Improving SECAS Gulf-wide Integration

Integrated data to support natural resource conservation and restoration in the northern Gulf of Mexico

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ABOUT THE WATER INSTITUTE OF THE GULF

The Water Institute of the Gulf is a not-for-profit, independent research institute dedicated to advancing the understanding of coastal, deltaic, river and water resource systems, both within the Gulf Coast and around the world. This mission supports the practical application of innovative science and engineering, providing solutions that benefit society. For more information, visit www.thewaterinstitute.org.

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Preface

This technical report summarizes the effort carried out by The Water Institute of the Gulf ("the Institute") for the U.S. Fish and Wildlife Service (USFWS) that integrated Gulf-wide spatial data to support conservation and restoration planning. The SECAS Southeast Conservation Blueprint (Southeast Blueprint) is an annually updated spatial plan that identifies places of high conservation and restoration value across the Southeast and Caribbean. The intention of this project is to build on existing Gulf-wide decision support tools, including the Southeast Blueprint through the integration of spatial ecosystem stressor and social vulnerability data sets along with the development of a regionally-consistent data layer of natural resource value (prototype Gulf-wide Blueprint). This project explored potential methods and input data that could inform future updates of the Southeast Blueprint in 2022 and beyond. During 2018 and 2019 two preceding projects carried out extensive stakeholder engagement, including state and federal agencies as well as university and independent research organization staff, to canvas input on key metrics, data sources, priority threats and resources. Both these initial efforts were funded, at least partially, by the RESTORE Council. RESTORE Council staff as well as the RESTORE Centre of Excellence from each of the five Gulf states, assisted in identifying and contacting key stakeholders and subject matter experts in each state (Figure P1).

This technical report and three spatial products (prototype Gulf-wide Blueprint, Integrated Ecosystem Stress, and Social Vulnerability) were produced through engagement, meetings, and discussions with many individuals across the northern Gulf of Mexico. The geospatial data layers were integrated to inform future conservation and restoration actions across the northern Gulf of Mexico project area through identifying potential additional benefits to natural resources and vulnerable human communities. This technical report focuses on the methods used to generate, compile, and synthesize the primary data layers as well as to present the resulting Gulf-wide Data Suite.

Ecologists, social scientists, and physical scientists from the Institute participated in the discussions and contributed to the development of this report. The cross-disciplinary focus of the Institute supported synthesis of the diverse information and technical information included within the report. The Institute is focused on assisting with data collection, analysis, and synthesis to facilitate increased use of best available science that will inform management, restoration, and conservation planning, implementation, and adaptive management.

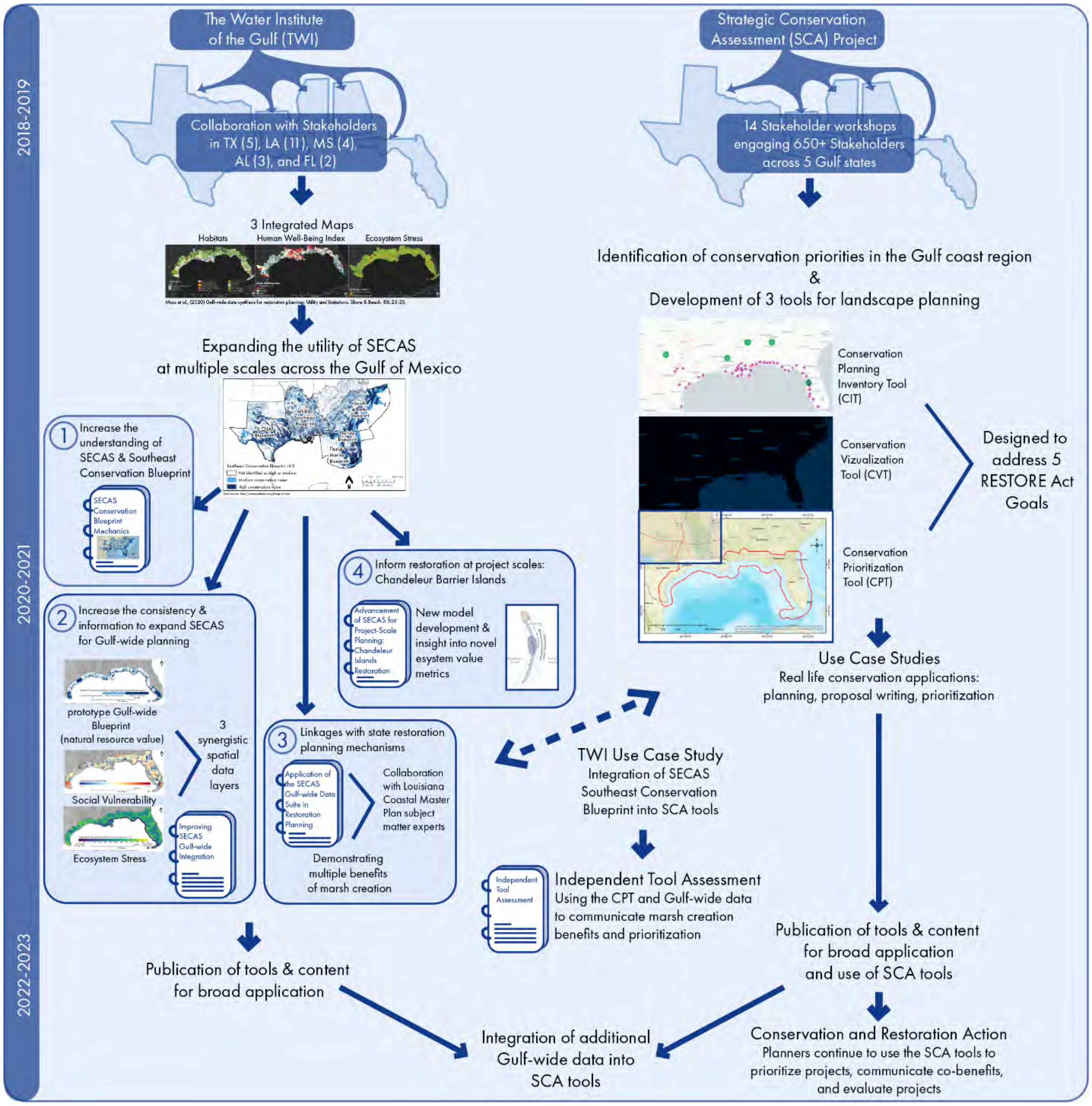

Figure P1. Schematic detailing the development of Gulf-wide data collection efforts funded through the RESTORE Act and the U.S. Fish and Wildlife Service highlighting the current and ongoing collaboration efforts between The Water Institute of the Gulf and the Strategic Conservation Assessment Project.

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List of Acronyms

Acronym	Term
CHAT	Crucial Habitat Assessment Tool
CZMA	Coastal Zone Management Act
DWH	*Deepwater Horizon*
EJSCREEN	USEPA Environmental Justice Screening and Mapping Tool
evt	Existing Vegetation Type
NDMC	National Drought Mitigation Center
NIDRM	National Insect and Disease Risk Map
NPL	National Priorities List
PCA	Principal Component Analysis
RESTORE	Resources and Ecosystems Sustainability, Tourist Opportunities, and Revived Economies of the Gulf States (Act)
RMP	Risk Management Plan
SCA	Strategic Conservation Assessment of Gulf Coast Landscapes
SECAS	Southeast Conservation Adaptation Strategy
SoVI	Social Vulnerability Index
TN	Total Nitrogen
TP	Total Phosphorus
TSDF	Treatment, Storage, and Disposal Facilities
USEPA	U.S. Environmental Protection Agency
USDA	U.S. Department of Agriculture

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Executive Summary

The goal of the Southeast Conservation Adaptation Strategy (SECAS) is to improve the health, function, and connectivity of southeastern United States (U.S.) ecosystems (SECAS, 2020). To meet these goals, SECAS developed a dynamic data synthesis process to produce a conservation prioritization spatial plan known as the Southeast Conservation Blueprint (the Southeast Blueprint) that can be used to inform a prioritization process for entities planning management, restoration, and conservation activities, or implementing restoration activities throughout the Gulf. The Southeast Blueprint delineates areas of high conservation value that are most important for conservation of ecosystem health, function, and connectivity, and areas of medium conservation value that may require restoration but may buffer high value areas and maintain connectivity (Southeast Conservation Adaptation Strategy, 2020). The Southeast Blueprint was built from a bottom-up stakeholder engagement process that combined smaller regional spatial plans into a mosaic of conservation values across the Southeastern US. This ensured local stakeholder engagement in the final product but had the unintended consequence of making direct comparisons between regions challenging (Cameron et al., 2020).

If the spatial conservation prioritization plan developed by SECAS (the Southeast Blueprint) could be utilized to inform the conservation and restoration prioritization and planning at a programmatic scale across the northern Gulf of Mexico coastal region, the synergy could benefit restoration and conservation outcomes of those programs as well as SECAS. The high level goals of both the Natural Resource and Damage Assessment (NRDA) and the Gulf Coast Ecosystem Restoration Council (RESTORE Council) specifically include wildlife resources (DWH NRDA Trustees, 2016; RESTORE Act, 2012; Vilsack, 2016). The U.S. Fish and Wildlife Service (USFWS), through the Department of Interior (DOI), is one of the Trustees for the NRDA Trustee Implementation Groups (TIG; both the Louisiana TIG as well as the Gulf-wide TIG). The Louisiana TIG representative for DOI was involved in the initial stages of this work and a representative from the regionwide DOI TIG office provided input and review for the final deliverables. The Southeast Blueprint is not designed to address questions specific to the northern Gulf of Mexico, improved consistency would greatly enhance the utility of the Southeast Blueprint for informing restoration in the northern Gulf of Mexico. This report details the development of regionally consistent conservation prioritization tools to improve future versions of the Southeast Blueprint that would be useful in prioritizing projects by informing the northern Gulf of Mexico regional conservation and restoration planning. It does this by contributing ideas on potential methods and input data identified during creation of a prototype Gulf-wide Blueprint. Also included are two additional data syntheses to support interpretation for project prioritization and planning: ecosystem stressors and social vulnerability (Figure E1-1).

To address landscape change caused by local stressors (e.g., development or transition of forest or wetland to agricultural land) and large-scale changes (e.g., rising sea level resulting in habitat succession and changes in temperature patterns), targeted actions are needed to increase the resilience of human communities to impacts such as flooding, land loss, and drought. Restoration or conservation projects that integrate habitat, ecosystem, or nature-based approaches with a socio-ecological framework have potential to be cost-effective approaches with multiple benefits. The Ecosystem Stressor and Social

Vulnerability integrated data across the northern Gulf of Mexico will help natural resource planners maximize additional benefits of conservation and restoration projects in the Gulf of Mexico if interested. These additional diverse benefits can include equitable access to green space, maximizing opportunities for natural resource preservation, and identification of the most desirable project locations for long-term ecological success that could be considered during the planning process.

The Gulf-wide Data Suite presented here are synthesized spatial data to inform conservation and land management planning at broad spatial scales, increasing opportunities for engaging programmatic, planning, and funding mechanisms across the Gulf of Mexico. These opportunities for engagement would be greatly enhanced if additional steps were added to: 1) assess the prototype Gulf-wide blueprint for further development within the Southeast Blueprint; 2) develop dynamic access to the integrated spatial data; and 3) apply the Gulf-wide integrated datasets and prototype Gulf-wide Blueprint to Louisiana's 2017 Coastal Master Plan identified suite of restoration projects to assess wildlife resource values of the entire Louisiana Coastal Master Plan project suite as well as resource values of specific restoration approaches. This would also provide an example for how to estimate the relative potential benefits to wildlife resources across projects, when the primary decision drivers are focused on other goals (in the case of Louisiana Coastal Master Plan, land creation and flood reduction).

The Gulf-wide conservation prioritization tools address Recommendations 1, 3, and 4 from Cameron et al. (2020) to increase the usefulness, and therefore the use, of the Southeast Blueprint within a broader context of land management, conservation, and restoration efforts at ecosystem and habitat scales.

Recommendation 1: "*Develop an example cross-regional blueprint for the northern Gulf of Mexico that is consistent with the aims and goals of all spatially relevant subregional blueprints and uses one consistent set of metrics and analysis approach. This blueprint would facilitate engagement of the Southeast Blueprint in conservation and restoration planning processes that cover the northern Gulf of Mexico*" (Cameron et al., 2020).

Recommendation 3: "*Compile an index of social data of human community resilience and vulnerability to directly overlay on the Southeast Blueprint. This effort would serve to increase utility of the Southeast Blueprint and provide an opportunity for utilization in identifying conservation and natural resource additional benefits from projects with a primary human community protection or resilience goal. Because policy and planning processes frequently focus on the needs of and opportunities for human communities, this recommendation will increase the potential for the blueprint to be utilized in decision-making processes*" (Cameron et al., 2020).

Recommendation 4: *Continue to develop synthesis of data related to threats to potential protection or restoration efforts. This would provide project and program planners with a high-level indication of project success, as well as provide context of a project footprint's surrounding area. This is especially relevant if aiming to identify areas valuable for restoration in addition to protection. (Recommendation 2)*" (Cameron et al., 2020).

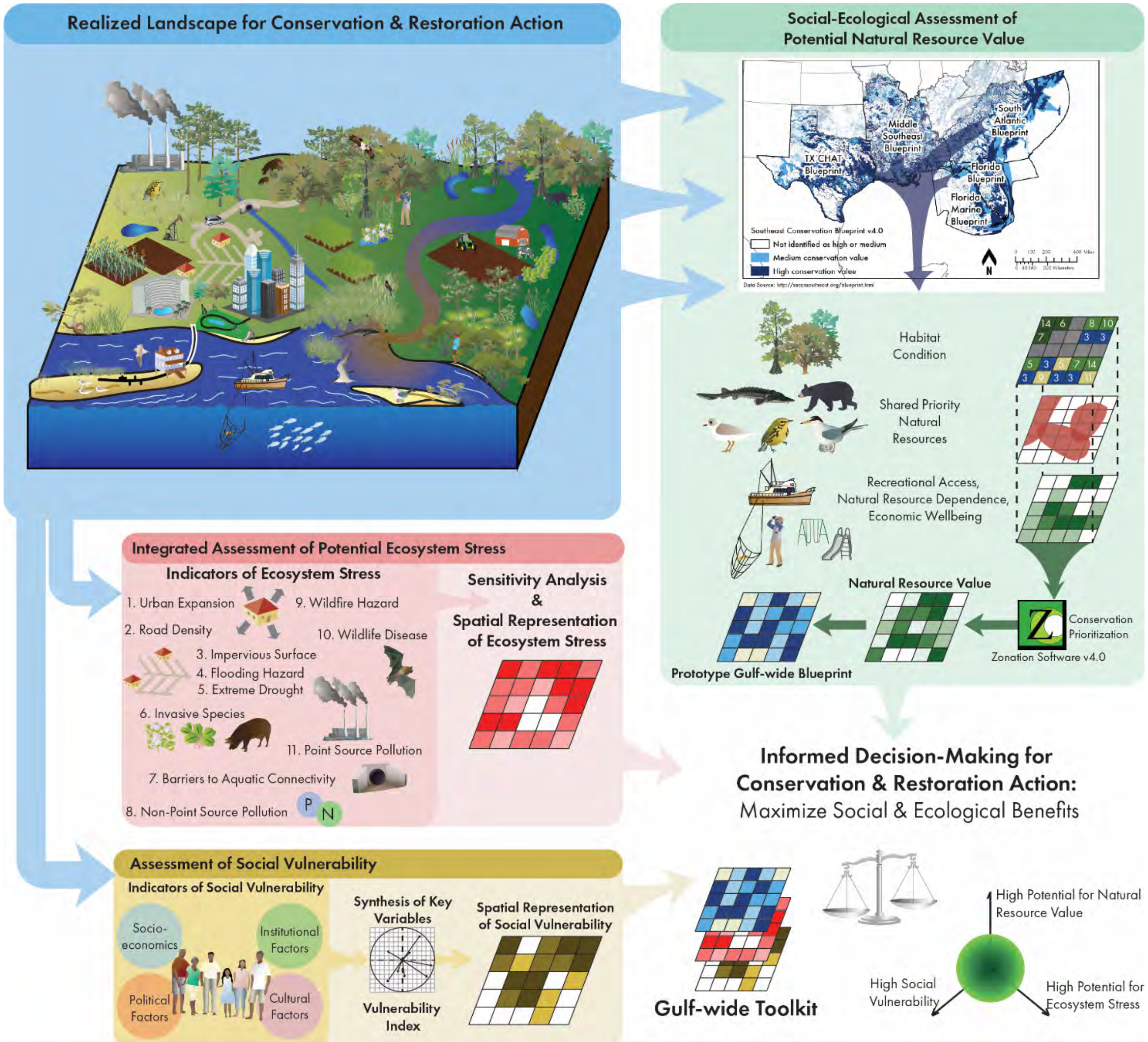


Figure E1- 1. Conceptual diagram illustrating the Gulf-wide Data Suite. Credit to Tracey Saxby and Jane Hawkey for symbology (CC BY-SA 4.0) (ian.umces.edu/media-library).

1.0 Introduction

The United States (U.S.) Gulf Coast is a large and ecologically diverse region, providing immense richness of natural ecosystems and valuable resources to humans (e.g., energy, seafood, recreation, cultural heritage) (Watson et al., 2015). In this region, both humans and ecosystems are increasingly threatened by a dynamically changing climate and coastal landscape, resulting in rapidly increasing investment (time, funding, and effort) devoted to conservation and restoration actions to maintain natural resource value and the societal services those natural resources provide (Perring et al., 2015; Toivonen et al., 2021; Watson & Venter, 2017). Opportunities for restoration action in the Gulf of Mexico have increased since the settlements from the 2010 *Deepwater Horizon* (DWH) oil spill (DWH NRDA Trustees, 2016; RESTORE Act, 2012; Vilsack, 2016). The total DWH settlement amounts to over USD$20.8 billion (Henkel & Dausman, 2020), and funding is diverted to the five Gulf states through multiple channels including: the National Fish and Wildlife Foundation's Environmental Benefit Fund (NFWF-GEBF; USD$2.54 billion); the Gulf Coast Ecosystem Trust Fund through the Resources and Ecosystem Sustainability, Tourist Opportunities and Revived Economies of the Gulf Coast States (RESTORE) Act (USD$5.33 billion), and the Natural Resources Damages Assessment and Restoration Program (NRDA; USD$8.8 billion) (Henkel & Dausman, 2020). This totals to more than USD$16 billion (including interest) specifically available for meaningful and important ecosystem restoration in the northern Gulf of Mexico (Consent Decree, 2016).

A common approach to measuring the diverse benefits of restoration across the northern Gulf of Mexico at both project and broad programmatic scales is needed for monitoring and adaptive management of large-scale restoration. While considerable work has been conducted to develop restoration indicators and frameworks for reporting (e.g., Baldera et al., 2018; Carl Kraft & Crandall, 2020; Olander et al., n.d.), few resources are available to restoration practitioners that allow quantitative spatial evaluations of diverse restoration benefits in a regionally-consistent way. In addition, accounting for money spent, tracking progress, and evaluating benefits are required components of reporting to the public and Congress on DWH restoration activities completed over the next decade (Baldera et al., 2018).

The Southeast Conservation Adaptation Strategy (SECAS) is a regional conservation initiative spanning the Southeastern United States and Caribbean. SECAS was started in 2011 by the states of the Southeastern Association of Fish and Wildlife Agencies (SEAFWA) and the U.S. Fish and Wildlife Service. SECAS also includes the federal agencies of the Southeast Natural Resources Leaders Group (SENRLG). SECAS operates around a shared vision for the future: "a connected network of lands and water supporting thriving fish and wildlife populations and improved quality of life for people" with the goal to improve the health, function, and connectivity of southeastern ecosystems 10 percent by 2060 (Cameron et al., 2020; SECAS, 2020). If the conservation prioritization map developed by SECAS (the Southeastern Blueprint) can be utilized to inform the conservation and restoration prioritization and planning in a uniform way across the Gulf of Mexico coastal region, this goal could also be effectively advanced. Thus, the goals of this Gulf-wide project were to: (1) develop a suite of spatially explicit tools and techniques that can be applied to future updates of the Southeast Blueprint across the northern Gulf of Mexico; and (2) examine how conservation prioritization, ecosystem stress, and social vulnerability can be used together to maximize additional benefits in project planning.

2.0 Methods

2.1. PROJECT AREA

The geographic focus of the Gulf-wide tools is the northern Gulf of Mexico coastal zone, spanning the Gulf of Mexico states of Texas, Louisiana, Mississippi, Alabama, and Florida. All spatial layers cover terrestrial, aquatic, and estuarine zones (excluding marine open water). The project areas differ by assessment type. First, the landward boundary of the prototype Gulf-wide Blueprint project area is 50 miles inland from the U.S. Coastal Zone Management Act (CZMA) boundary along the entire Gulf of Mexico coastline (Figure 1). This served as a consistent spatial domain across the entire Gulf of Mexico coastal region, avoiding terrestrial upland ecosystems and the eastern portion of Florida which were out of scope for this effort. Second, the Gulf-wide Ecosystem Stressor and Social Vulnerability assessment project areas cover the entire RESTORE Act boundary with an additional 25-mile land-ward buffer along the northern-most boundary (keeping the sea-ward boundary for both the prototype Gulf-wide Blueprint and the other assessments the same). For all project components, the southern-most boundary is the Texas state boundary on the West, and the Florida Keys on the East.

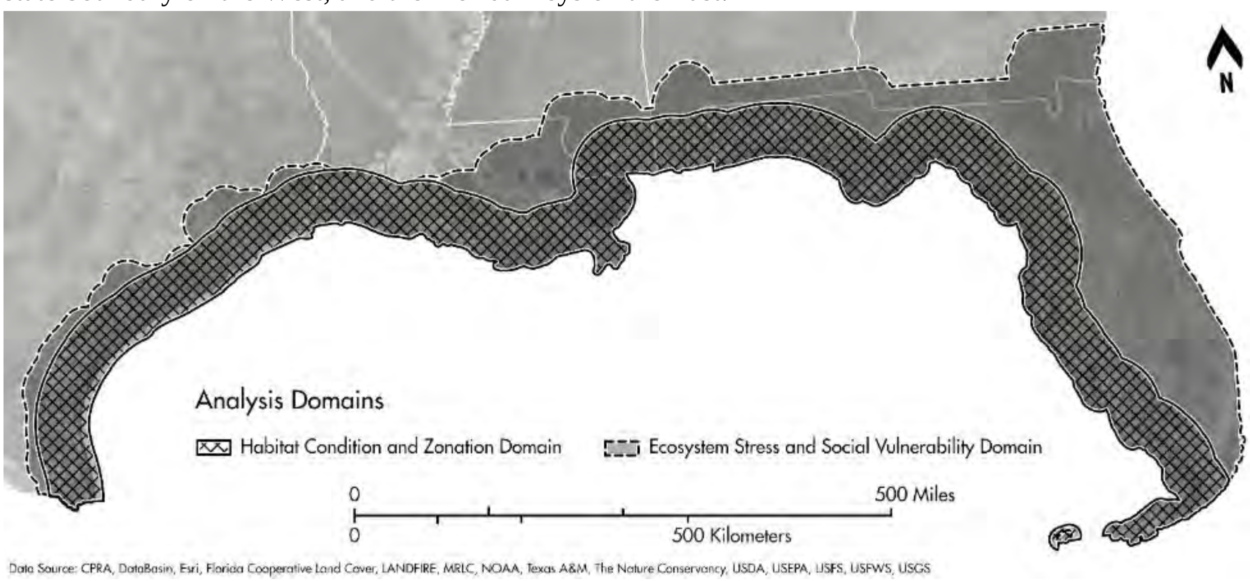


Figure 1. Spatial extent of all components in the Gulf-wide Data Suite. The prototype Gulf-wide Blueprint is limited to the coastal region (seaward CZMA boundary + 50 miles inland), whereas the spatial domain of the Ecosystem Stress and Social Vulnerability assessments extend from the same seaward boundary to 25 miles further landward from the northern RESTORE Act boundary.

2.2.1. Framework

A common framework was developed for the Prototype Gulf-wide Blueprint based upon the fundamental principles and goals of the subregional blueprints that it intersects; the Crucial Habitat Assessment Tool [CHAT] for Texas, Middle Southeast Blueprint, Florida Conservation Blueprint, and South Atlantic Conservation Blueprint. For more information on each of these subregional blueprints, Cameron et al., (2020) details the history, vision and goals, and methodologies of each subregional blueprint as well as how those were combined into the overall Southeast Conservation Blueprint.

The approach for the prototype Gulf-wide Blueprint paralleled the indicator framework and analytical methods developed for the South Atlantic Blueprint (South Atlantic Conservation Blueprint, 2020). First, in place of the natural land cover indicator layer used in the South Atlantic Blueprint, the prototype Gulf-wide Blueprint expanded upon the habitat condition evaluation developed for the Middle Southeast Blueprint (Middle Southeast Blueprint, 2020) and incorporated it into a Habitat Condition Indicator – a quantitative measure of habitat quality. Second, Natural Resource Indicators relevant to the Gulf-wide project area were translated from the South Atlantic Blueprint and applied to the Gulf-wide project area. Lastly, Socio-Ecological indicators were developed to more tightly intertwine both wildlife and human community considerations in the final conservation prioritization map. The modified indicator framework illustrated in Figure 2 is outlined in detailed below (Sections 2.2.2 – 2.2.4). This framework builds on the natural resource components of ecosystem integrity (e.g., species and habitats) as both the South Atlantic Blueprint and the Middle Southeast Blueprint, expanding the indicators for cultural resources and refining those that could be applied to the Gulf-wide area.

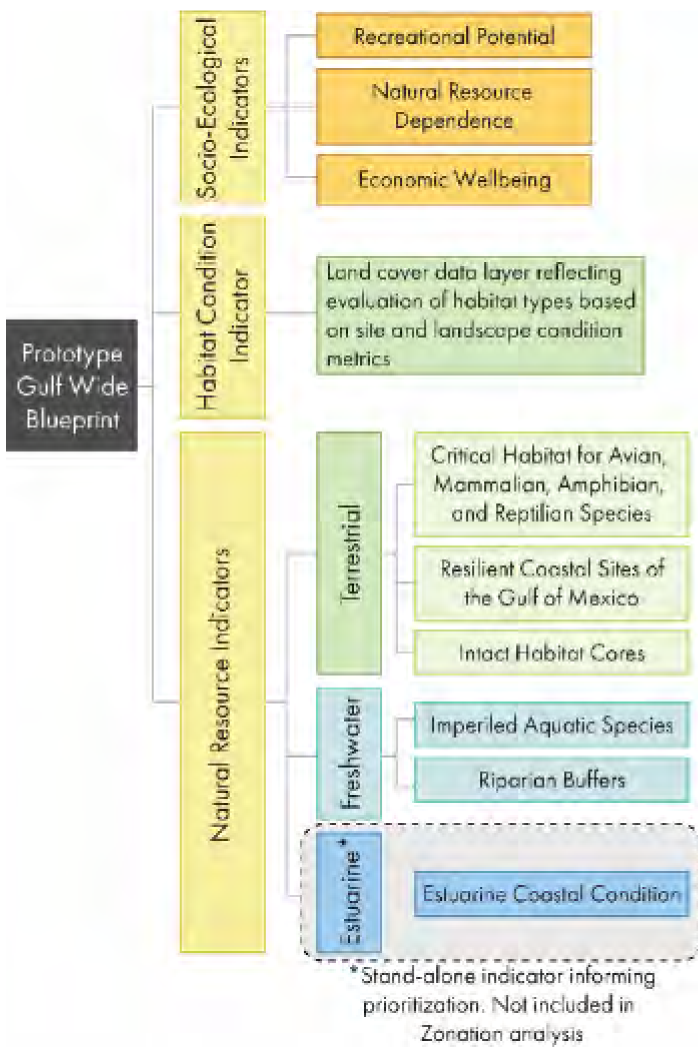


Figure 2. Input framework for the Prototype Gulf-wide Blueprint.

2.2.2. Habitat Condition Indicator

In this assessment, the term “habitat” is used broadly to characterize sub groupings within ecosystems rather than to strictly define the biotic and abiotic requirements of a single species. To provide regional consistency in habitat mapping and coordination with other ecological conservation plans, the 2020 LANDFIRE existing vegetation type (evt) dataset (https://www.landfire.gov/evt.php) was used to define most natural landcover types across the Gulf of Mexico (except for beaches, mangrove, and prairie). This land cover dataset categorizes vegetation using a widely-adopted vegetation classification system developed by NatureServe (Comer et al., 2003). The Broadly Defined Habitat categories defined for the Middle Southeast Blueprint V3.0 were modified to reflect habitat groups relevant to the Gulf of Mexico project area (Appendix A.1): mixed forest, pine (flatwoods, woodland, mixed), upland hardwood (forest and woodland), forested wetland, mangrove, grassland and prairie, unforested freshwater wetland, tidal marsh, beaches (barrier island beach and mainland beach), agriculture, open water (fresh [rivers, streams, lakes, ponds] and estuarine), and “Other” (Figure 3).

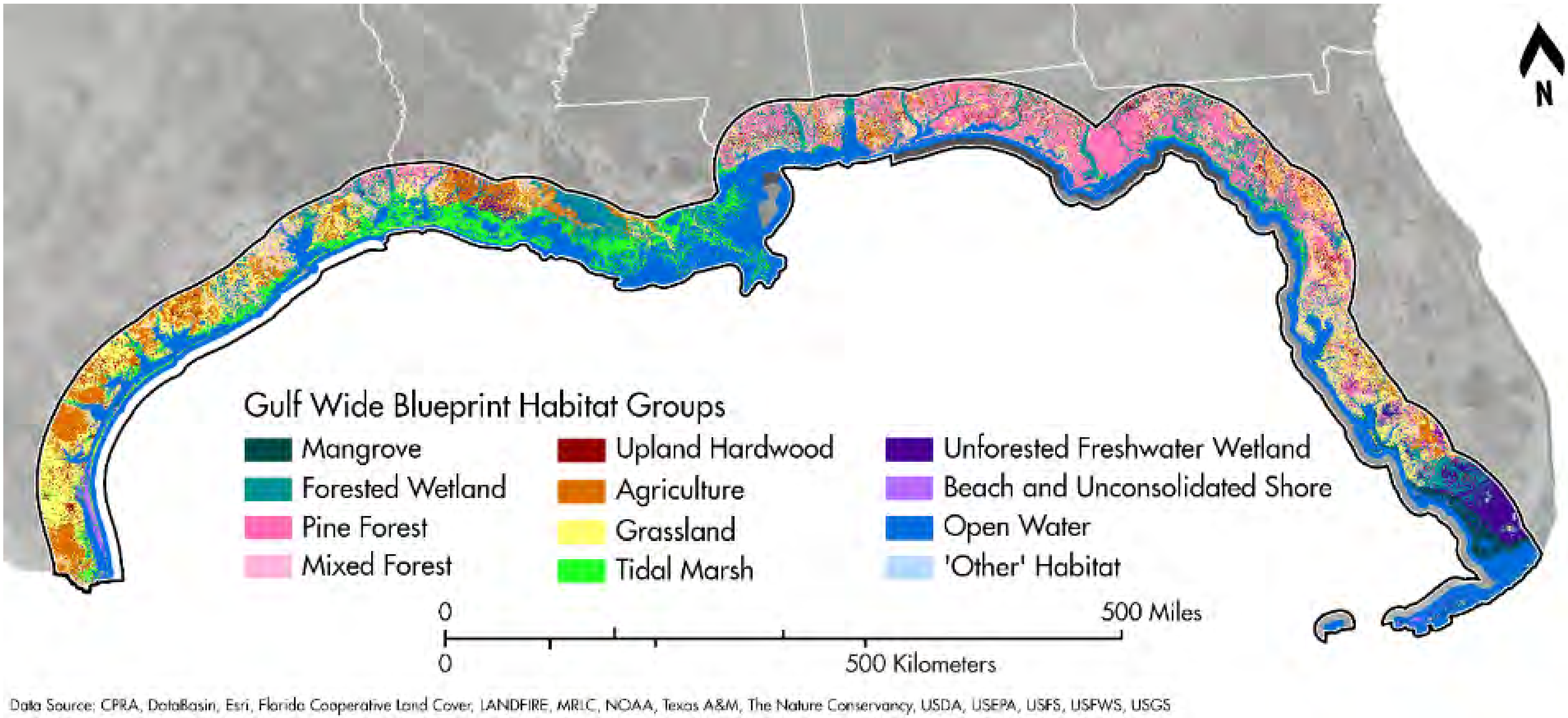


Figure 3. Habitat groups of the prototype Gulf-wide Blueprint.

Habitat condition evaluation is an important component of the Middle Southeast Blueprint V3.0 and was identified as a valuable tool for prioritizing areas for conservation (maximizing habitat with high quality) versus restoration (improving habitat quality) actions. Habitat condition was initially developed to evaluate habitats based on a defined "Desired Ecosystem State" (GCPOLCC, 2013) reflecting primary landscape attributes: amount (length or area) and configuration (patch size, connectivity, etc.), as well as site/stand attributes: local vegetation structure and composition.

Building on the Middle Southeast Blueprint V3.0 methodology, a Habitat Condition Indicator was developed for the prototype Gulf-wide Blueprint (Figure 2). Habitat condition metrics were refined and developed for each habitat type using expert elicitation from subject matter experts, U.S. Fish and Wildlife Service (USFWS), and other Blueprint developers. Not all habitat types could be assessed for condition (e.g., glades, rocky outcrops) due to a lack of ecological or reliable land cover information to provide an accurate condition assessment, or simply absence of those habitats in the northern Gulf of Mexico. Nevertheless, these areas as well as developed and low quality natural habitats (e.g., aquaculture) were retained in the overall prototype Gulf-wide Blueprint because of their potential value for wildlife. Appendix A.2 details the habitat condition metrics, the GIS evaluation methodology, and GIS steps for creating the final Habitat Condition Indicator data layer for the prototype Gulf-wide Blueprint.

2.2.3. Natural Resource Indicators

Following the development process of the 2020 South Atlantic Blueprint, the prototype Gulf-wide Blueprint also structured around "Natural Resource Indicators" (Figure 2): key ecosystem components that provide a simpler lens with which to assess ecosystem function across broad spatial scales (South Atlantic Conservation Blueprint, 2020). Terrestrial, aquatic, and estuarine Natural Resource Indicators were integrated into the prototype Gulf-wide Blueprint only if they could be directly expanded for the Gulf-wide project area. The Natural Resource Indicators used in the prototype Gulf-wide Blueprint include critical habitat (for threatened and endangered avian, mammalian, amphibian, and reptilian species), resilient coastal sites, intact habitat cores, imperiled aquatic species, riparian buffers, and estuarine coastal condition. Appendix A.3 details the development methodology and scoring of each Natural Resource Indicator.

2.2.4. Socioeconomic Analysis

The socioeconomic analysis for the Gulf-wide Data Suite focuses on two primary data types. The first examines those data that could be most directly influenced and changed by ecological management decisions and where therefore included as direct inputs (Socio-Ecological Indicators) to the prototype Gulf-wide Blueprint. This includes landscape-level features such as land available or potentially available for recreational usage. It also includes natural resource employment and economic wellbeing, which are conceptualized as being closely linked to the availability of renewable and nonrenewable natural resources. The second data type is related to the social vulnerability of the population (see section 2.4). On a broad level, social vulnerability involves those inherent characteristics of a population that make them vulnerable to threats and hazards, be these environmental or economic. These factors, which include variables such as race and ethnicity, income levels, and educational attainment, would likely not be directly altered by ecological management decisions. However, an analysis of the underlying social vulnerability of an area is critical to assessing the distributional equity of healthy ecosystems and assuring that underserved and socially vulnerable populations are not disproportionately burdened.

While each of these data types are conceptualized and analyzed separately, it is important to acknowledge that there are clear overlaps between them. For example, effective management of natural resources can enhance the economic wellbeing of those communities that rely on these. However, a community's over-reliance on any single source of employment, including the extraction of renewable and nonrenewable natural resources, is a recognized social vulnerability and is assessed when determining overall social vulnerability (Hemmerling & Hijuelos, 2016). While resource managers can potentially influence the former through effective planning and ecological site management, their influence on the latter is less direct.

Three Socio-Ecological Indicators were created to function alongside Natural Resource Indicators to inform conservation prioritization with a socioeconomic perspective (Figure 2). This section provides a detailed overview of each Socio-Economic Indicator to provide clear connection between human communities and natural resource values important for conservation and restoration prioritization. Detailed development methods for each socio-ecological indicator are given in Appendix A.3.

Socio-Ecological Indicator: Natural Resource Dependence

Natural resource-dependent communities are defined as those whose primary economic engine revolves around usage of natural resources. Such industries may include agriculture, forestry, fisheries, mining, petroleum extraction, tourism, and recreation. Natural resource dependence is generally measured by the proportion of employment in the sector or the income generated by natural resource utilization in relation to the aggregate economic activity of that area. The quantification of resource dependence on community well-being are highly dependent on the indicators chosen to represent well-being. Research shows, for example, that oil and gas dependence have a more positive effect when the measure of economic well-being is income rather than poverty or unemployment (Stedman et al., 2004). Natural resource dependence has also been found to be a significant determinant of vulnerability across a wide spectrum of stressors and hazards. In natural resource dependent communities, for example, disruption of livelihoods can result from the loss of land and animals for farmers, or boats and nets for fishers (Wisner et al., 2004). As a result, high levels of natural resource employment can be correlated with a coastal community's social vulnerability to the impacts of chronic and acute environmental stressors such as land loss, sea level rise, and tropical storm events.

Socio-Ecological Indicator: Economic Wellbeing

The economic status of census block groups in the study area was analyzed using census datasets that are closely correlated with income. Adapting methods developed by the U.S. Forest Service, an economic wellbeing index was derived which incorporates five primary categories of data that are consistently available in the decennial census and the American Community Survey (ACS): poverty, public assistance income, home ownership, educational attainment, and employment level (Doak & Kusel, 1996; Hemmerling et al., 2020). The primary assumptions behind the selection of these variables are that higher levels of poverty and residents receiving public assistance indicate lower levels of economic wellbeing and that higher levels of home ownership, education, and employment indicate higher levels of economic wellbeing (Doak & Kusel, 1996). Poverty is a ubiquitous factor that contributes negatively to well-being in resource-dependent communities (Doak & Kusel, 1996; Harrison, 2013; Stedman et al., 2004). Being impoverished may result in the inability to buy needed household items and services such as clothing, nutritious food, or safe housing (Harrison, 2013). This research uses the U.S. Census definition of poverty in which poverty thresholds are calculated by estimating the costs of a minimum adequate diet for families of different size and age structures multiplied by three to allow for other necessities. A family is considered in poverty if its annual before-tax money income is less than its poverty threshold (Harrison, 2013). The poverty score developed here includes two equally weighted components: the percentage of all persons in poverty and a measure of the relative intensity of poverty for those individuals with incomes below the poverty level (Doak & Kusel, 1996). Home ownership is measured by the percentage of all permanently owner-occupied housing units, a measure that is often suggestive of relative wealth and permanence of the population. Levels of employment are often negatively correlated with the percentage of low-income residents in a community (Tonts et al., 2012). Evidence also suggests that communities with higher levels of educational attainment, particularly rural communities, tend to have lower rates of poverty and unemployment (Tonts et al., 2012). Education is measured using a cumulative educational attainment score weighted toward higher levels of educational attainment for all persons 25 years and older (Doak & Kusel, 1996).

Socio-Ecological Indicator: Recreational Potential

One key component of a healthy human environment is the presence of blue and green spaces. Developed areas are made up of buildings, gray spaces, green spaces, and blue spaces. Gray spaces are those open expanses between buildings containing hard infrastructure while green spaces consist of open areas with natural elements such as parks, playgrounds, and recreational fields (van den Berg et al., 2015). Blue space summarizes all coastal and inland surface water features in the urban environment such as ponds, lakes, rivers, canals, and wetlands (Völker & Kistemann, 2011; Wheeler et al., 2015). Traditionally considered a sub-category of green space, blue space is now seen as analogous to green space. Cities that are located by rivers or lakes, for example, often have a distinctive and unique physiognomy which creates their own special character (Völker & Kistemann, 2011). Investments in blue and green spaces may provide benefits to human health that could outweigh the potential health costs of urban communities. This is especially relevant in low-income communities where a high percentage of income is spent on health care.

The recreational potential of the landscape is a function of several factors and includes a combination of both formal and informal space as well as active and passive uses of that space. To assess the recreational potential of the study area, areas of open water, green space, wetlands, and beaches were delineated and assigned values based upon landscape type and the overall ease of access (see Appendix A.3). For example, shoreline areas are generally more accessible than open water areas and therefore are rated and scored higher on the informal landscape rating scale. Such informal spaces are variable in scale and provide urban residents access to green spaces, such as vacant lots, street or railway rights-of-way, riverbanks, or levees, that are not delineated as a formal park or recreation area (Rupprecht & Byrne, 2014). While all informal greenspace provides some social value, larger contiguous areas would generally be expected to provide greater value to a larger number of residents and thus receive a higher recreational potential score.

The recreational potential of an area is increased when formal land uses occur within that space. In terms of value, the formal use of a space is cumulative with the informal landscape scores in that location. Areas designated as formal space include locations ranging from pocket parks to National Parks as well as officially designated wildlife areas, state and national forests, and other recreational areas. Each of these formal spaces can be differentiated by the types of activities allowed there and whether such activities are active or passive. Active recreation opportunities are considered “structured individual” or “team” activities requiring special facilities, courses, fields, or recreation equipment. Passive recreational uses do not require sports fields or pavilions while affording the community access to swimming pools, trails, conservation areas, or open space to do unstructured activities (U.S. Environmental Protection Agency, n.d.). Given that passive recreational spaces generally allow for a wider range of nonspecialized uses, these areas rank higher than active recreational space, which often cater to narrower group of users. In general, private parks would be valued the lowest since they provide limited access to community members. Community parks are ranked the highest because they provide multiple recreation opportunities and are designed to serve a larger area than just adjacent residents.

Finally, from a community health and wellbeing standpoint, the greatest value would be generated when parks and other recreational areas are easily accessed by residents. Availability of blue and green spaces provide opportunities for outdoor physical activities, social contacts, and relaxation and are often seen as determinants of the health of urban residents (van den Berg et al., 2015). Living near coastal environments has a positive effect on mental health, over and above the effects of green spaces (Wheeler et al., 2012, 2015). Locations with the greatest number of active and passive spaces within easy walking distance provide the greatest recreational value to residents.

2.2.5.Creation of the Prototype Gulf-wide Blueprint

Following the analytical methods developed for the 2020 South Atlantic Blueprint, Zonation v4.0 (Moilanen et al., 2014) software was used to spatially score and prioritize the Habitat Condition Indicator, the six Natural Resource Indicators, and the three Socio-Ecological Indicators (Figure 2). The Zonation output is the quantitative basis for the prototype Gulf-wide Blueprint’s prioritization designations across the project area. The “core area” algorithm within Zonation was used to maximize persistence of valued resources (i.e., the indicators) in a balanced way (Di Minin et al., 2014; Kremen et al., 2008; Moilanen et al., 2014; Pouzols et al., 2014). Appendix A.4 details the full methods used for running the analysis in Zonation and Figure 4 represents a simplified schematic of the core area Zonation algorithm.

To manage computational burden of Zonation analysis while still analyzing the entire spatial extent of the prototype Gulf-wide Blueprint, all input data sets were scaled to 100 x 100 m grid cells (often up from 30 x 30 m). Importantly, estuarine areas were <u>not</u> included in the Zonation analysis due to the low number of indicators evaluating those areas; estuary evaluation was included in the final Blueprint map manually (see Appendix A.4 for further information).

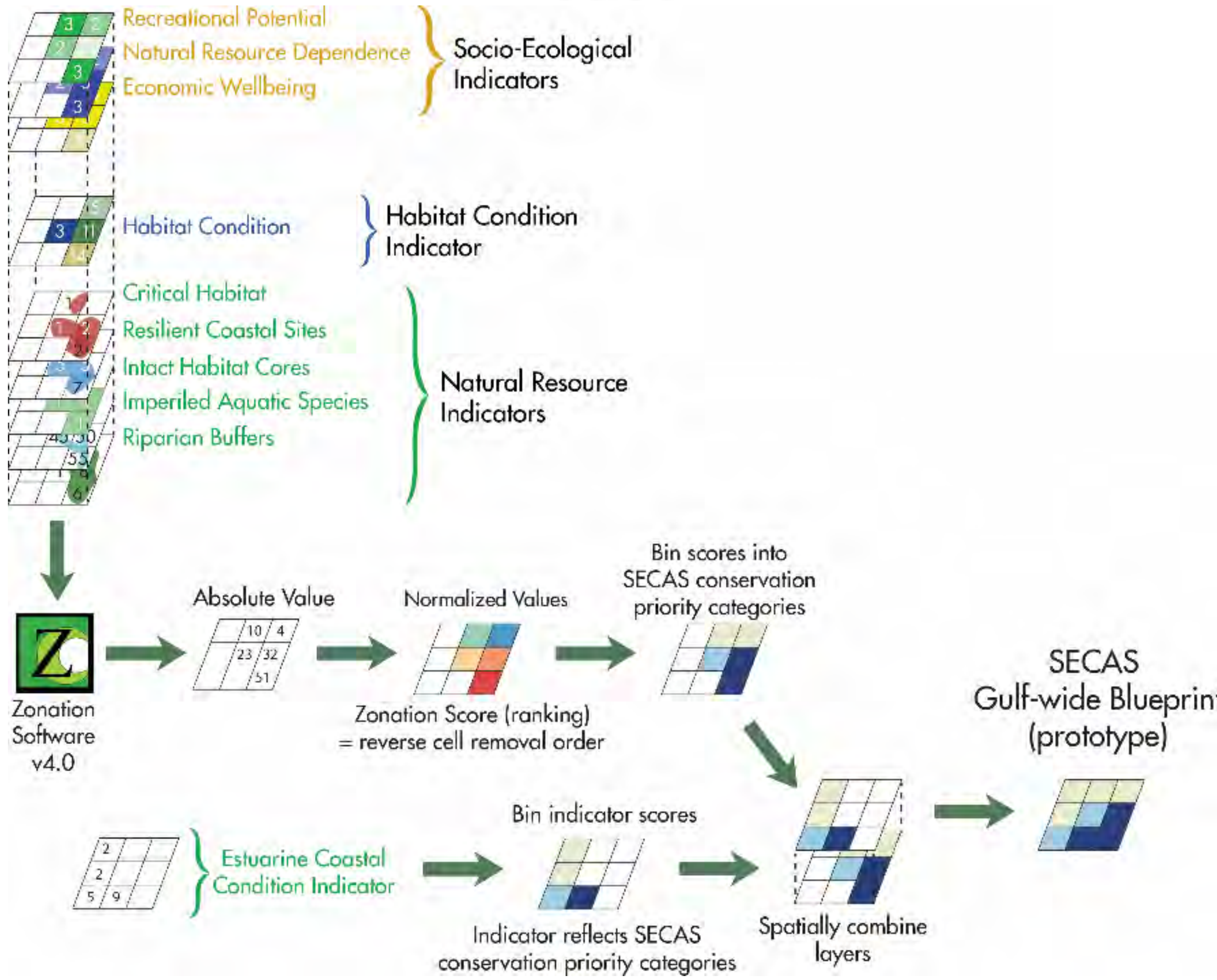


Figure 4. Simple schematic of prioritization analysis using Zonation software.

2.3. ECOSYSTEM STRESS

The second set of spatial information developed for the Gulf-wide Data Suite assesses ecosystem stress across the northern Gulf of Mexico project area. This assessment was conducted in an expanded spatial domain of the Gulf coast that includes the entire RESTORE Act boundary with an additional 25-mile buffer inland (Figure 1).

2.3.1. Ecosystem Stress Indicators

To provide a context of likelihood of long-term success of a project, Ecosystem Stress Indicators (chemical, physical, and biological) were used to evaluate a combined potential ecosystem stress across the northern Gulf of Mexico project area. This synthetic spatial data layer was developed as supporting data to the prototype Gulf-wide Blueprint to be used within the Gulf-wide Data Suite. Ecosystem Stress Indicators were identified to be specifically relevant to natural resource management and selected based on data availability across the entire northern Gulf of Mexico project area. Data for Ecosystem Stress Indicators covered a range of ecosystems (terrestrial and aquatic) and scales (temporal and spatial) (Figure 5).

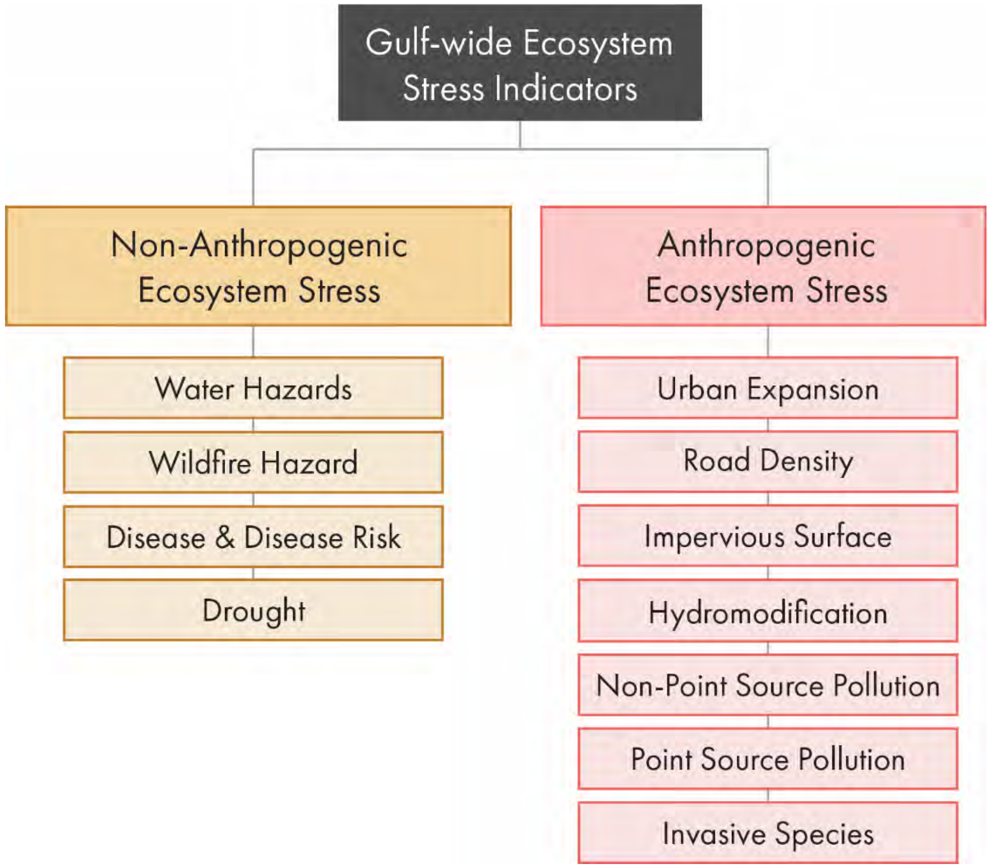


Figure 5. Ecosystem Stress Indicators.

Ecosystem stress was determined using thresholds to indicate points of transition or ranges of expected ecosystem response. Where possible, ecosystem thresholds were identified for each Ecosystem Stress Indicator based upon the scientific literature, but in some cases, it was necessary to rely on regulatory limits (e.g., defined by USEPA), further analysis of available data, or best professional judgment (Table 1; Appendix B).

Table 1. Ecosystem Stress Indicator metrics and associated thresholds for the Gulf-wide ecosystem stress assessment.

Stressor	Metric(s)	Threshold	Threshold Reference & Data Sources
Invasive Species	Presence/absence of prioritized invasive species	Stress based on presence of key invasive species: non-prioritized < state prioritized < both non-prioritized and state-prioritized co-occurring	Threshold: Developed with stakeholder engagement Data Sources: Early Detection and Distribution (EDD) Maps and the USGS Nonindigenous Aquatic Species (NAS) dataset
Disease & Disease Risk	Presence/absence of Chytrid infection (*Batrachochytrium dendobatidis*) or White-Nose Syndrome (WNS; *Pseudogymnoascus destructans*) or risk associated with forest disease	Presence of Chytrid or WNS disease or forest disease risk	Threshold: developed within the dataset and through stakeholder engagement Data Sources: National Insect and Disease Risk Map (NIDRM) model; USGS WNS dataset; Chytrid disease occurrence from scientific publications (see Appendix B)
Non-Point Source Pollution	Watershed-scale Total Phosphorus (TP), Total Nitrogen (TN), 303(d) Impaired Waters, and sand/gravel mines	TP: 0.04 mg/L (ecoregion IX); 0.13 mg/L (ecoregion X); 0.04 mg/L (ecoregion XII) TN: 0.69 mg/L (ecoregion IX); 0.76 mg/L (ecoregion X); 0.90 mg/L (ecoregion XII) Presence of 303(d) Impaired Water Sand & gravel mines: 500 m buffer	Threshold: USEPA ecoregion regulatory thresholds for TN and TP for streams and rivers; USEPA regulatory assessment protocols for 303(d) impaired waters; 500m buffer around mine locations (Hak & Comer, 2017) Data Sources: TP and TN from USGS 2012 SPARROW models for the Southwest, Midwest, and Southeast; USEPA 303(d) Impaired Waters dataset; and Homeland Infrastructure Foundation-Level Data for mine locations
Point Source Pollution	Cumulative density of Superfund (National Priorities List, NPL) locations, Risk Management Plan (RMP) facilities, and Treatment, Storage, and Disposal Facilities (TSDFs) by Census block	Continuous scale	Threshold and Data: USEPA 2020 Environmental Justice Screening and Mapping Tool (EJSCREEN)
Urban Expansion	Risk of projected urban expansion by 2060	Continuous scale	Threshold and Data: Slope, Land Use, Excluded, Urban, Transportation, and Hillshade (SLEUTH) model output (Candau et al., 2000; Terando et al., 2014)
Road Density	Road density (total road length per km^2) as indicative of ecosystem integrity	No/low stress (0.01-0.43); moderate stress (0.44-1.06); high stress (1.07-2.92); very high stress (>2.93)	Threshold: Quigley et al., (1996, 2001) and Haynes et al., (1996) Data Sources: U.S. Census Bureau TIGER/Line database
Impervious Surface	Proportion of HUC12 watershed characterized as impervious surface	Generally unimpaired, small impact (0-5%); sensitive/stressed (6-10%); impacted (11-24%); high stress (>25%)	Threshold: Schueler (1994) and Uphoff et al., (2011) Data Source: National Land Cover Database (NLCD) 2016 urban impervious surface geodatabase
Water Hazards	Overlapping hazard from high tide flooding, sea level rise scenarios (1, 2, and 3 ft), storm surge, FEMA flood hazard zones	Continuous scale based on overlapping hazards	Threshold: Developed with stakeholder engagement Data Source: NOAA Sea Level Rise and Coastal Impacts Viewer (high tide flooding and sea level rise scenarios); Sea, Lake, and Overland Surges from Hurricanes (SLOSH) model (storm surge); FEMA Map Service Center (flood data)

Stressor	Metric(s)	Threshold	Threshold Reference & Data Sources
Drought	Non-consecutive weeks of extreme and exceptional drought	Continuous scale reflecting that more drought imparts greater ecosystem stress; D3 and D4 defined by National Drought Mitigation Center (NDMC) reflect ecosystem stress thresholds	Threshold: (Clark et al., 2016) Data Source: U.S. Drought Monitor program data
Wildfire Hazard	Risk of unmanageable fire	Discrete scale, very low to very high risk	Threshold: Integrated into dataset Data Source: USDA Wildfire Hazard Potential map
Hydro-modification	Watershed health impaired due to dams, artificial drainage ditches, near-stream roads, and high intensity land use in the riparian zone	Continuous scale (original scale reversed), from no impairment to high impairment	Threshold: Integrated into dataset Data Source: USEPA Healthy Watersheds Project geomorphology sub-index

All Ecosystem Stress Indicators were mapped at 1000 m x 1000 m spatial resolution and the values scaled such that 0 indicates absence of stress from a given indicator, 1 indicates the lowest potential stress value, and 100 represents that the stress of the indicator is applying the maximum stress possible (where ecosystem response to additional stress cannot be detected). For Ecosystem Stress Indicators where ecosystem thresholds have been well-established in the literature (e.g., proportion of impervious surface), the maximum threshold given in the literature constituted the maximum level of potential stress (receiving a score of 100). For Ecosystem Stress Indicators where specific thresholds have not been sufficiently defined in peer-reviewed literature (e.g., drought), a separate analysis of mean and standard deviation of the indicator across the project area was conducted (see Appendix B). An unweighted sum of all eleven Ecosystem Stress Indicators were developed into an Integrated Ecosystem Stress Indicator layer given at 1000 x 1000 m grid scale.

2.3.2. Sensitivity of an Integrated Ecosystem Stress Indicator Layer

Sensitivity analysis was used to scrutinize the individual Ecosystem Stress Indicators for redundancy and to determine if the combined Integrated Ecosystem Stress Indicator layer was consistent with understanding of ecosystem stress in the Gulf of Mexico. In addition, this analysis provides insight into the indicators themselves. First, statistics of each Ecosystem Stress Indicator were used to identify if the thresholds used were appropriate. For example, if the average value of an Ecosystem Stress indictor that is not widespread in the Gulf of Mexico was high, it would suggest the threshold used in the analysis was too low. Next, the Ecosystem Stress Indicators were mapped in several ways to determine if a single indicator was dominating the Integrated Ecosystem Stress Indicator layer, which may also suggest the threshold values should be adjusted. This included mapping how many Ecosystem Stress Indicators contributed to the combined layer, which Ecosystem Indicator had the highest contribution, and what percentage it accounted for. The third type of analysis conducted was cross-correlating the individual Ecosystem Stress Indicators to identify if specific indicators tend to occur at the same place. High positive values would indicate that some Ecosystem Stress Indicators tend to occur together, while high negative values would indicate that some Ecosystem Stress Indicators are present when others are absent.

Finally, an analysis was conducted to evaluate how much “future” Ecosystem Stress Indicators are contributed to the Integrated Ecosystem Stress Layer. The two future Ecosystem Stress Indicators are Water Hazards, which includes the influence of relative sea level rise, and Urban Expansion, which represents the risk of future urbanization. These Ecosystem Stress Indicators reflect factors that are expected to cause stress on an ecosystem in the future, as opposed to the other indicators that include factors causing ecosystem stress now. For this evaluation, the Integrated Ecosystem Stress Indicator layer was divided by the maximum value so that it on the range of 0 (no stress) to 1 (most stress of anywhere in the study area). A “future” Integrated Ecosystem Stress Indicator layer was then calculated in the same way without the Water Hazards and Urban Expansion Ecosystem Stress Indicators, then divided by the Integrated Ecosystem Stress Indicator layer including all indicators. If that ratio is near one, the Integrated Ecosystem Stress Indicator layer is about the same whether “future” Indicators are included or not, and ecosystem stress is likely to be stable in the future. If the value is near zero, it indicates that there most of the calculated ecosystem stress is coming from “future” Indicators, and ecosystem stress in those areas is likely to increase in the future.

2.4. SOCIAL VULNERABILITY

The third set of spatial information developed for the Gulf-wide Data Suite reflects social vulnerability across the Gulf of Mexico project area. This assessment was conducted in the same expanded spatial domain as the ecosystem stress assessment (Figure 1).

Vulnerability is a function of local socioeconomic conditions and the nature of the hazard to which the human population is exposed (Adger et al., 2004). While overall vulnerability is dependent upon exposure to specific hazards, social vulnerability represents the inherent characteristics of a community or population group and its ability to respond to and recover from any number of potential hazard events. Many factors contribute to community ability to respond and adapt to changing conditions, and these factors can be represented by any number of indicator variables (Cutter et al., 2010). One method for identifying the locations of vulnerable populations is the Social Vulnerability Index (SoVI) approach, a statistical modeling approach that utilizes indicator variables to quantify relative levels of social vulnerability across space (Cutter et al., 2003). The SoVI approach enables relative vulnerability comparisons between communities and between geographical regions, which can aid in evaluating the susceptibility of communities to future hazardous threats. An enhanced understanding of the factors that determine social vulnerability will also aid in identifying actions to reduce vulnerability (Adger et al., 2004). Following methods developed for Louisiana’s Coastal Master Plan (Hemmerling & Hijuelos, 2016), this project utilized the SoVI approach to examine the underlying socioeconomic, institutional, political, and cultural factors that determine how people across the coastal zone of the Southeastern United States respond to a range of existing stressors. The approach identified the presence and location of socially vulnerable groups at the census block group level and used both disaggregated and combined indicator variables to assess social vulnerability.

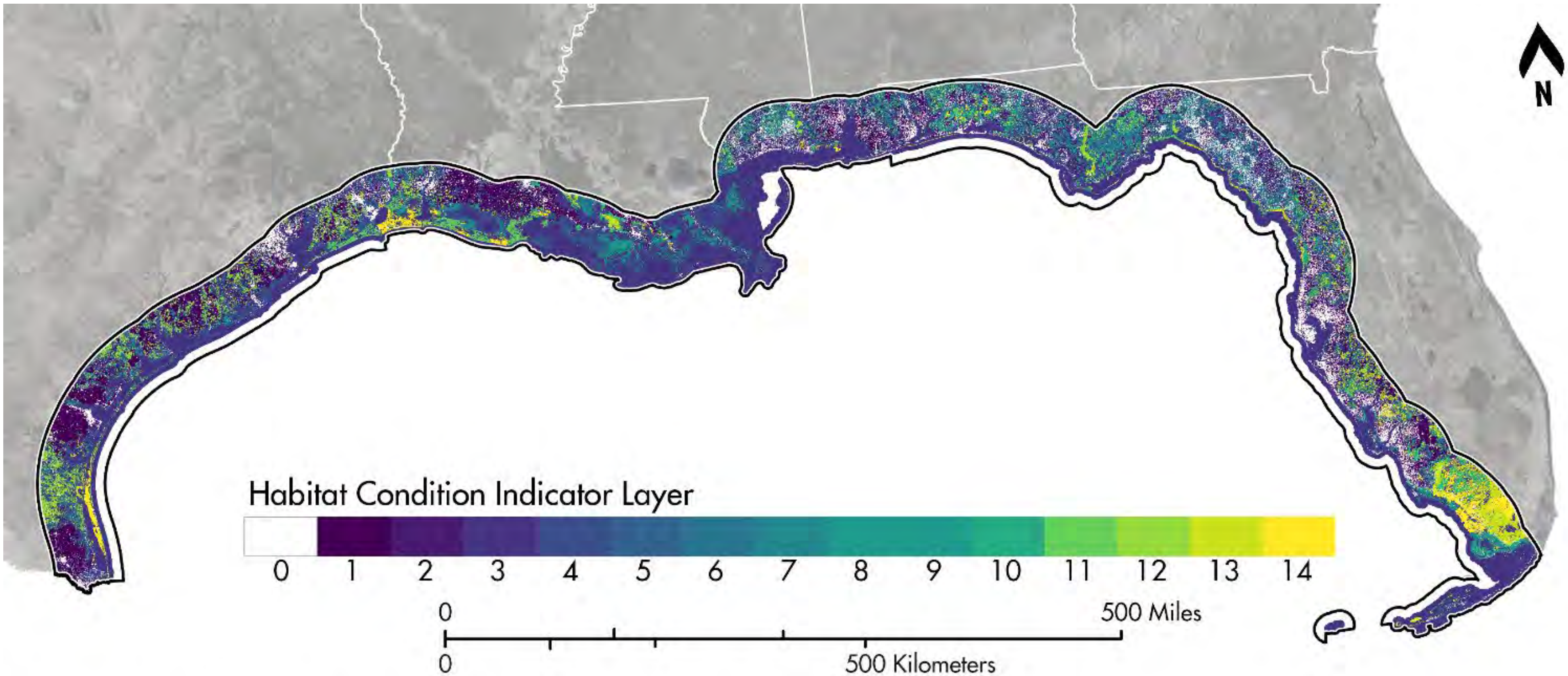
Construction of the coastwide SoVI began with the selection of socioeconomic variables identified in the literature and derived primarily from the 2010 Census and 2018 ACS. This analysis utilized 37 key variables directly related to the vulnerability factors to derive the SoVI (see Appendix C for detailed methods on the development and mapping of the SoVI Index). These variables were selected based on a review of existing literature, including the work of Cutter (2003), the State of Texas (Peacock et al., 2011), the State of Louisiana (Hemmerling et al., 2020; Hemmerling & Hijuelos, 2016) and US Army Corps of Engineers (Dunning & Durden, 2011) and were adapted to include factors specific to coastal environments (Hijuelos & Hemmerling, 2015; Jepson & Colburn, 2013). These variables were then synthesized using Principal Components Analysis (PCA), a statistical technique to reduce the dimensionality of large datasets and identify several uncorrelated components that represented broader categories of social and economic vulnerability. These “principal components” were weighted and combined into a single index to assess relative social vulnerability for populated census block groups across the coast. The SoVI score for each census block group was classified by standard deviation and mapped to identify locations ranging from high to low vulnerability.

3.0 Results

3.1. PROTOTYPE GULF-WIDE BLUEPRINT

3.1.1.Habitat Condition Indicator

The foundation of the prototype Gulf-wide Blueprint is the Habitat Condition Indicator (Figure 6), a spatial data layer that reflects habitat condition evaluated for relevant Gulf-wide habitat types (0 = not habitat, 1 = low quality habitat, 2 = degraded habitat, … 14 high quality habitat).



Data Source: CPRA, DataBasin, Esri, Florida Cooperative Land Cover, LANDFIRE, MRLC, NOAA, Texas A&M, The Nature Conservancy, USDA, USEPA, USFS, USFWS, USGS

Figure 6. Habitat Condition Indicator spatial data layer developed for the prototype Gulf-wide Blueprint. Values of 0 indicate not natural land cover. Values 1-2 indicate degraded or low-quality habitat types. Values >2 reflect habitat condition scores based on site and landscape level metrics where 14 indicates highest quality of a given habitat type. See Appendix A.2 for detailed information on the methods to develop this Habitat Condition Layer.

3.1.2. Creation of the Prototype Gulf-wide Blueprint

Habitat Condition, Natural Resources, and Socio-Ecological Indicators were analyzed spatially using the Zonation software. Sensitivity of prioritization scores to inclusion of the Habitat Condition Indicator was tested separately (Appendix A.4). Results indicate greater refinement in spatial prioritization with inclusion of the Habitat Condition Indicator layer in Zonation analysis. The output of the analysis was the final prototype Gulf-wide Blueprint that reflects conservation prioritization values across the project area at a 100 m scale (Figure 7).

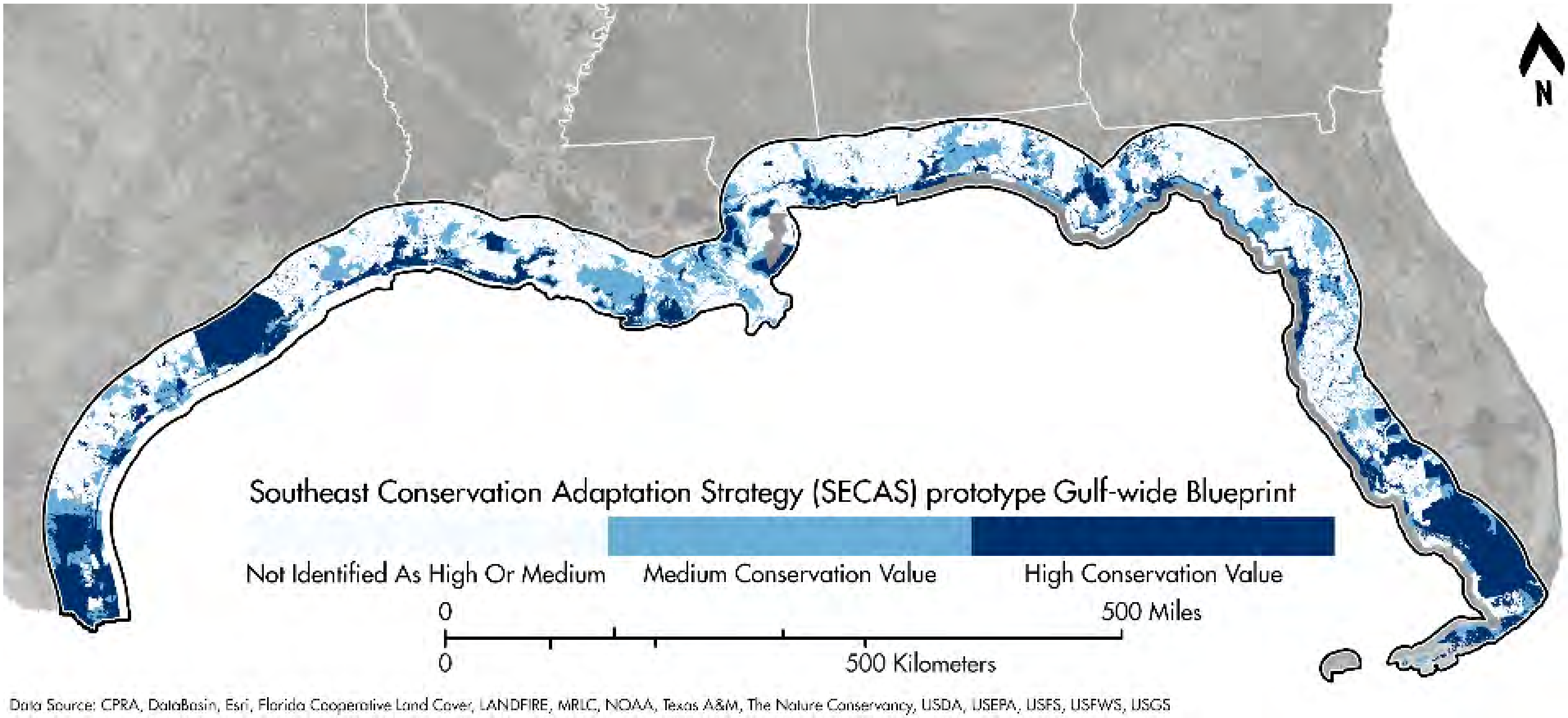


Figure 7. Final prototype Gulf-wide Blueprint reflecting prioritization categories defined by the Southeast Conservation Blueprint.

Further analysis of Zonation results for the final prototype Gulf-wide Blueprint highlights that certain indicators may be driving over-prioritization in some locations (e.g., Texas). This can partly be attributed to the nature of the Zonation algorithm that seeks to maximize representation of isolated blocks of high value for each indicator layer (e.g., those reflected in the Intact Habitat Cores indicator layer, Figure-A3 3 in Appendix A.3). Basic Zonation analysis with edge removal without removal of urban areas also likely contributed to over-prioritization of such areas (R. Mordecai, personal communication).

Additional refinement following the South Atlantic Blueprint methodology for the Intact Habitat Core Indicator (e.g., binning the indicator values by size of habitat core) would significantly address the over-prioritization of these large blocks of area (South Atlantic Conservation Blueprint, 2020). A continuing issue with this indicator, noted in the 2020 South Atlantic Blueprint development documentation, is that this that these large areas are often bisected by low-traffic dirt roads that result in fragmentation of the area for Zonation analysis; however, presence of a road may not necessarily reduce conservation priority of a large area and manual removal of roads through large habitat cores (e.g., National Parks) in GIS could be employed to refine this indicator.

Lastly, no indicator weights were used in this initial prototype Gulf-wide Blueprint. Without indicator weights, indicators that reflect small areas of high priority and span only a small portion of the total project area will likely be over-prioritized. This can notably over-prioritize entire beaches (R. Mordecai, personal communication). The addition of indicator weights can offset this Zonation artifact.

As a test-case prototype of a unified prioritization approach across the Gulf-wide project area, this analysis used only the most basic functions of the Zonation software. Used of additional data processing steps used for the 2020 South Atlantic Blueprint (e.g., removal of urban areas, refinement of the Intact Habitat Core Indicator, addition of indicator weighting) may have improved analysis.

Additional refinement of the prototype Gulf-wide Blueprint will further advance its utility. The following next steps are recommended:

- Further develop methods of habitat condition evaluation for the Habitat Condition Indicator, specifically for habitat types in Southern Texas and barrier islands
- Use the findings provided in Miner et al., (2021) to develop additional indicators of natural resource value for barrier island systems, specifically the Chandeleur barrier islands.
- Add indicator weights for analysis using Zonation. Future additional research outside the current project scope would be required to determine indicator thresholds to correctly assign weights
- Incorporation of Ecosystem Stress Indicators and negative weights could refine prioritization in SECAS conservation blueprints
- Implement a 'Boundary Quality Penalty' - a methodology to force clustering and refine Zonation analysis

This assessment demonstrates that the Zonation software can be a powerful tool for landscape conservation evaluation even at broad spatial scales such as the project area of the prototype Gulf-wide Blueprint.

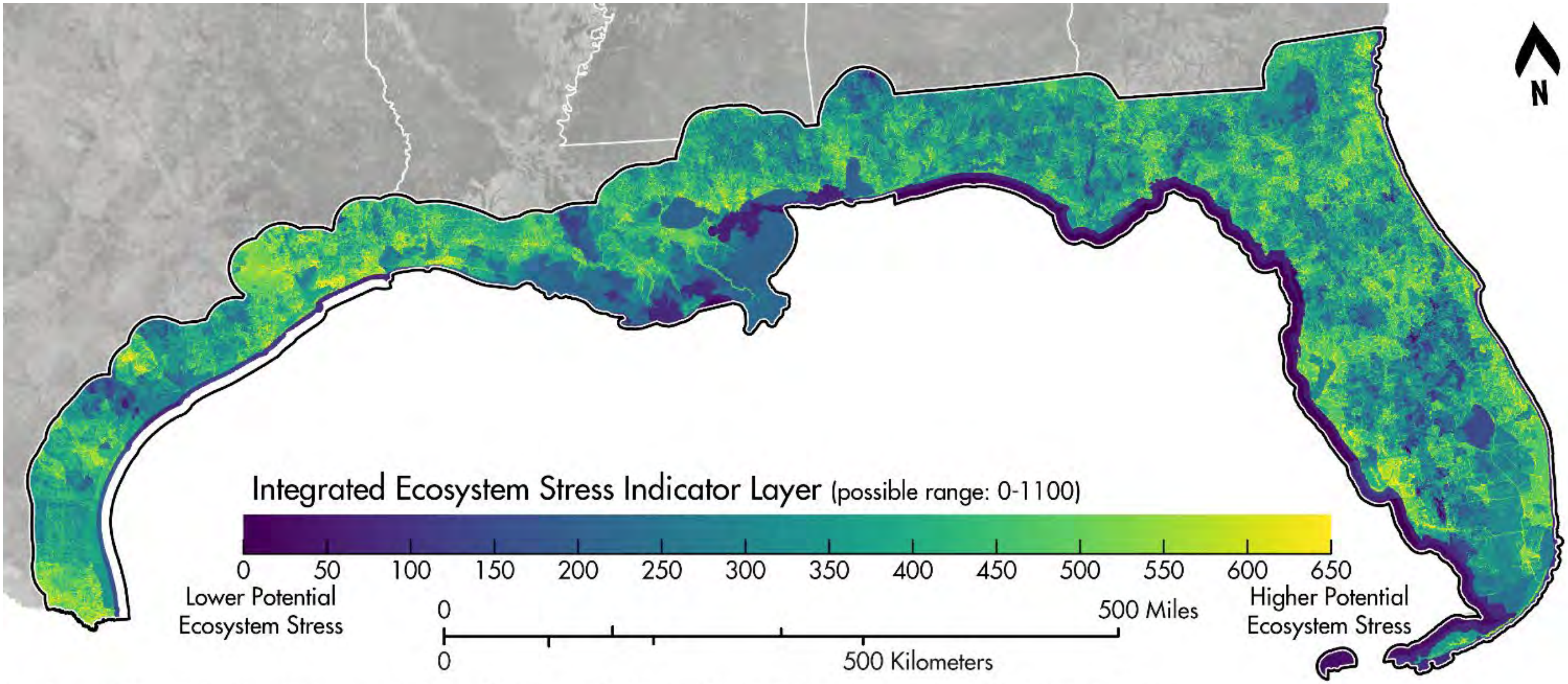
3.2. ECOSYSTEM STRESS

Eleven Ecosystem Stress Indicators were used in this assessment to produce an Integrated Ecosystem Stress Indicator layer. Total spatial area and proportion of the project area impacted by each Ecosystem Stress Indicator are provided in Table 2 as a high-level summary.

Table 2. Summary of Ecosystem Stress Indicators across the Gulf-wide project area. For reference, the total project area is 37,517,894 ha including terrestrial and aquatic areas

Indicator	Units	Threshold Attainment in Project Area
Invasive Species	State-prioritized invasive species occurrence	47 ha, <0.01% project area reflecting stress scores of 100
Disease & Disease Risk	Forest disease risk and presence of white-nose syndrome or chytrid fungus	526 ha, <0.01% project area reflecting stress scores of 100
Non-Point Source Pollution	TP & TN exceeding USEPA regulatory thresholds, and 303(d) impaired waters	19,095 ha, 0.05% project area reflecting stress scores of 100
Point Source Pollution	Density of superfund or potentially hazardous sites	6.4 ha, <0.01% project area reflecting stress scores >50
Urban Expansion Risk	Risk of urban expansion	102 ha, <0.01% project area reflecting stress scores of 100 (100% chance of urbanization by 2060)
Road Density	km road length/km^2	774.42 ha, <0.01% project area reflecting stress scores of 100 (>25%, highest stress category)
Impervious Surface	percent impervious	14,176 ha, 0.03% project area reflecting stress scores of 100 (>25% impervious surface by HUC12)
Water Hazards	Sea level rise (3ft) and FEMA floodplain hazard	13.5 ha, <0.01% project area reflecting stress scores of 100 (areas with all 9 overlapping hazards)
Drought	Non-cumulative occurrence of extreme drought (2011-2021)	1,624 ha, <0.01% project area reflecting stress scores of 90-100 (196-218 weeks of cumulative drought over 10 years)
Wildfire Hazard	Potential for unmanageable wildfire	2,112 ha, <0.01% project area reflecting stress scores of 100 (very high risk of wildfire hazard)
Hydromodification	Geomorphology sub-index of watershed health	13.5 ha, <0.01% project area reflecting stress scores >60 (by HUC12) (0 ha, 0% received a score of 100)

All Ecosystem Stress Indicators were summed across the spatial domain to produce an unweighted Integrated Ecosystem Stress Indicator layer (Figure 8). Due to the nature of the CZMA coastal boundary and the spatial extent of the Water Hazards Indicator, a strip of water along the Gulf coast of Florida is highlighted as low stress (present as a dark purple band in Figure 8); this is due to the presence of only one Ecosystem Stress Indicator (Water Hazards) that extends out into this area. For more detailed explanation, see Appendix B.



Data Source: CPRA, DataBasin, Esri, Florida Cooperative Land Cover, LANDFIRE, MRLC, NOAA, Texas A&M, The Nature Conservancy, USDA, USEPA, USFS, USFWS, USGS

Figure 8. Map of the Integrated Ecosystem Stress Indicator layer, calculated as the unweighted sum of 11 individual Ecosystem Stress Indicators.

One of the key findings of this analysis was that no single Ecosystem Stress Indicator dominated the Integrated Ecosystem Stress layer. Across the project area, a mean of 6.53 individual Ecosystem Stress Indicators contributed to the cumulative stress within grid cells in the Integrated Ecosystem Stress layer, with a mean contribution ranging from 12-29%. The Ecosystem Stress Indicators that had the highest contribution to the Integrated Ecosystem Stress layer were Non-Point Source Pollution, Road Density, and Impervious Surface, and these indicators had the maximum contribution to the Integrated Ecosystem Stress layer for 25-55% of the total number of grid cells across the project area (Figure 9). These Ecosystem Stress Indicators also had the highest correlation to one other (Figure 10).

