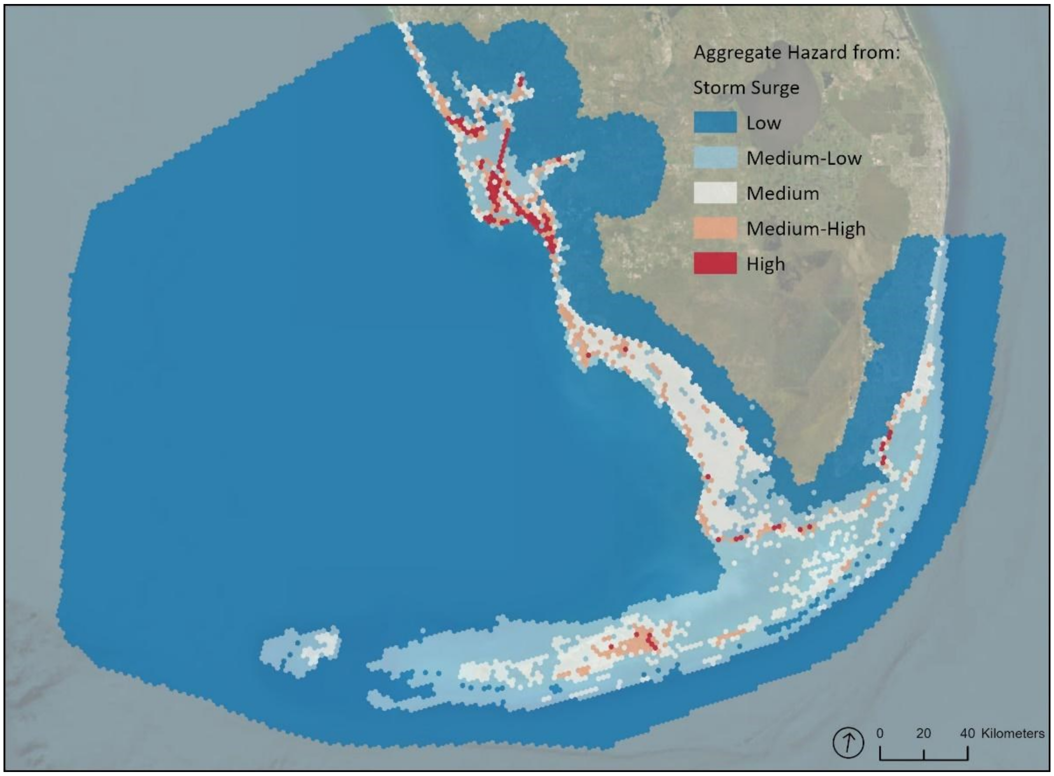

Figure 44. Aggregate hazard from storm surge and acute flooding to all natural resource receptors.

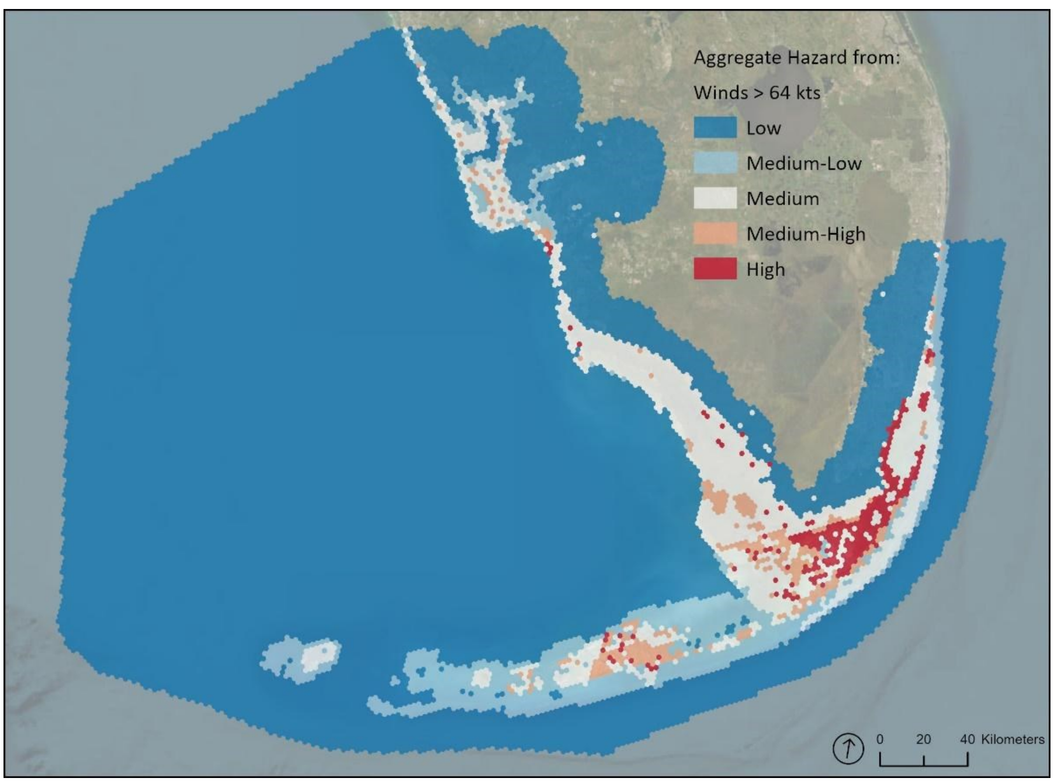

Figure 45. Aggregate hazard from winds greater than 64 kt to all natural resource receptors.

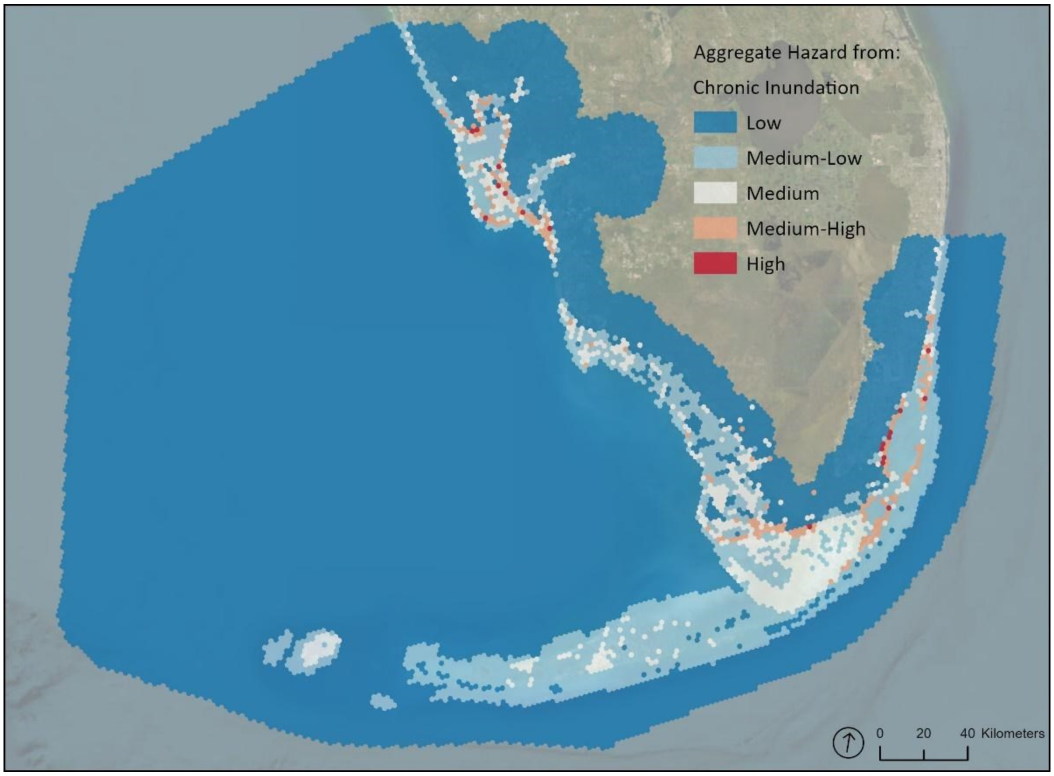

Figure 46. Aggregate hazard from chronic inundation to all natural resource receptors.

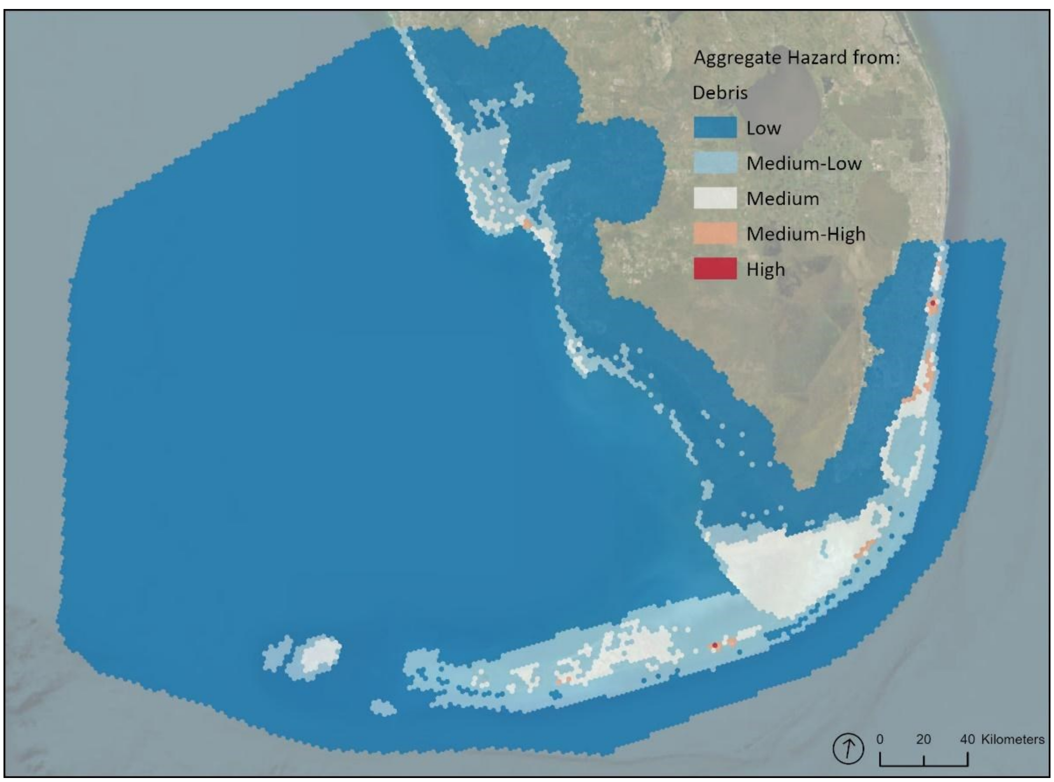

Figure 47. Aggregate hazard from event-generated marine debris to all natural resource receptors.

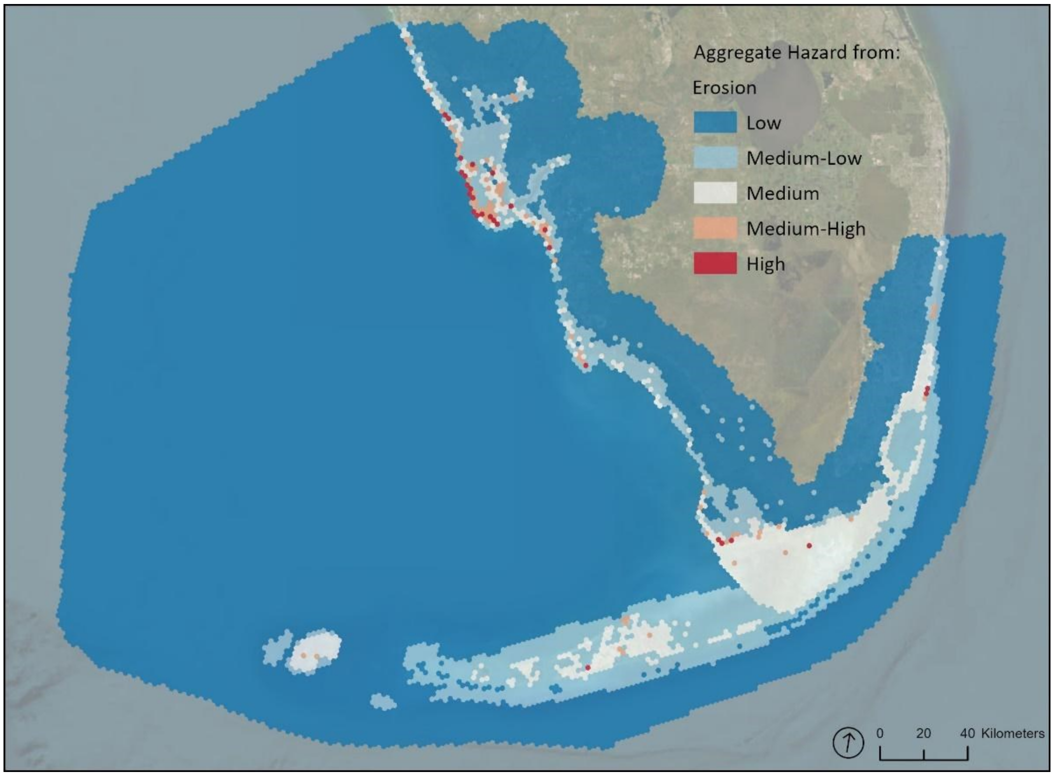

Figure 48. Aggregate hazard from shoreline erosion to all natural resource receptors.

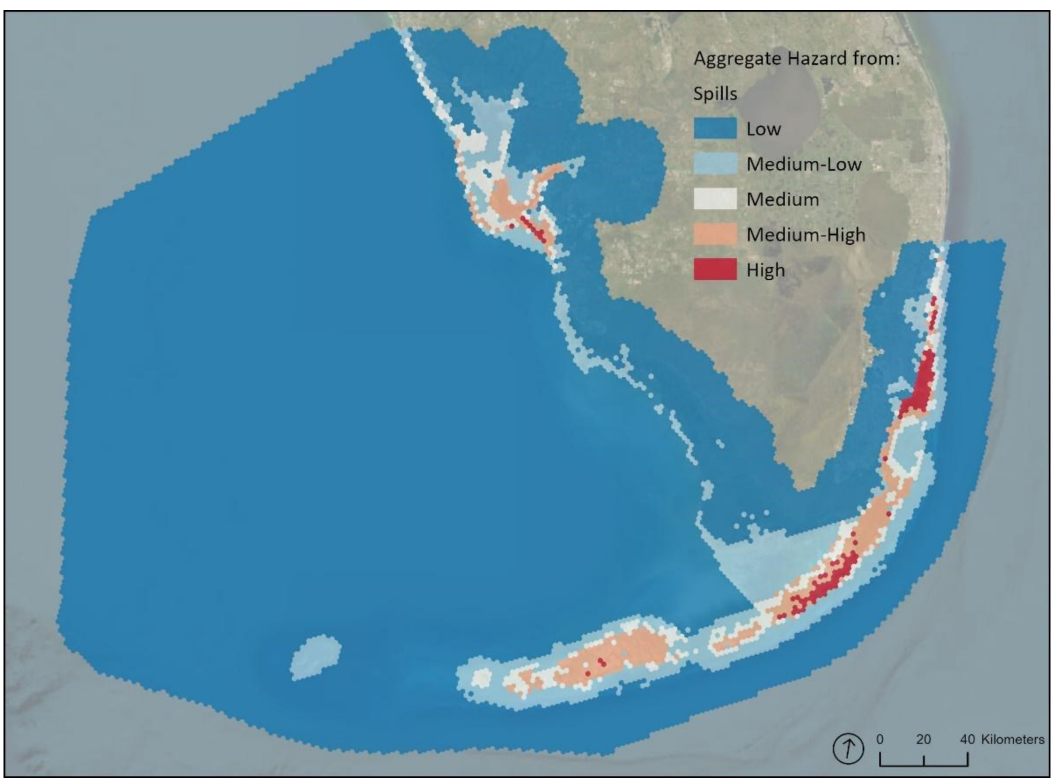

Figure 49. Aggregate hazard from oil and chemical spills to all natural resource receptors.

Data Structure Requirements

For the purposes of this project, it was assumed that data ESI data modified for storing sensitivity indices would be in the format of the ESI data delivered by NOAA to the public rather than the deliverables provided by contractors to NOAA. This would be the process if additional indices were to be developed for existing ESI data sets. As such, sensitivity index values were stored within the ESI data structure (Peterson et al. 2019) as a set of six signed integer attributes, one for each hazard/stressor, added to ESI polygon feature class and within the BIOFILE table (Figure 50). Table 63 summarizes the attributes used to store these sensitivity index values. Sensitivity index values were stored for each resource where rankings were developed as a signed integer: -1 for small positive effect, 0 for no effect, 1 for small negative effect, and 2 for large negative effect. If sensitivity indices for additional hazards were to be developed concurrently with development of new ESI data sets, then a similar set of signed integer attributes would be added to the ESI polygon feature class and within the BIORES table (Figure 51).

Table 63. Additional attributes required to store sensitivity index values within the ESI data structure.

Attribute	Type	Contents
SI_SURGE	Short integer	Resource sensitivity index value for acute coastal or storm surge flooding
SI_HTF	Short integer	Resource sensitivity index value chronic inundation
SI_DEBRIS	Short integer	Resource sensitivity index value for marine debris events
SI_TC_WIND	Short integer	Resource sensitivity index value for tropical cyclone or convective storm winds
SI_EROSION	Short integer	Resource sensitivity index value for shoreline erosion
SI_SPILLS	Short integer	Resource sensitivity index value for contaminants from spill events

A standardized set of attributes were generated for polygons for each grid cell resolution used to spatially aggregate and summarize stressor hazard intensity categories, natural and human resource presence and significance, cumulative risk, and aggregate hazard. These are summarized in Table 64.

Table 64. Attributes used to store hazard intensity categories, natural and human resource presence and significance, cumulative risk, and aggregate hazard at each resolution of H3 grid system.