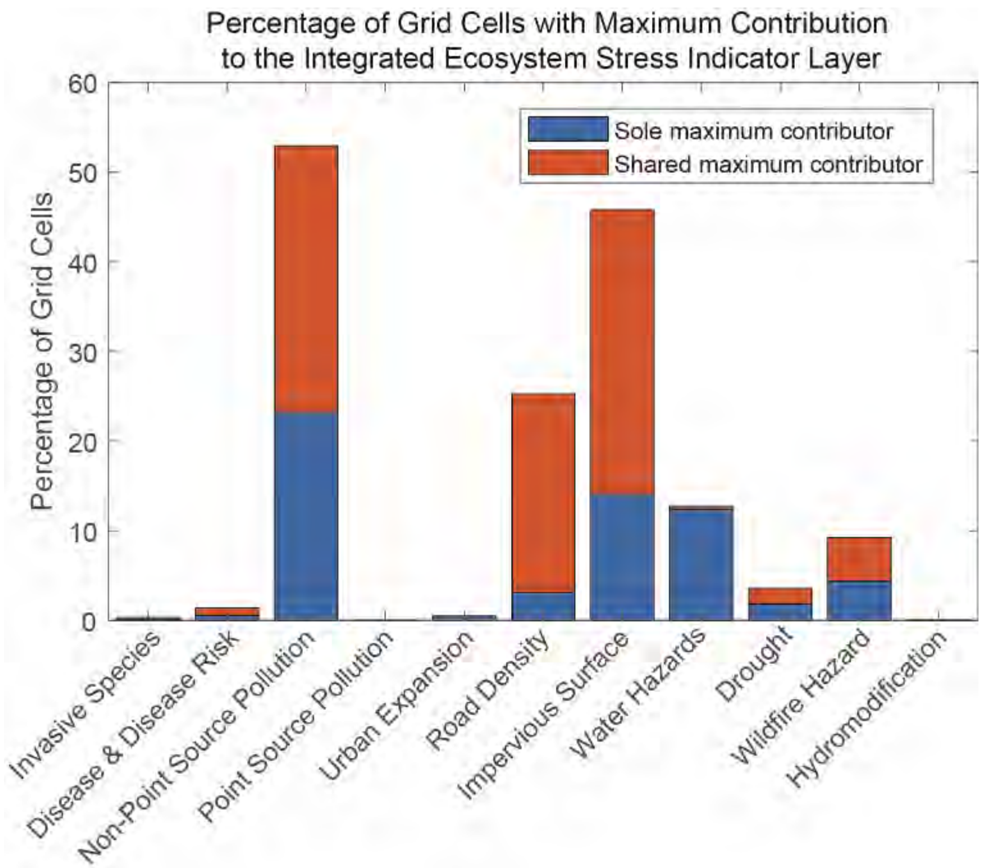


Figure 9. Percentage of 1 km^2 grid cells for which each Ecosystem Stress Indicator is providing the maximum contribution to the Integrated Ecosystem Stress Indicator layer.

It should be noted that the required use of thresholding to scale the Ecosystem Stress Indicators introduced some uncertainty into this analysis. For example, setting an Ecosystem Stress Indicator threshold for Point Source Pollution required defining the spatial area of influence of individual sites as well as scaling the indicator from 0 to 100. As a result, the spatial area of influence of Point Source Pollution is small, with only one grid cell reflecting a maximum value of 100 versus other Ecosystem Stress Indicators reflecting maximum values over a larger spatial areas. Similarly, the threshold ecosystem stress reflected in the Hydromodification Ecosystem Stress Indicator resulted in zero grid cells having a contributing value greater than 60, resulting in zero areas being dominated by this indicator and a low overall contribution of Ecosystem Stress Indicator to the overall stress value throughout the project area.

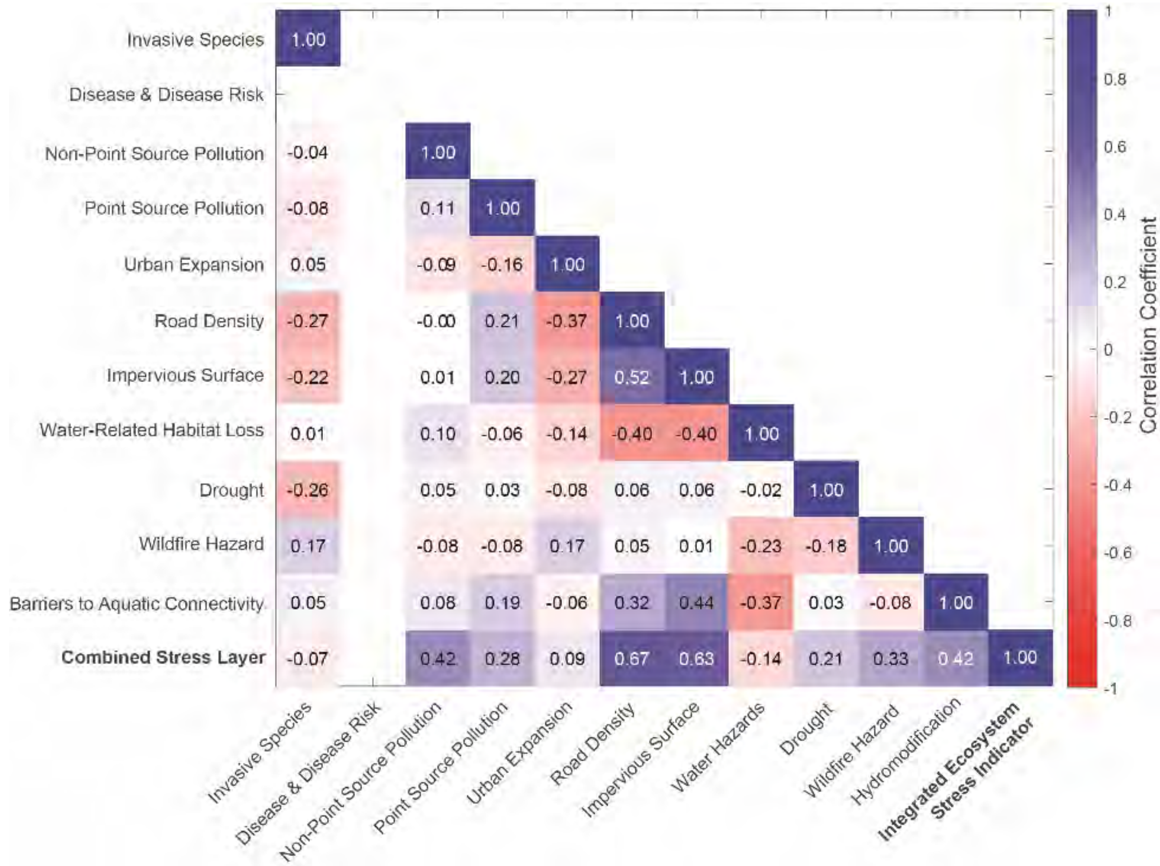
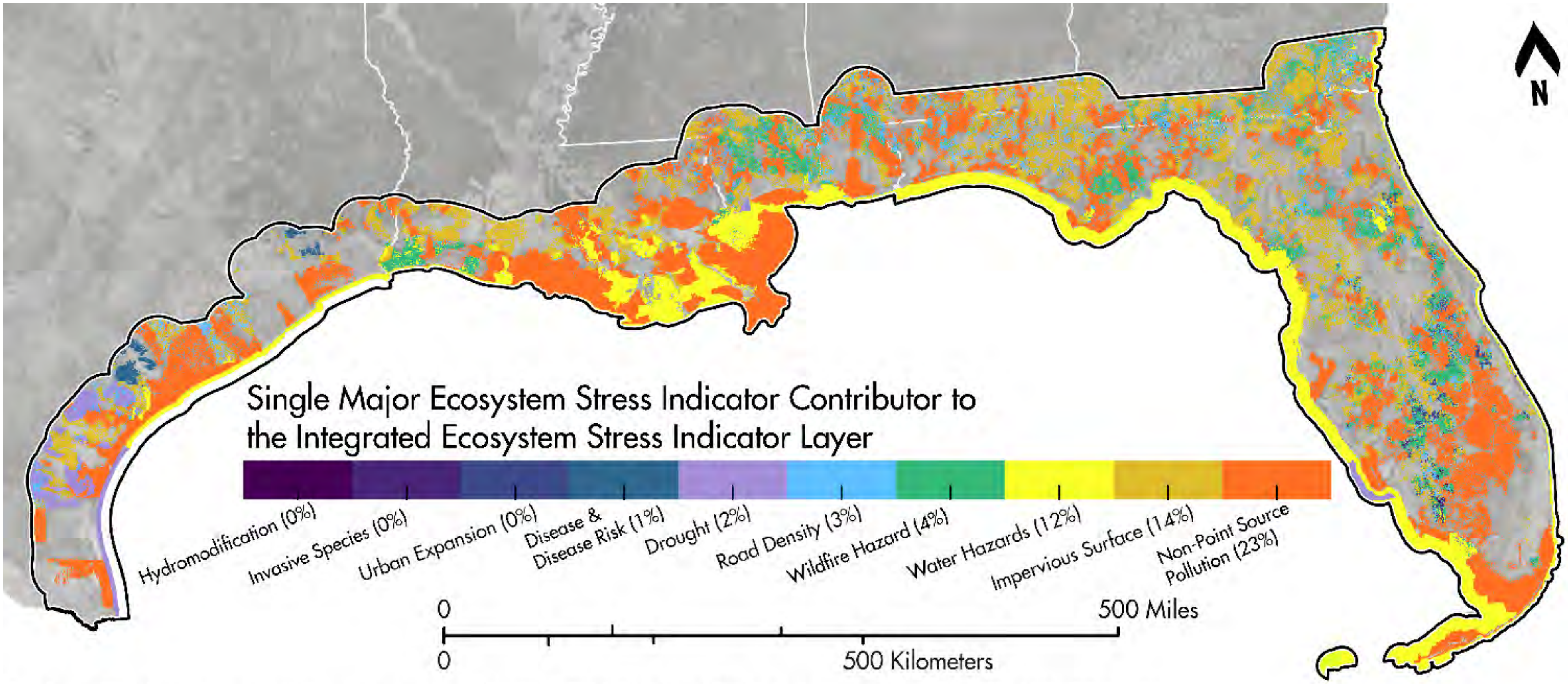


Figure 10. Correlation between each of the individual Ecosystem Stress Indicators and to the Integrated Ecosystem Stress Indicator layer. Integrated ecosystem stress was calculated as the unweighted sum of the individual Ecosystem Stress Indicators. The Disease & Disease Risk Ecosystem Indicator is a presence only metric (i.e., value of 100 if disease is present) and could not be correlated with the other stressors.

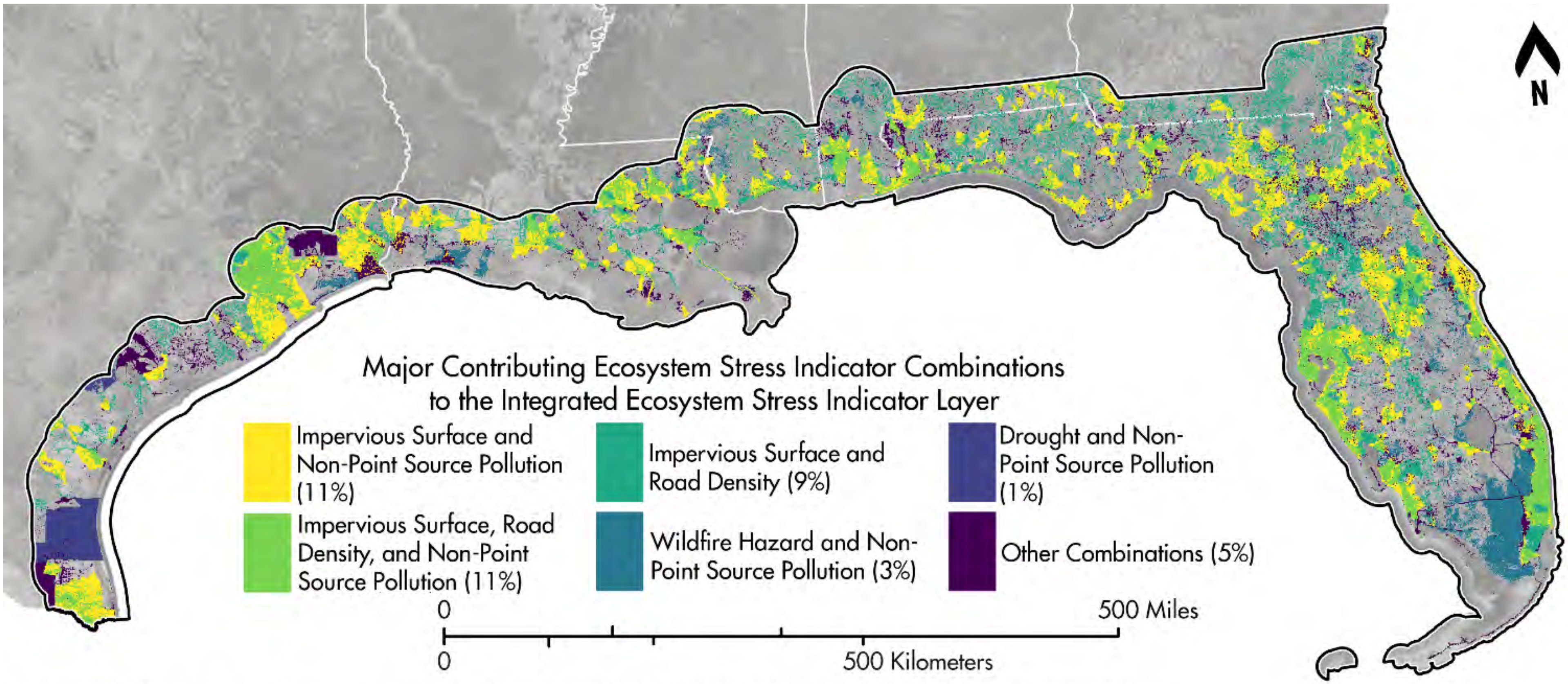
There was spatial variability in the distribution of the major contributor to the Integrated Ecosystem Stress Indicator layer (Figure 11), with Non-Point Source Pollution tending to be widespread and serving as the major contributor in rural areas. In urban, industrial, and agricultural areas, Road Density and Impervious Surface Ecosystem Stress Indicators also became major contributors to the Integrated Ecosystem Stress Indicator (Figure 12).

Analysis isolating the impacts of "future" Ecosystem Stress Indicators (i.e., Urban Expansion and Water Hazards, which includes the impacts of sea level rise) highlights those areas where there is a trajectory of increasing potential ecosystem stress over time (Figure 13). Along the coast, these two Ecosystem Stress Indicators had a relatively large contribution to the Integrated Ecosystem Stress Indicator when compared to inland areas. The Integrated Ecosystem Stress Indicator along the coast will therefore likely continue to increase in potential stress over time. As noted above, additional results and further detail related to the Ecosystem Stress sensitivity analysis are provided in Appendix B.



Data Source: CPRA, DataBasin, Esri, Florida Cooperative Land Cover, LANDFIRE, MRLC, NOAA, Texas A&M, The Nature Conservancy, USDA, USEPA, USFS, USFWS, USGS

Figure 11. Sole maximum contributors to the combined ecosystem stress layer. This indicator is contributing more to the combined layer than any other indicator.



Data Source: CPRA, DataBasin, Esri, Florida Cooperative Land Cover, LANDFIRE, MRLC, NOAA, Texas A&M, The Nature Conservancy, USDA, USEPA, USFS, USFWS, USGS

Figure 12. Shared Ecosystem Indicator maximum contributor combinations to the Integrated Ecosystem Stress Indicator layer. The Ecosystem Stress Indicators within each group are contributing the same percentage to the Integrated Ecosystem Stress Indicator layer, which is greater than the percentage of any other single Ecosystem Stress Indicator.

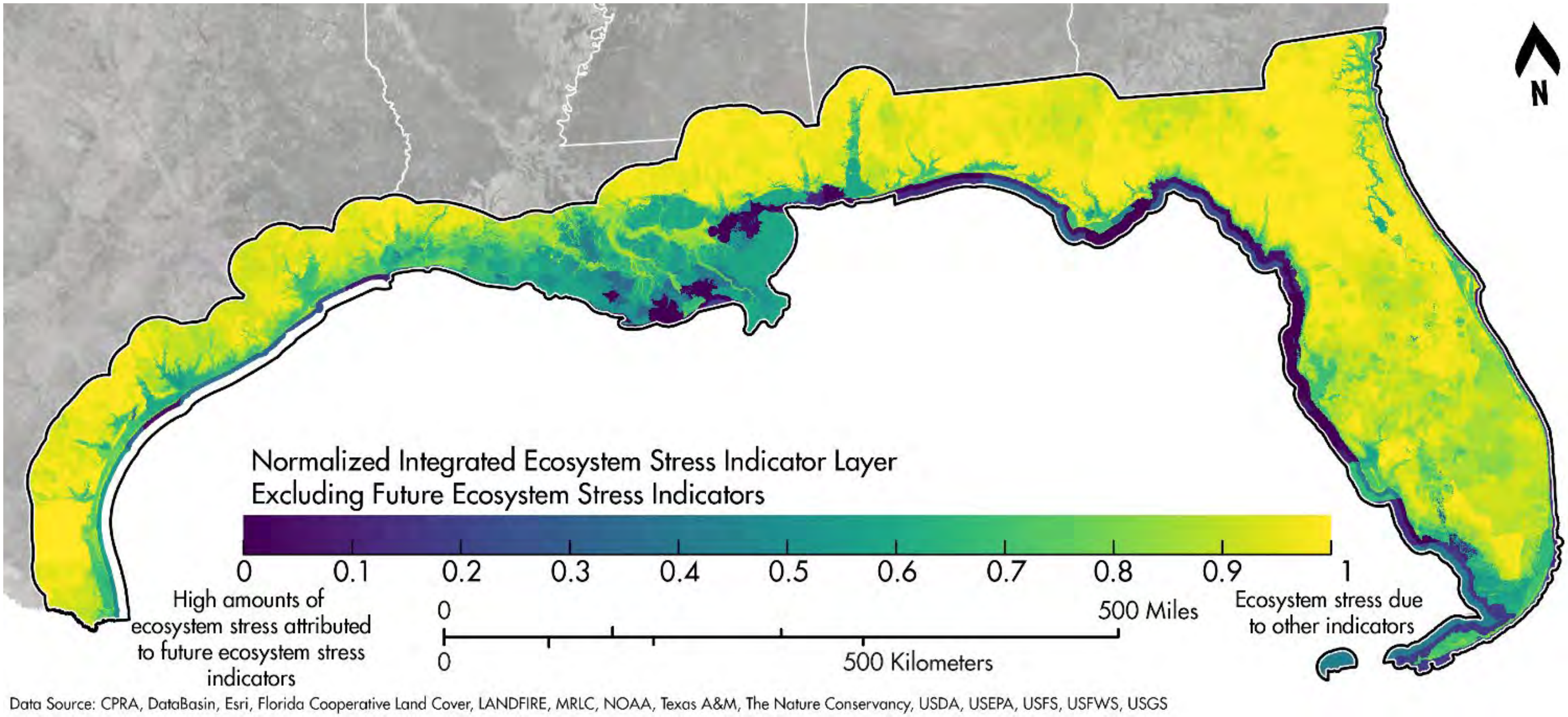


Figure 13. Ratio of the Integrated Ecosystem Stress Indicator layer excluding future Ecosystem Stress Indicators to the Integrated Ecosystem Stress Indicator layer including all indicators. The ratio was calculated by dividing the Integrated Ecosystem Stress Indicator layer including all indicators by the Integrated Ecosystem Stress Indicator layer excluding future indicators (Water Hazards and Urban Expansion). A value approaching zero indicates that much of the ecosystem stress in an area in the Integrated Ecosystem Stress Indicator is coming from anticipated future ecosystem stress indicators, whereas a value approaching one indicates Integrated Ecosystem Stress is predominantly attributed to indicators that are currently impacting an area. The band along the cost where this ratio is low is indicative of areas that are frequently submerged under current conditions. In these areas, the dominance of the Water Hazards stressor may also occur because most of the other Stress Indicators are terrestrial in nature and will have low values in water or very low-lying coastal areas.

3.3. SOCIAL VULNERABILITY

The social vulnerability spatial layer is the third and final spatial component of the Gulf-wide Data Suite. A total of 43 socioeconomic variables were analyzed using PCA and used to construct the SoVI for the SECAS study area (Figure 14). Five variables (the percent Native American population, percent Hawaiian population, percent of population employed in manufacturing, percent of households receiving public assistance, and percent of population in nursing facilities) did not contribute significantly on any of the components at the Gulf-wide scale and were not included in the final PCA run. The final 37 variables representing social vulnerability were grouped into six components based on the Kaiser-Guttman criterion. In total, most of the variance explained was captured by economic status (26%), educational professionals (22%), and elderly population (21%). Other significant socially vulnerable groupings include migrant workers (16%), rural population (9%), and locations with high population turnover (8%). See Appendix C for detailed results and individual component loading scores.

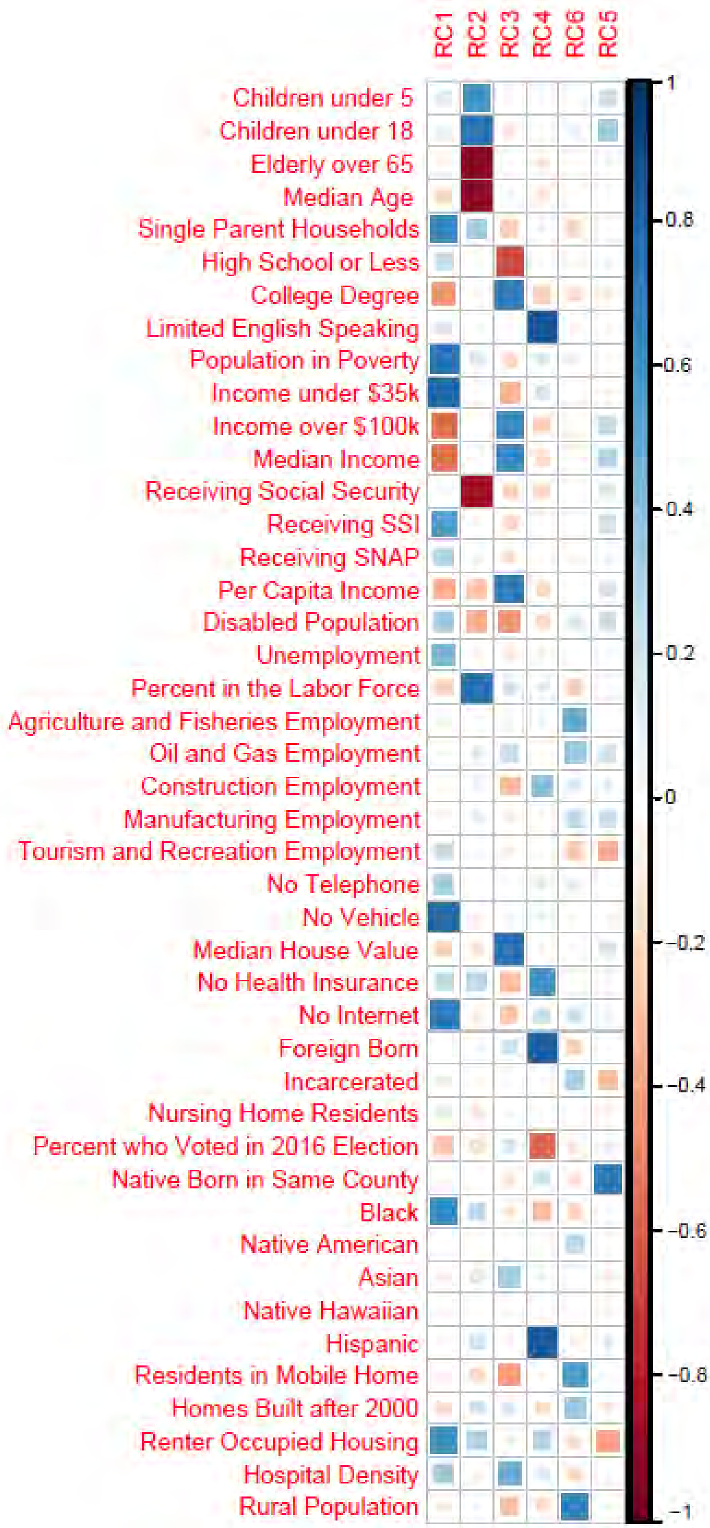


Figure 14. Correlation matrix showing the positive (dark blue) to negative (dark red) relationship between the socioeconomic variables and principal components used to construct the Social Vulnerability Index.

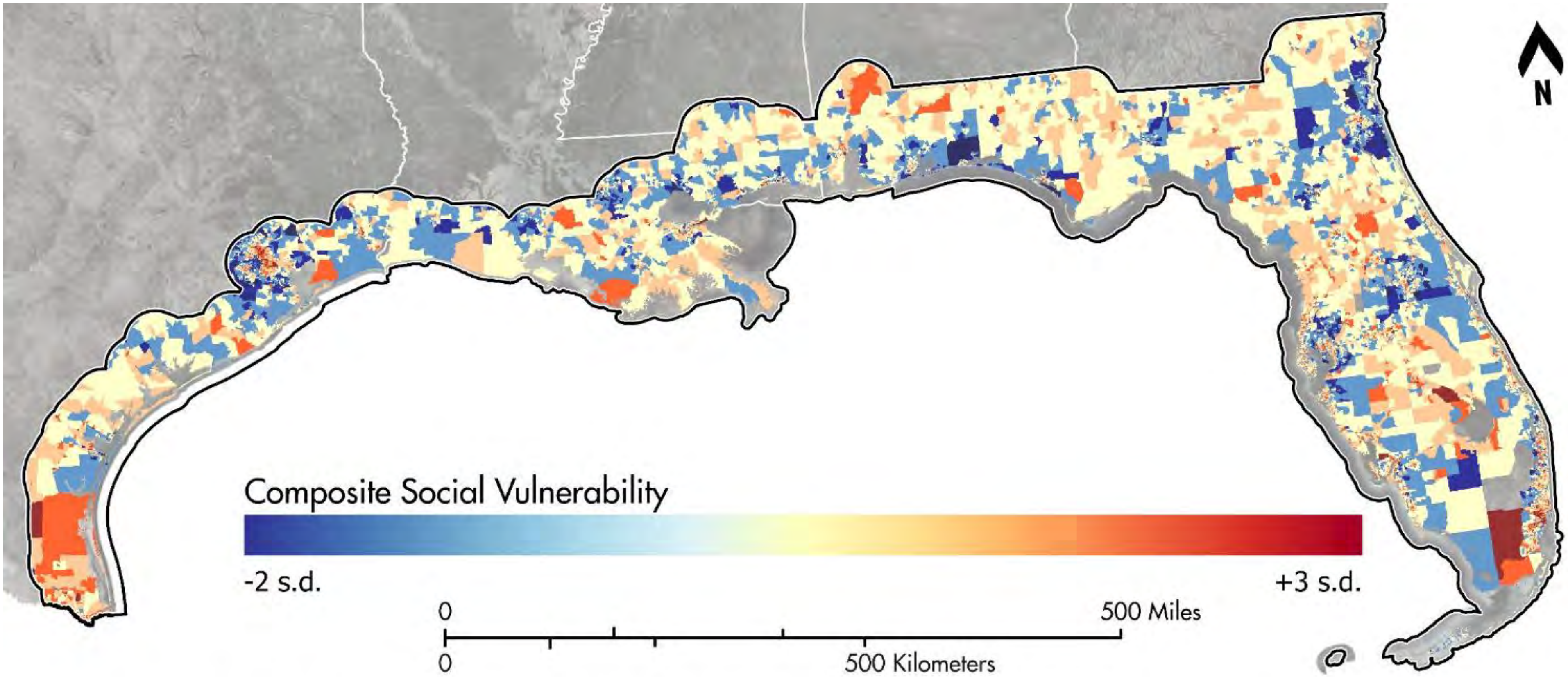
Although general descriptive component labels are applied during the interpretation of each component, more variables load highly onto those components than the labels can express (Rygel et al., 2006). For example, the first component was interpreted as “low economic status” because the percent households making less than $35,000 and percent of households with no vehicle loaded highest on it. This component also included high percentages of residents without internet, living in poverty, and the number of single parent households, categories that were statistically correlated with economic status. Similarly, the percentage of mobile homes and those employed in fisheries, construction, or oil and gas industries were strongly correlated with rural populations. Each of the other components was similarly interpreted. The non-English speaking, migrant component included the percentage of the population speaking little or no English, population born outside of the United States, households without insurance, employment in construction, and rental units. Within the study area, these populations also correlated closely with the Hispanic population.

The percent African American population loaded strongly on four component axes. In two instances, the percent African American population loaded negatively for the components representing migrant workers and rural populations. In three components (low economic status, elderly population, and rural populations), percent African American population was closely correlated to percent single parent household, with both loading high in the low economic status component. The percent of households that have no insurance correlated with percent renter housing units in three components (low economic status, elderly population, and migrant workers). This correlation suggests a potential link between lack of insurance with both income and employment in construction industries.

There are six variables that have split loadings, meaning that they load onto more than one factor. As each of these variables has loadings greater than 0.3, they can be interpreted as contributing to more than one factor. These split loadings (sometimes referred to as complex structures) are not uncommon in PCA and are not a concern if the components are interpretable. The percentage of adult population disabled is one item that has a split loading. It loads onto four components 1 “Low Economic Status,” component 2 “Elderly Population,” component 4 “Educated, Professional Workers,” and component 5 “Population Stability.” This can be explained by the fact that renter occupied units are often either elderly or disabled, two groups that are at times mutually exclusive. Similarly, the percent of renter-occupied housing units loads on component 1 “Low Economic Status,” component 2 “elderly population,” and component 5 “Population Stability.” Here, for example, the percent of renters in areas with high unemployment or areas where the population may be under employed or a single parent household. In other locations, however, households receiving social security income and age of householder is more indicative of lower economic standing.

While understanding the distribution of individual social vulnerability components can be useful, it is often helpful to assess overall social vulnerability if the multidimensional components can be combined into a single index (Rygel et al., 2006). Using the results from the PCA, the components were combined to derive a SoVI for all populated census block groups within the study area. Each of the six principal components output by the PCA had a component value that was adjusted for cardinality and weighted based upon the percentage of the total model variance that principal component explains. A weighted, additive model was used to derive the overall social vulnerability value for each census block group in the study area.

The resultant composite SoVI values were mapped and areas ranging from high to low vulnerability were identified across the coast (Figure 15). The urban cores, Miami, Tampa Bay, Orlando, Jacksonville, New Orleans, and Houston, as well as the extensively developed shoreline in Florida, show a bifurcation of social vulnerability, with areas of both high and low vulnerability in close proximity. Given the large geographic extent of the study area, the primarily rural areas display a patchwork of moderately low to moderately high.



Data Source: CPRA, DataBasin, Esri, Florida Cooperative Land Cover, LANDFIRE, MRLC, NOAA, Texas A&M, The Nature Conservancy, USDA, USEPA, USFS, USFWS, USGS

Figure 15. Composite Social Vulnerability score, displaying high (dark red) and low (dark blue) vulnerability as standard deviations from the mean.

There are two areas outside of urban areas that cluster moderate and high vulnerability. In Texas, Brownsville and Cameron County along with the rural block groups in Kenedy and Willacy counties to the north exhibit consistently high vulnerability. High vulnerability is consistent with certain household variables, such as only 55 percent having broadband internet, 77 percent speak a language other than English at home, 29 percent of people do not have insurance, having a median household income ($37,772) 60 percent lower than the national average, and having a percentage of persons in poverty (24.9%) 42 percent lower than the national average ("U.S. Census QuickFacts," 2021). In Alabama, the northern portion of the study area, which includes southern Clarke and Monroe counties, eastern/southeastern Washington County, and a small portion of northern rural Baldwin county[1], was another high vulnerability area. High vulnerability is consistent with certain household variables, such as 53 percent not having broadband internet in the home, 13 percent of people do not have insurance, only 45 percent of people are in the work force, having a median household income ($36,405) 57 percent lower than the national average, and having a percentage of persons in poverty (20.1%) 52 percent lower than the national average ("U.S. Census QuickFacts," 2021).

[1] Northern Baldwin County QuickFacts were not included in the demographic analysis because southern Baldwin County includes highly developed and vacation destinations (Gulf Shores, Orange Beach, and Fairhope). The overall values would skew the percentages for the other three predominately rural counties.

4.0 Conclusions

4.1. MAXIMIZING ADDITIONAL BENEFITS TO ACHIEVE CONSERVATION AND RESTORATION GOALS

The purpose of this work was to create a suite of spatial data that could be used to prioritize regional conservation and restoration for the northern Gulf of Mexico project area that included: 1) a uniform spatial prioritization prototype Gulf-wide Blueprint to visualize areas of high conservation value for the northern Gulf of Mexico, 2) provide a spatially comparable synthesis data layer of ecosystem stress (both current and future) to inform conservation and restoration project prioritization and planning, and 3) a spatially comparable synthesis data layer of social vulnerability. The analyses and spatial products presented in this report reflect an opportunity to inform the regional conservation and restoration prioritization for the northern Gulf of Mexico and advance SECAS's goal of improving the health, function, and connectivity of southeastern ecosystem 10 percent by 2060. This goal can best be accomplished by looking for synergies with the available funding resources for action implementation across the Gulf of Mexico, many of which include requirements for additional benefits of restoration to both natural resources and human communities. The prototype Gulf-wide Blueprint identifies locations that maximize natural resource values (e.g., habitat condition, key habitats for valued species, intact habitat cores) and human values (recreational potential, natural resource dependence, and economic wellbeing) for planners to begin directly visualizing where those locations might exist across the Gulf of Mexico project area (Figure 16).

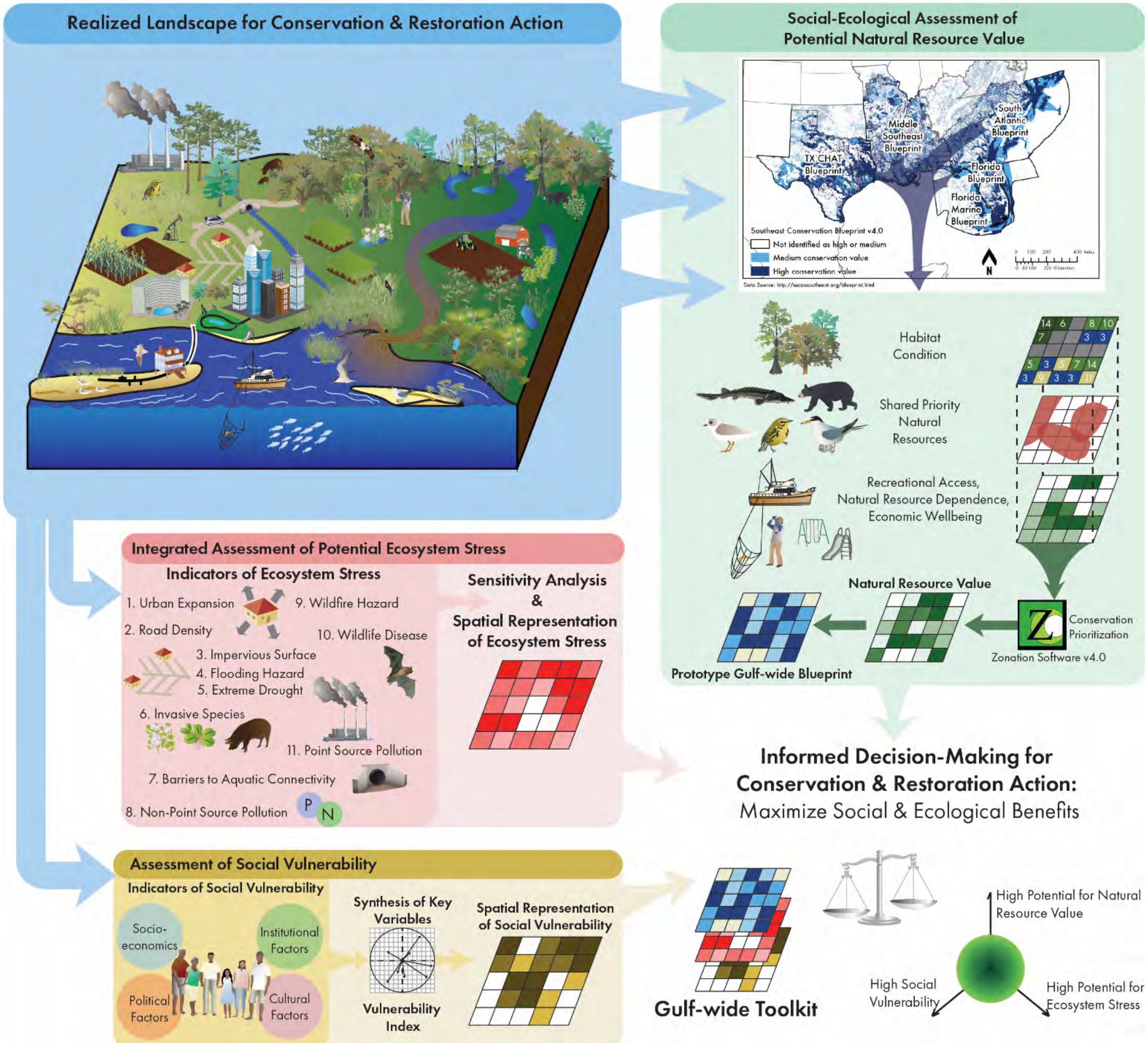


Figure 16. Conceptual diagram of the Gulf-wide Data Suite (same as figure E1-1). Credit to Tracey Saxby and Jane Hawkey for symbology (CC BY-SA 4.0) (ian.umces.edu/media-library).

Alongside the Gulf-wide Blueprint are two other highly valuable spatial tools that reflect Ecosystem Stress and Social Vulnerability. Visualization of potential environmental stress can assist northern Gulf of Mexico conservation and restoration project planners account for conditions that may reduce project resilience or limit project success. The northern Gulf of Mexico is geomorphically dynamic (large river deltas and coastal barrier islands) and impacted by annual hurricanes, with a range of social vulnerabilities and environmental stressors that make it challenging to assess likelihood of project success. Importantly, environmental stressors and restoration action influence natural resources and also human communities, with many vulnerable stakeholders co-located in areas most threatened by an uncertain future. Visualization of the most socially vulnerable communities directly compared with the Gulf-wide Blueprint and environmental threats gives the Gulf-wide Data Suite potential to quantify a range of benefits and costs between potential project locations. As noted in Section 2.2.4, these data provide an opportunity for conservation and restoration project planners to consider issues of social justice and equity in the distribution of healthy and stressed ecosystems.

4.2. PLANS TO INTEGRATE SOCIO-ECOLOGICAL VALUES

Restoration and conservation planning that is centered around key socio-ecological values and compares uncertain future threats and social vulnerabilities can result in a more robust and beneficial outcome for both natural resources and stakeholder communities (Wineland et al., 2021). Such cross-disciplinary planning that considers social constraints to achieve ecosystem objectives is critical for improving conservation and restoration project and programmatic success (Paloniemi et al., 2018).

Consideration of both social vulnerability, natural resource values, and potential ecological stressors during project planning and prioritization can then help inform subsequent project and programmatic evaluation. Gulf of Mexico restoration funding in the wake of the DWH event that is routed through the RESTORE Act program has specific socio-ecological goals, but currently no system to measure, assess, or report on how individual projects address social and economic goals. The Gulf of Mexico Service Logic Models & Socio-Economic Indicators (GEMS) program (https://nicholasinstitute.duke.edu/project/gems) is currently working to build those reporting and evaluation systems to understand potential social and economic impacts of different restoration strategies (e.g., building oyster reefs). The Gulf-wide Data Suite provides planners with a three-dimensional informational framework (potential socio-ecological value, environmental risk, and social vulnerability) to articulate potential for additional benefits and uncertainties before restoration strategies are in place and during initial project siting. This framework can help align expectations of project success (for both natural resources and human communities) to inform eventual evaluation. Coupling ecosystem conservation and restoration planning with social science, this work provides the tools to find solutions that meet both social and environmental goals (Perring et al., 2015).

4.3. OPPORTUNITIES TO AUGMENT EXISTING TOOLSETS: SCA PROGRAM

The Gulf-wide Data Suite, as a collection of regionally consistent spatial information for the Gulf of Mexico project area, can offer new data and insights to existing project planning frameworks. The Strategic Conservation Assessment Framework of Gulf Coast Landscapes (SCA) program, coordinated by the USFWS, integrates stakeholder input across the 5 Gulf states and is dedicated to identifying land conservation opportunities for the Gulf of Mexico project area based on the NOAA RESTORE goal structure (https://www.quest.fwrc.msstate.edu/sca-project.php). The current SCA tool suite provides a highly interactive user interface ("front end") for project planners to prioritize data types to inform their specific project needs. SECAS, the provisional Gulf-wide Blueprint, the integrated stressor and integrated social vulnerability data sets, and the SCA tool suite provide potential to develop stronger linkages to state and regional conservation and restoration planning programs. The Gulf-wide Data Suite provides novel information that may augment the value of the SCA tool and increase its utility, particularly by expanding on assessments of habitat condition and socio-ecological metrics that communicate potential value, uncertainty, and stress. The combined data between the projects is greater than the data in either project alone across the range of ecosystem threats and values, as well as community values and wellbeing. The inclusion of socio-ecological and social vulnerability data highlights the fact that conservation and restoration planning decisions do not occur in a vacuum. Changes in ecological conditions, planned or otherwise, have the potential to impact the health and wellbeing of nearby residents as well as those who rely on healthy ecosystems for their livelihoods. Further, the Gulf-wide Data Suite makes a distinction between socio-ecological factors that can be directly influenced by ecological management decisions and those inherent socioeconomic factors such as poverty, race, gender, and age that cannot. The inclusion of the latter is important in that it recognizes that there is an inherent social value associated with residents having access to safe and healthy environments and that there is a need to assure that issues of environmental justice and distributional equity are accounted for in the conservation and restoration project planning process. This reasoning could be carried over into conservation prioritization data metrics used within the SCA tools to expand the potential for restoration planners to evaluate additional benefits of restoration for human communities as well as natural resources.

Recognizing the well-developed front end of the SCA Conservation Prioritization tool (and potentially the Conservation Visualization tool), the Gulf-wide Data Suite can serve as an additional "back end" information resource for State and federal natural resource managers working on the restoration effort in the Gulf based upon SECAS with a uniform analytical approach across the northern Gulf of Mexico coast. This approach can be further augmented by establishing linkages and approaches to utilize the framework and, specifically, link the prototype Gulf-wide Blueprint layer or other SECAS prioritization data products into state level management planning mechanisms (e.g., the Louisiana Coastal Master Plan).

4.4. NEXT STEPS AND RECOMMENDATIONS

The Gulf-wide Data Suite, aligned with the goals and vision of SECAS, provides an important opportunity to inform conservation and land management decisions at broad spatial scales, increasing opportunity for engaging programmatic, planning, and funding mechanisms across the northern Gulf of Mexico coastal region. Buy-in from natural resource managers with these spatial prioritization tools would be greatly enhanced if additional steps were added to:

1) Fine-tune the prototype Gulf-wide Blueprint: apply differential indicator weights and refine the Zonation analysis (a powerful modeling tool for this effort) as conducted in the 2020 South Atlantic Blueprint to determine quantitatively how the inclusion of the Habitat Condition Indicator layer (scoring habitat types across the project area using site and landscape-scale metrics) refines Zonation prioritization scores;

2) Incorporate the integrated ecosystem stress and social vulnerability datasets into the SCA Conservation Prioritization tool (and potentially the Conservation Visualization tool) to augment the value of the SCA tool and increase its utility; and
3) Apply the Gulf-wide Data Suite to Louisiana's 2017 Coastal Master Plan identified suite of restoration projects to assess wildlife resource values of the whole Louisiana Coastal Master Plan project suite as well as resource values of key restoration approaches specifically. This will also provide a framework to understand the relative benefits to wildlife resources of one project over another, when the primary decision drivers of land building and flood reduction are both equal.
4) Seek opportunities to test and apply the Gulf-wide Data Suite to projects and programs in all northern Gulf States, refining where needed to meet the needs of individual states.

An active engagement with funding mechanisms for habitat and landscape restoration, in addition to habitat and landscape conservation, has potential to increase overall natural resource intactness in the gulf-wide restoration effort, and assist SECAS in achieving their goal.

References

Adger, W. N., Brooks, N., Bentham, G., Agnew, M., & Eriksen, S. (2004). *New indicators of vulnerability and adaptive capacity* (Vol. 122). Tyndall Centre for Climate Change Research Norwich.

Cameron, C., Kiskaddon, E., Parfait, J., Mcinnis, A., Courtois, A., & Carruthers, T. (2020). *Southeast Conservation Blueprint Mechanics* (p. 137). Baton Rouge, LA: The Water Institute of the Gulf. Prepared for and funded by the U.S. Fish and Wildlife Service.

Candau, J., Rasmussen, S., & Clarke, K. (2000). A coupled cellular automaton model for land use/land cover dynamics.

Clark, J. S., Iverson, L., Woodall, C. W., Allen, C. D., Bell, D. M., Bragg, D. C., D'Amato, A. W., Davis, F. W., Hersh, M. H., Ibanez, I., Jackson, S. T., Matthews, S., Pederson, N., Peters, M., Schwartz, M. W., Waring, K. M., & Zimmermann, N. E. (2016). The impacts of increasing drought on forest dynamics, structure, and biodiversity in the United States. *Global Change Biology*, *22*(7), 2329–2352.

Comer, Faber-Langendoen, D., Evans, R., Gawler, S., Josse, C., Kittel, G., Menard, S., Pyne, M., Reid, M., Schulz, K., Snow, K., & Teague, J. (2003). *Ecological Systems of the United States: A Working Classification of U.S. Terrestrial Systems*. Arlington, VA: NatureServe.

Consent Decree. (2016). *BP Exploration & Production Inc. ("BPXP") v. United States of America, and the States of Alabama, Florida, Louisiana, Mississippi, and Texas* (No. No. 2:10-cv-04536-CJB-SS).

Cutter, S. L., Boruff, B. J., & Shirley, W. L. (2003). Social vulnerability to environmental hazards. *Social Science Quarterly*, *84*(2), 242–261.

Cutter, S. L., Burton, C. G., & Emrich, C. T. (2010). Disaster Resilience Indicators for Benchmarking Baseline Conditions. *Journal of Homeland Security and Emergency Management*, *7*(1).

Di Minin, E., Veach, V., Lehtomäki, J., Pouzols, F., & Moilanen, A. (2014, June). A quick introduction to Zonation: Version 1 (for Zv4). C-BIG Conservation Biology Informatics Group, Department of Biosciences, University of Helsinki, Finland.

Dunning, C. M., & Durden, S. (2011). *Social vulnerability analysis methods for Corps planning*. Alexandria, VA: U.S. Army Corps of Engineers Institute for Water Resources.

DWH NRDA Trustees. (2016). Deepwater Horizon Oil Spill: Final Programmatic Damage Assessment and Restoration Plan (PDARP) and Final Programmatic Environmental Impact Statement (PEIS). Available: http://www.gulfspillrestoration.noaa.gov/restorationplanning/gulf-plan.

GCPOLCC. (2013). *Integrated Science Agenda DRAFT v4* (p. 55). Gulf Coastal Plains & Ozarks Landscape Conservation Cooperative.

Hak, J. C., & Comer, P. J. (2017). Modeling landscape condition for biodiversity assessment—Application in temperate North America. *Ecological Indicators*, *82*, 206–216.

Haynes, R. W., Graham, R. T., & Quigley, T. M. (1996). *A Framework for Ecosystem Management In the Interior Columbia Basin And Portions of the Klamath and Great Basins* (No. PNW-GTR-374) (p. 75). U.S. Forest Service and U.S. Bureau of Land Management with assistance from the Pacific Northwest Forest Experiment Station.

Hemmerling, S. A., & Hijuelos, A. C. (2016). *Coastal Louisiana Social Vulnerability Index (SVI). Version I.* (p. 27). Baton Rouge, LA: Coastal Protection and Restoration Authority.

Hemmerling, S. A., McHugh, C. M., DeMyers, C., Bienn, H. C., DeJong, A., Parfait, J., & Kiskaddon, E. (2020). *A community-informed framework for quantifying risk and resilience in southeast Louisiana*. Baton Rouge, LA: The Water Institute of the Gulf.

Hijuelos, A. C., & Hemmerling, S. A. (2015). *Coastwide and Barataria Basin Monitoring Plans for Louisiana's System-Wide Assessment and Monitoring Program (SWAMP)*. Baton Rouge, LA: The Water Institute of the Gulf.

Jepson, M., & Colburn, L. L. (2013). *Development of Social Indicators of Fishing Community Vulnerability and Resilience in the US Southeast and Northeast Regions* (NOAA Technical Memorandum No. NMFS-F/SPO-129) (p. 64). US Dept Commerce.

Kremen, C., Cameron, A., Moilanen, A., Phillips, S. J., Thomas, C. D., Beentje, H., Dransfield, J., Fisher, B. L., Glaw, F., Good, T. C., Harper, G. J., Hijmans, R. J., Lees, D. C., Louis, E., Nussbaum, R. A., Raxworthy, C. J., Razafimpahanana, A., Schatz, G. E., Vences, M., Vieites, D. R., Wright, P. C., & Zjhra, M. L. (2008). Aligning Conservation Priorities Across Taxa in Madagascar with High-Resolution Planning Tools. *Science*, *320*(5873), 222–226.

Middle Southeast Blueprint. (2020). *Middle Southeast Blueprint 3.0 Development Process*. Middle Southeast Blueprint.

Moilanen, A., Pouxols, F., Meller, L., Veach, V., Arponen, A., Leppanen, J., & Kujala, H. (2014). Zonation: Version 4 User Manual. C-BIG Conservation Biology Informatics Group, Department of Biosciences, University of Helsinki, Finland.

Paloniemi, R., Hujala, T., Rantala, S., Harlio, A., Salomaa, A., Primmer, E., Pynnönen, S., & Arponen, A. (2018). Integrating Social and Ecological Knowledge for Targeting Voluntary Biodiversity Conservation. *Conservation Letters*, *11*(1), e12340.

Peacock, W. G., Grover, H., Mayunga, J., Van Zandt, S., Brody, S. D., Kim, H. J., & Center, R. (2011). *The status and trends of population social vulnerabilities along the Texas Coast with special attention to the Coastal Management Zone and Hurricane Ike: The Coastal Planning Atlas and Social Vulnerability Mapping Tools*. A report prepared for the Texas General Land Office and The National Oceanic and Atmospheric Administration. College Station, TX: Texas A&M University.

Perring, M. P., Standish, R. J., Price, J. N., Craig, M. D., Erickson, T. E., Ruthrof, K. X., Whiteley, A. S., Valentine, L. E., & Hobbs, R. J. (2015). Advances in restoration ecology: rising to the challenges of the coming decades. *Ecosphere*, *6*(8), art131.

Pouzols, F., Toivonen, T., Di Minin, E., Kukkala, A. S., Kullberg, P., Kuusterä, J., Lehtomäki, J., Tenkanen, H., Verburg, P. H., & Moilanen, A. (2014). Global protected area expansion is compromised by projected land-use and parochialism. *Nature*, *516*(7531), 383–386.

Quigley, T., Haynes, R., & Graham, R. (1996). *Integrated scientific assessment for ecosystem management in the interior Columbia Basin and portions of the Klamath and Great Basins* (General Technical Report No. PNW-GTR382) (pp. viii–197). U.S. Department of Agriculture, Forest Service.

Quigley, T. M., Haynes, R. W., & Hann, W. J. (2001). Estimating ecological integrity in the interior Columbia River basin. *Forest Ecology and Management*, *153*(1–3), 161–178.

RESTORE Act (2011).

Rupprecht, C. D. D., & Byrne, J. A. (2014). Informal urban greenspace: A typology and trilingual systematic review of its role for urban residents and trends in the literature. *Urban Forestry & Urban Greening*, *13*(4), 597–611.

Rygel, L., O'sullivan, D., & Yarnal, B. (2006). A method for constructing a Social Vulnerability Index: An application to hurricane storm surges in a developed country. *Mitigation and Adaptation Strategies for Global Change*, *11*(3), 741–764.

Schueler, T. (1994). The Importance of Imperviousness. *Watershed Protection Techniques*, *1*(3), 100.

SECAS. (2020, May). Our goal [Organization].

South Atlantic Conservation Blueprint. (2020). South Atlantic Blueprint 2020 Development Process.

Southeast Conservation Adaptation Strategy. (2020, May). About SECAS.

Terando, A. J., Costanza, J., Belyea, C., Dunn, R. R., McKerrow, A., & Collazo, J. A. (2014). The Southern Megalopolis: Using the Past to Predict the Future of Urban Sprawl in the Southeast U.S. *PLoS ONE*, *9*(7), e102261.

Toivonen, T., Kuusterä, J., Jalkanen, J., Kukkala, A., Lehtomäki, J., Aalto, S., & Moilanen, A. (2021). *Spatial Conservation Prioritisation as Part of a General Land Use Planning Process * (preprint). In Review.

Uphoff, J. H., McGinty, M., Lukacovic, R., Mowrer, J., & Pyle, B. (2011). Impervious Surface, Summer Dissolved Oxygen, and Fish Distribution in Chesapeake Bay Subestuaries: Linking Watershed Development, Habitat Conditions, and Fisheries Management. *North American Journal of Fisheries Management*, *31*(3), 554–566.

U.S. Environmental Protection Agency. (n.d.). *Meeting Community Needs, Protecting Human Health and the Environment: Active and Passive Recreational Opportunities at Abandoned Mine Lands*.

van den Berg, M., Wendel-Vos, W., van Poppel, M., Kemper, H., van Mechelen, W., & Maas, J. (2015). Health benefits of green spaces in the living environment: A systematic review of epidemiological studies. *Urban Forestry & Urban Greening*, *14*(4), 806–816.

Vilsack, T. (2016). *Comprehensive plan update 2016: Restoring the Gulf Coast's ecosystem and economy* (p. 32). Gulf Coast Ecosystem Restoration Council.

Völker, S., & Kistemann, T. (2011). The impact of blue space on human health and well-being – Salutogenetic health effects of inland surface waters: A review. *International Journal of Hygiene and Environmental Health*, *214*(6), 449–460.

Wallace, R. L., Gilbert, S., & Reynolds, J. E., III. (2019). Improving the Integration of Restoration and Conservation in Marine and Coastal Ecosystems: Lessons from the Deepwater Horizon Disaster. *BioScience*, *69*(11), 920–927.

Watson, A., Reece, J., Tirpak, B. E., Edwards, C. K., Geselbracht, M., Woodrey, M., LaPeyre, M., & Dalyander, P. S. (2015). *The Gulf Coast vulnerability assessment: Mangrove, tidal emergent marsh, barrier islands, and oyster reef* (p. 132).

Watson, J., & Venter, O. (2017). Ecology: A global plan for nature conservation. *Nature*, *550*.

Wheeler, B. W., Lovell, R., Higgins, S. L., White, M. P., Alcock, I., Osborne, N. J., Husk, K., Sabel, C. E., & Depledge, M. H. (2015). Beyond greenspace: an ecological study of population general health and indicators of natural environment type and quality. *International Journal of Health Geographics*, *14*(1).

Wheeler, B. W., White, M., Stahl-Timmins, W., & Depledge, M. H. (2012). Does living by the coast improve health and wellbeing? *Health & Place*, *18*(5), 1198–1201.

Wineland, S. M., Fovargue, R., Gill, K. C., Rezapour, S., & Neeson, T. M. (2021). Conservation planning in an uncertain climate: Identifying projects that remain valuable and feasible across future scenarios. *People and Nature*, *3*(1), 221–235.

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APPENDIX A

A.1 HABITAT LAND COVER CLASSES FOR THE PROTOTYPE GULF-WIDE BLUEPRINT

The prototype Southeast Conservation Adaptation Strategy (SECAS) Gulf-wide Blueprint land cover indicator is primarily based on the 2020 LANDFIRE existing vegetation type (evt) dataset (except for mangroves, beaches, and open water). This appendix provides tables that summarize which LANDFIRE evt land cover classes define the habitat categories for the prototype Gulf-wide Blueprint. Habitat groups were developed with input from subject matter experts and Southeast Conservation Adaptation Strategy (SECAS) Blueprint technical developers. Grouping vegetation classes into broader groups for regional comparison was and continues to be a challenge Gulf-wide and nation-wide. For example, vegetation classes that define the grassland prairie habitat type in Texas may not be the same for Florida due to differences in temperature and precipitation regimes across ecoregions. The habitat classes defined here should not be used in place of local habitat maps (e.g., the Florida Cooperative Land Cover map) for site-level planning.

Table A-1. LANDFIRE evt classes of natural land cover types.

LANDFIRE evt Class Value	LANDFIRE Name
7980	Western Warm Temperate Orchard
7983	Western Warm Temperate Row Crop - Close Grown Crop
7984	Western Warm Temperate Row Crop
7985	Western Warm Temperate Close Grown Crop
7988	Western Warm Temperate Wheat
7990	Eastern Warm Temperate Orchard
7991	Eastern Warm Temperate Vineyard
7992	Eastern Warm Temperate Bush fruit and berries
7993	Eastern Warm Temperate Row Crop - Close Grown Crop
7994	Eastern Warm Temperate Row Crop
7995	Eastern Warm Temperate Close Grown Crop
7998	Eastern Warm Temperate Wheat
7500	South Texas Salt and Brackish Tidal Flat
9097	Florida Panhandle Beach Vegetation
9103	Gulf Coast Chenier Plain Beach
9122	Louisiana Beach
9221	South Florida Shell Hash Beach
9226	Southeast Florida Beach
9240	Southern Atlantic Coastal Plain Florida Beach
9244	Southern Atlantic Coastal Plain Sea Island Beach
9262	Southwest Florida Beach
9273	Texas Coast Beach

LANDFIRE evt Class Value	LANDFIRE Name
7336	Southwest Florida Maritime Hammock
7337	Southeast Florida Maritime Hammock
7380	East Gulf Coastal Plain Maritime Forest
7382	Southern Atlantic Coastal Plain Maritime Forest
7384	Mississippi Delta Maritime Forest
7445	South Florida Dwarf Cypress Savanna
7447	South Florida Cypress Dome
7452	Atlantic Coastal Plain Peatland Pocosin and Canebrake Woodland
7460	Southern Coastal Plain Nonriverine Cypress Dome
7461	Southern Coastal Plain Seepage Swamp and Baygall Woodland
7462	West Gulf Coastal Plain Seepage Swamp and Baygall
7467	Tamaulipan Floodplain Woodland
7468	Atlantic Coastal Plain Streamhead Seepage Swamp-Pocosin-Baygall Woodland
7474	Tamaulipan Floodplain Shrubland
7476	Tamaulipan Riparian Woodland
7501	Southern Atlantic Coastal Plain Nonriverine Swamp and Wet Hardwood Forest
7513	Lower Mississippi River Flatwoods
7562	Tamaulipan Riparian Shrubland
7571	Southern Coastal Plain Seepage Swamp and Baygall Shrubland
9041	Atlantic Coastal Plain Blackwater Stream Floodplain Forest
9050	Atlantic Coastal Plain Small Blackwater River Floodplain Forest
9068	Central Texas Coastal Prairie Riparian Forest
9069	Central Texas Coastal Prairie River Floodplain Forest
9071	Columbia Bottomlands Forest and Woodland
9077	East Gulf Coastal Plain Depression Pondshore
9080	East Gulf Coastal Plain Freshwater Tidal Wooded Swamp
9082	East Gulf Coastal Plain Large River Floodplain Forest
9085	East Gulf Coastal Plain Small Stream and River Floodplain Forest
9138	Mississippi River Bottomland Depression
9139	Mississippi River High Floodplain (Bottomland) Forest
9140	Mississippi River Low Floodplain (Bottomland) Forest
9141	Mississippi River Riparian Forest
9216	South Florida Bayhead Swamp
9218	South Florida Hydric Hammock
9220	South Florida Pond-apple/Popash Slough
9230	Southeastern Great Plains Floodplain Forest and Woodland
9231	Southeastern Great Plains Riparian Forest and Woodland
9239	Southern Atlantic Coastal Plain Depression Pondshore

LANDFIRE evt Class Value	LANDFIRE Name
9242	Southern Atlantic Coastal Plain Large River Floodplain Forest
9247	Southern Coastal Plain Blackwater River Floodplain Forest
9248	Southern Coastal Plain Hydric Hammock
9249	Southern Coastal Plain Nonriverine Basin Swamp
9266	Tamaulipan Closed Depression Wetland Woodland
9282	West Gulf Coastal Plain Large River Floodplain Forest
9283	West Gulf Coastal Plain Near-Coast Large River Swamp
9284	West Gulf Coastal Plain Small Stream and River Forest
9320	Southeastern Native Ruderal Flooded & Swamp Forest
9541	Atlantic Coastal Plain Blackwater Stream Floodplain Shrubland
9568	Central Texas Coastal Prairie Riparian Shrubland
9569	Central Texas Coastal Prairie River Floodplain Shrubland
9582	East Gulf Coastal Plain Large River Floodplain Shrubland
9585	East Gulf Coastal Plain Small Stream and River Floodplain Shrubland
9639	Mississippi River High Floodplain (Bottomland) Shrubland
9640	Mississippi River Low Floodplain (Bottomland) Shrubland
9722	South Florida Slough Gator Hole and Willow Head Woodland
9730	Southeastern Great Plains Floodplain Shrubland
9731	Southeastern Great Plains Riparian Shrubland
9742	Southern Atlantic Coastal Plain Large River Floodplain Shrubland
9766	Tamaulipan Closed Depression Wetland Shrubland
9782	West Gulf Coastal Plain Large River Floodplain Shrubland
9784	West Gulf Coastal Plain Small Stream and River Shrubland
9993	West Gulf Coastal Plain Flatwoods Pond
7425	Florida Dry Prairie Grassland
7426	Southern Atlantic Coastal Plain Dune and Maritime Grassland
7429	West Gulf Coastal Plain Southern Calcareous Prairie
7431	Southwest Florida Dune and Coastal Grassland
7434	Texas-Louisiana Coastal Prairie
7435	East Gulf Coastal Plain Dune and Coastal Grassland
7437	Texas Coast Dune and Coastal Grassland
7438	Tamaulipan Savanna Grassland
7566	Florida Dry Prairie Shrubland
7578	East Gulf Coastal Plain Wet Savanna
7987	Western Warm Temperate Pasture and Hayland
7997	Eastern Warm Temperate Pasture and Hayland
9063	Central Florida Wet Prairie and Herbaceous Seep
9270	Tamaulipan Saline Thornscrub

LANDFIRE evt Class Value	LANDFIRE Name
9332	Southeastern Exotic Ruderal Flooded & Swamp Forest
7191	Recently Logged-Herb and Grass Cover
7195	Recently Burned-Herb and Grass Cover
7198	Recently Disturbed Other-Herb and Grass Cover
9823	Southeastern Ruderal Grassland
9825	Great Plains Comanchian Ruderal Grassland
7192	Recently Logged-Shrub Cover
7196	Recently Burned-Shrub Cover
7197	Recently Burned-Tree Cover
7199	Recently Disturbed Other-Shrub Cover
7200	Recently Disturbed Other-Tree Cover
9319	Southeastern Exotic Ruderal Forest
9323	Southeastern Ruderal Shrubland
9325	Great Plains Comanchian Ruderal Shrubland
7989	Western Warm Temperate Aquaculture
7999	Eastern Warm Temperate Aquaculture
7357	Southern Coastal Plain Mesic Slope Forest
7565	Florida Peninsula Inland Scrub Woodland
7585	West Gulf Coastal Plain Pine-Hardwood Forest
7587	West Gulf Coastal Plain Sandhill Oak and Shortleaf Pine Forest and Woodland
7589	East Gulf Coastal Plain Southern Loblolly-Hardwood Flatwoods
7590	West Gulf Coastal Plain Hardwood Flatwoods
7591	West Gulf Coastal Plain Pine-Hardwood Flatwoods
9250	Southern Coastal Plain Oak Dome and Hammock
9321	Southeastern Native Ruderal Forest
7371	West Gulf Coastal Plain Pine Forest
9208	Panhandle Florida Limestone Glade
9227	Southeastern Coastal Plain Cliff
9251	Southern Coastal Plain Sinkhole
9290	Southeastern Great Plains Cliff
7446	South Florida Pine Flatwoods
7449	Central Atlantic Coastal Plain Wet Longleaf Pine Savanna and Flatwoods
7450	Southern Atlantic Coastal Plain Wet Pine Savanna and Flatwoods
7451	West Gulf Coastal Plain Wet Longleaf Pine Savanna and Flatwoods
7453	Central Florida Pine Flatwoods
7454	East Gulf Coastal Plain Near-Coast Pine Flatwoods
7458	West Gulf Coastal Plain Pine Flatwoods
7545	East Gulf Coastal Plain Near-Coast Pine Wet Flatwoods

LANDFIRE evt Class Value	LANDFIRE Name
7547	Central Florida Pine Wet Flatwoods
7548	South Florida Pine Wet Flatwoods
7378	West Gulf Coastal Plain Sandhill Shortleaf Pine Forest and Woodland
7455	East Gulf Coastal Plain Southern Loblolly Flatwoods
7347	Atlantic Coastal Plain Upland Longleaf Pine Woodland
7349	East Gulf Coastal Plain Interior Upland Longleaf Pine Woodland
7356	Florida Longleaf Pine Sandhill
7360	South Florida Pine Rockland
7471	Southwest Florida Coastal Strand Shrubland
7472	Southeast Florida Coastal Strand Shrubland
7486	Texas Saline Coastal Prairie
9094	Florida Big Bend Fresh and Oligohaline Tidal Marsh
9095	Florida Big Bend Salt and Brackish Tidal Marsh
9104	Gulf Coast Chenier Plain Fresh and Oligohaline Tidal Marsh
9105	Gulf Coast Chenier Plain Salt and Brackish Tidal Marsh
9136	Mississippi Delta Fresh and Oligohaline Tidal Marsh
9137	Mississippi Delta Salt and Brackish Tidal Marsh
9142	Mississippi Sound Fresh and Oligohaline Tidal Marsh
9143	Mississippi Sound Salt and Brackish Tidal Marsh
9228	Southeastern Coastal Plain Interdunal Wetland
9274	Texas Coast Fresh and Oligohaline Tidal Marsh
9275	Texas Coast Salt and Brackish Tidal Marsh
9604	Gulf Coast Chenier Plain Fresh and Oligohaline Tidal Marsh Shrubland
9605	Gulf Coast Chenier Plain Salt and Brackish Tidal Marsh Shrubland
9774	Texas Coast Fresh and Oligohaline Tidal Marsh Shrubland
9775	Texas Coast Salt and Brackish Tidal Marsh Shrubland
7193	Recently Logged-Tree Cover
9322	Southeastern North American Temperate Forest Plantation
7475	Tamaulipan Floodplain Herbaceous
7483	South Florida Everglades Sawgrass Marsh
7487	Texas-Louisiana Coastal Prairie Pondshore
7489	Floridian Highlands Freshwater Marsh
7514	Central Florida Herbaceous Pondshore
7515	Southern Coastal Plain Herbaceous Seep and Bog
7573	Tamaulipan Riparian Herbaceous
9098	Florida River Floodplain Marsh
9222	South Florida Slough Gator Hole and Willow Head Herbaceous
9324	Southeastern Ruderal Wet Meadow & Marsh

LANDFIRE evt Class Value	LANDFIRE Name
9542	Atlantic Coastal Plain Blackwater Stream Floodplain Herbaceous
9570	Central Texas Coastal Prairie Riparian Herbaceous
9571	Central Texas Coastal Prairie River Floodplain Herbaceous
9583	East Gulf Coastal Plain Large River Floodplain Herbaceous
9586	East Gulf Coastal Plain Small Stream and River Floodplain Herbaceous
9641	Mississippi River High Floodplain (Bottomland) Herbaceous
9642	Mississippi River Low Floodplain (Bottomland) Herbaceous
9732	Southeastern Great Plains Floodplain Herbaceous
9733	Southeastern Great Plains Riparian Herbaceous
9743	Southern Atlantic Coastal Plain Large River Floodplain Herbaceous
9783	West Gulf Coastal Plain Large River Floodplain Herbaceous
9785	West Gulf Coastal Plain Small Stream and River Herbaceous
9994	West Gulf Coastal Plain Herbaceous Seep and Bog
7323	West Gulf Coastal Plain Mesic Hardwood Forest
7330	Southern Coastal Plain Dry Upland Hardwood Forest
7333	South Florida Hardwood Hammock
7335	Southern Atlantic Coastal Plain Dry and Dry-Mesic Oak Forest
7339	West Gulf Coastal Plain Chenier and Upper Texas Coastal Fringe Forest and Woodland
7343	Southern Atlantic Coastal Plain Mesic Hardwood Forest
7387	Florida Peninsula Inland Scrub Shrubland
7391	Tamaulipan Mesquite Upland Woodland
7584	West Gulf Coastal Plain Hardwood Forest
7586	West Gulf Coastal Plain Sandhill Oak Forest and Woodland
7588	East Gulf Coastal Plain Southern Hardwood Flatwoods
7338	Central and South Texas Coastal Fringe Forest and Woodland
7381	Lower Mississippi River Dune Woodland and Forest
7390	Tamaulipan Mixed Deciduous Thornscrub
7392	Tamaulipan Calcareous Thornscrub
7506	West Gulf Coastal Plain Nonriverine Wet Hardwood Flatwoods
7519	East-Central Texas Plains Post Oak Savanna and Woodland
7560	Tamaulipan Mesquite Upland Scrub
7945	Western Warm Temperate Developed Ruderal Deciduous Forested Wetland
7946	Western Warm Temperate Developed Ruderal Evergreen Forested Wetland
7947	Western Warm Temperate Developed Ruderal Mixed Forested Wetland
7948	Western Warm Temperate Developed Ruderal Shrub Wetland
7955	Eastern Warm Temperate Developed Ruderal Deciduous Forested Wetland
7956	Eastern Warm Temperate Developed Ruderal Evergreen Forested Wetland
7957	Eastern Warm Temperate Developed Ruderal Mixed Forested Wetland

LANDFIRE evt Class Value	LANDFIRE Name
7958	Eastern Warm Temperate Developed Ruderal Shrub Wetland
7913	Western Warm Temperate Urban Herbaceous
7918	Eastern Warm Temperate Urban Herbaceous
7929	Western Warm Temperate Developed Ruderal Grassland
7939	Eastern Warm Temperate Developed Ruderal Grassland
7910	Western Warm Temperate Urban Deciduous Forest
7911	Western Warm Temperate Urban Evergreen Forest
7912	Western Warm Temperate Urban Mixed Forest
7914	Western Warm Temperate Urban Shrubland
7915	Eastern Warm Temperate Urban Deciduous Forest
7916	Eastern Warm Temperate Urban Evergreen Forest
7917	Eastern Warm Temperate Urban Mixed Forest
7919	Eastern Warm Temperate Urban Shrubland
7925	Western Warm Temperate Developed Ruderal Deciduous Forest
7926	Western Warm Temperate Developed Ruderal Evergreen Forest
7927	Western Warm Temperate Developed Ruderal Mixed Forest
7928	Western Warm Temperate Developed Ruderal Shrubland
7935	Eastern Warm Temperate Developed Ruderal Deciduous Forest
7936	Eastern Warm Temperate Developed Ruderal Evergreen Forest
7937	Eastern Warm Temperate Developed Ruderal Mixed Forest
7938	Eastern Warm Temperate Developed Ruderal Shrubland
7949	Western Warm Temperate Developed Ruderal Herbaceous Wetland
7954	Eastern Cool Temperate Developed Ruderal Herbaceous Wetland
7959	Eastern Warm Temperate Developed Ruderal Herbaceous Wetland
7861	Caribbean Coastal Mangrove
7867	Caribbean Estuary Mangrove

Table A-2. LANDFIRE evt classes of natural land cover types.

LANDFIRE evt Class Value	LANDFIRE Name	Habitat Type
9332	Southeastern Exotic Ruderal Flooded & Swamp Forest	Low-Quality Forested Wetland
7945	Western Warm Temperate Developed Ruderal Deciduous Forested Wetland	Urban/Developed Forested Wetland
7946	Western Warm Temperate Developed Ruderal Evergreen Forested Wetland	Urban/Developed Forested Wetland
7947	Western Warm Temperate Developed Ruderal Mixed Forested Wetland	Urban/Developed Forested Wetland
7948	Western Warm Temperate Developed Ruderal Shrub Wetland	Urban/Developed Forested Wetland

LANDFIRE evt Class Value	LANDFIRE Name	Habitat Type
7955	Eastern Warm Temperate Developed Ruderal Deciduous Forested Wetland	Urban/Developed Forested Wetland
7956	Eastern Warm Temperate Developed Ruderal Evergreen Forested Wetland	Urban/Developed Forested Wetland
7957	Eastern Warm Temperate Developed Ruderal Mixed Forested Wetland	Urban/Developed Forested Wetland
7958	Eastern Warm Temperate Developed Ruderal Shrub Wetland	Urban/Developed Forested Wetland

Table A-3. LANDFIRE evt classes for the Forested Wetland habitat type.

LANDFIRE evt Class Value	LANDFIRE evt name	Habitat Type
7336	Southwest Florida Maritime Hammock	Forested Wetland
7337	Southeast Florida Maritime Hammock	Forested Wetland
7380	East Gulf Coastal Plain Maritime Forest	Forested Wetland
7382	Southern Atlantic Coastal Plain Maritime Forest	Forested Wetland
7384	Mississippi Delta Maritime Forest	Forested Wetland
7445	South Florida Dwarf Cypress Savanna	Forested Wetland
7447	South Florida Cypress Dome	Forested Wetland
7452	Atlantic Coastal Plain Peatland Pocosin and Canebrake Woodland	Forested Wetland
7460	Southern Coastal Plain Nonriverine Cypress Dome	Forested Wetland
7461	Southern Coastal Plain Seepage Swamp and Baygall Woodland	Forested Wetland
7462	West Gulf Coastal Plain Seepage Swamp and Baygall	Forested Wetland
7467	Tamaulipan Floodplain Woodland	Forested Wetland
7468	Atlantic Coastal Plain Streamhead Seepage Swamp-Pocosin-Baygall Woodland	Forested Wetland
7474	Tamaulipan Floodplain Shrubland	Forested Wetland
7476	Tamaulipan Riparian Woodland	Forested Wetland
7501	Southern Atlantic Coastal Plain Nonriverine Swamp and Wet Hardwood Forest	Forested Wetland
7513	Lower Mississippi River Flatwoods	Forested Wetland

LANDFIRE evt Class Value	LANDFIRE evt name	Habitat Type
7562	Tamaulipan Riparian Shrubland	Forested Wetland
7571	Southern Coastal Plain Seepage Swamp and Baygall Shrubland	Forested Wetland
9041	Atlantic Coastal Plain Blackwater Stream Floodplain Forest	Forested Wetland
9050	Atlantic Coastal Plain Small Blackwater River Floodplain Forest	Forested Wetland
9068	Central Texas Coastal Prairie Riparian Forest	Forested Wetland
9069	Central Texas Coastal Prairie River Floodplain Forest	Forested Wetland
9071	Columbia Bottomlands Forest and Woodland	Forested Wetland
9077	East Gulf Coastal Plain Depression Pondshore	Forested Wetland
9080	East Gulf Coastal Plain Freshwater Tidal Wooded Swamp	Forested Wetland
9082	East Gulf Coastal Plain Large River Floodplain Forest	Forested Wetland
9085	East Gulf Coastal Plain Small Stream and River Floodplain Forest	Forested Wetland
9138	Mississippi River Bottomland Depression	Forested Wetland
9139	Mississippi River High Floodplain (Bottomland) Forest	Forested Wetland
9140	Mississippi River Low Floodplain (Bottomland) Forest	Forested Wetland
9141	Mississippi River Riparian Forest	Forested Wetland
9216	South Florida Bayhead Swamp	Forested Wetland
9218	South Florida Hydric Hammock	Forested Wetland
9220	South Florida Pond-apple/Popash Slough	Forested Wetland
9230	Southeastern Great Plains Floodplain Forest and Woodland	Forested Wetland
9231	Southeastern Great Plains Riparian Forest and Woodland	Forested Wetland
9239	Southern Atlantic Coastal Plain Depression Pondshore	Forested Wetland
9242	Southern Atlantic Coastal Plain Large River Floodplain Forest	Forested Wetland
9247	Southern Coastal Plain Blackwater River Floodplain Forest	Forested Wetland
9248	Southern Coastal Plain Hydric Hammock	Forested Wetland

LANDFIRE evt Class Value	LANDFIRE evt name	Habitat Type
9249	Southern Coastal Plain Nonriverine Basin Swamp	Forested Wetland
9266	Tamaulipan Closed Depression Wetland Woodland	Forested Wetland
9282	West Gulf Coastal Plain Large River Floodplain Forest	Forested Wetland
9283	West Gulf Coastal Plain Near-Coast Large River Swamp	Forested Wetland
9284	West Gulf Coastal Plain Small Stream and River Forest	Forested Wetland
9320	Southeastern Native Ruderal Flooded & Swamp Forest	Forested Wetland
9541	Atlantic Coastal Plain Blackwater Stream Floodplain Shrubland	Forested Wetland
9568	Central Texas Coastal Prairie Riparian Shrubland	Forested Wetland
9569	Central Texas Coastal Prairie River Floodplain Shrubland	Forested Wetland
9582	East Gulf Coastal Plain Large River Floodplain Shrubland	Forested Wetland
9585	East Gulf Coastal Plain Small Stream and River Floodplain Shrubland	Forested Wetland
9639	Mississippi River High Floodplain (Bottomland) Shrubland	Forested Wetland
9640	Mississippi River Low Floodplain (Bottomland) Shrubland	Forested Wetland
9722	South Florida Slough Gator Hole and Willow Head Woodland	Forested Wetland
9730	Southeastern Great Plains Floodplain Shrubland	Forested Wetland
9731	Southeastern Great Plains Riparian Shrubland	Forested Wetland
9742	Southern Atlantic Coastal Plain Large River Floodplain Shrubland	Forested Wetland
9766	Tamaulipan Closed Depression Wetland Shrubland	Forested Wetland
9782	West Gulf Coastal Plain Large River Floodplain Shrubland	Forested Wetland
9784	West Gulf Coastal Plain Small Stream and River Shrubland	Forested Wetland
9993	West Gulf Coastal Plain Flatwoods Pond	Forested Wetland

Table A-4. LANDFIRE evt classes for the Pine Forest habitat type (includes tree plantations).

LANDFIRE evt Class Value	LANDFIRE evt name	Habitat Type
7193	Recently Logged-Tree Cover	Tree Plantation

LANDFIRE evt Class Value	LANDFIRE evt name	Habitat Type
9322	Southeastern North American Temperate Forest Plantation	Tree Plantation
7446	South Florida Pine Flatwoods	Pine - Flatwoods
7449	Central Atlantic Coastal Plain Wet Longleaf Pine Savanna and Flatwoods	Pine - Flatwoods
7450	Southern Atlantic Coastal Plain Wet Pine Savanna and Flatwoods	Pine - Flatwoods
7451	West Gulf Coastal Plain Wet Longleaf Pine Savanna and Flatwoods	Pine - Flatwoods
7453	Central Florida Pine Flatwoods	Pine - Flatwoods
7454	East Gulf Coastal Plain Near-Coast Pine Flatwoods	Pine - Flatwoods
7458	West Gulf Coastal Plain Pine Flatwoods	Pine - Flatwoods
7545	East Gulf Coastal Plain Near-Coast Pine Wet Flatwoods	Pine - Flatwoods
7547	Central Florida Pine Wet Flatwoods	Pine - Flatwoods
7548	South Florida Pine Wet Flatwoods	Pine - Flatwoods
7378	West Gulf Coastal Plain Sandhill Shortleaf Pine Forest and Woodland	Pine - Shortleaf/Loblolly
7455	East Gulf Coastal Plain Southern Loblolly Flatwoods	Pine - Shortleaf/Loblolly
7347	Atlantic Coastal Plain Upland Longleaf Pine Woodland	Pine - Woodland
7349	East Gulf Coastal Plain Interior Upland Longleaf Pine Woodland	Pine - Woodland
7356	Florida Longleaf Pine Sandhill	Pine - Woodland
7360	South Florida Pine Rockland	Pine - Woodland

Table A-5. LANDFIRE evt classes for the Low-Quality and Urban/Developed Mixed Forest habitat type.

LANDFIRE evt Class Value	LANDFIRE evt name	Habitat Type
7910	Western Warm Temperate Urban Deciduous Forest	Urban/Developed Mixed Forest
7911	Western Warm Temperate Urban Evergreen Forest	Urban/Developed Mixed Forest
7912	Western Warm Temperate Urban Mixed Forest	Urban/Developed Mixed Forest
7914	Western Warm Temperate Urban Shrubland	Urban/Developed Mixed Forest
7915	Eastern Warm Temperate Urban Deciduous Forest	Urban/Developed Mixed Forest
7916	Eastern Warm Temperate Urban Evergreen Forest	Urban/Developed Mixed Forest
7917	Eastern Warm Temperate Urban Mixed Forest	Urban/Developed Mixed Forest
7919	Eastern Warm Temperate Urban Shrubland	Urban/Developed Mixed Forest
7925	Western Warm Temperate Developed Ruderal Deciduous Forest	Urban/Developed Mixed Forest
7926	Western Warm Temperate Developed Ruderal Evergreen Forest	Urban/Developed Mixed Forest
7927	Western Warm Temperate Developed Ruderal Mixed Forest	Urban/Developed Mixed Forest
7928	Western Warm Temperate Developed Ruderal Shrubland	Urban/Developed Mixed Forest
7935	Eastern Warm Temperate Developed Ruderal Deciduous Forest	Urban/Developed Mixed Forest
7936	Eastern Warm Temperate Developed Ruderal Evergreen Forest	Urban/Developed Mixed Forest

LANDFIRE evt Class Value	LANDFIRE evt name	Habitat Type
7937	Eastern Warm Temperate Developed Ruderal Mixed Forest	Urban/Developed Mixed Forest
7938	Eastern Warm Temperate Developed Ruderal Shrubland	Urban/Developed Mixed Forest
7192	Recently Logged-Shrub Cover	Low-Quality Mixed Forest
7196	Recently Burned-Shrub Cover	Low-Quality Mixed Forest
7197	Recently Burned-Tree Cover	Low-Quality Mixed Forest
7199	Recently Disturbed Other-Shrub Cover	Low-Quality Mixed Forest
7200	Recently Disturbed Other-Tree Cover	Low-Quality Mixed Forest
9319	Southeastern Exotic Ruderal Forest	Low-Quality Mixed Forest
9323	Southeastern Ruderal Shrubland	Low-Quality Mixed Forest
9325	Great Plains Comanchian Ruderal Shrubland	Low-Quality Mixed Forest

Table A-6. LANDFIRE evt classes for the Mixed Forest habitat type.

LANDFIRE evt Class Value	LANDFIRE evt name	Habitat Type
7357	Southern Coastal Plain Mesic Slope Forest	Mixed Forest
7565	Florida Peninsula Inland Scrub Woodland	Mixed Forest
7585	West Gulf Coastal Plain Pine-Hardwood Forest	Mixed Forest
7587	West Gulf Coastal Plain Sandhill Oak and Shortleaf Pine Forest and Woodland	Mixed Forest
7589	East Gulf Coastal Plain Southern Loblolly-Hardwood Flatwoods	Mixed Forest
7590	West Gulf Coastal Plain Hardwood Flatwoods	Mixed Forest
7591	West Gulf Coastal Plain Pine-Hardwood Flatwoods	Mixed Forest
9250	Southern Coastal Plain Oak Dome and Hammock	Mixed Forest
9321	Southeastern Native Ruderal Forest	Mixed Forest
7371	West Gulf Coastal Plain Pine Forest	Mixed Forest

Table A-7. LANDFIRE evt classes for the Upland Hardwood Forest/Woodland habitat type.

LANDFIRE evt Class Value	LANDFIRE evt name	Habitat Type
7323	West Gulf Coastal Plain Mesic Hardwood Forest	Upland Hardwood Forest
7330	Southern Coastal Plain Dry Upland Hardwood Forest	Upland Hardwood Forest
7333	South Florida Hardwood Hammock	Upland Hardwood Forest
7335	Southern Atlantic Coastal Plain Dry and Dry-Mesic Oak Forest	Upland Hardwood Forest
7339	West Gulf Coastal Plain Chenier and Upper Texas Coastal Fringe Forest and Woodland	Upland Hardwood Forest
7343	Southern Atlantic Coastal Plain Mesic Hardwood Forest	Upland Hardwood Forest
7387	Florida Peninsula Inland Scrub Shrubland	Upland Hardwood Forest
7391	Tamaulipan Mesquite Upland Woodland	Upland Hardwood Forest

LANDFIRE evt Class Value	LANDFIRE evt name	Habitat Type
7584	West Gulf Coastal Plain Hardwood Forest	Upland Hardwood Forest
7586	West Gulf Coastal Plain Sandhill Oak Forest and Woodland	Upland Hardwood Forest
7588	East Gulf Coastal Plain Southern Hardwood Flatwoods	Upland Hardwood Forest
7338	Central and South Texas Coastal Fringe Forest and Woodland	Upland Hardwood Woodland
7381	Lower Mississippi River Dune Woodland and Forest	Upland Hardwood Woodland
7390	Tamaulipan Mixed Deciduous Thornscrub	Upland Hardwood Woodland
7392	Tamaulipan Calcareous Thornscrub	Upland Hardwood Woodland
7506	West Gulf Coastal Plain Nonriverine Wet Hardwood Flatwoods	Upland Hardwood Woodland
7519	East-Central Texas Plains Post Oak Savanna and Woodland	Upland Hardwood Woodland
7560	Tamaulipan Mesquite Upland Scrub	Upland Hardwood Woodland

Table A-8. LANDFIRE evt classes for the Agriculture habitat type.

LANDFIRE evt Class Value	LANDFIRE Name	Habitat Type
7980	Western Warm Temperate Orchard	Agriculture
7983	Western Warm Temperate Row Crop - Close Grown Crop	Agriculture
7984	Western Warm Temperate Row Crop	Agriculture
7985	Western Warm Temperate Close Grown Crop	Agriculture
7986	Western Warm Temperate Fallow/Idle Cropland	Agriculture
7988	Western Warm Temperate Wheat	Agriculture
7990	Eastern Warm Temperate Orchard	Agriculture
7991	Eastern Warm Temperate Vineyard	Agriculture
7992	Eastern Warm Temperate Bush fruit and berries	Agriculture
7993	Eastern Warm Temperate Row Crop - Close Grown Crop	Agriculture
7994	Eastern Warm Temperate Row Crop	Agriculture
7995	Eastern Warm Temperate Close Grown Crop	Agriculture
7996	Eastern Warm Temperate Fallow/Idle Cropland	Agriculture
7998	Eastern Warm Temperate Wheat	Agriculture

Table A-9. LANDFIRE evt classes for the Low Quality and Urban agriculture habitat types.

LANDFIRE evt Class Value	LANDFIRE Name	Habitat Type
7913	Western Warm Temperate Urban Herbaceous	Urban/Developed Grassland
7918	Eastern Warm Temperate Urban Herbaceous	Urban/Developed Grassland
7929	Western Warm Temperate Developed Ruderal Grassland	Urban/Developed Grassland
7939	Eastern Warm Temperate Developed Ruderal Grassland	Urban/Developed Grassland

LANDFIRE evt Class Value	LANDFIRE Name	Habitat Type
7191	Recently Logged-Herb and Grass Cover	Low-Quality Grassland
7195	Recently Burned-Herb and Grass Cover	Low-Quality Grassland
7198	Recently Disturbed Other-Herb and Grass Cover	Low-Quality Grassland
9823	Southeastern Ruderal Grassland	Low-Quality Grassland
9825	Great Plains Comanchian Ruderal Grassland	Low-Quality Grassland

Table A-10. LANDFIRE evt classes for the Grassland habitat type*.

LANDFIRE evt Class Value	LANDFIRE Name	Habitat Type	Is it also Prairie?
7425	Florida Dry Prairie Grassland	Grassland	Yes
7429	West Gulf Coastal Plain Southern Calcareous Prairie	Grassland	Yes
7434	Texas-Louisiana Coastal Prairie	Grassland	Yes
7566	Florida Dry Prairie Shrubland	Grassland	Yes
9063	Central Florida Wet Prairie and Herbaceous Seep	Grassland	Yes
7426	Southern Atlantic Coastal Plain Dune and Maritime Grassland	Grassland	No
7431	Southwest Florida Dune and Coastal Grassland	Grassland	No
7435	East Gulf Coastal Plain Dune and Coastal Grassland	Grassland	No
7437	Texas Coast Dune and Coastal Grassland	Grassland	No
7438	Tamaulipan Savanna Grassland	Grassland	No
7578	East Gulf Coastal Plain Wet Savanna	Grassland	No
7987	Western Warm Temperate Pasture and Hayland	Grassland	No
7997	Eastern Warm Temperate Pasture and Hayland	Grassland	No
9270	Tamaulipan Saline Thornscrub	Grassland	No

*Note: classes 7425, 7566, and 9063 characterize vegetation in Florida that may occur in wetter locations (wet prairie and shrubland) (Beth Stys, personal communication). Therefore, the total area of “true” grasslands in Florida is slightly over-represented in the prototype Gulf-wide Blueprint.

Table A-11. LANDFIRE evt classes for the Tidal Marsh habitat type*.

LANDFIRE evt Class Value	LANDFIRE evt name	Habitat Type
7471	Southwest Florida Coastal Strand Shrubland	Tidal Marsh
7472	Southeast Florida Coastal Strand Shrubland	Tidal Marsh
7486	Texas Saline Coastal Prairie	Tidal Marsh
9094	Florida Big Bend Fresh and Oligohaline Tidal Marsh	Tidal Marsh
9095	Florida Big Bend Salt and Brackish Tidal Marsh	Tidal Marsh
9104	Gulf Coast Chenier Plain Fresh and Oligohaline Tidal Marsh	Tidal Marsh
9105	Gulf Coast Chenier Plain Salt and Brackish Tidal Marsh	Tidal Marsh
9136	Mississippi Delta Fresh and Oligohaline Tidal Marsh	Tidal Marsh

LANDFIRE evt Class Value	LANDFIRE evt name	Habitat Type
9137	Mississippi Delta Salt and Brackish Tidal Marsh	Tidal Marsh
9142	Mississippi Sound Fresh and Oligohaline Tidal Marsh	Tidal Marsh
9143	Mississippi Sound Salt and Brackish Tidal Marsh	Tidal Marsh
9228	Southeastern Coastal Plain Interdunal Wetland	Tidal Marsh
9274	Texas Coast Fresh and Oligohaline Tidal Marsh	Tidal Marsh
9275	Texas Coast Salt and Brackish Tidal Marsh	Tidal Marsh
9604	Gulf Coast Chenier Plain Fresh and Oligohaline Tidal Marsh Shrubland	Tidal Marsh
9605	Gulf Coast Chenier Plain Salt and Brackish Tidal Marsh Shrubland	Tidal Marsh
9774	Texas Coast Fresh and Oligohaline Tidal Marsh Shrubland	Tidal Marsh
9775	Texas Coast Salt and Brackish Tidal Marsh Shrubland	Tidal Marsh

*Note: classes 7471 and 7472 were included as Tidal Marsh due to poor distinction and separation of beach, bare sand, dune vegetation, and marsh vegetation mapped in the LANDFIRE evt dataset. These classes were included in the Tidal Marsh habitat type due to the saline influence of sea spray for these coastal vegetation types.

Table A-12. LANDFIRE evt classes used to map the Low Quality and Urban/Developed Unforested Freshwater Wetland habitat type.

LANDFIRE evt Class Value	LANDFIRE evt name	Habitat Type
7949	Western Warm Temperate Developed Ruderal Herbaceous Wetland	Urban/Developed Unforested Freshwater Wetland
7954	Eastern Cool Temperate Developed Ruderal Herbaceous Wetland	Urban/Developed Unforested Freshwater Wetland
7959	Eastern Warm Temperate Developed Ruderal Herbaceous Wetland	Urban/Developed Unforested Freshwater Wetland
7989	Western Warm Temperate Aquaculture	Low-Quality Unforested Freshwater Wetland
7999	Eastern Warm Temperate Aquaculture	Low-Quality Unforested Freshwater Wetland

Table A-13. LANDFIRE evt classes for the Unforested Freshwater Wetland habitat type. Note: for this habitat type, ruderal wet meadow and marsh is included as habitat (however, this class still excludes developed ruderal classes).

LANDFIRE evt Class Value	LANDFIRE evt name	Habitat Type
7475	Tamaulipan Floodplain Herbaceous	Unforested Freshwater Wetland
7483	South Florida Everglades Sawgrass Marsh	Unforested Freshwater Wetland
7487	Texas-Louisiana Coastal Prairie Pondshore	Unforested Freshwater Wetland
7489	Floridian Highlands Freshwater Marsh	Unforested Freshwater Wetland
7514	Central Florida Herbaceous Pondshore	Unforested Freshwater Wetland
7515	Southern Coastal Plain Herbaceous Seep and Bog	Unforested Freshwater Wetland
7573	Tamaulipan Riparian Herbaceous	Unforested Freshwater Wetland
9098	Florida River Floodplain Marsh	Unforested Freshwater Wetland

LANDFIRE evt Class Value	LANDFIRE evt name	Habitat Type
9222	South Florida Slough Gator Hole and Willow Head Herbaceous	Unforested Freshwater Wetland
9324	Southeastern Ruderal Wet Meadow & Marsh	Unforested Freshwater Wetland
9542	Atlantic Coastal Plain Blackwater Stream Floodplain Herbaceous	Unforested Freshwater Wetland
9570	Central Texas Coastal Prairie Riparian Herbaceous	Unforested Freshwater Wetland
9571	Central Texas Coastal Prairie River Floodplain Herbaceous	Unforested Freshwater Wetland
9583	East Gulf Coastal Plain Large River Floodplain Herbaceous	Unforested Freshwater Wetland
9586	East Gulf Coastal Plain Small Stream and River Floodplain Herbaceous	Unforested Freshwater Wetland
9641	Mississippi River High Floodplain (Bottomland) Herbaceous	Unforested Freshwater Wetland
9642	Mississippi River Low Floodplain (Bottomland) Herbaceous	Unforested Freshwater Wetland
9732	Southeastern Great Plains Floodplain Herbaceous	Unforested Freshwater Wetland
9733	Southeastern Great Plains Riparian Herbaceous	Unforested Freshwater Wetland
9743	Southern Atlantic Coastal Plain Large River Floodplain Herbaceous	Unforested Freshwater Wetland
9783	West Gulf Coastal Plain Large River Floodplain Herbaceous	Unforested Freshwater Wetland
9785	West Gulf Coastal Plain Small Stream and River Herbaceous	Unforested Freshwater Wetland
9994	West Gulf Coastal Plain Herbaceous Seep and Bog	Unforested Freshwater Wetland

Table A-14. LANDFIRE evt classes for the Mainland and Barrier Island Beach habitat type.

LANDFIRE evt Class Value	LANDFIRE evt name	Habitat Type
7500	South Texas Salt and Brackish Tidal Flat	Beach and Dune
9097	Florida Panhandle Beach Vegetation	Beach and Dune
9103	Gulf Coast Chenier Plain Beach	Beach and Dune
9122	Louisiana Beach	Beach and Dune
9221	South Florida Shell Hash Beach	Beach and Dune
9226	Southeast Florida Beach	Beach and Dune
9240	Southern Atlantic Coastal Plain Florida Beach	Beach and Dune
9244	Southern Atlantic Coastal Plain Sea Island Beach	Beach and Dune
9262	Southwest Florida Beach	Beach and Dune
9273	Texas Coast Beach	Beach and Dune

Table A-15. LANDFIRE evt classes for ‘Other’ habitat type. These are mapped and included in natural habitat in the Gulf Wide Blueprint, but not evaluated for condition.

LANDFIRE evt Class Value	LANDFIRE evt name	Habitat Type

9208	Panhandle Florida Limestone Glade	Glade
9227	Southeastern Coastal Plain Cliff	Bare Rock
9251	Southern Coastal Plain Sinkhole	Other
9290	Southeastern Great Plains Cliff	Bare Rock
7484	South Florida Wet Marl Prairie	Wet Prairie
7485	East Gulf Coastal Plain Wet Prairie	Wet Prairie

Table A-16. LANDFIRE evt classes for "All Forest" layer used in calculating %forest thresholds in condition assessments for forests (excludes urban/developed and low-quality forests, but includes tree plantations).

LANDFIRE evt Class Value	LANDFIRE evt name	Habitat Type
7336	Southwest Florida Maritime Hammock	Forested Wetland
7337	Southeast Florida Maritime Hammock	Forested Wetland
7380	East Gulf Coastal Plain Maritime Forest	Forested Wetland
7382	Southern Atlantic Coastal Plain Maritime Forest	Forested Wetland
7384	Mississippi Delta Maritime Forest	Forested Wetland
7445	South Florida Dwarf Cypress Savanna	Forested Wetland
7447	South Florida Cypress Dome	Forested Wetland
7452	Atlantic Coastal Plain Peatland Pocosin and Canebrake Woodland	Forested Wetland
7460	Southern Coastal Plain Nonriverine Cypress Dome	Forested Wetland
7461	Southern Coastal Plain Seepage Swamp and Baygall Woodland	Forested Wetland
7462	West Gulf Coastal Plain Seepage Swamp and Baygall	Forested Wetland
7467	Tamaulipan Floodplain Woodland	Forested Wetland
7468	Atlantic Coastal Plain Streamhead Seepage Swamp-Pocosin-Baygall Woodland	Forested Wetland
7474	Tamaulipan Floodplain Shrubland	Forested Wetland
7476	Tamaulipan Riparian Woodland	Forested Wetland
7501	Southern Atlantic Coastal Plain Nonriverine Swamp and Wet Hardwood Forest	Forested Wetland
7513	Lower Mississippi River Flatwoods	Forested Wetland
7562	Tamaulipan Riparian Shrubland	Forested Wetland
7571	Southern Coastal Plain Seepage Swamp and Baygall Shrubland	Forested Wetland
9041	Atlantic Coastal Plain Blackwater Stream Floodplain Forest	Forested Wetland
9050	Atlantic Coastal Plain Small Blackwater River Floodplain Forest	Forested Wetland
9068	Central Texas Coastal Prairie Riparian Forest	Forested Wetland
9069	Central Texas Coastal Prairie River Floodplain Forest	Forested Wetland
9071	Columbia Bottomlands Forest and Woodland	Forested Wetland
9077	East Gulf Coastal Plain Depression Pondshore	Forested Wetland
9080	East Gulf Coastal Plain Freshwater Tidal Wooded Swamp	Forested Wetland
9082	East Gulf Coastal Plain Large River Floodplain Forest	Forested Wetland
9085	East Gulf Coastal Plain Small Stream and River Floodplain Forest	Forested Wetland

LANDFIRE evt Class Value	LANDFIRE evt name	Habitat Type
9138	Mississippi River Bottomland Depression	Forested Wetland
9139	Mississippi River High Floodplain (Bottomland) Forest	Forested Wetland
9140	Mississippi River Low Floodplain (Bottomland) Forest	Forested Wetland
9141	Mississippi River Riparian Forest	Forested Wetland
9216	South Florida Bayhead Swamp	Forested Wetland
9218	South Florida Hydric Hammock	Forested Wetland
9220	South Florida Pond-apple/Popash Slough	Forested Wetland
9230	Southeastern Great Plains Floodplain Forest and Woodland	Forested Wetland
9231	Southeastern Great Plains Riparian Forest and Woodland	Forested Wetland
9239	Southern Atlantic Coastal Plain Depression Pondshore	Forested Wetland
9242	Southern Atlantic Coastal Plain Large River Floodplain Forest	Forested Wetland
9247	Southern Coastal Plain Blackwater River Floodplain Forest	Forested Wetland
9248	Southern Coastal Plain Hydric Hammock	Forested Wetland
9249	Southern Coastal Plain Nonriverine Basin Swamp	Forested Wetland
9266	Tamaulipan Closed Depression Wetland Woodland	Forested Wetland
9282	West Gulf Coastal Plain Large River Floodplain Forest	Forested Wetland
9283	West Gulf Coastal Plain Near-Coast Large River Swamp	Forested Wetland
9284	West Gulf Coastal Plain Small Stream and River Forest	Forested Wetland
9320	Southeastern Native Ruderal Flooded & Swamp Forest	Forested Wetland
9541	Atlantic Coastal Plain Blackwater Stream Floodplain Shrubland	Forested Wetland
9568	Central Texas Coastal Prairie Riparian Shrubland	Forested Wetland
9569	Central Texas Coastal Prairie River Floodplain Shrubland	Forested Wetland
9582	East Gulf Coastal Plain Large River Floodplain Shrubland	Forested Wetland
9585	East Gulf Coastal Plain Small Stream and River Floodplain Shrubland	Forested Wetland
9639	Mississippi River High Floodplain (Bottomland) Shrubland	Forested Wetland
9640	Mississippi River Low Floodplain (Bottomland) Shrubland	Forested Wetland
9722	South Florida Slough Gator Hole and Willow Head Woodland	Forested Wetland
9730	Southeastern Great Plains Floodplain Shrubland	Forested Wetland
9731	Southeastern Great Plains Riparian Shrubland	Forested Wetland
9742	Southern Atlantic Coastal Plain Large River Floodplain Shrubland	Forested Wetland
9766	Tamaulipan Closed Depression Wetland Shrubland	Forested Wetland
9782	West Gulf Coastal Plain Large River Floodplain Shrubland	Forested Wetland
9784	West Gulf Coastal Plain Small Stream and River Shrubland	Forested Wetland
9993	West Gulf Coastal Plain Flatwoods Pond	Forested Wetland
7357	Southern Coastal Plain Mesic Slope Forest	Mixed Forest
7565	Florida Peninsula Inland Scrub Woodland	Mixed Forest
7585	West Gulf Coastal Plain Pine-Hardwood Forest	Mixed Forest
7587	West Gulf Coastal Plain Sandhill Oak and Shortleaf Pine Forest and Woodland	Mixed Forest

LANDFIRE evt Class Value	LANDFIRE evt name	Habitat Type
7589	East Gulf Coastal Plain Southern Loblolly-Hardwood Flatwoods	Mixed Forest
7590	West Gulf Coastal Plain Hardwood Flatwoods	Mixed Forest
7591	West Gulf Coastal Plain Pine-Hardwood Flatwoods	Mixed Forest
9250	Southern Coastal Plain Oak Dome and Hammock	Mixed Forest
9321	Southeastern Native Ruderal Forest	Mixed Forest
7371	West Gulf Coastal Plain Pine Forest	Mixed Forest
7446	South Florida Pine Flatwoods	Pine - Flatwoods
7449	Central Atlantic Coastal Plain Wet Longleaf Pine Savanna and Flatwoods	Pine - Flatwoods
7450	Southern Atlantic Coastal Plain Wet Pine Savanna and Flatwoods	Pine - Flatwoods
7451	West Gulf Coastal Plain Wet Longleaf Pine Savanna and Flatwoods	Pine - Flatwoods
7453	Central Florida Pine Flatwoods	Pine - Flatwoods
7454	East Gulf Coastal Plain Near-Coast Pine Flatwoods	Pine - Flatwoods
7458	West Gulf Coastal Plain Pine Flatwoods	Pine - Flatwoods
7545	East Gulf Coastal Plain Near-Coast Pine Wet Flatwoods	Pine - Flatwoods
7547	Central Florida Pine Wet Flatwoods	Pine - Flatwoods
7548	South Florida Pine Wet Flatwoods	Pine - Flatwoods
7378	West Gulf Coastal Plain Sandhill Shortleaf Pine Forest and Woodland	Pine - Shortleaf/Loblolly
7455	East Gulf Coastal Plain Southern Loblolly Flatwoods	Pine - Shortleaf/Loblolly
7347	Atlantic Coastal Plain Upland Longleaf Pine Woodland	Pine - Woodland
7349	East Gulf Coastal Plain Interior Upland Longleaf Pine Woodland	Pine - Woodland
7356	Florida Longleaf Pine Sandhill	Pine - Woodland
7360	South Florida Pine Rockland	Pine - Woodland
7193	Recently Logged-Tree Cover	Tree Plantation
9322	Southeastern North American Temperate Forest Plantation	Tree Plantation
7323	West Gulf Coastal Plain Mesic Hardwood Forest	Upland Hardwood Forest
7330	Southern Coastal Plain Dry Upland Hardwood Forest	Upland Hardwood Forest
7333	South Florida Hardwood Hammock	Upland Hardwood Forest
7335	Southern Atlantic Coastal Plain Dry and Dry-Mesic Oak Forest	Upland Hardwood Forest
7339	West Gulf Coastal Plain Chenier and Upper Texas Coastal Fringe Forest and Woodland	Upland Hardwood Forest
7343	Southern Atlantic Coastal Plain Mesic Hardwood Forest	Upland Hardwood Forest
7387	Florida Peninsula Inland Scrub Shrubland	Upland Hardwood Forest

LANDFIRE evt Class Value	LANDFIRE evt name	Habitat Type
7391	Tamaulipan Mesquite Upland Woodland	Upland Hardwood Forest
7584	West Gulf Coastal Plain Hardwood Forest	Upland Hardwood Forest
7586	West Gulf Coastal Plain Sandhill Oak Forest and Woodland	Upland Hardwood Forest
7588	East Gulf Coastal Plain Southern Hardwood Flatwoods	Upland Hardwood Forest
7338	Central and South Texas Coastal Fringe Forest and Woodland	Upland Hardwood Woodland
7381	Lower Mississippi River Dune Woodland and Forest	Upland Hardwood Woodland
7390	Tamaulipan Mixed Deciduous Thornscrub	Upland Hardwood Woodland
7392	Tamaulipan Calcareous Thornscrub	Upland Hardwood Woodland
7506	West Gulf Coastal Plain Nonriverine Wet Hardwood Flatwoods	Upland Hardwood Woodland
7519	East-Central Texas Plains Post Oak Savanna and Woodland	Upland Hardwood Woodland
7560	Tamaulipan Mesquite Upland Scrub	Upland Hardwood Woodland

APPENDIX A

A.2 HABITAT CONDITION INDICATOR: CONDITION METRICS AND GIS PROCESSES

This appendix provides detail on the technical geospatial mapping steps used to calculate habitat condition for Habitat Condition Indicator layer for the Southeast Conservation Adaptation Strategy (SECAS) prototype Gulf-wide Blueprint. The inclusion of detailed methodology facilitates transparent communication of technical components while also streamlining potential future refinement and adaptation.

This assessment is based land cover data from the national 2020 LANDFIRE existing vegetation type (evt) dataset. See Appendix A.1 for more detail on which LANDFIRE evt classes characterize each habitat type. It is acknowledged that other highly developed sub-regional SECAS Blueprints that rely on detailed land cover maps and other ground-truthed information sources (e.g., the Florida Blueprint, the Middle Southeast Blueprint) will reflect more accurate habitat distributions. The methods used here to map and evaluate habitats using only nation-wide data (except mangrove, beaches, and grassland prairie) provides a regional snapshot of habitat quality across the prototype Gulf-wide Blueprint domain with the expectation that site-level planning will rely on more detailed datasets and local information.

The methodology of this habitat condition assessment was based on the framework developed for the Middle Southeast Blueprint V3.0 (Middle Southeast Blueprint, 2020). In some instances, modifications to the original assessment methodology were required to facilitate application of this analysis across the project area. The output of the habitat condition assessment outlined here is a single map, scaled to 30 x 30m (900 sq. meter) cells, formed by combining all individual terrestrial habitat condition index map layers (as well as open water and 'other' habitats not assessed for condition) into a unified spatial layer representing the Habitat Condition Indicator.

Standard Protocol

To remain consistent with methods developed for the Middle Southeast Blueprint V3.0, the prototype Gulf-wide Blueprint followed a standardized process of assessing a similar set of habitat condition "endpoints" reflecting desired ecosystem state for each terrestrial habitat type. A habitat condition score, ranging from 1-14, was assigned to each 30 x 30 cell based on the scoring framework below:

1) Low quality habitat: 1 point (not assessed further)
2) Urban/developed habitat: 2 points (not assessed further)
3) Targeted ecological system (habitat type) is present: 3 points (baseline score for any recognized habitat type)
4) Patch metric: 3 or 6 points
5) Landscape-level configuration metric: 3 or 6 points
6) Site level endpoint (e.g., basal area for forested systems): 1 point
7) Site level endpoint (e.g., % overstory canopy cover for forested systems): 1 point

Based on this habitat condition assessment scoring framework, the final Habitat Condition Indicator spatial layer assigns each natural land cover cells a score between 1 and 14. Sores of 9-14 indicates high quality habitat ideal for conservation and areas scoring between 3 and 9 have the potential for restoration. Areas scoring below 3 points are considered low quality habitats, however it is acknowledged that some of these areas may still be important for use by vulnerable species and are therefore retained in the overall habitat map.

Each habitat has unique qualifiers of the scoring framework based on habitat-specific considerations. Subject matter experts and SECAS Southeast Conservation Blueprint developers from the Gulf of Mexico region were consulted in determining the development of some habitat assessment metrics (i.e., mangroves, tidal marsh, unforested freshwater wetlands). All conditions evaluated for each habitat type are summarized in Figure A-17.

Table A-17. Table summarizing habitat condition assessment metrics by habitat type for the Habitat Condition Indicator. *Indicates low quality habitat (scored as 2 pts) and urban/developed habitat (scored as 1 pt) is associated with the defined habitat type.

Gulf-wide Broadly Defined Habitat Type	Habitat Sub-Type	Habitat Exists	Landscape Condition 1	Landscape Condition 2	Site Condition 1	Site Condition 2
Forest	Mixed Forest*	3 pts	500 acres patch size (3 pts)	70% forested in a 10km radius (6 pts)	50-90 sq. ft/acre basal area (1 pt)	50-100% canopy cover (1 pt)
	Pine: flatwoods, woodland, mixed	3 pts	600 acres patch size of a variety of pine types – including plantations (6 pts)	<3 km to large patch (applies to patches defined above as >600 acres) – including plantations (3 pts)	Longleaf pine woodlands: 10-90 sq. ft/acre basal area (1 pt) Longleaf pine flatwoods: 15-90 sq. ft/acre basal area (1 pt) Shortleaf/loblolly pine woodland: 20-100 sq. ft/acre basal area (1 pt)	Pine (longleaf): 15-75% canopy cover (1 pt) Pine (loblolly): 15-85% canopy cover (1 pt)
	Upland Hardwood: forest, woodland	3 pts	3000 acres patch size (3 pts)	70% forested (any type of forest) in a 10km radius (6 pts)	Upland hardwood forest: 80-100 sq. ft/acre basal area AND proportion of oak hickory >70% (1 pt) Upland hardwood woodland: 30-80 sq. ft/acre basal area AND proportion of oak-hickory >90% (1 pt)	Upland hardwood forest: >80% canopy cover (1 pt) Upland hardwood woodland: 20-80% canopy cover (1 pt)
	Forested Wetlands*	3 pts	2500 ha patch size (6 pts)	70% forest in 10,000 acre landscape (3 pts)	60-80 sq. ft/acre basal area (1 pt)	60-90% canopy cover (1 pt)
	Estuarine Intertidal Forest (Mangrove)	3 pts	>75% natural habitat within 100m buffer of mangrove + tidal marsh landscape patches greater than 250 acres (6 pts)		>1km from medium-high intensity urban areas (3 pts)	>100m from nearest road (2 pts)

Gulf-wide Broadly Defined Habitat Type	Habitat Sub-Type	Habitat Exists	Landscape Condition 1	Landscape Condition 2	Site Condition 1	Site Condition 2
Grassland*		3 pts	Grassland is also prairie – presence of warm season native grasses and forbs (6 pts)	Patch (general grass, prairie, or mix of both) > 100 acres (3 pts)	Burned at least once during the period 2006-2015 (1 pt)	Vegetation height >1 m (1 pt)
Unforested Freshwater Wetlands*		3 pts	<10% impervious surface (HUC12 scale) (3 pts)	Within 500 meters of a protected area occurrence (6 pts)	Burned at least once during the period 2006-2015 (1 pt)	>100m from nearest road (1 pt)
Estuarine Tidal Marsh		3 pts	Above average and far above average resilience score (TNC Resilient Coastal Sites) (6 pts)	Not in a 303(d) listed EPA impaired watershed (3 pts)	Fragmentation: ≤0.25 Unvegetated to vegetated (UVVR) wetland ratio (2014-2018) (1 pt)	<10% impervious surface (HUC12 scale) (1 pt)
Beaches and Unconsolidated Shore	Barrier Island Beach Mainland Beach	3 pts	>250 acres patch size (6 pts)	Barrier Island: <25% developed land cover in a 5km radius (3 pts) Mainland Beach: >3km from high intensity developed areas (3 pts)	Engineered shorelines condition: Is not a sensitive area (1 pt)	Shoreline change: >300m away from areas characterized as likely to experience significant (> 2 m/year change) long term (100+ years) shoreline loss (1 pt)
Agriculture		1 pt				
"Other" Habitat		*3 pts, mapped only*				
Open water (fresh and estuarine)		*3 pts, mapped only*				

Excluded Land Cover Types

Some LANDFIRE evt classes were not included in the overall habitat map (Table A-18). These classes are not considered viable potential habitat (e.g., roads and developed areas).

Table A-18. LANDFIRE evt classes omitted from defining habitat classes for the prototype Gulf-wide Blueprint.

LANDFIRE evt class	Class Name
7296	Developed-Low Intensity
7297	Developed-Medium Intensity
7298	Developed-High Intensity
7299	Developed-Roads
7295	Quarries-Strip Mines-Gravel Pits-Well and Wind Pads

Prototype Gulf-wide Blueprint Habitat Condition Assessments

Habitat Group: Forests

1. *Habitat Type: Intertidal Forest (Mangrove)*

Mapping mangroves in the Gulf of Mexico has traditionally covered only the southern part of Florida. However, the black mangrove (*Avicennia germinans*) can also be found in the northern Gulf of Mexico. Although one of the objectives of this project was to use only region-wide datasets, the LANDFIRE evt does not include mangrove extent in the northern Gulf of Mexico. Therefore, in order to map and assess the condition of this habitat type, multiple datasets were leveraged, mosaiced together, and extracted from datasets used in the subsequent habitat assessments. For pixels that overlap in vegetation classification, mangrove class was prioritized because LANDFIRE evt does not accurately map mangroves in the northern Gulf of Mexico. Evaluation metrics for the mangrove habitat type are given in Table A-19.

Table A-19. Condition evaluation metrics for the Intertidal Forest (Mangrove) habitat type.

Desired Condition	Metric	CI Score
Is desired habitat	Desired habitat type is present	3 pts
Habitat isolation	>1km from medium-high intensity urban areas	3 pts
Landscape configuration	>75% natural habitat within 100m buffer of mangrove + tidal marsh landscape patches greater than 250 acres	6 pts
Resilience	>100m from nearest road	2 pt

The occurrence of the Intertidal Forest (Mangrove) habitat type within the project area is shown in Figure A-1 and Figure A-2, and the resulting habitat condition map is given in Figure A-3.

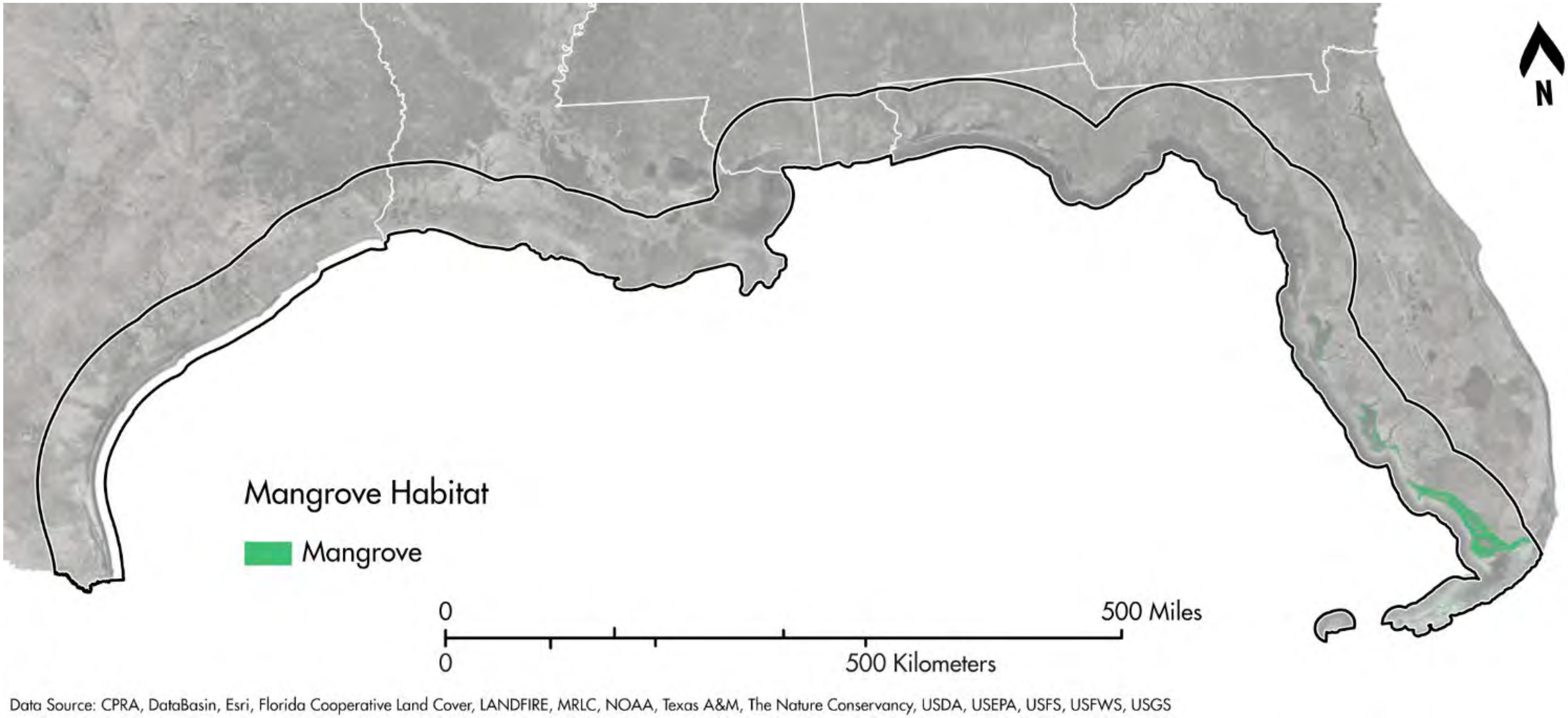


Figure A-1. Presence of Intertidal Forest (mangrove) habitat type in the Gulf-wide project area.

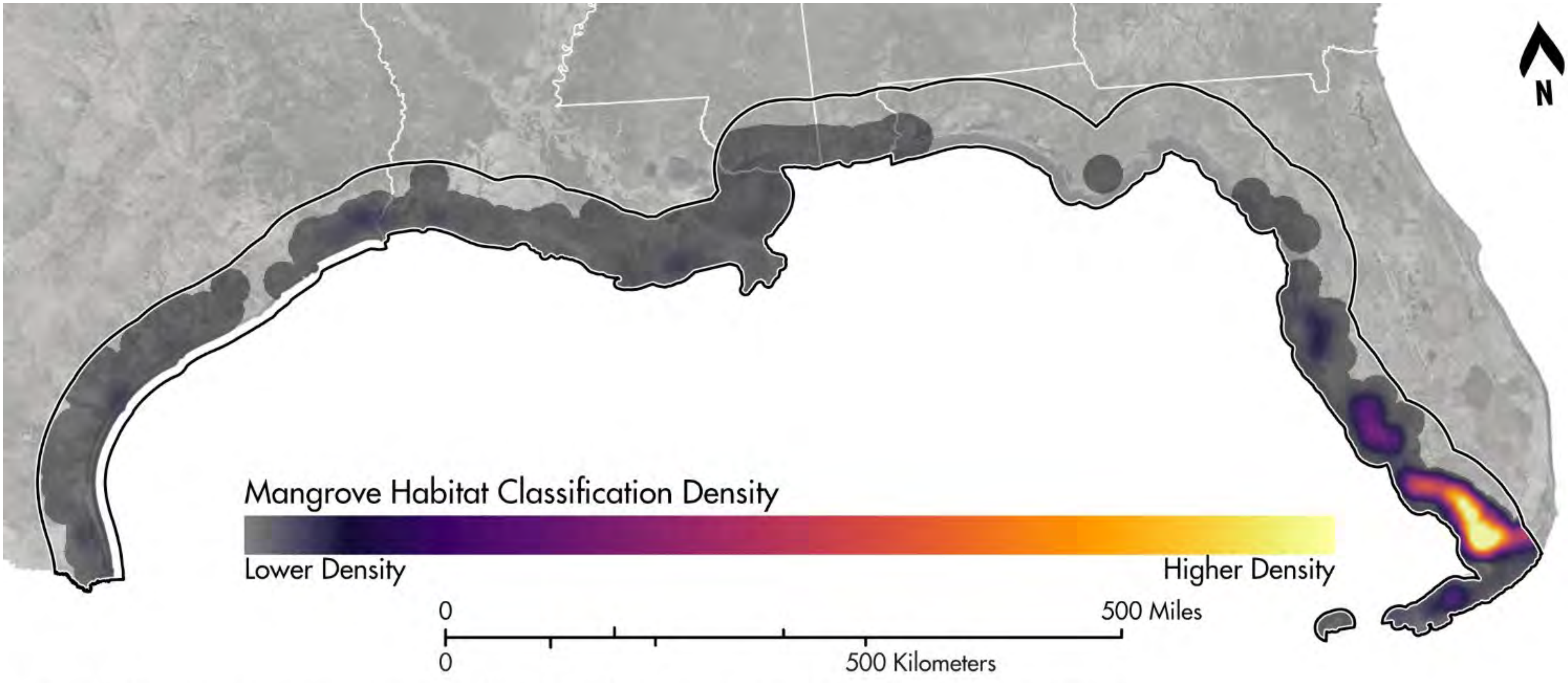
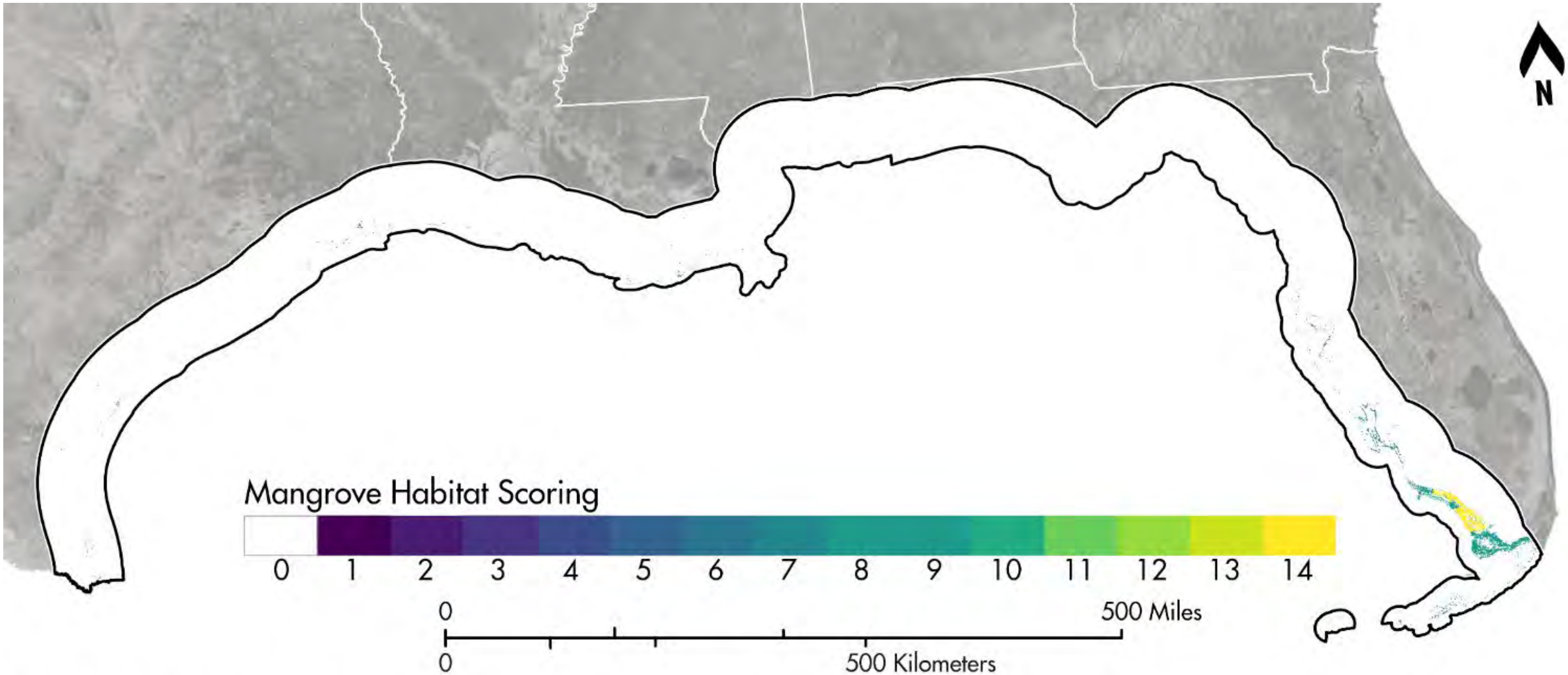


Figure A-2. Density map highlighting areas with highest concentrations of 30 m Intertidal Forest (mangrove) habitat type pixels in the Gulf-wide project area.



Data Source: CPRA, DataBasin, Esri, Florida Cooperative Land Cover, LANDFIRE, MRLC, NOAA, Texas A&M, The Nature Conservancy, USDA, USEPA, USFS, USFWS, USGS

Figure A-3. Result of habitat condition assessment for the Intertidal Forest (mangrove) habitat type.

Detailed GIS Protocol:

Step 1) Create the mangrove desired habitat dataset.

- 1A: Combine the following datasets:
    - Louisiana - Two data sources were combined to generate the spatial extent of mangroves in Louisiana: habitat mapping from the Barrier Island Comprehensive Monitoring (BICM) program and Land Use Land Cover (LULC) data developed for the 2023 LA Coastal Master Plan. Dataset derived from personal communication.
        - Download BICM habitat mapping for barrier islands. Extract the "mangrove" class and resample to 30 m LANDFIRE evt grid resolution. Reclassify such that pixels classified as mangroves are assigned a value of **1**, all others **0**.
        - The 2023 LA Coastal Master Plan LULC dataset is not publicly available. When made publicly available it can be accessed here. Note: LULC data utilized in the 2017 LA Coastal Master Plan is available for public download. Extract the "AVGE" class and resample to 30 m LF evt grid resolution. Reclassify such that pixels classified as mangroves are assigned a value of **1**, all others **0**.
        - Using Cell Statistics join the output from both Louisiana data sources to create a seamless mangrove surface statewide. Reclassify such that pixels classified as mangroves are assigned a value of **1**, all others **0**.
    - Texas - Data created by Texas A&M University researchers was used to generate the spatial extent of mangroves in Texas. Dataset was derived from personal communication.
        - Reclassify such that pixels classified as mangroves are assigned a value of **1**, all others **0**.
    - Florida: Cooperative Land Cover (CLC) v3.4 data was used to generate the spatial extent of mangroves in Florida.
        - Download the CLC v3.4 dataset and extract the "mangrove swamp" and "scrub mangrove" features through the "STATE_NAMES" field and resample to 30 m LANDFIRE evt grid resolution.
        - Reclassify such that pixels classified as mangroves are assigned a value of **1**, all others **0**.
- 1B: Select Caribbean Coastal Mangrove and Caribbean Estuary Mangrove vegetation types out of the LANDFIRE evt dataset (7861 and 7867); clip layer to the spatial extent of the project. Reclassify pixels to produce a binary layer such that if a pixel is mangrove, it is assigned a value of **1**, all others **0**.
- 1C: Sum all statewide datasets and the LF data using cell statistics and set the extent to the project domain. Ensure that the output is snapped to the LANDFIRE evt grid.
- 1D: Reclassify pixels for mangrove desired habitat.

- OUTPUT: Seamless mangrove cover dataset where pixels classified as mangrove are assigned a value of **3**, all others **0**.

Step 2) Create the high intensity urban mask by extracting the LANDFIRE evt classes: #7297 (Developed-Medium Intensity), and #7298 (Developed-High Intensity).

- 2A: Convert the raster extract to a polygon feature class.
- 2B: Create a 1 km buffer around all polygons/pixels classified as medium- and high-intensity developed. Note: Euclidean buffers are created automatically for features with a projected coordinate system (as opposed to a geographic coordinate system) by selecting the planar method in the buffer geoprocessing tool dialogue.
- 2C: Rasterize the polygon buffers at 30 m LANDFIRE evt grid resolution across the extent of the project domain. Ensure that the output is snapped to the LANDFIRE evt grid. Reclassify such that pixels within the buffer (including the developed areas) are assigned a value of **1**, all others **0**.

Step 3) Assess habitat isolation endpoint.

- 3A: Overlay the mangrove desired habitat output from Step 1C with the buffered medium and high intensity developed raster from 2C.
- 3B: Reclass pixels for the mangrove habitat isolation endpoint. Reclassify such that any mangrove pixels overlapping with the 1km buffer of medium and high intensity developed areas are given a value of 0, all others (pixels of mangrove outside of the 1 km buffer) are given a value of 3.
    - OUTPUT: Pixels that are mangrove desired habitat and that lay outside the buffered developed areas assigned a value of **3**, all others **0**.

Step 4) Assess the Landscape Configuration endpoint: >75% natural habitat within 100 m buffer of mangrove + tidal marsh landscape patches greater than 250 acres

- 4A: Extract the Tidal Marsh habitat classes from the LANDFIRE evt dataset (see section below on Tidal Marsh). Reclassify such that tidal marsh areas reflect a value of **1**, all others **0**.
- 4B: Reclassify mangrove output from Step 1C such that mangrove pixels are classed a value of **1**, all others **NODATA.**
- 4C: Polygonise the single value mangrove raster and create a 500 m buffer around each mangrove patch, then rasterize the buffer output based on the value field.
- 4C: Identify marsh that falls within the buffer. Using Cell Statistics, combine the buffered mangrove raster with the tidal marsh binary layer, retaining the tidal marsh pixels that fall within the 500 m buffer around mangrove pixels and excluding all tidal marsh pixels that fall outside the buffer (e.g., buffer = 1, marsh = 2).
- 4D: Combine the mangrove desired habitat raster from Step 1C with the tidal marsh cells that fit the buffer criteria from Step 4C and reclassify the output to a single value.

- 4E: Run ‘Region Group’ on the output from Step 4D specifying 8 neighbors and the ‘within’ zone grouping method. Extract region groups (patches) greater than or equal to **250 acres in size (>1,124 pixel count)** and polygonise the patch extract.
- 4F: Buffer the polygon output from 4E by 100 m (i.e., mangrove polygons that fulfill the >250 acres criteria)
- 4G: Create the **Natural Habitat Mask**: Extract the existing vegetation classes from the LANDFIRE existing vegetation dataset (this includes classes used later as low-quality habitat, but not urban or developed habitat classes), see Appendix A.1. Combine this with the output from Step 1C and the Step 1H from Beaches and Unconsolidated Shore. Reclassify pixels such that any pixel reflecting a habitat class listed below is classified as **1**, all others **0**.
- 4H: Overlay buffered large mangrove polygons with the above **Natural Habitat Mask.** Calculate proportion of each buffered large mangrove polygon that is natural habitat using the Zonal Statistics as Table geoprocessing tool with the output statistic set to mean. Set the buffered mangrove polygons as input zones and binary natural landcover raster (0 = absent, 1 = natural landcover) as the value raster that zonal statistics are calculated against. Given that the value pixels all have the same size, the mean value will be the sum of all pixels with a value of 1 (natural landcover) divided by the total number of pixels (total zone) equaling percentage area.
- 4I: Join the table with polygon output from 4E and retain only the polygons that whose 100m buffer contains 75% or more natural landcover.
- 4J: Using the 30 m LANDFIRE grid, rasterize the Step 4I polygons matching the 75% criteria and reclassify so that pixel values fitting the natural habitat criteria are assigned a value of **6**, all others **0**.
    - OUTPUT: Layer where mangrove pixels located within large mangrove polygons (>250 acres) characterized by having >75% natural land cover within a 100 m buffer are given a value of **6**, all others **0**.

Step 5) Create the buffered road mask by extracting the LANDFIRE evt class #7299 (Developed-Roads).
- 5A: Convert the raster extract to a polygon feature class.
- 5B: Create a 100 m buffer around all polygons/pixels classified as developed roads.
- 5C: Rasterize the polygon buffers at the 30 m LANDFIRE evt grid resolution across the extent of the project domain. Ensure that the output is snapped to the LANDFIRE evt grid. Reclassify such that pixels within the buffer (including the developed roads) are assigned a value of **1**, all others **0**.

Step 6) Assess Resilience metric (>100 m from road)
- 6A: Overlay the mangrove desired habitat output from Step 1C the buffered developed roads raster from 5C.

- 6B: Reclass pixels for the mangrove resilience endpoint. Reclassify such that any mangrove pixels overlapping with the 100 m buffer of developed roads are given a value of 0, all others (pixels of mangrove outside of the 100 m buffer) are given a value of 2.
    - OUTPUT: Layer where mangrove desired habitat pixels that lay outside the developed roads buffer are assigned a value of **2**, all others **0**.

Step 7) Calculate the Condition using the output layers created above:

- 7A: Overlay all OUTPUT layers that have condition index values for each of the **4 endpoints.**
    - Output from Step 1
    - Output from Step 3B
    - Output from Step 4J
    - Output from step 6B
- Theoretically if a pixel fulfills ALL conditions, the value will be **14.**

Step 8) Develop final map for the Mangrove habitat class.

- 8A: Finalize the layer and check that condition indices are fully calculated.

2. *Habitat Type: Forested Wetlands*

The evaluation metrics for the Forested Wetland CI were directly carried over from the Middle Southeast Blueprint V2.0. Habitat condition metrics are listed below in Table A-20.

Table A-20. Condition evaluation metrics for the Forested Wetlands habitat type.

Desired Condition	Metric	CI Score
Is Urban/Developed Forested Wetland	Pixel is urban/developed wetland	1 pt
Is Low-Quality Forested Wetland	Pixel is low-quality forested wetland	2 pts
Is desired habitat	Desired habitat type is present	3 pts
Patch size	2500 ha	6 pts
Landscape configuration	70% forest in 10,000 acre landscape	3 pts
Basal area	60-80 sq. ft/acre	1 pt
Canopy cover	60-90%	1 pt

The occurrence of the Forested Wetland habitat type within the project area is shown in Figure A-4 and Figure A-5, and the resulting habitat condition map is given in Figure A-6.

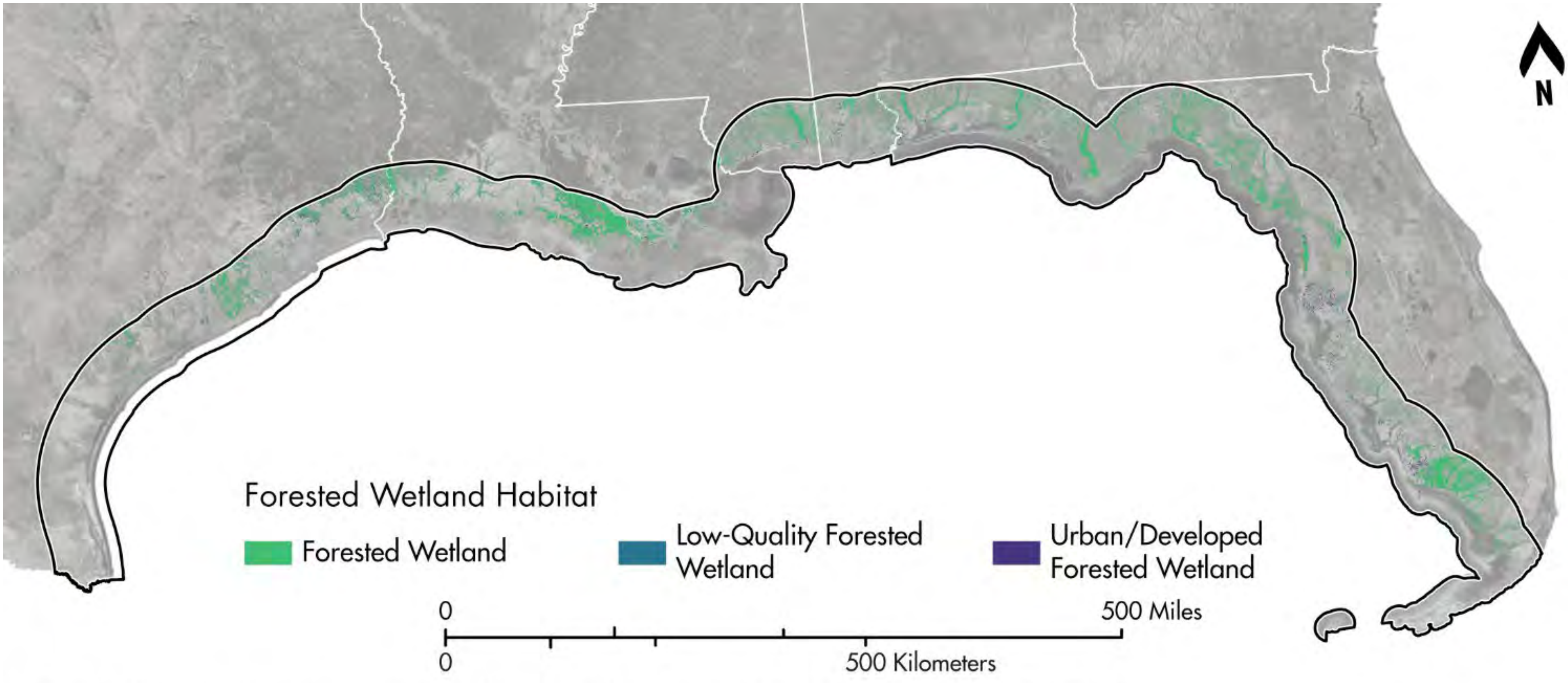


Figure A-4. Presence of the Forested Wetland habitat type in the Gulf-wide project area.

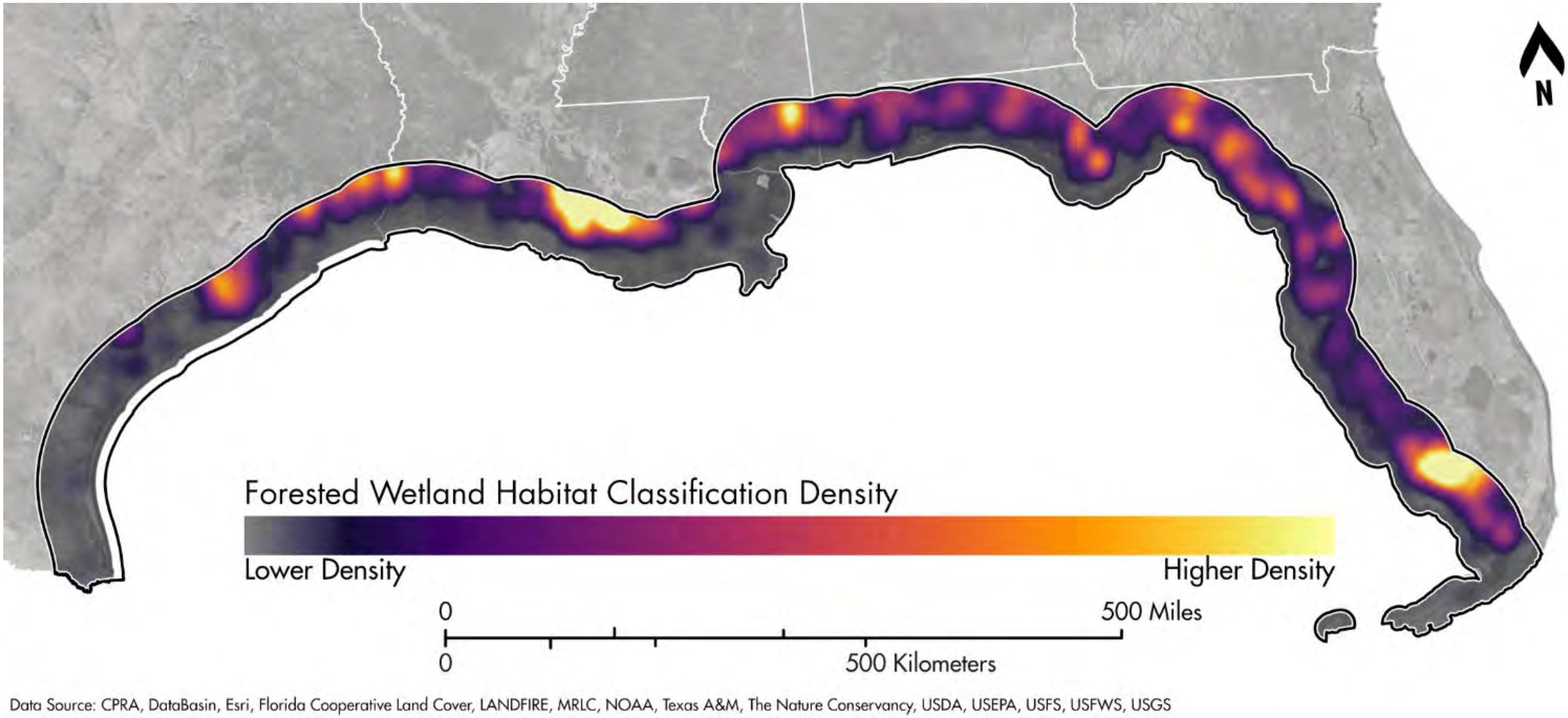
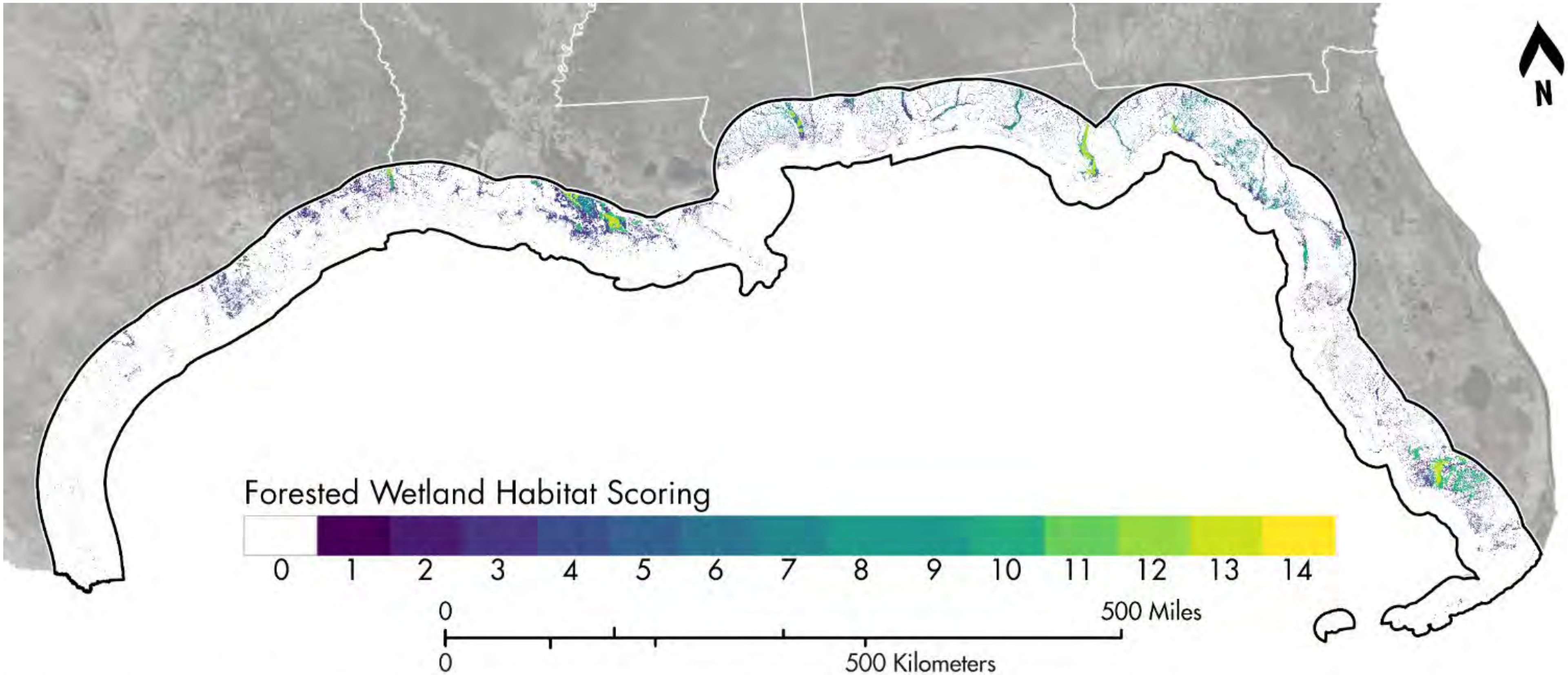


Figure A-5. Density map highlighting areas with highest concentrations of 30 m Forested Wetland habitat type pixels in the Gulf-wide project area.



Data Source: CPRA, DataBasin, Esri, Florida Cooperative Land Cover, LANDFIRE, MRLC, NOAA, Texas A&M, The Nature Conservancy, USDA, USEPA, USFS, USFWS, USGS

Figure A-6. Result of habitat condition assessment for the Forested Wetlands habitat type.

Detailed GIS Protocol:

Step 1) Extract out urban/developed forested wetland vegetation type classes from the project area and score them low

- 1A: Select Urban/Developed Wetland Forest vegetation types out of the LANDFIRE evt dataset using the classes listed in Appendix A.1; clip layer to the spatial extent of the project.
    - o Reclassify pixels to produce a binary layer such that if a pixel is Urban/Developed Forested Wetland, it is assigned a value of **1**, all others **0**.
- 1B: Select Low-Quality Wetland Forest vegetation types out of the LANDFIRE evt dataset using the classes listed below; clip layer to the spatial extent of the project.
    - o Reclassify pixels to produce a binary layer such that if a pixel is Low-Quality Forested Wetland, it is assigned a value of **2**, all others **0**.

Step 2) Develop the Forested Wetlands Mask

- 2A: Select all Forested Wetland veg classes out of the LANDFIRE evt dataset using all the classes listed in Appendix A.1 into an overall **Forested Wetlands mask**
- 2B: OUTPUT: A binary layer in which pixels that are classified as Forested Wetland are assigned a pixel value of **3**, all others **0**.

Step 3) Assess patch size endpoint

- 3A: Infer patch size by using pixel counts of groups. Using "Region Group", assess connectivity where pixels share common sides and values (number of neighbors = 4, within zone grouping).
- 3B: Create a new layer for **Forested Wetlands** that meets the threshold for patch size (2500 ha)
    - o Use the output from step 3 above (binary layer that just identifies Forested Wetlands, all other areas 0).
    - o (Reclassify on pixel count: 27,778 pixels = 2500 ha
        - ▪ This value was amended from the literature to be closer to 2500 ha. Originally, 27,788 pixels
    - o OUTPUT: reclassify pixels that satisfy that patch requirement for Forested Wetlands (2500 ha) with a value of **6**, , all others **0**.

Step 4) Calculate the landscape configuration endpoint for **Forested Wetland**

NOTE: All three forest types have the same requirement "70% forest" but differ in the spatial context (10,000 acres vs. within 10 km radius). For reference, a 10 km radius = about 77,631 acres (31,416 ha) and 10,000 acres = 4047 ha. This difference is because Forested Wetlands are associated with riparian zones and floodplains characterized by open land and agriculture, and therefore use a smaller local landscape.

- 4A: Create a **Total Forest mask**:

- Extract all classes of forest types (see Table A-16 for list of LANDFIRE evt classes) and combine with mangrove layer to create a **Total Forest mask** (note this does not include low-quality or urban forest classes)
- Assign a value of 1 to pixels described as "forest", all other pixels given a value of 0.

- 4B: Create circular windows
  - For **Forested Wetlands**: Create a circle window radius of 333pixels (10,000/30 = 10,000 meter radius described in pixels)
    - Use focal mean statistics to calculate % forest cover using the **Total Forest mask**
- 4C: OUTPUT: One layer where pixels with %cover forest values >0.7 were retained:
  - **Mixed Forest**: reclassify so that pixels meeting the required >0.7 condition were given a value of **3**, all others **0.**

Step 5) Calculate the site endpoint for Basal Area:

- 5A: Download the 'USFS Live tree species basal area of the contiguous United States (2000-2009) data product'[1].
  - This dataset maps vegetation phenology from MODIS imagery with FIA field data – resolution is 250 m scale for the entire US. Since this dataset represents BA of multiple species, calculate the sum total basal area across all species for each 250m pixel.
- 5B: Extract the basal area sum total surface to the study spatial domain and resample to 30 meters using the LANDFIRE evt grid.
- 5C: Create a binary layer (1 = condition met, 0 = condition not met) for the Forested Wetland habitat type by reclassify the pixels that satisfy the following condition:
  - Forested Wetland: basal area between 60-80 sq. ft/acre
- 5D: OUTPUT: a binary layer where **1** represents the basal area condition is fulfilled, all others **0**.

Step 6) Assess the % canopy endpoint:

- 6A: Download the 2016 NLCD USFS Tree Canopy analytical (CONUS) layer[2].
- 6B: Extract the tree canopy layer through to the project spatial extent and common projection.
- 6C: This will follow the same type of procedure listed in step 5 to create a binary layer where 1 indicates that the endpoint condition is met:
  - Forested Wetland: canopy cover between 60-90%

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[1] Wilson et al., 2013

[2] USDA Forest Service. 2019. NLCD 2016 Tree Canopy Cover (CONUS). Salt Lake City, UT.: U.S. Department of Agriculture.

- 6D: OUTPUT: binary layer where **__1__** represents the % canopy condition is fulfilled, all others **__0__**.

Step 7) Calculate the Condition using the output layers created above:

- 7A: Overlay all OUTPUT layers that have condition index values for each of the 5 endpoints *including* the Urban/Developed Forested Wetland layer and the Low Quality Forest Wetland layer.
    - Theoretically if a pixel fulfills ALL conditions the **pixel value is 14,** and Urban/Developed Forested Wetland pixels score **__1__** and Low-Quality Forested Wetlands score **__2__**.

Step 8: Develop final map for the Forested Wetlands habitat type

- 10A: Finalize the layer and check that condition indices are fully calculated
- 10B: Scale to the appropriate hex size – original documentation scaled each habitat output to 30x30 m cell sizes to facilitate combining all layers at the end into a final habitat map.

3. Habitat Type: Pine Habitats

The evaluation metrics for the Pine forest subtype CIs were based on methodology from the Middle Southeast Blueprint and are summarized below (Table A-21). Pine plantation landcover classes are included in the pine habitat assessment because pine plantations still serve as habitat for many birds although these lands are managed.

Table A-21. Condition evaluation metrics for the Pine habitat types.

Desired Condition	Forest Subtype	Metric	CI Score
Is desired habitat	- Pine: longleaf pine woodlands - Pine: longleaf pine flatwoods - Pine: shortleaf/loblolly pine woodland	Desired habitat type is present	3 pts
Patch Size	Pine (all types including plantations)	600 acres of a variety of pine types	6 pts
Landscape configuration	Pine (all types including plantations)	<3 km to large patch (applies to patches defined above as >600 acres)	3 pts
Basal area	- Pine: longleaf pine woodlands - Pine: longleaf pine flatwoods - Pine: shortleaf/loblolly pine woodland	- 10-90 sq. ft/acre - 15-90 sq. ft/acre - 20-100 sq. ft/acre	1 pt
Canopy cover	- Pine (longleaf) - Pine (loblolly)	- 15-75% - 15-85%	1 pt

The occurrence of the Pine habitat types within the project area is shown in Figure A-7 and Figure A-8, and the resulting habitat condition map is given in Figure A-9..

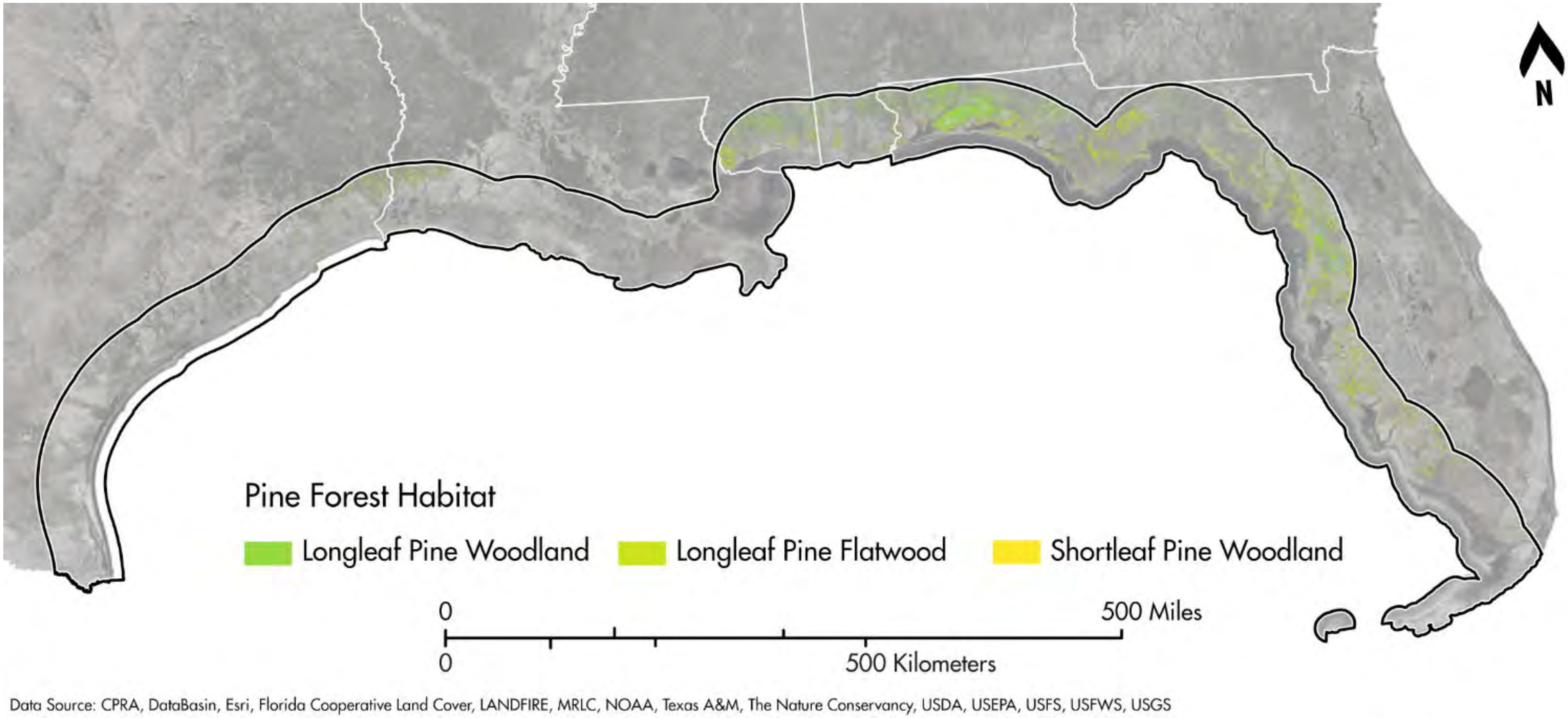
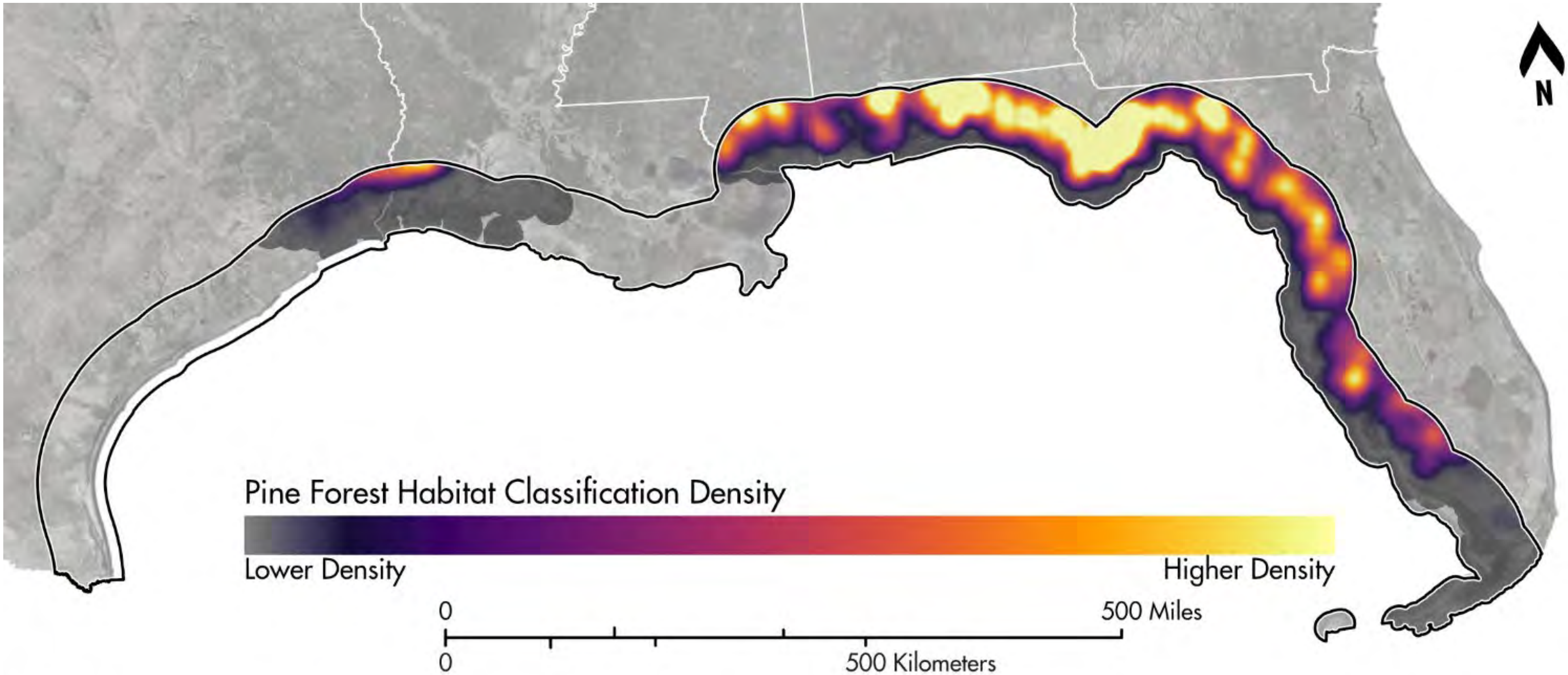
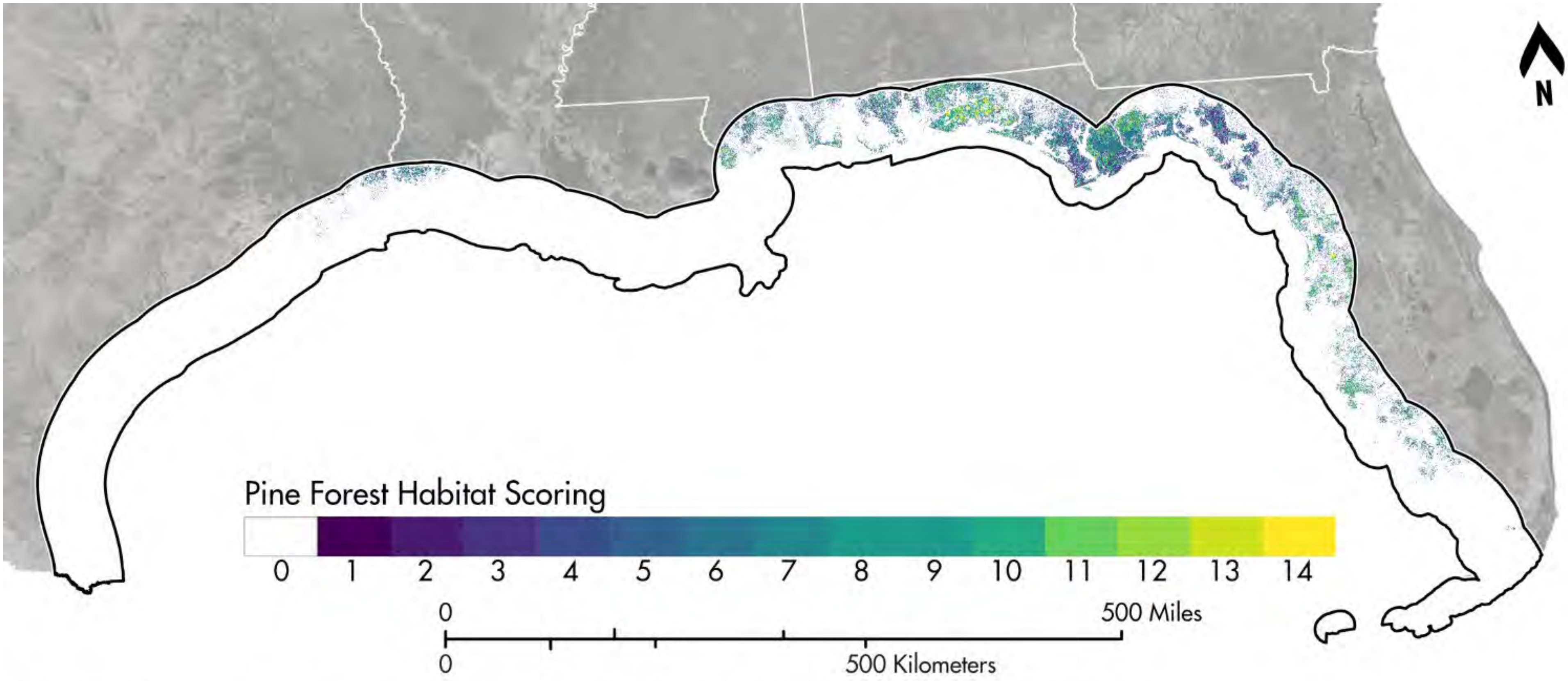


Figure A-7. Presence of the Pine habitat types in the Gulf-wide project area.