Attribute	Type	Contents
GRID_ID	Text (17)	H3 Grid ID
SURGE_M3	Double	Acute raw coastal flooding stressor metric value: expected m^3 per year
DEBRIS_N_YR	Double	marine debris stressor metric value: expected items per year
EROSION_M2_YR	Double	Shoreline erosion stressor metric value: expected m^2 per year
WIND_64K_N_YR	Double	Tropical storm wind stressor metric value: expected frequency per year
HTF_DAYS_YR	Double	Chronic inundation stressor metric value: expected HTF days per year
SPILL_KM2_N_YR	Double	Contaminant spill stressor metric value: expected count per km^2 per year
SURGE_M3_NATURAL_BREAKS	Long integer	5 class categorization of storm surge hazard
DEBRIS_N_YR_NATURAL_BREAKS	Long integer	5 class categorization of marine debris hazard
EROSION_M2_YR_NATURAL_BREAKS	Long integer	5 class categorization of shoreline erosion hazard
WIND_64K_N_YR_NATURAL_BREAKS	Long integer	5 class categorization of tropical storm wind surge hazard
HTF_DAYS_YR_NATURAL_BREAKS	Long integer	5 class categorization of chronic inundation hazard
SPILL_KM2_N_YR_NATURAL_BREAKS	Long integer	5 class categorization of contaminant spill hazard
RES_MANGROVES	Long integer	3 class resource density categories for mangroves
RES_KEY_DEER	Long integer	3 class resource density categories for Key deer
RES_CONCH	Long integer	3 class resource density categories for Queen conch
RES_CORAL	Long integer	3 class resource density categories for corals
RES_SHOREBIRDS	Long integer	3 class resource density categories for shorebirds
RES_WADING	Long integer	3 class resource density categories for wading birds
RES_TURTLES	Long integer	3 class resource density categories for sea turtles
RES_MANATEE	Long integer	3 class resource density categories for manatees
RES_SAWFISH	Long integer	3 class resource density categories for sawfish
RES_SEAGRASS	Long integer	3 class resource density categories for seagrass
AGG_SURGE	Double	Aggregate hazard score for storm surge hazard
AGG_HTF	Double	Aggregate hazard score for marine debris hazard
AGG_DEBRIS	Double	Aggregate hazard score for shoreline erosion hazard
AGG_TC_WIND	Double	Aggregate hazard score for tropical storm wind surge hazard
AGG_EROSION	Double	Aggregate hazard score for chronic inundation hazard
AGG_SPILLS	Double	Aggregate hazard score for contaminant spill hazard
MAX_SOVI	Double	Aggregate hazard score for storm surge hazard
AGG_SURGE_NATURAL_BREAKS	Long integer	5 class categorization of aggregate hazard from storm surge
AGG_TC_WIND_NATURAL_BREAKS	Long integer	5 class categorization of aggregate hazard from marine debris
AGG_HTF_NATURAL_BREAKS	Long integer	5 class categorization of aggregate hazard from shoreline erosion
AGG_DEBRIS_NATURAL_BREAKS	Long integer	5 class categorization of aggregate hazard from tropical storm wind surge
AGG_EROSION_NATURAL_BREAKS	Long integer	5 class categorization of aggregate hazard from chronic inundation
AGG_SPILLS_NATURAL_BREAKS	Long integer	5 class categorization of aggregate hazard from contaminant spill

Attribute	Type	Contents
CML_KEY_DEER	Long integer	Cumulative risk score for Key deer
CML_MANATEE	Long integer	Cumulative risk score for manatees
CML_SHOREBIRDS	Long integer	Cumulative risk score for shorebirds
CML_WADING	Long integer	Cumulative risk score for wading birds
CML_SAWFISH	Long integer	Cumulative risk score for sawfish
CML_CONCH	Long integer	Cumulative risk score Queen conch
CML_TURTLES	Long integer	Cumulative risk score for sea turtles
CML_MANGROVES	Long integer	Cumulative risk score for mangroves
CML_SEAGRASS	Long integer	Cumulative risk score for seagrass
CML_CORAL	Long integer	Cumulative risk score for corals
CML_SOVI	Long integer	Cumulative risk score for vulnerable populations
CML_KEY_DEER_NATURAL_BREAKS	Long integer	5 class categorization of cumulative risk for Key deer
CML_MANATEE_NATURAL_BREAKS	Long integer	5 class categorization of cumulative risk for manatees
CML_SHOREBIRDS_NATURAL_BREAKS	Long integer	5 class categorization of cumulative risk for shorebirds
CML_WADING_NATURAL_BREAKS	Long integer	5 class categorization of cumulative risk for wading birds
CML_SAWFISH_NATURAL_BREAKS	Long integer	5 class categorization of cumulative risk for sawfish
CML_CONCH_NATURAL_BREAKS	Long integer	5 class categorization of cumulative risk Queen conch
CML_TURTLES_NATURAL_BREAKS	Long integer	5 class categorization of cumulative risk for sea turtles
CML_MANGROVES_NATURAL_BREAKS	Long integer	5 class categorization of cumulative risk for mangroves
CML_SEAGRASS_NATURAL_BREAKS	Long integer	5 class categorization of cumulative risk for seagrass
CML_CORAL_NATURAL_BREAKS	Long integer	5 class categorization of cumulative risk for corals
CML_SOVI_NATURAL_BREAKS	Long integer	5 class categorization of cumulative risk for vulnerable populations

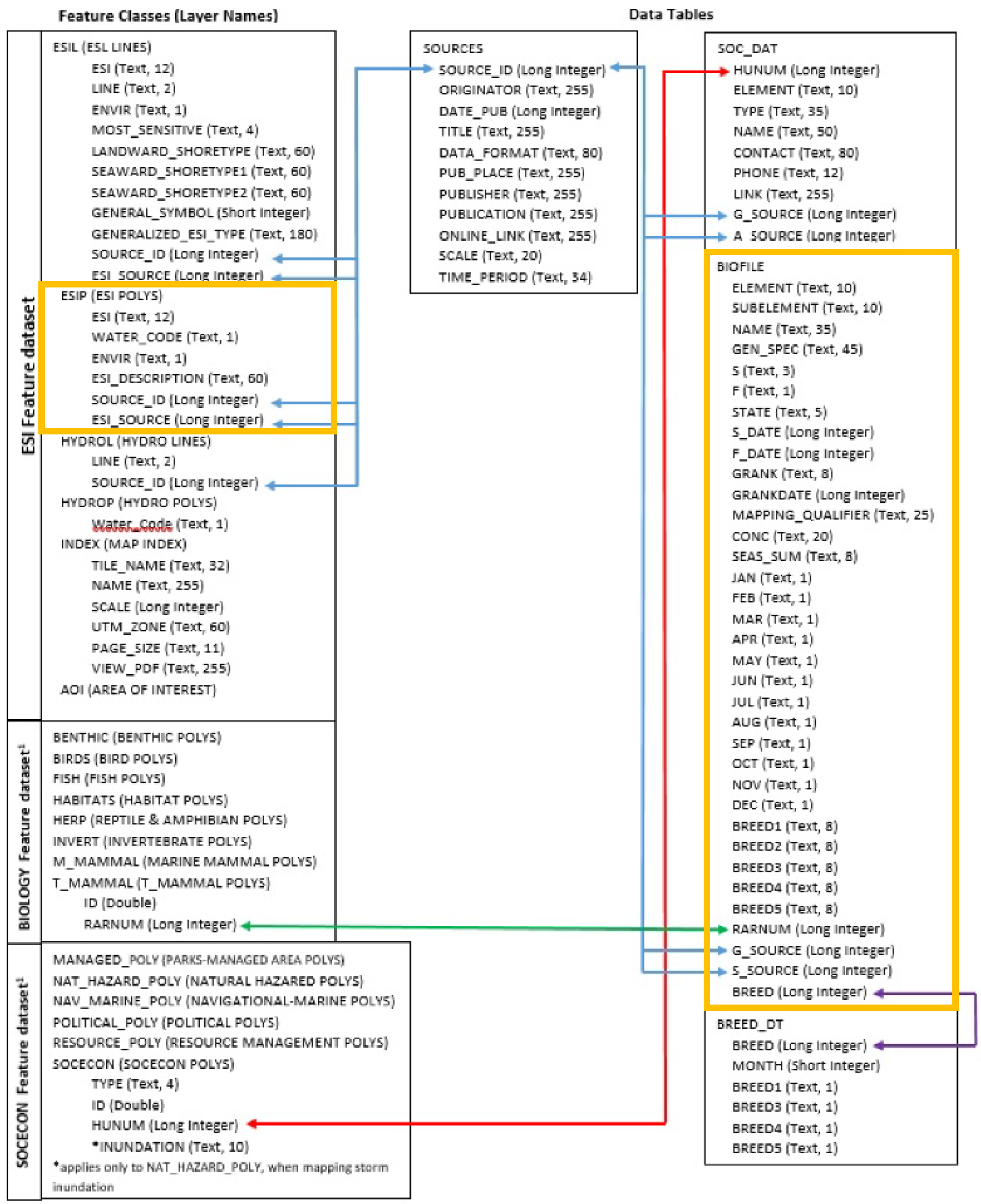

Figure 50. Entity-relationship diagram for ESI data delivered by NOAA and specific tables modified to store additional sensitivity index modifiers (gold boxes).

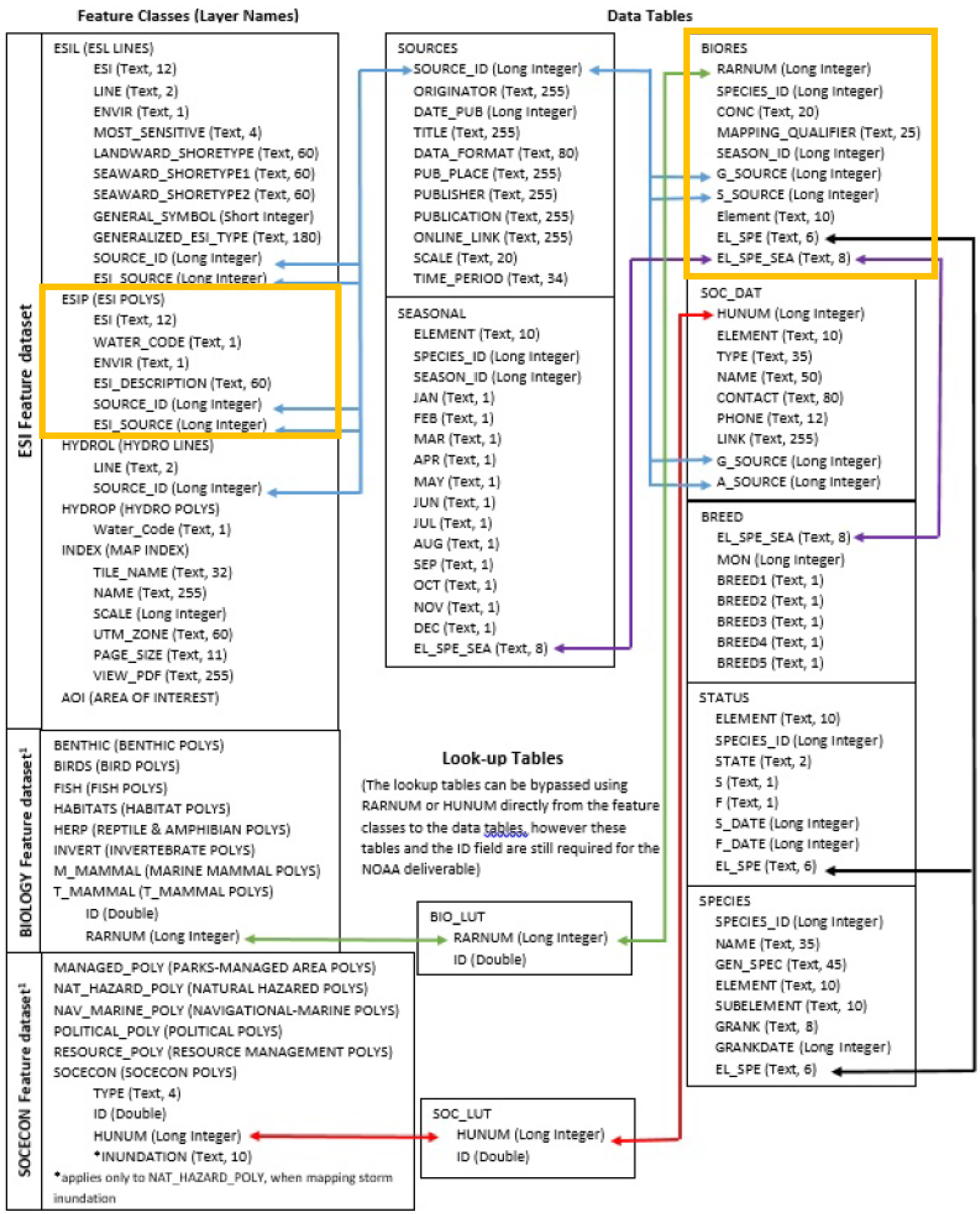

Figure 51. Entity-relationship diagram for ESI deliverables to NOAA and specific tables modified to store additional sensitivity index modifiers.

Findings

The primary focus of this project is to serve as a feasibility study. To this end, the most critical finding is that the overall goal of developing and applying new sensitivity indices for a wide spectrum of resources currently included in ESI atlases, or that may be potentially included in the future, to a broader range of hazards is both feasible and useful. The overall results visualizing the distribution of cumulative risk help visualize meaningful patterns and are useful in assessing the most threatened populations or habitats, or where vulnerable human populations are most at-risk. Few similar quantitative assessments exist at a national or regional scale. Aggregate hazard visualizations are also likely to have significant utility in guiding where hazard mitigation methods are likely to be most useful. A number of additional findings are summarized below which may inform and improve subsequent efforts to undertake similar work.

One of the primary concerns in undertaking this work is that the source data, contents, and methods used to compile biological data for different ESI atlases may vary widely from atlas to atlas. While the biological resources mapped as part of ESI atlas compilation are as standardized as possible (Peterson et al. 2019), at-risk resources vary from region to region and data sources used to compile biological information are generally compiled at the state or regional level with fixed extents. Further, the criteria for resource inclusion and available quantity and quality of relevant data have changed over time. ESI atlases are not updated on fixed schedules and so publication dates of adjacent ESI atlases may differ by decades. As such, substantial differences may arise in the character or relative quality of biological data for the same resource when analysis over the extent of more than one ESI atlas is undertaken. This may require additional data manipulation or collection to address. Grouping of some resources into general distribution and important areas, as undertaken in this work, may require particular care, given the wide variety of concentration, and other information, across all resources.

This work involved sensitivity indices for each stressor for biological resource groups of different specificity including habitats, species guilds (ESI sub-elements), and individual species. The work required to construct these sensitivity indices is substantial, involving time-consuming literature review and subjective application of professional judgment. Given this, in future work it is recommended to focus on the development of sensitivity rankings at the habitat, sub-element or other level of guild or species group (e.g., small coastal terrestrial mammals, or large pelagic fish) rather than individual species. This will allow re-useability of developed sensitivity indices more broadly across atlases and geographies.

Of direct interest are the timescales at which the phenomena included in this effort change and how that may be related to the potential required update frequency of these indices. The core concept of assigning indices reflecting the relative sensitivity of species, species groups, habitats and human populations to various hazards generally is intended to reflect largely immutable characteristics of those resources (e.g. the relative sensitivity of wading birds to contaminant spills), and so would only need to be undertaken once per resource. The spatial data compiled to assess the distribution of hazards/stressors is generally compiled from long-term data sets, required to accurately assess the hazard probabilities of relatively rare events at local spatial scales (e.g. tropical storms or contaminant spills) or noisy physical phenomena (e.g. erosion). Given this, the overall distribution of hazard probability is unlikely to meaningfully and discernably change except at decadal timescales. One exception may be the frequency of chronic inundation which has only recently been studied in detail. Finally, the distribution of resources themselves are, of course, variable through time. The distribution of both human populations and of species and habitats changes, but the data available to accurately assess these changes (e.g. Census data and various ecological and natural resource mapping data) typically are suitable for evaluating change over, generally, timescales of multiple years. All told, it is unlikely that any of the components of hazard risk used in this project would vary appreciably over timescales of less than 5 to 10 years – approaching the typical update frequency of ESI data themselves. It is recommended however to revisit the topic of chronic inundation in the near future to potentially incorporate improved spatial assessment of existing risk or to update indices based upon possibly rapidly changing conditions.

The use of standardized methods for classification of numeric metrics and scores is critical to the visualization and communication of spatial patterns in risk and hazards depicted as part of this project. The primary method used here is the Jenks natural breaks method which is used to re-standardize hazard metric and scores to a 5-class ranks for visualization and comparison, but other methods may provide more statistically robust results. A challenge in adopting methods that depend upon statistical distributions such as the z-score method (e.g., Emrich et al. 2022b) is that the inclusion of large open water areas in many ESI atlases yields strong deviations from distributional assumptions. Additional investigation may be required on this topic.

The methods and data sources used for hazard quantification as part of this work are fairly standardized. However, the intermediate spatial data and summary methods required to derive a single quantification of hazard occurrence frequency, intensity, and areal extent often yields single intermediate metrics that are confusing. For example, to accurately quantify storm surge hazard in a given spatial extent, a metric that incorporates probability of storm surge flooding occurring, the anticipated depth of flooding if present, and the extent of flooding within a spatial unit is required. The intermediate metric used is the average expected cubic meters of flooding per year, but this metric has an abstract and unintuitive physical meaning. It may be preferable to develop analysis methods that separately integrate concepts like occurrence rate, intensity and areal extent. Review of other ongoing work on this topic may be instructive (e.g., Zuzek et al. 2022; 2023), particularly if such efforts are undertaken for a broader suite of stressors/hazards.

The methods for storing sensitivity index values within the ESI data structure used here (e.g., as a set of attributes, one for each hazard/stressor, attached to ESI polygon feature class and within the BIOFILE table) proved feasible for this work. However, this may not scale well to the development of sensitivity index values for a much larger set of resources without additional effort. Even with only ten resources selected for index development, substantial code and toolset development was required to carry out the analyses presented here. Analyses requiring spatial summaries over one or more ESI data sets where many resources would have to be assigned sensitivity index values (i.e., more than the ten used here) will require additional automation, tool development, and alternative visualization methods.

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Appendix A

Comparative Analysis of Social Vulnerability and Equity Models

Submitted to RPI, Inc in partial fulfillment of the deliverables associated with a contract between RPI and Disaster Metrics, LLC.

By: Dr. Christopher T. Emrich, Principle at Disaster Metrics LLC.

Disaster Metrics

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List of Acronyms

ADI – Area Deprivation Index

AIC – Akaike information criterion

ATSDR – Agency for Toxic Substances and Disease Registry

BIC – Bayesian information criterion

CDC – United State Centers for Disease Control

CJEST – Climate and Economic Justice Screening Tool

CVI – Environmental Defense Fund Climate Vulnerability Index

EDF – Environmental Defense Fund

EJ – Environmental Justice

EJSCREEN – US EPA Environmental Justice Screening Tool

EPA – United States Environmental Protection Agency

FEMA – Federal Emergency Management Agency

GEORGETOWN – Early model of Social Vulnerability produced by UofSC HVRI

GRASP – US EPA ATSDR Geospatial Research, Analysis, and Services Program

HRRC – Texas A&M University Hazard Reduction and Recovery Center

HVRI – University of South Carolina Hazards, Vulnerability, and Resilience Institute

NOAA – National Oceanic and Atmospheric Administration

PCA – Principal Component Analysis

SoVI – University of Central Florida and University of South Carolina Social Vulnerability Index

SVI – Centers for Disease Control Social Vulnerability Index

UCF – University of Central Florida

UofSC – University of South Carolina

USACE – United States Army Corps of Engineers

U.S. – United States

USA – United States of America

VMAP – UCF Vulnerability Mapping and Analysis Platform

Executive Summary

Ease of data availability and increases in computational capabilities have made it possible for anyone with internet access and spreadsheet software to pull social data from the US Census or other sources and create social vulnerability measures. However, differences in the conceptual framework on which each model is built, input variables utilized for each model, and the methods used to combine the data (deductive, inductive, hierarchical) each lead to variance in model outputs. Simply put, all models of social vulnerability are not created equally. As such extreme caution should be taken when utilizing social vulnerability measures, especially if users are unaware that currently available social vulnerability measures are neither replicate of each other nor built to answer the same question.

This report provides both a quantitative and qualitative exposition of several leading social vulnerability and equity models to demystify the growing landscape of indicators. The report is divided into several sections building upon each other, including:

1. An introduction to the concept of social vulnerability indicators.
2. An overview of several seminal and current models of social vulnerability and equity being utilized in the United States.
3. A visual and analytic comparison of the models and datasets including ranking on various aspects/characteristics of each model/dataset.
4. An overall model assessment ranking based on visual and analytic comparisons and brief set of takeaways for decision makers interested current social vulnerability or equity models or implementing their own.

Where possibly, each measurable concept captured in this assessment was ranked from Low (1) to High (7) for each social vulnerability or equity dataset to present a matrix of the utility/goodness of each model and present a practical guide for utilizing these indicators/models/data in decision making. The ranking process for each measurable concept is detailed in Table 1 located within the analytic comparison section.

1.0 Introduction to Social Vulnerability Measures

Understanding the needs of vulnerable people is important in its own right, especially among public health, social work, and social services professionals. However, in cases of disasters or emergencies where sensitive populations may require aid in adequately preparing for, responding to, recovering from, or mitigating hazards, emergency management officials and healthcare providers need detailed information to anticipate and meet often very specific needs. In this context, vulnerability represents the potential for loss or harm among individuals and communities facing hazards and disasters (Cutter et al. 2003[1]; Sarewitz et al. 2003[2]). Determining what supplies, equipment, and personnel are needed to respond effectively in emergency situations requires sound knowledge of a region's social, economic, and baseline health conditions (Noji 1997, 2000[3]).