Data Source: CPRA, DataBasin, Esri, Florida Cooperative Land Cover, LANDFIRE, MRLC, NOAA, Texas A&M, The Nature Conservancy, USDA, USEPA, USFS, USFWS, USGS

Figure A-8. Density map highlighting areas with highest concentrations of 30 m Pine Forest habitat type pixels in the Gulf-wide project area.



Data Source: CPRA, DataBasin, Esri, Florida Cooperative Land Cover, LANDFIRE, MRLC, NOAA, Texas A&M, The Nature Conservancy, USDA, USEPA, USFS, USFWS, USGS

Figure A-9. Result of habitat condition assessment for the Pine habitat types.

Detailed GIS Protocol:

Step 1) Develop the Pine base mask

- 1A: Select all Pine vegetation types out of the LANDFIRE evt dataset using all the classes listed in Appendix A.1 into an overall **Pine mask**
- 1B: Subset the overall **Pine mask** for the individual pine types assessed here (3 types).
- 1C: OUTPUT: Create 3 binary layers, one for each pine habitat type. For each layer, pixels that are classified as the given habitat are assigned a pixel value of **3**, all others **0**.

Step 2) Assess patch size endpoint

- 2A: Infer patch size by using pixel counts of groups. Using "Region Group", assess connectivity where pixels share common sides and values (number of neighbors = 4, within zone grouping).
- 2B: Create a new layer from 2A for **Pine (all varieties together)** that meets the threshold for patch size (600 acres)
    - OUTPUT: reclassify pixels that satisfy the patch requirement for Pine (600 acres) with a value of **6**, all others **0**.

Step 3) Calculate the landscape configuration endpoint for **Pine habitats**

- Note: All pine habitat classes here share the same endpoint for landscape patch and configuration: 600 acre patch within 3km of another patch.
    - In addition, due to the fact that pine is generally mixed in other forest types and large areas of pure pine are scarce, the original Middle Southeast Blueprint V2.0 methodology included classes of managed forest. This analysis does **not** include those classes.
- 3A: Using the pine patch layer derived above (reflecting pixels within patches >600 acres) and the all pine types layer developed from prior step to do the following:
    - Identify all patches in the "all pine types" layer that are:
        - 1-4 pixels in group size (this is ~ a quarter acre to an acre) assigned configuration score if they were completely within the 3 km buffer of a large patch.
        - Patches of 5 pixels or more (but total patch size less than 600 acres/2698 pixels, Count >= 5 AND Count <= 2697) assigned configuration score if any part of the small patch intersected the 3km large patch buffer.
        - Patches greater than 600 acres (>=2698 pixels) assigned a configuration score only if they were completely within the buffer of another large patch.
    - With those selected, identify all pixels that lay within a 3 km buffer around all large pine patches
- 3B: OUTPUT: one layer for each pine type (longleaf flatwood, woodland, shortleaf/loblolly) where pixels are classified as **3** if they are within range of another patch

Step 4) Calculate the site endpoint for Basal Area:

- 4A: Download the 'USFS Live tree species basal area of the contiguous United States (2000-2009) data product' (Wilson et al., 2013).
    - This dataset maps vegetation phenology from MODIS imagery with FIA field data – resolution is 250 m scale for the entire U.S. Since this dataset represents BA of multiple species, calculate the sum total basal area across all species for each 250 m pixel.
- 4B: Extract the basal area sum total surface to the study spatial domain and resample to 30 m using the LANDFIRE evt grid.
- 4C: Create a binary layer (1 = condition met, 0 = condition not met) for the Forested Wetland habitat type by reclassify the pixels that satisfy the following condition:
    - Pine
        - Longleaf pine woodlands: 10-90 sq. ft/acre
        - Longleaf pine flatwoods: 15-90 sq. ft/acre
        - Shortleaf/loblolly pine woodland: 20-100 sq. ft/acre
- 4D: OUTPUT: a binary layer for each pine habitat type (a total of 3 layers) where **1** represents the basal area condition is fulfilled, all others **0**.

Step 5) Assess the % canopy endpoint:

- 5A: Download the 2016 NLCD USFS Tree Canopy analytical (CONUS) layer (USGS, 2019).
- 5B: Extract the tree canopy layer through to the project spatial extent and common projection.
- 5C: This will follow the same type of procedure listed in step 5 to create a binary layer where 1 indicates that the endpoint condition is met:
    - Pine (longleaf pine woodlands + flatwoods): 15-75%
    - Pine (loblolly): 15-85%
- 5D: OUTPUT: binary layer for each pine habitat type (a total of 3 layers) where **1** represents the % canopy condition is fulfilled, all others **0**.

Step 6) Calculate the Condition Index for each forest habitat type using the output layers created above:

- 6A: Overlay all pine habitat OUTPUT layers that have condition index values for each of the 5 endpoints
    - Theoretically if a pixel fulfills ALL conditions the **pixel value is 14**

Step 7) Develop final map for the Pine forest habitat type

- 7A: Finalize all pine forest habitat layers and check that condition indices are fully calculated – combine all on one figure using colors to indicate different pine habitat types

- 7B: Scale to the appropriate hex size – original documentation scaled each habitat output to 30x30 m cell sizes to facilitate combining all layers at the end into a final habitat map.

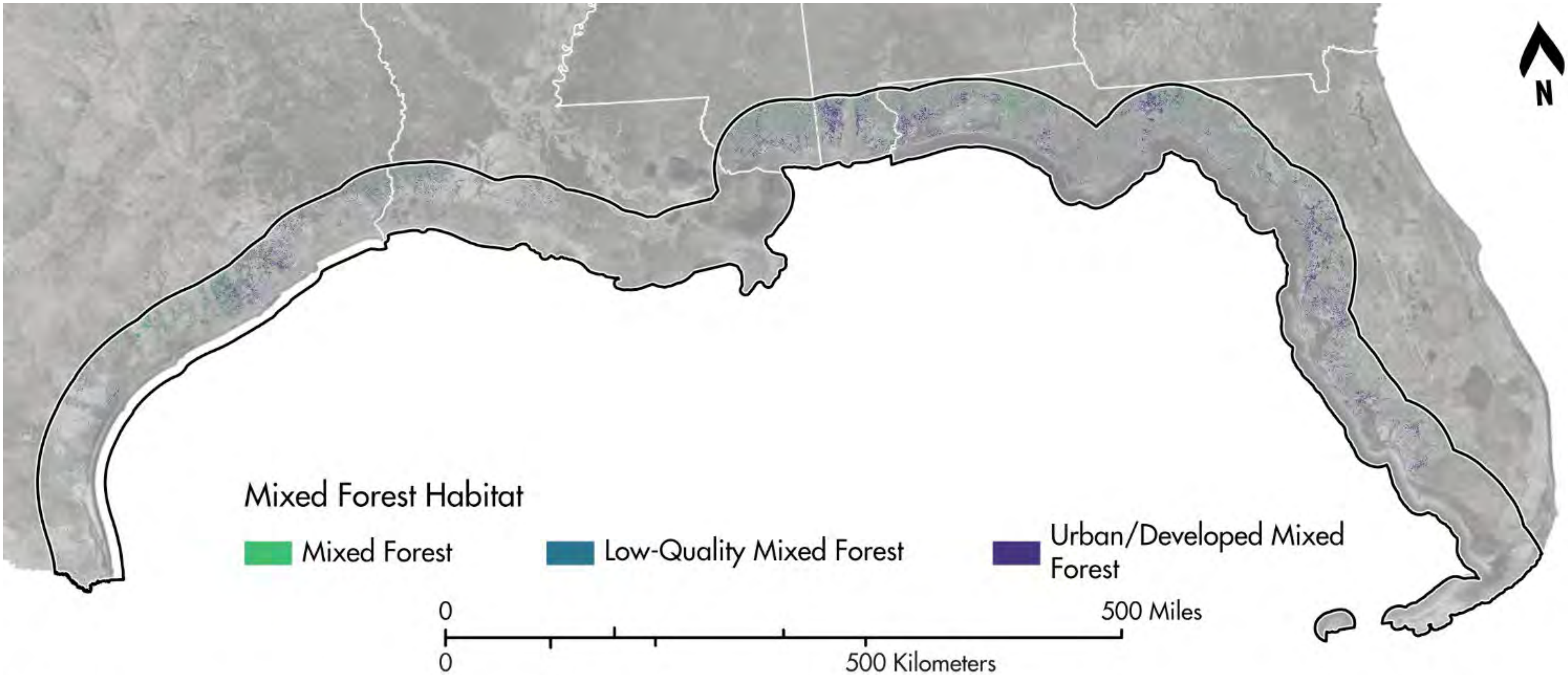
4. *Habitat* Type: Mixed Forest

The evaluation metrics for the Mixed Forest subtype CI was directly carried over from the Middle Southeast blueprint methodologies and are summarized in Table A-22.

Table A-22. Condition evaluation metrics for the Mixed Forest habitat type.

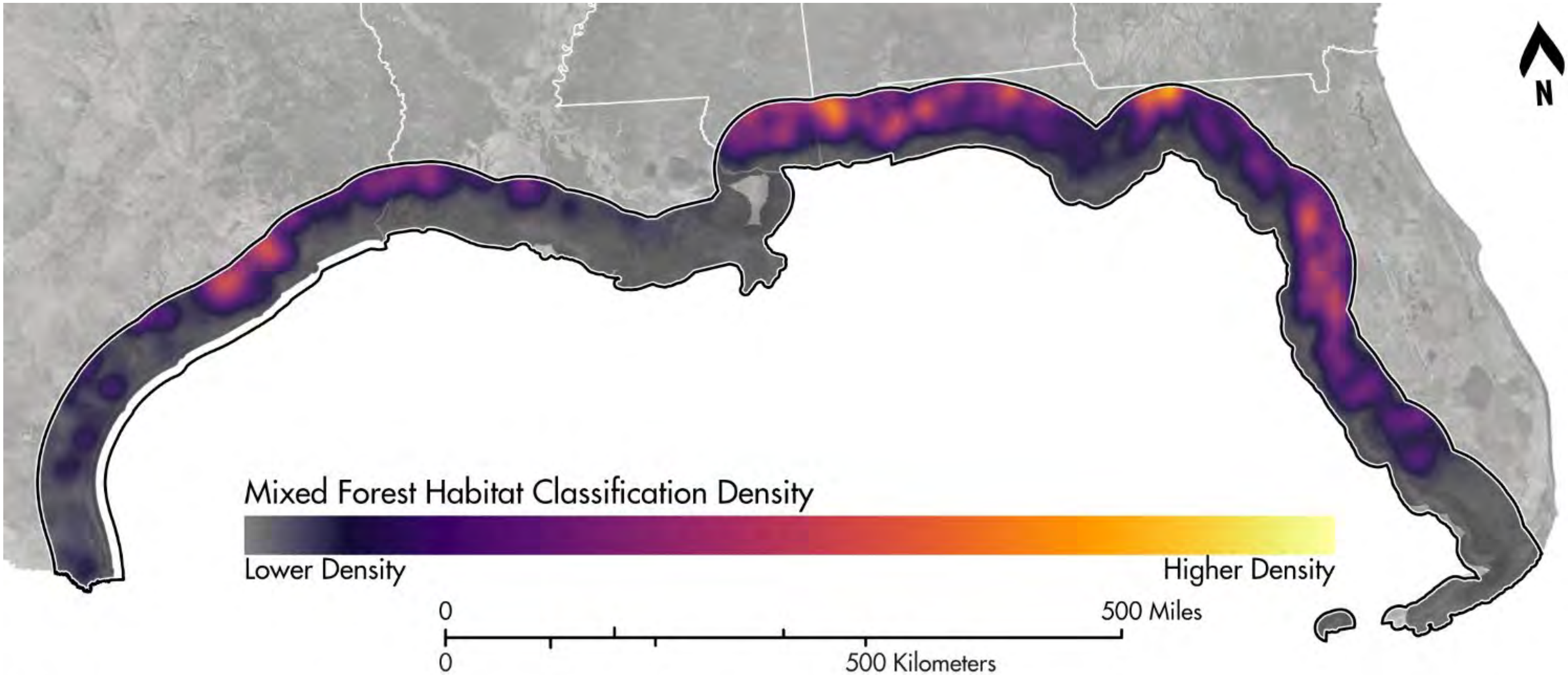
Desired Condition	Forest Subtype	Metric	CI Score
Low-Quality Forest	Low-Quality Forest	Is a low-quality forest class	2 pts
Urban/Developed Forest	Urban/Developed Forest	Is urban/developed forest class	1 pt
Is desired habitat	All	Desired habitat type is present	3 pts
Patch size	Mixed Forest	500 acres	3 pts
Landscape configuration	Mixed Forest	70% forested in a 10km radius	6 pts
Basal area	Mixed Forest	50-90 sq. ft/acre	1 pt
Canopy cover	Mixed Forest	50-100%	1 pt

The occurrence of the Mixed Forest habitat type within the project area is shown in Figure A-10 and Figure A-11, and the resulting habitat condition map is given in Figure A-12.



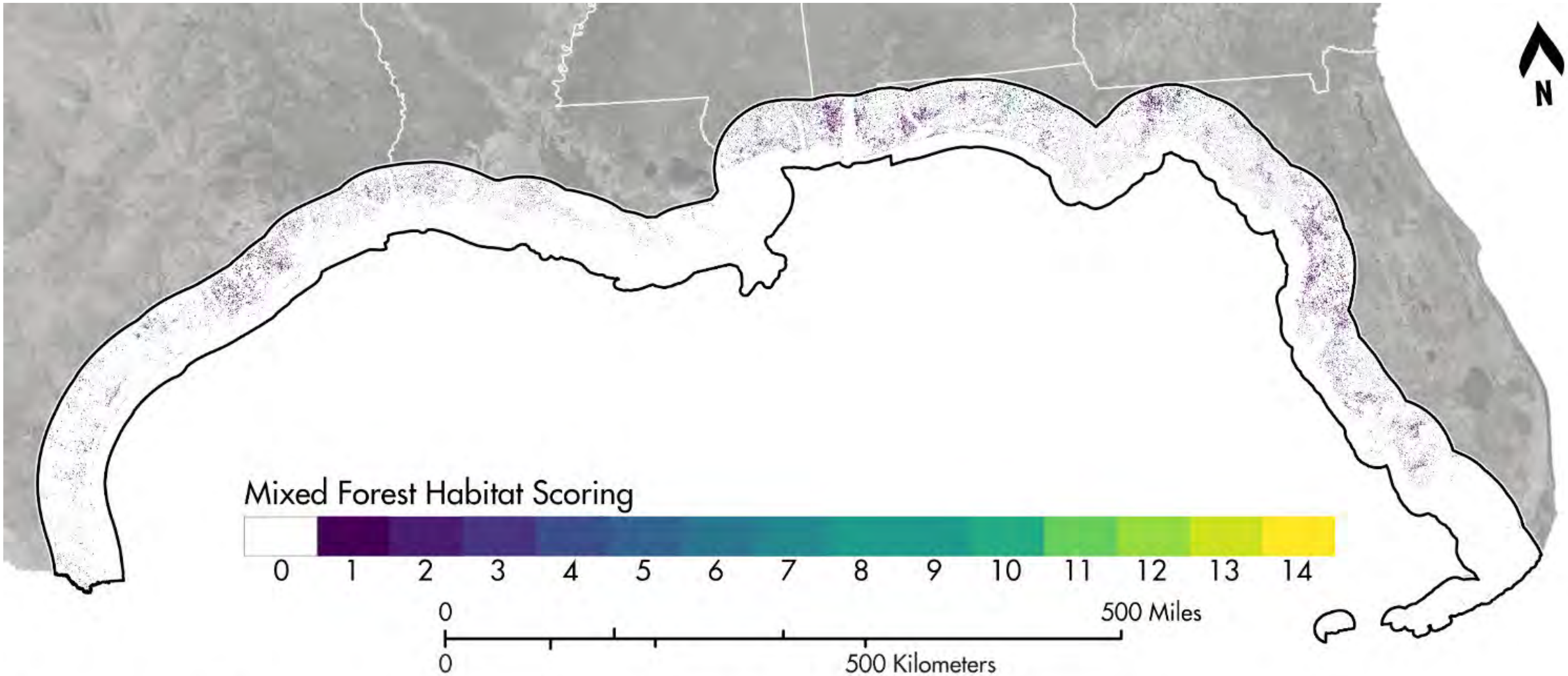
Data Source: CPRA, DataBasin, Esri, Florida Cooperative Land Cover, LANDFIRE, MRLC, NOAA, Texas A&M, The Nature Conservancy, USDA, USEPA, USFS, USFWS, USGS

Figure A-10. Presence of the Mixed Forest habitat type in the Gulf-wide project area.



Data Source: CPRA, DataBasin, Esri, Florida Cooperative Land Cover, LANDFIRE, MRLC, NOAA, Texas A&M, The Nature Conservancy, USDA, USEPA, USFS, USFWS, USGS

Figure A-11. Density map highlighting areas with highest concentrations of 30 m Mixed Forest habitat type pixels in the Gulf-wide project area.



Data Source: CPRA, DataBasin, Esri, Florida Cooperative Land Cover, LANDFIRE, MRLC, NOAA, Texas A&M, The Nature Conservancy, USDA, USEPA, USFS, USFWS, USGS

Figure A-12. Result of habitat condition assessment for the Mixed Forest habitat type.

Detailed GIS Protocol:

Step 1) Extract out low-quality and urban/developed Mixed Forest vegetation type classes from the project area and score them separately as 2 binary layers with LOW values

- 1A: Select the Low-Quality Forest vegetation types out of the LANDFIRE evt dataset using the classes listed in Appendix A.1 for low-quality forest; clip layer to the spatial extent of the project.
    - Reclassify pixels to produce a binary layer such that if a pixel is Low-Quality Forest, it is assigned a value of **2**, all others **0**.
- 1B: Select the Urban/Developed Forest classes (see table below); clip layer to the spatial extent of the project
    - Reclassify pixels to produce a binary layer such that if a pixel is Urban/Developed Forest, it is assigned a value of **1**, all others **0**.

Step 2) Develop Mixed Forest/Non-Forest map

- 2A: Select all Mixed Forest vegetation types out of the LANDFIRE evt dataset using all the classes listed in Appendix A.1 into an overall **Mixed Forest mask**
- 2B: OUTPUT: Create a binary layer where pixels that are classified as the given habitat are assigned a pixel value of **3**, all others **0** (i.e., each mixed forest pixel that is classified as mixed forest in the mixed forest layer should have a value of 3).

Step 3) Assess patch size endpoint

- 3A: Infer patch size by using pixel counts of groups. Use the "Region Group" tool which groups pixels where they share common sides but not corners; pixel values are the same within groups but vary across groups.
- 3B: Create a new layer from the step above for **Mixed Forest** that meets the 500-acre threshold for patch size (2,248 30 m pixels)
    - OUTPUT: reclassify pixels that satisfy the patch requirement with a value of **3**.

Step 4) Calculate the landscape configuration endpoint for **Mixed Forest**

    - NOTE: All three forest types have the same requirement "70% forest" but differ in the spatial context (10,000 acres vs. within 10 km radius). A 10km radius = about 77,631 acres (31,416 ha).

- 4A: Use the **Total Forest mask** created for the step 6A of the Forested Wetlands habitat condition layer.
- 4B: Create circular windows
    - Create a circle window radius of 120 pixels (roughly equivalent to 3589 meters, the radius of a circle with an area of 10,000 acres

- Use focal mean statistics to calculate % forest cover using the **Total Forest mask**

- 4C: OUTPUT: One layer where pixels with % cover forest values >0.7 were retained:
    - reclassify so that **Mixed Forest** pixels meeting the required >0.7 condition were given a value of **6**, all others **0**.

Step 5) Calculate the site endpoint for Basal Area:

- 5A: Download the 'USFS Live tree species basal area of the contiguous United States (2000-2009) data product' (Wilson et al., 2013).
    - This dataset maps vegetation phenology from MODIS imagery with FIA field data – resolution is 250 m scale for the entire U.S. Since this dataset represents BA of multiple species, calculate the sum total basal area across all species for each 250 m pixel.
- 5B: Extract the basal area sum total surface to the study spatial domain and resample to 30 m using the LANDFIRE evt grid.
- 5C: Create a binary layer (1 = condition met, 0 = condition not met) for the Forested Wetland habitat type by reclassify the pixels that satisfy the following condition:
    - Mixed Forest: 50-90 sq. ft/acre
- 5D: OUTPUT: a binary layer where **1** represents the basal area condition is fulfilled, all others **0**.

Step 6) Assess the % canopy endpoint:

- 6A: Download the 2016 NLCD USFS Tree Canopy analytical (CONUS) layer (USGS, 2019).
- 6B: Extract the tree canopy layer through to the project spatial extent and common projection.
- 6C: This will follow the same type of procedure listed in step 5 to create a binary layer where 1 indicates that the endpoint condition is met:
    - Mixed Forest: 50-100%
- 6D: OUTPUT: binary layer where **1** represents the % canopy condition is fulfilled, all others **0**.

Step 7) Calculate the Condition Index for the Mixed Forest habitat type using the output layers created above:

- 7A: Overlay all OUTPUT layers that have condition index values for each of the 5 endpoints – *including* the low-quality forest layer and the urban/developed forest layer.
    - Theoretically if a pixel fulfills ALL conditions the **pixel value is 14.** Low-quality Forest habitat will be scored as **2**, and urban/developed forest will be scored as **1**.

Step 8) Develop final map for the Mixed Forest habitat type:

- 8A: Finalize the Mixed Forest habitat type layer and check that condition indices are fully calculated
- 8B: Scale to the appropriate hex size – original documentation scaled each habitat output to 30x30 m cell sizes to facilitate combining all layers at the end into a final habitat map.

5. Habitat Type: Upland Hardwood Forest & Woodland

The evaluation metrics for the Upland Forest habitat subtype CIs were directly carried over from the Middle Southeast blueprint methodologies and are summarized in Table A-23.

Table A-23. Condition evaluation metrics for the Upland Hardwood Forests & Woodland habitat types

Desired Condition	Forest Subtype	Metric	CI Score
Is desired habitat	All	Desired habitat type is present	3 pts
Patch size	Upland hardwood (forest & woodland combined)	3000 acres	3 pts
Landscape configuration	Upland hardwood forest & woodland	70% forested (any type of forest) in a 10km radius	6 pts
Basal area	- Upland hardwood forest - Upland hardwood woodland	- 80-100 sq. ft/acre AND proportion of oak hickory >70% - 30-80 sq. ft/acre AND proportion of oak-hickory >90%	1 pt
Canopy cover	- Upland hardwood forest - Upland hardwood woodland	- >80% - 20-80%	1 pt

The occurrence of the Mixed Forest habitat type within the project area is shown in Figure A-13 and Figure A-14, and the resulting habitat condition map is given in Figure A-15.

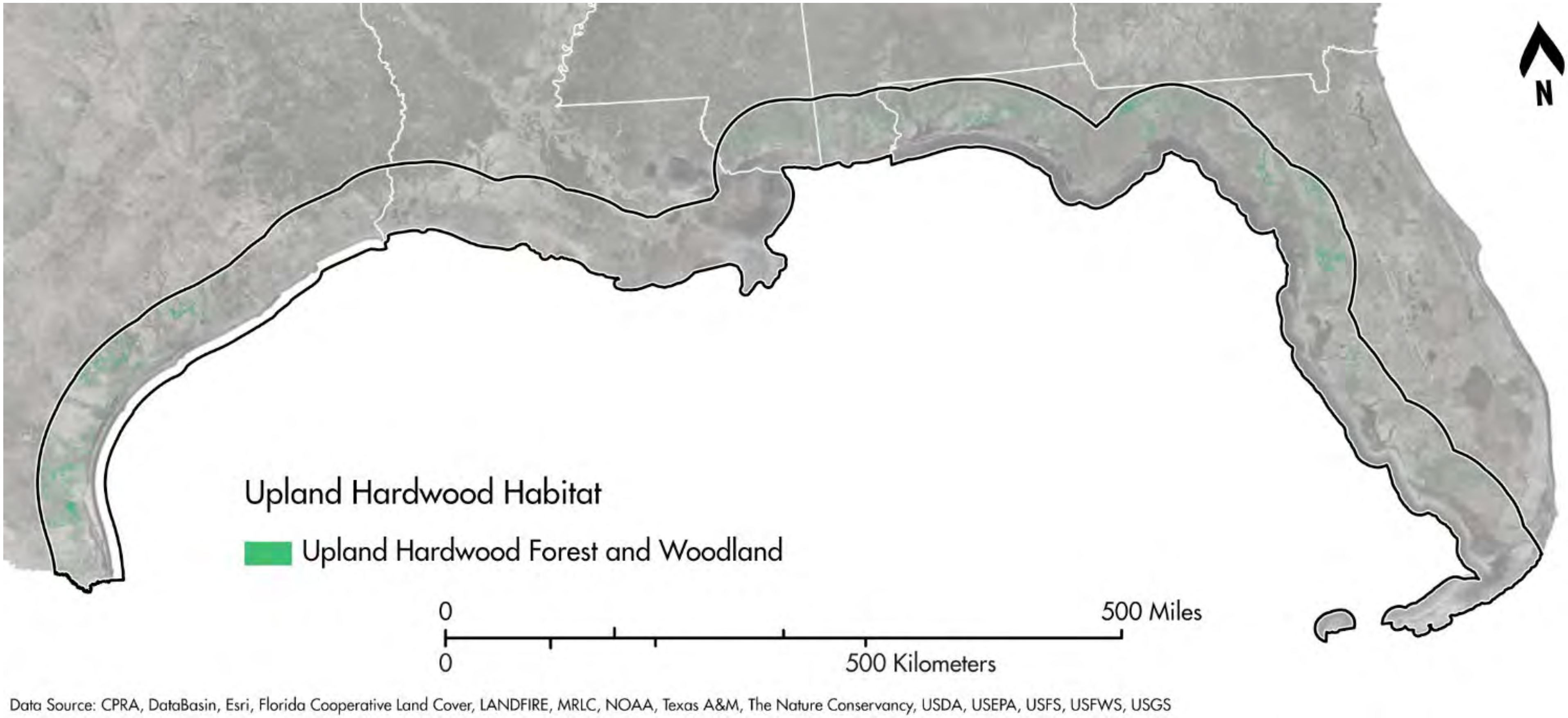


Figure A-13. Presence of the Upland Hardwood habitat type in the Gulf-wide project area.

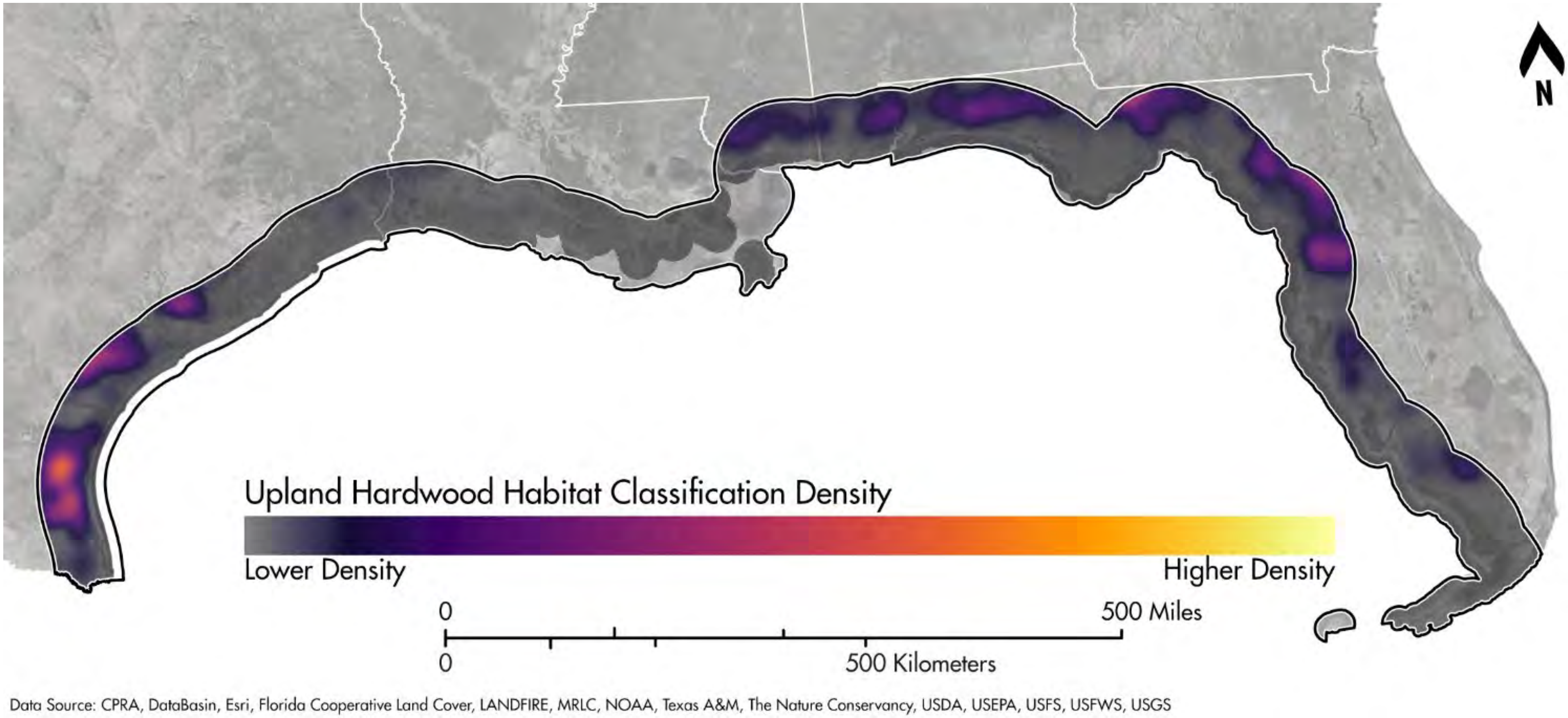


Figure A-14. Density map highlighting areas with highest concentrations of 30 m Upland Hardwood habitat type pixels in the Gulf-wide project area.

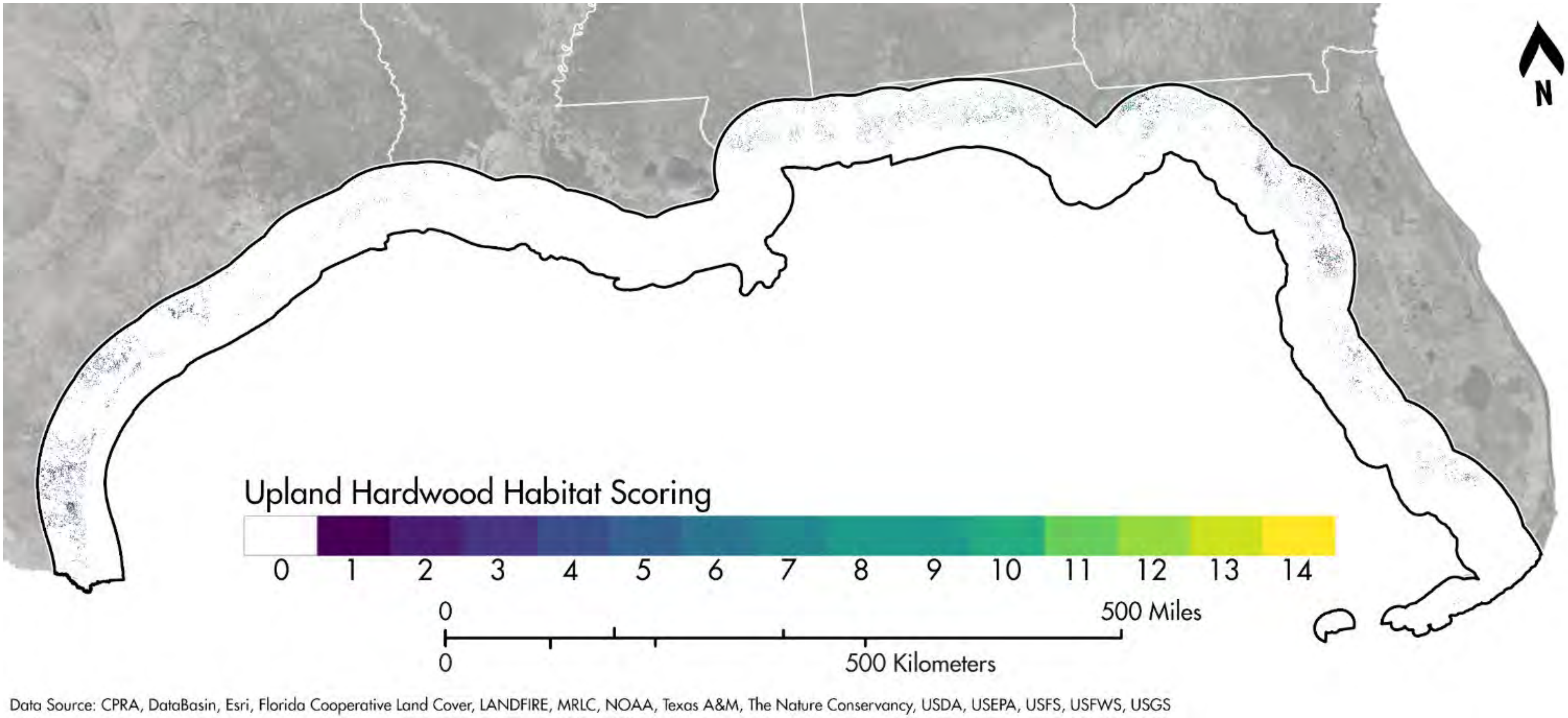


Figure A-15. Result of the habitat condition assessment for the Upland Hardwood Forest & Woodland habitat type.

Detailed GIS Protocol:

Step 1) Develop Upland Hardwood Forest map

- 1A: Select all Upland Forest vegetation types out of the LANDFIRE evt dataset using all the classes listed in Appendix A.1 into an overall **Upland Forest mask**
- 1B: Subset the overall **Upland Forest mask** for Upland Forest and Upland Woodland separately.
- 1C: OUTPUT: Create 2 binary layers, one for Upland Hardwood Woodlands and one for Upland Hardwood Forest, where pixels assigned to one of those habitat classes are given a value of **3**, all others **0**.
- 1D: OUTPUT: Create a third binary layer from the product of Step 1A – an Upland Forest mask that includes forest and woodland classes. Reclassify such that areas of upland forest are 1, all others 0.

Step 2) Assess patch size endpoint

- 2A: Using the Upland Forest binary mask produced in 1D above, infer patch size by using pixel counts of groups. Use the “Region Group” tool which groups pixels where they share common sides but not corners; pixel values are the same within groups but vary across groups.
- 2B: Create a new layer from 3A for that meets the threshold for patch size (3,000 acres)
  - Reclassify on pixel count: 13,490 pixels = 3,000 acres
  - OUTPUT: reclassify pixels that satisfy that patch requirement for **Upland Forest** (3,000 acres) with a value of **3**, all others **0**.

Step 3) Calculate the landscape configuration endpoint for **Hardwood Forest & Woodland**

  - *NOTE: All three forest types have the same requirement “70% forest” but differ in the spatial context (10,000 acres vs. within 10 km radius). A 10 km radius = about 77,631 acres (31,416 ha)*

- 3A: Use the **Total Forest mask** created for the Forested Wetlands habitat condition layer where all forest type pixels are assigned a value of 1, all others 0
- 3B: Create circular windows
  - Create a circle window radius of 120 pixels (roughly equivalent to 3589 m, the radius of a circle with an area of 10,000 acres)
    - Use focal mean statistics to calculate % forest cover using the **Total Forest mask**
- 3C: OUTPUT: One layer where pixels with % cover forest values >0.7 were retained:
  - Reclassify so that **Upland Hardwood Forest and Upland Hardwood Woodland** pixels meeting the required >0.7 condition were given a value of **6**, all others **0**.

Step 4) Calculate the site endpoint for Basal Area:

- 4A: Download the 'USFS Live tree species basal area of the contiguous United States (2000-2009) data product' (Wilson et al., 2013).
    - This dataset maps vegetation phenology from MODIS imagery with FIA field data – resolution is 250 m scale for the entire U.S. Since this dataset represents BA of multiple species, calculate the sum total basal area across all species for each 250 m pixel.
- 4B: Extract the basal area sum total surface to the study spatial domain and resample to 30 m using the LANDFIRE evt grid.
- 4C: Calculate a percentage oak and hickory layer by dividing the basal area sum for oak and hickory species by the sum total basal area of all species.
- 4D: Create a binary layer (1 = condition met, 0 = condition not met) for the Forested Wetland habitat type by reclassify the pixels that satisfy the following condition:
    - Upland hardwood forest: 80-100 sq. ft/acre AND proportion of oak hickory >70%
    - Upland hardwood woodland: 30-80 sq. ft/acre AND proportion of oak-hickory >90%
- 4E: OUTPUT: a binary layer for each Upland habitat type (a total of 2 layers) where **1** represents the basal area condition is fulfilled, all others **0**.

Step 5) Assess the % canopy endpoint:

- 5A: Download the 2016 NLCD USFS Tree Canopy analytical (CONUS) layer (USGS, 2019).
- 6B: Extract the tree canopy layer through to the project spatial extent and common projection.
- 6C: This will follow the same type of procedure listed in step 5 to create a binary layer where 1 indicates that the endpoint condition is met:
    - Upland Hardwood forest: >80%
    - Upland Hardwood Woodland: 20-80%
- 5D: OUTPUT: binary layer for each habitat type (a total of 2 layers) where **1** represents the % canopy condition is fulfilled, all others **0**.

Step 6) Calculate the Condition Index for each Upland Hardwood forest habitat type using the output layers created above:

- 7A: Overlay all OUTPUT layers that have condition index values for each of the 5 endpoints for each of the 2 habitat types
    - Theoretically if a pixel fulfills ALL conditions the **pixel value is 14**

Step 7) Develop final map for each Upland Hardwood Forest Type

- 8A: Finalize all Upland Hardwood forest habitat type layers and check that condition indices are fully calculated

- 8B: Scale to the appropriate hex size – original documentation scaled each habitat output to 30x30 m cell sizes to facilitate combining all layers at the end into a final habitat map.

Habitat: Agriculture

This assessment considers agricultural row-crops and plantation land cover types, scored evenly low in condition to separate their scores from other habitats included in this analysis. These areas were included in the overall prototype Gulf-wide Blueprint due to large number of species that rely on agricultural lands as nesting, stopover, or foraging habitat. This habitat type was not evaluated for condition but is mapped region-wide with a low habitat condition score (Table A-24).

Table A-24. Scoring of the Agriculture land cover type

Desired Condition	Metric	CI Score
Agricultural Habitats	Pixel is classified as row crop, orchard, wheat, vineyard, bush fruit/berries, or forest plantation	1

The occurrence of the Agriculture land cover type within the project area is shown in Figure A-16 and Figure A-17 and the resulting habitat condition map (assigning all agricultural land a value of 1) is given in Figure A-18

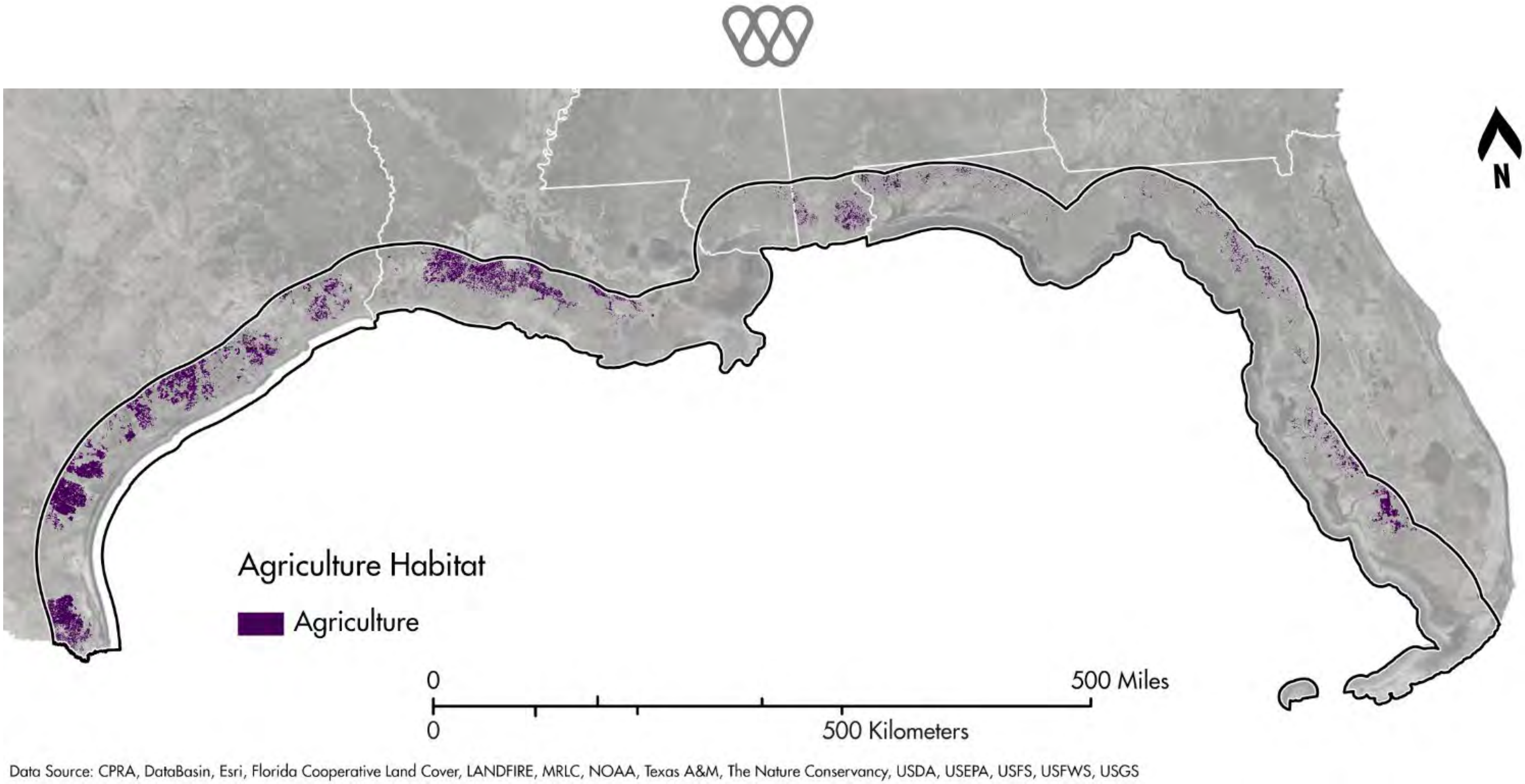


Figure A-16. Presence of the Agriculture land cover type in the Gulf-wide project area.

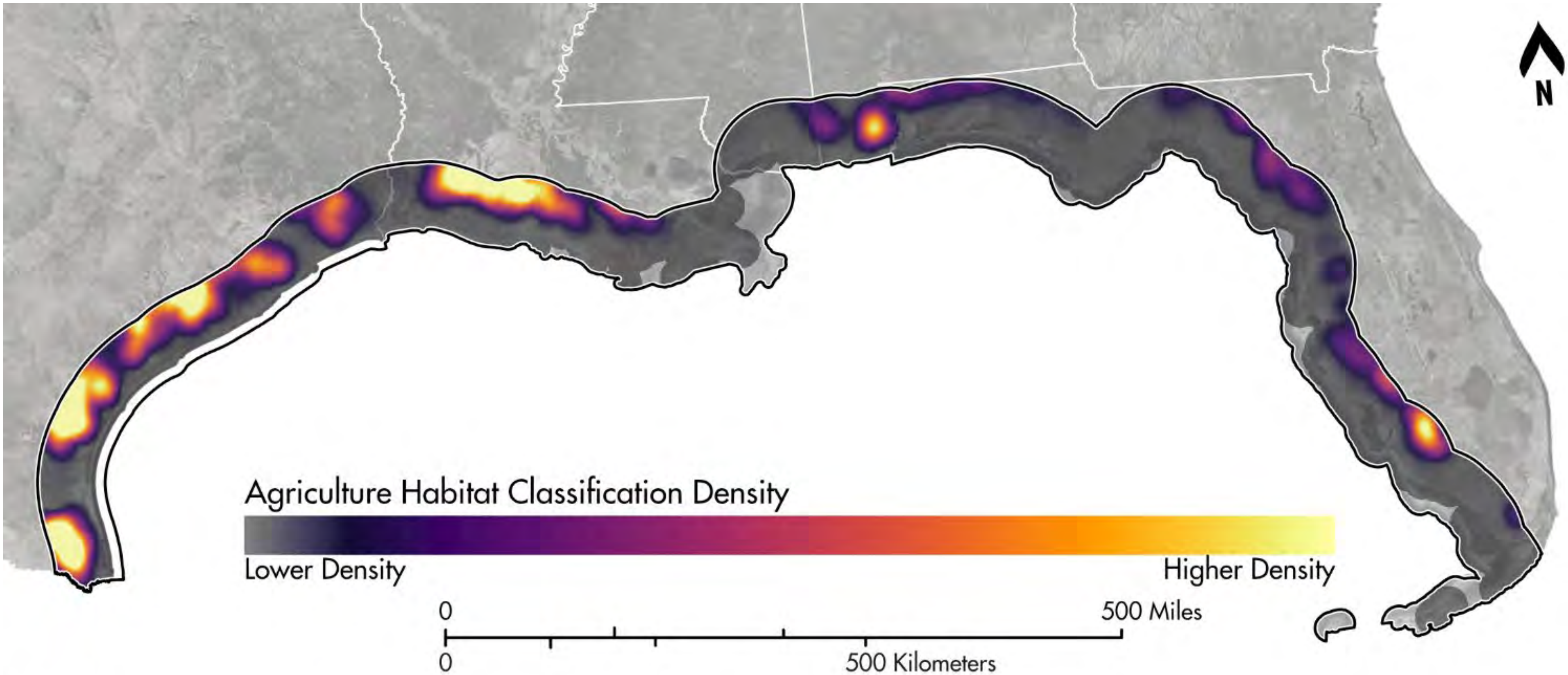
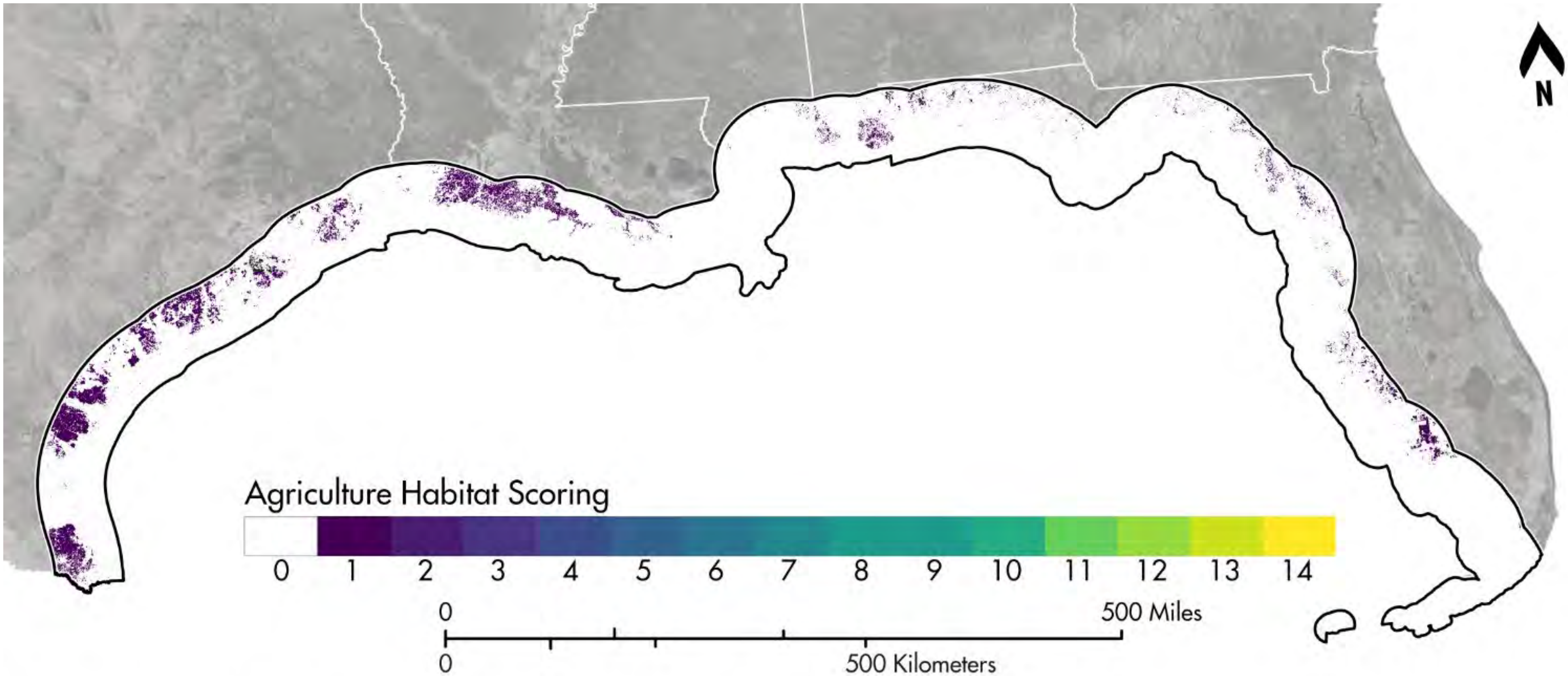


Figure A-17. Density map highlighting areas with highest concentrations of 30 m Agriculture land cover type pixels in the Gulf-wide project area.



Data Source: CPRA, DataBasin, Esri, Florida Cooperative Land Cover, LANDFIRE, MRLC, NOAA, Texas A&M, The Nature Conservancy, USDA, USEPA, USFS, USFWS, USGS

Figure A-18. Result of landcover scoring for the Agriculture habitat type.

Detailed GIS Protocol:

Step 1) Extract out agriculture classes from the project area and score them low

- 1A: Select vegetation types out of the LANDFIRE evt dataset using the classes listed in Appendix A.1 for agriculture; clip layer to the spatial extent of the project.
- 1B: Reclassify pixels to produce a binary layer such that if a pixel is Agriculture, it is assigned a value of **1**, all others **0**.

Habitat: Grassland

This habitat assessment considers natural grasslands dominated by native grasses and forbes as a subset of a broader set of grass-dominated landscapes. This habitat type includes pastures and/or early successional land cover types where the presence of nonnative species is assumed. The habitat definition considers all prairies to be grasslands, but not all grasslands to be prairies. More specifically, grasslands:

- **Excludes**: woodlands (addressed in other habitat types), glades (address separately), classes associated with water bodies (marshes, sedgelands, pondshore, riparian), and developed areas (herbaceous or grass cover, i.e., parks and airports)
- **Includes**: wet prairies, “floodplain herbaceous” classes, and some agricultural lands (but scored low)

Misclassification of prairie as pasture/hay, cultivated crops, harvested forest/successional regeneration, or other herbaceous classes is a known limitation when selecting a land use/land cover map for this habitat type, as noted in the initial mapping efforts for the Middle Southeast blueprint (D. Jones-Farrand, personal communication). It is recommended that areas classified as prairie should be ground-truthed prior to assessing any potential project areas.

The evaluation metrics for the Grassland habitat type condition index (CI) were carried over directly from the Middle Southeast blueprint methodologies and are summarized below in Table A-25. This evaluation includes CI scores for low-quality land cover types such as urban/developed and cropland that could function as grassland.

Table A-25. Condition evaluation metrics for the Grassland habitat type.

Desired Condition	Metric	CI Score
Urban/Developed Grassland	Land cover classified as urban/developed herbaceous	1 pt
Low-Quality Agricultural Grassland	Land cover classified as pasture/hay or idle cropland	2 pts
General Grassland	A land unit dominated by grass species	3 pts
Grassland Prairie	Presence of warm season native grasses and forbs	6 pts
Patch	Patch (general grass, prairie, or mix of both) > 100 acres	3 pts
Disturbance	Burned at least once during the period 2006-2015	1 pt
Vegetation Height	>1 meter	1 pt

The occurrence of the Grassland habitat type within the project area is shown in Figure A-19 and Figure A-20, and the resulting habitat condition map is given in Figure A-21.

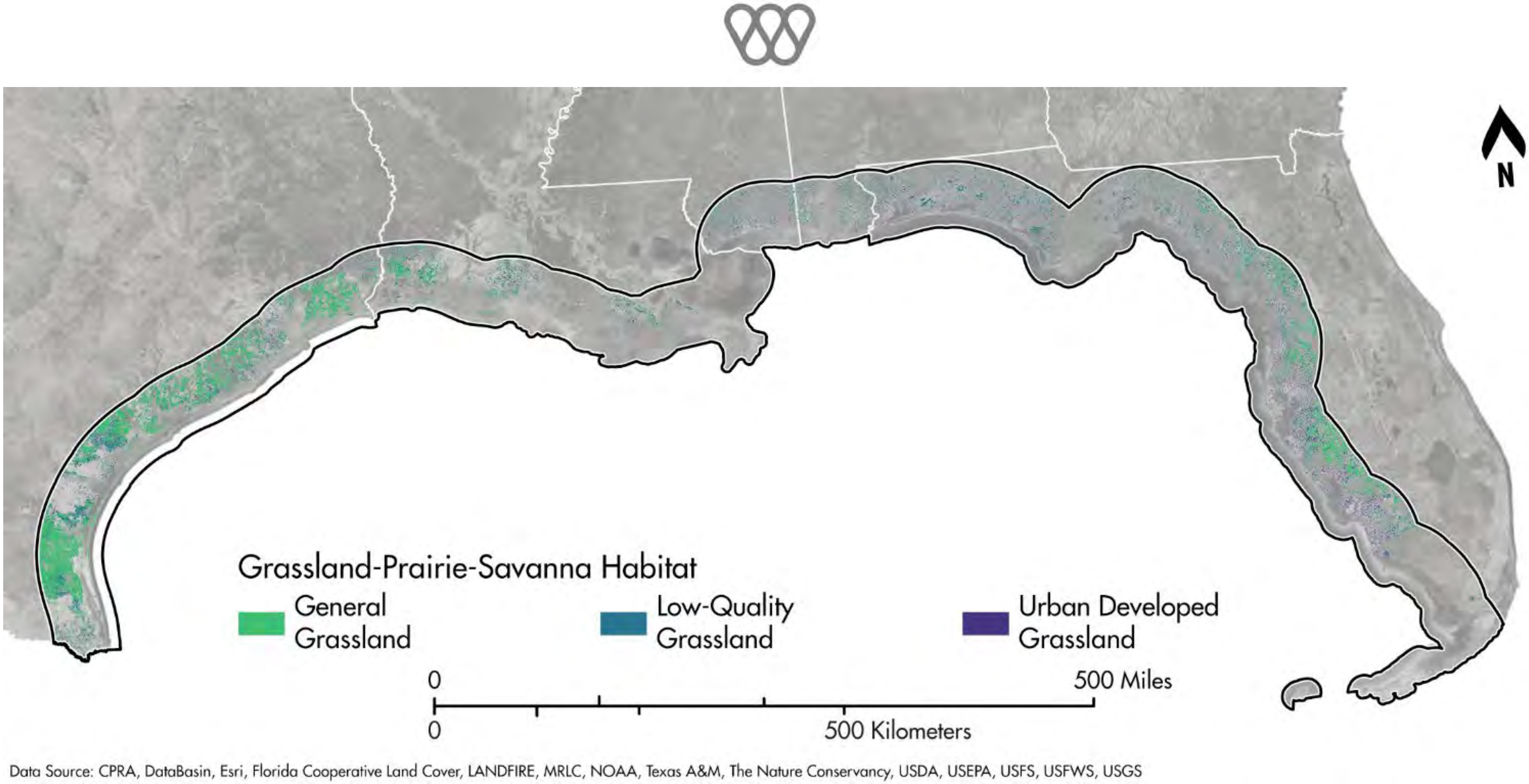
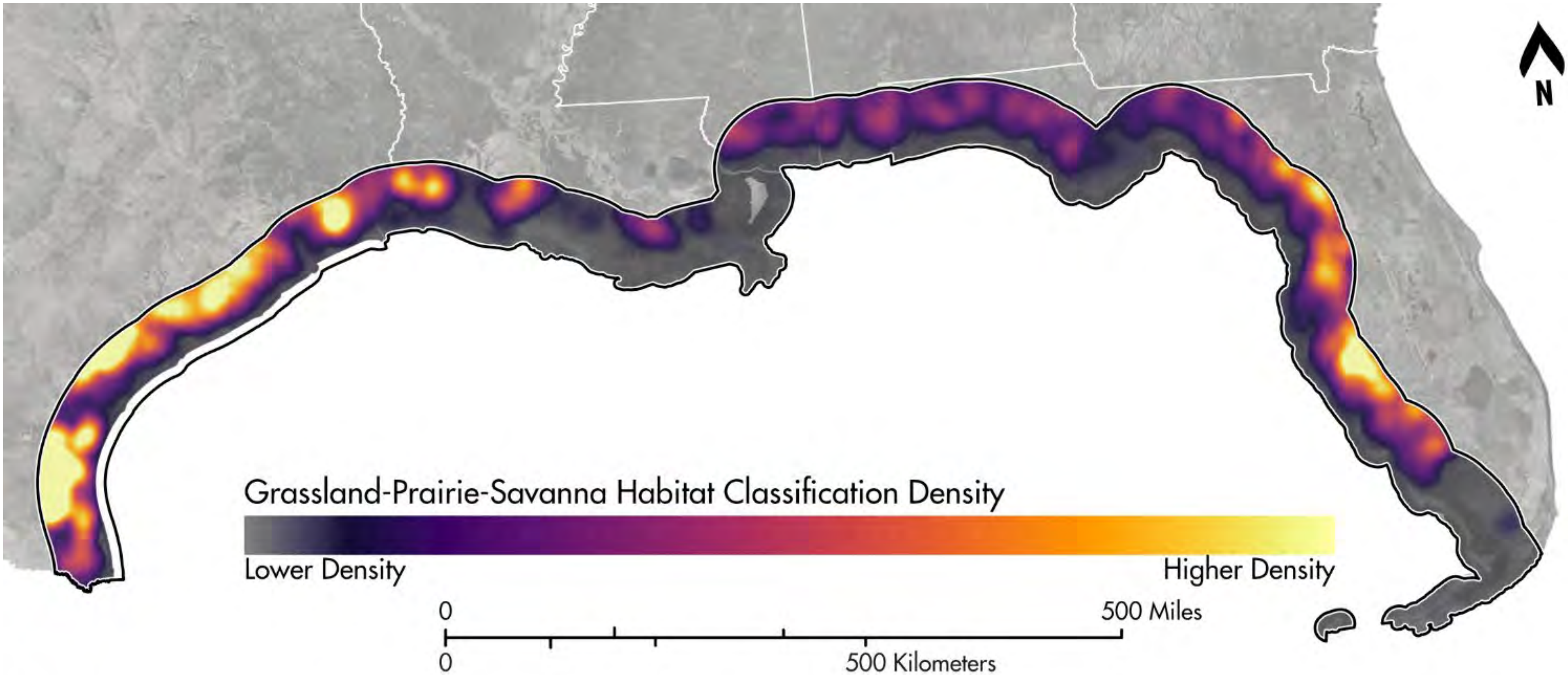
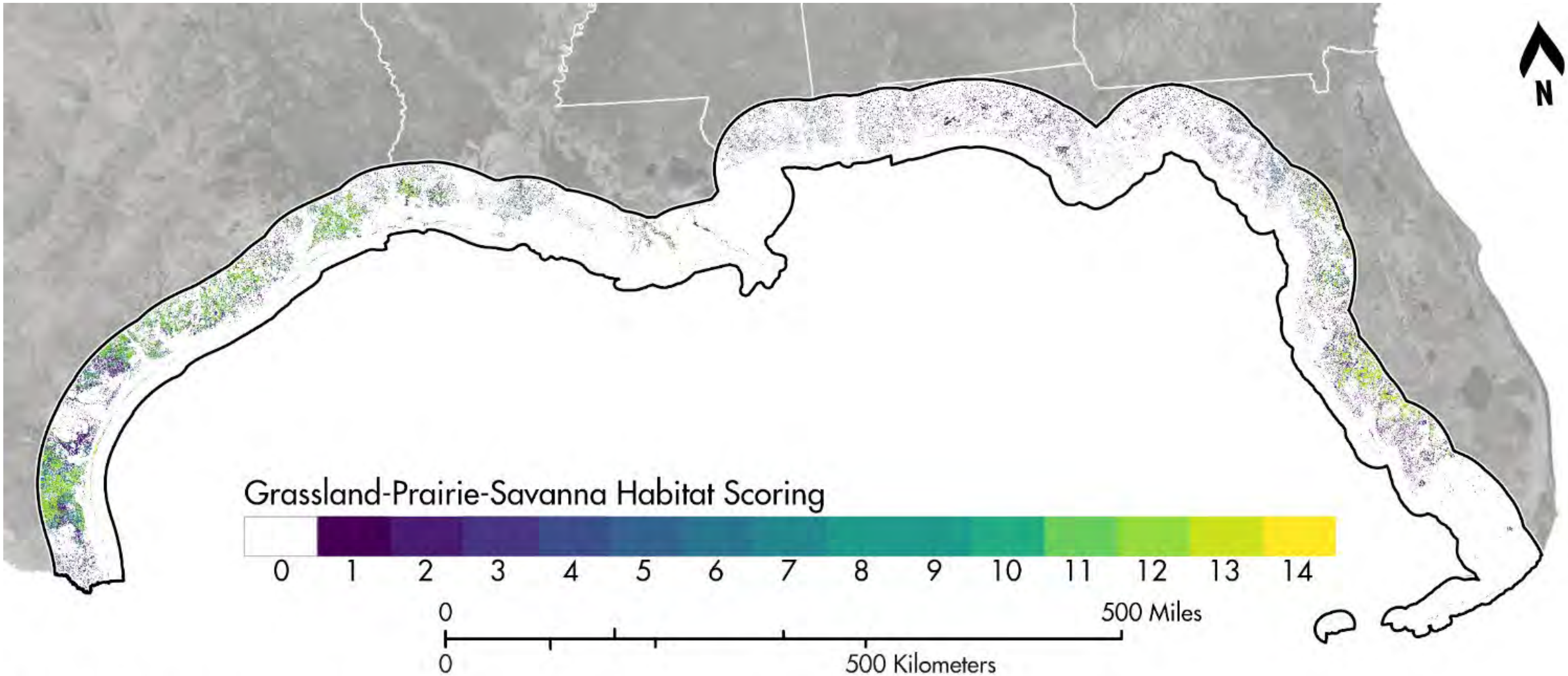


Figure A-19. Presence of the Grassland habitat type in the Gulf-wide project area.



Data Source: CPRA, DataBasin, Esri, Florida Cooperative Land Cover, LANDFIRE, MRLC, NOAA, Texas A&M, The Nature Conservancy, USDA, USEPA, USFS, USFWS, USGS

Figure A-20. Density map highlighting areas with highest concentrations of 30 m Grassland habitat type pixels in the Gulf-wide project area.



Data Source: CPRA, DataBasin, Esri, Florida Cooperative Land Cover, LANDFIRE, MRLC, NOAA, Texas A&M, The Nature Conservancy, USDA, USEPA, USFS, USFWS, USGS

Figure A-21. Result of habitat condition assessment for the Grassland habitat type.

Detailed GIS Protocol:

Step 1) Extract out low-quality agricultural grassland and urban/developed grassland vegetation type classes from the project area and score them low.

- 1A: Select Low-Quality Agricultural Grassland vegetation types out of the LANDFIRE evt dataset using the classes listed in Appendix A.1 for low-quality agricultural grassland; clip layer to the spatial extent of the project.
    - Reclassify pixels to produce a binary layer such that if a pixel is Low-Quality Grassland, it is assigned a value of **2**, all others **0**.
- 1B: Select Urban/Developed Grassland vegetation types out of the LANDFIRE evt dataset using the classes listed Appendix A.1 for urban/developed grassland; clip layer to the spatial extent of the project.
    - Reclassify pixels to produce a binary layer such that if a pixel is Urban/Developed Grassland, it is assigned a value of **1**, all others **0**.

Step 2) Generate the Grassland + Prairie Unified Mask (this will include prairie classes)

- 2A: Select all grassland vegetation types out of the LANDFIRE evt dataset using all the classes listed in Table A-10 into an overall **Grassland mask.**
- 2B: Create a binary layer where pixels that are classified as the given habitat are assigned a pixel value of **3**, all others **0** (i.e., each pixel that is classified as grassland in the grassland layer should have a value of 3).

Step 3) Generate a Prairie-specific dataset (aka the **Prairie mask**)

- 3A: Select vegetation types out of the Cropland Data Layer (CDL) from the NASS. Reclassify the layer to retain classes (58) Clover/Wildflowers and (176) Grass/Pasture; remove all others and resample to the LANDFIRE grid.
- 3B: Extract pixels from 3A that are collocated with cells in the LANDFIRE Grassland mask developed in Step 2. This is the CDL component of the Prairie mask. Only keeping cells from the CDL that align with the overall LANDFIRE Grassland mask prevents the classification of a cell as more than one habitat and preserves LANDFIRE-dependent habitat classes developed in other steps.
- 3C: Select all prairie vegetation types out of the LANDFIRE evt dataset using the grassland classes that are also indicated as prairie in (Table A-10) into the LANDFIRE component of the Prairie mask**.**
- 3D: Combine the outputs from 3B and 3C (i.e. the pixels classified as *both* prairie by the LANDFIRE evt classes and the CDL classes for prairie). These pixels satisfy the condition of ‘if it is grassland, is it also prairie?’ and constitute the **Prairie mask**.
- 3E: Reclassify so that all **Prairie mask** pixels are given a value of **6**, all others **0**.

Step 4) Assess patch size (Patch Endpoint): patch >100 acres [includes general grass, prairie, or a mix of both]

- 4A: Convert the **Grassland mask** from 2B to polygons and calculate acreage amounts for all features.
    - **Notes**: “Prairie and general classes are intermixed in the landscape, so a requirement that the entire patch consist of prairie classes only would have excluded large areas dominated by prairie conditions”
- 4B: Reclassify layer so that pixels that are in patches >100 acres in size are given a value of **<u>3</u>**, all others **<u>0</u>**.

Step 5) Assess disturbance return interval

- 5A: Download the LANDFIRE CONUS Vegetation Disturbance 2014 (v1.4) data product.
- 5B: Select data from all disturbance bins (include all time interval classes) and pixels associated with disturbance types: chemical, fire, and mechanical add
- 5C: Extract the layer through the **Grassland mask** and reclassify so that all pixels meeting the disturbance and the **Grassland mask** criteria were given a value of **<u>1</u>** and everything else 0.
- OUTPUT: a raster layer in which each pixel described by LANDFIRE’s vegetation disturbance layer as having been disturbed at a rate of at least once a year for 14 years, and also described independently as part of the **Grassland mask**, is given a value of **<u>1</u>**, all others **<u>0</u>**.

Step 6) Assess vegetation height

- 6A: Download the LANDFIRE Existing Vegetation Height (v2.0).
- 6B: Generate a raster layer from pixels in the “herbaceous height >1 meter” class that are **also** included in the **Grassland mask**
- 6C: OUTPUT: a raster data layer in which each pixel described as herbaceous and >1 meter in height, and also described as part of the **Grassland mask**, is given a value of **<u>1</u>**, all others **<u>0</u>**.

Step 7) Calculate the Condition Index using the above layer outputs:

- 7A: Overlay all OUTPUT layers from previous endpoint steps above
    - Theoretically if a cell fulfills ALL conditions above (is grassland, is prairie, is in patch >100 acres, is in correct disturbance return interval, and has appropriate veg height) the **pixel value is 14.** The lowest scoring class should be urban/developed grassland scoring at **<u>1</u>**.

Known Issues

Future iterations of the grasslands habitat condition assessment will more closely evaluate which LANDFIRE evt classes are truly grassland/prairie for the Gulf of Mexico coastal area. Coastal grasslands can be heavily influenced by air-born sea spray, high energy coastal storms, or saltwater intrusion into groundwater, creating uniquely saline terrestrial environments. The LANDCOVER evt classes ‘South Florida Wet Marl Prairie’ (#7484) and ‘East Gulf Coastal Plain Wet Prairie’ (#7485), currently classified as ‘Other’ habitat types due to this ecological uncertainty, may be included in this habitat class in future Blueprint development iterations.

LF 2014 (v1.4) historic disturbance was used in the Middle Southeast Blueprint and the specific disturbance categorizations were used as a guide for the prototype Gulf-wide Blueprint.

From the original LF 2014 (v1.4) metadata the desired classes are detailed as:

- Mechanical Add: Means by which vegetation is mechanically "mowed" or "chipped" into small pieces and changed from a vertical to horizontal arrangement.
- Fire: A catch all term used to describe any non-structure fire that occurs in the wildland. Three distinct types of wildland fire have been defined: wildfire, wildland fire use, and prescribed fire.
- Chemical: Application of a chemical substance.

Research detailed a newer iteration of LANDFIRE vegetation disturbance completed during the 2016 remap process (v2.0). Notably, comparison of the disturbance classifications considered by the LF 2014 (v1.4) and the LF 2016 (v2.0) iterations detailed limited matching classifications between the two datasets and no direct matches for the v1.4 classifications used in the Middle Southeast Blueprint. Additionally, no crosswalk between the two version is detailed in the metadata and none could be located through additional investigation. For the disturbance data product from the LF 2016 (v2.0) remap, metadata is noticeable undescriptive. Comparing against class definitions from LF 2014 (v1.4) there are no longer any chemical disturbance types, fire is split out into four subcategorizations, and there is no classification that corresponds to mechanical add. The field descriptions from the data dictionary that the metadata references are circular and drilling down into the data lineage is largely impossible.

The disturbance data from the LF 2014 (v1.4) data product covers the period between 2005 and 2014 while the LF 2016 (v2.0) remap considers the period between 2006 and 2015. Given this minor shift temporal coverage and based on the inadequate metadata documentation of the LF 2016 (v2.0) remap disturbance product, it was deemed more prudent to continue leveraging the LF 2014 (v1.4) disturbance dataset to assess disturbance return interval for this habitat classification.

Habitat: Tidal Marsh

This class includes tidally-influenced fresh, brackish and saline marshes and shrubland. We acknowledge that mapping based on LANDFIRE evt may overestimate marsh area in some locations. The evaluation metrics for this habitat were developed through expert elicitation and USFWS blueprint developer input, and are shown below in Table A-26. Condition evaluation metrics for the Tidal Marsh habitat type.

Table A-26. Condition evaluation metrics for the Tidal Marsh habitat type

Desired Condition	Metric	CI Score
Habitat exists	Desired habitat type is present	3 pts
Landscape Configuration: Resilience	Above average and far above average resilience score (TNC Resilient Coastal Sites)	6 pts
Landscape Configuration: Watershed Condition	Not in a 303(d) listed EPA impaired watershed	3 pts
Site Condition	≤0.25 Unvegetated to vegetated (UVVR) wetland ratio (2014-2018)	1 pt
Site: Condition	<10% impervious surface (HUC12 scale)	1 pt

The occurrence of the Tidal Marsh habitat type within the project area is shown in Figure A-22 and Figure A-23, and the resulting habitat condition map is given in Figure A-24.

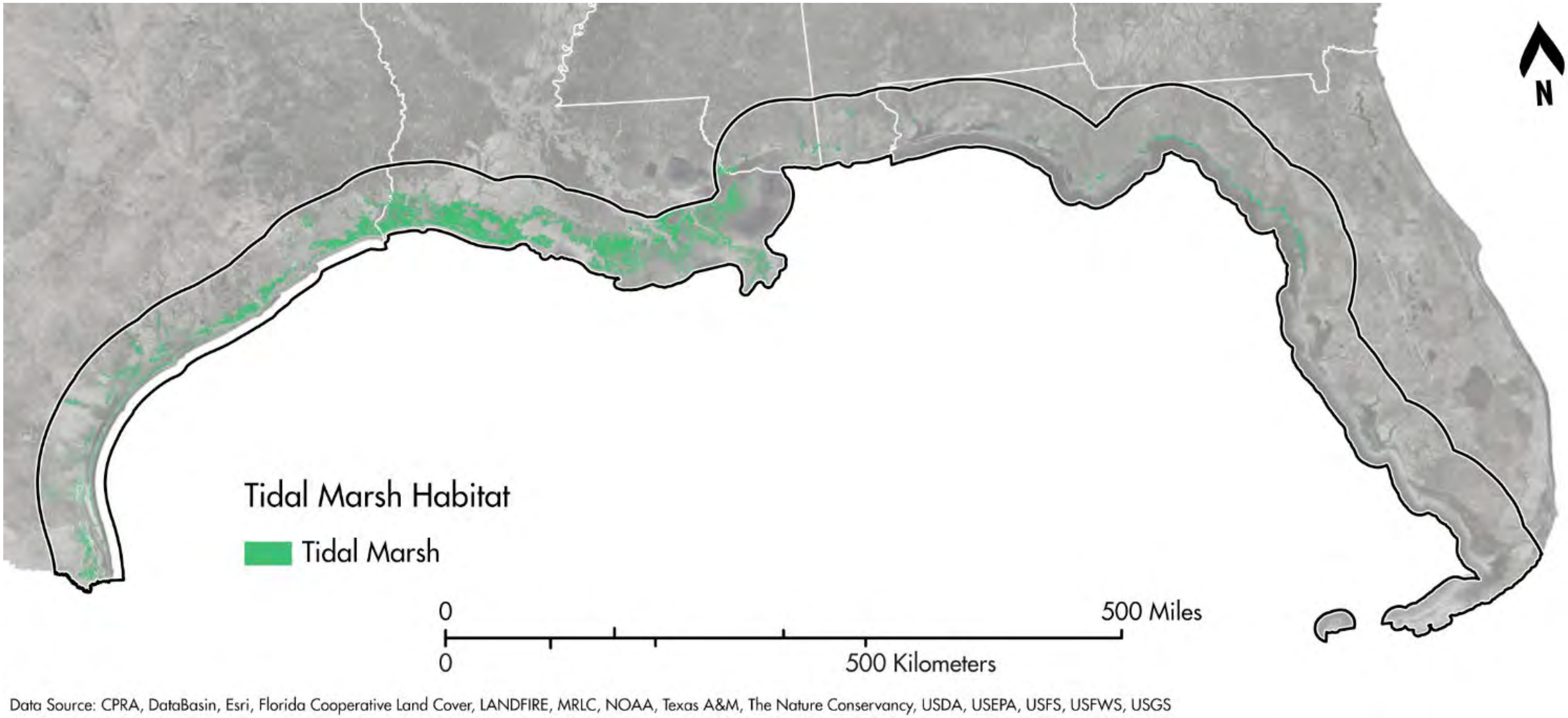


Figure A-22. Presence of the Tidal Marsh habitat type in the Gulf-wide project area.

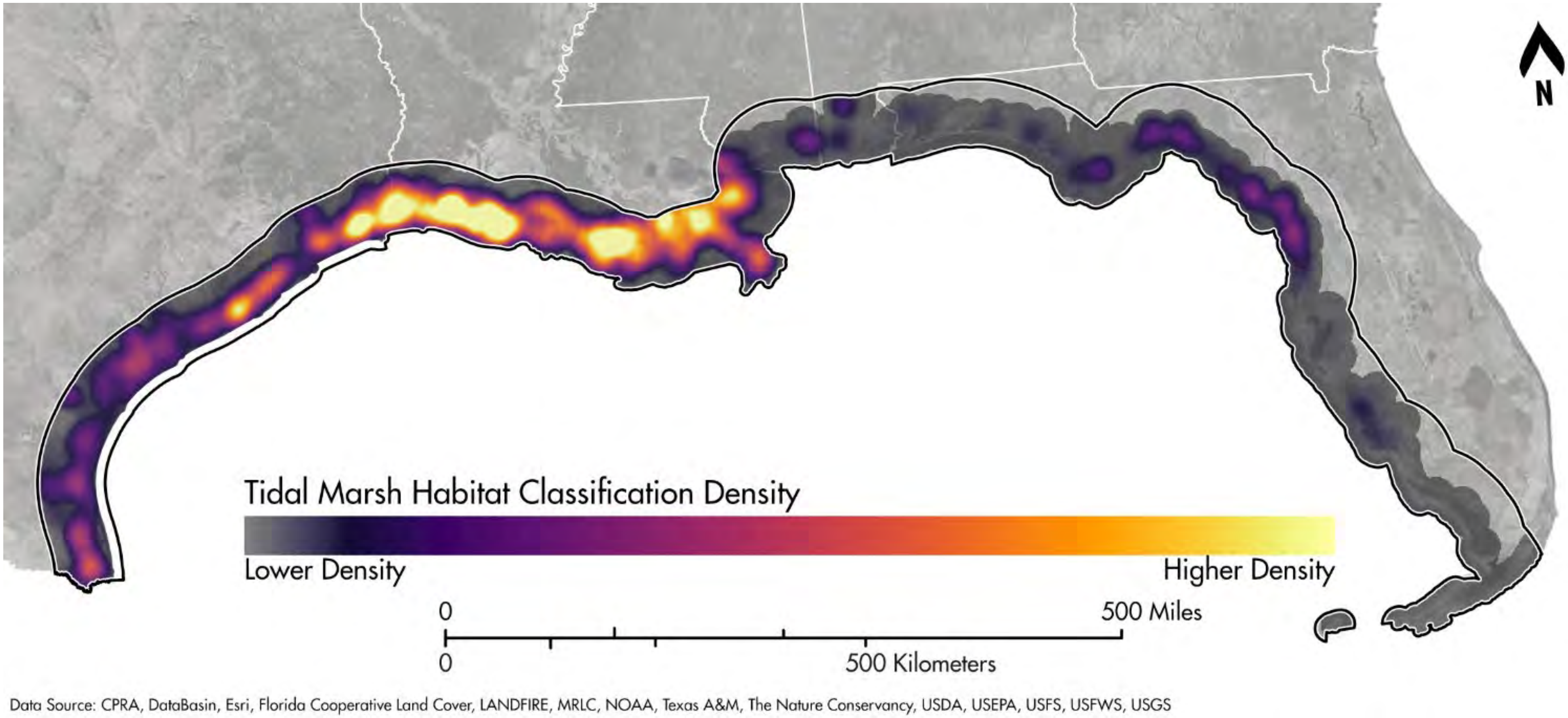
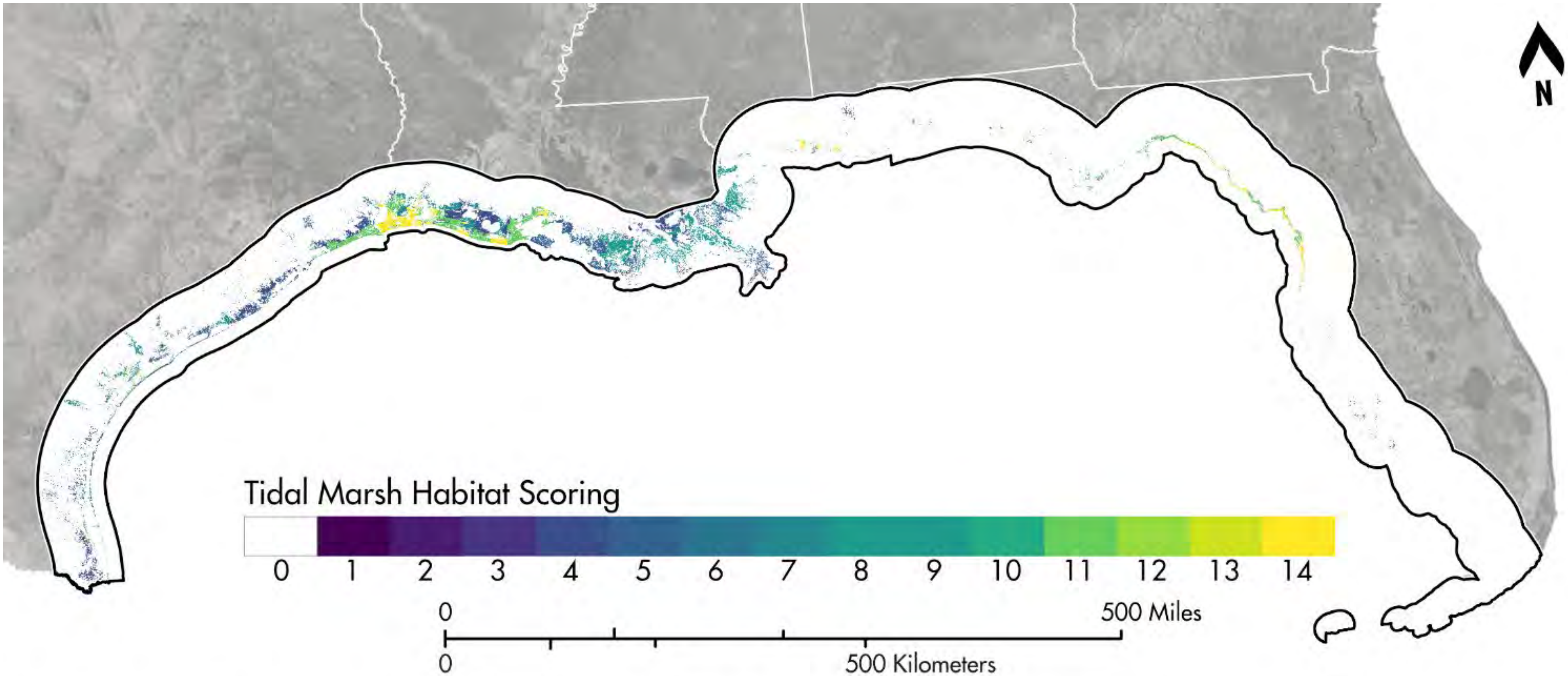


Figure A-23. Density map highlighting areas with highest concentrations of 30 m Tidal Marsh habitat type pixels in the Gulf-wide project area.



Data Source: CPRA, DataBasin, Esri, Florida Cooperative Land Cover, LANDFIRE, MRLC, NOAA, Texas A&M, The Nature Conservancy, USDA, USEPA, USFS, USFWS, USGS

Figure A-24. Result of habitat condition assessment for the Tidal Marsh habitat type.

Detailed GIS Protocol:

Step 1) Develop the Tidal Marsh map

- 1A: Select all Tidal Marsh vegetation types out of the LANDFIRE evt dataset using all the classes listed in Appendix A.1 into an overall **Tidal Marsh mask**
- 1B: Reclassify the **Tidal Marsh Mask.**
    - OUTPUT: Layer in which pixels classified as **tidal marsh** are assigned a value of **3**, all others **0.**

Note: The LANDFIRE evt dataset maps herbaceous freshwater wetlands in south Florida, however it does not map estuarine tidal marsh as a separate class. Some freshwater marsh may actually be tidally influenced, but it was not possible to detect that resolution from the LANDFIRE dataset.

Step 2) Assess the Resilience endpoint

- 2A: Download the Unstratified Resilience Scores for the 3ft Sea Level Rise scenario (with trend) from the Gulf of Mexico Resilient Coastal Sites data product from The Nature Conservancy "Resilient Coastal Sites for Conservation in the Gulf of Mexico" project. Data from the April 2020 project update was used in this analysis.
- 2B: Extract the following classes "Above average resilience" and "Far above average resilience" for the field "RESILB1stC" from the unstratified, aggregated "Resilience Score With Trend" datatype for the 3ft SLR classification.
- 2C: Rasterize the extracted resilience polygon and reclassify such that pixels representing "Above average resilience" and "Far above average resilience" are assigned a value of **1**, all others **0**.
- 2D: Extract the resilience classes through the **Tidal Marsh Mask** created in step 1B and reclassify to identify **tidal marsh** pixels with high resilience values.
    - OUTPUT: Layer in which pixels classified as **tidal marsh** and located within "Above average resilience" and "Far above average resilience" regions are assigned a value of **6**, all others **0.**

Step 3) Assess the Watershed Condition endpoint

- 3A: Download the EPA 303(d) impaired waters data by watershed and extract to to the spatial extent of the project. Rasterize the polygons to retain only watersheds classified as impaired under EPA 303(d) criteria.
- 3B: Extract the impaired watershed raster from step 3A through the **Tidal Marsh Mask.**
- 3C: Reclassify tidal marsh pixels that are not located in impaired watersheds.
    - OUTPUT: Layer in which pixels classified as **tidal marsh** that do not intersect with 303(d) impaired watersheds are assigned a value of **3**, all others **0.**

Step 4) Assess the Site Condition Endpoint (≤0.25 Unvegetated to vegetated (UVVR) wetland ratio (2014-2018)

- 4A: Download the 2021 Unvegetated to Vegetated Ratio (UVVR) of the US coastal wetlands – a dataset based on a multiyear-composite computed from Landsat data (2014-2018).
- 4B: Extract UVVR pixels that reflect a ratio ≤ 0.25 using the spatial domain of the project as the processing extent.
- 4C: Overlay the UVVR extract with the **Tidal Marsh Mask**. Reclassify tidal marsh pixels that intersect with UVVR pixels reflecting a UVVR ratio ≤0.25.
    - OUTPUT: Binary layer in which pixels classified as **tidal marsh** that meet the required UVVR ≤ 0.25 threshold are assigned a value of **1**, all others **0.**

Step 5) Assess the site condition endpoint related to impervious surface.

- 5A: Download the 2016 NLCD Percent Developed Impervious Surface dataset. Run Zonal Statistics to produce a raster where the value of the output pixel is the mean value of impervious surface within the boundary of a given HUC12.
- 5B: Isolate HUC12 watersheds in which less than 10% of the total area is characterized as impervious. Create a binary layer (reclassify pixels) in which pixels within watersheds with <10% total impervious surface are assigned a value of **1**, all others **0**.
- 5C: Overlay the output of step 5B with the **Tidal Marsh Mask.** Reclassify tidal marsh pixels that are characterized as being within watersheds with <10% impervious surface.
    - OUTPUT: Binary layer in which pixels classified as **tidal marsh** within a watershed with <10% impervious surface are assigned a value of **1**, all others **0**

Step 6) Calculate the Condition Index using the output layers created above:

- 6A: Overlay all OUTPUT layers that have condition index values for each of the 5 endpoints.
    - Theoretically if a pixel fulfills ALL conditions the **pixel value is 14.**

Step 7) Develop final map for the Tidal Marsh habitat type.

- 7A: Finalize all habitat type layers and check that condition indices are fully calculated.
- 7B: Scale to the appropriate hex size – original documentation scaled each habitat output to 30x30 m cell sizes to facilitate combining all layers at the end into a final habitat map.

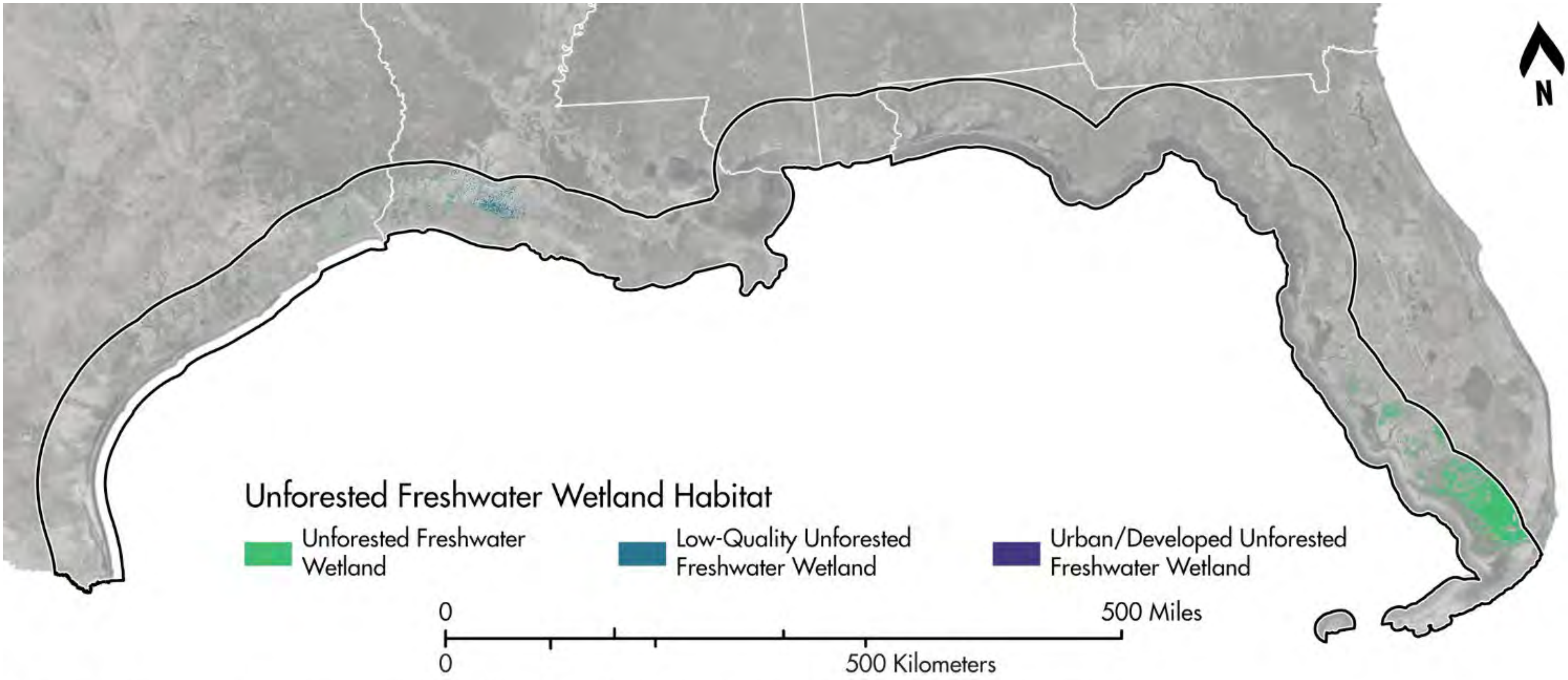
Habitat: Unforested Freshwater Wetland

The evaluation metrics for the Unforested Freshwater Wetland habitat type were developed through expert elicitation and USFWS blueprint developer consultation. The metrics follow the structure outlined in the Middle Southeast blueprint and are summarized in Table A-27.

Table A-27. Condition evaluation metrics for the Unforested Freshwater Wetland habitat type.

Desired Condition	Metric	CI Score
Urban/Developed Unforested Freshwater Wetland	Land cover classified as urban/developed freshwater herbaceous wetland	1 pt
Low-Quality Unforested Freshwater Wetland	Land cover classified as aquaculture	2 pts
Is desired habitat	Desired habitat type is present	3 pts
Landscape Configuration: watershed condition	<10% impervious surface (HUC12 scale)	3 pts
Landscape Configuration: proximity to protected areas	Within 500 meters of a protected area occurrence	6 pts
Site: Resilience	>100m from nearest road	1 pts
Site: Fire Disturbance	Burned at least once during the period 2006-2015	1 pts

The occurrence of the Unforested Freshwater Wetland habitat type within the project area is shown in Figure A-25 and Figure A-26, and the resulting habitat condition map is given in Figure A-27.



Data Source: CPRA, DataBasin, Esri, Florida Cooperative Land Cover, LANDFIRE, MRLC, NOAA, Texas A&M, The Nature Conservancy, USDA, USEPA, USFS, USFWS, USGS

Figure A-25. Presence of the Unforested Freshwater Wetland habitat type in the Gulf-wide project area.

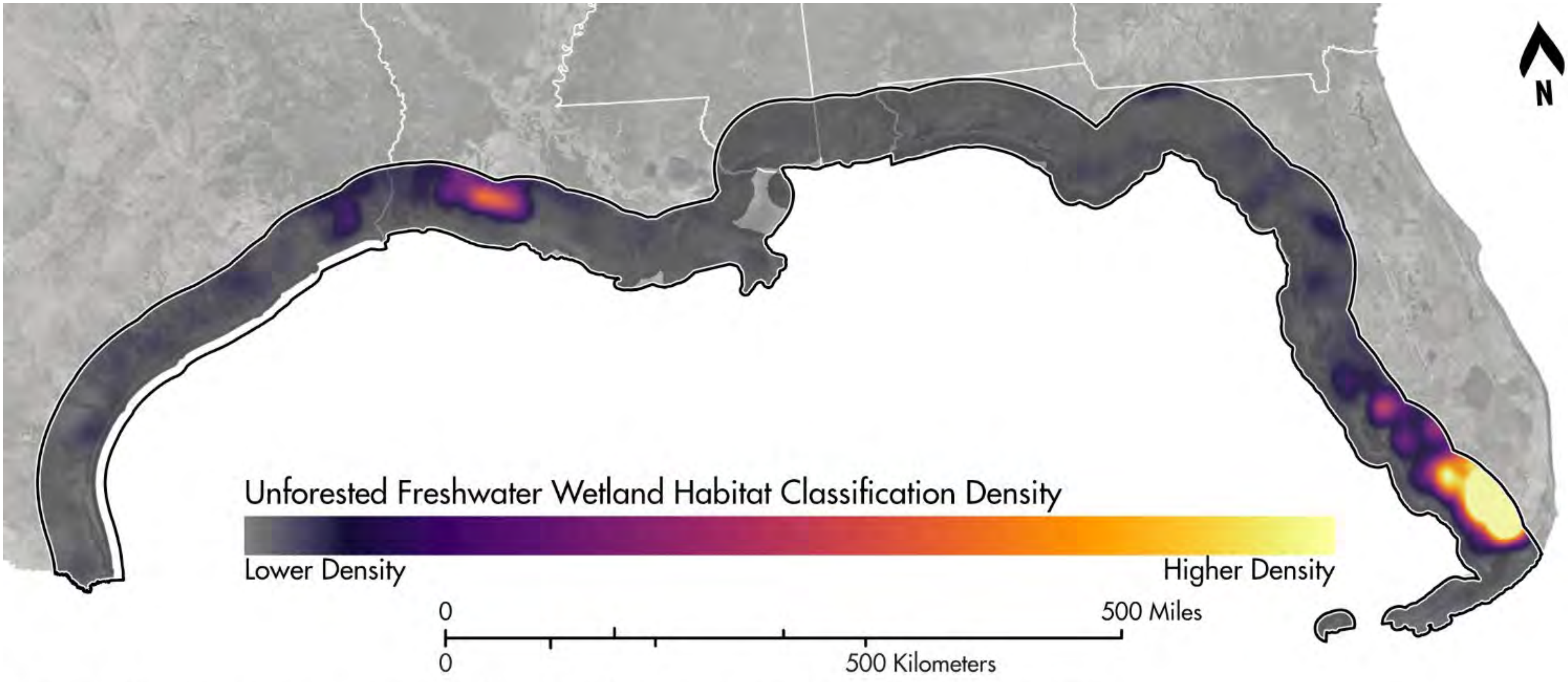


Figure A-26. Density map highlighting areas with highest concentrations of 30 m Unforested Freshwater Wetland habitat type pixels in the Gulf-wide project area.

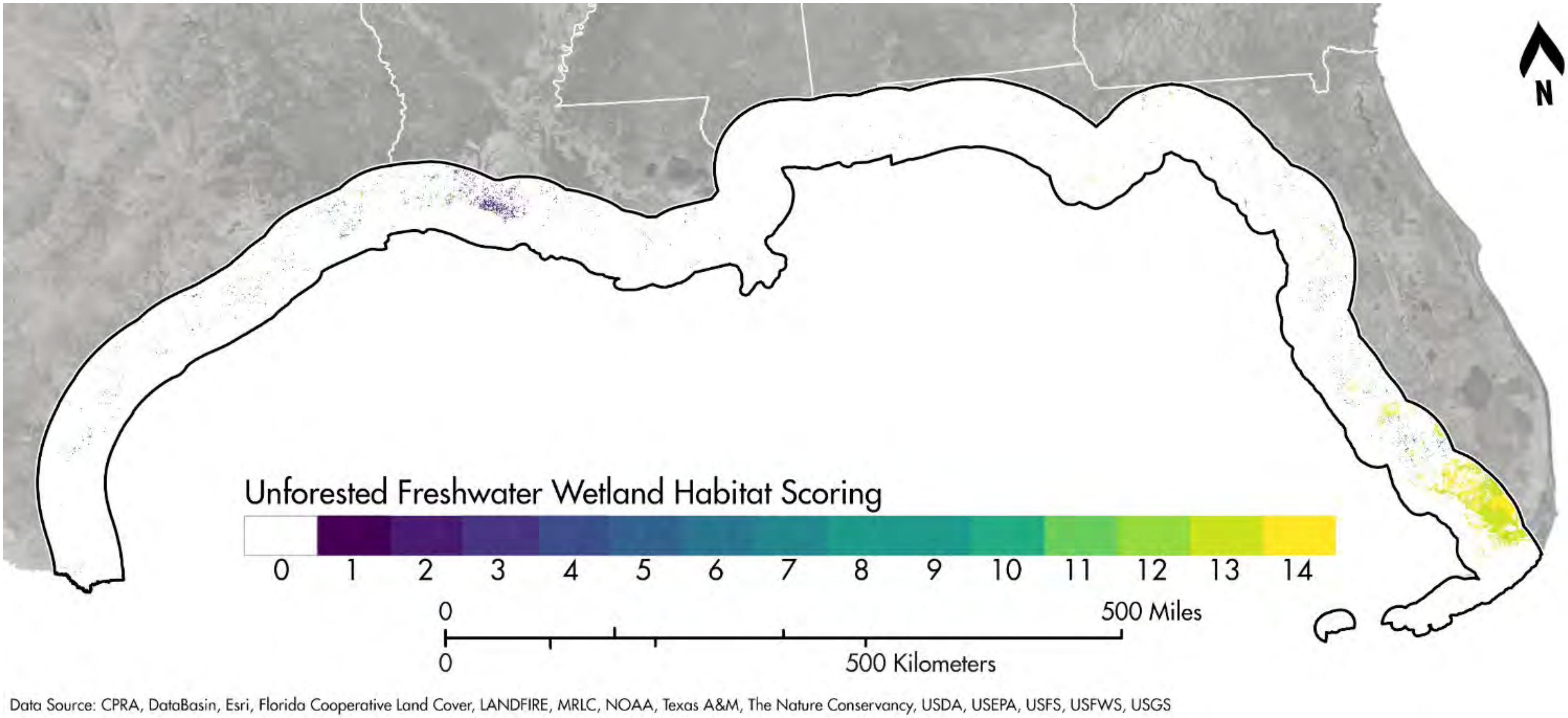


Figure A-27. Result of habitat condition assessment for the Unforested Wetland habitat type.

Detailed GIS Protocol:

Step 1) Create the **Low Quality Unforested Freshwater Wetland** and **Urban/Developed Unforested Freshwater Wetland Masks**.

- 1A: Extract Low-Quality Unforested Freshwater Wetland vegetation types from the LANDFIRE evt dataset using the classes listed in Appendix A.1 and extract to the spatial extent of the project.
  - OUTPUT: Reclassify pixels to produce a single value layer such that Low-Quality Unforested Freshwater Wetland pixels are assigned a value of **2**, all others are **NODATA**.
- 1B: Select Urban/Developed Unforested Freshwater Wetland vegetation types from the LANDFIRE evt dataset using the classes listed in Appendix A.1 and extract to the spatial extent of the project.
  - OUTPUT: Reclassify pixels to produce a single value layer such that Urban/Developed Unforested Freshwater Wetland pixels are assigned a value of **1**, all others are **NODATA**.

Step 2) Generate the **Unforested Freshwater Wetland Mask**.

- 2A: Select all Unforested Freshwater Wetland vegetation types out of the LANDFIRE evt dataset using the classes listed in Appendix A.1; clip layer to the spatial extent of the project.
  - OUTPUT: Reclassify pixels to produce a layer such that **Unforested Freshwater Wetland** pixels are assigned a value of **3**, all others **0**.

Step 3) Assess the watershed condition endpoint.

- 3A: Download the 2016 NLCD Percent Developed Impervious Surface dataset. Run Zonal Statistics to produce a raster where the value of the output pixel is the mean value of impervious surface within the boundary of a given HUC12.
- 3B: Isolate HUC12 watersheds in which less than 10% of the total area is characterized as impervious. Create a binary layer (reclassify pixels) in which pixels within watersheds with <10% total impervious surface area are assigned a value of **1**, all others **0**.
  - *Note: Use the same layer produced above in step 5 of the tidal marsh habitat classification.*
- 3C: Overlay the output of step 3B with the Unforested Freshwater Wetland Mask. Reclassify tidal marsh pixels that are characterized as being within watersheds with <10% impervious surface.
  - OUTPUT: Binary layer in which pixels classified as **Unforested Freshwater Wetland** within a watershed with <10% impervious surface are assigned a value of **3**, all others **0**

Step 4) Asses the Proximity to Protected Areas endpoint

- 4A: Download the PAD US dataset and extract GAP codes 1 through 3 (excluding 4) to the project spatial domain.
- 4B: Buffer the extracted PADUS polygons by 500 m and rasterize.

- 4C: Extract the Unforested Freshwater Wetland Mask through the PADUS buffer raster to identify cells within 500 m of the protected area occurrence.
- 4C: Reclassify the Unforested Freshwater Wetland Mask cells that fall within the PADUS buffer.
    - OUTPUT: Layer where **Unforested Freshwater Wetland** cells within 500 m of protected area occurrence are assigned a value of **6**, all others **0**.

Step 5) Assess Resilience metric (>100m from road)

- 5A: Create the buffered road mask by extracting the following LANDFIRE evt classes and converting to polygons: #7299 (Developed-Roads)
- 5B: Create a 100m buffer around all polygons/pixels classified as developed roads.
- 5C: Rasterize the polygon buffers at the 30 m LANDFIRE evt grid resolution across the extent of the project domain. Ensure that the output is snapped to the LANDFIRE evt grid. Reclassify such that pixels within the buffer (including the developed roads) are assigned a value of **1**, all others **0**.

  Note: Use the same layer produced above in step 5 of the mangrove habitat classification.
- 5C: Extract the Unforested Freshwater Wetland Mask through the buffered road layer and reclassify.
    - OUTPUT: Layer where **Unforested Freshwater Wetland** pixels that lay outside the buffered road areas are assigned a value of **1**, all others **0**.

Step 6) Assess disturbance return interval.

- 6A: Download the LANDFIRE CONUS Vegetation Disturbance data product.
- 6B: Extract data from all disturbance bins (include all time interval classes) and pixels associated with disturbance types: chemical, fire, and mechanical add and reclassify to binary where a value of **1** indicates a pixel meets the disturbance criteria.
- 6C: Extract the layer through the Unforested Freshwater Wetland Mask and reclassify to retain pixels that meet the disturbance criteria.
    - OUTPUT: Layer in which **Unforested Freshwater Wetland** pixels detailed by LANDFIRE's vegetation disturbance layer as having been disturbed at a rate of at least once a year for 14 years are assigned a value of **3**, all others **0**.

Step 7) Calculate the Condition Index for the Unforested Freshwater Wetland habitat type using the output layers created above:

- 7A: Overlay all OUTPUT layers that have condition index values for each of the 7 endpoints (5 habitat endpoints as well as the 2 layers produced for low quality and urban/developed unforested freshwater wetland land cover)
    - Theoretically if a pixel fulfills ALL conditions the **pixel value is 14**

Step 9) Develop final map for Unforested Freshwater Wetland habitat

- 9A: Finalize all Unforested Freshwater Wetland habitat type layers and check that condition indices are fully calculated
- 9B: Scale to the appropriate hex size – 30x30 m cell size will facilitate combining all layers at the end into a final habitat map

Known Issues

LF 2014 (v1.4) historic disturbance was used in the Middle Southeast Blueprint and the specific disturbance categorizations were used as a guide for the prototype Gulf-wide Blueprint.

From the original LF 2014 (v1.4) metadata the desired classes are detailed as:

- Mechanical Add: Means by which vegetation is mechanically "mowed" or "chipped" into small pieces and changed from a vertical to horizontal arrangement.
- Fire: A catch all term used to describe any non-structure fire that occurs in the wildland. Three distinct types of wildland fire have been defined: wildfire, wildland fire use, and prescribed fire.
- Chemical: Application of a chemical substance.

Research detailed a newer iteration of LANDFIRE vegetation disturbance completed during the 2016 remap process (v2.0). Notably, comparison of the disturbance classifications considered by the LF 2014 (v1.4) and the LF 2016 (v2.0) iterations detailed limited matching classifications between the two datasets and no direct matches for the v1.4 classifications used in the Middle Southeast Blueprint. Additionally, no crosswalk between the two version is detailed in the metadata and none could be located through additional investigation. For the disturbance data product from the LF 2016 (v2.0) remap, metadata is noticeable undescriptive. Comparing against class definitions from LF 2014 (v1.4) there are no longer any chemical disturbance types, fire is split out into four subcategorizations, and there is no classification that corresponds to mechanical add. The field descriptions from the data dictionary that the metadata references are circular and drilling down into the data lineage is largely impossible.

The disturbance data from the LF 2014 (v1.4) data product covers the period between 2005 and 2014 while the LF 2016 (v2.0) remap considers the period between 2006 and 2015. Given this minor shift temporal coverage, and based on the inadequate metadata documentation of the LF 2016 (v2.0) remap disturbance product, it was deemed more prudent to continue leveraging the LF 2014 (v1.4) disturbance dataset to assess disturbance return interval for this habitat classification.

Habitat: Beach and Unconsolidated Shore

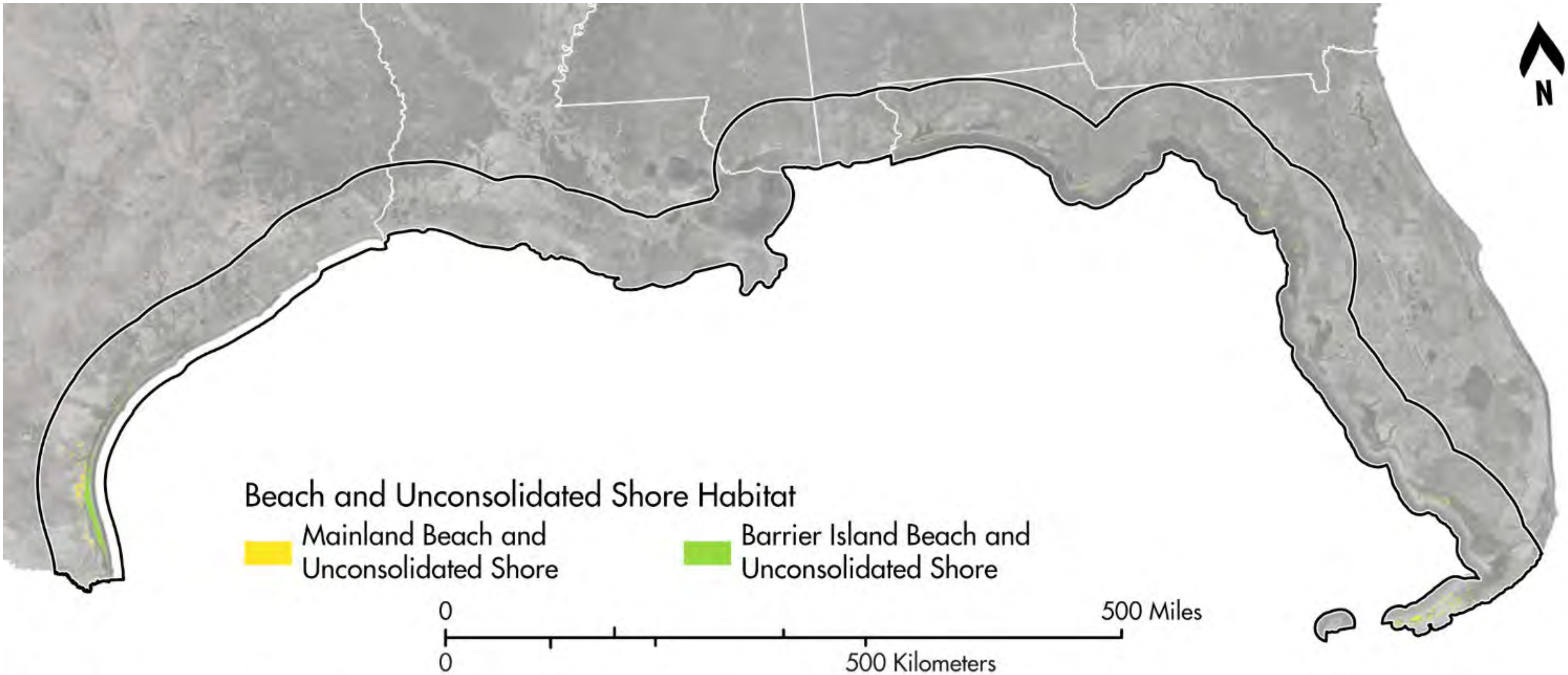
The evaluation metrics for Beaches and Unconsolidated Shore were developed through expert elicitation and USFWS blueprint developer engagement. The condition evaluation metrics follow the structure outlined in the Middle Southeast blueprint, and the metrics are summarized below:

Table A-28. Condition evaluation metrics for the Beaches and Unconsolidated Shore habitat type.

Desired Condition	Habitat Sub-Category	Metric	CI Score
Is desired habitat	Barrier Island Mainland Beach	Desired habitat type is present	3 pts
Patch size	Barrier Island Mainland Beach	>250 acres	6 pts
Landscape Configuration	Barrier Island	<25% developed land cover in a 5km radius	3 pts
	Mainland Beach	>3km from high intensity developed areas	
Site: Engineered Shoreline Condition	Barrier Island Mainland Beach	Is not a sensitive area	1 pts
Site: Shoreline Change	Barrier Island Mainland Beach	>300m away from areas characterized as likely to experience significant (> 2 m/year change) long term (100+ years) shoreline loss	1 pts

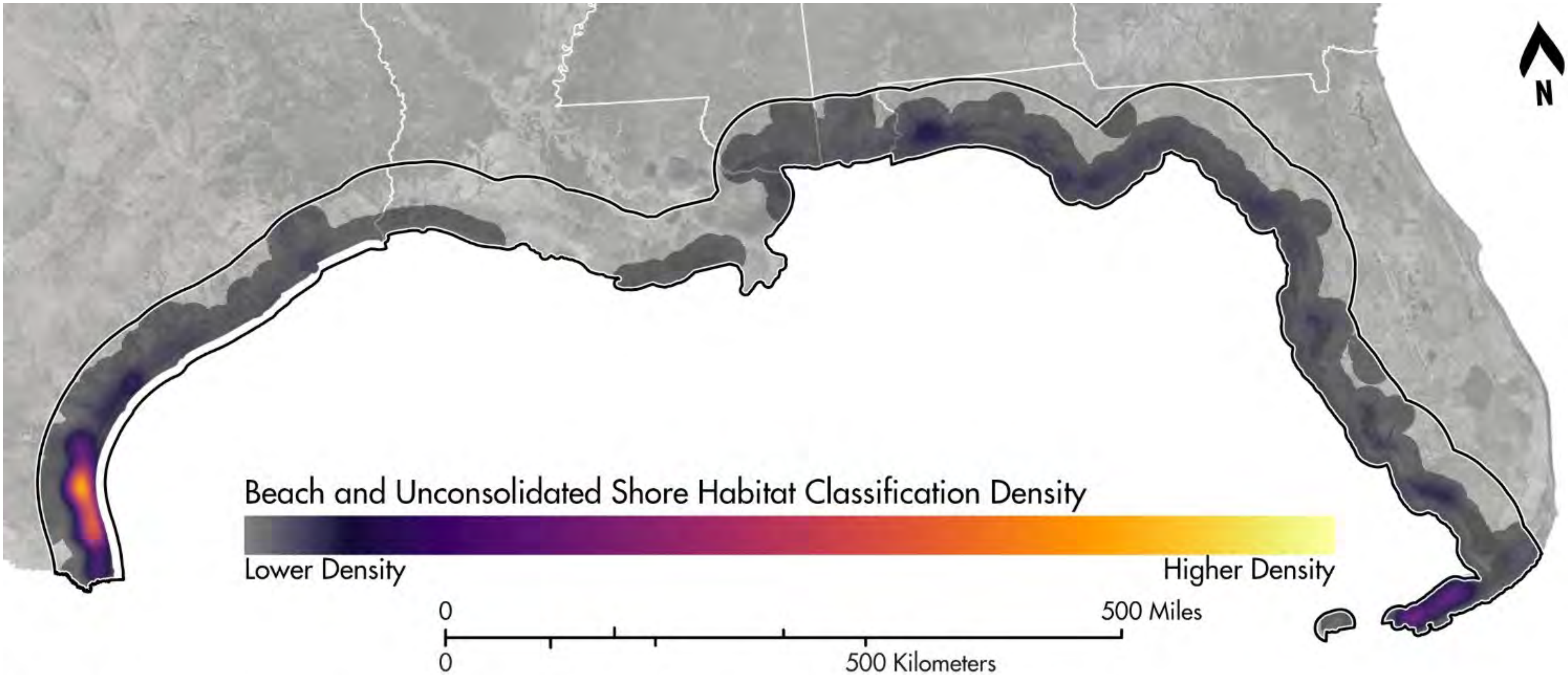
Note: To reduce the impact of human bias on mask generation, manual editing of features was minimized to the maximum extent practicable.

The occurrence of the Beach and Unconsolidated Shore habitat type within the project area is shown in Figure A-28 and Figure A-29, and the resulting habitat condition map is given in Figure A-30.



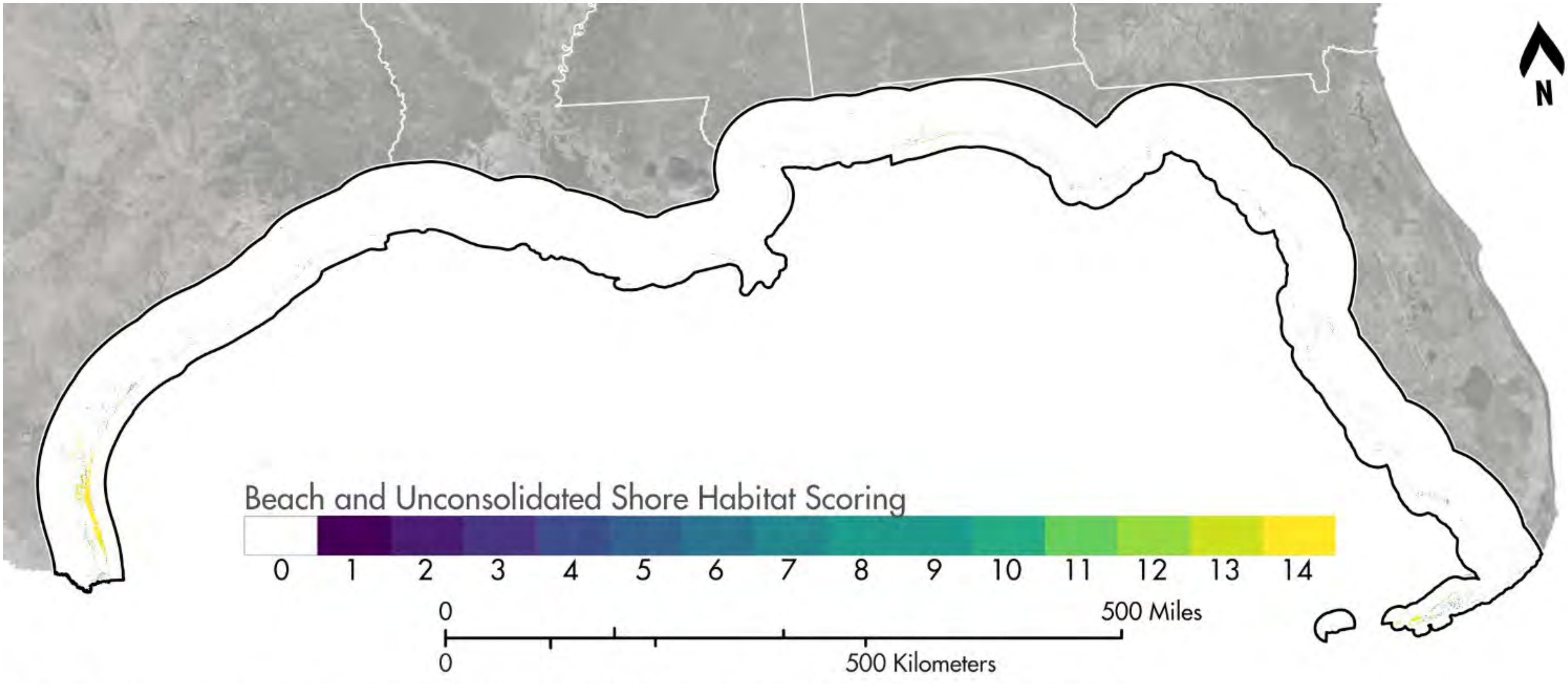
Data Source: CPRA, DataBasin, Esri, Florida Cooperative Land Cover, LANDFIRE, MRLC, NOAA, Texas A&M, The Nature Conservancy, USDA, USEPA, USFS, USFWS, USGS

Figure A-28. Presence of the Beach and Unconsolidated Shore habitat type in the Gulf-wide project area.



Data Source: CPRA, DataBasin, Esri, Florida Cooperative Land Cover, LANDFIRE, MRLC, NOAA, Texas A&M, The Nature Conservancy, USDA, USEPA, USFS, USFWS, USGS

Figure A-29. Density map highlighting areas with highest concentrations of 30 m Beach and Unconsolidated Shore habitat type pixels in the Gulf-wide project area.



Data Source: CPRA, DataBasin, Esri, Florida Cooperative Land Cover, LANDFIRE, MRLC, NOAA, Texas A&M, The Nature Conservancy, USDA, USEPA, USFS, USFWS, USGS

Figure A-30. Result of habitat condition assessment for the Beach and Unconsolidated Shore habitat type.

Detailed GIS Protocol:

Step 1) Create the **Overall Beach and Unconsolidated Shore Habitat Mask**:

- 1A: Select all Beach and Dune land cover types out of the LANDFIRE evt dataset using the classes listed in Appendix A.1 and extract to the project's spatial domain. Reclass pixels to binary values, 1 indicating habitat type is present, 0 indicating habitat type is absent.
- 1B: Download NHDPlus High Resolution geodatabases for each HUC04 in the project spatial domain (Moore et al., 2019). Merge each NHD Flowline feature class from contributing HUC04 geodatabases then extract coastline features (FCode = 56600) and buffer by 250 m.
- 1C: Download barrier island delineations from Data Basin (Ocean Conservancy, 2013). Dissolve all polygons and create a new field, 'Value', use field calculator to assign a value of 1. Using updated imagery, manually QC and redraw barrier island polygons to adjust for shifts in island footprint. This edited output will serve as the basis of the barrier island mask. Convert polygon to raster using the assigned field value and snap to the LF evt 30 m grid.
- 1D: Download 2016 Coastal Change Analysis Program (C-CAP) derived landcover data for states in the project spatial domain (NOAA Office for Coastal Management, 2020). Extract pixels with a value of 19 (Unconsolidated Shoreline) and set the extent to the project domain.
- 1E: Merge buffered NHD coastline polygons with barrier island polygons. This merged output will be used to augment the Beach and Dune LF evt classes with (C-CAP) unconsolidated shoreline pixels. Using updated imagery, manually QC merged polygons by comparing against to limit the C-CAP extract to areas dominated by sandy shorelines. Remove areas known to not contain beach and dune habitat types (i.e. Louisiana Bird's Foot Delta). Expand polygon in areas where C-CAP unconsolidated shore is dense (i.e., Florida Keys and Louisiana barrier island footprints).
- 1F: Extract C-CAP consolidate shoreline pixels through the combined coastline/barrier island polygon mask and reclassify to binary values, 1 indicating habitat type is present, 0 indicating habitat type is absent.
- 1G: Using cells statistics, determine the maximum pixel value between the LF evt beach and dune binary habitat raster (30 m resolution) with C-CAP unconsolidated shore binary raster (10 m resolution). Set the output cell size to match the 10 m resolution of the CCAP data. Output should be a binary raster unifying the extent of cells considered for the beach and unconsolidated shoreline mask.
- 1H: Resample the cell statistics output to the 30 m LF evt grid using natural neighbors. The natural neighbors interpolation technique is a suitable method for discrete data classification such as landcover. Reclassify such that pixels classified as beach or unconsolidated shore are assigned a value of 1, all others 0.
- This output is the unified beach and unconsolidated shoreline raster.
- 1I: Separate Barrier Island-associated classes from Mainland Beach classes using the barrier island mask output from 1C. Reclassify pixels to produce two layers (**Mainland Beach Mask**

and **Barrier Island Beach Mask**) such that if: 1) a pixel is Barrier Island, it is assigned a value of **3**, all others **0**; and 2) if a pixel is Mainland Beach, it is assigned a value of **3**, all others **0**.

Step 2) Assess the patch size endpoint for Mainland Beaches and Barrier Island Beaches

- 2A: Using the **Barrier Island Beach Mask**, infer patch size by using pixel counts of groups. Use the "Region Group" tool which groups pixels where they share common sides but not corners and pixel values are the same within groups.
- 2B: Using the **Mainland Beach Mask**, infer patch size by using pixel counts of groups. Use the "Region Group" tool which groups pixels where they share common sides but not corners and pixel values are the same within groups.
- 2C: Create a new layer from 2A for **Barrier Island Beaches** that meets the threshold for patch size (>250 acres). Reclassify pixels that satisfy that threshold.
    - OUTPUT: reclassify pixels that satisfy that patch requirement (>250 acres) with a value of **6**, all others **0**.
- 2D: Create a new layer from 2B for **Mainland Beaches** that meets the threshold for patch size (>250 acres). Reclassify pixels that satisfy that threshold.
    - OUTPUT: reclassify pixels that satisfy that patch requirement (>250 acres) with a value of **6**, all others **0**.

Step 3) Assess the Landscape Configuration Endpoint for **Barrier Island Beaches:** <25% developed land cover in a 5 km radius (apply only to large patches >250 acres)

- 3A: Extract the following land cover classes from the LANDFIRE evt dataset, clip to the spatial extent, and reclassify to create a binary layer such that all developed pixels are given a value of 1, all others 0. LANDFIRE evt classes to be extracted: #7296 (Developed-Low Intensity), #7297 (Developed-Medium Intensity), and #7298 (Developed-High Intensity)
- 3B: Create a circle window radius of 167 pixels (equivalent to 5km radius described in pixels)
    - Use focal mean statistics to calculate % developed cover using the developed land layer created in step 3A.
    - Reclassify such that only windows with <25% developed are retained
- 3C: Extract the **Barrier Island Beach** layer (>250 acres) through the focal statistics of urban cover layer (Step 3B) to create a layer in which pixels of barrier island polygons >250 acres are retained only if they intersect with windows with <25% developed cover. All pixels outside of the polygons should be 0.
- 3D: OUTPUT: One layer where pixels with beach/dune >250 acres within areas with <25% developed windows were retained. Reclassify so that pixels meeting the condition were given a value of **3**, all others **0**.

Step 4) Assess the Landscape Configuration Endpoint for **Mainland Beaches**: >3 km from high intensity developed areas

- 4A: Extract the LANDFIRE evt class #7298 (Developed-High Intensity), clip to the spatial extent, and reclassify to create a binary layer such that all high-intensity developed pixels are given a value of 1, all others 0.
- 4B: Convert the output of 4A from raster to polygon. Create a 3 km buffer around each polygon of high-intensity developed landcover. Reclassify as a binary layer.
- 4C: Overlay the output from step 4B with the **Mainland Beach Mask** layer (output from 1B above – not restricting to >250 acres). Reclassify such that any beach pixels overlapping with the 3km buffer and high intensity developed areas are given a value of 0, all others (pixels of mainland beach outside of a 3 km buffer) are given a value of 3.
    - OUTPUT: a binary layer reflecting mainland beach pixels at least 3km away from high intensity developed polygons given a value of **3**, all others **0**.

Step 5) Assess Site Endpoint: Engineered Shoreline Condition: Is not a sensitive area

- 5A) Download the Environmental Sensitivity Index (ESI) dataset from NOAA. Extract the following feature types and buffer by 100m:
    - Habitat rankings: **1B (exposed, solid man-made structures), 6B (riprap), 8B (sheltered, solid man-made structures), 8C (sheltered riprap)**
- 5B) Rasterize the ESI vectors and reclassify into a binary layer such that all pixels characterized as sensitive are given a value of 1, all others 0.
- 5C) Overlay the **Barrier Island Beach Mask** with the sensitive area dataset. Exclude pixels where these overlap.
    - OUTPUT: Binary layer in which pixels characterized as Barrier Island Bach but that are not considered sensitive (due to riprap, etc) are given a value of **1**, all others **0**.
- 5D) Overlay the **Mainland Beach Mask** with the sensitive area dataset. Exclude pixels where these overlap.
    - OUTPUT: Binary layer in which pixels characterized as Mainland Island Bach but that are not considered sensitive (due to riprap, etc) are given a value of **1**, all others **0**.

Step 6) Assess the Site Endpoint: Shoreline Change: >300 m away from areas characterized as likely to experience significant (> 2 m/year change) long term (100+ years) shoreline loss

- 6A: Download the USGS Gulf of Mexico Long-Term Shoreline Change dataset:
    - https://go.usa.gov/x5bSu
- 6B: Extract data points that reflect more than -2 m/year shoreline change (indicating loss of shoreline)

- 6C: Create a buffer of 300 m around each data point. Reclassify into binary such that all buffered areas are given a value of 1, all others 0.
- 6D) Overlay the **Barrier Island Beach Mask** with the buffered shoreline change dataset (from 6C above). Exclude pixels where these overlap.
    - OUTPUT: Binary layer in which pixels characterized as Barrier Island Bach but that are not considered areas subject to long term shoreline change are given a value of **<u>1</u>**, all others **<u>0</u>**.
- 6E) Overlay the **Mainland Beach Mask** with the buffered shoreline change dataset (from 6C above). Exclude pixels where these overlap.
    - OUTPUT: Binary layer in which pixels characterized as Mainland Island Bach but that are not considered areas subject to long term shoreline change are given a value of **<u>1</u>**, all others **<u>0</u>**.

Step 7) Calculate the Condition Index for the **Mainland Beach** and **Barrier Island Bach** habitat types using the output layers created above:

- 7A: Overlay all OUTPUT layers that have condition index values for each of the 5 endpoints
    - Theoretically if a pixel fulfills ALL conditions the **pixel value is 14**

Step 9) Develop final map for **Beaches and Dune** by combining the habitat condition maps for **Mainland Beaches** and **Barrier Island Beaches**

- 9A: Finalize the habitat type layers and check that condition indices are fully calculated for each
- 9B: Scale to the appropriate hex size – 30x30 m cell size will facilitate combining all layers at the end into a final habitat map

<u>Known Issues</u>

Beach and unconsolidated shore required the most manual intervention to assess when compared against other habitat types considered by the prototype Gulf-wide Blueprint. This habitat type leveraged two data sources at differing resolutions and was extracted through a barrier island vector feature that required significant modification to adjust for landscape shift between its publication year (2013) and the present (2021).

Additionally, the unconsolidated shore landcover C-CAP classification ostensibly considers a broad array of sand-dominated land types with photogrammetric imagery classification occurring across all water levels in the tidal cycle. As a result, the beach and unconsolidated shore habitat coverage developed for the prototype Gulf-wide Blueprint might overestimate or underestimate the coverage and distribution of this habitat type across the study domain.

Habitat Group: Open Water

1. Habitat Type: Estuarine Open Water

This habitat type was mapped according to methods developed by the South Atlantic Blueprint and is *not* evaluated for condition. Open water estuaries were defined using the National Wetlands Inventory (NWI) (U.S. Fish and Wildlife Service 2014) using the classification estuarine open water class: "Estuarine and Marine Deepwater." Full details on how this habitat was delineated are located here. Extract that class for this habitat layer.

Detailed GIS Protocol:

- 1A) Download and extract NWI data for all states in the project domain.
- 1B) Merge state polygons together, rasterize at the 30 m LANDFIRE grid resolution,
- 1C) Reclassify such that a pixel is valued at 3 if it represents estuarine open water and 0 for other habitat types
    - OUTPUT: A binary layer in which the above open water (Fresh and Estuarine) are classified as **3**, all others **0** for ultimate integration into the overall habitat condition map. This is not a habitat condition assessment score, but rather shows it as non-degraded habitat.

2. Habitat Type: Freshwater Lakes, Rivers, & Streams

This habitat type was mapped but not assessed for habitat condition.

Table A-29. LANDFIRE evt classes for freshwater lakes, rivers, and streams.

LANDFIRE evt Class Value	LANDFIRE evt name	Category
7292	Open Water	Open Water

Detailed GIS Protocol:

- 1) Download and extract the data
    - 1A: Extract the above "Open Water" class from LANDFIRE evt, reclassifying such that open water cells are coded as 1, all others 0.
    - 1B: Download the National Hydrography Dataset Plus Version 2 (NHDPlus V2): Extract Feature Types (FType) equal to 'CanalDitch', 'LakePond', 'Lock Chamber', 'Spillway', 'StreamRiver', and 'Submerged Stream'
- 2) Combine all open water cells from LANDFIRE evt and the NHDPlus V2 dataset.
- 3) OUTPUT: A binary layer in which the above "Open Water" habitat type is classified as **3**, all others **0** for ultimate integration into the overall habitat condition map. This is not a true habitat condition assessment score.

The occurrence of the Open Water habitat type within the project area is shown in Figure A-31 and Figure A-32, and the resulting habitat condition map (assigning all open water a value of 3) is given in Figure A-33.

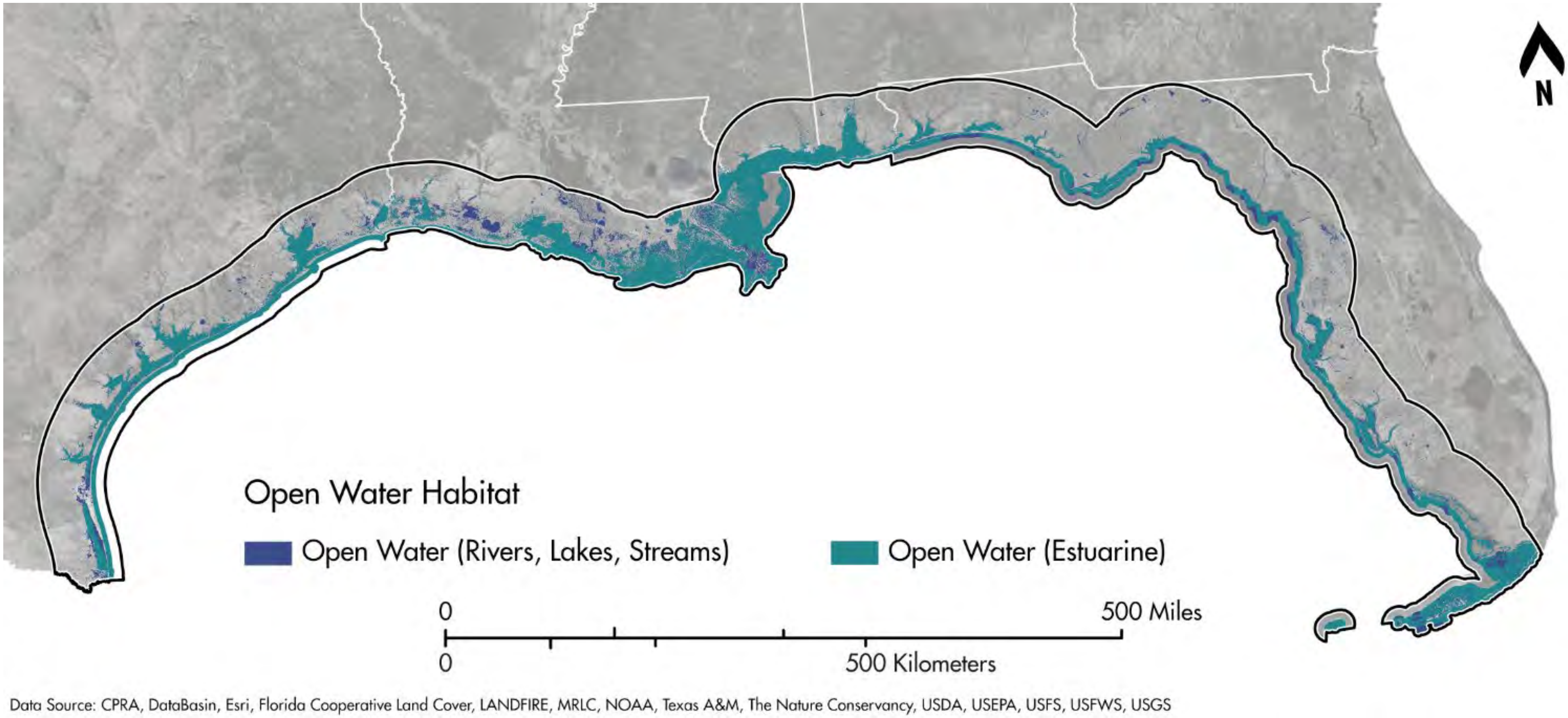
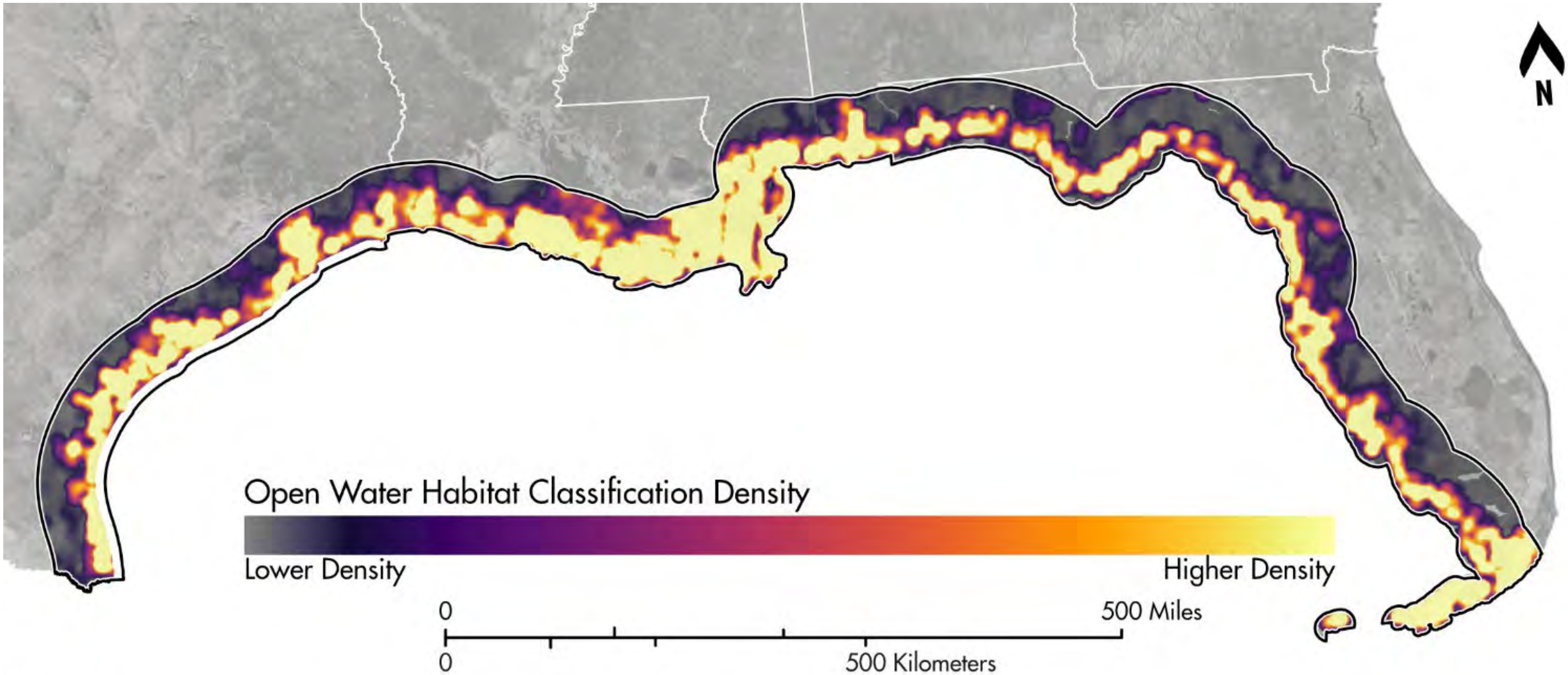
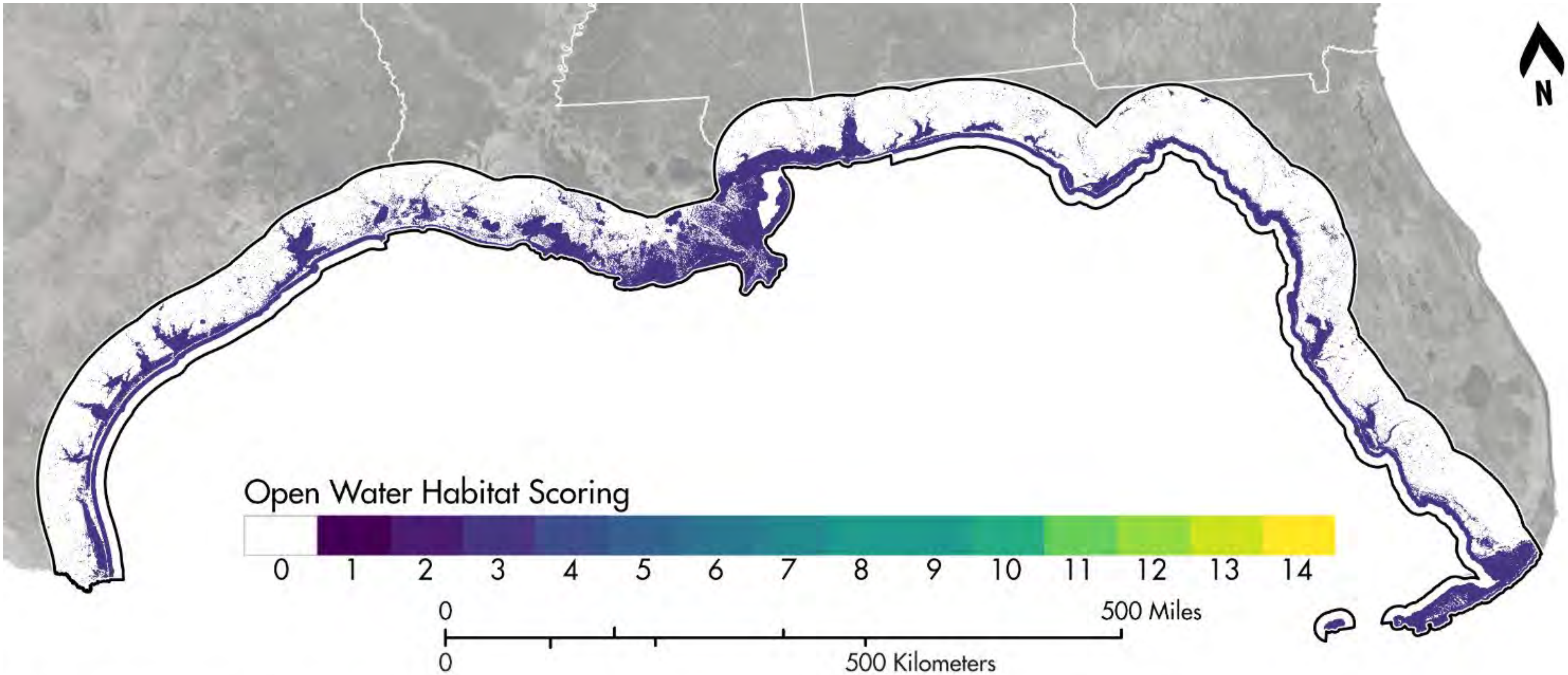


Figure A-31. Presence of the Open Water habitat type in the Gulf-wide project area.



Data Source: CPRA, DataBasin, Esri, Florida Cooperative Land Cover, LANDFIRE, MRLC, NOAA, Texas A&M, The Nature Conservancy, USDA, USEPA, USFS, USFWS, USGS

Figure A-32. Density map highlighting areas with highest concentrations of 30 m Open Water habitat type pixels in the Gulf-wide project area.



Data Source: CPRA, DataBasin, Esri, Florida Cooperative Land Cover, LANDFIRE, MRLC, NOAA, Texas A&M, The Nature Conservancy, USDA, USEPA, USFS, USFWS, USGS

Figure A-33. Result of landcover scoring for the Open Water habitat group.

Habitat: “Other”

Some landcover types could not be combined into the above habitat categories, however they could represent an area important for priority species. Habitats classified as “other” were mapped but not assessed for habitat condition. Appendix A.1 summarizes the LANDFIRE evt classes that were included in this category. These pixels were assigned a value of **3**.

OUTPUT: A binary layer in which the above “Other” habitat types are classified as **3**, all others **0** for ultimate integration into the overall habitat condition map. This is not a true habitat condition assessment score.

The occurrence of the “Other” land cover type within the project area is shown in Figure A-34 and Figure A-35, and the resulting habitat condition map (assigning all ‘Other’ land cover areas a value of 3) is given in Figure A-36

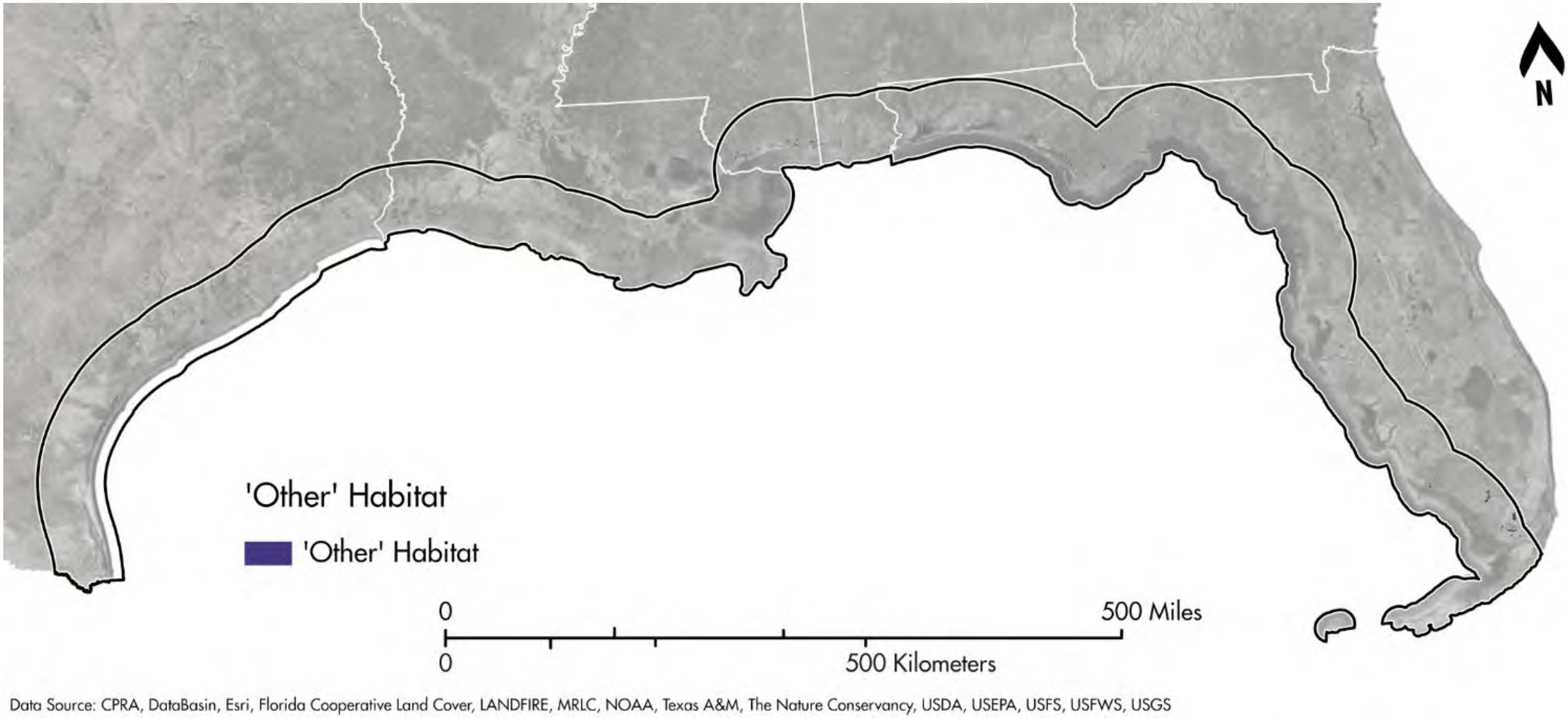


Figure A-34. Presence of the 'Other' land cover type in the Gulf-wide project area.

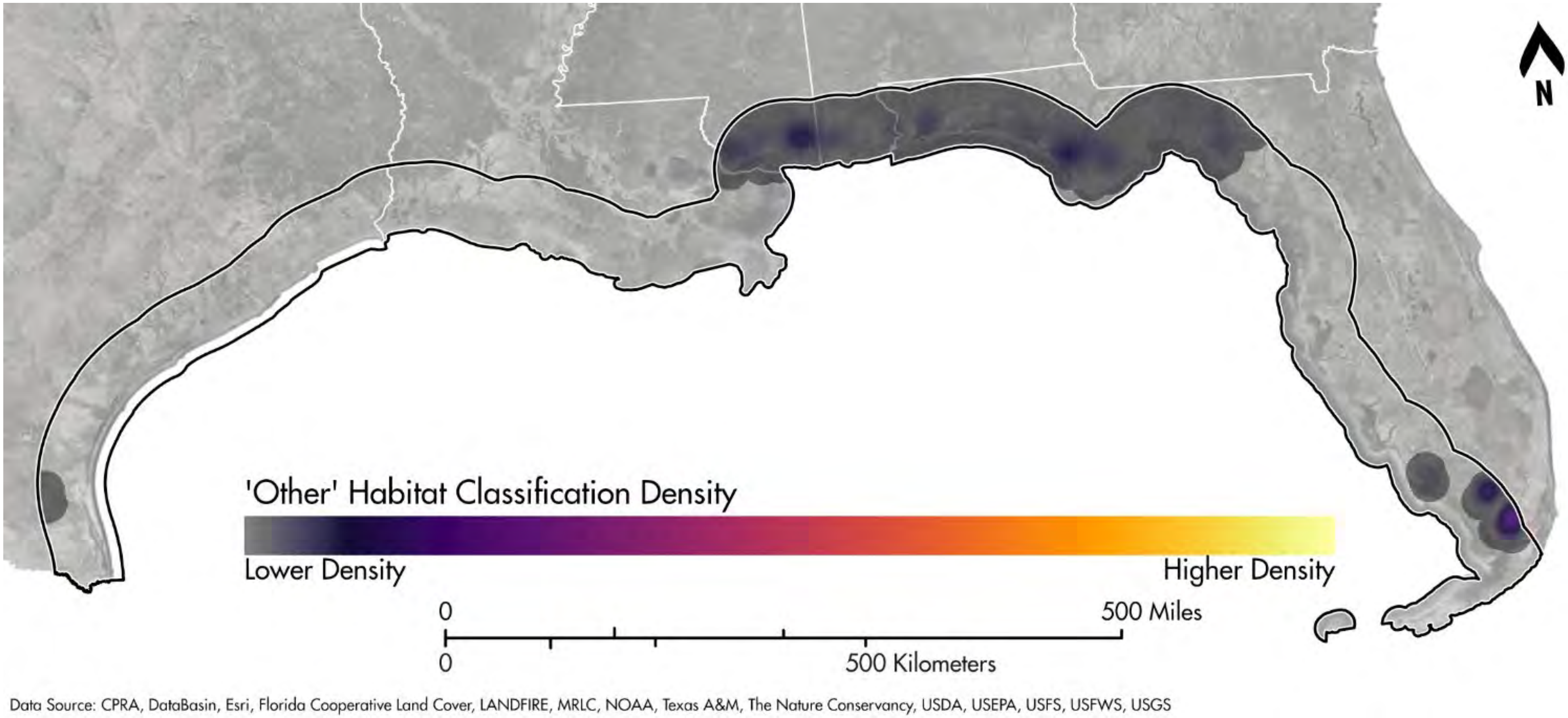
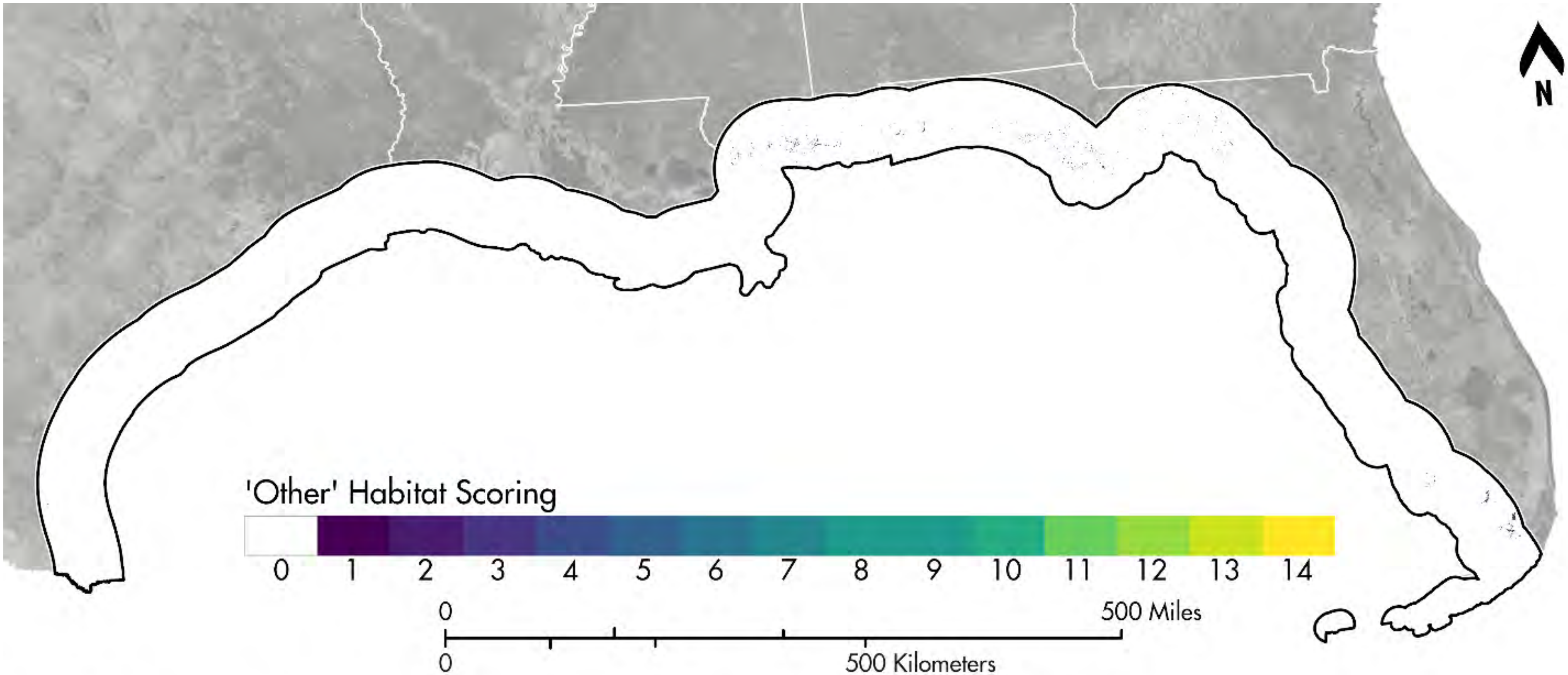


Figure A-35. Density map highlighting areas with highest concentrations of 30 m 'Other' land cover type pixels in the Gulf-wide project area.



Data Source: CPRA, DataBasin, Esri, Florida Cooperative Land Cover, LANDFIRE, MRLC, NOAA, Texas A&M, The Nature Conservancy, USDA, USEPA, USFS, USFWS, USGS

Figure A-36. Result of landcover scoring for the 'Other' habitat type.

Combining Habitat Assessments for the Habitat Condition Indicator Layer

Gulf-wide habitats are diverse, spanning multiple ecoregions and climate zones (Figure A-37). Due to the use of multiple, potentially overlapping data sources, development of an ultimate habitat combination methodology required careful consideration as to the specific prioritization of competing habitat classifications in areas where source data overlaps were identified.

Primary-source habitat categories (i.e., those habitats who only utilized LANDFIRE evt data as input into the assessment methodology) were summed using cell statistics to provide a basis for cell conflict determination and accounted for more than 90% of the processing domain. While LANDFIRE evt data contributed the largest total combined area in this assessment, state-level data for mangrove habitat coverage was deemed most authoritative and identified as the highest priority habitat classification for any conflicts (Table 1). The limited conflicting area of the beach and unconsolidated shore classification (a combination of C-CAP 'Unconsolidated Shore' and LANDFIRE evt 'Beach and Dune' data sources) with the LANDFIRE evt primary-source habitat classifications in addition to the identification of conflict cells as being predominantly open water resulted in this habitat classification being assigned the second highest combination priority. The final theoretically overlapping data source, the open water classification (a combination of NHD, NWI, and LF evt 'Open Water' data sources), was assigned the lowest prioritization level given that this habitat was only mapped and not assessed for condition.

Table 1: Priority ranks for potentially competing habitat classification cells. Mangrove habitats were assigned the highest priority based on the resolution and authority of the contributing data.

Priority Ranking	Habitat Class(es)	Data Source
1	Mangrove Forest	CLC, CPRA, LF, and TAMU
2	Beach and Unconsolidated Shore	C-CAP and LF
3	Forests (excluding Mangrove), Agriculture, Grassland[3], Tidal Marsh, Unforested Freshwater Wetland, "Other"	LF
4	Open Water	LF, NHD, and NWI

The "Pick" geoprocessing tool, available in the Esri desktop GIS environment, was used to combine potentially competing habitats. This tool uses the value of an integer raster (defined as the input position raster) to determine an output cell assignment based on the listed order, or position, of several input rasters (Table 2). Creation of the input position raster was facilitated by reclassing the four competing rasters to non-conflicting, widely separated integer values. The reclassed conflicting habitat rasters, represented as constant values, were then summed using cell statistics. The unique cell value output by this geoprocessing operation detailed the specific conflicts between habitat classification and was categorized to determine value reclassifications as the "Pick" input position raster.

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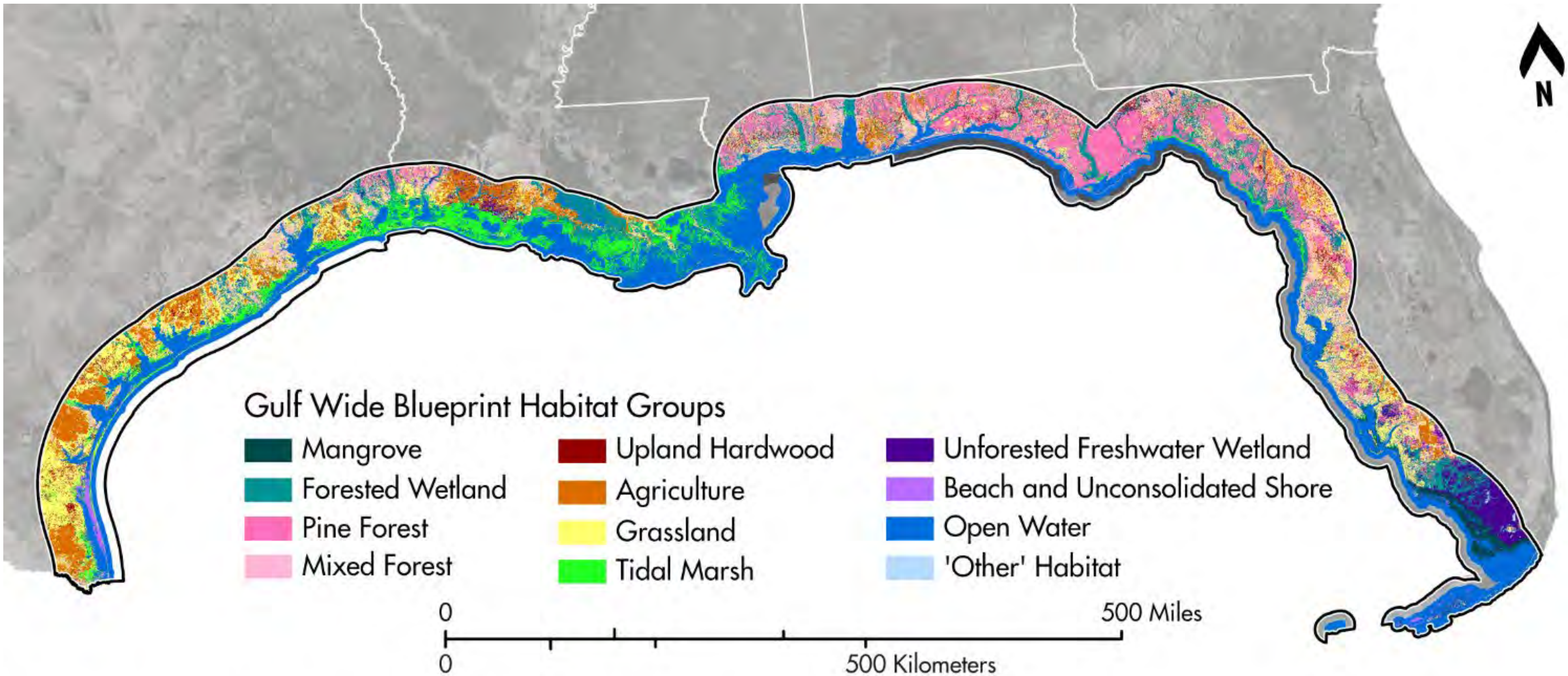
[3] The grassland habitat classification assessment leveraged an additional data set (NASS CDL) in the assessment methodology but used this external source to augment the scoring of LF evt grassland vegetation classes rather than expand their extent and is considered a primary-source habitat classification

Table 2: Detailed habitat classification cell conflicts, their ultimate assignment, and reclassification value to create the input position raster for use in the "Pick" geoprocessing tool.

Habitat Classification Conflict	Final Assignment	"Pick" input position raster value
None, only Mangrove	Mangrove	1
None, only Beach and Unconsolidated Shore	Beach and Unconsolidated Shore	2
Mangrove, Beach and Unconsolidated Shore	Mangrove	1
None, Primary-source Habitat	Primary-source Habitat	3
Mangrove, Primary-source Habitat	Mangrove	1
Beach, Primary-source Habitat	Beach	2
Mangrove, Beach, and Primary-source Habitat	Mangrove	1
Primary-source Habitat, Open Water	Primary-source Habitat	3
Mangrove, Primary-source Habitat, Open Water	Mangrove	1
Beach, Primary-source Habitat, Open Water	Beach	2
Mangrove, Beach, Primary-source Habitat, Open Water	Mangrove	1
None, only Open Water	Open Water	4
Mangrove, Open Water	Mangrove	1
Beach, Open Water	Beach	2
Mangrove, Beach, Open Water	Mangrove	1

The output of the "Pick" geoprocessing tool is detailed as the unified Habitat Condition Indicator layer (Figure A-38). This final data layer includes habitat scores ranging from 1-2 reflecting low-quality and degraded habitat as these land cover types may still be important for key species. Non-evaluated habitats (e.g., open water) were also included in mapped habitat. The result is a single surface with a Condition Index score for each grid cell that represents current habitat land cover; values of 0 reflect non-mapped habitats (e.g., urban development, quarries/mines; see Table A-18). Removing habitat condition scores from the natural land cover layer, Figure A-39 (Unified Habitat Mask) reflects presence/absence of natural land cover (0 = not natural land cover, 1 = natural land cover).