Consequently, understanding the vulnerability of a population necessitates a location-based assessment of both socioeconomic sensitivities, community resilience, and special medical needs, which may, in fact, represent different sub-populations. These underlying population or community vulnerabilities (social and health) complicate emergency management planning and action, so it is vital to identify, understand, and incorporate such information into emergency response planning, and link information to decision-making. Social vulnerability describes those characteristics of a population that affect their ability to prepare for, respond to, and recover from adverse events such as disasters, and includes things like lack of wealth, education, age, gender, race/ethnicity, and occupation. Social vulnerability is built upon the understanding that human characteristics intervene between natural processes and the built environment to redistribute the social burden of disaster impacts (Cutter 2006[4]; Thomas et al. 2013[5]). These characteristics are independent of hazard type and magnitude but when intersected with disasters tend to produce negative outcomes (Emrich and Cutter 2011[6]).

The ability to compare social vulnerability between places has become widely applied because of two main reasons: First, Cutter et al. (2003) and researchers at the University of South Carolina conducted a detailed analysis of the disaster case study literature to identify which characteristics were coming up over and over again for different hazards and in different parts of the U.S. They compared an initial list of (>200) unique characteristics to those available from the U.S. decennial census (1990 and 2000) to ascertain which social vulnerability indicators had surrogates that could be measured over time and across space, concluding that an empirical

[1] https://onlinelibrary.wiley.com/doi/full/10.1111/1540-6237.8402002
[2] https://pubmed.ncbi.nlm.nih.gov/12926572/
[3] https://www.cambridge.org/core/journals/prehospital-and-disaster-medicine/article/abs/public-health-consequences-of-disasters/02F6B8FEEAC2A36F13C0EC4A84710D73
[4] https://www.taylorfrancis.com/books/edit/10.4324/9781849771542/hazards-vulnerability-environmental-justice-susan-cutter
[5] https://www.routledge.com/Social-Vulnerability-to-Disasters/Thomas-Phillips-Lovekamp-Fothergill/p/book/9781466516373
[6] https://doi.org/10.1175/2011WCAS1092.1

and place-based (mappable) measure of social vulnerability could be created with a list of roughly 30 (non collinear) freely accessible census variables. From this scaled down list of vulnerability indicators, these geographers successfully built the first county level social vulnerability map of the U.S. (Figure 1).

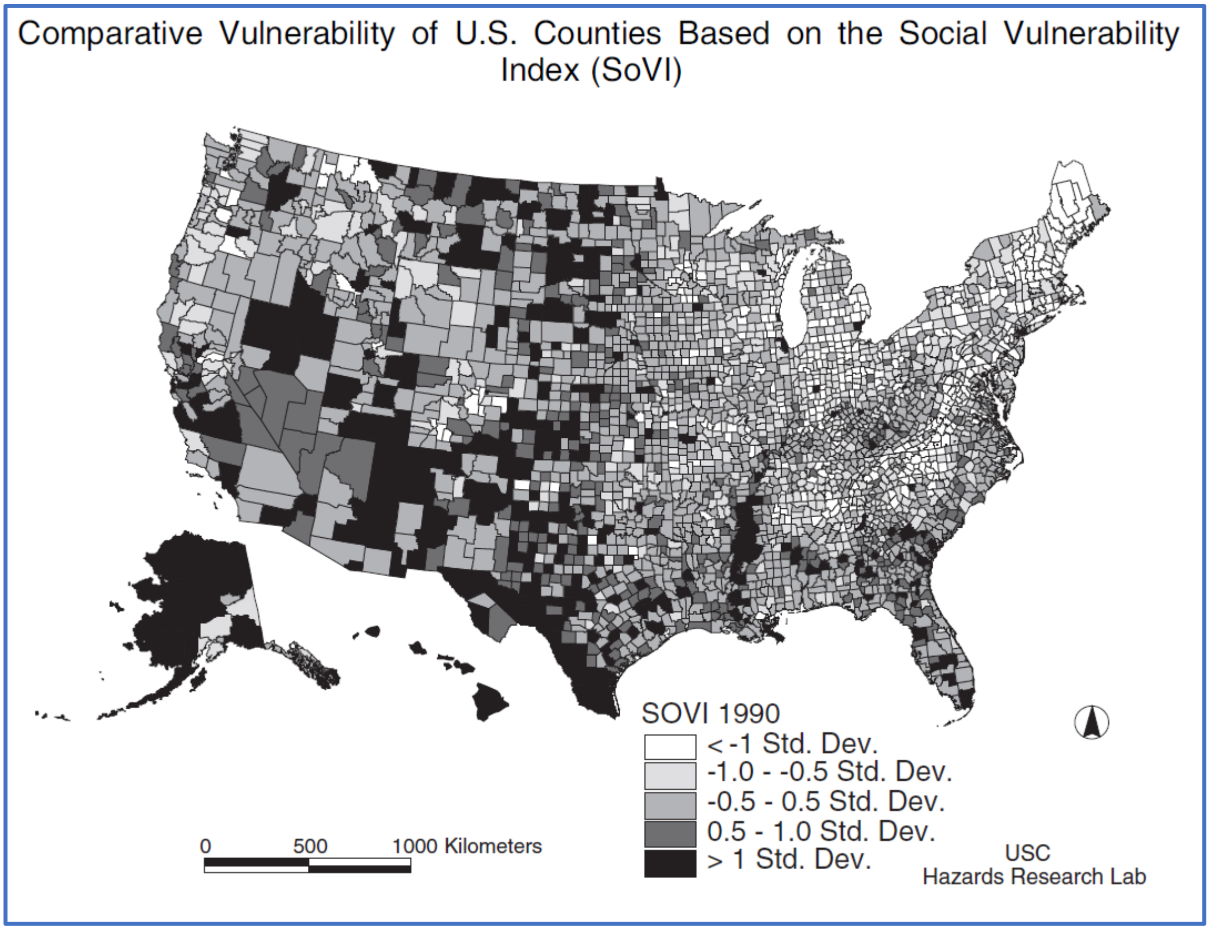

Figure 1: Seminal social vulnerability index (SoVI) model results for U.S. counties adapted from Cutter et al. (2003)

Burton et al. (2022[7]) provide a detailed exposition on the evolution of social vulnerability analysis, Rufat et al. (2015[8]) delve into flood specific vulnerability, and Cutter and Morth (2014[9]) highlight SoVI's and application in science and practice. In summarizing the highlights, from SoVI's initial proof that social vulnerability could be measured and mapped came

[7] https://www.cambridge.org/core/books/vulnerability-and-resilience-to-natural-hazards/FCBF5405C7FEA415ECF600A6B26FBA93
[8] https://doi.org/10.1016/j.ijdrr.2015.09.013
[9] Cutter, S.L., and D.P. Morath. 2014. The evolution of the social vulnerability index (SoVI). In Measuring vulnerability to natural hazards: Towards disaster resilient societies, 2nd edn., ed. J. Birkmann, 304–321. New York: United Nations University Press.

expansions in time (Cutter and Finch 2008[10]), in other places (Portugal[11], China[12], Brazil[13]) the application of SoVI to disaster exposure (Boruff et al. 2005[14], Cutter and Emrich 2006[15], Cutter et al. 2009[16], Emrich and Cutter 2011, Tate et al. 2015[17], Tate et al. 2021[18], Ali et al. 2023[19] Schumann et al. 2024[20]), outcomes (Drakes and Tate 2022[21]), resilience (Burton[22]), and a host of papers examining robustness, utility, consistency, validity, and other aspects of the model itself (Gall 2007[23], Tate 2011[24], Tate 2012[25], Schmidtlein, Rufat et al. 2020[26], Speilman et al. 2020[27]). Most recently, scholarship utilizing SoVI has pivoted away from its measurement and toward its application for understanding how it is linked to disaster response and recovery decision-making for associated programs supporting disaster recovery, resilience, and disparities (Finch et al. 2010[28], Gall 2013[29],Muñoz and Tate 2016[30], Emrich et al. 2020[31], Drakes et al. 2021[32], Tate and Emrich 2021[33], Wilson et al. 2021[34] Emrich et al. 2022[35], Blackwood and Cutter 2023[36]).

SoVI has be utilized by federal (NOAA, FEMA, USACE) partners, states, and locals[37] and has proven to be a useful resource for those attempting to understand and compare social

[10] https://www.pnas.org/doi/abs/10.1073/pnas.0710375105
[11] https://doi.org/10.1080/13669877.2014.910689
[12] https://link.springer.com/article/10.1007/s13753-013-0018-6
[13] https://doi.org/10.1007/s13753-016-0090-9
[14] https://doi.org/10.2112/04-0172.1
[15] https://doi.org/10.1177/0002716205285515
[16] https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=e0708976f51536074aba4cf7fd5375d9c8f58c2b
[17] https://doi.org/10.1016/j.ijdrr.2015.09.013
[18] https://link.springer.com/article/10.1007/s11069-020-04470-2
[19] https://www.sciencedirect.com/science/article/pii/S2212094723000786
[20] https://link.springer.com/article/10.1007/s11069-023-06367-2
[21] 10.1088/1748-9326/ac5140
[22] https://doi.org/10.1061/(asce)1527-6988(2010)11:2(58)
[23] https://www.researchgate.net/profile/Melanie-Gall/publication/324822909_Indices_of_social_vulnerability_to_natural_hazards_A_comparative_evaluation/links/6100afcb169a1a0103bf7ba5/Indices-of-social-vulnerability-to-natural-hazards-A-comparative-evaluation.pdf
[24] https://doi.org/10.1080/00045608.2012.700616
[25] https://link.springer.com/article/10.1007/s11069-012-0152-2
[26] https://doi.org/10.1080/24694452.2018.1535887
[27] https://link.springer.com/article/10.1007/s11069-019-03820-z
[28] https://doi.org/10.1007/s11111-009-0099-8
[29] https://collections.unu.edu/view/UNU:1867
[30] https://doi.org/10.3390/ijerph13050507
[31] https://doi.org/10.1080/17477891.2019.1675578
[32] https://doi.org/10.1016/j.ijdrr.2020.102010
[33] https://doi.org/10.1029/2021eo154548
[34] https://doi.org/10.3389/frwa.2021.752307
[35] https://doi.org/10.1016/j.ijdrr.2022.102855
[36] https://doi.org/10.1016/j.ijdrr.2023.103722
[37] See SoVI publications at https://www.vulnerabilitymap.org/Resources/Publications

vulnerability among and between places. Today, UCF's Vulnerability Mapping and Analysis Platform has revolutionized how social vulnerability can be measured and monitored. VMAP now enables users can create on-demand SoVI measures along with three other social vulnerability measures (CDC's SVI[38], SoVI's predecessor – the Georgetown Approach[39], and a model from Scholars at TA&M (HRRC)[40]).

The Vulnerability Mapping Analysis Platform (VMAP) turns complex socio-demographic, environmental, and medical data into applied tools for emergency and crisis management decision makers by utilizing the most appropriate scientific methods. VMAP can help you measure and visualize disaster losses and human impacts through the lens of evidenced based vulnerability analysis.

Even still, others have attempted to replicate, augment, or otherwise modify the SoVI model for similar purposes begging the question **"Is Better" the enemy of "Good" or "New" the enemy of "Longstanding."**

Although new models aimed at understanding social vulnerability and exploring equity analysis seem to materialize frequently, each is based on the same premise as SoVI – that specific and measurable sets of underlying socio-economic and demographic characteristics can help us pinpoint which places have a lower capacity to prepare for, respond to, and rebound from environmental shocks and stresses, such as disasters.

This report provide a summary and comparison of the various social vulnerability and equity models that are in use today as well as those (such as EJ Screen and the Justice 40 Initiative) aimed to ensure that equity is a lynchpin in current and future efforts to build resilience and reduce vulnerability in the face of ever-changing shocks and stresses.

The report takes the following format. First, a description of each model assessed provides a basis from which readers can understand basic details about the models (UofSC/UCF Social Vulnerability Index (SoVI, UofSC's "Georgetown" model of social vulnerability, Texas A&M (TA&M) Hazard Reduction and Recovery Center (HRRC) Vulnerability Index, CDC Social Vulnerability Index (SVI), EPA EJ Screen, and the Climate Vulnerability Index (CVI)), their inputs, and the processes utilized to combine the data. Second, the results from a series of analytic operations (correlations and regressions) aimed identifying overlaps and redundancies between the models will aid in pinpointing key similarities and differences in the model data inputs and outputs. Finally, a review of important findings will support decision makers as they continue to utilize vulnerability and equity indicators in models.

[38] https://www.degruyter.com/document/doi/10.2202/1547-7355.1792/html
[39] https://www.taylorfrancis.com/chapters/edit/10.4324/9781849771542-16/evacuation-behaviour-three-mile-island-susan-cutter-kent-barnes
[40] https://www.tandfonline.com/doi/full/10.1080/10511482.2011.624528

2.0 Analytic Comparisons

The utility of a model is often linked with how well it applies to a specific situation or the manner in which it informs the user based on the users' needs. Users are often looking for different measures of a model's "goodness" when making decisions on its application to decision making. Several measures of a utility or "goodness" can be measured empirically, and others are more qualitative in nature, including those listed in Table 1. Each measure was assessed for each model/data set to create a comparison matrix for decision makers to better understand how each model compares to other models.

Table 1. Select measures of model validity or "Goodness".

"Goodness" Measure	Definition used in this assessment	Quantitative/Qualitative	Measured/Included in this assessment
#1- Conceptually framed in peer-reviewed outlet	Is model/metric or dataset supported by a peer-reviewed citation?	Quantitative – Ranked based on existence of supporting peer reviewed literature.	Score based on existence of peer-reviewed article (1 = no, 7 = yes)
#2- Number of Citations	How often in the model cited in other peer-reviewed manuscripts?	Quantitative – Ranked sum of citations.	Ranked lowest (1) to highest (7) based on number of citations
#3- Number of Inputs	Do models/data capture concepts?	Quantitative - Using SoVI as a baseline, how do the other models compare in terms of number of inputs.	Ranked lowest (1) to highest (7) based on number of inputs
#4- Visual Inspection of Accuracy Possible via web	How closely the model's predictions align with the actual observed values?	Qualitative – Are maps available online?	Scored lowest to highest where (1= not available, 4 = available through VMAP, 7 = available through original developer)
#5- Correlation Analysis	Do models contain collinear data?	Quantitative – Correlation analysis.	Ranked lowest (1) to highest (7) based on the percentage of inputs that were correlated)
#6- Model based Correlation Correction	Do models/inputs deal with or correct for collinear data	Qualitative – Do models correct for correlation in inputs?	Scored (1 = Does not correct for correlation, 7 = Corrects for correlation)
#7- Internal Consistency	Are models internally consistent? Should social models reflecting diverse vulnerabilities be internally consistent?	Quantitative – Cronbach's Alpha tests performed on each model/dataset's indicators.	Ranked two different ways to capture low internal consistency as "good" lowest Alpha = 7 to highest Alpha = 1 and low internal consistency as "bad" where lowest Alpha = 1 and highest Alpha = 7

"Goodness" Measure	Definition used in this assessment	Quantitative/Qualitative	Measured/Included in this assessment
#8- Exploratory/ Explanatory Regression Analysis	Can inputs from one model/dataset explain outputs (scores from other datasets)?	Quantitative – Linear regression yielding Adjusted R2 values.	Ranked highest Adj. R2 = 7 to lowest Adj. R2 = 1
#9- Ease of Access via internet	Are data easily accessible via internet?	Qualitative – Can data be easily accessed online?	Scored where no data available via internet = 1, single or non-concurrent year data available through original developers = 3, data available through VMAP for concurrent years = 4, data available through original developer for concurrent years = 7
#10- GIS data provided for visual comparison (1 = No, 4 = through VMAP, 7 = Yes, through original developer)	Are data in a format making them easily mappable?	Qualitative – Are GIS data available via internet.	Scored where no GIS data available via internet = 1, single or non-concurrent year GIS data available through original developers = 3, data available through VMAP for concurrent years = 4, data available through original developer for concurrent years = 7
#11- Update frequency	Are data available annually? If not, what is the update frequency?	Qualitative – How often are data updated?	Scored where no update schedule = 1, updated every 2 years = 4, updated annually = 7
#12- Accessibility	Are the data free or is there a cost associated?	Qualitative – Is there a cost associated with the data?	Scored where data/GIS costs to access = 1, method free but Time and Effort required to build and produce, and data/GIS are free = 7

Beyond those listed and tested here, other measures of a "good" model include precision, robustness, and transferability. These were not tested in this assessment for a variety of reasons including the need for:

- Lack of multiple study areas/case studies zones to assess precision, robustness, and reliability and

- Lack of specific outcome measures linking social vulnerability to ESIs which are themselves often huge and diverse datasets.

However, those indicators of model "goodness" that were tested are detailed below and summarized in the ***Takeaways for Decision Makers*** section and Table 15 and Table 16.

3.0 Social Vulnerability and Equity Model Review

In this section, each social vulnerability/equity model or dataset is summarized in as much detail as possible through a process meant to describe the background/rationale, data inputs,

Some aspects of each model/dataset lend themselves well to an overview in tabular format. As such, Table 2 provides an overview of the qualitative and quantitative measures used to compare/contrast the social vulnerability/equity models and datasets assessed herein.

Table 2. How Social vulnerability/equity models and datasets define vulnerability.

	Define or operationalize their focus (vulnerability or equity)
UCF and UofSC SoVI®	The socio-economic factors driving uneven capacity for hazard/disaster preparedness, response, and recovery. It highlights where resources might be used most effectively to minimize adverse disaster outcomes.
UofSC Georgetown Model	The potential for loss of property or life from environmental hazards. Social vulnerability refers to social groups and landscapes that have the potential for loss from environmental hazards events.
Texas A&M	The characteristics of a person or group in terms of their capacity to anticipate, cope with, resist and recover from the impacts of a natural hazard.
CDC SVI	The resilience of communities when confronted by external stresses on human health, stresses such as natural or human-caused disasters, or disease outbreaks.
EJ Screen	EJ Screen simply provides a way to display this information and includes a method for combining environmental and demographic indicators into EJ indexes.
CEJST	A geospatial mapping tool to identify disadvantaged communities that face burdens.
CVI	Baseline vulnerability indicators reflect factors that may reduce resilience or are potential sources of long-standing community inequity or injustice. These were divided into four categories: Health, Social & Economic, Infrastructure, and Environment.

"Goodness" Measure #1- Conceptually framed in peer-reviewed outlet and 2- Number of Citations are scored using simple qualitative and quantitative assessment respectively. To answer the question (and score each measure based on its link to supporting peer reviewed literature, one must first identify the associated manuscript. Table 3 indicates which model or dataset had a supporting peer reviewed manuscript (scored 7) and those that do not (scored 1) in the overall scores presented in Table 15 and Table 16. Here only EJ Screen, CJEST, and CVI were scored 1 and all the other models and datasets scored 7.

Likewise, “Goodness” Measure #2- Number of citations was determined by ranking each model/dataset based on the number of peer-reviewed citations identified by Google Scholar. Here, SoVI landed on top with more than 7,700 citations and the HRRC model from Texas A&M ranked last with just shy of 300 citations. Refer to Table 15 and Table 16 for final scores.

Table 3. Social vulnerability/equity model comparisons across several key aspects/characteristics.