Data Source: CPRA, DataBasin, Esri, Florida Cooperative Land Cover, LANDFIRE, MRLC, NOAA, Texas A&M, The Nature Conservancy, USDA, USEPA, USFS, USFWS, USGS

Figure A-37. Habitat land cover designations across the Gulf-wide project area (also referred to as the Unified Habitat Mask for GIS processes in Appendix A.3).

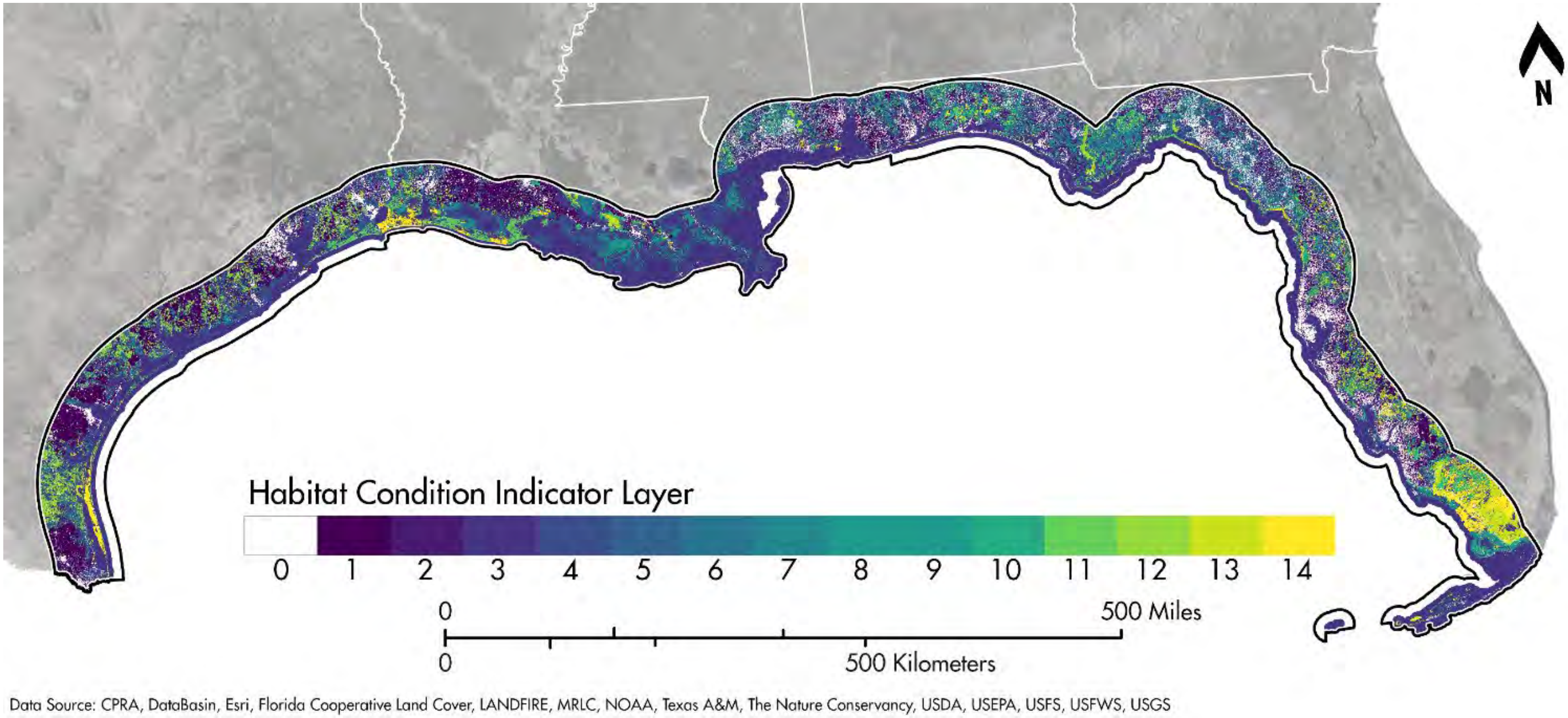


Figure A-38. Habitat Condition Indicator spatial data layer developed for the prototype Gulf-wide Blueprint. Values of 0 indicate not natural land cover. Values 1-2 indicate degraded or low-quality habitat types. Values >2 reflect habitat condition scores based on site and landscape level metrics where 14 indicates highest quality of a given habitat type.

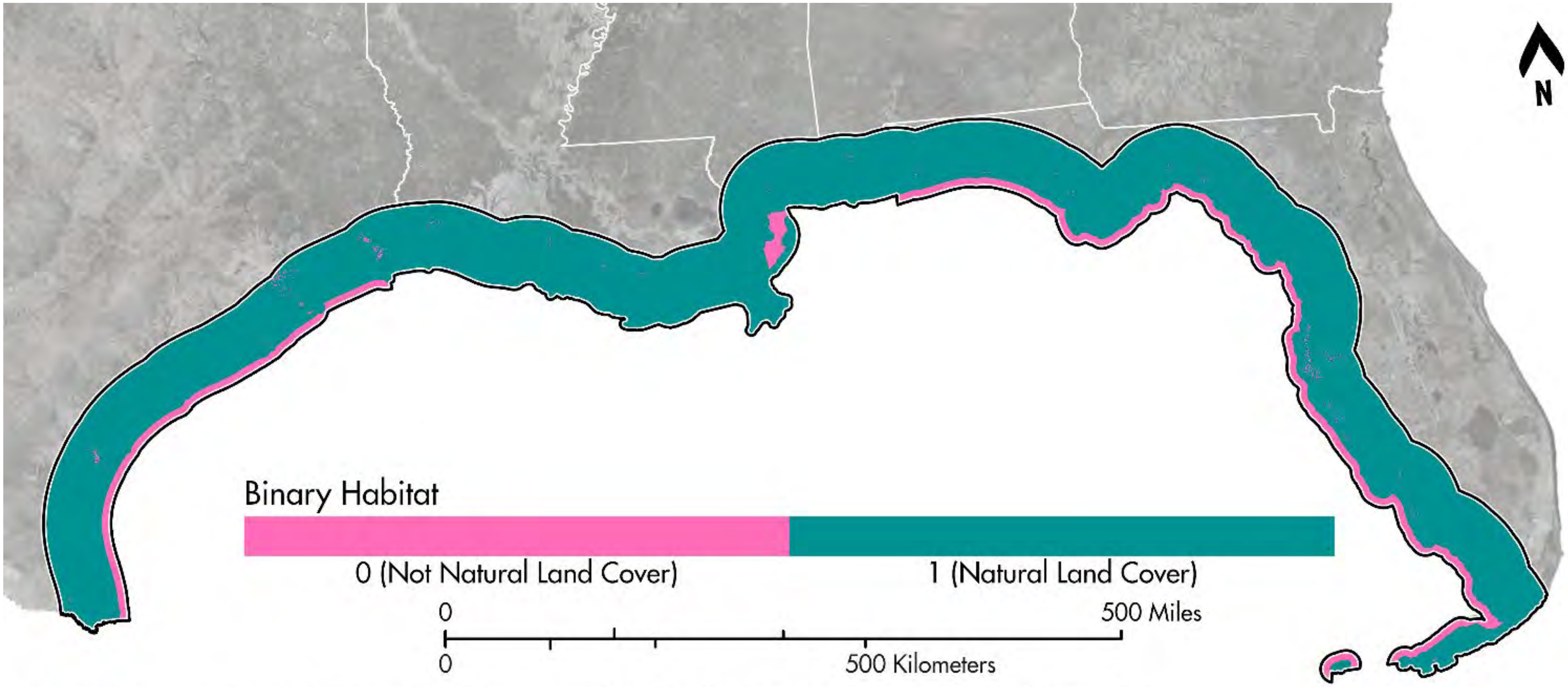


Figure A-39. Habitat Condition Indicator reflecting only presence/absence of natural land cover across the Gulf-wide project area. Note: viewed at this spatial scale, locations of not natural land cover may be difficult to discern. This data layer was used for the Zonation sensitivity analysis presented in Appendix A.4.

REFERENCES

Middle Southeast Blueprint. (2020). *Middle Southeast Blueprint 3.0 Development Process*. Middle Southeast Blueprint.

Moore, R., McKay, L., Rea, A., Bondelid, T., Price, C., Dewald, T., & Johnston, C. (2019). *User's guide for the national hydrography dataset plus (NHDPlus) high resolution* (U.S. Geological Survey Open-File Report No. 2019–1096) (p. 66).

NOAA Office for Coastal Management. (2020). 2016 C-CAP Derived Land Cover BETA. Coastal Change Analysis Program (C-CAP) Regional Land Cover. Charleston, SC.

Ocean Conservancy. (2013). Gulf of Mexico barrier islands using scale 1:30,000. Esri shapefile based on Microsoft Corporation, 2011.

South Atlantic Conservation Blueprint. (2020). South Atlantic Blueprint 2020 Development Process.

USGS. (2019). *NLCD 2016 Tree Canopy Cover (CONUS)*. USGS/EROS, 47914 252nd Street, Sioux Falls, SD, 57198-0001, US: U.S. Geological Survey.

Wilson, B. T., Lister, A. J., Riemann, R. I., & Griffith, D. M. (2013). Live tree species basal area of the contiguous United States (2000-2009). Newtown Square, PA: USDA Forest Service, Northern Research Station.

APPENDIX A

A.3 ECOSYSTEM AND SOCIO-ECOLOGICAL INDICATORS

The indicators used in the Southeast Conservation Adaptation Strategy (SECAS) prototype Gulf-wide Blueprint are based on a subset of indicators developed for the 2020 South Atlantic Blueprint. The South Atlantic Blueprint methodology defines an indicator as “a metric that is designed to inform us easily and quickly about the conditions of a system (e.g., riparian buffers); used to measure progress toward a goal (a desired conservation outcome)” (South Atlantic Conservation Blueprint, 2020). The prototype Gulf-wide Blueprint relied on as many 2020 South Atlantic Blueprint indicators as possible that could be developed for the Gulf-wide project area. The indicators deviate from the 2020 South Atlantic Blueprint methodology in a couple of ways:

1) Indicators that involved datasets that were highly localized, species-specific, lacked freely available nation-wide data, or could not be easily replicated across the entire Gulf-wide project area for the prototype Gulf-wide Blueprint were omitted. For example, the indicators of Beach Birds and Forest Birds were omitted because they are based on habitat suitability models relevant only to the South Atlantic geography. Omitted indicators (aside from individual habitat indicators) include Beach Birds, Unaltered Beach, Forest Birds, Marsh Patch Size (although similar metric used in calculating Tidal Marsh condition index for the prototype Gulf-wide Blueprint), Pine Birds, Amphibian and Reptile Areas, Resilient Terrestrial Sites, Migratory Fish Connectivity, Network Complexity, Potential Hardbottom Condition, Marine Mammals, and Marine Birds.
2) Socio-ecological indicators were developed *de-novo* for the prototype Gulf-wide Blueprint. These parallel some of the 2020 South Atlantic Blueprint indicators of Greenways and Trails (prototype Gulf-wide: Recreational Access). South Atlantic Blueprint indicators not used include: Low-Urban Historic Landscapes and Urban Open Space.
3) The final prototype Gulf-wide Blueprint relies on a single land cover map as the natural land cover (habitat) indicator (the Habitat Condition Indicator), reflecting values of habitat condition across the landscape. The 2020 South Atlantic Blueprint includes an ecosystem map as well as separate indicators for different habitat types (e.g., forested wetland extent, maritime forest extent) to restrict the spatial extent of certain indicators for more accurate analysis. For some South Atlantic Blueprint indicators (e.g., marsh) the habitat is both mapped as presence AND evaluated for condition (e.g., marsh patch size) in separate but overlapping indicators. Lastly, multiple land cover datasets were used to define habitats in the South Atlantic Blueprint whereas only a single land cover dataset was used in the prototype Gulf-wide Blueprint (except for mangroves, beaches, and to define prairie grasslands).

This document outlines the steps used to map each prototype Gulf-wide Blueprint indicator. For further detail on metrics as they relate to the South Atlantic Blueprint, please see the 2020 South Atlantic Blueprint Development Documentation (South Atlantic Conservation Blueprint, 2020).

Habitat Condition Indicator

A single spatial data layer reflecting habitat condition scores for natural land cover types across the project area. See Appendix A.2 for more detail on the development of this indicator.

Natural Resource Indicators: Terrestrial

1. *Critical Habitat*

A uniform approach to mapping species rather than a mosaic of localized datasets was used for the prototype Gulf-wide Blueprint. Critical habitat spatial data was included for avian, terrestrial mammalian, amphibian (of the class *Amphibia*), and reptilian (of the class *Reptilia*) species recognized as threatened and endangered (both final and proposed) at the federal level by U.S. Fish and Wildlife (USFWS). Unfortunately, the dataset for priority amphibian and reptile areas (the South Atlantic Priority Amphibian and Reptile Conservation Areas) used in the 2020 South Atlantic Blueprint does not extend across the Gulf coast and therefore does not fulfill the guidelines of the prototype Gulf-wide Blueprint uniform approach. Therefore, we did not use the South Atlantic Priority Amphibian and Reptile Conservation Areas dataset in this indicator.

Input Data

- Critical Habitat data was downloaded from the USFWS Threatened and Endangered Species Active Critical Habitat report ("ECOS: USFWS Threatened & Endangered Species Active Critical Habitat Report," 2021). The most recent data update used in the prototype Gulf-wide Blueprint was released on February 10, 2021
    - Download the dataset and parse by taxa group (avian, mammalian, amphibian, reptile, other)
- The Estuarine Open Water habitat class from the Habitat Condition Indicator layer (see Appendix A.2)

Endangered and threatened avian, mammalian, amphibian, and reptilian species assessed for the Gulf coast are those listed in Table A-29.

Table A-29. List of endangered and threatened species included in the Critical Habitat Indicator of the prototype Gulf-wide Blueprint.

Species Group	Scientific Name	Common Name	ESA Listing Status
Amphibian	*Ambystoma bishopi*	Salamander, Reticulated Flatwoods	Endangered
Amphibian	*Ambystoma cingulatum*	Salamander, Frosted Flatwoods	Threatened
Amphibian	*Rana sevosa*	Frog, Dusky Gopher	Endangered
Avian	*Ammodramus maritimus mirabilis*	Sparrow, Cape Sable seaside	Endangered
Avian	*Charadrius melodus*	Plover, Piping	Endangered
Avian	*Grus americana*	Crane, Whooping	Endangered
Avian	*Grus canadensis pulla*	Crane, Mississippi Sandhill	Endangered

Species Group	Scientific Name	Common Name	ESA Listing Status
Avian	*Rostrhamus sociabilis plumbeus*	Kite, Everglade Snail	Endangered
Mammalian	*Eumops floridanus*	Bat, Florida Bonneted	Endangered
Mammalian	*Oryzomys palustris natator*	Rice Rat, Silver	Endangered
Mammalian	*Peromyscus polionotus allophrys*	Mouse, Choctawhatchee Beach	Endangered
Mammalian	*Peromyscus polionotus ammobates*	Mouse, Alabama Beach	Endangered
Mammalian	*Peromyscus polionotus peninsularis*	Mouse, St. Andrew Beach	Endangered
Mammalian	*Peromyscus polionotus trissyllepsis*	Mouse, Perdido Key Beach	Endangered
Mammalian	*Trichechus manatus*	Manatee, West Indian	Threatened
Reptilian	*Caretta caretta*	Sea Turtle, Loggerhead	Threatened
Reptilian	*Crocodylus acutus*	Crocodile, American	Threatened
Reptilian	*Pituophis melanoleucus lodingi*	Snake, Black Pine	Threatened

Mapping Steps

- Initial processing was needed given that the input data was a mixture of polygons and polylines. Data was extracted to the spatial domain of the project and split into individual features classes based on the species group
- The geoprocessing tool "Count Overlapping Features" was used to determine the overlap between the individual species group polygons. This tool was run twice, once for polygons and once for polylines. To avoid double counting portions of critical habitat, polylines for one species (Loggerhead Sea Turtle) were erased from the input dataset where they overlapped their species' critical habitat polygon
- The polygon output of the "Count Overlapping Features" tool was rasterized at 100 m resolution based on the 'COUNT_' field (the number of overlapping features)
- The total number of overlapping species critical habitat was assessed by summing the individual rasterized polygon and point features then extracting through the National Wetlands Inventory (NWI) open water layer (see Appendix A.2) to remove estuarine open water
    - OUTPUT: Critical habitat map of all species. Each cell value represents a count of how many polygons and polylines of species distribution overlap with that pixel, ranging from 0 (no species) to 4 (4 overlapping species distribution polygons/polylines)

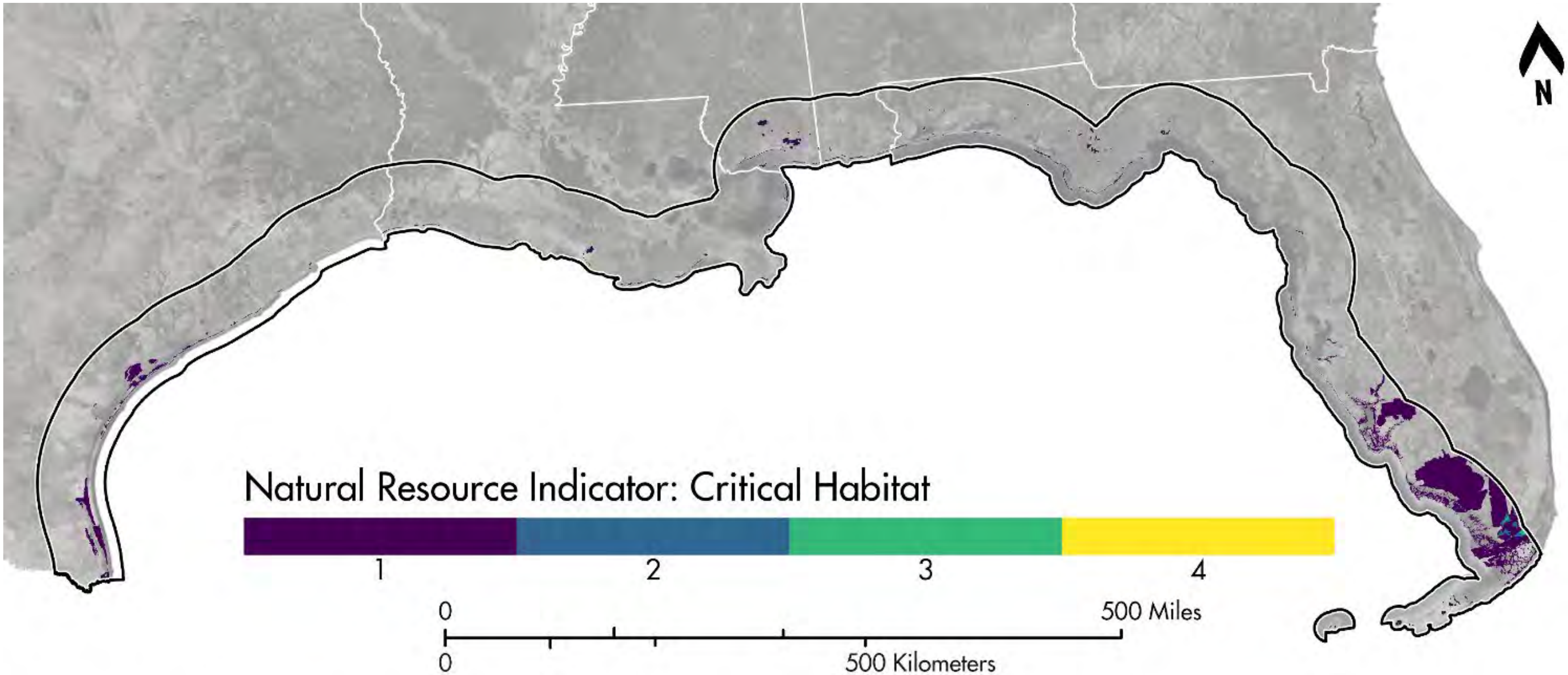
Final Indicator Values

The final indicator is continuous, with values ranging from:

- Low: 0 (no endangered or threatened critical habitat present)
- High: 4 (4 overlapping critical habitat areas are present)

Mapped Indicator

The resulting spatial layer depicting the Critical Habitat prototype Gulf-wide Blueprint indicator is given in Figure A-40.



Data Source: CPRA, DataBasin, Esri, Florida Cooperative Land Cover, LANDFIRE, MRLC, NOAA, Texas A&M, The Nature Conservancy, USDA, USEPA, USFS, USFWS, USGS

2. Resilient Coastal Sites of the Gulf of Mexico

The prototype Gulf-wide Blueprint uses The Nature Conservancy (TNC) Resilient Coastal Sites Gulf of Mexico dataset to map estimated coastal resilience, a score that reflects the ability of coastal habitats to migrate landward (to adjacent lowlands) under increasing sea level rise inundation scenarios. This is a key indicator for the coastal focus of the prototype Gulf-wide Blueprint and may de-prioritize inland areas. Future iterations should seek to include the Resilient Terrestrial Sites indicator used in the 2020 South Atlantic Blueprint based on a similar TNC Resilient Land dataset that would extend resilience values further inland.

Input Data

- TNC Resilient Coastal Sites Gulf of Mexico Tidal Complex Resilience Scores SLR65

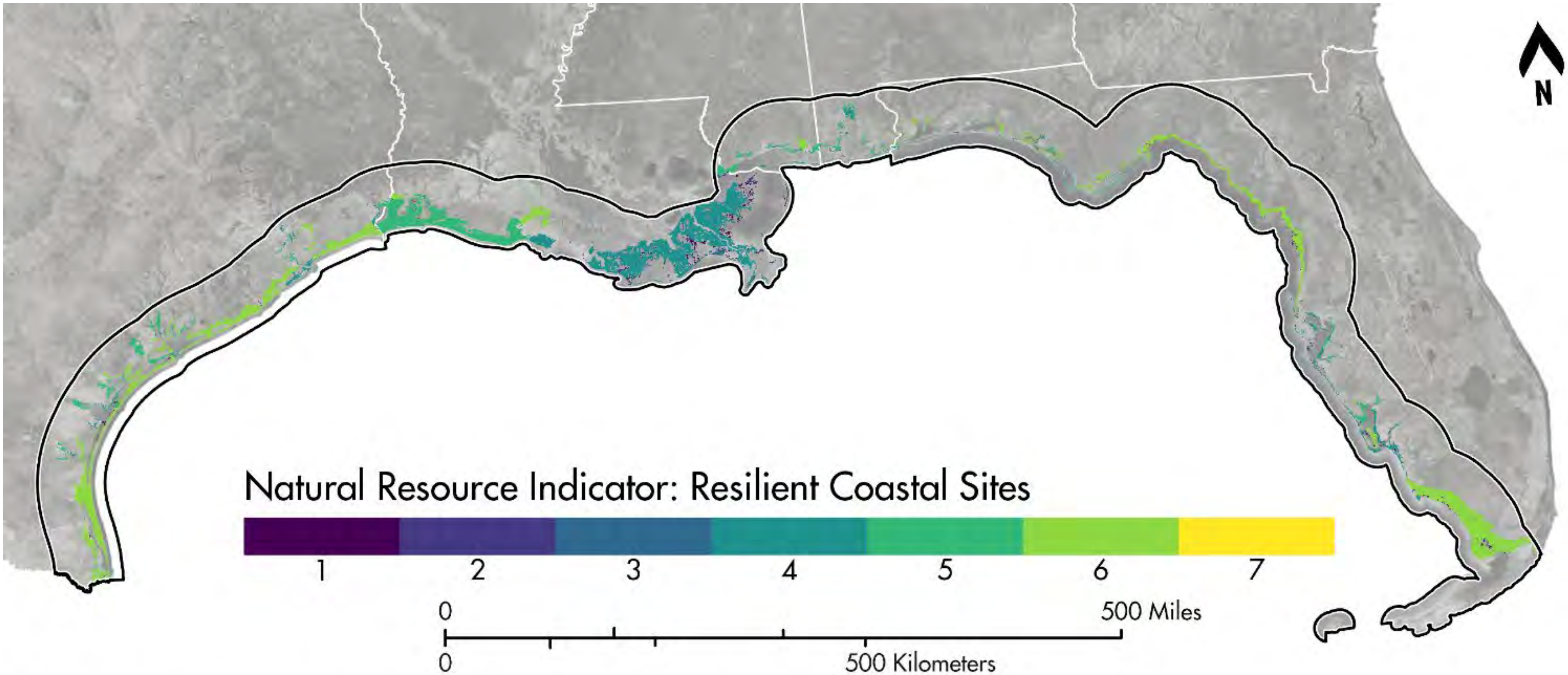
Mapping Steps

- Clip the TNC dataset to the spatial extent of the project and rasterize at 100 m resolution
- Reclassify to score each pixel according to the given TNC coastal resilience scores (see below)

Final Indicator Value:
The scoring of this indicator is identical to the scoring used in the South Atlantic Blueprint and is reproduced below. Values range from:

- 7 = Far above average (high resilience)
- 6 = Above average
- 5 = Slightly above average
- 4 = Average
- 3 = Slightly below average
- 2 = Below average
- 1 = Far below average (low resilience)

Mapped Indicator
The resulting spatial layer depicting the Resilient Coastal Sites of the Gulf of Mexico indicator for the prototype Gulf-wide Blueprint is given in Figure A-41.



Data Source: CPRA, DataBasin, Esri, Florida Cooperative Land Cover, LANDFIRE, MRLC, NOAA, Texas A&M, The Nature Conservancy, USDA, USEPA, USFS, USFWS, USGS

Figure A-41. Resilient Coastal Sites of the Gulf of Mexico Indicator for the prototype Gulf-wide Blueprint.

3. Intact Habitat Cores

This indicator was used in the 2020 South Atlantic Blueprint to represent large, continuous (unfragmented) patches of natural land cover (minimally disturbed areas at least 100 acres in size and greater than 200 m wide). The prototype Gulf-wide Blueprint follows the same methodology for this indicator, relying on the Esri Green Infrastructure Dataset, but also adds the Protected Areas dataset for the U.S. (PAD US).

Input Data

- Esri Green Infrastructure Data (download by state):
  - Alabama, Florida, Louisiana, Mississippi, Texas – released March 2017
- The PAD US dataset (v2.1):
  - Combined (Proclamation, Marine, Fee, Designation, Easement) feature class queried to remove marine areas. All GAP codes (1 through 4) were preserved
- The Estuarine Open Water habitat class from the Unified Habitat Mask (see Figure A-37 in Appendix A.2)

Mapping Steps

The following mapping steps were summarized from the 202 South Atlantic Blueprint documentation.

- Create a new feature class by merging all the state-level "Intact Habitat Cores (March 2017)" polygon feature classes that covered the Gulf coast region (Texas, Louisiana, Mississippi, Alabama, Florida)
- Delete identical polygons from the merged feature class using the Delete Identical geoprocessing tool. Application of this tool removes duplicate polygons that cross individual state boundaries and are duplicated by merging adjoining state data
- Rasterize the polygon data using the value field of "Acres". This resulted in a raster dataset with 30 m cell size with values based on the "Core Size (acres)" field calculated by the ESRI Green Infrastructure Data group
- Combine areas with those in the PAD US dataset. PAD US habitat cores that overlapped the Esri dataset were erased and further limited if the resulting clipped area was calculated at less than 100 acres
- Extract the resulting habitat layer through the NWI open water layer (see Supplemental 1B) to remove estuarine open water cells

Final Indicator Values

This indicator is scored continuously, with values ranging from:

- High: 2,051,993-acre core
- Low: 100-acre core (NODATA indicates no core present or core <100 acres)

Mapped Indicator: The resulting spatial layer depicting the Intact Habitat Cores Indicator for the prototype Gulf-wide Blueprint is given in Figure A-42.

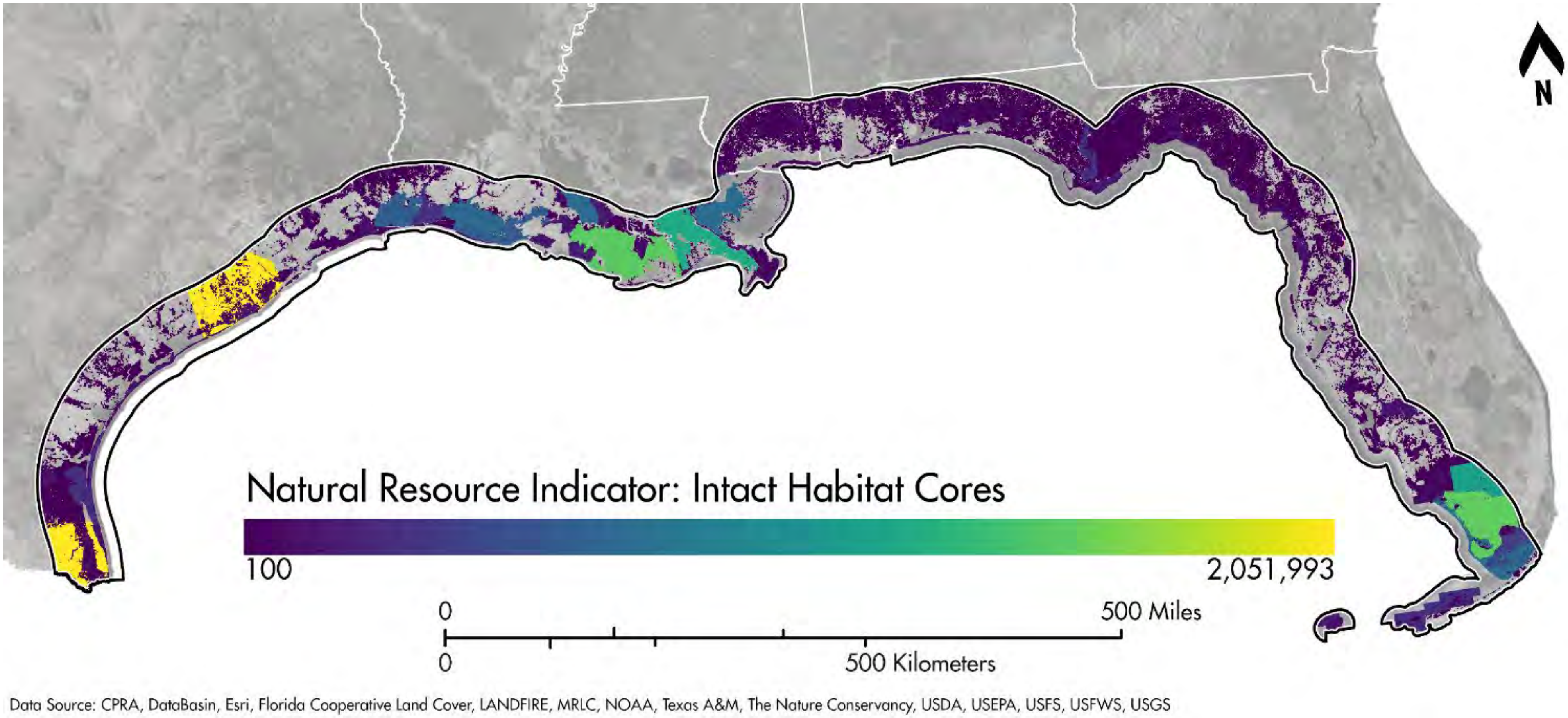


Figure A-42. Intact Habitat Cores Indicator for the prototype Gulf-wide Blueprint.

Natural Resource Indicators: Freshwater

1. Imperiled Aquatic Species

This indicator reflects the number of aquatic (freshwater) species within each watershed that are listed as G1 (globally critically imperiled), G2 (globally imperiled), or threatened/endangered defined by the Ecological Society of America (ESA). This indicator is based on patterns of species distribution models by HUC12 area.

Input Data

- Estimated Floodplain Map of the Conterminous U.S. from the USEPA EnviroAtlas
- National metric tables data by 12-digit HUC from the USEPA EnviroAtlas:
    - This dataset includes analysis by NatureServe of species associated with aquatic habitat that are G1-G2, ESA listed species
    - Desired data: total number of Aquatic Associated G1-G2/ESA species (AQ_TOT field)
- The Open Water class from the Unified Habitat Mask (see Figure A-37 in Appendix A.2)

Mapping Steps

- Download the watershed boundary dataset and the national metric tables from the USEPA EnviroAtlas and join the tabular and spatial data by HUC12
- Identify the field depicting total number of Aquatic Associated G1-G2 or ESA species in each HUC12 (AQ_TOT)
- Use the above field to convert the vector HUC12 layer to a raster with 100 m assigning the cell value using the maximum combined area method
- Extract the resulting raster through the USEPA Estimated Floodplain layer and retain only cells within the estimated floodplain
- Reclassify the values depicting the total number of aquatic associated G1-G2 or ESA species in each HUC12
- Clip the resulting raster to the extent of the NHDPlus catchments layer to remove values in the nearshore marine environment
- Extract the final output to the spatial extent of Open Water cells from the Unified Habitat Mask (see Figure A-37 in Appendix A.2).

Final Indicator Values

- 4 = 4 or more aquatic imperiled (G1/G2) or threatened/endangered species observed (high)
- 3 = 3 aquatic imperiled (G1/G2) or threatened/endangered species observed
- 2 = 2 aquatic imperiled (G1/G2) or threatened/endangered species observed

- 1 = 1 aquatic imperiled (G1/G2) or threatened/endangered species observed
- 0 = No aquatic imperiled (G1/G2) or threatened/endangered species observed (low)

Mapped Indicator

The resulting spatial layer depicting Imperiled Aquatic Species (Freshwater) is given in Figure A-43.

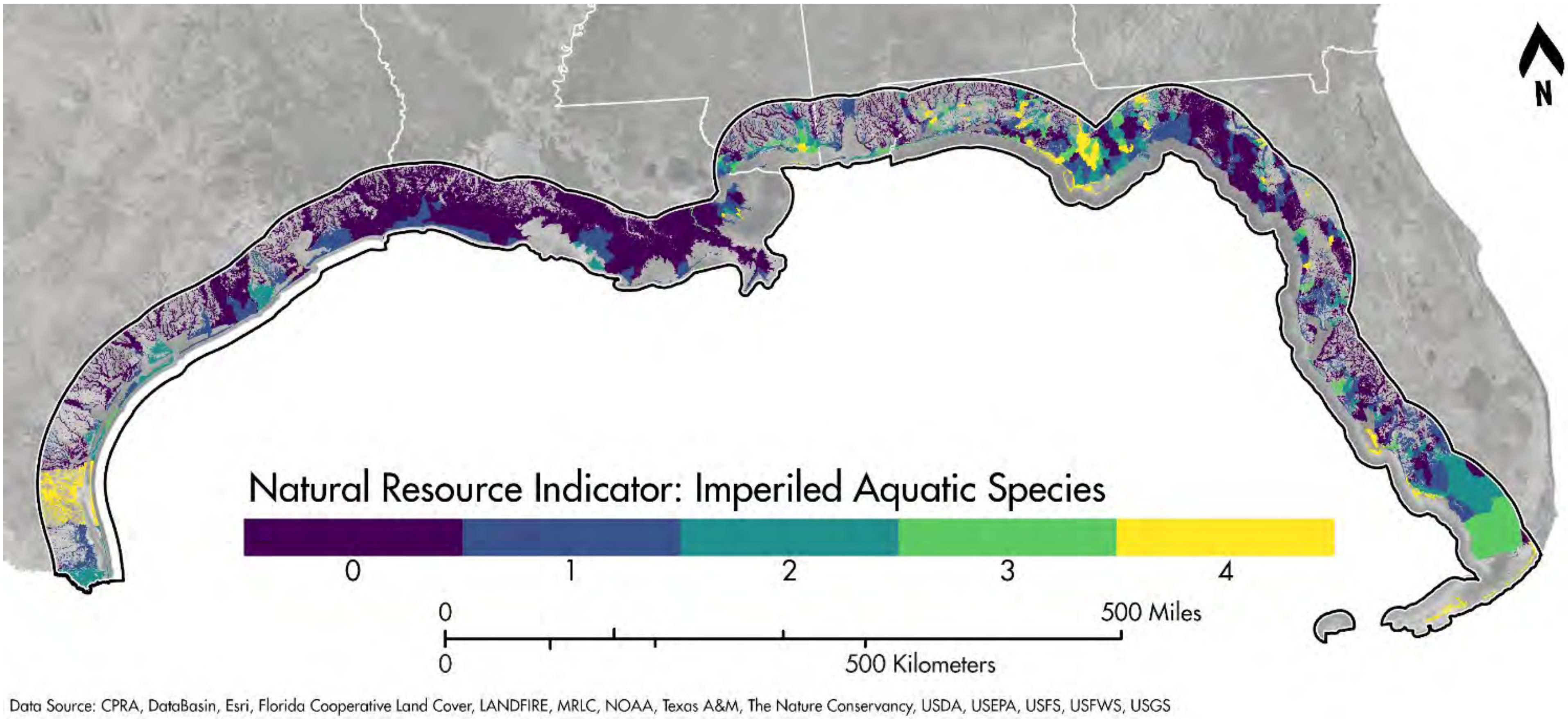


Figure A-43. Imperiled Aquatic Species Indicator for the prototype Gulf-wide Blueprint.

2. Riparian Buffers

This indicator was developed for the 2020 South Atlantic Blueprint and recreated for use across the Gulf coast project area. This indicator reflects the amount (%) of natural landcover in the estimated floodplain, by catchment. See the 2020 South Atlantic Blueprint methodology for further detail and rationale for indicator selection.

Input Data

- Estimated Floodplain Map of the Conterminous U.S. from the USEPA EnviroAtlas
- NHDPlus V2 catchment dataset available here
- Unified Habitat Mask (see Figure A-37 in Appendix A.2)

Mapping Steps

The following steps were summarized from the 2020 South Atlantic Blueprint technical documentation and modified for the prototype Gulf-wide Blueprint:

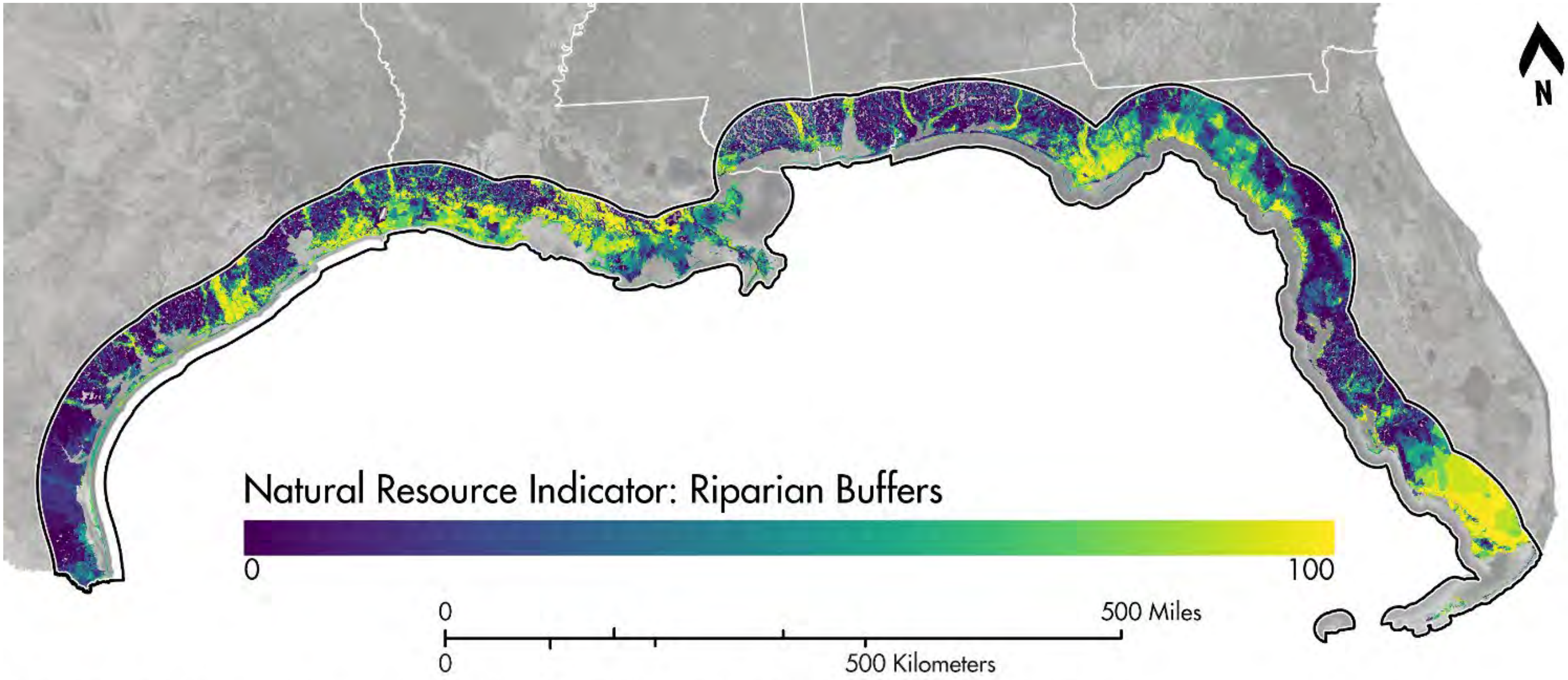
- Download the USEPA estimated floodplain layer
- Combine the USEPA estimated floodplain layer and the Unified Habitat Mask (see Figure A-37 in Appendix A.2) to capture the natural landcover classes that fall within the estimated floodplains at 30 m resolution
- Calculate percent of natural landcover inside each NHDPlus Version 2 catchment using the ArcGIS Zonal Statistics tool
- Take the resulting raster times 100 and use a conditional statement to remove catchment floodplain percentages equal to 0 retaining only catchments with a nonzero percentage that intersect the floodplain
- Convert the output to integer so that percentages are shown in whole numbers and resample to 100 m resolution

Final Indicator Value

The final indicator is continuous, ranging from Low (0% natural habitat within the estimated floodplain, by catchment) to High (100% natural habitat within the estimated floodplain, by catchment).

Mapped Indicator

The resulting spatial layer depicting the Riparian Buffers Indicator is given in Figure A-44.



Data Source: CPRA, DataBasin, Esri, Florida Cooperative Land Cover, LANDFIRE, MRLC, NOAA, Texas A&M, The Nature Conservancy, USDA, USEPA, USFS, USFWS, USGS

Figure A-44. Riparian Buffers Indicator for the prototype Gulf-wide Blueprint. Note that some catchment values may be lower than expected (e.g., Barataria and Terrebonne, Louisiana) due to the small catchment size and coverage of open water in those locations.

Natural Resource Indicators: Estuarine

Due to the limited marine area included in the prototype Gulf-wide Blueprint project area, only one estuarine indicator was used. Since there is only one indicator evaluating estuarine open water priority in this prototype, this indicator is *not* used in Zonation calculations. See Appendix A.4 for details on how this indicator was incorporated into the final prototype Gulf-wide Blueprint.

1. Estuarine Coastal Condition

This indicator represents a continuous index of water quality, sediment quality, and benthic community condition. This indicator was used in the 2020 South Atlantic Blueprint to reflect the overall status of open water estuaries (South Atlantic Conservation Blueprint, 2020).

Input Data

- The Estuarine Open Water habitat class from the Unified Habitat Mask (see Figure A-37 in Appendix A.2) served as the spatial extent of this indicator.
- The USEPA Coastal Condition Index (CCI) was used to map condition. Following 2020 South Atlantic Blueprint methods, only indices derived from point sampling were used: water quality index, sediment quality index, and benthic index. Scoring was based on the same USEPA scoring scale: 1 = poor, 3 = fair, 5 = good.
  - Data download: 2006 and 2010 surveys were utilized.
  - In calculating the overall rank of each point, the mean of the three indices was taken for each sampling period.

Mapping Steps

The following steps were adapted from the 2020 South Atlantic Blueprint methodology:

- Convert the 2006 and 2010 tabular data to points using the latitude and longitude fields in decimal degrees. Extract points along the Gulf coast and interpolate to separate rasters at 200 m resolution
  - Interpolation of point data from the CCI was conducted using the Inverse Distance Weighted function. This function interpolates among points by weighting a specified number of nearby points with high influence if they are in close proximity and declining influence as distance increases away from the input point.
  - The power function was set to 5 to emphasize local samples using the nearest 3 points and a maximum search distance of 36,000 m. Resulting interpolated CCI scores ranged continuously from 1-5.
- The average cell value between the 2006 and 2010 interpolated rasters was calculated and floating-point values were converted to an integer-based final score.
- The resulting raster (with values from 1 to 5) was extracted through the open water (estuarine) layer (see Figure A-37 in Appendix A.2) to isolate estuarine cells.

Final Indicator Value

The final indicator is continuous, ranging from Low (1 indicating poor water quality, sediment quality, and benthic community composition) to High (5, good water quality, sediment quality, and benthic community condition).

Mapped Indicator

The resulting spatial layer depicting the Estuarine Coastal Condition Indicator is given in Figure A-45.

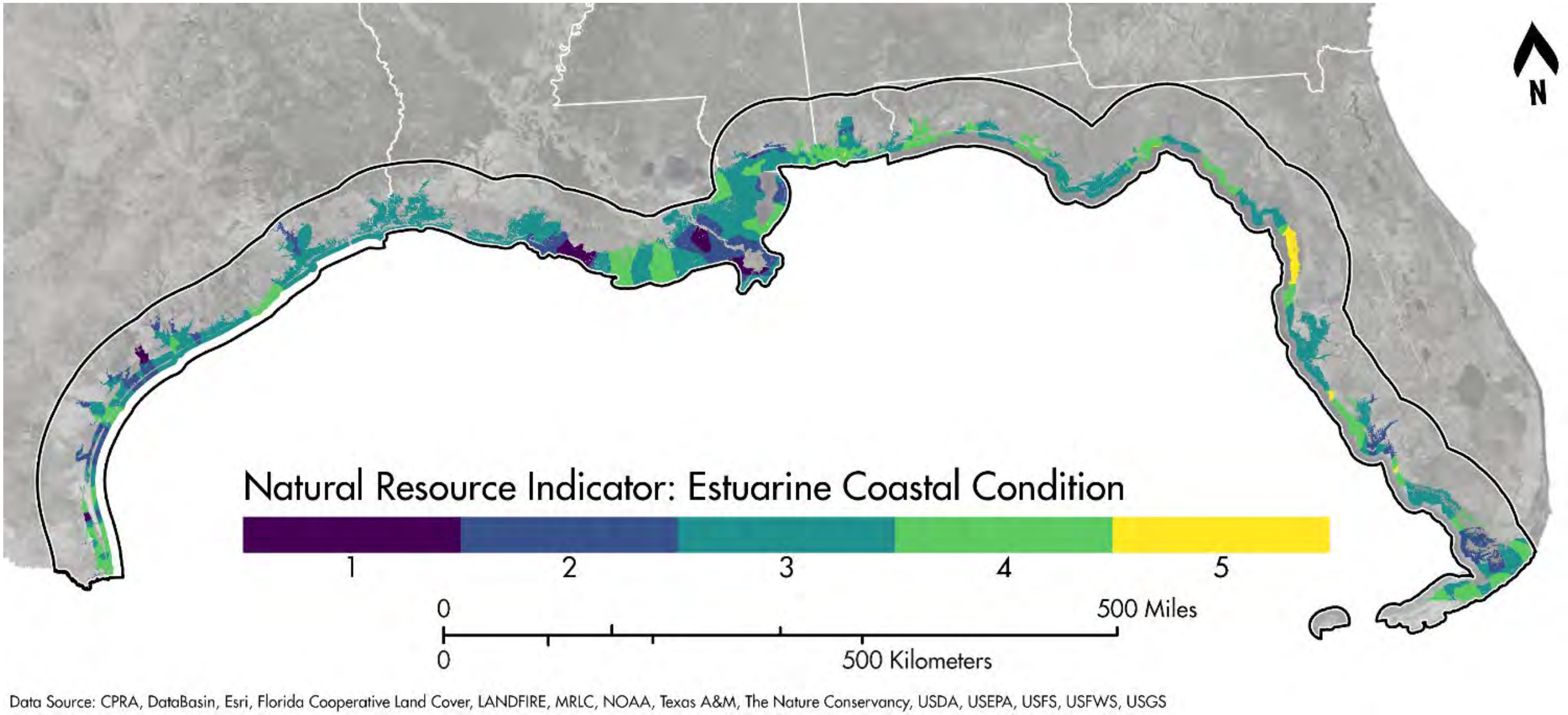


Figure A-45. Estuarine Coastal Condition Indicator for the prototype Gulf-wide Blueprint.

Socio-Ecological Indicators

1. Recreational Potential

An indicator of Recreational Potential was developed for the prototype Gulf-wide Blueprint to assess the quality and ease of accessibility of natural space for urban communities within the study area. To calculate this indicator, areas of open water, green space, wetlands, and beaches were delineated and assigned values based upon landscape type and the overall ease of access (not including access by boat). A more detailed explanation and rationale for this indicator is given in main section of this report (Section 2.2.4).

Input Data

- National Oceanic and Atmospheric Administration (NOAA)'s 2015-2017 Coastal Change Analysis Program (C-CAP) 10 m Land Cover – BETA land cover and change data were used to identify areas of open water, green space, wetlands, and beaches
    - Use the Extract by Attributes ArcGIS tool to extract the following datasets for the Gulf Coast study area:
        - Beach
            - 19 Unconsolidated Shore
        - Greenspace
            - 8 Grassland
            - 11 Upland Trees
            - 12 Scrub/Shrub
        - Water Features
            - 21 Water
        - Wetlands
            - 13 Palustrine Forested Wetland
            - 14 Palustrine Scrub/Shrub Wetland
            - 15 Palustrine Emergent Wetland
            - 16 Estuarine Forested Wetland
            - 17 Estuarine Scrub/Shrub Wetland
            - 18 Estuarine Emergent Wetland
- USEPA Beaches Environmental Assessment and Coastal Health (BEACH) data were downloaded from the Watershed Assessment, Tracking & Environmental Results System (WATERS) geospatial data downloads page

- The Trust for Public Land's ParkServe Dataset served as the primary dataset for publicly owned local, state, and national parks, trails, and open space, school parks, and privately owned parks that are managed for full public use
    - Key data extracted from the ParkServe dataset for the study area included:
        - Park footprints
        - 10-minute walkable service areas
- The Esri USA Parks dataset was used to supplement the ParkServe data as required

Mapping Steps

The following steps were used to classify the landscape based upon potential for recreational usage:

- The C-CAP data were used to provide an informal space score that served as the base layer for the recreation potential analysis. Informal spaces provide residents access to green spaces, such as vacant lots, street or railway rights-of-way, riverbanks, or levees, that are not delineated as a formal park or recreation area yet may still provide a suite of ecological benefits and ecosystem services (Rupprecht & Byrne, 2014). In this analysis, locations that were identified as informal received no additional scoring and were assigned a final value equal to their base land use value (Table A-30)

Table A-30. Base informal lands use valuation for the Recreational Potential Indicator.

Formal and Informal Landscape Type	Value
Wetlands	100
Open Water	500
Beach and Shore	500
Greenspace – Less than 1 Acre	200
Greenspace – Between 1 and 5 Acres	400
Greenspace – Between 5 and 20 Acres	600
Greenspace – Between 20 and 50 Acres	800
Greenspace – More than 50 Acres	1000

- The ParkServe data were used to identify formal space, those that include locations ranging from pocket parks to National Parks as well as officially designated wildlife areas, state and national forests, and other recreational areas. The USA Parks dataset was queried to identify formal spaces that were not included in the ParkServe dataset.

- The ArcGIS Make Service Area Analysis Layer tool was used to derive a 10-minute walking buffer around the parks extracted from the USA Parks layer. The output data was merged with the ParkServe 10-minute walkable service area layer.

- Each of the parks in the combined service area layer were classified as either active or passive (Table A-31). Active recreation opportunities are considered structured individual or team activities requiring special facilities, courses, fields, or recreation equipment. Passive recreational uses do not require sports fields or pavilions while affording the community access to swimming pools, trails, conservation areas, or open space to do unstructured activities (U.S. Environmental Protection Agency, n.d.).

Table A-31. Active and passive landscape valuations for the Recreational Potential Indicator.

Active and Passive Formal Landscape Type	Value
Active spaces	100
Both passive and active spaces	150
Passive spaces	200

- All formal spaces in the combined service area layer were next scored based on the classification system for public parks and open space used by the National Recreation and Park Association (Table A-32). These have been described by Mertes and Hall with later simplification by Nicholls (1996; 2001). Private parks were valued the lowest since they have limited access. Regional parks were ranked the highest because they provide multiple recreation opportunities and are designed to serve a larger area than just adjacent residents

Table A-32. Park classification valuation for the Recreational Potential Indicator.

Type of Park	Description	Site Criteria	Value
Private Park	Parks and recreation facilities that are privately owned	Variable	0
Pocket Park	Provide greenspace	Less than 1 acre	20
Mini Park	Used to address limited, isolated or unique recreational needs.	Between 1 acre and 5 acres	30
Special Use Facility	Covers a broad range of parks and recreation facilities oriented toward single-purpose use.	Variable	40
Natural Resource Area	Land set aside for the preservation of significant natural resources, remnant landscapes, open space, and visual aesthetics/buffering.	Variable	50
Sports Complex	Consolidates heavily programmed athletic fields and associated facilities to larger and fewer sites strategically located throughout the community.	Usually a minimum of 25 acres	60
Greenway	Ties the park system components together to form a continuous park environment.	Variable	70

Type of Park	Description	Site Criteria	Value
Neighborhood Park	The basic unit of a park system. Serves the recreational and social focus of the neighborhood. Emphasis is on informal active and passive recreation.	Between 5 acres and 25 acres	80
Regional, State, and National Parks	Serves a broader purpose than a neighborhood park. Focus is on meeting community-based recreation needs.	More than 25 acres	90

- The ArcGIS field calculator summed the active/passive score and the park classification score for each of the park in the combined service area layer.
- The ArcGIS Count Overlapping Features geoprocessing tool identified locations in the combined service area layer where multiple park buffers overlapped and provided a count of overlapping features in each location of the study area.
- A spatial join combined the service area layer with the overlapping features layer.
  - The spatial join utilized the following settings:

    Join Operation: 1 to 1
    Keep All Target Features
    Match Option: Have their center in
    Field Map: Total Recreation Value (Source: Combined Service Area Layer)
    Merge Rule: Sum
- The resultant vector dataset was converted to a 10m raster and snapped to the C-CAP informal space raster dataset using the ArcGIS Feature to Raster tool and assigned a value equal to the summed recreation value.
- The ArcGIS buffer tool created a 0.31-mile buffer around each of the linear public beach features in the USEPA BEACH dataset, an area roughly equivalent to a 10 minute walking distance. Each buffer was assigned a recreation value of 290, the combined value of regional passive recreational space. The buffered beach dataset was converted to a 10 m raster and snapped to the C-CAP informal space raster dataset using the ArcGIS Feature to Raster tool and assigned a value equal to the recreation value.
- To develop the final recreation potential indictor value, the informal space rasters for beach, greenspace, open waters, and wetlands were summed to the formal space beach and greenspace rasters using the ArcGIS Cell Statistics tool, summing the base land use and summed recreational values from each raster.
- To enable direct comparison of socioeconomic data with the ecosystem indicators, the resultant vector dataset was converted to a 100 m raster and snapped to the ecosystem indicator rasters using the ArcGIS Resample tool.

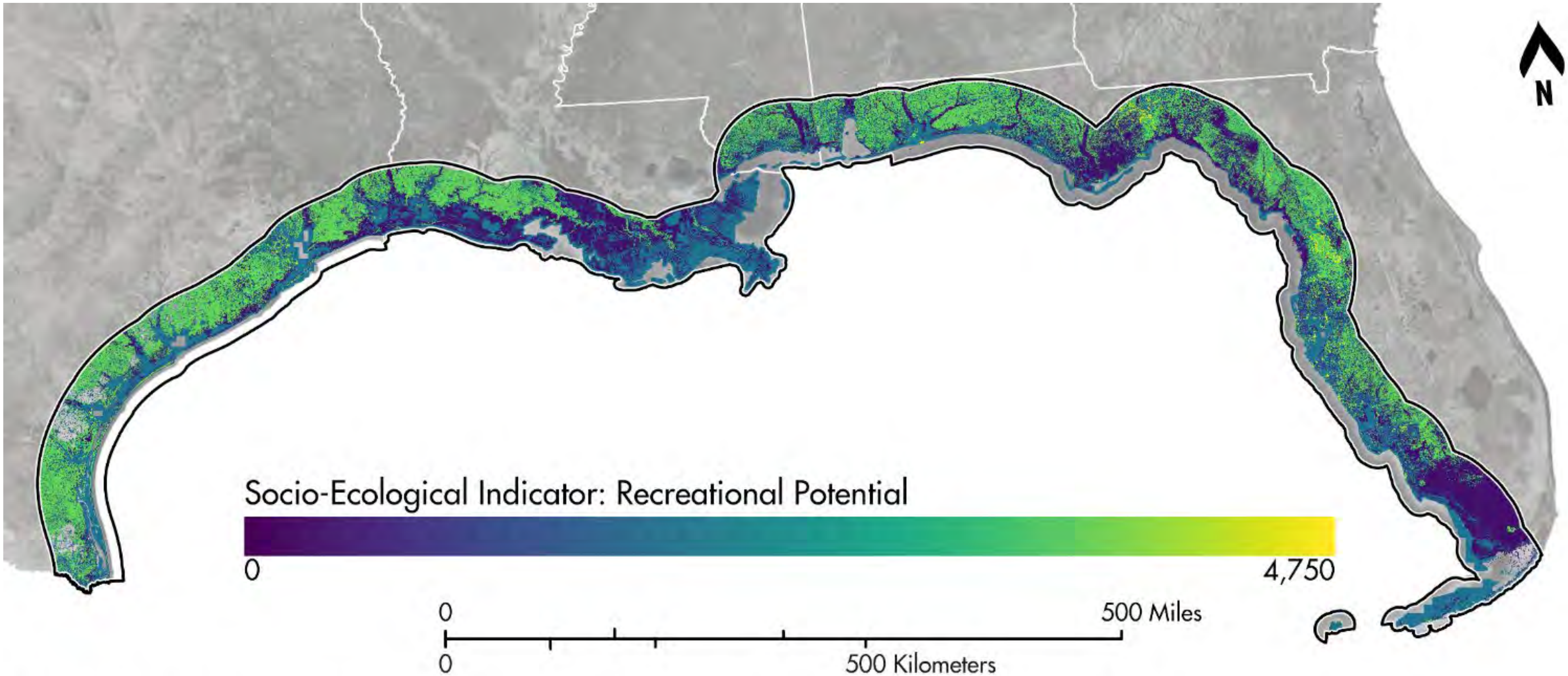
- OUTPUT: Recreational potential maps showing the combined formal and informal values for each location within the study area at both 10 m and 100 m resolution.

Final Indicator Value

The final indicator is continuous, ranging from Low (0, indicating gray spaces and developed areas, including open expanses between buildings containing hard infrastructure) to High (4750, indicating locations with a high number of accessible passive recreation space within walking distance).

Mapped Indicator

The resulting spatial layer depicting the Recreational Potential Indicator is given in Figure A-46.



Data Source: CPRA, DataBasin, Esri, Florida Cooperative Land Cover, LANDFIRE, MRLC, NOAA, Texas A&M, The Nature Conservancy, USDA, USEPA, USFS, USFWS, USGS

Figure A-46. Recreational Potential Indicator for the prototype Gulf-wide Blueprint.

2. Natural Resource Dependance

Resource-dependent communities are defined as those whose primary economic engine revolves around usage of natural resources. Such industries may include agriculture, forestry, fisheries, mining, petroleum extraction, and tourism and recreation. Resource dependence is generally measured by the proportion of employment or the income generated by natural resource utilization in relation to the aggregate economic activity of that area (Hemmerling et al., 2020). The effects of resource dependence on community well-being are highly dependent on the indicators chosen to represent well-being. Research shows, for example, that oil and gas dependence have a more positive effect when the measure of economic well-being is income rather than poverty or unemployment (Stedman et al., 2004). Natural resource dependence has also been found to be a significant determinant of vulnerability across a wide spectrum of stressors and hazards. In resource-dependent communities, for example, disruption of livelihoods can result from the loss of land and animals for farmers, or boats and nets for fishers (Wisner et al., 2004). As a result, high levels of natural resource employment can be considered an important determinant of a coastal community's social vulnerability to the impacts of land loss, sea level rise, and tropical storm events.

Input Data

- U.S. Census Bureau block group level employment data from the 2015-2019 American Community Survey was downloaded from the IPUMS National Historical Geographic Information System (NHGIS) website (Manson et al., 2020).
    - Query and download the Sex by Industry for the Civilian Employed Population 16 Years and Over dataset
    - Key employment categories assessed for the Gulf Coast include:
        - Agriculture, forestry, fishing and hunting
        - Mining, quarrying, and oil and gas extraction
        - Arts, entertainment, and recreation

Mapping Steps

- Initial data processing on the vector block group data included calculating the percentage of employment by type, which involved dividing the total number employed by the total population of that block group age 16 years and over. This is considered the minimum working age by the U.S. Census Bureau.
- To enable direct comparison of socioeconomic data with the ecosystem indicators, the resultant vector dataset was converted to a 100 m raster and snapped to the ecosystem indicator rasters using the ArcGIS Feature to Raster tool.
- To develop a single composite coastal resources employment dataset, the output rasters were summed using the ArcGIS Cell Statistics tool, with each employment type being equally weighted.

- OUTPUT: Census block group maps showing the percentage employment in each key industry for that block group and a single composite map of combined employment. Each cell value represents the percent employment by category for the block group that cell is located in, a ranging from 0 (no employment in that industry) to 100 (full employment in that industry).

Final Indicator Values

The final indicator is continuous, with values ranging from:

- Low: 0 (no employment in the identified industry)
- High: 100 (full census block employment in the identified industry)

Mapped Indicator

The resulting spatial layer depicting the Natural Resource Dependence Indicator is given in Figure A-47. Note that while the index is continuous up to 100, the maximum value observed across the study area is 33.

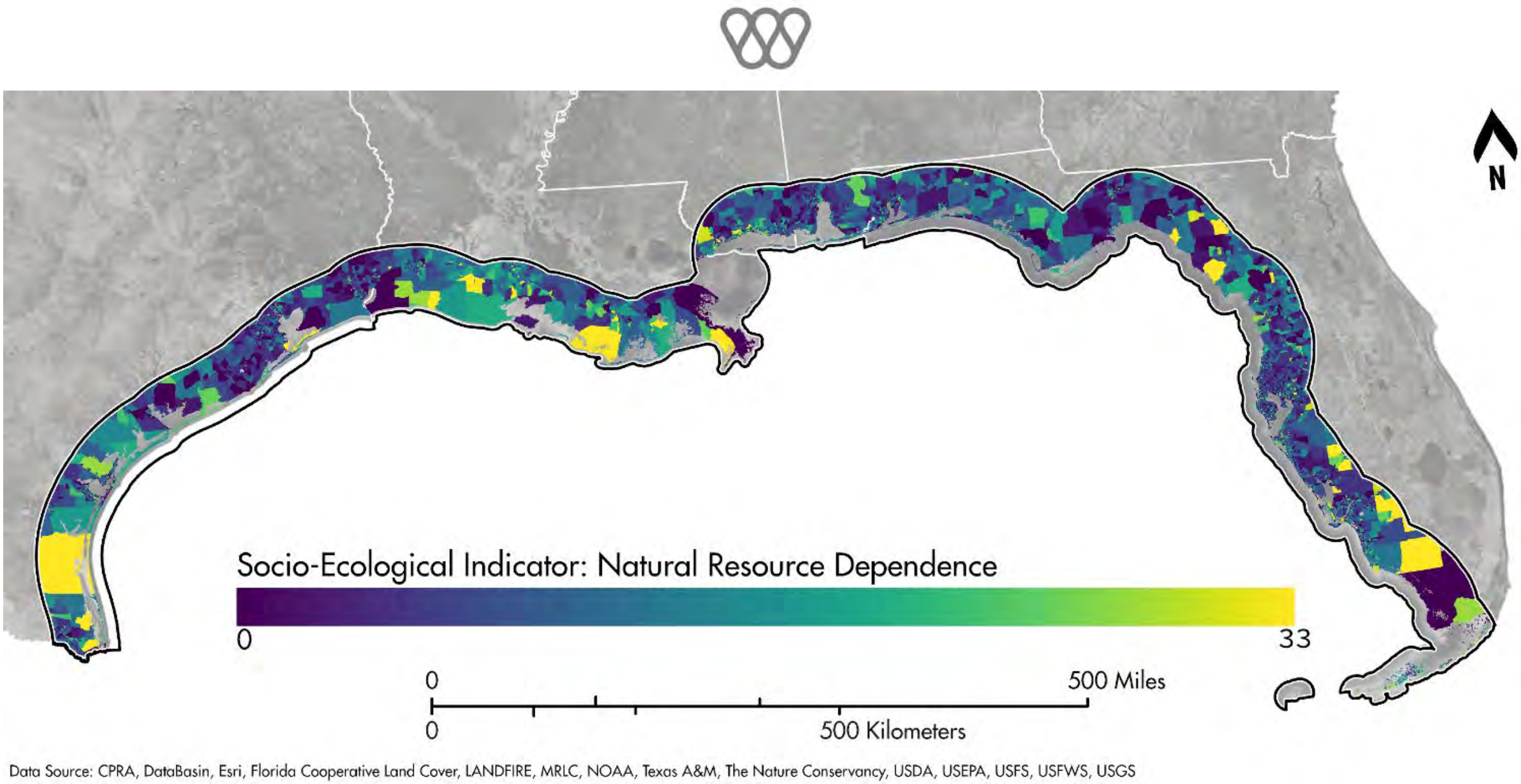


Figure A-47. Natural Resource Dependence Indicator for the prototype Gulf-wide Blueprint.

3. Economic Wellbeing

The economic status by block group in the prototype Gulf-wide Blueprint study area was analyzed using census datasets that are closely correlated with income. Adapting methods developed by the U.S. Forest Service, an economic wellbeing index was derived which incorporates four primary categories of data that are consistently available in each decennial census: poverty, persons receiving public assistance income, persons without health insurance, home ownership, educational attainment, and employment level (Doak & Kusel, 1996; Hemmerling et al., 2020).

Input Data

- U.S. Census Bureau block group level data from the 2015-2019 American Community Survey was downloaded from the IPUMS National Historical Geographic Information System (NHGIS) website (Manson et al., 2020)
    - Query and download the following datasets assessed for the Gulf Coast:
        - Education
            - Educational Attainment for the Population 25 Years and Over
        - Employment and Commuting
            - Sex by Industry for the Civilian Employed Population 16 Years and Over dataset
        - Health Insurance
            - No health insurance coverage
        - Income
            - Ratio of Income to Poverty Level in the Past 12 Months
            - Income in the past 12 months below poverty level
            - With Social Security income
            - With Supplemental Security Income
            - With cash public assistance or Food Stamps/SNAP
        - Occupancy and Tenure
            - Owner occupied

Mapping Steps

- Initial data processing on the vector block group data included calculating percentages for the employment, individuals with income below the poverty line, health insurance, public assistance income, and housing tenure variables, dividing each by its respective universe. In most cases, this was the total number of individuals or households in each block group. The exceptions were employment, which involved dividing the total number employed by the total population of that block group age 16 years and over and educational attainment, which was divided by the population age 25 years and over

- The raw educational attainment data were combined to developed a cumulative educational attainment score weighted toward higher levels of educational attainment using the following formula (Doak & Kusel, 1996):

  $S = \Sigma[A, (B * 2), (C * 3), (D * 4), (E * 5), (F * 6), (G * 7)]$
  where
  S = educational attainment score
  A = percentage of persons with less than a ninth-grade education
  B = percentage of persons with a ninth to twelfth-grade education, no diploma
  C = percentage of persons who are high school graduates or the equivalent
  D =percentage of persons with some college, no degree
  E = percentage of persons with an associate degree
  F = percentage of persons with a bachelor's degree
  G =percentage of persons with a graduate or professional degree

- A measure of the relative intensity of poverty of those individuals with incomes below the poverty level was developed from the Ratio of Income to Poverty Level in the Past 12 Months data. Three variables from this dataset were combined to capture the intensity of poverty within each block group, using the following formula:

  $S = \Sigma [(1 * X), (3 * Y), (9 * Z)]$
  where
  S = poverty intensity
  X = percentage of persons with incomes between 75% and 99% of the poverty level
  Y = percentage of persons with incomes between 50% and 74% of the poverty level
  Z = percentage of persons with incomes less than 50% of the poverty level

- Z-score standardization was performed on each of the profile indicators to assure the data could be compared across categories. Z-scores represent the number of standard deviations that an observed value is above the mean value of a sample set and allow for the comparison of scores from distributions and were calculated for each block group using the following formula:

  $z=(x-\mu)/\sigma$
  where
  z is the tabulated standard score
  x is the observed value
  μ is the mean study area value of what is being measured
  σ is the standard deviation study area value of what is being measured

- To develop a single composite economic wellbeing score, A composite economic wellbeing score was derived from the standardized Z scores using the following formula:

$$X = (S_1 + S_2 + S_3 + S_4 – S_5 - (S_6 + S_7)/6)$$

where

X = Economic wellbeing score

S_1 = Standardized educational attainment score

S_2 = Standardized percentage of home ownership

S_3 = Standardized percentage of persons employed

S_4 = Standardized percentage of persons with health insurance

S_5 = Standardized percentage of persons with health insurance

S_6 = Standardized percentage poverty intensity score

S_7 = Standardized percentage of persons in poverty

*Note that all signs were directionally adjusted to assure that higher values are associated with higher levels of economic wellbeing. The composite economic wellbeing score was normalized to a base 100

- To enable direct comparison of socioeconomic data with the ecosystem indicators, the resultant vector dataset was converted to a 100 m raster and snapped to the ecosystem indicator rasters using the ArcGIS Feature to Raster tool
    - OUTPUT: Census block group maps showing the level of economic wellbeing for each populated block group within the study area. Each cell value represents the economic wellbeing score for the block group that cell is located in, a ranging from 0 to 100

Final Indicator Values

The final indicator is continuous, with values ranging from:

- Low: 0 (Minimum possible economic wellbeing score within the study area)
- High: 100 (Maximum possible economic wellbeing score within the study area)

Mapped Indicator

The resulting spatial layer depicting the Economic Wellbeing Indicator is given in Figure A-48.

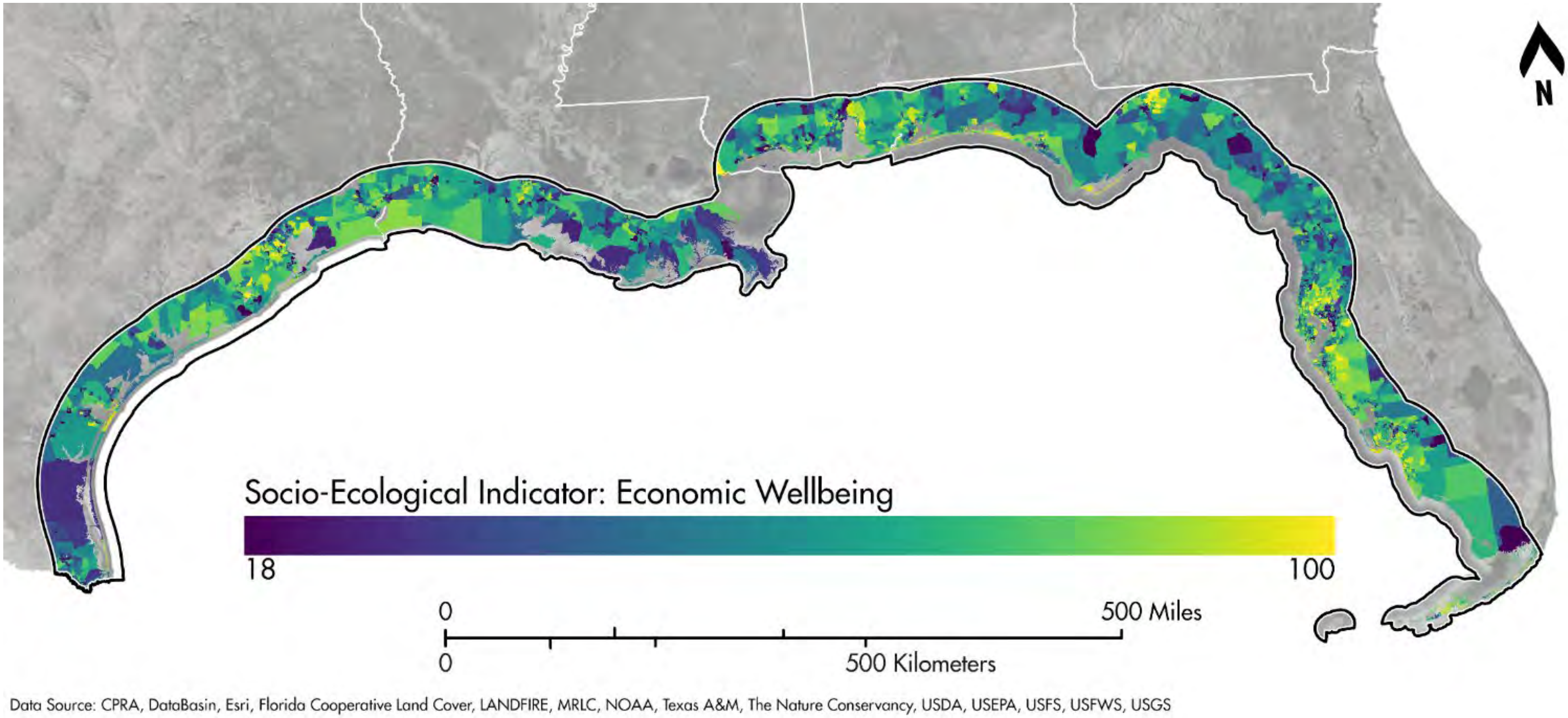


Figure A-48. Economic Wellbeing Indicator for the prototype Gulf-wide Blueprint.

References

Doak, S. C., & Kusel, J. (1996). *Well-being in forest-dependent communities, Part II: a social assessment focus* (pp. 375–402). University of California, Davis Centers for Water and Wildland Resouces.
ECOS: USFWS Threatened & Endangered Species Active Critical Habitat Report. (2021, May).
Hemmerling, S. A., Carruthers, C., Tim J. B., Hijuelos, A. C., & Bienn, H. (2020). Double exposure and dynamic vulnerability: Assessing economic well-being, ecological change and the development of the oil and gas industry in coastal Louisiana. *Shore & Beach*, *88*(1), 72–82.
Manson, S., Shroeder, J., Van Ripper, D., Kugler, T., & Ruggles, S. (2020). *IPUMS National Historical Geographic Information System: Version 15.0 [dataset]*. Minneapolis, MN: IPUMS.
Mertes, J. D., Hall, J. R., National Recreation and Park Association, & American Academy for Park and Recreation Administration. (1996). *Park, recreation, open space and greenway guidelines*. Arlington, Va.? National Recreation and Park Association.
Nicholls, S. (2001). Measuring the accessibility and equity of public parks: a case study using GIS. *Managing Leisure*, *6*(4), 201–219.
Rupprecht, C. D. D., & Byrne, J. A. (2014). Informal urban greenspace: A typology and trilingual systematic review of its role for urban residents and trends in the literature. *Urban Forestry & Urban Greening*, *13*(4), 597–611.
South Atlantic Conservation Blueprint. (2020). South Atlantic Blueprint 2020 Development Process.
U.S. Environmental Protection Agency. (n.d.). *Meeting Community Needs, Protecting Human Health and the Environment: Active and Passive Recreational Opportunities at Abandoned Mine Lands*.

APPENDIX A

A.4 ANALYTICAL PROTOTYPE GULF-WIDE BLUEPRINT METHODS

The Habitat Condition Indicator outlined in Appendix A.2 and the Natural Resource Indicators and Socio-Ecological Indicators outlined in Appendix A.3 all serve as inputs to Zonation to create the final Southeast Conservation Adaptation Strategy (SECAS) prototype Gulf-wide Blueprint. The methods to develop those indicators parallel the methods developed for the Middle Southeast Blueprint V3.0 (Middle Southeast Blueprint, 2020) and the 2020 South Atlantic Blueprint (South Atlantic Conservation Blueprint, 2020). This appendix outlines the key steps taken to prep the final raster datasets ahead of analysis with Zonation, the specific Zonation parameters set for analysis, Zonation detailed outputs and final assembly of the prototype Gulf-wide Blueprint, and results of a sensitivity analysis around two different land cover inputs to the Zonation subroutine.

Prepping the Final Dataset: Removing Areas of Low Conservation Value

Following the technical documentation of the 2020 South Atlantic Blueprint, certain areas were removed prior to running Zonation. However, the prototype Gulf-wide Blueprint methodology deviates from the 2020 South Atlantic Blueprint methods in the following ways:

- Developed or mine LANDFIRE existing vegetation type (evt) classes (classes: 7295-7299) were *not* removed from analysis. These areas were retained due to the inclusion of social indicators throughout developed areas. Developed and mine LANDFIRE evt classes were retained in the land cover habitat map as zeros
- Reservoir removal was conducted differently because no general shape of reservoirs could be calculated across the Gulf-wide project area. Only areas listed as ‘reservoirs’ in the National Hydrography Dataset (NHD)Waterbody dataset were omitted
    - Step 1) The NHDWaterbody dataset was downloaded for the entire project area.
    - Step 2) Features identified as “Reservoir” were extracted from the NHDWaterbody layer,
    - Step 3) The extracted Reservoirs were rasterized and overlaid with the unified habitat layer.
    - Step 4) The extracted Reservoir features from Step 3 were used to set collocated cells in the indicator layers to “no data” (-9999).

Future revisions to the Gulf-wide Blueprint may include indicators that specifically reflect habitat quality of reservoirs.

Zonation Run Parameters for Terrestrial & Freshwater Habitats

The following methods direct the Zonation software to assess conservation prioritization of terrestrial and freshwater aquatic habitats. The open water Estuarine Coastal Condition Indicator was examined *separately* to develop prioritization for those areas and added in after the Zonation analysis was completed.

1. Indicator Weight

Zonation has the flexibility to allow differential weighting for each indicator layer. The 2020 South Atlantic Blueprint development adjusted weights for each indicator to de-prioritize outdated data and spatially-limited datasets. For development of the prototype Gulf-wide Blueprint, *indicators were weighted equally*. Subsequent revisions of this Gulf-wide Blueprint may revisit this process.

2. Removal Rule

Setting: 1. This reflects that the basic core-area Zonation (CAZ) cell removal algorithm is employed.

3. Boundary Length Penalty

Setting: 0 (not used)

4. Warp Factor

Setting: 10,000. Defines how many cells are removed at a time per iteration.

5. Edge Removal

Setting: 1. Indicates that the program will remove cells from the edges of remaining landscape instead of from anywhere in the landscape.

Zonation Results for Terrestrial and Freshwater Conservation Prioritization

The output of Zonation is a final raster layer where the value of each cell reflects the percent of the input area ranked from highest to lowest priority, ranging from 1 to tiny fractions close to 0. Rebalancing of scores as conducted for the 2020 South Atlantic Blueprint was not needed for the prototype Gulf-wide Blueprint as developed areas were included and reservoirs were extracted as “no data”. The output of Zonation for the prototype Gulf-wide Blueprint only scores terrestrial and freshwater areas. The following section details the scoring and incorporation of estuarine open water areas.

The following scheme converted raw Zonation numerical output to conservation prioritization categories that align with the 2020 South Atlantic Blueprint:

- Values ranging from 0.9 and 1 reflect the “best 10%” of the input area and were classified as “very high priority”
- Values ranging from 0.75 to 0.9 (the next 15%) reflect “high priority”
- Values ranging from 0.55 to 0.75 (the next 20%) reflect “medium priority”

Conservation Prioritization for Estuarine Areas

Zonation analysis was not required for estuarine open water areas because only one indicator was used to determine prioritization: the Estuarine Coastal Condition Indicator. Following 2020 South Atlantic Blueprint methodology, running Zonation for one indicator is not necessary. Appendix A.3 details the development of the Estuarine Coastal Condition Indicator. The GIS steps to bin the indicator values into corresponding 2020 South Atlantic Blueprint categories are given below:

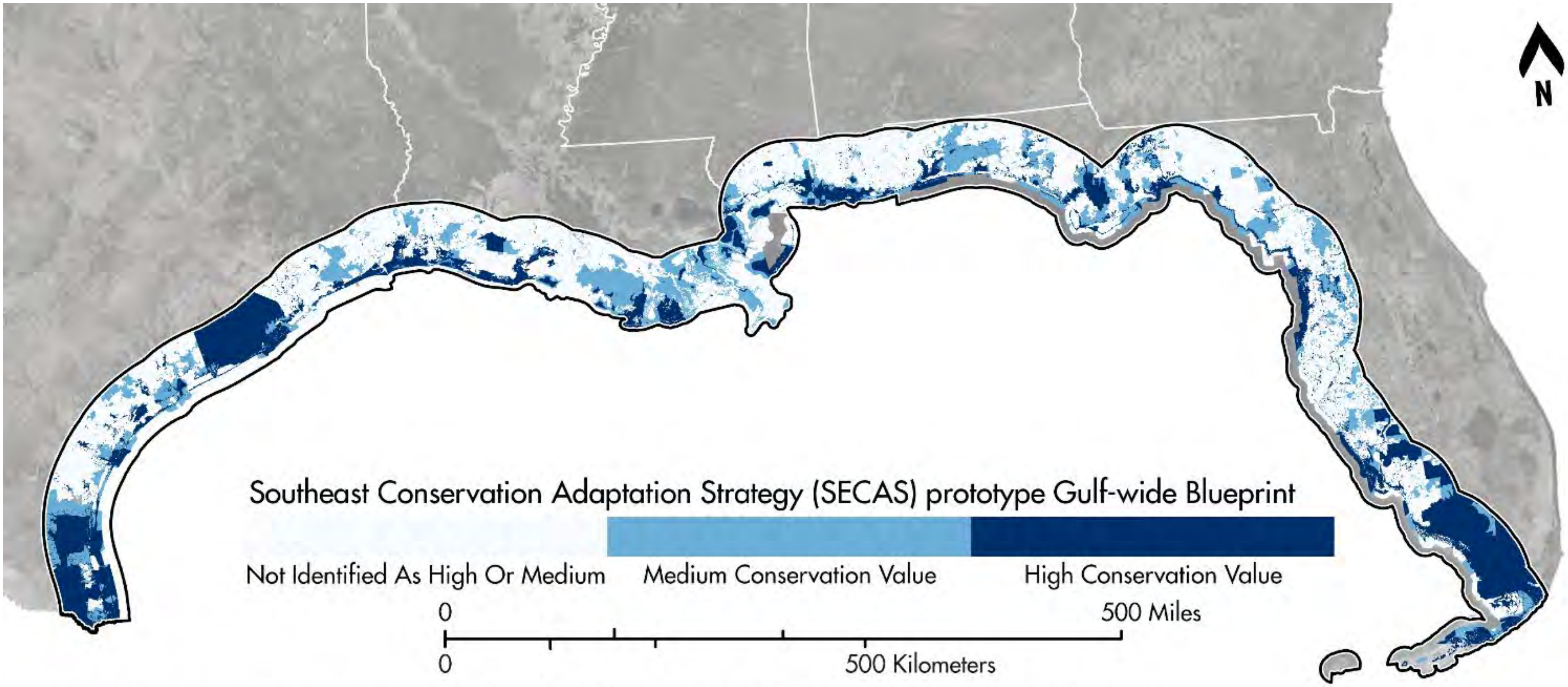
- Step 1) Use the ArcGIS Slice function to bin the coastal condition indicator into 100 equal area classes, each of which covers roughly the same area (1% of open water estuaries)
- Step 2) Bin values for estuarine open water areas to align with the SECAS Southeast Blueprint categories:
  - Values ranging from 0.9 and 1 reflect the “best 10%” of the input area and were classified as “very high priority.”
  - Values ranging from 0.75 to 0.9 (the next 15%) reflect “high priority.”
  - Values ranging from 0.55 to 0.75 (the next 20%) reflect “medium priority.”

Note: Due to the limited spatial extent of the Gulf-wide Blueprint into the marine environment, no indicators were used in the prototype Gulf-wide Blueprint to prioritize marine areas.

Creating the Final Prototype Gulf-wide Blueprint

The Estuarine Coastal Condition Indicator values were combined with the results of Zonation to create the final prototype Gulf-wide Blueprint. No spatial overlap between the terrestrial and freshwater Zonation output and the open water Estuarine Coastal Condition indicator rasters allowed for a direct merge of the two layers with no conflicts.

Next, the 2020 South Atlantic Blueprint aligns with the SECAS Southeast Conservation Blueprint prioritization categories by combining the areas of “Very High Priority” and “High Priority” into a single category of “High Priority” (South Atlantic Conservation Blueprint, 2020). Areas classified as “Medium Priority” remain unchanged. The final prototype Gulf-wide Blueprint with SECAS category alignment is given in Figure **A**-49.



Data Source: CPRA, DataBasin, Esri, Florida Cooperative Land Cover, LANDFIRE, MRLC, NOAA, Texas A&M, The Nature Conservancy, USDA, USEPA, USFS, USFWS, USGS

Sensitivity of Zonation Prioritization to Inclusion of the Habitat Condition Indicator

Due to the labor-intensive nature of calculating the Habitat Condition Indicator for multiple habitats, sensitivity analysis was conducted to determine how final Zonation prioritization scores shift based on adjustment of *only* the land cover input indicator. The following scenarios were tested using identical Zonation parameters (those outlined above for the prototype Gulf-wide Blueprint).

- Alternative 1: Habitat Condition Indicator reflects scored habitat (i.e., the Habitat Condition Indicator; Figure A-38, Appendix A.2)
- Alternative 2: Habitat Condition Indicator reflects presence/absence of natural land cover *without* habitat condition (e.g., where natural land cover is all scored as 1, and areas that are not are scored as 0) (see Figure A-39, Appendix A.2).

All other indicator inputs remained the same for this comparison (Figure A-50).

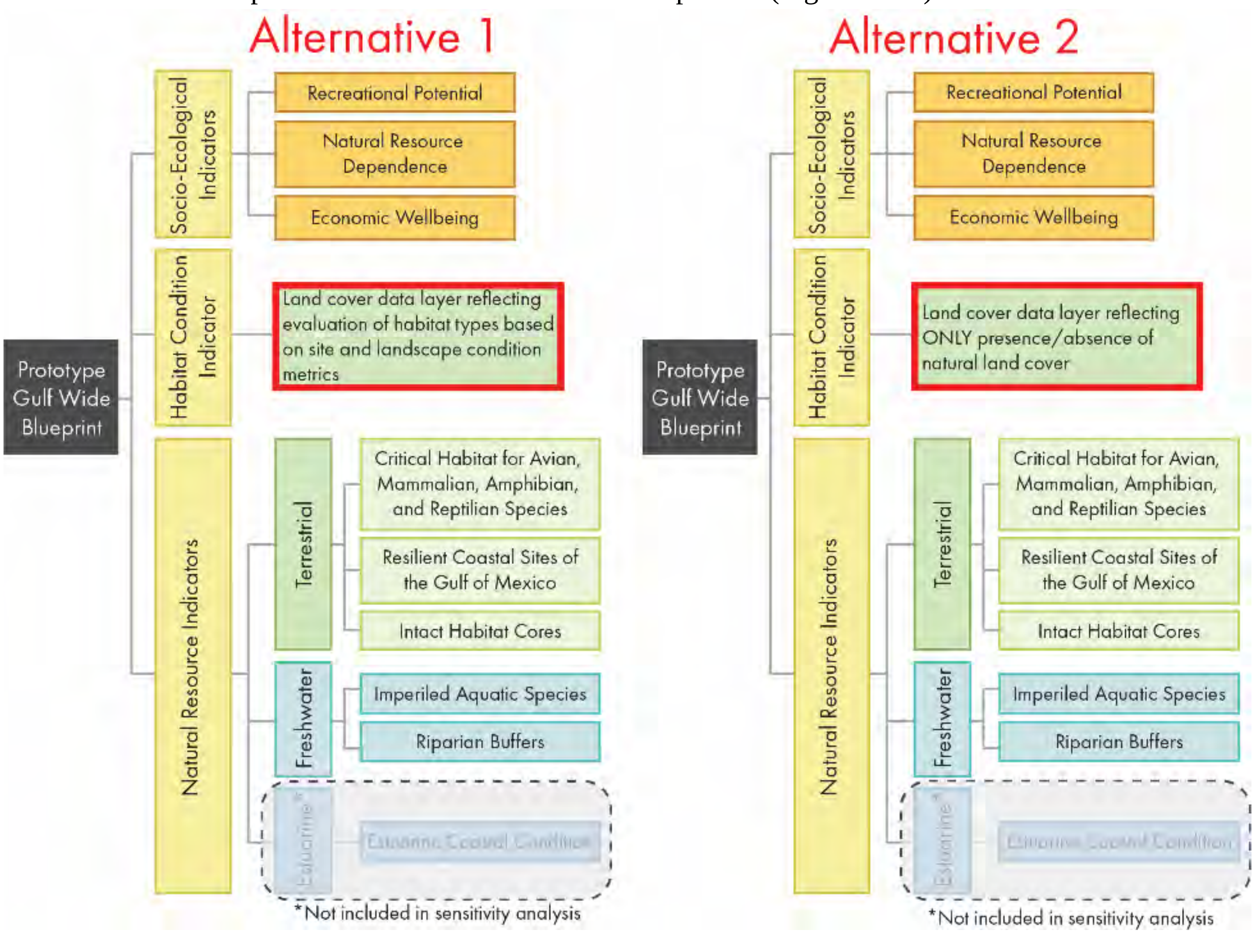
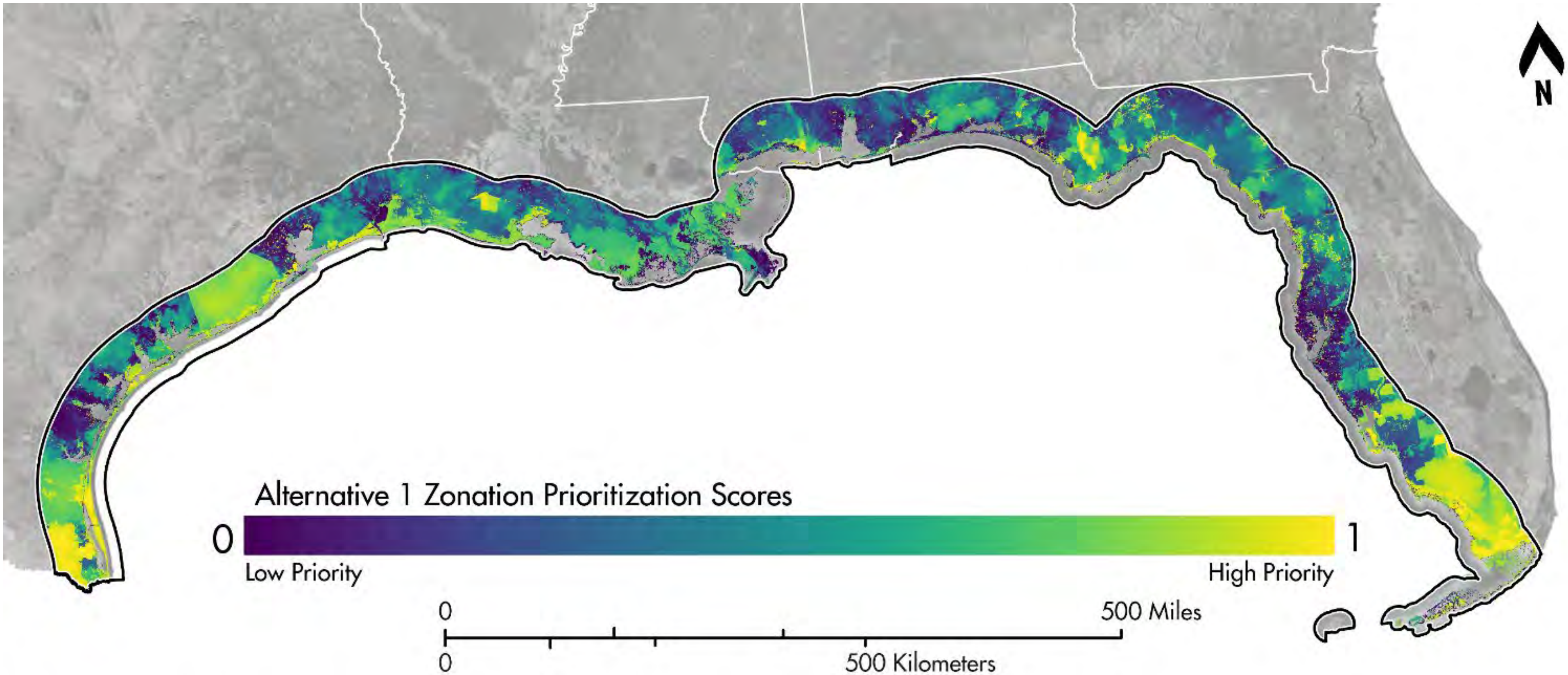


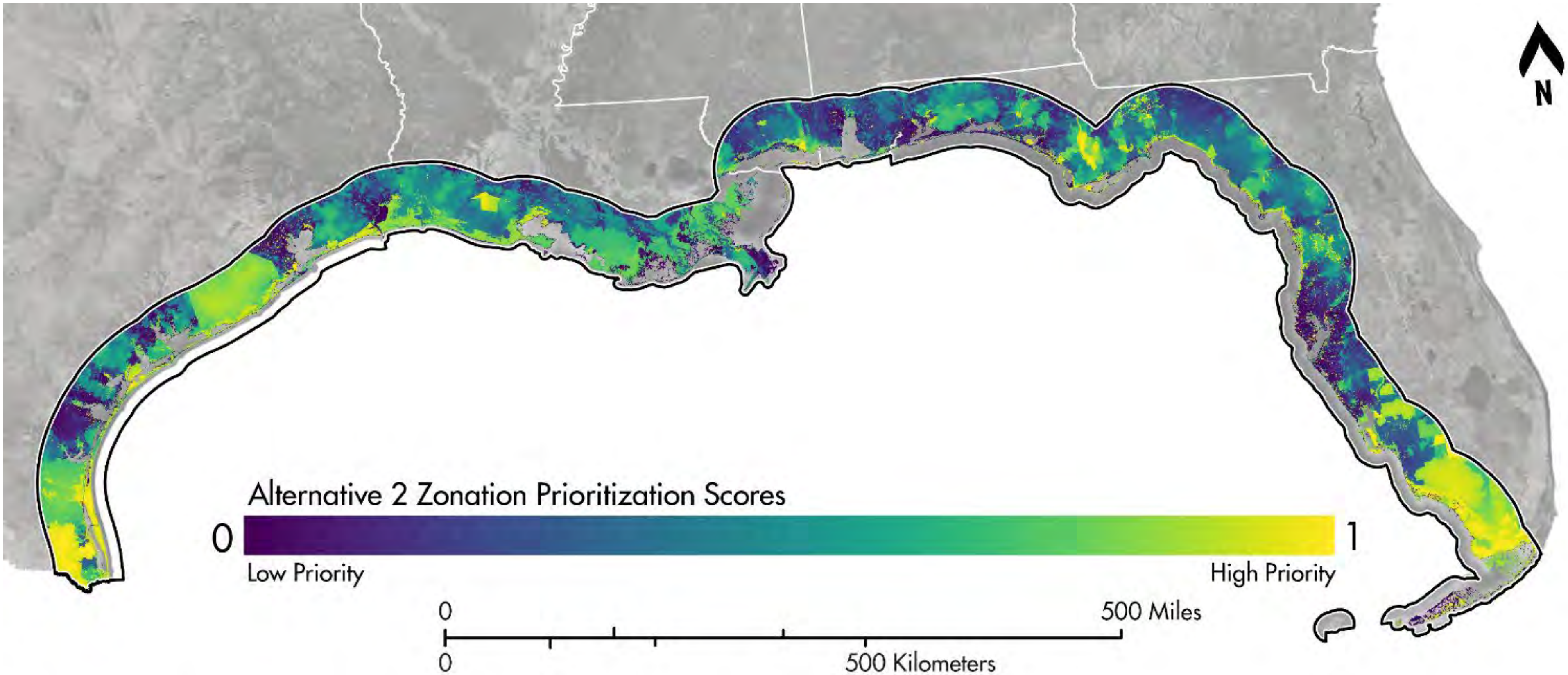
Figure A-50. Framework of prototype Gulf-wide Blueprint indicators for sensitivity analysis.

Zonation prioritization across the prototype Gulf-wide Blueprint project area was conducted for Alternative 1 (Figure A-51) and Alternative 2 (Figure A-52).



Data Source: CPRA, DataBasin, Esri, Florida Cooperative Land Cover, LANDFIRE, MRLC, NOAA, Texas A&M, The Nature Conservancy, USDA, USEPA, USFS, USFWS, USGS

Figure A-51. Zonation output for Alternative 1 based on habitat condition evaluation across the prototype Gulf-wide Blueprint project area.



Data Source: CPRA, DataBasin, Esri, Florida Cooperative Land Cover, LANDFIRE, MRLC, NOAA, Texas A&M, The Nature Conservancy, USDA, USEPA, USFS, USFWS, USGS

Figure A-52. Zonation output for Alternative 2 based on presence/absence of natural land cover across the prototype Gulf-wide Blueprint project area.

The Zonation output of Alternative 1 that integrated scored habitat condition was noticeably different compared to Alternative 2. Figure A-53 highlights the differences in Zonation prioritization scores between Alternative 2 (based on presence/absence of natural land cover) and Alternative 1 (based on habitat condition evaluation) at a relative pixel scale. Many areas saw priority reductions when including a natural land cover layer with habitat condition scores in the Zonation analysis. This is likely driven by de-prioritization of agricultural lands and low-quality and degraded and cover types.

In total, 2,296,534 acres of habitat (6.64% of the prototype Gulf-wide Blueprint domain) were reassigned conservation priority categories when comparing Alternative 1 to Alternative 2 Zonation outputs. Alternative 1 based on habitat condition scores deprioritized and reprioritized cells in nearly equal amounts, with 1,146,126 total acres (3.31% of the prototype Gulf-wide Blueprint project area) assigned a reduced conservation priority and 1,150,408 total acres (3.33% of the prototype Gulf-wide Blueprint project area) assigned an elevated conservation priority.

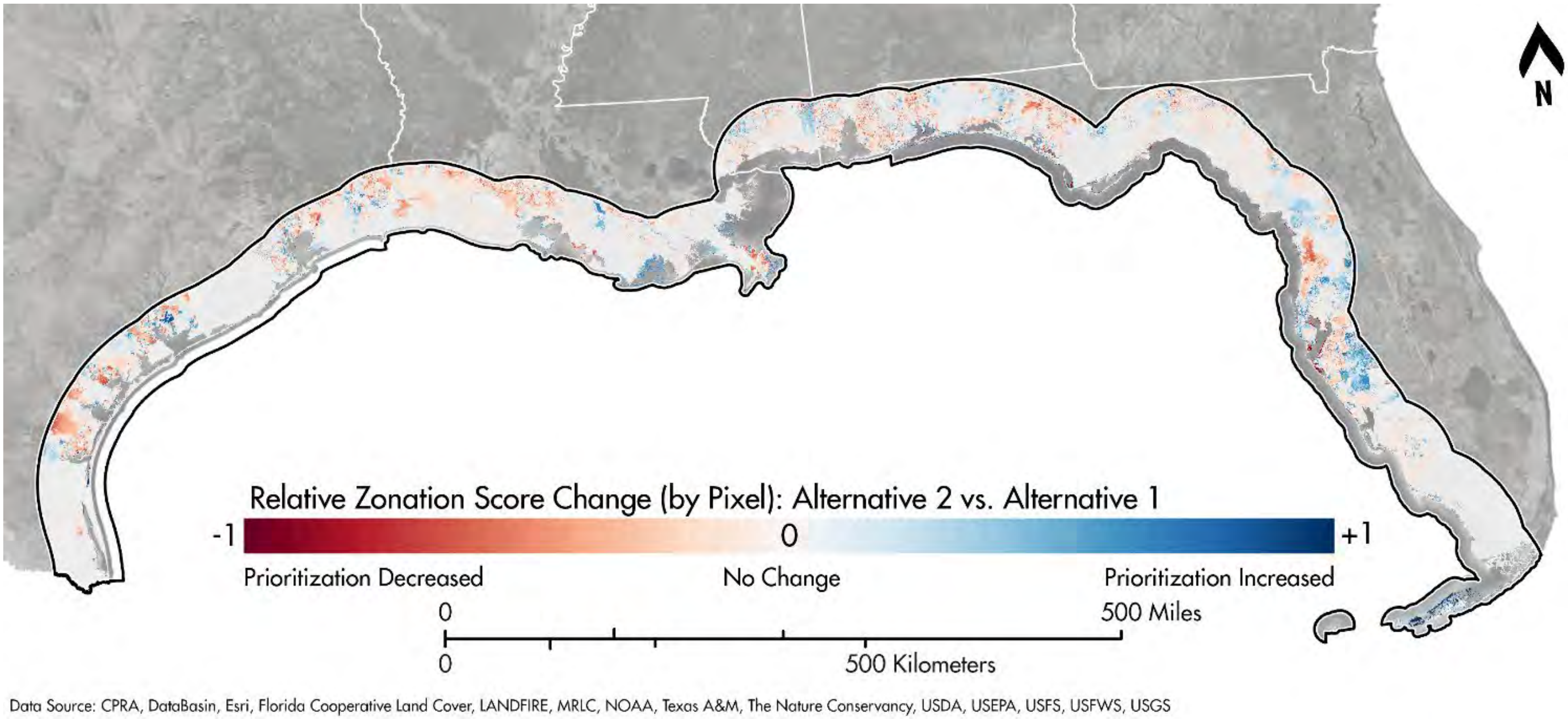


Figure A-53 Comparison of Zonation scores between Alternative 2 and Alternative 1. Locations that were reduced in Zonation priority with inclusion of a habitat condition land cover layer are colored red, whereas areas that increased in priority are in blue. White areas indicate no difference between prioritization scores between Alternative 1 and Alternative 2, therefore no change was observed.

The differences between alternative scenarios can also be visualized at the prioritization category scale to further tease apart whether differences between the two approaches resulted in significant prioritization shifts that would be meaningful at a 2020 South Atlantic Blueprint scale. Figure A-54 and Figure A-55 illustrate the Zonation outputs for Alternatives 1 and 2 as categorized for the 2020 South Atlantic Blueprint. To relate these to the SECAS Southeast Conservation Blueprint, the categories of “very high” and “high” priority would be combined into a single “high priority” category.

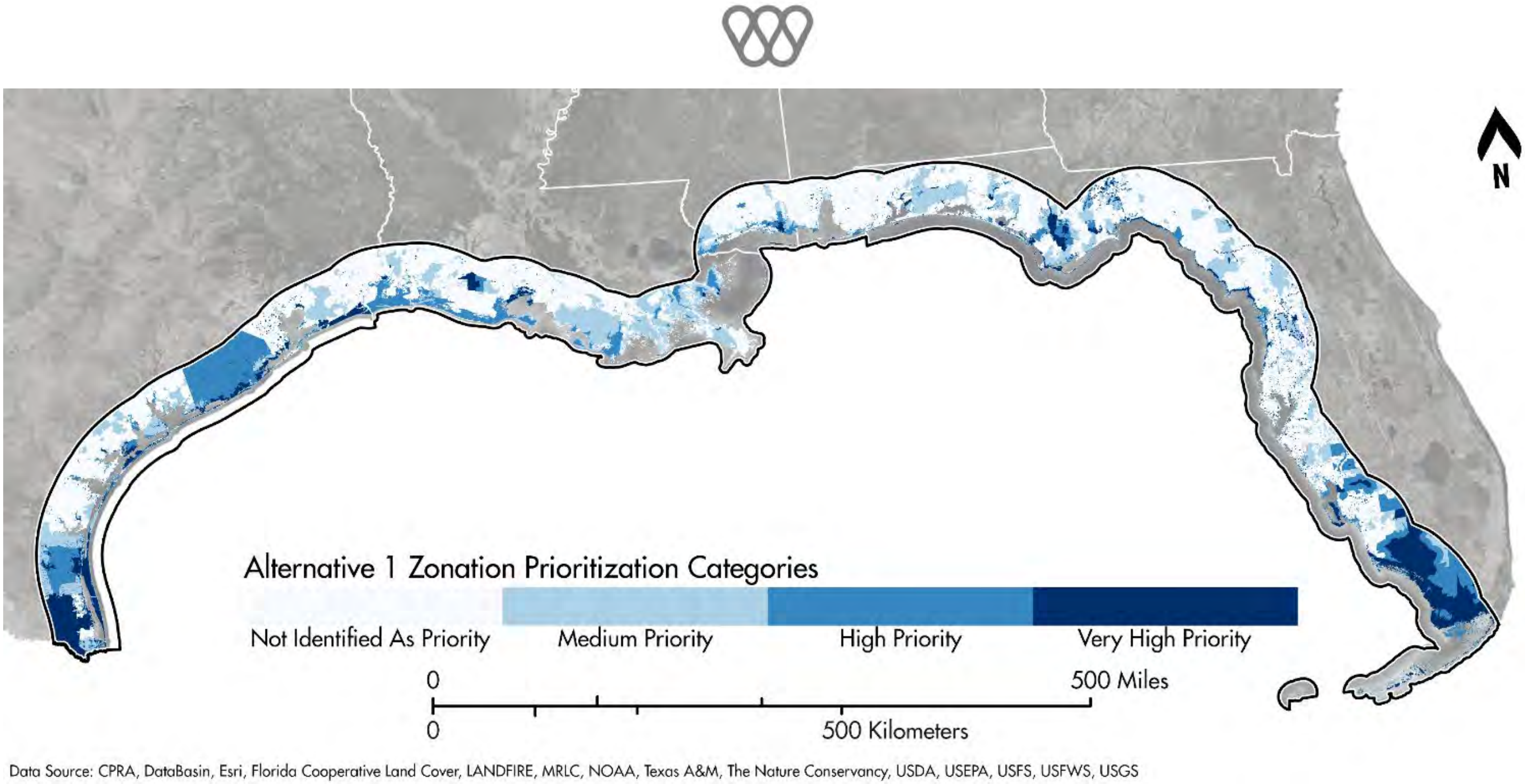
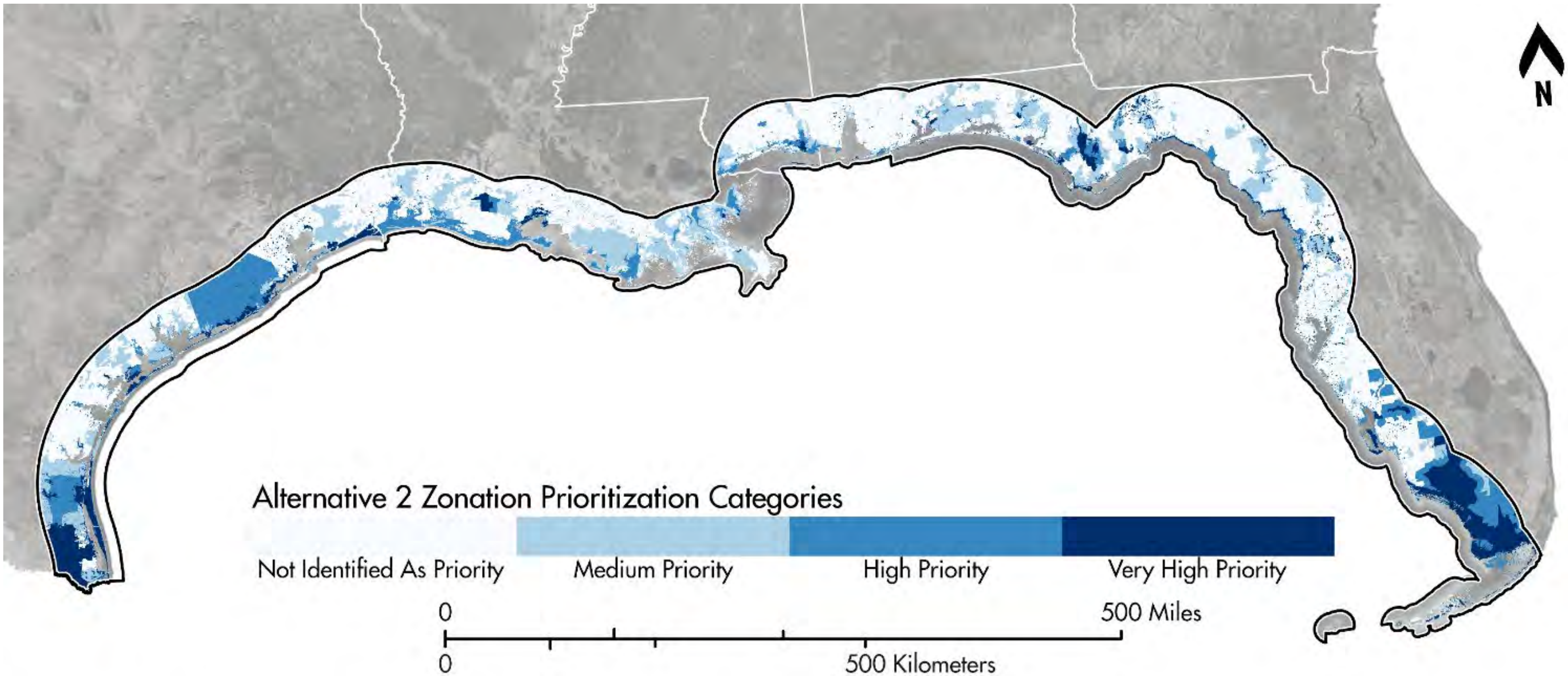


Figure A-54. Zonation output in 2020 South Atlantic Blueprint prioritization categories for Alternative 1 based on habitat condition evaluation.



Data Source: CPRA, DataBasin, Esri, Florida Cooperative Land Cover, LANDFIRE, MRLC, NOAA, Texas A&M, The Nature Conservancy, USDA, USEPA, USFS, USFWS, USGS

Figure A-55. Zonation output in 2020 South Atlantic Blueprint prioritization categories for Alternative 2 based on presence/absence of natural land cover.

Comparing Alternatives 1 and 2 at the category scale (Figure A-56), some locations did not result in any change of prioritization category. However, some locations reflect noticeably different conservation prioritization categories when Zonation is run with a land cover layer based on habitat condition scores. For example, areas north of Apalachicola and the landscape surrounding Tampa Bay, Florida, highlight significant reprioritization. However, most categorization shifts that occurred appear to be limited to the shift between “not a priority” and “medium priority” categories.

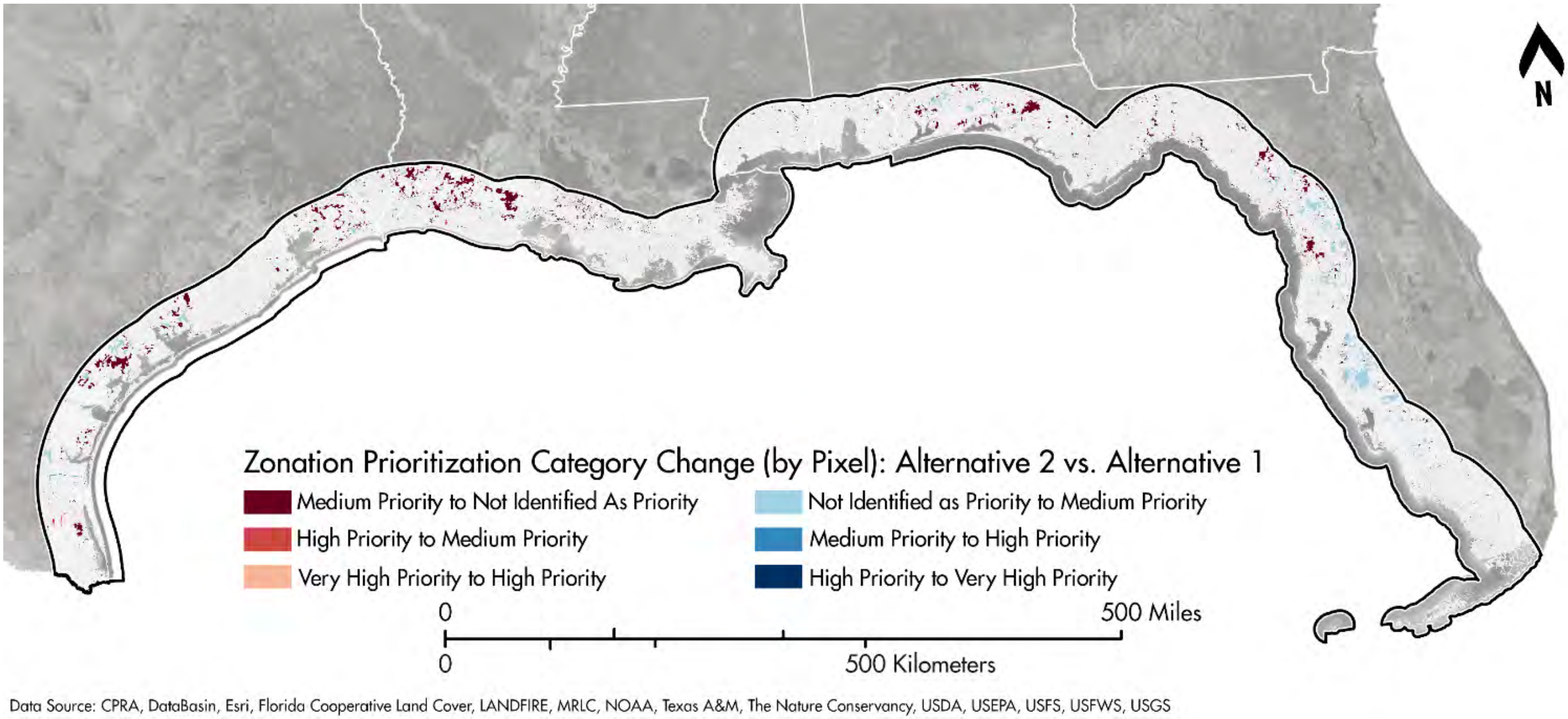


Figure A-56. Comparison of prioritization categories (based on 2020 South Atlantic Blueprint) between Alternative 2 and Alternative 1. Key shifts that highlight significant increased prioritization include pixels changed from Not Identified as Priority to Medium Priority and Medium Priority to High Priority. Key shifts that highlight significant decreased prioritization include pixels changed from Medium Priority to Not Identified as Priority and High Priority to Medium Priority. White indicates no change between Alternative 1 and Alternative 2 at the category level.

The amount of area (acreage) that shifted from high priority to medium priority mirrors the acreage shifted from medium priority to high priority at 23,224 acres (.07%) and 21,997 acres (.06%), respectively. Acreage shifts between medium priority and no priority experienced the largest change with 1,061,230 acres (3.07%) deprioritized and 1,066,904 acres (3.08%) with increased priority. Nearly equal numbers of cells shifted from high priority to very high priority (61,507) as cells shifted from very high priority to high priority (61,673 acres) impacting 0.18% of the total project area. This symmetry is useful in gauging whether changes to Zonation inputs (e.g., Alternative 1 and Alternative 2) are well balanced as large shifts between priority categorizations could be indicative of an unstable modification to the indicator framework. The histogram given in Figure A-57 details the relative pixel change between the Alternative 2 and Alternative 1, highlighting a normal distribution with a slightly negative skew.

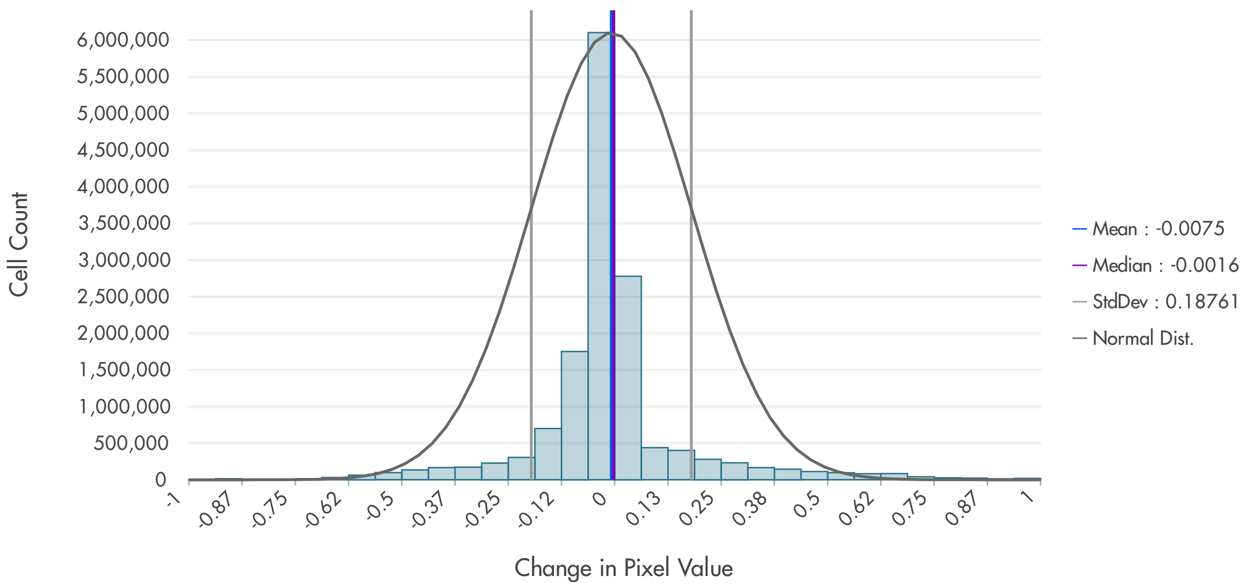


Figure A-57. Histogram of relative pixel change between comparison of Alternative 2 to Alternative 1.

References

Middle Southeast Blueprint. (2020). *Middle Southeast Blueprint 3.0 Development Process*. Middle Southeast Blueprint.

South Atlantic Conservation Blueprint. (2020). South Atlantic Blueprint 2020 Development Process.

APPENDIX B. ECOSYSTEM STRESS

INTRODUCTION

Coastal habitats of the Gulf of Mexico are ecologically diverse and highly valuable (Harwell et al., 2019). The objective of this work was to create a geospatial layer around the framework of ecosystem stress indicators of the Gulf of Mexico project area that, when used alongside existing tools like the prototype Gulf-wide Blueprint, can better-inform project planning. However, some metrics used in reporting on ecosystem stress can provide indications of current ecosystem health as well as progress towards stakeholder identified desired conditions. Integrated spatial maps of ecosystem stress can also be used to make inferences about ecosystem status at landscape scales and identify the most intact landscape patches (Hak & Comer, 2017). In programmatic and project planning, this map of ecosystem stress could be used to understand potential project failure by considering sources, concentrations, and the diversity of ecosystem stressors across the northern Gulf of Mexico region.

This appendix details the development of a uniform geospatial stressor layer (an Integrated Ecosystem Stress Indicator layer) and Ecosystem Stress Indicator sensitivity assessment across the Gulf of Mexico project area. Each Ecosystem Stress Indicator is outlined in detail, explaining rationale for inclusion, known thresholds to scale ecosystem stress, and key assumptions and limitations. This spatial assessment was developed to inform project planning at the 1 km^2 hex grid scale. Tessellated hexagons rather than squares were used for two main reasons. First, to integrate with other Gulf-wide efforts (e.g., the Strategic Conservation Assessment [SCA] project) and therefore ensure leveraging of additional efforts and datasets through funding pathways across both efforts (e.g., RESTORE). Second, from a data analysis perspective, a hexagon is more appropriate than a square grid due to its lower perimeter-to-area ratio, which decreases sampling bias from edge effects and makes the use of a centroid measure more meaningful.

A NOTE ON ASSUMPTIONS AND INTERPRETATION

Ecosystem stressors in the Gulf of Mexico are diverse with consequences that interact in ways that are often unknown. Addressing stressors (both natural and anthropogenic) that operate at multiple scales requires assumptions and acknowledgement of uncertainty, and assessment is limited to the extent of current scientific understanding. The Integrated Ecosystem Stress Indicator geospatial layer developed for this project is applicable across the northern Gulf of Mexico project area and was based on best available science; this dataset represents a series of complex relationships between stressors and the ecosystem. However, this geospatial layer does not address how an ecosystem may respond to those stressors (i.e., whether a ‘resilient’ ecosystem can return to pre-disturbance conditions if the stressor is removed, or whether a ‘resistant’ ecosystem may be able to maintain functions and processes intact while experiencing the stress; Clements & Rohr, 2009). The resilience and resistance of an ecosystem is important to consider if planning restoration or conservation projects and is different not only between ecosystems but between habitat types within each ecosystem.

Cumulative effects of multiple stressors are poorly understood for many ecosystems. There are multiple ecological theories related to how an ecosystem may respond to stress. For example, chronic exposure to a stressor may increase the likelihood of shifting to an alternative stable state (Bellwood et al., 2004;

Gunderson, 2000); ecosystems exposed to high stress environments may be more tolerant than those from stable environments (Kaufman, 1982); low species diversity may impart greater vulnerability to stressors (Adams et al., 2005; Vinebrooke et al., 2003); and ecosystems in naturally disturbed habitats may be preadapted to disturbance and may be more resistant to anthropogenic stressors (Kiffney & Clements, 1996). Furthermore, ecosystem stress (like ecosystem services) do not compound in a linear fashion and can result in variable cascades of responses and feedbacks (Cobb et al., 2017; Koch et al., 2009).

Although reaching consensus on these scientific questions is not an objective of this project, it is important to acknowledge that filling this scientific gap will improve geospatial analysis and understanding of synthesized or ‘overall’ ecosystem stress. The Integrated Ecosystem Stress Indicator layer and the analyses presented in this technical appendix form a useful and powerful data suite for restoration and conservation planners who might use this information in project development and prioritization especially in the context of rapidly changing global and environmental conditions.

INDICATORS OF ECOSYSTEM STRESS

Indicator: Invasive Species

Relevance and Context:

Invasive species are species of animals, plants, microbes, and fungi that are introduced to an ecosystem from other parts of the world; the ability of an invasive species to outcompete native species and their potential to disrupt natural ecosystem function are broadly recognized ecological threats. A recent review by Dueñas et al. (2021) states that invasive species threaten over ten percent of critically endangered terrestrial vertebrate species globally. Therefore, control and management of invasive species can be critical for collective efforts of biological conservation. The threat of invasive species is of particular concern in ecosystems that are already facing threats of rising sea levels which can reduce the potential for long-term resilience. Areas of high coastal urbanization are also highly vulnerable as anthropogenic activity can act as a conduit for invasive species spread and establishment (Johnson et al., 2020). Addressing invasive species as an ecosystem threat has been included in many ecosystem health reports relevant to the Gulf of Mexico (Brown et al., 2011; Carruthers et al., 2017; CERP, 2019; Harwell et al., 2016).

For restoration and conservation planning, cost of controlling invasive species can be a significant planning consideration (varying considerably by type of invasive species and geographic location), and may be an inevitable factor to consider during project planning due to the rapid-pace of invasive species spread (Weidlich et al., 2020). Furthermore, invasive species are widely recognized as a stressor across the Gulf of Mexico as highlighted in wildlife action plans drafted by all five U.S. Gulf States (Table B-1).

Table B-1. Summary of invasive species prioritization from US Gulf State Wildlife Action Plans.

State	Reference	Summarized Statement of Threat
Texas	(Texas Parks and Wildlife Department, 2012a, 2012b)	Non-native plants & animals, terrestrial and aquatic (including marine), damage existing native habitats (especially native grasslands); damage to habitats leads to reduced productivity of native species (e.g., pollinators, birds)
Louisiana	(Holcomb et al., 2015)	Invasive species (plant and animal) are the greatest source of threat to species of conservation need and habitats of Louisiana (LA). They threaten multiple habitat types including: forests (e.g., barrier island live oak forests, batture forests, bayhead swamp/forested seep (especially feral hogs), bottomland hardwoods, coastal live oak-hackberry forest, cypress-tupelo-blackgum swamp, hardwood flatwoods, and others), grasslands/savanna (eastern longleaf pine flatwoods savanna, eastern upland longleaf pine woodland, calcareous prairie), bogs and ephemeral ponds, coastal prairie, freshwater marsh, coastal beaches, and freshwater water bodies (lakes and reservoirs) to name only a few. Invasive species are also noted as vectors of diseases (e.g., Norway Rat *Rattus norvegicus* and feral cats *Felis catus).*
Mississippi	(Mississippi Museum of Natural Science, 2015)	Nonnative/alien species, both plant and animal, impact multiple habitats (86 out of 106 total sub-habitat types) throughout the state.
Alabama	(Alabama Department of Conservation and Natural Resources, 2015)	Invasive species (and some native species) can have negative effects on biodiversity. Problematic native species include white-tailed deer which have become overabundant in some areas.
Florida	(Florida Fish and Wildlife Conservation Commission (FWC), 2019)	Invasive species, both animal and plant, terrestrial and aquatic, are threats along with some native plants that can grow in abundance and disrupt the natural balance.

Key invasive species were compiled based on literature review, leveraging special invasive-focused groups, municipal, regional, state, and government agencies including U.S. Fish and Wildlife (USFWS). Five priority species (selected based on potential impact/threat) were identified for each state intersecting with the Gulf of Mexico project area as well as invasive species commonly found throughout all Gulf of Mexico coastal states. A total of 22 species were identified for this assessment (Table B-2).

Table B-2. Priority and common invasive taxa by state within the Gulf of Mexico project area.States where a given invasive taxa is recognizes as a top priority are highlighted in bold.

Species (common name)	Species (scientific name)	State
Zebra mussel	*Dreissena polymorpha*	**TX,** LA, MS
Chinese tallow tree	*Triadica sebifera*	TX, **LA**, MS, AL, FL
Wild boar	*Sus scrofa*	TX, **LA**, MS, AL, FL

Species (common name)	Species (scientific name)	State
Nutria	*Myocastor coypus*	**LA**, MS
Melaleuca	*Melaleuca quinquenervia*	AL, **FL**
Kudzu	*Pueraria montana*	**AL**, FL
Japanese honeysuckle	*Lonicera japonica*	TX, LA, MS, **AL**, FL
Japanese climbing fern	*Lygodium japonicum*	MS, AL
Hydrilla	*Hydrilla verticillate*	**TX**, LA, **MS**, AL, **FL**
Hyacinth	*Eichhornia crassipes*	**TX**, LA, **MS**, AL, **FL**
Giant and common salvinia	*Salvinia molesta* and *S. minima*	**TX**, **LA**, **MS**, **AL**, FL
Chinese privet	*Ligustrum sinense*	**LA**, AL
Cane toad	*Bufo marinus*	**FL**
Brazilian pepper tree	*Schinus terebinthifolius*	**FL**
Asian clam	*Corbicula fluminea*	TX, LA
Carp (bighead, silver, grass, black, and common)	Hyp*ophthalmichthys nobilis, H. molitrix, Ctenopharyngodon Idella, Mylopharyngodon piceus,* and *Cyprinus carpio*	**TX**, LA, MS
Red imported fire ant	*Solenopsis invicta*	TX, LA, MS, AL, FL

Data & Method

Invasive species spatial data (presence/absence point data) was derived from the Early Detection and Distribution (EDD) Maps (https://www.eddmaps.org/distribution/) and the USGS Nonindigenous Aquatic Species (NAS) dataset (https://nas.er.usgs.gov/), summarized in Table B-3.

Table B-3. Data sources and availability for the Invasive Species Ecosystem Stress Indicator.

Species List	Data Source and Web Link	Notes on Data Availability
Asian clam, zebra mussel, hyacinth, hydrilla, carp, giant and common salvinia	USGS Nonindigenous Aquatic Species (NAS) dataset (https://nas.er.usgs.gov/)	Asian clam data not available for TX
Chinese privet, Japanese honeysuckle, Japanese climbing fern, nutria, kudzu, red imported fire ant, wild boar, Brazillian pepper tree, cane toad, maleleuca, Chinese tallow tree	Early Detection and Distribution (EDD) Maps (https://www.eddmaps.org/distribution/)	Chinese privet data not available for AL; Japanese honeysuckle data not available for MS; Japanese climbing fern data not available for MS; nutria data not available for MS; kudzu data not available for FL; red imported fire ant data not available for TX or MS; wild boar data not available for MS

The spatial data for all species was derived by state from point data. The state priority species identified in Table B-2 were grouped into one layer and the nonpriority species in another. The point data was converted to 30 m raster based on the presence, receiving a value of 1, or absence of an invasive species point. These two layers were then combined using raster math and reclassified using Equation 1 to create a uniform 1 to 100 new scale, where No Data reflects no invasive species recorded in that cell. Zonal statistics were then utilized to resample the 30 m raster into 1 km^2 hexagon grid.

Equation 1. Re-Scaling Formula

$$\begin{aligned} \mathit{reclassified\ grid\ cell\ value} \\ &= [(\mathit{existing\ raw\ value} - \mathit{min\ value\ from\ raw\ scale}) \\ &\times (\mathit{max\ value\ of\ new\ scale} - \mathit{min\ value\ of\ new\ scale}) \\ &\div (\mathit{max\ value\ from\ raw\ scale} - \mathit{min\ value\ from\ raw\ scale})] \\ &+ \mathit{min\ value\ of\ new\ scale} \end{aligned}$$

where:

existing raw value = unscaled cell value from the original (raw) dataset;
min value from raw scale = lowest potential cell value from raw dataset;
max value from raw scale = highest potential cell value from raw dataset;
max value of new scale = 100;
min value of new scale = 1.

Ecological Threshold:
Due to the widespread distribution and adaptability of invasive species, habitat-specific thresholds were not developed for this Ecosystem Stress Indicator. In some conservation assessments, presence alone can disqualify an area for potential conservation/restoration. Ecosystem stress caused by invasive species was expressed in values scored from 1 to 100 for each 1 km^2 hexagon cell (Table B-4). No data (grey) reflects no information on the identified invasive species was available.

Table B-4. Interpretation of cell values for the Invasive Species Ecosystem Stress Indicator.

1 km^2 Hex Cell Value	Interpretation
50	Non-prioritized key invasive species present
75	State-prioritized key invasive species present
100	Both state-prioritized and non-prioritized key invasive species present

Current Condition:
First, the invasive species datasets were combined and resampled to a 1,000 m cell grid and clipped to the ecosystem stress spatial domain (Figure B-1). Next, the threshold was applied and the data scaled such that cell values of 50 indicate low stress, 100 reflect maximum stress, and cells less than 50 reflect no data (Figure B-2).

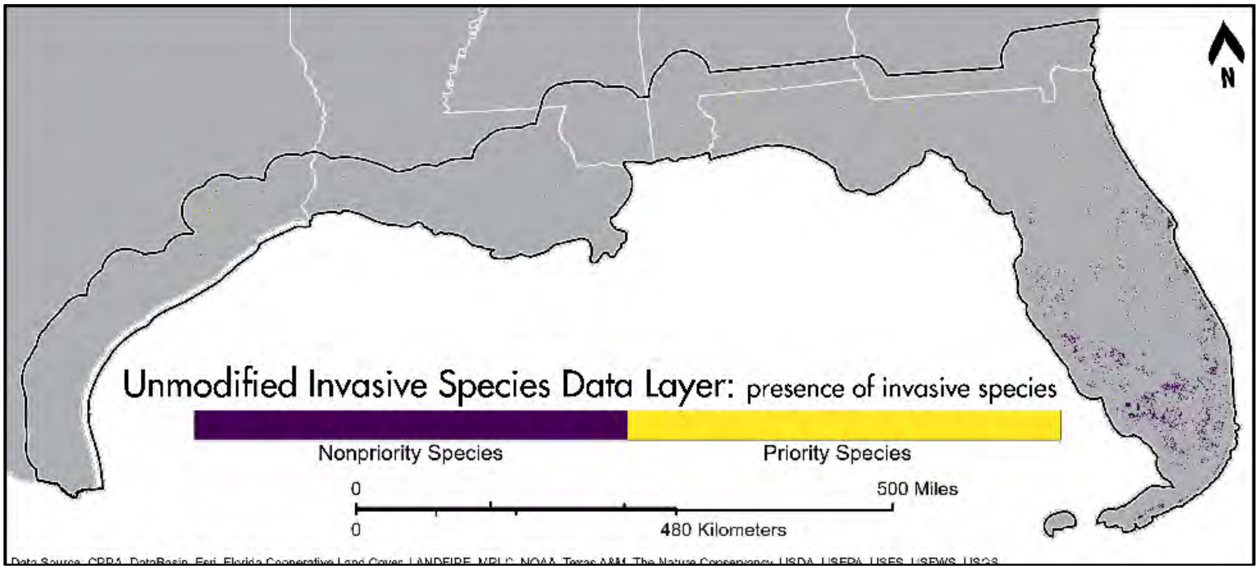


Figure B-1. Unmodified invasive species dataset (point data). Nonpriority and priority species distinctions are reflected in Table B-2. Data was resampled to 1,000 m grid cell size and clipped to the ecosystem stressor spatial domain. Note: points may be difficult to discern at this spatial scale.

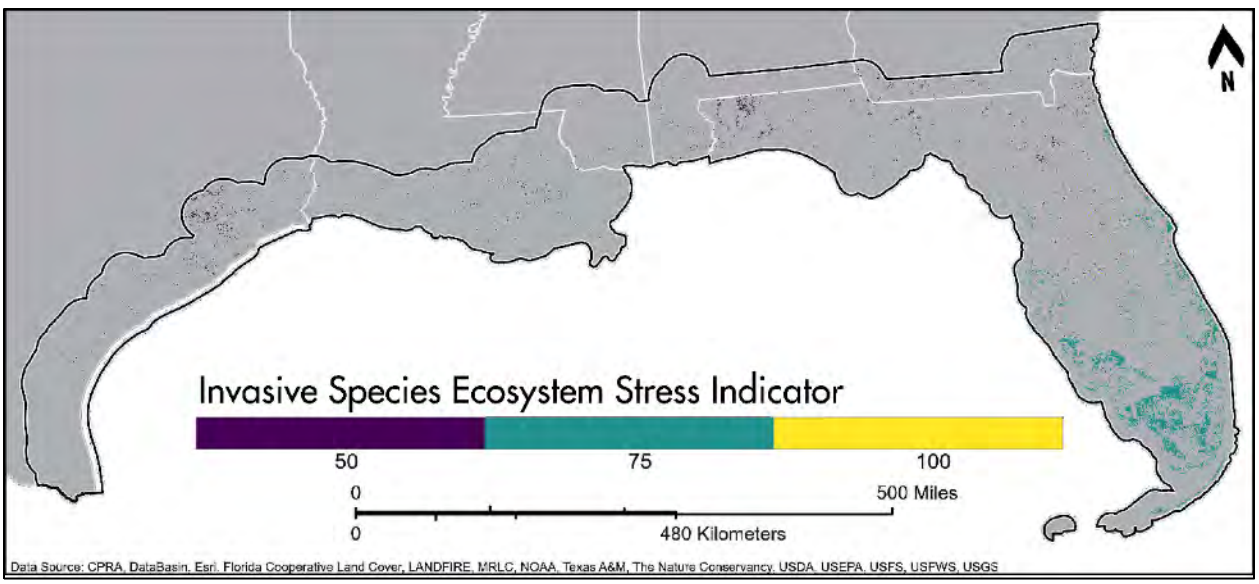


Figure B-2. Invasive species Ecosystem Stress Indicator layer mapped across the project area. A score of 100 reflects the highest ecosystem stress possible based on applied thresholds. Values less than 50 reflect No Data.

Data Gaps and Limitations:

Comprehensive assessments of individual invasive species at large spatial scales are rare, most of the available data results from detailed, purpose driven, surveys at a local scale. Due to the diverse adaptations and strategies employed by invasive species, it is difficult to accurately predict impacts of these species by ecosystem, singularly or in combination, based on the current scientific information available. Although a simple assessment was employed here, it is acknowledged that some invasive species may be more impactful in some habitats over others depending on the existing ecology and other confounding abiotic conditions (Paine et al., 1998). Additionally, this assessment does not consider density of invasive species in a given area. One important caveat of this stressor layer is that a value of “1” only indicates the absence of any documented occurrence of key invasive species and this value cannot easily be distinguished from a value of “No Data”. Species occurrence datasets like those employed here are based on documented occurrences, with little information to appropriately map true absence. Furthermore, this assessment does not include all invasive species and this information should not be used to determine areas without invasive species presence. Local examination of invasive species presence and potential management costs may be required for project planning at smaller scales.

Indicator: Disease & Disease Risk

Relevance and Context:

Disease risk is broadly recognized as an Ecosystem Stress Indicator, impacting both terrestrial and aquatic systems along the northern Gulf of Mexico (Carruthers et al., 2017; Harte Research Institute for Gulf of Mexico Studies, 2019; Harwell et al., 2016; IAN UMCES, 2019; Integration and Application Network, 2015). Diseases can impact primary producers (plants) as well as animals directly (e.g., pathogen/host relationships, habitat loss) and indirectly (e.g., poor habitat quality, fragmentation). Wildlife disease is also recognized in state wildlife action plans across all Gulf of Mexico states (Table B-5).

Table B-5. Summary of diseases highlighted in U.S. Gulf State Wildlife Action Plans that could pose potential threat to wildlife.

State	Reference	Summarized Statement of Threat
Texas	(Texas Parks and Wildlife Department, 2012a, 2012b)	Pathogens impact plant assemblages such as hardwoods, woodlands, riparian borders, and open savanna habitats. Pathogens can also directly impact fauna including birds (avian botulism, cholera, duck plague, waterfowl influenza), bats (White-Nose Syndrome), and oysters (vibrio and water borne viruses). Pathogens can be introduced from livestock and development (making vegetation assemblages more vulnerable to disease and infestation).
Louisiana	(Holcomb et al., 2015)	Disease is noted as an emerging threat to wildlife in Louisiana, specifically: amphibian disease (Chytrid), reptile diseases (snake fungal disease), emerging avian diseases, and diseases threatening crustaceans (e.g., crawfish).
Mississippi	(Mississippi Museum of Natural Science, 2015)	Fungal pathogens are an emerging concern in Mississippi, specifically the fungus that causes White-Nose Syndrome in bats, the Chytrid fungus impacting amphibians, and snake fungal disease (a new emerging disease).
Alabama	(Alabama Department of Conservation and Natural Resources, 2015)	Disease pathogens prioritized in Alabama that impact wildlife include fungal pathogens like the Chytrid fungus, snake fungal disease, and White-Nose Syndrome.
Florida	(Florida Fish and Wildlife Conservation Commission (FWC), 2019)	Disease is flagged as an emerging threat to Florida’s wildlife along with pests and invasive species. Although not yet detected in FL, White-Nose Syndrome impacting bats is highlighted as a known threat to watch.

To address the threat of emerging diseases in the region, this Ecosystem Stress Indicator addresses a few of the critical floral, mammalian, and amphibian diseases for which data were available across the project area: forest disease, *Pseudogymnoascus destructans* (White-Nose Syndrome, WNS, impacting bats), and *Batrachochytrium dendrobatidis* (Chytrid fungal disease, impacting amphibians).

Data & Method:

1. **Forest Disease Risk**: To map forest disease, the 2018 National Insect and Disease Risk Map (NIDRM) dataset developed by the U.S. Forest Service (USFS) for the U.S. Department of Agriculture (USDA) was used. This dataset is the result of a nationwide strategic assessment of the potential hazard for tree mortality due to major forest insects and diseases, applicable for the 2013-2027 timeframe. NIDRM products are compiled on a national extent with 240 m (~14 acres) spatial resolution, with datasets available as composite risk, % of treed area at risk by watershed, and watersheds ranked by basal area loss hazard. Estimates do not include future hazard related to projected climate change. The composite insect and disease risk map identifies areas with risk (hazard) of mortality defined as: "the expectation that, without remediation, at least 25% of standing live basal area greater than 1 inch in diameter will die over a 15-year time frame (2013-2017) due to insects and diseases" (Krist et al., 2014). Datasets was accessed via: USDA USFS Risk Species https://www.fs.fed.us/foresthealth/applied-sciences/mapping-reporting/national-risk-maps.shtml.
2. **White-Nose Syndrome (WNS) Disease Occurrence**: Bats in the U.S. are increasingly at risk for WNS. This fungal disease (*Pseudogymnoascus destructans*) infects hibernating bats and has been confirmed in over 30 states as well as Canada (Alves et al., 2014). The USGS is currently involved in multiple research programs related to WNS, collaborating with both state and federal wildlife agencies to develop tools and assist with early detection of this disease across the US (https://www.usgs.gov/ecosystems/invasive-species-program/science/white-nose-syndrome). Within the northern Gulf of Mexico, two counties reported that at least one or more bats of at least one species had been observed with signs of WNS or were tested to confirm infection by *P. destructans*; both observed instances occurred in the winter of 2018-2019. Data was downloaded from https://www.whitenosesyndrome.org/where-is-wns and reflect occurrence (presence/absence) of WNS or causative fungus in one or more species at a county level.
3. **Chytrid Disease Occurrence:** *Batrachochytrium dendrobatidis* (*Bd,* Chytrid fungal disease) is well-known for being the causative agent behind global amphibian declines (Olson et al., 2013). For this stressor, multiple datasets and databases were combined to reflect known presence of Chytrid between 2007-2019 based on published literature sources. Here, no measure of disease density or disease prevalence in a given amphibian population was provided. Georeferenced data was compiled from multiple sources: Chiari et al., 2017; Cohen et al., 2019; Glorioso et al., 2017; Marshall et al., 2019; Olson et al., 2013; and Villamizar Gulf of Mexicoez et al., 2016.

The disease spatial data was derived from vector (WNS and Chytrid disease) and raster data (NIDRM). The vector data was converted to 30 m raster based on the presence, receiving a value of 1, or absence (0) of WNS or Chytrid. The NIDRM raster was resampled to 30 m resolution and reclassified for pixels at risk of forest disease, receiving a value of 1, or not at risk (0) based on the original values provided in NIRDRM. These layers were then combined using raster math and cells with values indicating the presence of disease were reclassified to 100 and those not reporting disease were given a value of No Data. Zonal statistics were then utilized to resample the 30 m raster into 1 km^2 hexagon grid.

Ecological Threshold:

The Disease & Disease Risk Ecosystem Stress Indicator is based on presence of disease (Chytrid, WNS) and risk of forest disease. The ecological threshold present in the NIDRM dataset represents risk of a forest area to a particular forest pest or pathogen within the next 15 years (2013-2017). This threshold is based on models that integrate multiple parameters that describe host-tree species distributions (e.g., basal area, stand density, mean diameter, etc., as well as type and distribution of pest/disease; Krist et al., 2014). The resulting stress threshold is binary, where a forest is either at risk or not at risk. For Chytrid and WNS, no relevant spatial threshold based on disease occurrence was available from the peer-reviewed scientific literature. For this assessment, the ecological threshold for the Disease & Disease Risk Ecosystem Indicator was based only on presence of any disease (WNS, Chytrid, or Forest Disease Risk) in the combined dataset. Ecosystem stress caused by wildlife disease is expressed as values of 100 for each 1 km^2 hexagon cell where disease has been recorded (Table B-6). No data (grey) reflects no information is available on the presence or absence of wildlife disease or forest disease risk.

Table B-6. Interpretation of cell values for the Disease & Disease Risk Ecosystem Stress Indicator.

1 km^2 Hex Cell Value	Interpretation
100	Disease present (either WNS, Chytrid, or Forest Disease Risk)

Current Condition:

First, the Disease & Disease Risk Ecosystem Stress Indicator datasets were combined and resampled to a 1,000 m cell grid and clipped to the ecosystem stress spatial domain (Figure B-3). Next, the threshold was applied and the data scaled such that cell values of 100 reflect maximum stress imparted by this indicator and grey areas reflect no data (Figure B-4).

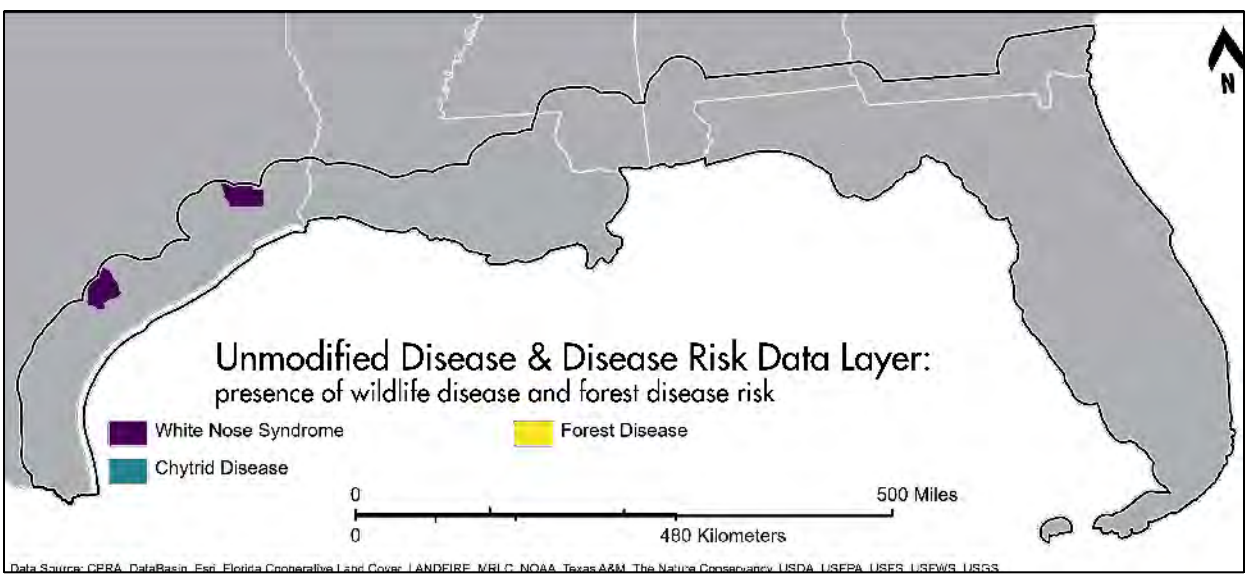


Figure B-3. Unmodified disease (Chytrid: point data, White Nose Syndrome: county data) and forest disease risk (point data) datasets. Data was resampled to 1,000 m grid cell size and clipped to the ecosystem stressor spatial domain. Note: points may be difficult to discern at this spatial scale.

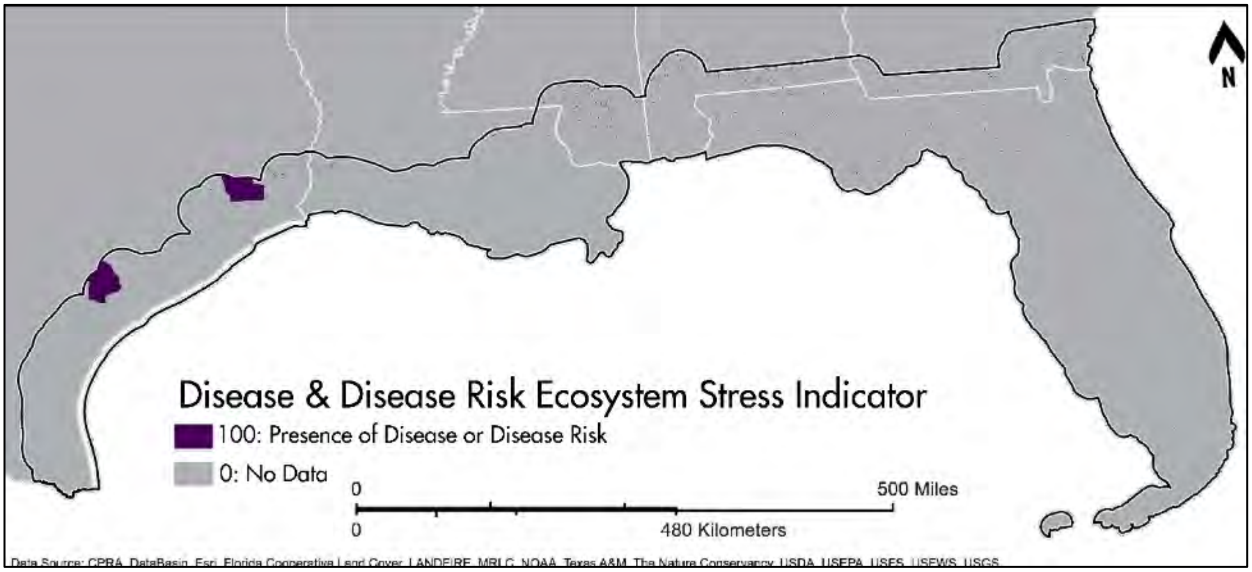


Figure B-4. Disease & Disease Risk Ecosystem Stress Indicator layer mapped across the project area. A score of 100 reflects presence of any disease or disease risk based on applied thresholds. Values less than 100 reflect No Data.

Data Gaps and Limitations:
Mapping disease as point occurrence or even presence within a county does not address the realized threat of disease occurrence; this Ecosystem Stress Indicator likely has a much greater spatial footprint than point data can provide. In addition, the disease datasets selected here are representative of only a few of the many known diseases that occur across this region. Project planners should carefully consider how wildlife disease might impact project success at a particular location in relation to habitats and prioritized flora and fauna locally. This Ecosystem Stress Indicator does not reflect metrics of prevalence, any assumptions about current disease spatial distribution outside of the base datasets and should not be used to make inferences about potential spread of these diseases.

Chronic wasting disease is another potential and emerging threat for deer populations in the southern US, however data for this disease does not yet show occurrence within the spatial footprint of our project area. Therefore, chronic wasting disease was not included in this assessment. Much of the focus on chronic wasting disease has occurred in the Northeast of the U.S. (https://www.usgs.gov/media/images/distribution-chronic-wasting-disease-north-america-0). However, it is important to acknowledge that some state wildlife action plans recognize this disease as a potentially significant threat in the future (e.g., in Texas).

Indicator: Non-Point Source Pollution

Relevance and Context:

The Gulf of Mexico watershed spans more area than half the continental U.S. (US Environmental Protection Agency, 2011), and 40% of that watershed is comprised of the Mississippi River Basin (Harwell et al., 2019). Under natural conditions, water chemistry in a waterbody varies within a characteristic range that is determined by multiple factors including geography, topography, and geology. Scientific research links non-point source nutrient input into coastal estuaries with degraded water quality and hypoxic conditions in the northern Gulf of Mexico (Baker et al., 2018; Tian et al., 2020). The impacts of sand and gravel mines can also contribute to increased sediment loads to neighboring aquatic systems, both at local stream and watershed scales, impairing water quality and ecosystem function. The culmination of excessive nutrient inputs, suspended sediment loads, and other water contaminants can result in a USEPA impaired waterbody listing for remedial action. Water quality is broadly recognized as an ecosystem threat across all Gulf of Mexico states (Figure B-7). Here, water quality was characterized by nutrient inputs from USGS Spatially Referenced Regression on Watershed Attributes (SPARROW) models, proximity to sand and gravel mines, and USEPA's listed 303(d) impaired waters.

Table B-7. Summary of non-point source stressors highlighted in US Gulf State Wildlife Action Plans that could pose potential threat to wildlife.

State	Reference	Summarized Statement of Threat
Texas	(Texas Parks and Wildlife Department, 2012a, 2012b)	Nutrient loading in waterways as a consequence of agricultural and/or ranching practices can result in harmful algal blooms (HABs), reduced seagrass cover, and low water quality for estuarine animals.
Louisiana	(Holcomb et al., 2015)	Non-point source pollution impacting water quality threatens forested wetland habitats like cypress-tupelo-blackgum swamp and pondcypress-blackgum swamp as well as other water-driven habitats (e.g., freshwater floating marsh). Water bodies (e.g., lakes and reservoirs) are threatened by agricultural, municipal, and industrial effluents. Pollution is highlighted as a threat to all major groups of species of greatest conservation need (SGCN).
Mississippi	(Mississippi Museum of Natural Science, 2015)	Industrial/military effluents along with agriculture and forestry effluents are a noted as threats.
Alabama	(Alabama Department of Conservation and Natural Resources, 2015)	Pollution is a threat to multiple habitats (riparian areas, aquatic and terrestrial habitats). Water quality is negatively impacted by runoff from agricultural/ranching lands as well as from aquaculture (e.g., catfish ponds).
Florida	(Florida Fish and Wildlife Conservation Commission (FWC), 2019)	Water management can exacerbate water quality issues. Pollution (point and non-point) is highlighted as a significant threat to aquatic habitats.

SPARROW models were developed by USGS to quantify current streamflow and water quality conditions for large regions of the conterminous U.S. as part of a larger USGS effort, the National Water Quality Assessment (Preston et al., 2011). SPARROW models were developed to understand how climate, land use, and other landscape characteristics control mean-annual streamflow, total nitrogen (TN), total phosphorus (TP), and suspended sediment/turbidity (SS) transport (Robertson & Saad, 2019). SPARROW models intersecting with this project include the Southwest, Midwest, and Southeast regions models. A description of these regions and the dominant TN and TP sources identified from the SPARROW models are summarized in Figure B-8.

Table B-8. Summary of SPARROW regions and dominant TN and TP sources identified from model outputs.

Region	Dominant TN, TP, and SS Sources
Southwest: U.S. sections of the Rio Grande and Colorado River Basins, several rivers in Texas that drain to the Gulf of Mexico, and many internally drained basins	Wastewater discharge (TN, TP) was the dominant source at regional scales; atmospheric N deposition, agricultural runoff, and runoff from developed land were dominant at local scales (Wise et al., 2019).
Midwest: Mississippi River, Great Lakes, and Red River of the North Basins	Atmospheric deposition and natural (background) sources of TN and TP were dominant in anthropogenically unaffected areas; fertilizers, manure, and fixation sources were dominant in agricultural areas. Urban sources of TN and TP were important at more local scales but were still important for some larger areas (e.g., Lake Erie basin) (Robertson & Saad, 2019).
Southeast: all tributaries draining to the US coast between and including the Chowan-Roanoke River and Pascagoula River Basins (excluding drainage basins downstream from the Tsala Apopka chain of lakes in central Florida)	The top three TN sources (by mass contribution to streams) that explain variability in TN transport include atmospheric deposition, agricultural fertilizer, and municipal wastewater. Delivery of TN from source to stream were attributed to variation in climate, soil texture, and vegetative cover (including agriculture) in the watershed. Top TP sources that explain variability in TP transport include parent rock minerals, urban land, and manure from livestock, and delivery of TP was attributed to variation in climate, soil erodibility, and depth to water table (Hoos & Roland, 2019).

SPARROW models provide a nutrient-based context to view water quality impairment. Turbidity and sedimentation of waterways due to sand and gravel mining operations is also a significant non-point source to aquatic systems at local and watershed scales. The Louisiana Department of Environmental Quality (LDEQ) established best management practices for the sand and gravel mining industry specifically to address the potential non-point source pollution hazards posed by such activities to local ecosystems (LDEQ, 2007). However, such practices are not applied in every state. Koehnken et al. (2020) describe that the ecological impacts of mining activities are diverse and can result in both direct (loss of habitat, changes to physical condition of stream locally) and indirect ecosystem effects (habitat alteration due to changes in sediment grain size composition, impacts to water clarity, and hydraulic changes impacting fish movement and habitat availability).

Nutrient loads, sedimentation, and other pollution loads in a water body can be reflected at a national level as well. The USEPA’s list of 303(d) impaired waters is the result of state-based reporting of impaired waters as defined under section 303(d) of the Clean Water Act (US Environmental Protection Agency, 2009). The list tracks all impaired and threatened waters (e.g., stream/river segments, lakes) submitted by each state and the USA 303(d) listing reflects "where the state has identified that required pollution controls are not sufficient to attain or maintain applicable water quality standards," requiring states to develop pollution reduction strategies before the waterbody can be removed from the list (US Environmental Protection Agency, 2009).

Data & Method:

1) **303(d) Impaired Waters**: The list of 303(d) Impaired Waters was extracted from USEPA's Assessment and Total Maximum Daily Load Tracking and Implementation System (ATTAINS) database (https://ofmpub.epa.gov/waters10/attains_index.home). The "Impaired Waters with TMDLs NHDPlus Indexed Dataset with Program Attributes in the File Geodatabase Format" dataset was used: https://www.epa.gov/waterdata/waters-geospatial-data-downloads. This dataset contains nationwide data on assessed and impaired waters assembled from state-specific biennial assessment reports. Data was sourced from the ATTAINS database on 3/24/2021 and downloaded by region.
2) **Watershed Nutrient Loads**: USGS 2012 SPARROW models at HUC12 resolution for TN and TP were downloaded for the Southwest, Midwest, and Southeast regions (https://sparrow.wim.usgs.gov/sparrow-midwest-2012/, https://sparrow.wim.usgs.gov/sparrow-southeast-2012/, https://sparrow.wim.usgs.gov/sparrow-southwest-2012/). All data was downloaded on 3/25/2021.
3) **Sand and Gravel Mines**: Locations of mines (sand and gravel) within this project area were identified from Homeland Infrastructure Foundation-Level Data (HIFLD) database (https://hifld-geoplatform.opendata.arcgis.com/datasets/sand-and-gravel-operations?geometry=-126.901%2C24.269%2C-60.148%2C37.424. Data was downloaded on 3/23/2021.

SPARROW model outputs of concentration (accumulated load divided by accumulated flow) at HUC12 scale were used in the development of this Ecosystem Stress Indicator. Concentration values can be interpreted as the mean-annual flow-weighted concentration in mg/L as recommended in the SPARROW documentation. Concentrations of TP and TN were downloaded from the SPARROW models for each HUC12 within the project area. Each watershed concentration (TP and TN) was compared against the USEPA regulatory criteria to determine whether to assign the hexagons within the watershed a value of 0, 50, or 75 (see final scoring below). Maximum ecological stress (value of 100) was assigned to all 303(d) impaired waters and hexagons that intersect with a 500 m buffer around each sand and gravel mine in the project area due to the known stress caused by these features. Zonal statistics were then utilized to resample the 30 m raster into 1 km^2 hexagon grid.

Ecological Threshold:

Due to the river and stream focus within the SPARROW models, the nutrient thresholds used in this analysis were based on USEPA regulatory thresholds for rivers and streams (USEPA, 2020). The criteria for TS and TP, aggregated by Level III Ecoregions (USEPA, 2015), reflect the recommended water quality standards in accordance with the Clean Water Act (CWA). For more information on how the USEPA developed these guidelines please see USEPA (2000). These threshold criteria are summarized below (Table B-9). The Level III Ecoregions that intersect the Gulf of Mexico include Ecoregions X (Texas-Louisiana Coastal and Mississippi Alluvial Plains), IX (Southeastern Temperate Forested Plains and Hills), XII (Southern Coastal Plain), and XIII (Southern Florida Coastal Plain). Nutrient criteria for rivers and streams have not yet been developed for region XIII.

Table B-9. Summary of the available USEPA river and stream ecoregional nutrient parameters for ecoregions that intersect with the Gulf of Mexico. Note: Ecoregion XIII is not shown because criteria for rivers and streams have not yet been developed. The asterisk reflects that the reported threshold has been flagged by the USEPA as possibly too high due to a statistical anomaly and may not be representative of the larger ecoregion.

Parameter	Ecoregion IX	Ecoregion X	Ecoregion XII
TP mg/L	0.03656	0.128*	0.040
TN mg/L	0.69	0.76	0.90

The USEPA regulatory criteria and the SPARROW model outputs for TP and TN at HUC12 watershed scale were used as a base threshold to determine the lowest tier of ecosystem stress used in this assessment.

Locations of acute ecosystem stress (mines and 303(d) impaired waters) resulted in the classification highest possible ecosystem stress for this Ecosytem Stress Indicator. The distance decay function described by Hak and Comer (2017) was used to buffer mine locations by 500 m to represent their short-range ecological impacts. It is acknowledged that mines can impact entire watersheds, but impacts at large scales are location specific and not predictable from an overall dataset. Project planners are encouraged to assess the specific characteristics of local mines and their impacts on local and watershed scales when planning projects. Lastly, it was not possible to determine spatial thresholds around 303(d) listed impaired waterbodies due to the specificity of pollution conditions for each waterbody, therefore listing as 303(d) alone was determined as an appropriate threshold for maximum ecosystem stress.

Ecosystem stress caused by non-point source pollution is expressed in values scored from 0 to 100 for each 1 km^2 hexagon cell (Table B-10).

Table B-10. Interpretation of cell values for the Non-Point Source Pollution Ecosystem Stress Indicator.