	Social Vulnerability or Equity Model/Dataset						
	UCF and UofSC SoVI®	**UofSC Georgetown**	**Texas A&M (HRRC)**	**CDC SVI**	**EJ Screen**	**CEJST**	**CVI**
Model / Dataset Characteristic							
Literature Basis	2003 – Social Vulnerability to Environmental Hazards Cutter et al.	2000 – Revealing the Vulnerability of People and Places	2012 – Mapping social vulnerability to enhance housing and neighborhood resilience.	2011 – A Social Vulnerability Index for Emergency Managers and Planners	Online data/tool https://www.epa.gov/ejscreen	Online data/tool https://screeningtool.geoplatform.gov/en/#3/33.47/-97.5	Online data/tool https://map.climatevulnerabilityindex.org/map/cvi_overall/usa?mapBoundaries=Tract&mapFilter=0&reportBoundaries=Tract&geoContext=State
Number of Citations (as of 3/31/2024)	> 7,775 academic citations	> 2,152 academic citations	> 285 academic citations	> 1,758 academic citations	> 1,580 articles cite EJ Screen - https://scholar.google.com/scholar?hl=en&as_sdt=0%2C10&q=EJ Screen&btnG=	> 435 articles cite CEJST- https://scholar.google.com/scholar?hl=en&as_sdt=0%2C10&q=%22climate+and+Economic+Justice+Screening+Tool%22&btnG=	> 1,650 articles cite https://scholar.google.com/scholar?hl=en&as_sdt=0%2C10&q=%22climate+vulnerability+index%22&btnG=

	Social Vulnerability or Equity Model/Dataset						
	UCF and UofSC SoVI®	**UofSC Georgetown**	**Texas A&M (HRRC)**	**CDC SVI**	**EJ Screen**	**CEJST**	**CVI**
Number of Variables in Model	31 variables selected from a deep dive into disasters literature	8 variables selected from literature	17 variables selected from previous models and literature	16 variables selected from previous models and literature	7 nationally consistent and freely available socio-economic indicators	20 demo-graphic	28 baseline social
Type of Model	Inductive - typically begin with more than 20 variables, which are reduced to a smaller number of latent variables using principal components analysis and aggregated to compute the index	Deductive - consists of up to 8 normalized variables that are assembled to compute the index	Quasi Hierarchical (Deductive) - Using a use a greater number of indicators that are grouped into thematic subindexes, which are then combined to form the index	Quasi Hierarchi-cal (Deductive) - Using a greater number of indicators that are grouped into thematic subindexes which are then combined to form the index	No model EJ Screen is just data	No model CEJST is just data	Quasi Hierarchi-cal (Deductive) 2 themes with multiple sub-categories
Indicator Measurement	***Place Specific.*** Because vulnerability is highly dependent on where you live, SoVI is relative to only those places modeled. Not cross comparative.	**Not place specific.** Absolute differences between places and scores can be compared	**Not place specific.** Absolute differences between places and scores can be compared	**Not place specific.** Absolute differences between places and scores can be compared	**Not place specific.** Absolute differences between places can be compared	**Not place specific.** Absolute differences between places can be compared	**Not place specific.** Absolute differences between places and scores can be compared

	Social Vulnerability or Equity Model/Dataset						
	UCF and UofSC SoVI®	UofSC Georgetown	Texas A&M (HRRC)	CDC SVI	EJ Screen	CEJST	CVI
Applications	FEMA's National Risk Index (v1), Climate Central's Surging Seas, Florida's Public Health Risk Assessment Tool, NOAA's Digital Coast		National Environmental Public Health Tracking Network	National Environmental Public Health Tracking Network, FEMA's National Risk Index (v2),	Calls for use of EJ Screen are increasing, but specific program adoption is unclear	Calls for use of CJEST are increasing, but specific program adoption is unclear	No specific calls for use or application in federal, state, or local programs

3.1 Social Vulnerability Model (SoVI)

SoVI is a model that measures vulnerability to the environment. It included 27 variables (*VMAP > Resources*. VMAP. 2023[41]). Since 2016 two additional variables are included, and these are the percent of household spending more than 40% of their income on housing costs (QHSEBURDEN) and percent of population without health insurance (QUNINSURED), for a total of 29 variables. The variables are grouped into six pillars of vulnerability that include: Employment Structure (includes four variables), Housing (three variables), Population Structure (six variables), Race and Ethnicity (four variables), Socioeconomic Status (seven variables), and Special Needs (four variables) (Emrich, Aksha, and Zhou 2022[42]).

Utilizing SoVI researchers have identified areas with different indices of social vulnerability; for example, describe those areas with lower scores of vulnerabilities utilizing SoVI index with higher located in the Midwest and Northeast regions of the U.S. (Tate, Rahman, Emrich, and Sampson 2021[43]). Tate, Rahman, Emrich and Sampson (2021) also highlight that, in terms of flooding for example, some areas that have high vulnerability to flooding have low social vulnerability indices and that the approach of these areas would include implementing strategies to reduce the exposure to floods. In studying SoVI as a predictor of health outcomes, risk behaviors, or preventative measures, researchers need to evaluate the social vulnerability index of the area and establish the best strategies to address the wellbeing of the population in terms of behavior and health. For example, as Tate Rahman, Emrich and Sampson (2021) describe when evaluating the risk of flood considering SoVI results to make decisions and address what they call hotspots could likely be extrapolated to health as well in terms of addressing, for example, rurality, resource allocation, and insurance coverage just to name a few questions that could be addressed with studies that combine SoVI and disease. The model has been updated since that publication and two previous exploratory variables are now included in the pillars. These include the Percent of population without health insurance and Percent of parcels classified as Heir's Properties in the Special needs pillar.

The Social Vulnerability Index (SoVI)

THE SOCIAL VULNERABILITY INDEX (SoVI) IS A WIDELY USED TOOL FOR ASSESSING SOCIAL VULNERABILITY TO NATURAL HAZARDS. IT INCORPORATES FACTORS SUCH AS SOCIOECONOMIC STATUS, DEMOGRAPHIC CHARACTERISTICS, AND COMMUNITY INFRASTRUCTURE TO PROVIDE A COMPREHENSIVE PICTURE OF VULNERABILITY. SOVI IS OFTEN USED IN DISASTER PLANNING AND RESPONSE TO IDENTIFY AT-RISK COMMUNITIES AND PRIORITIZE RESOURCES. IT IS A SPATIALLY EXPLICIT INDEX THAT ALLOWS FOR THE IDENTIFICATION OF VULNERABLE AREAS WITHIN A REGION.

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[41] https://www.vulnerabilitymap.org/

[42] https://www.sciencedirect.com/science/article/pii/S2212420922000747

[43] https://link.springer.com/article/10.1007/s11069-020-04470-2

SoVI has an inductive approach utilizing latent variables and using principal component analysis, and the index is calculated representing the level of vulnerability in an area (Burton and Cutter 2003; Tate, Cutter, and Berry 2010[44]; VMAP tools[45] 2022). This directionality issue was previously described by Burton and Cutter in 2008[46] where scholars' expertise is required to improve the analysis and likely the utility of the index. Spielman et al. (2020)[47] agree with Burton and Cutter (2008) in referring to the literature to find the contribution of the variable to the vulnerability model which Burton and Cutter (2008) explain the theoretical portion of assessing each variable in terms of directionality, explaining that this has already been determined by previous research establishing background knowledge. Therefore, literature findings appear to be the best guidance in helping to determine the direction of the association between the variable and outcome. In terms of this expert knowledge, Schmidtlein et al. (2008)[48] also found that interpretation of the data generated using SoVI is also a factor as knowledgeable researchers have a central role in determining the absolute value of the components of SoVI in generating this index. Schmidtlein et al. (2008) suggest that working together with local experts and perhaps with the help of qualitative research in the area of study vulnerability could be a good guide for social vulnerability assessment and that likely SoVI results can also guide researchers to collaborate and explore qualitative studies in the area. Schmidtlein et al. (2008) also describe issues with the sensitivity of SoVI in terms of the generation of the index that requires expert knowledge and further qualitative analysis of the place.

Several researchers describe the limitations of SoVI derived from the variable choice and due to subjectivity when evaluating the directionality of some variables used in the model that can be corrected by reviewing the literature (Burton and Cutter 2008). Spielman et al. (2020) are critical of the use of indices in general, favoring an approach that includes expertise input in terms of the issue being studied and in the place context that could lead in the selection of the appropriate variables to measure social vulnerability to a specific situation. Spielman et al. (2020) therefore suggest that researchers analyze each of the variables in the SoVI and that this practice could improve what they call the limitations of this index. However, Schimdtlein et al. (2008) evaluated SoVI's sensitivity, finding that the index is robust in terms of not displaying significant alterations in vulnerability in their results related to the variable structure or to the scale chosen. Therefore, it is important to remember when working with the index that it is an inductive model that is place-specific (VMAP Social Vulnerability 2022) as there is awareness in this study of the critical analysis of the model that has some limitations (Spielman et al. 2020). Also, in working with this index to compare counties from different states in this sense, Schmidtlein et al. (2008) acknowledged that the place is relevant for SoVI.

[44] https://journals.sagepub.com/doi/abs/10.1068/b35157
[45] https://www.vulnerabilitymap.org/Mapping-Tools/Social-Vulnerability
[46] https://ascelibrary.org/doi/full/10.1061/%28ASCE%291527-6988%282008%299%3A3%28136%29
[47] https://link.springer.com/article/10.1007/S11069-019-03820-Z
[48] https://onlinelibrary.wiley.com/doi/full/10.1111/j.1539-6924.2008.01072.x

Table 4. SoVI pillars, sub pillars, and variables[49].

Pillar	Sub Pillar	Description	Variable Name
Employment Structure	Employment	Percent Civilian Unemployment	QCVLUN
	Employment Type	Percent Employment in Extractive Industries	QEXTRACT
	Employment Type	Percent Employment in Service Industry	QSERV
	Gendered Employment	Percent Female Participation in Labor Force	QFEMLBR
Housing	Housing Tenure	Percent Renters	QRENTER
	Housing Type	Percent Mobile Homes	QMOHO
	Housing Availability	Percent Unoccupied Housing Units	QUNOCCHU
Population structure	Age	Percent Population under 5 years or 65 and over	QAGEDEP
	Household Structure	Percent of Children Living in 2-Parent Families	QFAM
	Age	Median Age	MEDAGE
	Gender	Percent Female	QFEMALE
	Household Type	Percent Female Headed Households	QFHH
	Household Size	People per Unit	PPUNIT
Race/ Ethnicity	Race	Percent Asian	QASIAN
	Race	Percent Black	QBLACK
	Ethnicity	Percent Hispanic	QSPANISH
	Race	Percent Native American	QINDIAN
Socioeconomic Status	Poverty	Percent Poverty	QPOVTY
	Wealth	Percent Households Earning over $200,000 Annually	QRICH
	Wealth	Per Capita Income	PERCAP
	Social Status	Percent with Less than 12th Grade Education	QED12LES
	Wealth	Median Housing Value	MDHSEVAL
	Wealth	Median Gross Rent	MDGRENT
	Financial Precariousness	Percent of Households Spending more than 40% of Their Income on Housing Costs	QHSEBURDEN
Special Needs	Dependance	Percent Households Receiving Social Security Benefits	QSSBEN
	Access Barrier	Percent Speaking English as a Second Language with Limited English Proficiency	QSEL
	Dependance	Nursing Home Residents Per Capita	QNRRES

[49] *Source Adapted from* Emrich, C. T., Aksha, S. K., & Zhou, Y. (2022) and from Yu, C.-Y., Woo, A., Emrich, C. T., & Wang, B. (2019

Pillar	Sub Pillar	Description	Variable Name
	Access Barrier	Percent of Population without Health Insurance	QNOHLTH
	Access Barrier	Percent of Housing Units with No Car	QNOAUTO
	Access Barrier	Percent of Parcels Classified as Heir's Properties	QHEIRS

3.2 CDC/ASTDR SVI

The U.S. Centers for Disease Control (CDC) began producing a bi-annual social vulnerability model in 2014 that includes variables from the U.S. Census at census tract and county levels of geography, and it determines vulnerability at the census tract level (Flanagan et al. 2011)[50]. It is updated every two years to reflect changes in the population (Center for Disease Control *CDC/ATSDR SVI frequently,* 2022)[51]. This model is maintained by the Geospatial Research Analysis and Services Program (GRASP) (Center for Disease Control *CDC/ATSDR SVI frequently,* 2022).

In 2011 the first model of the CDC/ATSDR was created by GRASP (Center for Disease Control; At a glance, 2022)[52]. In March 2020 the CDC/GRASP released the update to the SVI of 2018 as expected; however, this study will use the data from the 2020 release that includes data from the ACS for the years 2016-2020 (Center for Disease Control, CDC/ATSDR SVI data, March 2023)[53].

The CDC SVI at a national level allows for comparison of the social vulnerability, for example, of the SVI of one census tract compared to other tracts in the nation; or of one county to other the counties in the U.S. (Agency for Toxic Substances and Disease Registry, October 26, 2022)[54]. In general, the purpose of the CDC/ATSDR SVI is to aid in the allocation of emergency personnel and other resources, i.e., water, to identity areas in need of places to host population like shelters, to plan for the evacuation and recovering of communities in case of emergency or disasters (Center for

The CDC Social Vulnerability Index (SVI)

THE CENTERS FOR DISEASE CONTROL AND PREVENTION'S SOCIAL VULNERABILITY INDEX (SVI) IS ANOTHER COMMONLY USED TOOL FOR ASSESSING SOCIAL VULNERABILITY. SVI FOCUSES ON THE SOCIAL DETERMINANTS OF HEALTH AND INCLUDES INDICATORS SUCH AS RACE/ETHNICITY, POVERTY, ACCESS TO TRANSPORTATION, AND HOUSING QUALITY. IT IS DESIGNED TO HELP PUBLIC HEALTH PROFESSIONALS UNDERSTAND AND ADDRESS HEALTH DISPARITIES IN AT-RISK COMMUNITIES. SVI PROVIDES A RANKING OF NEIGHBORHOODS OR CENSUS TRACTS BASED ON THEIR VULNERABILITY TO A RANGE OF HEALTH-RELATED HAZARDS.

[50] https://www.degruyter.com/document/doi/10.2202/1547-7355.1792/html
[51] https://www.atsdr.cdc.gov/placeandhealth/svi/faq_svi.html
[52] https://www.atsdr.cdc.gov/placeandhealth/svi/at-a-glance_svi.html#:~:text=Social%20Vulnerability%20refers%20to%20the,human%20suffering%20and%20economic%20loss.
[53] https://www.atsdr.cdc.gov/placeandhealth/svi/index.html
[5454] https://www.atsdr.cdc.gov/placeandhealth/svi/at-a-glance_svi.html

Disease Control; At a glance, 2022). However, the SVI has been studied for noninfectious chronic conditions, infectious conditions like COVID-19 (Tipirneni et al. 2022)[55] in which SVI performed similarly to indices like the Area Deprivation Index (ADI) when assessing mortality associated to the infection, highlighting the relevance of SVI indexes to evaluate outcomes at a census tract level even in the face of novel diseases. When evaluating themes, the CDC SVI has found that some themes tend to be more related to health outcomes. For example, for Medicare beneficiaries the themes of socioeconomic status and the one for household composition and disability were found to be associated with more negative outcomes after surgeries including the odds of being remitted or having a complication (Zhang et al. 2023)[56].

In the CDC SVI model, 16 variables are grouped under four different categories called themes: Socioeconomic Status, Household Characteristics, Minority Status, and Housing and Transportation (Vo et al. 2020; Centers for Disease Control and Prevention *CDC/ATSDR SVI frequently asked questions Oct 26, 2022).* The CDC SVI is advantageous for researchers as it is readily available and "free" to the public.

This is a deductive model top-down approach that uses hierarchies distributed in themes similarly to the Texas A&M model. Flannagan et al. (2018)[57] explain that the variables are ranked using a percentile rank for each variable and for the themes. Furthermore, as explained by Flannagan et al. (2018), in addition the model identifies tracts with high vulnerability and has procedures in place to avoid the interaction of overall scores with individual variable vulnerabilities. The index has scores from 0 to 1 with the higher vulnerability associated with the higher scores (Karaye and Horney 2020)[58].

The CDC SVI has been used to study areas where accessibility to emergency assistance including to health care is low in populations who are socially vulnerable with the goal to plan and prepare for emergencies as well as the usage of those resources to help vulnerable populations (Vo et al. 2020)[59]. Some researchers, for example when studying COVID-19, prefer the CDC SVI as they describe limitations with SoVI as this later index is place-specific (Page-Ton and Corbin 2021)[60].

TA&M Social Vulnerability

THE STUDY "MAPPING SOCIAL VULNERABILITY TO ENHANCE HOUSING AND NEIGHBORHOOD RESILIENCE" PRESENTS A METHODOLOGY FOR MAPPING SOCIAL VULNERABILITY THAT EMPHASIZES HOUSING-RELATED INDICATORS. THIS APPROACH RECOGNIZES THE CRITICAL ROLE OF HOUSING CONDITIONS IN DETERMINING VULNERABILITY AND INCORPORATES INDICATORS SUCH AS HOUSING AGE, HOUSING UNIT TYPE, OVERCROWDING, AND HOUSING COST BURDEN. BY FOCUSING ON HOUSING-RELATED FACTORS, THIS MODEL PROVIDES INSIGHTS INTO THE VULNERABILITIES ASSOCIATED WITH INADEQUATE HOUSING AND ITS IMPACT ON OVERALL COMMUNITY RESILIENCE.

[55] https://ajph.aphapublications.org/doi/abs/10.2105/AJPH.2022.307018
[56] https://www.sciencedirect.com/science/article/pii/S2347562523000847
[57] https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7179070/
[58] https://www.sciencedirect.com/science/article/pii/S0749379720302592
[59] https://www.tandfonline.com/doi/full/10.1080/12460125.2020.1796300
[60] https://onlinelibrary.wiley.com/doi/full/10.1111/disa.12525

The CDC SVI has also been used to evaluate changes in insurance enrollment during the pandemic. For example, the CDC SVI identified an increase in Medicaid enrollment in North Carolina that corresponded to counties with higher SVI in an environment where unemployment increased (Shafer et al. 2021)[61].

It is important to clarify that there is a within and between state database difference in which within the state the scores compare social vulnerability of the counties in that state, whereas the between states U.S. database in which the vulnerability of a county is assessed in relation to all the counties in the nation (Center for Disease Control *CDC/ATSDR SVI frequently,* 2022) For the purpose of this study, we will be using the U.S based CDC/ATSDR SVI database.

Today the CDC SVI model is being used in several publications to assess COVID-19 vulnerability in the U.S. Some publications have described an association of SVI with the number of infections (Rifat et al. 2021[62], Karaye and Horney 2020), and with deaths (Rifat et al. 2021). However, Karaye and Horney (2020) describe that, when evaluating SVI at a local level using the CDC model, the vulnerability varied widely depending on geographic location. In terms of prevention, as expected SVI was inversely associated. In the case of COVID-19, this was manifested by lower vaccinations uptake (Al Rifai et al. 2021).

The CDC SVI has also been used to evaluate the impact of individual variables on COVID-19; Karaye and Horney (2020) found that in terms of COVID-19 numbers, housing and disability, as well as minority status and language were better predictors of the contagion. Furthermore, Islam et al. (2021)[63] found that geographic areas with highly elevated social vulnerability had more COVID-19 contagion and negative outcomes related to the infection. In those areas chronic conditions were prevalent, Islam et al. (2021) explained that the findings could help guide the pandemic response. Other researchers have used the SVI to assess other outcomes, including teen pregnancy (Yee, Cunningham, and Ickovics 2019)[64].

Table 5. CDC SVI Themes with variables.

Socioeconomic Status (Theme 1)	**Household Characteristics (Theme 2)**	**Racial and Ethnic Minority Status (Theme 3)**	**Housing Type and Transportation (Theme 4)**
Persons below 150% poverty estimate **E_POV150**	Persons aged 65 or older estimates ACS **E_AGE65**	Minority (all persons except white, non-Hispanic estimate) ACS **E_MINRTY**	Housing in structures with 10 or more units estimate 2014-2018 ACS **E_MUNIT**
Civilian (age 16+) unemployed estimate ACS **E_UNEMP**	Persons aged 17 or younger estimates ACS **E_AGE17**		Mobile homes estimate ACS **E-MOBILE**

[61] https://www.healthaffairs.org/doi/full/10.1377/hlthaff.2021.00377
[62] https://www.tandfonline.com/doi/full/10.1080/09603123.2021.1979196
[63] https://bmjopen.bmj.com/content/11/7/e048086.abstract
[64] https://link.springer.com/article/10.1007/s10995-019-02792-7

Socioeconomic Status (Theme 1)	Household Characteristics (Theme 2)	Racial and Ethnic Minority Status (Theme 3)	Housing Type and Transportation (Theme 4)
Housing cost burden **E_HBURD**	Civilian non institutionalize population with a disability estimates ACS **E_DISABL**		At household level (occupied housing units) more people than rooms estimate 2014-2018 ACS **E_CROWD**
Persons (age 25+) with no high school diploma estimate ACS **E_NOHSDP**	Single-parent households with children under 18 **E_SNGPNT**		Households with no vehicle available estimate ACS **E_NOVEH**
Adjunct variable uninsured in total civilian noninstitutionalized population estimates **E_UNINSUR**	Persons (age 5+ who speak English "less than well" (Estimate ACS) **E_LIMENG**		Persons in group quarters estimate 2014-2018 ACS **E_GROUPQ**

Adapted from Center for Disease Control and Prevention. CDC/ASTDR SVI data (2022).aa

3.3 Texas A&M HRRC Model

The Texas A&M model of social vulnerability was built as part of an academic exploration aimed at pinpointing community social vulnerability in the context of enhancing housing and neighborhood resilience. The resulting model is a quasi-hierarchical deductive model utilizing 17 census-derived variables. The variables are grouped into second- and third-order measures that, when combined, generate a single index score that can be viewed as an unweighted or area-weighted measure (Van Zandt et al. 2012) [65]. Capacity needs is included as a second-order measure as VanZandt et al. (2012) indicate "The ability to share information and communicate with others, particularly those within one's social network can be extremely important for the dissemination of warning and mitigation information" (p.26).

Table 6. Order and variables Texas A&M HRRC Model[66].

1st Order	2nd Order	3rd Order
% single parent households with children **QSFAM**	Childcare Needs	
% Population <= 5 **QUNDER5**		
% population >=65 **QOVER65**	Elder Care Needs	

[65] https://www.tandfonline.com/doi/full/10.1080/10511482.2011.624528

[66] Modified from Masterson et al (2014) p. 104.

1st Order	2nd Order	3rd Order
% population > 65 and in poverty **QOVER65POV**		Social Vulnerability Hot Spot
% using public transportation/civilian labor force 16+ employed **QPUBTRANSPORT**	Transportation Needs	
% occupied housing units with no auto **QNOAUTO_ACS**		
% unoccupied housing units **QUNOCCHU_ACS**	Housing and Shelter Needs	
% units renter occupied housing units **QRENTER_ACS**		
% non-white population **QNONWHITE**		
% population living in group quarters **QGROUPQRTRS**		
% housing units built 20 years old or more ago **QHOMEPRE2000**		
% units that are mobile homes **QMOHO**		
% population in poverty **QPOVTY**		
% occupied units without a telephone **QNOPHONE**	Civic Capacity Needs	
% population > 25 with less than a high school education **QED12LES_ALT**		
% population > 16 and in labor force and unemployed **QCVLUN**		
% population > 5 who speak English not well or not at all **QESL_ALT**		

HRRC's model of social vulnerability includes characteristics at the census tract level including: the ability to communicate using a phone, a common language (therefore one variable includes the ability to speak English), and educational level and employment where individuals also exchange and gather information and could find a support system. This second-order measure as grouped could also identify groups of individuals living in census tracts that could be also susceptible to diseases and who can have local support systems and shared values that could increase their adherence to preventative measures and reduce the prevalence of engaging in unhealthy behaviors. The Texas A&M model is not specific to place (unlike SoVI), and it is used by the National Environmental Public Health Tracking Network (similarly to the CDC SVI) (*VMAP Mapping Tools social vulnerability models* 2022).

In building the index researchers divide the indicators have values with scores from 0-1 with higher scores indicating higher vulnerability (Van Zandt et al. 2012).

Social vulnerability analyzes predisposition to adverse events of people (Drakes et al. 2021; Van Zandt et al. 2012) from a lens that includes the evaluation of social aspects of communities and of individuals who dwell in them that also accounts for the culture, economy, dynamics of these factors that shape the social determinants evaluated in different studies (Van Zandt et al. 2012). These initially studied in the realm of disaster and emergency preparedness to natural events extrapolated in the last decade to an evaluation of the impact of these social determinants on vulnerability of communities influencing health and health outcomes.

Van Zandt et al. (2012) explain that social factors impact the ability to plan in anticipation to even as well and respond during the event and their resiliency in the aftermath. Communities are heterogeneous in terms of poverty, employment opportunities, violence, and in providing recreational opportunities for their populations (Van Zandt et al. 2012). The vulnerability of that community exposes the risk or their dwellers to negative outcomes for example natural events (Van Zandt et al. 2012).

Georgetown Model of Social Vulnerability

THE GEORGETOWN MODEL, AS DESCRIBED IN THE STUDY "REVEALING THE VULNERABILITY OF PEOPLE AND PLACES: A CASE STUDY OF GEORGETOWN COUNTY, SOUTH CAROLINA," FOCUSES SPECIFICALLY ON ASSESSING SOCIAL VULNERABILITY TO NATURAL HAZARDS AT A NEIGHBORHOOD LEVEL. IT INCORPORATES A RANGE OF INDICATORS RELATED TO SOCIOECONOMIC CHARACTERISTICS, HOUSING QUALITY, AND ENVIRONMENTAL FACTORS. THE MODEL UTILIZES A MULTI-DIMENSIONAL APPROACH TO ANALYZE VULNERABILITY, CONSIDERING FACTORS SUCH AS AGE, POVERTY, EDUCATION, ETHNICITY, HOUSING CONDITIONS, AND PROXIMITY TO HAZARDOUS AREAS.

Van Zandt et al 2012 explain that many times the policies in place for response and mitigation can be adapted to account for their vulnerability as social factors like having a reliable form of transportation and housing influences the individual ability to respond to unexpected events. People who rent lack civil engagement, low influence in community decisions, which were studied for disasters (Lee and Van Zandt 2019)[67], but this could also extrapolate to advocacy to improve opportunities of recreation in communities negatively impacting health outcomes. Study of social vulnerability and risk, planning, resiliency, and recovery related to Hurricane (Peacock et al. 2015)[68].

3.4 Georgetown Model

The Georgetown model of social vulnerability, created as part of an academic exploration of vulnerability in Georgetown County, South Carolina, is the predecessor to the current SoVI

[67] https://journals.sagepub.com/doi/full/10.1177/0885412218812080
[68] https://www.tandfonline.com/doi/full/10.1080/01944363.2014.980440

model. Georgetown combines nine variables grouped into four characteristics that include population and structure, differential access to resources, wealth and poverty, and level of physical or structural vulnerability (Cutter, Mitchell, and Scott 2000).[69]

Table 7. Variables Georgetown Model.

Characteristic	Variable (as a number or as a ratio)
Population and Structure	-Total population **Total_POP** or **-R**atio of tract people to total population in dataset **Pop_MMSTD**
	Total housing units or **-Housing_Unit_RAT** Ratio of housing units to total housing units in dataset
Differential access to resources/ greater susceptibility to hazards due to physical weakness	-Number of females or **-FEMALE_RAT** Ratio of tract female total to total females in dataset
	-Number of nonwhite residents or **-Non-White_RAT** Ratio of non-White population in tract to total non-White population in dataset
	-Number of people under 19 or **-AGE UNDER 19_RAT** Ratio of under 19 population in tract to total under 19 population in dataset
	-Number of people over 65 or **-AgeOver65_RAT** Ratio of over 65 population in tract to total over 65 in dataset
Wealthy or poverty	-Median house value in a tract **MHSEVAL_ALT**
Level of physical of structural vulnerability	-Number of mobile homes or **-MH_RAT** Ratio of mobile homes in tract to total mobile homes in dataset

[69] https://www.taylorfrancis.com/chapters/edit/10.4324/9781849771542-16/evacuation-behaviour-three-mile-island-susan-cutter-kent-barnes

Source: Revealing the vulnerability of People and Places: A case study of Georgetown County, South Carolina by Cutter, Mitchel, and Scott (2000)[70].

EPA's Environmental Justice Screening Tool

THE ENVIRONMENTAL JUSTICE SCREENING AND MAPPING TOOL, ALSO KNOWN AS EJ SCREEN, IS A MAPPING TOOL THAT COMBINES ENVIRONMENTAL AND DEMOGRAPHIC DATA TO IDENTIFY AREAS WITH POTENTIAL ENVIRONMENTAL JUSTICE CONCERNS. IT INCLUDES INDICATORS SUCH AS AIR QUALITY, PROXIMITY TO HAZARDOUS WASTE SITES, AND DEMOGRAPHIC CHARACTERISTICS. EJ SCREEN IS USED TO VISUALLY DEPICT AREAS THAT MAY BE DISPROPORTIONATELY BURDENED BY ENVIRONMENTAL HAZARDS AND IS OFTEN USED IN ENVIRONMENTAL JUSTICE RESEARCH AND

3.5 EJ Screen

EJ Screen[71] is a mapping tool developed by the U.S. Environmental Protection Agency (EPA) to support the analysis and visualization of environmental and socio-demographic data in order to assess and address environmental justice (EJ) issues. This tool utilizes a wide range of data sources, including national demographic and environmental indicators, to identify communities facing disproportionate environmental burdens and vulnerabilities.

One of the key aspects of EJ Screen is the inclusion of socio-demographic variables that help capture the characteristics of potentially vulnerable communities. These variables are selected based on their relevance to understanding environmental justice, and they play a significant role in identifying and quantifying environmental disparities. Some of the socio-demographic variables used in EJ Screen include race and ethnicity, income, age, educational attainment, linguistic isolation, and housing burden.

Table 8. Variables in EJ Screen.

Variable Name	Description
DEMOGIDX_5	Supplemental Demographic Index
PEOPCOLORPCT	% people of color
LOWINCPCT	% low income
UNEMPPCT	% unemployed
LINGISOPCT	% Limited English-speaking households
LESSHSPCT	% less than high school education
UNDER5PCT	% under age 5
OVER64PCT	% over age 64

[70] https://www.tandfonline.com/doi/abs/10.1111/0004-5608.00219
[71] https://www.epa.gov/ejscreen

Race and ethnicity are considered critical variables in understanding environmental justice, as studies have consistently shown that minority communities, particularly African American and Hispanic populations, face a higher burden of environmental hazards. EJ Screen includes data on the percentage of minority residents in a particular area, allowing for the identification of communities with a high concentration of minority populations experiencing environmental injustices.

Income levels are another important socio-demographic variable used in EJ Screen. Low-income communities often face disproportionate environmental burdens, as they may lack resources and political power to prevent or mitigate environmental hazards. EJ Screen incorporates data on the percentage of residents living below the poverty line or receiving government assistance, allowing for the identification of economically marginalized communities.

Age is also considered in EJ Screen, as vulnerable populations such as children and the elderly may be more susceptible to the health impacts of environmental hazards. The tool includes data on the percentage of children and elderly populations, aiding in the identification of areas with potentially heightened vulnerability.

Educational attainment is another socio-demographic variable used in EJ Screen. Communities with lower levels of education may face challenges in understanding and addressing environmental risks. By incorporating data on educational attainment, EJ Screen can identify communities that may require targeted education and outreach efforts.

Additionally, linguistic isolation is considered as a socio-demographic variable in EJ Screen. Communities where a significant percentage of residents speak limited English may have difficulties accessing information and participating in decision-making processes related to environmental issues. By mapping areas with high linguistic isolation, EJ Screen helps ensure that language barriers are acknowledged and addressed in environmental justice efforts.

Housing burden, which refers to the percentage of households paying a high proportion of their income on housing costs, is also taken into account in EJ Screen. Affordability and housing instability are significant factors that can influence a community's vulnerability to environmental hazards and contribute to overall environmental injustice.

In conclusion, EJ Screen incorporates multiple socio-demographic variables to comprehensively assess and address environmental justice concerns. The inclusion of race and ethnicity, income, age, educational attainment, linguistic isolation, and housing burden helps identify communities facing disproportionate environmental burdens and vulnerabilities. By analyzing and visualizing these variables, the tool supports evidence-based decision making and facilitates the development of targeted environmental justice policies and interventions.

3.6 Environmental Defense Fund Climate Vulnerability Index (CVI)

EDA's Climate Vulnerability Index
THE CLIMATE VULNERABILITY INDEX (CVI) IS A TOOL THAT ASSESSES VULNERABILITY TO CLIMATE CHANGE IMPACTS. IT INCLUDES INDICATORS SUCH AS EXPOSURE TO CLIMATE HAZARDS, SENSITIVITY TO IMPACTS, AND ADAPTIVE CAPACITY. CVI IS OFTEN USED IN CLIMATE CHANGE ADAPTATION PLANNING TO IDENTIFY AREAS THAT ARE MOST VULNERABLE AND PRIORITIZE ADAPTATION MEASURES. IT TAKES INTO ACCOUNT POTENTIAL CLIMATE IMPACTS, SUCH AS SEA-LEVEL RISE, EXTREME WEATHER EVENTS, AND CHANGING PRECIPITATION PATTERNS, AND ASSESSES VULNERABILITY AT VARIOUS SPATIAL SCALES.

The Climate Vulnerability Index (CVI)[72] developed by the Environmental Defense Fund (EDF)[73] is a comprehensive tool that assesses the vulnerability of communities to the impacts of climate change, including socio-demographic variables. The CVI incorporates multiple indicators to identify and prioritize areas that are most vulnerable to climate change, taking into account both biophysical and socio-demographic factors.

One of the key aspects of the CVI is the inclusion of socio-demographic variables to capture the social and economic characteristics of vulnerable communities. These variables help to understand the differential impacts of climate change on different population groups and ensure that climate resilience efforts are equitable and inclusive. The socio-demographic variables used in the CVI include race and ethnicity, income, age, educational attainment, and housing conditions.

Race and ethnicity are essential socio-demographic variables in the CVI, as research has consistently shown that minority communities often face higher climate vulnerability. The CVI incorporates data on the percentage of minority populations in a given area, allowing for the identification of communities with a concentration of minority residents who may be disproportionately affected by climate impacts. This indicator helps to highlight environmental justice concerns and address disparities in climate resilience.

Income levels are another significant socio-demographic variable considered in the CVI. Low-income communities often have limited resources and infrastructure to adapt to climate change impacts. The CVI includes data on median household income and poverty rates,

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72 https://map.climatevulnerabilityindex.org/map/cvi_overall/usa?mapBoundaries=Tract&mapFilter=0&reportBoundaries=Tract&geoContext=State

73 Environmental Defense Fund. (2018). Climate Vulnerability Index: Technical Documentation. Retrieved from https://www.edf.org/sites/default/files/cvi_technical_documentation_august_2018.pdf

allowing for the identification of economically vulnerable areas that require targeted interventions to enhance resilience.

Age is also a critical socio-demographic variable in the CVI. Certain age groups, such as children and the elderly, are more vulnerable to the health impacts of climate change. The CVI incorporates data on the percentage of the population that is under the age of 5 and over the age of 65, helping to identify communities with potentially heightened vulnerability due to age-related factors.

Educational attainment is another socio-demographic variable used in the CVI. Communities with lower levels of education may have limited access to information and resources necessary for climate adaptation and mitigation. The CVI considers data on educational attainment, helping to identify areas that may require targeted educational and outreach efforts to enhance climate resilience.

Housing conditions are also considered in the CVI. Vulnerable housing, such as inadequate infrastructure or high housing costs, can exacerbate the impacts of climate change on communities. The CVI incorporates data on housing quality and affordability, allowing for the identification of communities that are more susceptible to climate impacts due to housing conditions.

Justice 40 Climate and Economic Justice Screening Tool

INITIATIVE IN THE UNITED STATES AIMED AT ADDRESSING ENVIRONMENTAL INJUSTICES AND ADVANCING ENVIRONMENTAL AND CLIMATE JUSTICE. THE INITIATIVE AIMS TO DIRECT 40% OF FEDERAL INVESTMENTS IN CLIMATE CHANGE MITIGATION, RESILIENCE, AND CLEAN ENERGY TOWARDS DISADVANTAGED COMMUNITIES. IT FOCUSES ON ENSURING THAT VULNERABLE COMMUNITIES RECEIVE THE NECESSARY RESOURCES TO MITIGATE AND ADAPT TO CLIMATE CHANGE AND IMPROVE THEIR OVERALL WELL-BEING.

In conclusion, the CVI developed by the Environmental Defense Fund incorporates various socio-demographic variables to assess the vulnerability of communities to climate change. By considering race and ethnicity, income, age, educational attainment, and housing conditions, the CVI enables equitable and inclusive decision-making in climate resilience planning. These socio-demographic variables help to identify and prioritize interventions that address the specific vulnerabilities faced by different population groups, ensuring more effective and socially just climate adaptation and mitigation strategies.

3.7 Climate and Economic Justice Screening Tool[74]

Executive Order 14008, titled "Tackling the Climate Crisis at Home and Abroad," was issued by President Biden on January 27, 2021. The order itself focuses on addressing climate change and promoting environmental justice by prioritizing addressing climate change in various aspects of

[74] https://screeningtool.geoplatform.gov/en/

government policies and actions. It establishes a commitment to environmental justice and supports investment in disadvantaged communities. This includes efforts to advance economic opportunities, clean energy development, and equitable access to environmental benefits.

The Climate and Economic Justice Screening Tool mentioned in the executive order is a mechanism/ framework to ensure that proposed actions and investments consider potential impacts on economically disadvantaged communities and prioritize equitable outcomes. The tool helps to identify disadvantaged census tracts across all 50 states, the District of Columbia, and the U.S. territories. Under the CJEST framework, communities are considered disadvantaged if they are in census tracts that meet the thresholds for at least one of the tool's categories of burden, or if they are on land within the boundaries of Federally Recognized Tribes. In addition, census tracts that are completely surrounded by disadvantaged communities are also considered disadvantaged if they meet an adjusted low-income threshold.

Table 9. CJEST Categories of Burden and Variables.

Category	Environmental, climate, or other burdens	Socioeconomic burden
Climate change	1. Expected agriculture loss rate ≥ 90th percentile OR 2. Expected building loss rate ≥ 90th percentile OR 3. Expected population loss rate ≥ 90th percentile OR 4. Projected flood risk ≥ 90th percentile **(NEW)** OR 5. Projected wildfire risk ≥ 90th percentile **(NEW)**	Low income*
Energy	1. Energy cost ≥ 90th percentile OR 2. PM 2.5 in the air ≥ 90th percentile	Low income*
Health	1. Asthma ≥ 90th percentile OR 2. Diabetes ≥ 90th percentile OR 3. Heart disease ≥ 90th percentile OR 4. Low life expectancy ≥ 90th percentile	Low income*
Housing	1. Historic underinvestment = Yes **(NEW)** 2. Housing cost ≥ 90th percentile OR 3. Lack of green space ≥ 90th percentile **(NEW)** OR 4. Lack of indoor plumbing ≥ 90th percentile **(NEW)** OR 5. Lead paint ≥ 90th percentile	Low income*
Legacy pollution	1. Abandoned mine land present = Yes **(NEW)** OR 2. Formerly Used Defense Site (FUDS) present = Yes **(NEW)** OR 3. Proximity to hazardous waste facilities ≥ 90th percentile OR 4. Proximity to Superfund or National Priorities List (NPL) sites ≥ 90th percentile OR 5. Proximity to Risk Management Plan (RMP) sites ≥ 90th percentile	Low income*
Transportation	1. Diesel particulate matter ≥ 90th percentile OR 2. Transportation barriers ≥ 90th percentile **(NEW)** OR 3. Traffic proximity and volume ≥ 90th percentile	Low income*
Water and wastewater	1. Underground storage tanks and releases ≥ 90th percentile **(NEW)** OR 2. Wastewater discharge ≥ 90th percentile	Low income*
Workforce development	1. Linguistic isolation ≥ 90th percentile OR 2. Low median income ≥ 90th percentile OR 3. Poverty ≥ 90th percentile OR 4. Unemployment ≥ 90th percentile	High school education < 10%

* Low Income = 65th percentile or above for census tracts that have people in households whose income is less than or equal to twice the federal poverty level, not including students enrolled in higher education **(NEW method of calculation)**

Currently, CJEST only provides data linked to 2010 census tracts, making it extremely complicated to compare with data from 2020 for the other models. Working between decadal census geographies, specifically 2010 and 2020 census tracts, presents several challenges due to the changes in population dynamics, shifts in boundaries, and inconsistent data. The U.S. Census Bureau conducts a census every ten years to gather data on the country's population, housing, and other demographic information. However, over time, changes in population size, migration patterns, and urban development necessitate updates to geographic boundaries like census tracts. One of the major difficulties faced while working with different census tracts is the shift in population distribution. Certain areas might experience significant population growth while others might see a decline. As a result, the boundaries of census tracts are altered to accommodate these changes. This can make it challenging to compare data across different decennial census years as the geographic units do not align perfectly. Moreover, changes in census tract boundaries can also lead to inconsistencies in the data. For example, if a census tract is split into two or merged with another, it becomes difficult to accurately track changes in population and demographics. Researchers and analysts often must resort to complex methods, such as spatial interpolation or estimation techniques, to estimate and compare the data accurately. Another issue is that the release of data between different census years may not be synchronized. Some data may be available for the 2010 census but not yet for the 2020 census, creating gaps in information and making it challenging to conduct meaningful analyses and draw accurate conclusions. Furthermore, changes in census tracts can disrupt historical continuity. Researchers relying on consistent geographic units across multiple census years may find it difficult to track changes in specific areas over time. Despite these challenges, efforts are made to provide crosswalks or equivalents between the old and new census geographies to ease the transition. In some cases, statistical techniques are applied to bridge the gaps between different census years, ensuring researchers can make meaningful comparisons. Although it is possible to utilize CJEST data (linked with 2010 geography) in an analysis with data based on 2020 geography, such analysis would rely heavily on averages of CJEST inputs – effectively diminishing instance where both high and low values may occur in a single geographic unit. Here, we cross walked the 2010 CJEST variables to the 2020 geography to gain a sense for the relationships between the datasets, but it should be noted that utilizing average values is potentially underestimating the real differences between the datasets.

4.0 A Review and Comparison Across Social Vulnerability Models/Date sets

The previous section provides an overview of each model, but it does not compare across models. This section attempts to summarize each model in a comparative way so that readers can understand how each model differs or who has used it.

The Social Vulnerability Index (SoVI), the CDC SVI (Social Vulnerability Index), EJ Screen, and the Climate Vulnerability Index (CVI) are all tools used to assess the vulnerability of communities to various social and environmental factors. However, they differ in their specific focuses, indicators used, and intended applications.

The SoVI is a widely used index developed by the Hazards and Vulnerability Research Institute at the University of South Carolina. It primarily focuses on the social vulnerabilities of communities and aims to capture a wide range of social and economic factors that contribute to vulnerability. The SoVI incorporates indicators such as income, education, age, housing quality, and minority population concentrations. It is often used to identify areas that may be more susceptible to the impacts of natural hazards such as floods or hurricanes. The SoVI is primarily used for research purposes and helps inform policy interventions to enhance social resilience.

The CDC SVI is another social vulnerability index that was developed specifically by the Centers for Disease Control and Prevention. It also focuses on social vulnerabilities but places a particular emphasis on health-related factors. The CDC SVI incorporates indicators such as poverty, education, housing quality, minority status, and access to healthcare facilities. It is primarily used for public health planning and to identify areas that may require greater resources for health preparedness and response. The CDC SVI is often used in conjunction with other health-related indicators to target interventions for marginalized communities.

EJ Screen is a mapping and screening tool developed by the Environmental Protection Agency (EPA). Its main focus is on environmental justice issues, including a wide range of socio-demographic and environmental indicators. EJ Screen incorporates indicators such as race, income, education, proximity to pollution sources, and health risk factors. It is used to identify areas that may face disproportionate environmental burdens and to prioritize environmental justice initiatives. EJ Screen provides a visual representation of environmental disparities and helps inform policy decisions related to environmental equity.

The CVI, developed by the Environmental Defense Fund, is specifically designed to assess the vulnerability of communities to the impacts of climate change. It incorporates both biophysical and socio-demographic indicators to identify areas at risk. In addition to climate-related factors, the CVI includes socio-demographic variables such as race, income, age, educational attainment, and housing conditions. The CVI helps prioritize climate resilience interventions and identifies areas that may require targeted assistance. It aims to ensure equitable climate adaptation and mitigation strategies and highlight environmental justice concerns.

In summary, the SoVI, CDC SVI, EJ Screen, and the CVI are all valuable tools for assessing social vulnerability and informing decision-making processes. While they share a common goal of highlighting areas that may be more vulnerable to various stressors, they differ in their specific focuses, indicators used, and intended applications. These indexes complement each other and can be used in combination to provide a comprehensive understanding of vulnerabilities and inform targeted interventions for social and environmental resilience.

The Georgetown model, as described in the study "Revealing the Vulnerability of People and Places: A Case Study of Georgetown County, South Carolina," focuses specifically on assessing social vulnerability to natural hazards at a neighborhood level. It incorporates a range of indicators related to socioeconomic characteristics, housing quality, and environmental factors. The model utilizes a multi-dimensional approach to analyze vulnerability, considering factors such as age, poverty, education, ethnicity, housing conditions, and proximity to hazardous areas.

On the other hand, the study "Mapping Social Vulnerability to Enhance Housing and Neighborhood Resilience" presents a methodology for mapping social vulnerability that emphasizes housing-related indicators. This approach recognizes the critical role of housing conditions in determining vulnerability and incorporates indicators such as housing age, housing unit type, overcrowding, and housing cost burden. By focusing on housing-related factors, this model provides insights into the vulnerabilities associated with inadequate housing and its impact on overall community resilience.

While both studies share the goal of assessing social vulnerability, they differ in their specific indicators and emphasis. The Georgetown model takes a broader approach, considering a wide range of factors beyond housing to capture the multi-dimensional nature of vulnerability. In contrast, the study on housing and neighborhood resilience specifically focuses on housing-related factors as a key driver of vulnerability. This narrower focus allows for a more nuanced assessment of vulnerabilities related to housing quality, affordability, and resilience.

Both models, however, contribute valuable insights to understanding social vulnerability and inform targeted interventions. The Georgetown model provides a comprehensive assessment of vulnerability at the neighborhood level, considering a wide array of factors that contribute to vulnerability. In comparison, the housing-focused model hones in on a critical aspect of vulnerability related to housing conditions, offering specific insights into challenges associated with inadequate housing and outlining potential strategies to enhance housing and neighborhood resilience.

In summary, while the Georgetown model provides a broader and more comprehensive assessment of social vulnerability, the housing-focused approach described in "Mapping Social Vulnerability to Enhance Housing and Neighborhood Resilience" delves specifically into the relationship between housing conditions and vulnerability. Both models are useful for understanding and addressing social vulnerability but with different foci and strategies. Each of these tools and models contributes to our understanding of social vulnerability and assists in targeting interventions. SoVI and the CDC SVI offer comprehensive assessments of social vulnerability, with the former focusing on natural hazards and the latter on health-related hazards. The Georgetown model and the housing-focused approach offer specific insights into vulnerabilities related to socioeconomic characteristics, housing conditions, and neighborhood resilience, with the former taking a broader multi-dimensional approach and the latter focusing specifically on housing-related factors. EJ Screen focuses on environmental justice concerns, while the Climate Vulnerability Index assesses vulnerability to climate change impacts. The Justice 40 Initiative is a policy initiative aimed at addressing environmental injustices and advancing climate justice. As such, the CJEST is a screening tool providing data for comparative purposes and not a model of vulnerability per-se. Finally, the CVI appears to be a composite of many other model data rather than a specific conceptualization of vulnerability.

4.1 Variable Composition across models

Although the academic and practical literature does not specify the absolute number of variables needed to create a good social vulnerability indicator, it is clear that any model or dataset should capture the essence of what makes a place or people vulnerable (Heinz Center

2000)[75]. Unfortunately, ease of access to data and the ability to rapidly put data into spreadsheets/mapping applications for analysis has moved some practitioners and researchers toward a situation where models are being develop without strong connections to concepts and background literature on social vulnerability. Indeed, attempts have been made to reduce the number of input variables (Cutter et al. 2013)[76] with a clear result – that reducing inputs results in a measure of social vulnerability that cannot replicate a measure produced from the full complement of social indicators derived from disaster case study literature.

From this perspective, it is important to first understand which models contain which indicators and attempt to pinpoint deficiencies in models based on the primary consideration of data representing all aspects of social vulnerability to environmental hazards. To that end, Table 10 provides a listing of each variable included in each model/dataset under current consideration compared to the seminal social vulnerability model, Cutter et al. (2003) Social Vulnerability to Environmental Hazards (or SoVI).

"Goodness" Measure #3- Number of Inputs was created by ranking each model/data based on the number of inputs from least (1) to most (7) put SoVI at the top of the list and UofSC's Georgetown model at the bottom of the list. See Table 15 and Table 16 for overall rankings across all measurable characteristics.

Table 10. Variables by social vulnerability model/dataset

			Vulnerability/Equity Model/Dataset ✓					
Vulnerability Variable	**SoVI (n=31)**	**EJ Screen (n= 7)**	**Georgetown (n=8)**	**HRRC (n=17)**	**CDC SVI (n=16)**	**CJEST (n= 20)**	**CVI (n=28)**	**Number of Models/ Datasets in which Indicator Appears**
Percent Population under 5 years or 65 and over	✓	✓ (% Over 65 years and % Under 5 years)	✓ (% Over 65 years and % Under 5 years)	✓ (% Over 65 years and % Under 5 years)	✓ (% Over 65 years and % Under 17 years)		✓ (% Over 65 years and % Under 17 years)	6
Percent Asian	✓	✓ % People of Color	✓ (% Non-White)	✓ (% Non-White)	✓ (% Minority)		✓	6
Percent Black	✓	✓ % People of Color	✓ (% Non-White)	✓ (% Non-White)	✓ (% Minority)		✓	6

[75] Heinz Center for Science, Economics, and the Environment. 2000. The Hidden Costs of Coastal Hazards: Implications for Risk Assessment and Mitigation. Covello, Cal.: Island Press.
[76] Cutter, S. L., Emrich, C. T., Morath, D. P., & Dunning, C. M. (2013). Integrating social vulnerability into federal flood risk management planning. Journal of Flood Risk Management, 6(4), 332-344.

Vulnerability Variable	Vulnerability/Equity Model/Dataset ✓							
	SoVI (n=31)	**EJ Screen (n= 7)**	**Georgetown (n=8)**	**HRRC (n=17)**	**CDC SVI (n=16)**	**CJEST (n= 20)**	**CVI (n=28)**	**Number of Models/ Datasets in which Indicator Appears**
Percent Hispanic	✓	✓ % People of Color	✓ (% Non-White)	✓ (% Non-White)	✓ (% Minority)		✓	6
Percent Poverty	✓	✓ % Low Income		✓	✓	✓ (% impover-ished)	✓	6
Percent Civilian Unemployment	✓	✓		✓	✓	✓	✓	6
Percent with Less than 12th Grade Education	✓	✓		✓	✓	✓	✓	6
Percent Speaking English as a Second Language with Limited English Proficiency	✓	✓		✓	✓	✓	✓	6
Percent Mobile Homes	✓		✓	✓	✓		✓	5
Percent Native American	✓		✓ (% Non-White)	✓ (% Non-White)	✓ (% Minority)		✓	5
Percent of Housing Units with No Car	✓			✓	✓		✓	4
Median Housing Value	✓		✓			✓		3
People per Unit	✓				✓ Crowding		✓ Crowding	3
Percent with a Disability	✓				✓		✓	3
Percent Renters	✓			✓				2
Percent Unoccupied Housing Units	✓			✓				2
Percent Female	✓		✓					2
Percent of population without health insurance	✓				✓		✓	3
Percent of Children in Single-Parent Families	✓				✓			2

Vulnerability Variable	Vulnerability/Equity Model/Dataset ✓							
	SoVI (n=31)	EJ Screen (n= 7)	Georgetown (n=8)	HRRC (n=17)	CDC SVI (n=16)	CJEST (n= 20)	CVI (n=28)	Number of Models/ Datasets in which Indicator Appears
Median Gross Rent	✓					✓		2
Percent Female Headed Households	✓						✓ (% Single parent house-holds)	2
Per Capita Income	✓						✓	2
Percent Employment in Extractive Industries	✓							1
Percent Employment in Service Industry	✓							1
Percent Female Participation in Labor Force	✓							1
Median Age	✓							1
Percent Households Earning over $200,000 annually	✓							1
Percent of families spending more than 40% of their earnings on rent/mortgage payments	✓							1
Percent Households Receiving Social Security Benefits	✓							1
Nursing Home Residents Per Capita	✓							1
Percent of Households with No Broadband	✓							1
Percent Living in Group Quarters				✓	✓		✓	3
Multi-Unit Structures				✓	✓		✓	2

Vulnerability Variable	Vulnerability/Equity Model/Dataset ✓							
	SoVI (n=31)	EJ Screen (n= 7)	Georgetown (n=8)	HRRC (n=17)	CDC SVI (n=16)	CJEST (n= 20)	CVI (n=28)	Number of Models/ Datasets in which Indicator Appears
Percent Homes built pre-2000				✓			✓ (% of homes built pre-1970)	2
Percent Over Age over 65 + Poverty				✓				1
Percent of Labor Force Using Public Transportation				✓				1
Percent without Telephone				✓				1
Population Percentage			✓					1
Percentage of total Housing Units			✓					1
Number of Deaths by Homicide per 100,000 people							✓	1
Number of Deaths by Firearm per 100,000							✓	1
Number of Religious Organizations per 1,000 people							✓	1
Number of Civic and Social Organizations per 1,000 people							✓	1
Percentage of children in foster care							✓	1
Percentage (of state population) who is an undocumented immigrant							✓	1
Hate crimes by state per 100,000 people.							✓	1

Vulnerability Variable	SoVI (n=31)	EJ Screen (n= 7)	Georgetown (n=8)	HRRC (n=17)	CDC SVI (n=16)	CJEST (n= 20)	CVI (n=28)	Number of Models/ Datasets in which Indicator Appears
	Vulnerability/Equity Model/Dataset ✓							
Adult Population residing in correctional facilities							✓	1
Redlined areas							✓	1
Count of homeless populations by state							✓	1
Percent military veterans							✓	1
Percent of Housing Loans at risk of foreclosure							✓	1

4.2 Visual Comparison

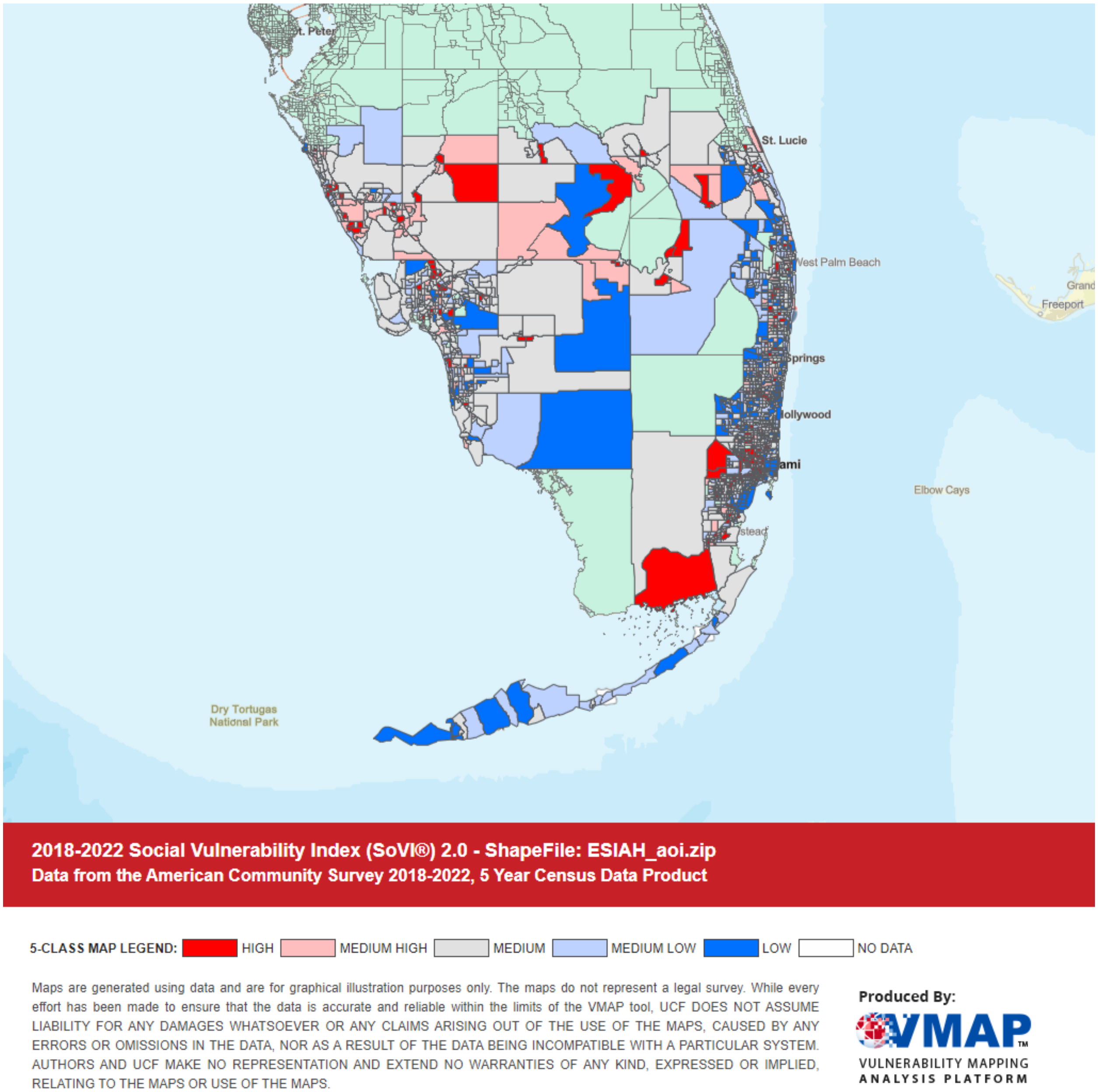
Several of the datasets/models under current consideration do not provide data in online mapping format and although their data could be converted to a map through known and relatively simple GIS processes there are several considerations that resulted in these not being mapped in the current assessment, including:

1. Data not provided in spatial format (EJ Screen)
2. No final score provided (EJ Screen and CJEST)
3. Data not provided in spatial format.
4. No symbology provided to understand high vs low areas.

"Goodness" Measure #4-Visual Inspection scored each model/data based on the ability to quickly visually inspect differences across space through an online mapping interface from (1= not available, 4 = available through VMAP, 7 = available through original developer) resulted in a 5-way tie for best between SoVI, Georgetown, SVI, CJEST, and CVI with HRRC coming in second because of their ability to be visually inspected through VMAP. Only the EJ Screen model does not have a mapping interface available online. See Table 15 and Table 16 for overall rankings across all measurable characteristics.

4.2.1 SoVI

Figure 2: Social vulnerability index (SoVI) model results for the current area of interest.

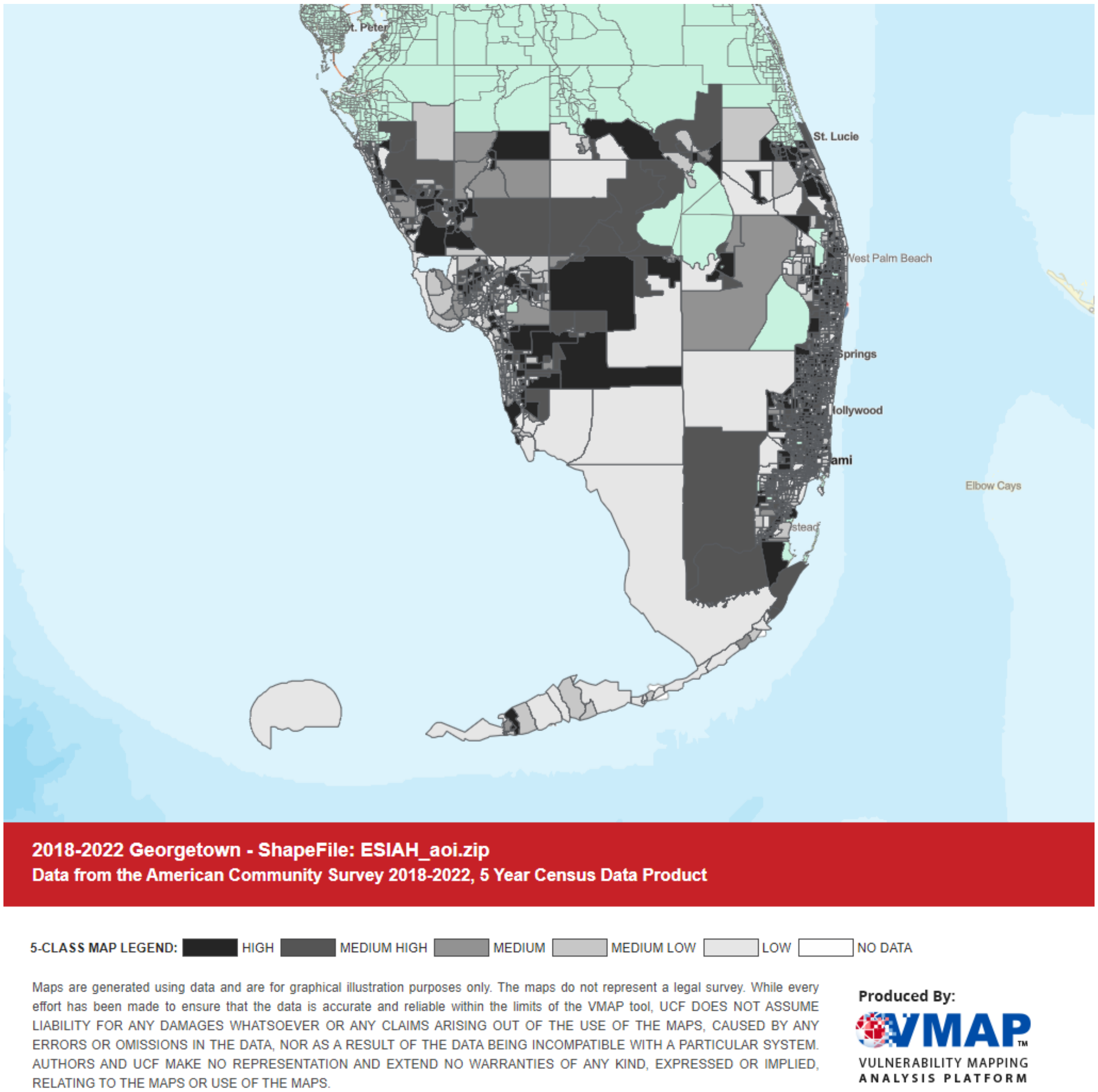


4.2.2 EPA's Environmental Justice Screening Tool (EJ Screen)

No mapping component is available at present.

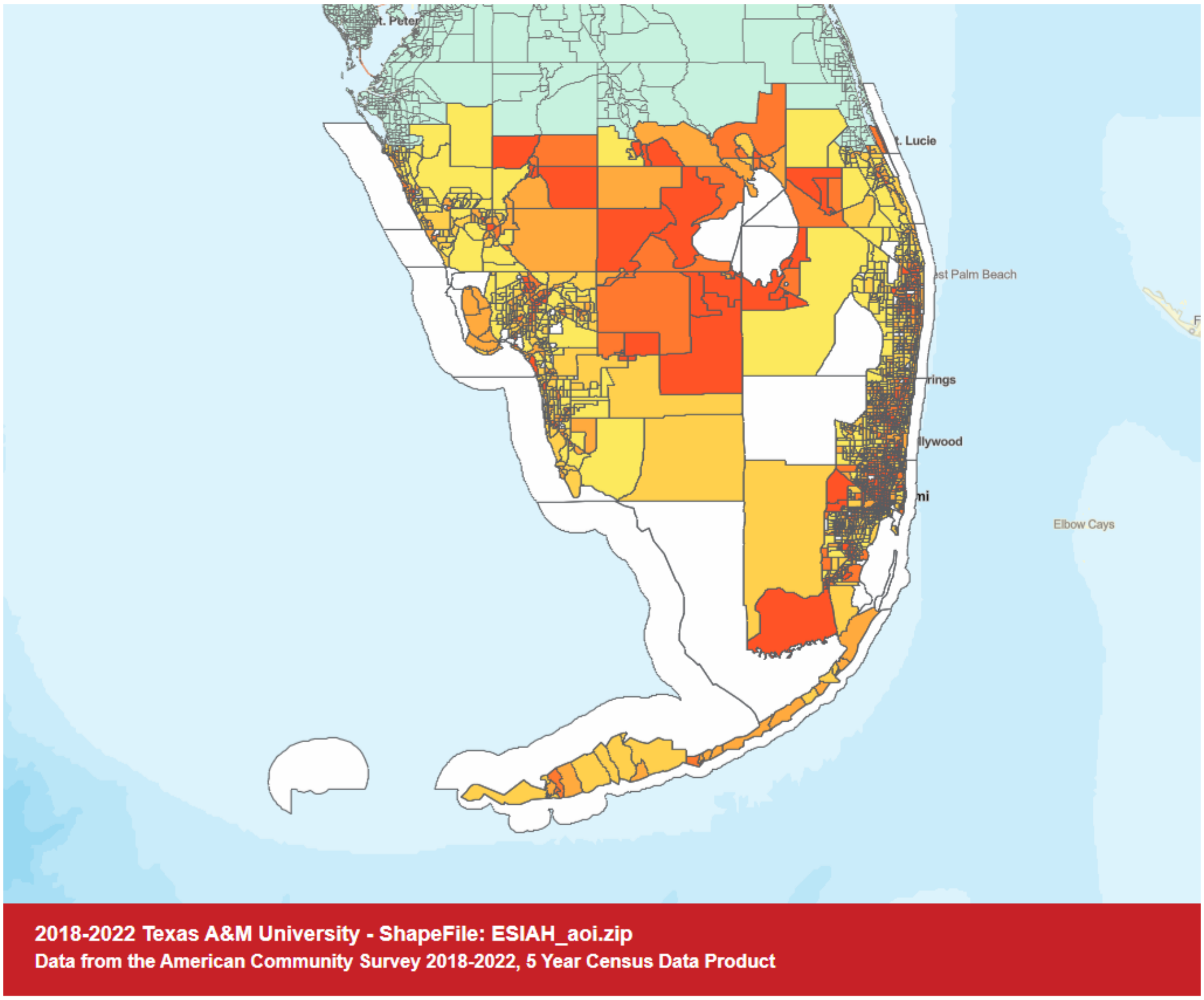
4.2.3 UofSC **Georgetown** Model

Figure 3: Georgetown model of social vulnerability index results for the current area of interest.



4.2.4 HRRC Model of Social Vulnerability

Figure 4: HRRC model of social vulnerability results for the current area of interest.



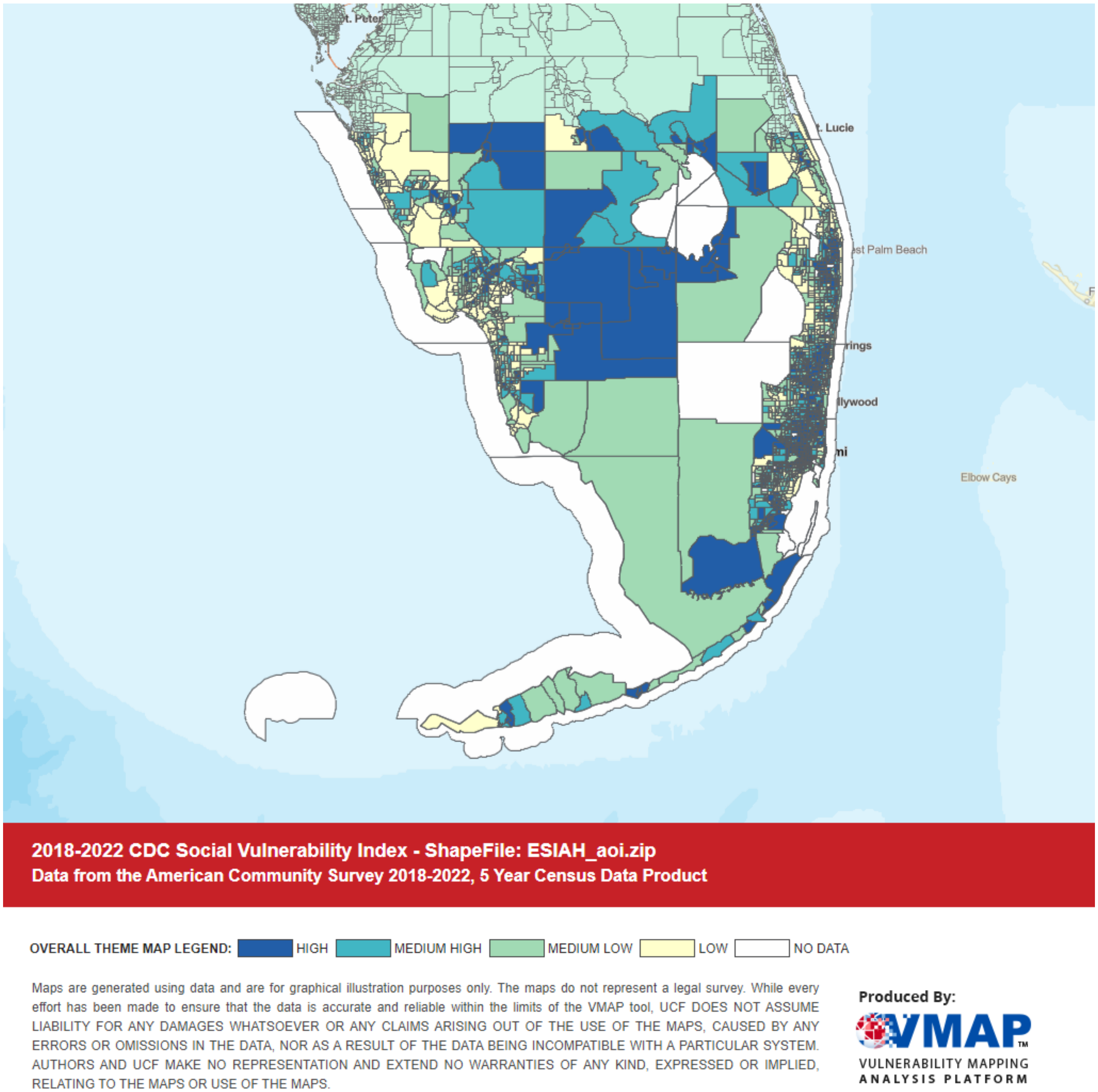
RAW SCORE MAP LEGEND: HIGH | MEDIUM HIGH | MEDIUM | MEDIUM LOW | LOW | NO DATA

Maps are generated using data and are for graphical illustration purposes only. The maps do not represent a legal survey. While every effort has been made to ensure that the data is accurate and reliable within the limits of the VMAP tool, UCF DOES NOT ASSUME LIABILITY FOR ANY DAMAGES WHATSOEVER OR ANY CLAIMS ARISING OUT OF THE USE OF THE MAPS, CAUSED BY ANY ERRORS OR OMISSIONS IN THE DATA, NOR AS A RESULT OF THE DATA BEING INCOMPATIBLE WITH A PARTICULAR SYSTEM. AUTHORS AND UCF MAKE NO REPRESENTATION AND EXTEND NO WARRANTIES OF ANY KIND, EXPRESSED OR IMPLIED, RELATING TO THE MAPS OR USE OF THE MAPS.

Produced By:
VMAP
VULNERABILITY MAPPING ANALYSIS PLATFORM

4.2.5 CDC's Social Vulnerability Index (SVI)

Figure 5: CDC SVI model of social vulnerability results for the current area of interest.

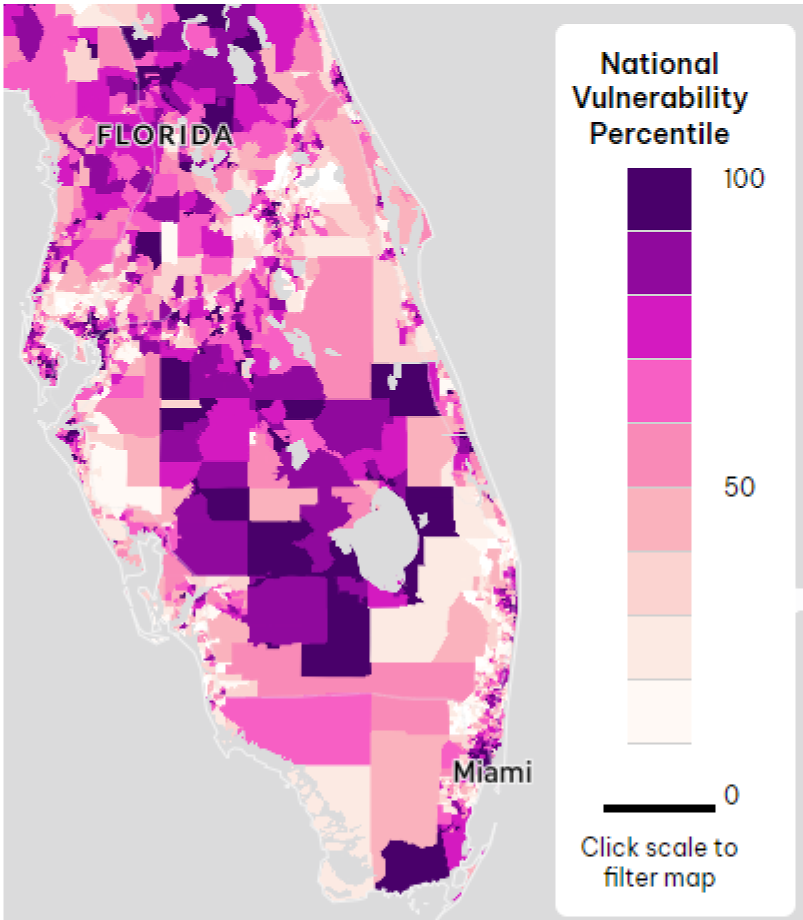


4.2.6 Climate and Environmental Justice Screening Tool (CJEST)

No mapping component is available at present.

4.2.7 Climate Vulnerability Index (CVI)

Figure 6: Climate Vulnerability Index social and economic community baseline results zoomed to current study area.



4.3 Correlation Analysis

Collinearity is a condition that arises when two or more predictor variables in a statistical model are highly correlated. Variables that are "colinear" or linearly related, can cause challenges in statistical analyses, particularly in additive models such as Georgetown, SVI, and TA&M (HRRC) as well as regression models. Collinearity can pose problems such as instability of parameter estimates, reduced precision of coefficient estimates, and difficulty in interpreting the effects of individual predictors. In extreme cases, collinearity can render the estimation of regression coefficients impossible.

In regression models, one of the main challenges of collinearity is that it inflates the standard errors of the estimated regression coefficients. This leads to wider confidence intervals, making it harder to determine the statistical significance of individual predictors. With increased standard errors, it becomes more challenging to distinguish the true effects of the independent variables from random variation. Consequently, hypothesis testing, model selection, and interpretation of coefficients become unreliable and less informative.

Collinearity can also be problematic in deductive models such as Georgetown, SVI, and TA&M (HRRC), especially those that involve the specification and testing of causal relationships. In deductive modeling, researchers attempt to establish cause-and-effect relationships between variables based on theory and prior knowledge. When collinearity exists in a deductive model, it can lead to challenges in interpreting and validating causal pathways. The high correlation between predictor variables can make it difficult to identify the unique contribution of each variable and determine their relative importance in the model. This, in turn, hampers the ability to determine the direction and magnitude of causal effects accurately. Collinearity can also lead to multicollinearity in deductive models, which occurs when three or more variables are highly correlated. In this case, disentangling the individual effects of the predictor variables on the outcome variable becomes even more complicated. Multicollinearity in deductive models can lead to a phenomenon known as specification error. This occurs when the model incorrectly specifies the relationships between variables due to the presence of collinearity. As a result, the estimated coefficients may not accurately reflect the true causal relationships, leading to biased and misleading results.

4.4 Collinearity of Various Social Vulnerability/Equity Models

"Goodness" Measure #5- Correlation Analysis was undertaken by assessing all the models/datasets based on the collinearity of inputs (Table 11). Results were ranked lowest (1) to highest (7) based on the percentage of inputs that were correlated great than 0.7 or less than -0.7. Here, SVI was the best with no collinear inputs and the Georgetown model was the worst with 62.5% of inputs collinear with each other. See Table 15 and Table 16 for overall rankings across all measurable characteristics.

Table 11. Collinearity of Social Vulnerability Indicator/Model Inputs.

Model + Collinear Inputs	Correlation
SVI – 0 of 16 inputs are collinear	
SoVI – 3 of 31 (9.7%) are collinear	
% Speaking English < "Very Well" and % Hispanic Population	0.76
% Social Security Beneficiaries and % of Population Under 5 Years or Over 65 Years	0.78
Per Capita Income and % of Households Earning > $200,000	0.849
TA&M (HRRC) Model – 1 of 17 (5.8%) are collinear	
% Unemployed and % of Population Under 5 Years of Age	0.831
Georgetown Model – 5 of 8 (62.5%) are collinear	
Population Score and Housing Unit Score	0.754
Population Score and Female Score	0.971
Population Score and Under 18 Score	0.844
Housing Unit Score and Female Score	0.761
Female Score and Under 18 Score	0.833
Non-White Score and Age over 65 Score	0.913
EJ Screen – 1 of 7 (14.3%) are collinear	
% Unemployed and % of Population Under 5 Years of Age	0.831
CJEST – 1 of 20 (5%) are collinear	

Model + Collinear Inputs	Correlation
% Below 100% and % Below 200% Federal Poverty Line	0.903
CVI – 4/28 (14.3%) are collinear	
% Low Income and % without Health Insurance	0.752
% low Income and % Impoverished	0.784
% without a High School Diploma and % without Health Insurance	0.771
% without a High School Diploma and % Low Income	0.771

4.5 Correcting for Collinearity

To address collinearity in deductive models, researchers typically employ strategies similar to those used in statistical models. These include variable selection techniques, such as using stepwise regression or information criteria like AIC or BIC, to determine the most informative predictors to include in the model. Additionally, techniques like Principal Components Analysis (PCA) - the statistical model SoVI is built upon - can be utilized to create new variables that are less correlated and better capture the underlying variation in the data. Principle Components Analysis (PCA) is a technique implemented to address collinearity issues. PCA transforms a set of correlated variables into linearly uncorrelated components called principal components. These components are orthogonal to each other and capture the maximum amount of variation present in the original variables. By deriving these components, PCA effectively reduces the dimensionality of the data. PCA can help alleviate collinearity by creating linear combinations of the original variables that capture the majority of the variation. As a result, these new components are less correlated, making them suitable for regression analysis. By using principal components as predictors instead of the original variables, one can mitigate the collinearity problem and obtain more reliable coefficient estimates.

"Goodness" Measure #6- Model based Correlation Correction was scored based on the use of statistical measures such as PCA or stepwise regression to correct for collinear data where a model was scored (1) if it does not correct for correlation or (7) if it corrects for correlation. Only SoVI, which uses PCA to combine inputs through a process where variables are transformed orthogonally through varimax rotation to correct for PCA. The other models either do not have a specific method for combination or combine variables in a deductive (straight line additive fashion) resulting in potential double counting variables that are co-linear.

Table 12. Social vulnerability/equity models and their effect on co-linearity.

Model	**Effect on Co-Linearity in input data**
SoVI	✓ Uses Principal components analysis which **overcomes collinearity.**
SVI	– Quasi-Hierarchical deductive model utilizing a straight-line additive method. **Does not overcome collinearity.**
TA&M (HRRC)	– Deductive model utilizing a straight-line additive method. **Does not overcome collinearity.**
Georgetown	– Deductive model utilizing a straight-line additive method. **Does not overcome collinearity.**

Model	Effect on Co-Linearity in input data
EJSCREEN	Raw Data Only. No modeled outputs. **Does not overcome collinearity.**
CJEST	Raw Data Only. No modeled outputs. **Does not overcome collinearity.**

Additionally, PCA can assist in identifying the most influential variables. The principal components that explain the majority of the variation in the original data can be ranked in terms of their importance. This aids in variable selection and prioritization, allowing researchers to focus on the most informative predictors to include in their model.

It is important to note that while addressing collinearity can improve the estimation and interpretation of coefficients in deductive models, it does not guarantee the establishment of causal relationships. Collinearity is just one of many factors that need to be considered when constructing deductive models, and researchers should ensure that their models are grounded in strong theoretical foundations and supported by rigorous empirical evidence.

Although collinearity presents challenges in most of the models assessed herein, mainly because it can hamper estimation, interpretation, and inference of regression coefficients, SoVI offers a solution by transforming correlated variables into uncorrelated components, reducing dimensionality, and improving the reliability of the statistical analysis. PCA is a valuable tool in addressing collinearity and enhancing the quality of statistical models.

4.6 Internal Consistency Analysis

Cronbach's alpha is a measure of internal consistency reliability, which is used to assess how closely related a set of items in a questionnaire or scale are as a group. It quantifies the reliability or consistency of the measurements obtained from multiple items or indicators that are intended to measure the same construct. Cronbach's alpha ranges from 0 to 1, where a value closer to 1 indicates higher internal consistency or reliability. It is typically used in psychometrics and research to evaluate the interrelatedness of items and to determine if they are measuring the same underlying construct.

Cronbach's alpha can tell us several things about data:

1. Reliability: It indicates the extent to which the items or indicators consistently measure the same construct. A higher alpha value suggests greater internal consistency reliability, indicating that the items are cohesive and closely related.

2. Homogeneity: Alpha helps assess the homogeneity or similarity among the items. A higher alpha indicates greater homogeneity, meaning that the items are more similar in content and are measuring the same construct.

3. Suitability for Aggregation: If a set of items has high internal consistency (high alpha value), it suggests that the items can be combined to form a composite score. This aggregation can provide a more reliable and accurate representation of the construct being measured.

4. Item Redundancy: Cronbach's alpha can also reveal whether some items within a questionnaire or scale are redundant or unnecessary. If removing an item increases the alpha value, it suggests that the item is not strongly related to the other items and may be redundant.

Overall, Cronbach's alpha is a useful tool for examining the internal consistency and reliability of data obtained from multiple items or indicators. It helps researchers determine if their measures are reliable and consistent, and whether the items are measuring the desired construct effectively. This test may be very useful for some hard sciences where understanding how well model data is aligned conceptually. However, for social vulnerability measures – which are multi-faceted and manifest themselves differently in every place, one might argue that social vulnerability models should not be internally consistent and that any model with high internal consistency is only measuring social vulnerability on one facet at the expense of other important contributors.

"Goodness" Measure #7- Internal Consistency can be viewed from two perspectives. Some think that all models should have high internal consistency in order to prove reliability with the idea that higher Cronbach's Alpha scores across the various measures of social vulnerability and equity may help us understand which models have data measuring similar concepts. Others believe that lower Cronbach's scores identify models that have a breadth of data aligned with social vulnerability indicators that transcend individual determinants (pillars) of social vulnerability and therefor are not internally consistent. These lower Cronbach's Alpha scores often occur with research/baseline data aimed at understanding how social vulnerability is created before, during, or after disasters in multi-faceted ways.

Here, both views of Cronbach's were utilized to gain perspective on each model/dataset and resulted in opposite rankings depending on how one views internal consistency (higher is better vs lower is better. Table 13 shows that (depending on the perspective, CJEST and SoVI are either the best models (with the lowest Alphas) indicating that their inputs are capturing different concepts of social vulnerability or that they are the worst in that their inputs are not internally consistent. Each of these perspectives is played out in Table 15 and Table 16 respectively so that users can see how the internal consistency may influence the overall "goodness" of any given model/dataset.

Table 13. Social vulnerability/equity models ranked (low – high) by their internal consistency.

Social Vulnerability / Equity Model Inputs	**Cronbach's Alpha Score (0 – 1)**	**Rank Based on Cronbach's Alpha (Low = Good)**	**Rank Based on Cronbach's Alpha (High = Good)**
CJEST	-0.000024	7	1
SoVI	0.096	6	2
Georgetown	0.596	5	3
EJ Screen	0.612	4	4
TA&M (HRRC)	0.726	3	5

Social Vulnerability / Equity Model Inputs	Cronbach's Alpha Score (0 – 1)	Rank Based on Cronbach's Alpha (Low = Good)	Rank Based on Cronbach's Alpha (High = Good)
SVI	0.725	2	6
CVI	0.741	1	7

4.7 Regression Analysis

The current work implements a mixture of exploratory and explanatory regression analysis to uncover how these different models of social vulnerability and equity are linked with underlying data from other models. In essence, we are interested in answering the question. "Can and how well do variables from one model predict the overall score from other models."

4.7.1 Background on Explanatory Regression Analysis

Explanatory regression analysis, also known as multiple regression analysis, is a statistical technique used to examine the relationship between a dependent variable and multiple independent variables. It aims to understand how changes in the independent variables are associated with changes in the dependent variable.

In explanatory regression analysis, the dependent variable is the variable of interest that is being explained or predicted, while the independent variables are the factors that may potentially explain or influence the values of the dependent variable. The goal of explanatory regression analysis is to estimate the regression coefficients, also known as the beta coefficients or regression weights, which represent the strength and direction of the relationship between the independent variables and the dependent variable. The analysis involves fitting a regression equation to the data, typically using least squares estimation, to find the best-fit line or curve that minimizes the difference between the observed data and the predicted values. The regression equation allows us to estimate the expected value of the dependent variable based on the values of the independent variables.

Explanatory regression analysis provides several benefits:

1. Prediction: It can be used to predict the values of the dependent variable based on known values of the independent variables. This is particularly useful when researchers want to forecast outcomes based on certain predictors.

2. Explanation: It helps identify and quantify the relationships between the independent variables and the dependent variable. By analyzing the regression coefficients, researchers can determine which independent variables have a significant impact on the dependent variable and in what direction.

3. Control: Regression analysis can be used to control for confounding factors or other variables that may influence the relationship between the independent and dependent variables. By

including these variables as additional independent variables in the regression model, researchers can isolate the specific effects of the variables of interest.

4. Hypothesis Testing: Regression analysis allows researchers to test hypotheses about the relationships between variables. By examining the significance of the regression coefficients and performing hypothesis tests, researchers can determine whether the observed relationships are statistically significant.

Overall, explanatory regression analysis is a powerful statistical tool for investigating the relationships between variables, predicting outcomes, and providing evidence for causal relationships.

4.7.2 Background on Exploratory Regression Analysis

Exploratory regression analysis is a statistical technique used to explore and understand the relationships between variables in a dataset. It is primarily focused on discovering patterns, associations, and potential relationships between the variables, rather than establishing a causal relationship or predicting future outcomes.

The purpose of exploratory regression analysis is to generate hypotheses or initial insights about the relationships between variables, which can then be further investigated using more rigorous statistical methods, such as explanatory regression analysis.

In exploratory regression analysis, there may not be a specific dependent variable that is being explained or predicted. Instead, the focus is on examining the relationships between all the variables in the dataset. Exploratory regression analysis involves visually exploring scatter plots, correlation matrices, and other graphical techniques to identify potential relationships and associations between variables.

On the other hand, explanatory regression analysis specifically aims to explain or predict the values of a dependent variable using one or more independent variables. It involves fitting a regression model to the data and estimating the regression coefficients to quantitatively describe the relationships between the variables.

While exploratory regression analysis is more focused on exploring and describing the relationships between variables, explanatory regression analysis is concerned with understanding and explaining the relationships, as well as making predictions or testing hypotheses about the variables.

In summary, the key difference between exploratory and explanatory regression analysis lies in their goals and objectives. Exploratory regression analysis focuses on exploring and discovering relationships between variables, while explanatory regression analysis aims to explain, predict, and test hypotheses about the relationships between variables.

Outcomes related to social vulnerability have largely been conceptual or qualitative. Answering the question, if you have high social vulnerability, you have higher {insert outcome measure here} is not a simple task because tract level measure for the US are not readily available. Preliminary studies of these models' predictive power related to 30 different health outcomes shows the SoVI is a better predictor than to the others. We can, however, assess how each model inputs predict the "scores" from each of the other models. Using regression analysis in this way provides us a simple way of understanding how the vulnerability indicators of one model explain the final score of another model. "Goodness" measure #8 was assessed by undertaking linear regressions of each model's dataset's inputs as the predictor and available model "final scores" as the dependent variable. Here, the model with the highest explanatory power would be a good candidate for use because it would capture the explanatory power present in other models. All the model Adjusted R2 were averaged and ranked low (1) to high (7) based on their ability to predict the other models' scores. Here, we see that SoVI inputs have (both individually and on average) higher predictive power in most instances and the Georgetown inputs had the lowest predictive power. See Table 15 and Table 16 for overall rankings across all measurable characteristics.

Table 14. Social vulnerability/equity models ranked (high = 7 to low = 1) by their average adjusted R2.

Model/Data Inputs	**SoVI**	**EJ Screen Inputs**	**TA&M (HRRC)**	**George town**	**SVI**	**CJEST Inputs**	**CVI (Social variables)**	**Average Adjusted R2**	**Rank (low = 1 and high =7)**
SoVI	--	--	0.929	0.289	0.808	--	0.726	0.688	7
EJ Screen	.571	--	0.729	0.072	0.708	--	0.602	0.5364	2
TA&M (HRRC)	0.609	--	--	0.181	0.742	--	0.667	0.5498	3
Georgetown	0.423	--	0.420	--	0.361	--	0.353	0.3893	1
SVI Inputs	0.619	--	0.866	0.153	--	--	0.697	0.5838	5
CJEST Inputs	0.625	--	0.729	0.206	0.671	--	0.685	0.5832	4
CVI Inputs	0.558	--	0.758	0.222	0.886	--	--	0.6092	6

4.8 Other "Goodness" Measures Determined in this Assessment.

Several other measures of goodness are more qualitative in nature and will be discussed here, including: #9- Data Available; #10- GIS Data Available, #11- Update Frequency; and #12- Data Accessibility/Cost. Each was scored between 1 (Low) and 7 (High) based on the following criteria.

"Goodness" Method #9 was scored (1) where no tabular data available via internet, (4) where tabular data available through VMAP or are not available from original develop for multiple concurrent years, and (7) where data available through original developer. Here, all models have data available via the internet, however only the SoVI model has data for multiple concurrent years. Although the CDC SVI has data, it is only available for 2014, 2016, 2018, and

2020 and not for odd years or for 2022[77]. Both the HRRC and Georgetown model data is only available through VMAP other models have data only for one year.

Similarly, "Goodness" Method #10 was scored (1) where no GIS data available via internet, (4) where GIS data available through VMAP or are not available from original develop for multiple concurrent years, and (7) where GIS data available through original developer. Here, all models except EJ Screen have GIS data available via the internet, however, like the tabular data, several models, including HRRC, Georgetown, and SVI only have yearly data available via the VMAP interface. CJEST and CVI have spatial data only for one year.

"Goodness" Measure #11, update frequency as scored based on data updates as described in the websites and associated materials for each of these models. This method appraised each model/dataset and scored where no update schedule = 1, updated every 2 years = 4, updated annually = 7. Here, only those models maintained by UCF's VMAP are updated annually. Of note, although the CDC SVI model is not updated annually by the original development team, it is updated annually by UCF's VMAP team.

Finally, "Goodness" Measure #12, accessibility in terms of costs is scored (for each model/dataset) where data/GIS costs to access = 1, method free but Time and Effort required to build and produce = 4, and data/GIS are free = 7). Here, all models linked with peer reviewed manuscripts were scored (4) and those without manuscripts but with free data were scored (7). Of note, VMAP has data for four of these models at a cost, but because the methods are available, and users can create these datasets from scratch with time and effort these were scored a 4. However, had these models (SoVI, HRRC, Georgetown, and SVI) been scored a (1) it would not have changed the rank of the overall scores seen in Table 15 and Table 16.

5.0 Take Aways for Decision Makers

This assessment provided an overview of seven leading models of social vulnerability or equity either used by the federal government of cited in official government documents as useful for understanding social vulnerability or equity. Each model was assessed based on twelve (12) different measures of model "goodness" in an attempt to create a matrix enabling decision makers to understand the range of utility and a composite score for each model/dataset.

Table 15 and Table 16 provide the overview of scores for each model/dataset based on these measures of "goodness" and point toward one model (SoVI) as the leader across all these measures with the CDC SVI coming in 2nd. Of note, the CDC SVI score is high on some "goodness" measures because data and GIS are available via UCF's VMAP application. Without the vulnerability mapping and analysis capabilities of VMAP, the CDC SVI model would score considerably lower in several categories and overall.

[77] As of the completion of this assessment.

Table 15. Social vulnerability/equity models and datasets ranked by various measures assessed in this report (where low internal consistency = good).

"Goodness" Measure	SoVI	EJ Screen	Georgetown	TA&M (HRRC)	CDC SVI	CJEST	CVI	"Best"
#1- Conceptually framed in peer-reviewed outlet - Ranked based on existence of peer reviewed article (1 = no, 7 = yes)	7	1	7	7	7	1	1	Tie
#2- Number of Citations - Ranked lowest (1) to highest (7) based on number of citations	7	3	6	1	5	2	4	SoVI
#3- Number of Inputs - Ranked lowest (1) to highest (7) based on number of inputs	7	1	2	4	3	5	6	SoVI
#4- Visual Inspection of Accuracy Possible via web - Scored lowest to highest where (1= not available, 4 = available through VMAP, 7 = available through original developer)	7	1	7	4	7	7	7	Tie
#5- Correlation Analysis - Ranked lowest (1) to highest (7) based on the percentage of inputs that were correlated	4	3	1	5	7	6	3	SVI
#6- Model based Correlation Correction - Scored (1 = Does not correct for correlation, 7 = Corrects for correlation)	7	1	1	1	1	1	1	SoVI
#7- Internal Consistency - Ranked (Lowest Alpha = 7 to Highest Alpha = 1)	6	4	5	3	2	7	1	CVI
#8- Exploratory/ Explanatory Regression Analysis - Ranked Highest Adj. R2 = 7 to lowest Adj. R2 = 1	7	2	1	3	5	4	6	SoVI
#9- Data provided via internet - Scored where no data available via internet = 1, single or non-	7	3	4	4	4	3	3	SoVI

“Goodness” Measure	SoVI	EJ Screen	Georgetown	TA&M (HRRC)	CDC SVI	CJEST	CVI	“Best”
concurrent year data available through original developers = 3, data available through VMAP for concurrent years = 4, data available through original developer for concurrent years = 7								
#10- GIS data provided for visual comparison - Scored where no GIS data available via internet = 1, single or non-concurrent year GIS data available through original developers = 3, data available through VMAP for concurrent years = 4, data available through original developer for concurrent years = 7	7	1	4	4	4	3	3	SoVI
#11- Update frequency - Scored where no update schedule = 1, updated every 2 years via original developer = 3, updated every year by VMAP = 4, updated annually = 7	7	1	7	7	4	1	1	Tie
#12- Accessibility - Scored where data/GIS costs to access = 1, method free but Time and Effort required to build and produce, and data/GIS are free = 7	4	7	4	4	7	7	7	Tie
Overall Score	**77**	28	49	47	56	47	43	**SoVI**

*Lowest Cronbach’s Alpha Scores represent “goodness” in the model/data

Table 16. Social vulnerability/equity models and datasets ranked by various measures assessed in this report (where high internal consistency = good).

"Goodness" Measure	SoVI	EJ Screen	Georgetown	TA&M (HRRC)	CDC SVI	CJEST	CVI	"Best"
#1- Conceptually framed in peer-reviewed outlet - Ranked based on existence of peer reviewed article (1 = no, 7 = yes)	7	1	7	7	7	1	1	Tie
#2- Number of Citations - Ranked lowest (1) to highest (7) based on number of citations	7	3	6	1	5	2	4	SoVI
#3- Number of Inputs - Ranked lowest (1) to highest (7) based on number of inputs	7	1	2	4	3	5	6	SoVI
#4- Visual Inspection of Accuracy Possible via web - Scored lowest to highest where (1= not available, 4 = available through VMAP, 7 = available through original developer)	7	1	7	4	7	7	7	Tie
#5- Correlation Analysis - Ranked lowest (1) to highest (7) based on the percentage of inputs that were correlated	4	3	1	5	7	6	3	SVI
#6- Model based Correlation Correction - Scored (1 = Does not correct for correlation, 7 = Corrects for correlation)	7	1	1	1	1	1	1	SoVI
#7- Internal Consistency - Ranked (Lowest Alpha = 1 to Highest Alpha = 7)	2	5	3	5	6	1	7	CVI
#8- Exploratory/ Explanatory Regression Analysis - Ranked Highest Adj. R2 = 7 to lowest Adj. R2 = 1	7	2	1	3	5	4	6	SoVI
#9- Data provided via internet - Scored where no data available via internet = 1, single or non-concurrent year data available through original developers = 3, data available through VMAP for concurrent years = 4, data available	7	4	4	4	4	4	4	SoVI

“Goodness” Measure	SoVI	EJ Screen	Georgetown	TA&M (HRRC)	CDC SVI	CJEST	CVI	“Best”
through original developer for concurrent years = 7								
#10- GIS data provided for visual comparison - Scored where no GIS data available via internet = 1, single or non-concurrent year GIS data available through original developers = 3, data available through VMAP for concurrent years = 4, data available through original developer for concurrent years = 7	7	1	4	4	4	3	3	SoVI, SVI
#11- Update frequency - Scored where no update schedule = 1, updated every 2 years via original developer = 3, updated every year by VMAP = 4, updated annually = 7	7	1	7	7	4	1	1	SoVI
#12- Accessibility - Scored where data/GIS costs to access = 1, method free but Time and Effort required to build and produce, and data/GIS are free = 7	4	7	4	4	7	7	7	Tie
Overall Score	**73**	30	47	49	60	42	50	**SoVI**

*Highest Cronbach’s Alpha Scores represent “goodness” in the model/data

Beyond the “Goodness” measures assessed herein, decision makers may also be interested in several aspects related to model accuracy, precision, internal consistency, robustness, and other tests that were not carried out in this assessment. These factors are important in assessing the reliability and usefulness of a model for decision-making purposes. Here are some key considerations:

- Accuracy: Decision makers should consider the overall accuracy of the model in making predictions or estimating outcomes. This involves assessing how closely the model's predictions align with the actual observed values. High accuracy indicates that the model is reliable and trustworthy.
- Precision: Precision refers to the level of detail and granularity in the model's predictions or estimates. Decision makers should evaluate the model's precision in order to understand its ability to provide specific and detailed information. A more

precise model can provide valuable insights and facilitate more informed decision-making.

- Internal consistency: Decision makers should assess the internal consistency of the model. This refers to the alignment and coherence between different components or variables within the model. Inconsistencies or contradictions within the model can undermine its reliability and make it difficult to trust its outputs.
- Robustness: Decision makers should evaluate the robustness of the model by testing its performance under different scenarios or assumptions. Robustness analysis helps determine if the model's predictions or estimates hold up well across various conditions and inputs. A robust model is more likely to provide reliable insights for decision-making.
- Reliability: Decision makers should evaluate the reliability of the model by assessing its consistency and dependability. This involves examining whether the model consistently produces similar results when applied to the same inputs or under similar conditions. A reliable model is one that can be trusted to generate consistent and repeatable outcomes, ensuring that decisions based on the model are reliable and consistent as well.
- Explanatory Power: Decision makers should also consider the model's ability to explain the relationships and factors underlying the phenomenon being modeled. A model with high explanatory power can help decision makers understand the key variables and mechanisms driving the outcomes of interest. This understanding aids in decision-making, as it enables decision makers to identify the most influential factors and make more informed choices.
- Other tests: Decision makers should consider additional tests or evaluations specific to their domain or context. These could include sensitivity analysis, validation against known benchmarks or industry standards, and comparison with alternative models or approaches. These tests help verify the model's validity and provide additional confidence in its outputs.

Reliability and explanatory power complement accuracy, precision, internal consistency, and robustness in assessing model quality and usefulness. Decision makers should seek models that exhibit all these qualities to enhance their confidence in the model's predictions or estimates and enable more effective decision-making. Ultimately, decision makers should ensure that the model they rely on is accurate, precise, internally consistent, and robust. Regularly updating and refining the model based on new data and insights is also crucial to maintaining its relevance and usefulness in decision-making processes.