1 km^2 Hex Cell Value	Interpretation
0	Area reflects no potential water quality impairment from SPARROW models and does not intersect with a 303(d) impaired water or a 500 m buffer around a sand/gravel mine
50	Area reflects SPARROW concentrations of TP or TN exceed USEPA criteria and does not intersect with a 303(d) impaired water or a 500 m buffer around a sand/gravel mine

1 km^2 Hex Cell Value	Interpretation
75	Area reflects SPARROW concentrations of TP and TN exceed USEPA criteria and does not intersect with a 303(d) impaired water or a 500 m buffer around a sand/gravel mine
100	Area intersects with a 303(d) impaired water or a 500 m buffer around a sand/gravel mine location

Current Condition:

First, the non-point source datasets were resampled to a 1,000 m cell grid and clipped to the ecosystem stress spatial domain (Figure B-5–Figure B-8). Next, the threshold was applied and the data scaled such that cell values of 1 reflect lowest ecosystem stress and values of 100 reflect maximum stress (Figure B-9).

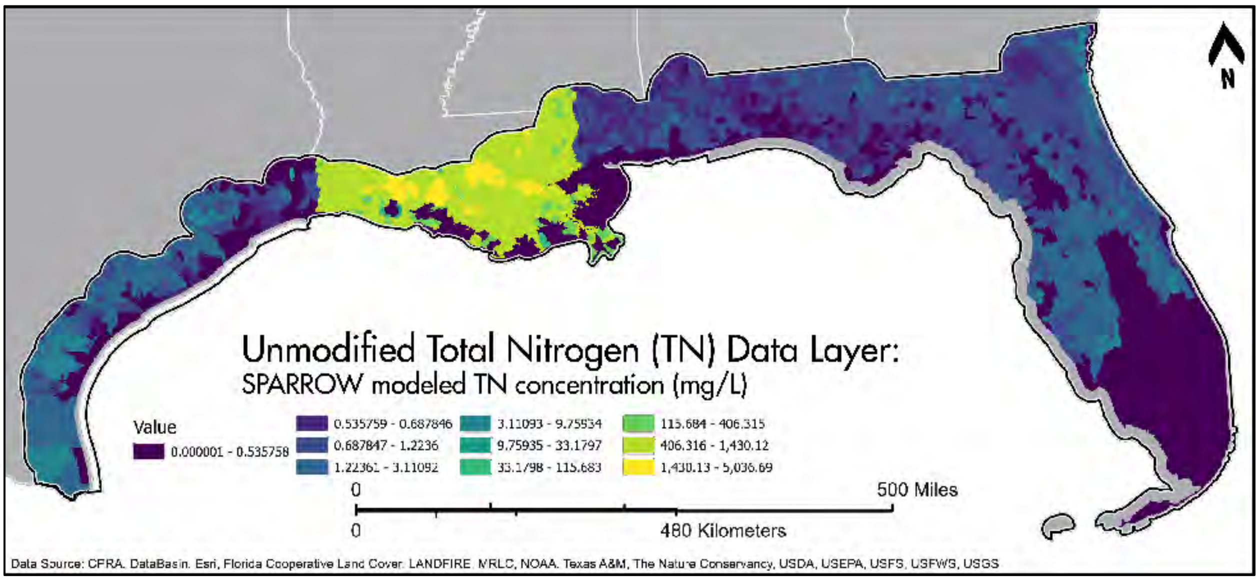


Figure B-5. Unmodified SPARROW model outputs for Total Nitrogen (TN) nutrient concentrations (mg/L per HUC12 watershed). Layer combines models for the Southwest, Midwest, and Southeast regions. High TN concentrations resulting from outflow of the Mississippi river appear to drive the highest values observed across the spatial domain. Data was resampled to 1,000 m grid cell size and clipped to the ecosystem stressor spatial domain.

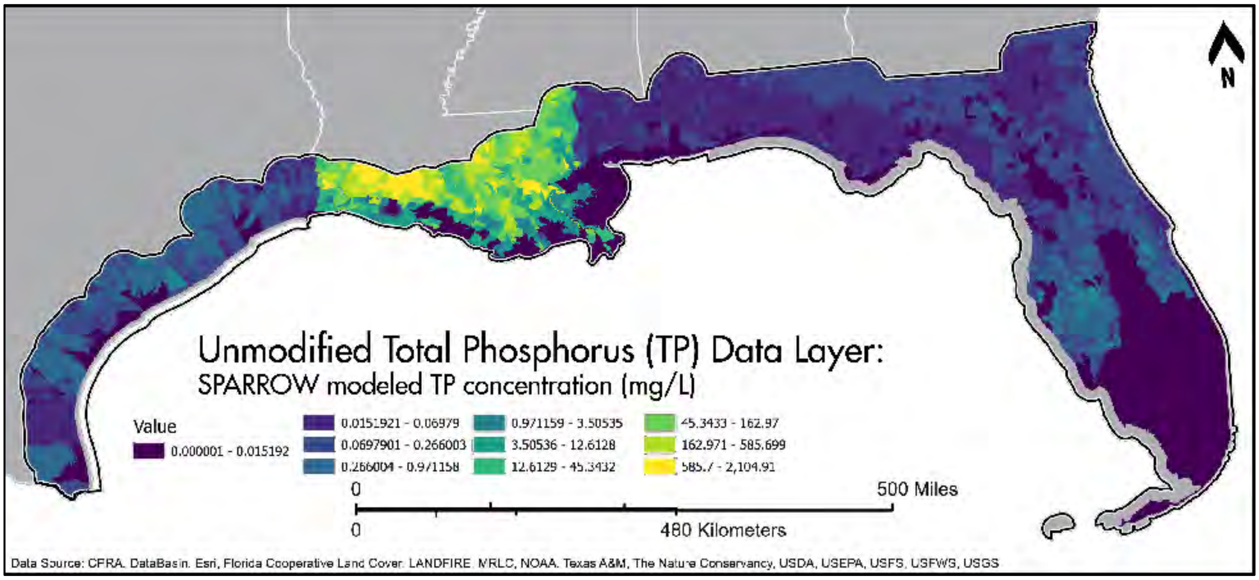


Figure B-6. Unmodified SPARROW model outputs for Total Phosphorus (TP) nutrient concentrations (mg/L per HUC12 watershed). Layer combines models for the Southwest, Midwest, and Southeast regions. High TP concentrations resulting from outflow of the Mississippi river appear to drive the highest values observed across the spatial domain. Data was resampled to 1,000 m grid cell size and clipped to the ecosystem stressor spatial domain.

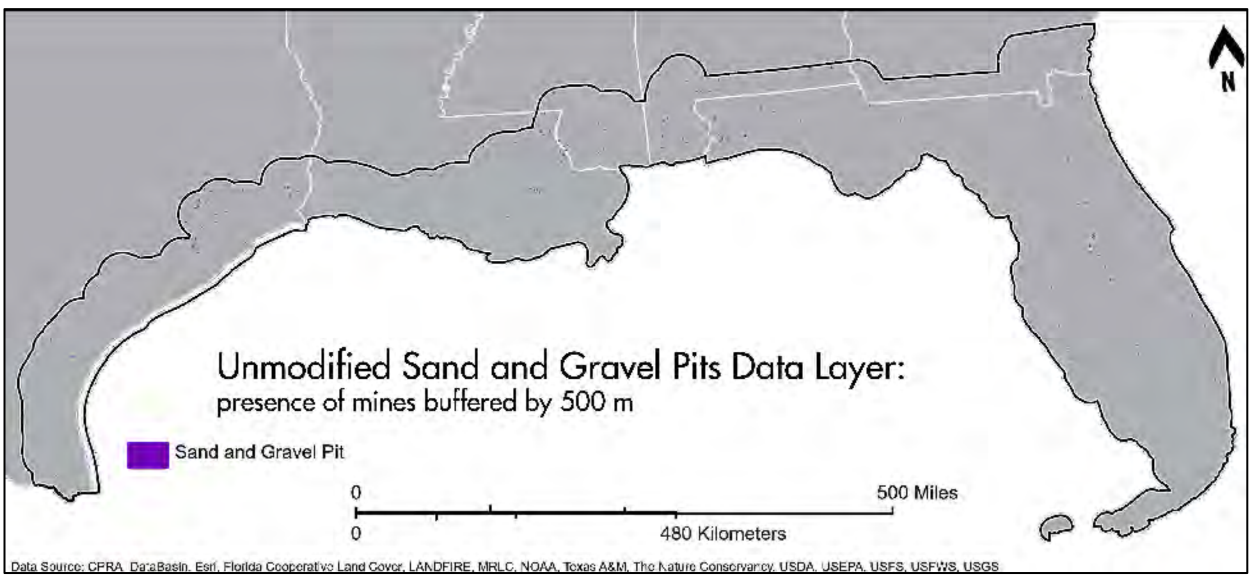


Figure B-7. Unmodified sand and gravel mines dataset. Note: points may be difficult to discern at this spatial scale. Data was resampled to 1,000 m grid cell size and clipped to the ecosystem stressor spatial domain.

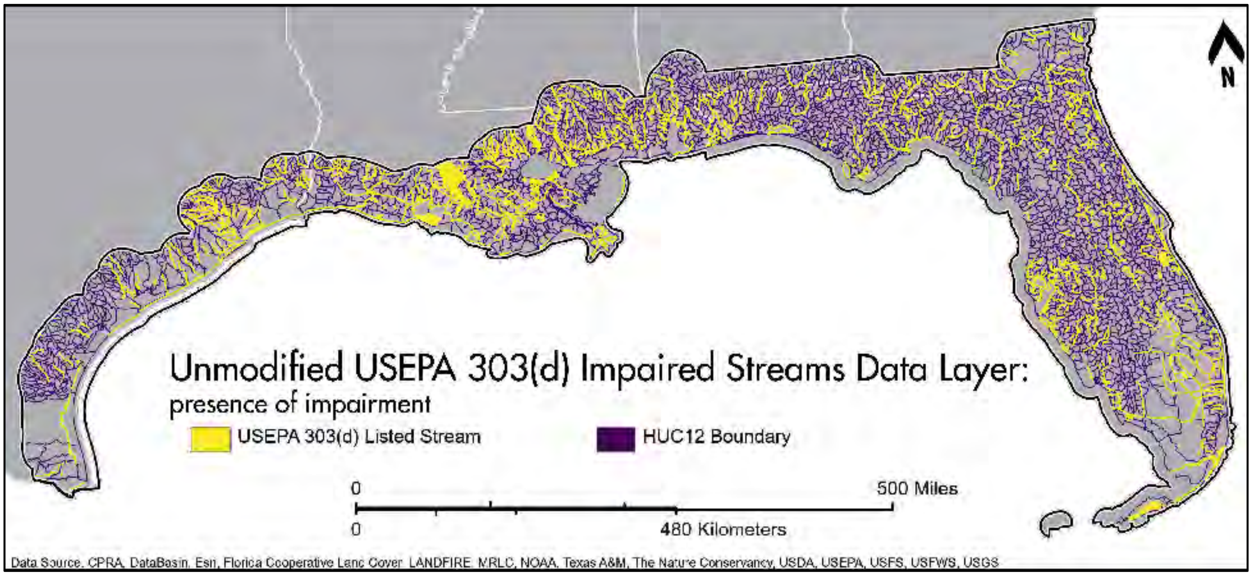


Figure B-8. Unmodified USEPA 303(d) impaired streams dataset mapped with HUC12 boundaries. Data was resampled to 1,000 m grid cell size and clipped to the ecosystem stressor spatial domain.

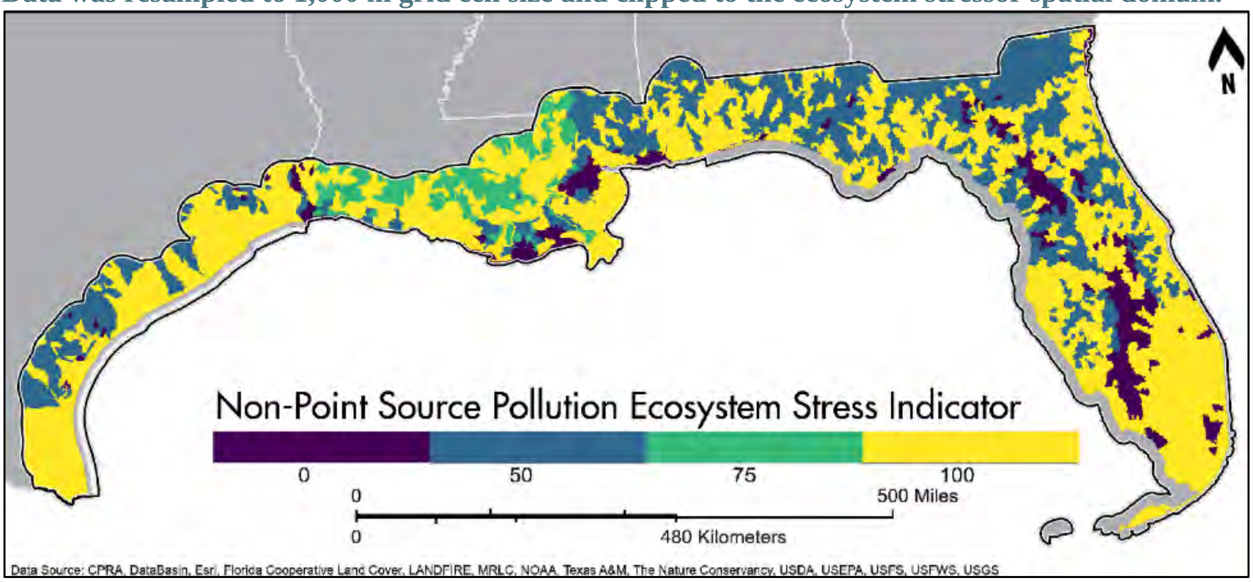


Figure B-9. Non-point Source Pollution Ecosystem Stress Indicator layer mapped across the project area. A score of 100 reflects highest ecosystem stress based on applied thresholds, and zero indicates absence of ecosystem stress from this indicator.

Data Gaps and Limitations:

The development of water quality indicators of ecosystem stress was challenging because of data limitations and state-to-state differences in assessment and reporting for 303(d) listed waters and nutrient concentrations. Without regional thresholds that reflect a more accurate representation of ecosystem stress due to non-point source pollution, this Ecosystem Stress Indicator provides a high-level overview of water quality stress based on regulatory criteria for watersheds across the project area. Other ecosystem assessments have similarly shown that regulatory criteria may not be specific enough to detect meaningful ecological stress (Carruthers et al., 2009; Longstaff et al., 2010); further research is needed to develop more indicative thresholds for non-point source ecosystem stress across the Gulf of Mexico.

The USEPA's 303(d) list provides a regulatory of potential water quality impairments across the U.S. and should be interpreted accordingly. This study does not reflect impaired waters previously listed under 303(d) that may still be impaired while improvement implementations are underway; the state that lists the water body can have it removed from the list if a plan has been put in place to bring the water body into compliance within 8-13 years from it being listed or other changes have been made to correct the water quality problems (US Environmental Protection Agency, 2009).

SPARROW models were used to provide wholistic watershed assessments of key water quality indicators consistent with the regional perspective of this project; however, SPARROW models also involve many assumptions and project managers can find additional details in the associated SPARROW documentation (Hoos & Roland, 2019; Robertson & Saad, 2019; Wise et al., 2019). In addition, SPARROW models do not span the entire project spatial extent due to the substantial anthropogenic diversions of water and a lack of data necessary to describe stream basins in South Florida and the Withlacoochee River downstream from Tsala Apopka chain of lakes in central Florida (Hoos & Roland, 2019). Lack of spatial coverage of nonpoint source nutrients for southern Florida is a known limitation of this assessment and results in an under-reporting of total potential ecosystem stress in that region. However, listing of 303(d) impaired waters still provides some indication of impaired water quality for southern Florida. Project managers interested in developing projects in southern Florida should additionally review local water quality information where available. This uncertainty also applies to the Integrated Ecosystem Stress Indicator layer for this geography of the state of Florida.

Indicator: Point Source Pollution

Relevance and Context:

Past, current, and potential future point-source contamination by chemical stressors can pose a significant threat to natural ecosystems as well as humans. The Point Source Pollution Ecosystem Stress Indicator includes the following types of sites listed by the USEPA as known or potential sources of point source pollution: National Priorities List (NPL) sites (a key subset of all "Superfund" sites), Risk Management Plan (RMP) facilities, and Treatment, Storage, and Disposal Facilities (TSDFs).

NPL/Superfund sites are listed as national priority areas based on the known releases or potential releases of hazardous substances, pollutants, or contaminants that may require long-term cleanup actions. The USEPA identifies and tracks these locations to determine the potential threats to human health and environmental risks associated with each site and to determine necessary remedial actions. For more information on Superfund sites, visit the USEPA webpage: https://www.epa.gov/superfund/basic-npl-information. Superfund sites have been cited in other ecosystem health assessments as they can leave legacy contamination that may result in chronic impacts to an ecosystem over extended time periods (decades) (Costanzo et al., 2015).

Whereas NPL/Superfund sites are known sources of chemical contaminants, the USEPA also lists areas of potential threat based on the hazardous chemicals used at that location. Those facilities include RMP sites and TSDFs. The USEPAs RMP database stores information reported by companies that handle, manufacture, use, or store certain flammable or toxic substances, as required by the Clean Air Act. RMP facilities are required by the USEPA to develop a plan which identifies the potential impacts of a chemical release, identifies steps the facility has taken to prevent a spill, and clearly communicates the necessary emergency response procedures in the event of a spill (https://www.epa.gov/rmp). RMP facilities can be diverse in size, structure, activities, and the chemical makeup of the regulated substances. The USEPA's primary concern with RMP facilities are the accidental release of substances and fires or explosions; these sudden releases can be acutely toxic and result in severe harm to living organisms via inhalation or dermal exposure (US Environmental Protection Agency, 2019). TSDFs include facilities that have stored hazardous waste for longer timeframes than allowed, received hazardous waste from off-site, treated hazardous waste, or disposed of hazardous waste. The USEPA regulates requirements for TSDFs to protect human health and the environment from the risks posed by hazardous waste (https://www.epa.gov/hwpermitting/hazardous-waste-management-facilities-and-units). Substances at TSDF facilities may reach living organisms in a number of ways, including inhalation (via atmospheric dispersal of volatile substances), dermal exposure, or ingestion via drinking water (US Environmental Protection Agency, 2019). The USEPA has specific regulations for a wide range of potential contaminants. For a full description of USEPA regulations, visit https://www.epa.gov/regulatory-information-topic/regulatory-and-guidance-information-topic-toxic-substances.

In the Gulf of Mexico, point source pollutants are recognized as threats to local ecosystems and human communities. Gulf of Mexico coastal state wildlife action plans highlight the potential environmental hazards posed by toxic (or potentially toxic) facilities (Table B-11).

Table B-11. Summary of point source pollution ecosystem stressors highlighted in US Gulf State Wildlife Action Plans that could pose potential threat to wildlife.

State	Reference	Summarized Statement of Threat
Texas	(Texas Parks and Wildlife Department, 2012a, 2012b)	Contamination associated with coal-fired powerplants is highlighted as a potential point source for polluting surface and groundwater resources. Lack of reclamation (unregulated decay of obsolete production sites) is also cited as a potential threat caused by releasing toxic chemicals into soils. Traditional oil/natural gas extraction sites (as well as associated distribution lines) are also noted as sources of toxins.
Louisiana	(Holcomb et al., 2015)	Poisoning from toxic releases is a known source of direct mortality for birds and mammals.
Mississippi	(Mississippi Museum of Natural Science, 2015)	Point source pollution from industrial and military effluents (both water-borne and atmospheric) are a threat to wildlife.
Alabama	(Alabama Department of Conservation and Natural Resources, 2015)	The condition of Alabama's river basins and surface waters are threatened by toxic effluents from industrial and military sources (mining, energy production, road building, and resource extraction). Waterways not supporting designated uses are partially related to historic as well as recent PCB contamination.
Florida	(Florida Fish and Wildlife Conservation Commission (FWC), 2019)	Point source pollution is a recognized hazard to aquatic and terrestrial ecosystems in Florida. Industrial and military effluents are cited as potential sources of toxic chemicals that may harm aquatic fauna.

The ecological stress imparted by hazardous facilities on the landscape can vary widely based on which chemical contaminants are present and the characteristics of the surrounding landcover (e.g., geology, vegetation assemblages, local hydrology, etc.). This high variability and specificity of potential stress for each facility makes large-scale ecological stress assessments more challenging (Chen & Liu, 2014). In lieu of ecosystem-specific indicators of stress caused by these point source pollutants, a human-based assessment was used as a proxy for potential harm to wildlife.

The USEPA serves a regulatory role for the use, handling, and disposal of specific contaminants and also serves to identify potential impacts of such contaminants on human communities. Environmental justice (EJ) as defined by the USEPA is "the fair treatment and meaningful involvement of all people regardless of race, color, national origin, or income, with respect to the development, implementation, and enforcement of environmental laws, regulations, and policies" (https://www.epa.gov/environmentaljustice). The USEPA developed a screening and mapping tool (EJSCREEN) to provide additional support for determining how USEPA programs, policies, and activities may affect human health. While the USEPA does not use EJSCREEN to quantify specific risk or for any decision-making regarding the presence or absence of EJ concerns, this tool can support the USEPA in permitting, enforcement, compliance, voluntary reporting programs, and for screening areas that may be candidates for additional consideration, analysis, or outreach. Currently, EJSCREEN uses 11 environmental and demographic indicators within the tool that reflect both point source and non-point source pollution types that could negatively impact human health. The three EJSCREEN indices used in this assessment include: proximity to RMP sites, proximity to TSDFs, and proximity to NPL/Superfund sites (US Environmental Protection Agency, 2019).

For NPL/Superfund sites, RMP sites, and TSDFs, the USEPA EJSCREEN technical documentation outlines how the indicators were calculated. All three of these indicators are based on Census block groups and block-level proximity scores. To calculate the individual NPL/Superfund, RMP, and TSDF indicators, each Census block was first given a proximity score that was the sum of the inverse distance-weighted count of sites anywhere within 5 km of the block's centroid internal point – this score can be interpreted as the number of sites per kilometer of distance from the average person. It is also equal to the number of sites divided by the harmonic mean of their distances. This means one site 2 km away gives a score of ½, while three sites each 4 km away give a score of ¾, and five sites all at 1 km away give a score of 5. If there is no site within 5 km of a block centroid, 1 divided by the distance to the single nearest facility at any distance is used (US Environmental Protection Agency, 2019). 2018 Census boundaries form the basis of the block groups displayed by the 2020 EJSCREEN tool.

Data & Method:
NPL/Superfund, RMP, and TSDF indices were downloaded from the USEPA 2020 EJSCREEN tool portal: EJSCREEN 2020 USA File Geodatabase, https://gaftp.epa.gov/EJSCREEN/2020/. Data was downloaded on 3/23/2021. The desired EJSCREEN variables, NPL, RMP, and TSDFs, were selected and exported to a new vector file. The vector was then converted to a 30 m raster. To more accurately scale this assessment to reflect known sources of significant environmental stress (e.g., NPL/Superfund sites), the NPL/Superfund indicator layer was weighted by a factor of 2 whereas RMP and TSDFs were weighted by a factor of 1 (Equation 2, see below). The resulting value from Equation 2 was reclassified using Equation 1 to create a uniform 1 to 100 scale. Zonal statistics were then utilized to resample the 30 m raster into 1 km^2 hexagon grid.

Equation 2. Point Source Pollution Ecosystem Indicator Value

$$point\ source\ pollution\ value\ = (NPL\ value\ \times 2) + RMP\ value\ + TSDF\ value$$

Ecological Threshold:
Basing this analysis on the EJCREEN tool, evaluation for the Point Source Pollution Ecosystem Stress Indicator is derived from potential hazard to human communities (US Environmental Protection Agency, 2019). This ecosystem indicator is expressed in values scored on a continuous scale from 1 to 100 for each 1 km^2 hexagon cell (Table B-12). Values of 0 indicate water (no human population is present).

Table B-12. Interpretation of cell values for the Point Source Pollution Ecosystem Stress Indicator layer.

1 km^2 Hex Cell Value	Interpretation
1	Census block is characterized by lowest potential cumulative density of NPL/Superfund, RMP, and TSDF sites within 5 km (lowest potential ecosystem stress)
100	Census block is characterized by highest potential cumulative density of NPL/Superfund, RMP, and TSDF sites within 5 km (highest potential ecosystem stress)

Current Condition:

First, the point source datasets were resampled to a 1,000 m cell grid and clipped to the ecosystem stressor spatial domain (Figure B-10 – Figure B-12). Next, the threshold was applied and the data scaled such that cell values of 1 reflect lowest ecosystem stress and values of 100 reflect maximum ecosystem stress (Figure B-13).

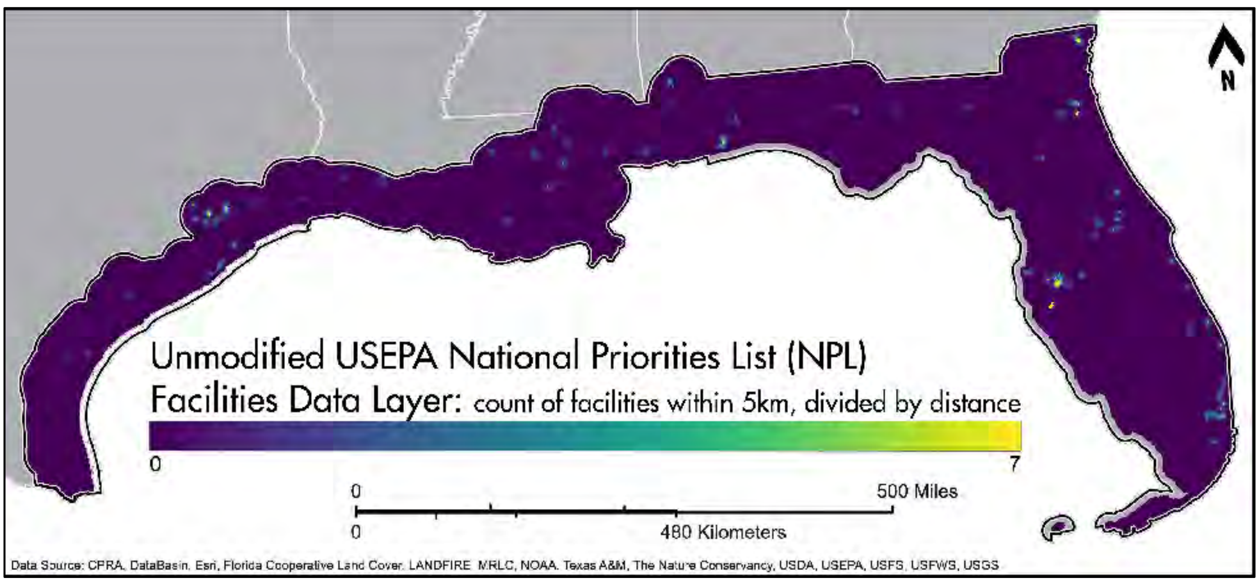


Figure B-10. Unmodified EJSCREEN National Priorities List (NPL, i.e., Superfund) dataset. Data was resampled to 1,000 m grid cell size and clipped to the ecosystem stressor spatial domain.

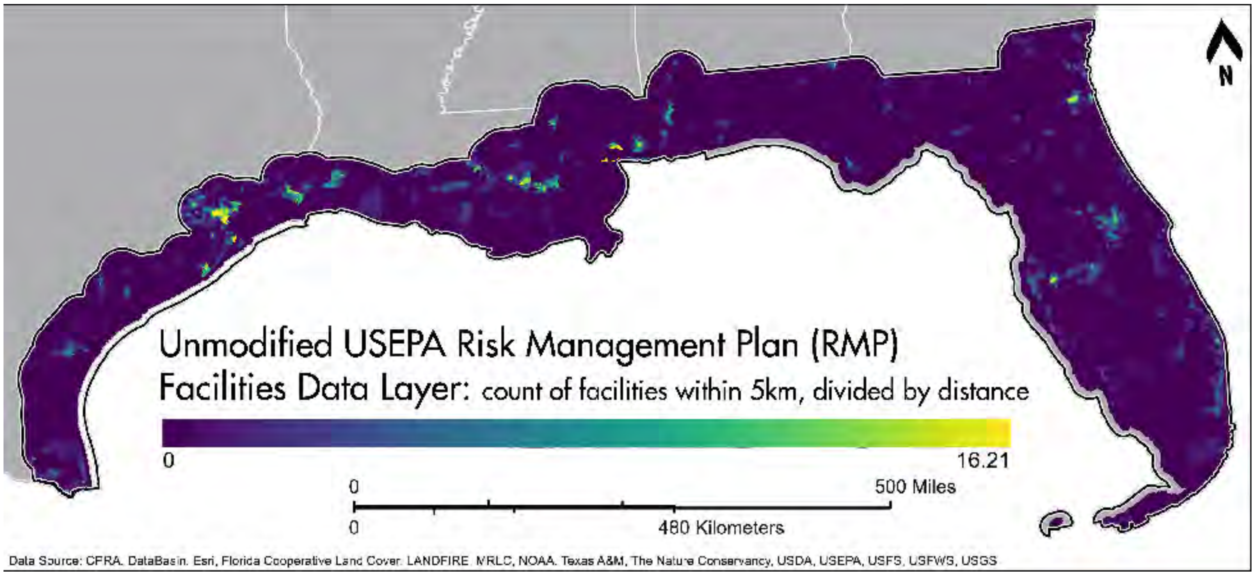


Figure B-11**. Unmodified EJSCREEN Risk Management Plan (RMP) dataset. Data was resampled to 1,000 m grid cell size and clipped to the ecosystem stressor spatial domain.**

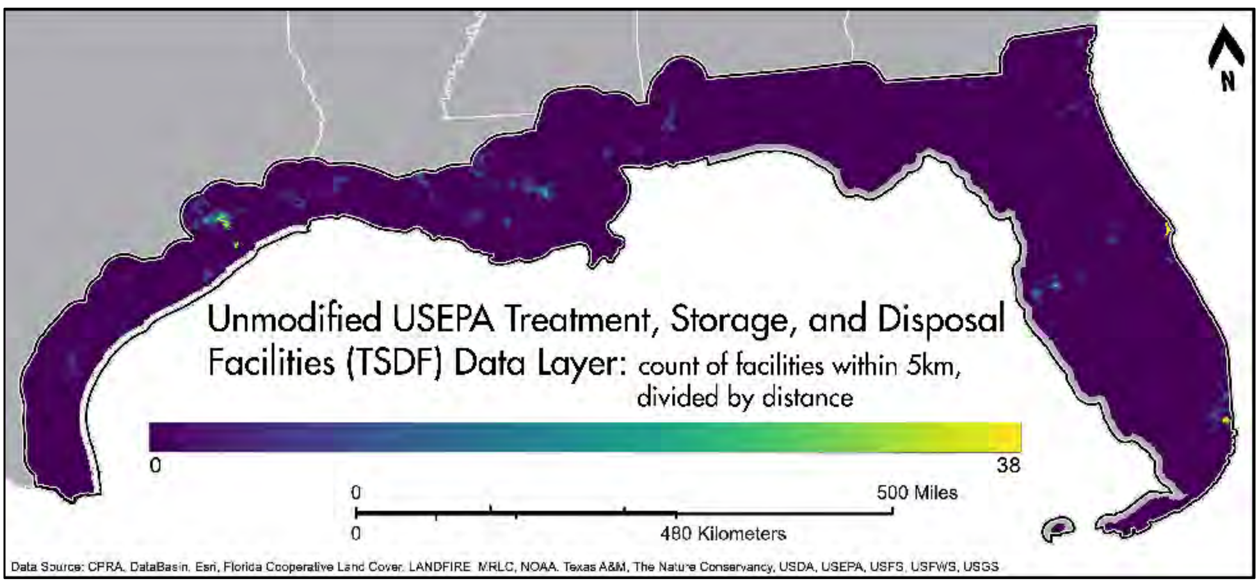


Figure B-12**. Unmodified EJSCREEN Treatment, Storage, and Disposal Facilities (TSDF) dataset. Data was resampled to 1,000 m grid cell size and clipped to the ecosystem stressor spatial domain.**

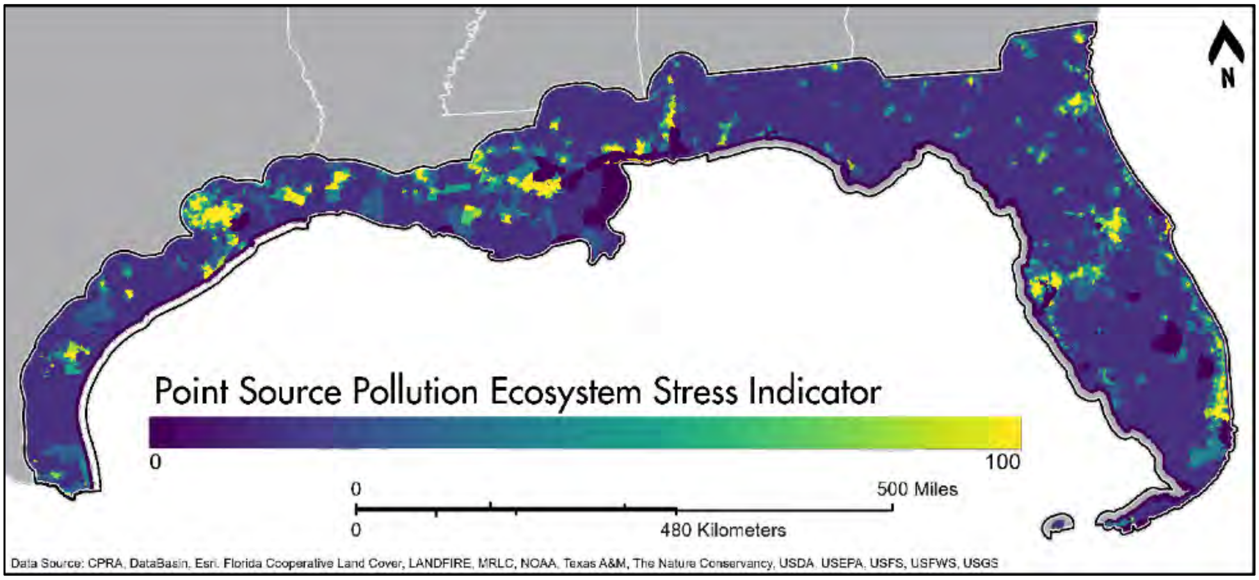


Figure B-13. Point Source Pollution Ecosystem Stress Indicator layer mapped across the project area. A score of 100 reflects highest ecosystem stress based on applied thresholds, and zero indicates absence of ecosystem stress from this indicator.

Data Gaps and Limitations:

For a full explanation of the assumptions, methods, and caveats of EJCREEN, please visit the technical documentation (US Environmental Protection Agency, 2019). For NPL/Superfund sites, data is based on individual points (not polygons), therefore this index should not be used for fine-scale assessment of proximity to relevant portions of the site. For all proximity-based indicators, proximity alone may not represent any actual risk or even exposure. Lastly, EJSCREEN was developed for assessments on human populations, not ecosystems. Further refinement to develop ecologically relevant thresholds of point source pollution stress could increase the potential application and utility of this indicator of stress.

Indicator: Urban Expansion

Relevance and Context:

Significant scientific evidence supports that urbanization caused by human development and expansion results in direct (land cover change leading to habitat loss) and indirect (degradation) impacts to natural ecosystems (McDonald et al., 2020). Habitat loss and fragmentation usually occur in parallel, both processes altering biodiversity and ecological processes at multiple temporal and spatial scales (Liu et al., 2016; Wilson et al., 2016). Effects of urbanization are not only restricted to terrestrial environments; runoff of surface pollutants from urban areas can directly impact water quality (Coles et al., 2012) and increasing size and density of urban populations can result in recreational pressures on submerged habitats (e.g., increased seagrass habitat fragmentation as a result of recreational boating) (Hallac et al., 2012)

The most rapid period of urban population growth in human history is expected to occur over the next few decades (United Nations Population Division, 2018). With many urban centers located near the coast, the ecological threat of urbanization is significant in the northern Gulf of Mexico coastal region. Coastal urbanization can result in replacement of natural habitats, installation of hardened shorelines, and disruption of natural habitat spatial shifts (Lowe & Peterson, 2014; Peterson & Lowe, 2009). The dynamics of human expansion and development are highlighted as significant threats to wildlife conservation in all Gulf states (Table B-13).

Table B-13. Summary of human development risk highlighted in US Gulf State Wildlife Action Plans that could pose potential threat to wildlife.

State	Reference	Summarized Statement of Threat
Texas	(Texas Parks and Wildlife Department, 2012a, 2012b)	The Texas wildlife action plan highlights development as one of the core stressor facing wildlife and lists additional elements of human expansion contributing to development-induced stress: infrastructure for power development and transmission, oil and natural gas production and delivery; mining; communications infrastructure; roads and impervious surface; development of waterways and ports; border fence (restricting habitat connectivity between Gulf of Mexico and Texas at the Rio Grande); conversion of natural habitat (namely prairie and wet prairie) to agricultural land and the consequences of agricultural practices.
Louisiana	(Holcomb et al., 2015)	Development (residential, commercial) and agricultural/forestry practices resulting in habitat loss, soil disturbance, and altered hydrologic regimes are known to stress forest habitats (e.g., bottomland hardwoods, cypress-tupelo-blackgum swamp, and many others), grassland/savanna habitats (e.g., calcareous prairie), coastal shrublands (e.g., mangrove-marsh shrubland), bogs/seeps, and beaches & dunes. Transportation and service corridors are also a known stressor to multiple habitat types. Loss of coastal wooded habitats due to human development is of particular concern as this serves as an important stopover habitat for migratory birds (especially on the Chenier Plain).
Mississippi	(Mississippi Museum of Natural Science, 2015)	Development (urban/suburban and industrial) is identified as a threat to multiple habitats by direct habitat alteration, fragmentation, and/or by hydrologic alteration. Energy development may be an emerging threat in the future.

State	Reference	Summarized Statement of Threat
Alabama	(Alabama Department of Conservation and Natural Resources, 2015)	Residential and commercial development that remove natural habitats is an increasing threat to wildlife in Alabama. Commercial and industrial areas also consume large areas of natural habitat. Agricultural expansion (farming and ranching) can also result in declines of multiple habitat types (principally forests) and can degrade water quality. Human development can also result in other ecosystem modifications including hydrologic changes (dams, etc) that degrade wetlands and aquatic habitat quality.
Florida	(Florida Fish and Wildlife Conservation Commission (FWC), 2019)	Residential and commercial development (human settlements or other non-agriculture land uses) result in conversion of natural habitat to developed areas and other negative consequences (e.g., fragmentation, altered hydrology, etc.). Agriculture and silviculture can provide some benefits, but it is still a conversion of natural habitat and mismanagement (over-fertilizing, pesticide use, and overgrazing. Florida recognizes the contribution of private working lands to the conservation of at-risk species even though the land has been altered. Beach nourishment (natural system modification) is a noted threat that can result in changes to vegetation assemblages, soil chemistry, and water levels.

The Urban Expansion Ecosystem Stress Indicator is based on a model known as SLEUTH originally developed from the Clarke Urban Growth Model created by Keith Clarke, PhD, at the University of California Santa Barbara (Candau et al., 2000). SLEUTH is named based on the model inputs (Slope, Land use, Excluded, Urban, Transportation, and Hillshade) and provides urban growth projections that have been used widely for wildlife habitat analysis, conservation planning, and land cover dynamics analysis (Belyea & Terando, 2013b; Jantz et al., 2010; Jantz & Goetz, 2005). SLEUTH model projections are based on spontaneous growth, new spreading centers, edge growth, and road influenced growth to show the rate and spatial pattern of urbanization (among other parameter coefficients). The result is a spatial map representing the probability of urbanization for each pixel (Belyea & Terando, 2013a). SLEUTH is currently being used by USGS in “Project Gigalopolis” (http://www.ncgia.ucsb.edu/projects/gig/) to investigate urban growth in the US.

Data & Method:
Multiple SLEUTH datasets exist based on the various modifications and specific projects for which the model was used. This work utilized the SLEUTH Projected Urban Growth model that was modified and adapted for the following projects/groups and then mosaiced together to span the entire Southeast region: Southeast Regional Assessment Project, Appalachian Landscape Conservation Cooperative (LCC), Gulf Coast Prairie LCC, and Gulf Coastal Plains and Ozarks LCC. SLEUTH urbanization 2020-2100 for the 2060 projection was downloaded from: https://www.sciencebase.gov/catalog/item/544f9f7ae4b0f97badbc547d on 3/24/2021. The SLEUTH raster dataset was resampled from 60 m to 30 m cells and the cell values were reclassified to align with the 0 to 100 scale using Equation 1 where a score of 100 reflects the highest potential threat and 1 reflects the lowest potential threat. Zonal statistics were then utilized to resample the 30 m raster into 1 km^2 hexagon grid.

Ecological Threshold:

Urbanization in the context of this Ecosystem Stress Indicator represents total replacement of natural land cover with urban land cover on a 2060 projection. The SLEUTH dataset used here represents the probability of risk due to urbanization, and thus specific ecological thresholds were not appropriate for this stressor. Ecosystem stress caused by urban expansion is expressed as probability of a natural landcover type to be converted to urban area by 2060 (1 - 100) for each 1 km^2 hexagon (Table B-14).

Table B-14. Interpretation of cell values for the Urban Expansion Ecosystem Stress Indicator.

1 km^2 Hex Cell Value	Interpretation (probability of urbanization by 2060)
1	cell is already classified as urban land cover
3	0-2.5%
6	2.5-5%
10	5-10%
11	10-20%
21	20-30%
31	30-40%
41	40-50%
50	50-60%
60	60-70%
70	70-80%
80	80-90%
90	90-95%
95	95-97.5%
98-100	97.5-100%

Current Condition:
First, the urban expansion risk dataset was resampled to a 1,000 m cell grid and clipped to the ecosystem stressor spatial domain (Figure B-14). Next, the threshold was applied and the data scaled such that cell values of 1 reflect lowest ecosystem stress and values of 100 reflect maximum stress (Figure B-15). Based on this model algorithm that reflects probability of urbanization as it grows from existing locations, locations in grey reflect no data (locations not modelled to have risk of urbanization by 2060).

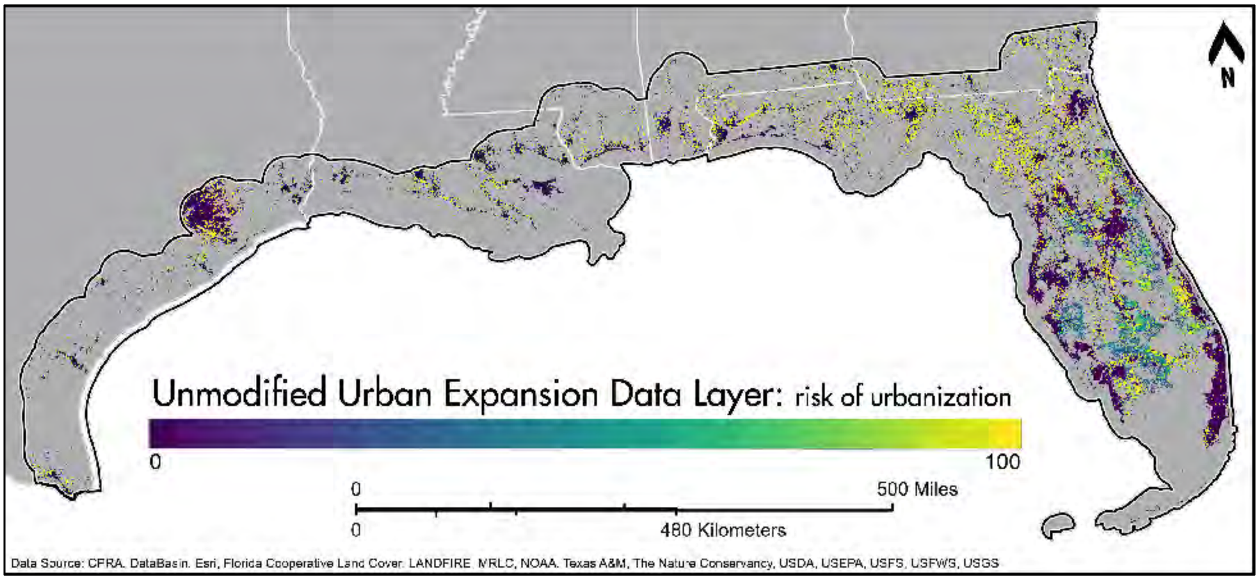


Figure B-14. Unmodified SLEUTH urban expansion data layer. Scale reflects risk (0-100%) that a cell of natural land cover will be converted to urban land cover by 2060. Grey reflects no data. Data was resampled to 1,000 m grid cell size and clipped to the ecosystem stressor spatial domain.

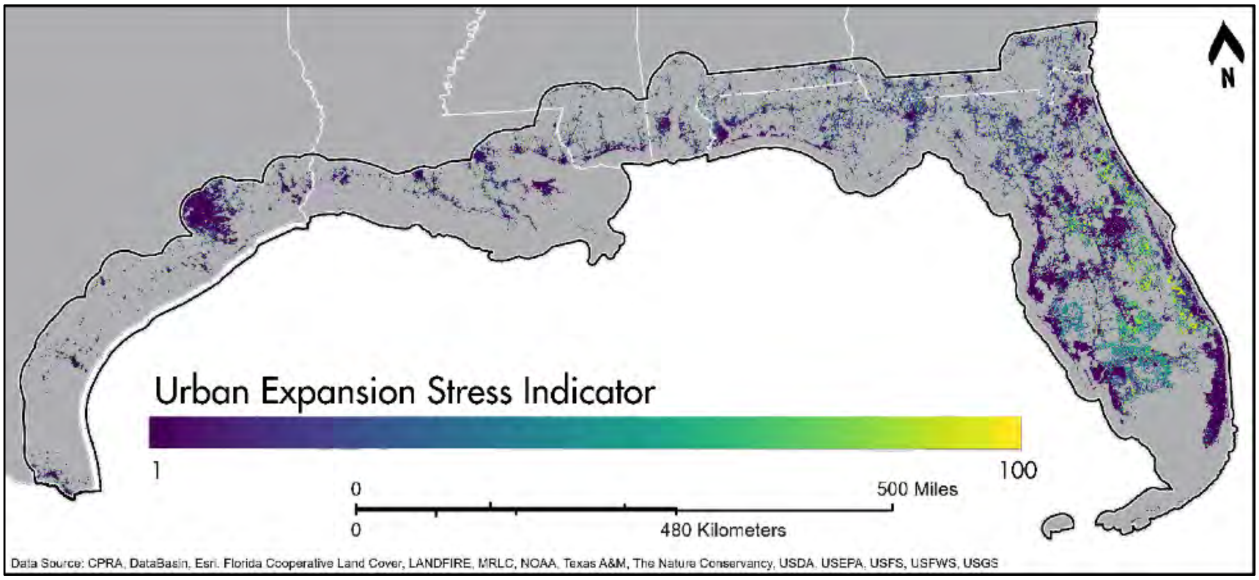


Figure B-15. Urban Expansion Ecosystem Stress Indicator layer mapped across the project area. A score of 100 reflects highest ecosystem stress based on applied thresholds, 1 indicates absence of ecosystem stress from this indicator (already urban), and grey reflects no data.

Data Gaps and Limitations:

Models of future projections are inherently uncertain, and risk may not indicate the current condition of ecosystem stress in any given area. Importantly, the SLEUTH model does not account for land use change from natural to agricultural land nor does it account for population dynamics (e.g., exodus of population from the area, shifts in demographic structure, of 'smart growth' practices that may account for conservation/social priorities). Chadhuri and Clarke (2014) assessed the accuracy of SLEUTH models in Italy and illustrated that accuracy of the predictions by SLEUTH were dependent on urban history, input data uncertainty, and accuracy of reference maps. A recent study by Clarke and Johnson (2020) investigated SLEUTH projections for California and highlights important considerations when interpreting the model: significant autocorrelation can occur in the model resulting in major differences in land use change and change rates; most forecasted urban growth (99%) comes from outward spread from now and existing population settlements and does not account for the creation of new population centers.

Indicator: Road Density

Relevance and Context:

While roads are included in measures of impervious surface, roads may also serve as a unique source of ecosystem stress to wildlife beyond their contribution to impervious surface. The ecosystem stress resulting from roads is diverse in impact: a source of direct wildlife mortality, habitat fragmentation and degradation, a conduit for invasive species spread, a barrier to wildlife migration, traffic noise pollution, and a source of nonpoint source pollution to waterways (Bennett, 2017; Heilman et al., 2002). Roads are identified in state wildlife action plans highlighting the broad range of potential impacts posed by roads for wildlife across the northern Gulf of Mexico states (Table B-15).

Table B-15. Summary of the impacts of road density highlighted in US Gulf State Wildlife Action Plans that could pose potential threat to wildlife.

State	Reference	Summarized Statement of Threat
Texas	(Texas Parks and Wildlife Department, 2012a, 2012b)	Roads (associated with industry and urban development) and road maintenance can have direct impacts upon wildlife as well as impacts upon wildlife habitats
Louisiana	(Holcomb et al., 2015)	Roads and infrastructure associated with timber harvest and oil/gas extraction are a threat to forest habitats (calcareous forest and live oak natural levee forest), and grasslands (calcareous prairie). Application of pesticides to control vegetation growth along roads/waterways can also negatively impact biota. Lastly, roads causing habitat fragmentation can negatively impact reptile species in the state by reducing patch size
Mississippi	(Mississippi Museum of Natural Science, 2015)	Roads/railways and utility/service lines impact multiple habitat types
Alabama	(Alabama Department of Conservation and Natural Resources, 2015)	Construction of roads and railways for oil/gas development and service corridors can cause increased habitat fragmentation. New roadways can also result in multiple negative direct impacts to wildlife, including direct wildlife mortality on roads and obstruction of migratory corridors
Florida	(Florida Fish and Wildlife Conservation Commission (FWC), 2019)	Transportation and service corridors are associated with wildlife mortality and can result in habitat fragmentation, sediment movement, altered fire/hydrology, and invasive species spread

Data & Method:

The U.S. Census Bureau maintains a shapefile database of geographic and cartographic information for all 50 states called TIGER/Line (https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.html). Each downloadable shapefile from this source contains a range of datasets from polygon boundaries of geographic areas/features to linear roads and hydrography features. The shapefiles for all roads were downloaded by state from https://www.census.gov/cgi-bin/geo/shapefiles/index.php?year=2020&layergroup=Roads on 3/23/2021.

The linear road features (lines) for each state were merged into a single vector file and converted to 30 m raster. Using the ArcGIS Pro 2.7 line density tool, the density of linear features using a search radius of

564 m (roughly equivalent to 1 km^2, the basis for our stress threshold outlined below) was calculated across the entire project area. To scale cell values similarly to the other stress layers (1 - 100), the line density values were first binned into four categories and then Equation 1 was used to reclassify the binned values for each cell. Zonal statistics were then utilized to resample the 30 m raster into 1 km^2 hexagon grid.

Ecological Threshold:

Investigations of ecosystem stress caused by road density have largely been based on broad groups of animals (e.g., impacts of roads on bird diversity, large mammal behavior) (Bennett, 2017): Duchardt et al. (2020) investigated the impacts of road density on sage grouse (*Centrocercus urophasianus*) populations in Wyoming; Cooke et al. (2020) highlights that impacts of road density is species-specific for many bird species in the United Kingdom; impact of road density on large mammals like grizzly bears (*Ursus arctos horribillis*) has been investigated in Canada and British Columbia (Lamb et al., 2018; McLellan & Hovey, 2001); Rieman et al. (1997) and Cederholm et al. (1981) highlight the impacts of road density on fish habitat quality; and Patrick and Gibbs (2010) illustrate the impacts of urban road density on freshwater turtle population demographics and dispersal.

The thresholds selected for this Road Density Ecosystem Stress Indicator were based on work by Quigley et al., (1996, 2001) and Haynes et al., (1996) who estimated ecological integrity of basins within the U.S. Pacific Northwest. The original assessment scale developed by Haynes et al., (1996) was created for spawning salmon. Road density thresholds developed for large mammals reflect a similar threshold scales, suggesting that these road densities are appropriate for a variety of species (Bechtold et al., 1996; Krichbaum & Horvath, 2001 and refs. therein; Proctor et al., 2020). Ecosystem stress based around road density thresholds developed by Haynes et al., (1996) was expressed from 1 to 100 for each 1 km^2 hexagon cell (Table B-16). A value of 0 represents cells that did not have roads within the 564 m search radius.

Table B-16. Interpretation of cell values for the Road Density Ecosystem Stress Indicator.

1 km² Hex Cell Value	Interpretation (km average road length/km² by HUC12)
0	No roads within the 564m search radius
1	0.01-0.43, no/low stress
34	0.44-1.06, moderate stress
67	1.07-2.92, high stress
100	> 2.93, very high stress

Current Condition:

First, the road density dataset was resampled to a 1,000 m cell grid and clipped to the ecosystem stressor spatial domain (Figure B-16). Next, the threshold was applied and the data scaled such that cell values of 1 reflect lowest ecosystem stress and values of 100 reflect maximum stress (Figure B-17).

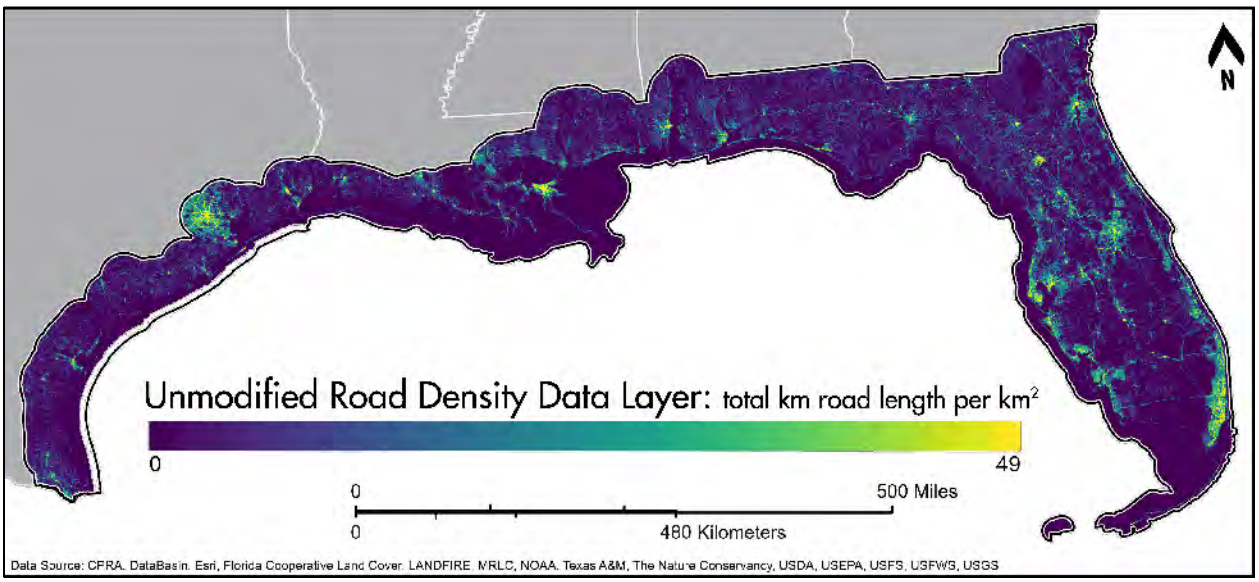


Figure B-16. Unmodified road density data layer. Data reflects total km of road length per square km area across the project area. Data was resampled to 1,000 m grid cell size and clipped to the ecosystem stressor spatial domain.

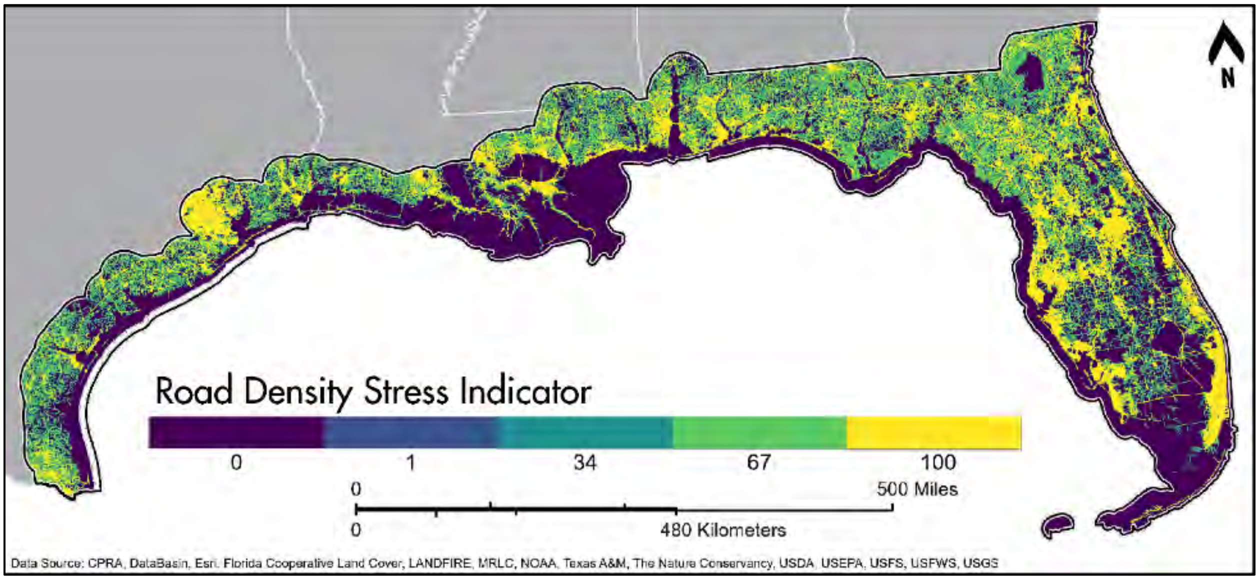


Figure B-17. Road Density Ecosystem Stress Indicator layer mapped across the project area. A score of 100 reflects highest ecosystem stress based on applied thresholds, one indicates very low ecosystem stress from this indicator, and zero reflects no roads within 564 m.

Data Gaps and Limitations:

Development of ecological thresholds of road density on wildlife has largely been species specific, and surprisingly very few studies have been conducted on the impacts of road density on wildlife along the northern Gulf of Mexico. A single threshold to communicate ecosystem stress caused by road density may not be appropriate for all wildlife and all ecosystems. This Road Density Ecosystem Stress Indicator also does not distinguish between road type (paved vs. unpaved) or type of road such as interstate versus neighborhood street (i.e., volume of traffic), both have potential to impact the type and extent of ecological stress on wildlife. Furthermore, this assessment depends on the accuracy of U.S. Census Bureau TIGER/Line data. For example, a known data gap is that unpaved gravel service roads are not reliably mapped across the U.S. (Y. Allen, *personal communications*).

Indicator: Impervious Surface

Relevance and Context:

Impervious surface (commonly defined as paved surfaces, buildings, and compacted soils) has been used as an indicator of watershed development for many water quality and water quantity models due to its impact on habitat and freshwater aquatic ecosystems (Uphoff et al., 2011). Impervious surface has been used as an indicator of potential ecosystem stress, particularly at watershed scales, in multiple ecosystem assessments (Carruthers et al., 2009, 2011; SALCC, 2015). Greater proportions of impervious surface (particularly when paired with agricultural landcover) can result in higher rates, volumes, and intensities of water runoff capable of causing local flooding and higher rates of erosion, sedimentation, temperature alteration, and nutrient contamination, all of which can impact non flood-tolerant plant and animal species as well as water quality of aquatic ecosystems (Walsh et al., 2016; Wheeler et al., 2005). The proportion of a watershed that is hardened (impervious) results in multiple dimensions of stress: 2% impervious surface within a watershed can result in altered stream pH (Conway, 2007), 10% can result in measurable impacts on floral and faunal assemblages in freshwater systems (Arnold & Gibbons, 1996; Lussier et al., 2008), 10-20% impervious can negatively impact sensitive macrobenthos, penaeid shrimp, and spot fish (*Leiostomus xanthurus*) (Holland et al., 2004), and fecal coliform loadings have been shown to increase linearly with impervious surface proportion in coastal watersheds (Holland et al., 2004; Mallin et al., 2000). Introduction of nutrients from fertilizer can result in algal blooms, aquatic hypoxia, and other symptoms of degraded water quality measured in the northern Gulf of Mexico and around the globe (Mitsch et al., 2001; Rabalais et al., 2009; Rabalais & Turner, 2001). Uphoff et al., (2011) suggests that managers should target restoration efforts in watersheds with lower impervious surface where there is a higher likelihood of a positive ecosystem outcome for aquatic ecosystems.

Condition of northern Gulf of Mexico coastal ecosystems, particularly near major river outlets, estuaries, and coastlines, are particularly vulnerable to impervious surface. The US states along the northern Gulf of Mexico highlight the threats of impervious surface tied both to urban development and roads (see Table B-13 and Table B-15 above for a summary of impacts).

Data & Method:

The National Land Cover Database (NCLD) 2016 urban impervious surface geodatabase gives the percentage of developed surface at 30 m spatial resolution for the contiguous United States. Data was downloaded from https://www.mrlc.gov/data?f%5B0%5D=category%3Aurban%20imperviousness&f%5B1%5D=region%3Aconus on 3/14/2021. The NLCD raster layer percentages were used to calculate the mean impervious surface proportion of all 30 m cells within each HUC12. Cells (1 km^2 hexagons) within each HUC12 watershed were assigned an ecosystem stress score based on the corresponding HUC12 average impervious surface value. To scale cell values similarly to the other stress layers (1 - 100), the mean HUC12 impervious values were first binned into four categories and then Equation 1 was used to reclassify the binned values for each 1 km^2 hexagon cell. Zonal statistics were then utilized to resample the 30 m raster into 1 km^2 hexagon grid.

Ecological Threshold:

The ecological thresholds of the Impervious Surface Ecosystem Stress Indicator used in this assessment were developed by Schueler (1994) and refined by Uphoff et al., (2011); these thresholds were developed to evaluate ecosystem condition of Chesapeake Bay estuaries, specifically targeted for these estuarine species: white perch (*Morone americana*), striped bass (*Morone saxatilis*), spot (*L. xanthurus*), and blue crab (*Callinectes sapidus*). Ecosystem stress caused by impervious surface is expressed in values scored from 1 to 100 for each 1 km^2 hexagon (Table B-17).

Table B-17. Interpretation of cell values for Impervious Surface Ecosystem Stress Indicator.

1 km^2 Hex Cell Value	Interpretation (average percent impervious surface of 30 m cells by HUC12)
1	0-5%, fish habitat generally considered unimpaired, small potential impact to ecosystems
34	6-10% ecosystem is sensitive/stressed
67	11-24%, ecosystem impacted
100	>25%, highest potential ecosystem stress

Current Condition:

First, the impervious surface dataset was resampled to a 1,000 m cell grid and clipped to the ecosystem stressor spatial domain (Figure B-18). Next, the threshold was applied, and the data scaled such that cell values of 1 reflect lowest ecosystem stress and values of 100 reflect maximum stress (Figure B-19).

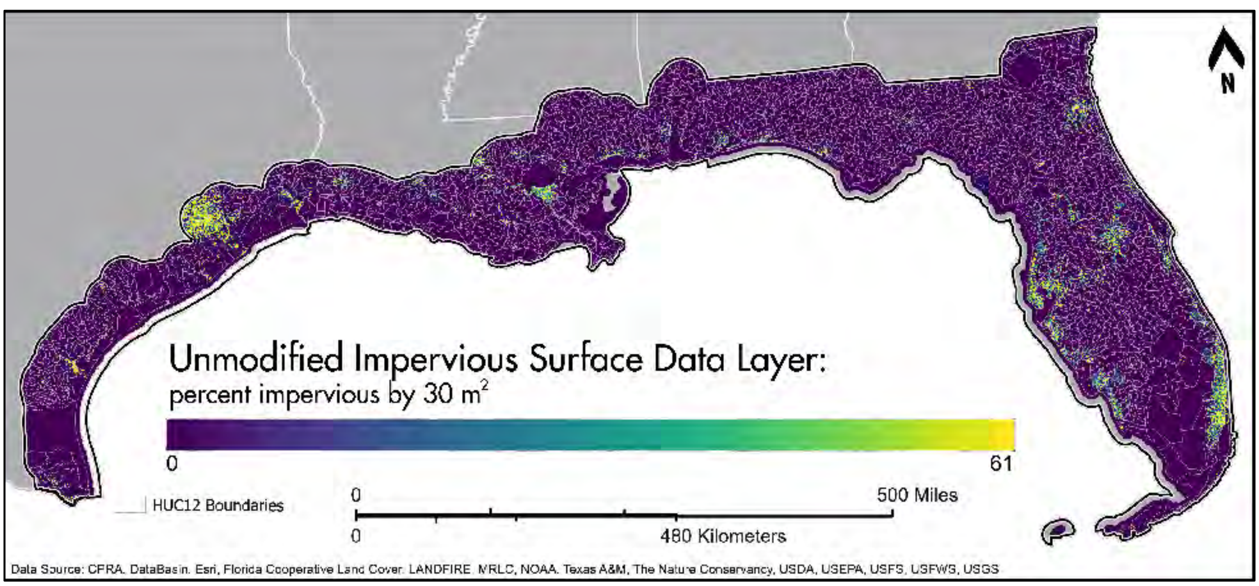


Figure B-18. Unmodified impervious surface dataset mapped alongside HUC12 boundaries. Cells were resampled to 1,000 m grid cell size and clipped to the ecosystem stressor spatial domain.

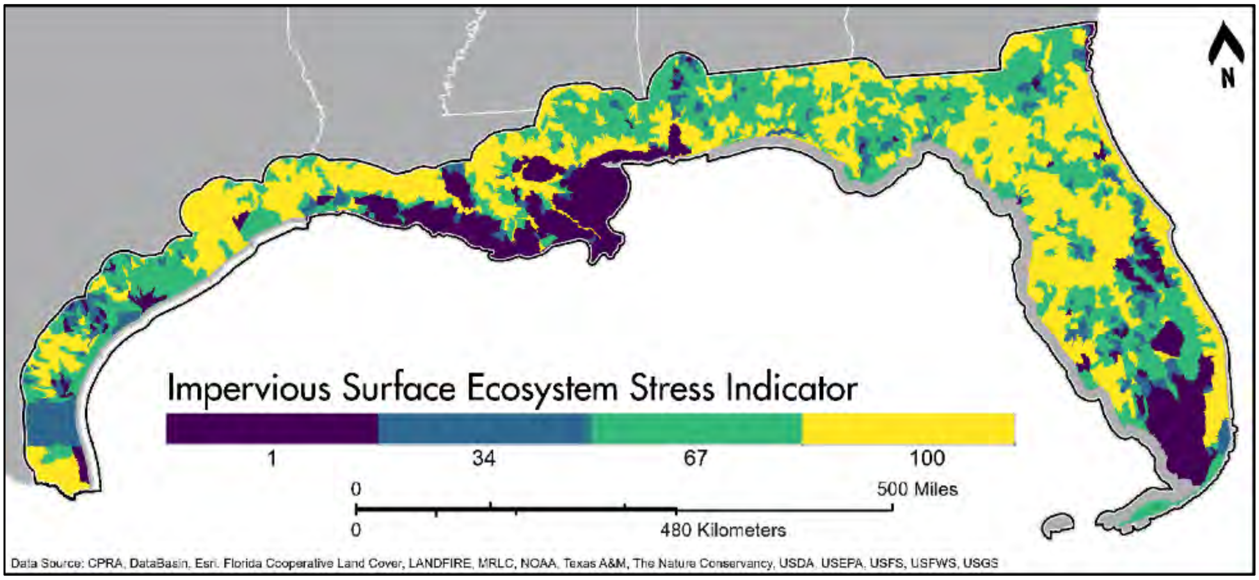


Figure B-19. Impervious Surface Ecosystem Stress Indicator layer mapped across the project area. A score of 100 reflects highest ecosystem stress based on applied thresholds (highest ecosystem stress to aquatic ecosystems), one indicates very low ecosystem stress from this indicator, and zero reflects no roads within 564 m.

Data Gaps and Limitations:

Impervious surface is a well-established indicator of aquatic ecosystem condition and the terrestrial habitats containing those waterways. Less work on impervious surface impacts has been done specifically in the northern Gulf of Mexico, the only limitation in interpretation of this metric.

Indicator: Water Hazards

Relevance and Context:

Due to the location of this project along the coastal zone of the northern Gulf of Mexico, water factors that impact future land cover type must be included as indicators of potential ecosystem stress. Water-related habitat loss linked to sea level rise and shifting precipitation patterns resulting in severe inland flooding are broadly acknowledged as key long-term ecosystem threats across northern Gulf of Mexico states (Table B-18). Ecosystem assessments conducted in many coastal areas incorporate an indicator of the potential threat caused by water-related habitat loss (Carruthers et al., 2017; Harte Research Institute for Gulf of Mexico Studies, 2019; IAN UMCES, 2019; Karnauskas et al., 2017; SALCC, 2015), therefore sea level rise (reflecting coastal risk) and flooding potential (reflecting inland risk) were important to include in this assessment. Sea level rise projections by NOAA and inland flood hazard mapped by FEMA are the two most widely used sources of water-related habitat risk data available to date and both are used in this assessment.

Table B-18. Summary of the impacts of water-related hazards (sea level rise and inland flooding) highlighted in U.S. Gulf State Wildlife Action Plans that could pose potential threat to wildlife.

State	Reference	Summarized Statement of Threat
Texas	(Texas Parks and Wildlife Department, 2012a, 2012b)	Sea level rise poses a significant threat to key coastal bird species (piping plover, reddish egret, etc.) that nest on coastal beaches
Louisiana	(Holcomb et al., 2015)	Sea level rise is noted as a threat to barrier island and coastal habitat types due to land loss (subsidence) and subsequent higher wave action and erosion. Coastal shrublands (mangrove-marsh shrubland), SAV, and saltmarsh habitats are threatened by sea level rise. Freshwater areas (freshwater marsh, floating freshwater aquatic vegetation, and associated fauna) are also threatened by increased salinity levels as a consequence of saltwater encroachment. Sea level rise is likely to impact multiple taxa valued by Louisiana including birds, amphibians, reptiles, and marine fishes
Mississippi	(Mississippi Museum of Natural Science, 2015)	The various impacts of climate change, specifically habitat shifts and alteration due to sea level rise, are highlighted as important threats throughout Mississippi

State	Reference	Summarized Statement of Threat
Alabama	(Alabama Department of Conservation and Natural Resources, 2015)	Habitat alteration as a result of sea level rise is a significant threat to coastal habitats – maritime forest and coastal scrub, beach and dune, and estuarine and marine habitats are noted as the most vulnerable to the impacts of climate change in Alabama
Florida	(Florida Fish and Wildlife Conservation Commission (FWC), 2019)	Sea level rise is a known threat to coastal habitats of Florida and may cause encroachment of habitats and species due to shifting abiotic habitat conditions

Paralleling NOAA's Coastal Flood Hazard Composite Map (available at https://coast.noaa.gov/arcgis/rest/services/FloodExposureMapper/CFEM_CoastalFloodHazardComposite/MapServer), this Ecosystem Stress Indicator incorporates high tide flooding, sea level rise, storm surge, and high risk flooding areas into a sum composite layer depicting the general cumulative potential impacts of multiple forms of water inundation-related ecosystem stress.

Data & Method:

1) **High tide flooding:** Everyday coastal flooding from tides are anticipated to become more frequent as sea level rises (Marcy et al., 2011). To map areas currently subject to shallow coastal flooding (as determined by NOAA National Weather Service criteria), the NOAA flood frequency data layer was used. This dataset is one component of the Sea Level Rise and Coastal Impacts Viewer (https://coast.noaa.gov/slr/). Methods for how this layer was developed can be found in Marcy et al., (2011) and NOAA (date unavailable). Data was downloaded by state from the Sea Level Rise Data Download site https://coast.noaa.gov/slrdata/ on 4/6/2021.
2) **Sea level rise scenarios:** Sea level rise scenarios developed by NOAA utilized a "modified bathtub approach" (a linear superposition method) to represent terrestrial areas that would be inundated through various sea level rise heights beyond mean higher high water (MHHW) levels (Marcy et al., 2011; NOAA, 2017). This data layer created from elevation data, literature-supported sea level rise values, MHHW values, local and regional variation in MHHW, and hydrological connectivity. NOAA utilized the Sea Level Rise and Coastal Flood Impact Viewer to calculate sea level rise scenarios from zero to six feet above the MHHW. The geodatabase data layers for one, two, and three feet of sea level rise were for each state from the Sea Level Rise Data Download site, https://coast.noaa.gov/slrdata/. Data was downloaded on 4/6/2021.
3) **Storm surge:** The National Hurricane Center's Storm Surge Unit created the Sea, Lake, and Overland Surges from Hurricanes (SLOSH) model that is used to derive potential storm surge flooding scenarios along the Gulf of Mexico, Continental U.S. Atlantic coasts, and select areas in the Caribbean and Pacific Islands (https://slosh.nws.noaa.gov/). SLOSH outputs two stimulation grid products, Maximum Envelope of Water (MEOWs) and Maximum of MEOW (MOMs). The MEOW grid is a composite of the maximum value the SLOSH model attains during any model run. The MOM grid cell is the maximum of MEOWs for all hurricanes of a given category. For

more information on SLOSH model products, see https://slosh.nws.noaa.gov/sloshPub/. The vector data for MOMs above ground level storm surge for category 1, 2, and 3 storms were downloaded for the study area by basin at https://slosh.nws.noaa.gov/sloshPriv/momShp_AGL.php. Data was downloaded on 4/6/2021.

4) **High risk (1% annual chance for A and V zones) and moderate risk (2% annual chance) flooding:** FEMA has delineated riverine and coastal flood zones. For this study, the areas of high risk (1% annual chance) and moderate risk (2% annual chance) were utilized to represent areas at risk from flooding. The high and moderate risk layer geodatabases were extracted for each state from the FEMA Map Service Center, https://msc.fema.gov/portal/advanceSearch. Data was downloaded on 4/6/2021.

A total of nine individual vector layers (high tide flooding, high risk for flooding [1% annual chance], moderate risk for flooding [2% annual chance], category 1 storm surge, category 2 storm surge, category 3 storm surge, sea level rise scenario 1, sea level rise scenario 2, and sea level rise scenario 3) were used in the Water Hazards Ecosystem Stress Indicator. Layers were merged and clipped to create unified layers for each data type and then converted to 30 m raster files. Layers were combined using raster math to produce a single layer in which each 30 m cell contained a value from 1 to 9 reflecting the number of co-occurring hazards in that cell. These cell values were then reclassified using Equation 1 to maintain a consistent 1 to 100 scale. Zonal statistics were then utilized to resample the 30 m raster into 1 km^2 hexagon grid.

Ecological Threshold:

Ecosystem-specific thresholds are unknown to estimate potential stress exerted by sea level rise or inland flooding, therefore the scale of this assessment is relatively coarse. Ecosystem stress caused by water-related habitat loss is expressed in values scored from 1 to 100 for each 1 km^2 hexagon (Table B-19). NODATA reflects background value (outside the project's spatial domain)

Table B-19. Interpretation of cell values for the Water Hazards Ecosystem Stress Indicator.

1 km^2 Hex Cell Value	Interpretation (total # of overlapping hazards)
1	1
13	2
26	3
38	4
50	5
63	6
75	7
88	8
100	9

Current Condition:

First, the water hazard datasets were resampled to a 1,000 m cell grid and clipped to the ecosystem stressor spatial domain (Figure B-20– Figure B-23). Next, the threshold was applied and the data scaled such that cell values of 1 reflect lowest ecosystem stress and values of 100 reflect maximum stress (Figure B-24).

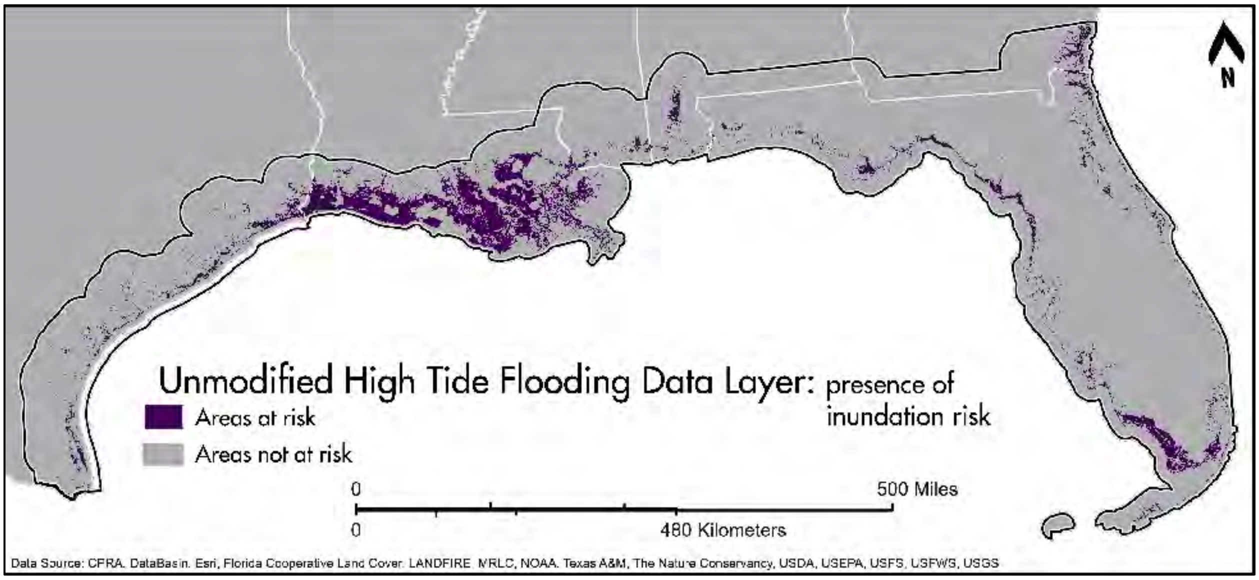


Figure B-20. Unmodified high tide flooding dataset. Cells were resampled to 1,000 m grid cell size and clipped to the ecosystem stressor spatial domain.

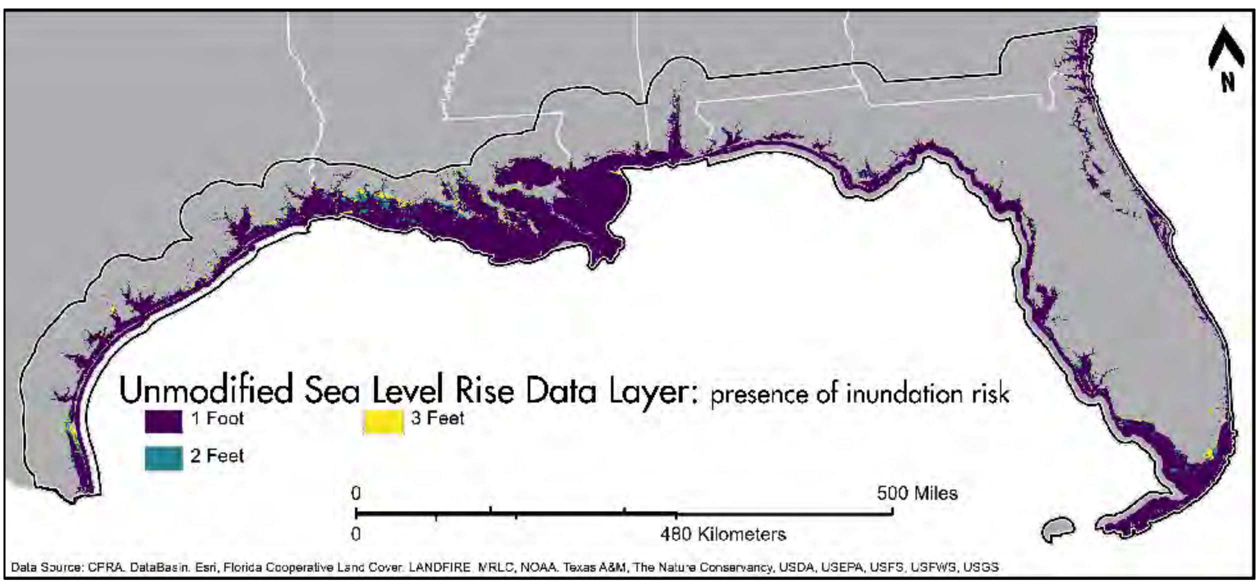


Figure B-21. Unmodified sea level rise dataset reflecting 1, 2, and 3 ft scenarios. Cells were resampled to 1,000 m grid cell size and clipped to the ecosystem stressor spatial domain.

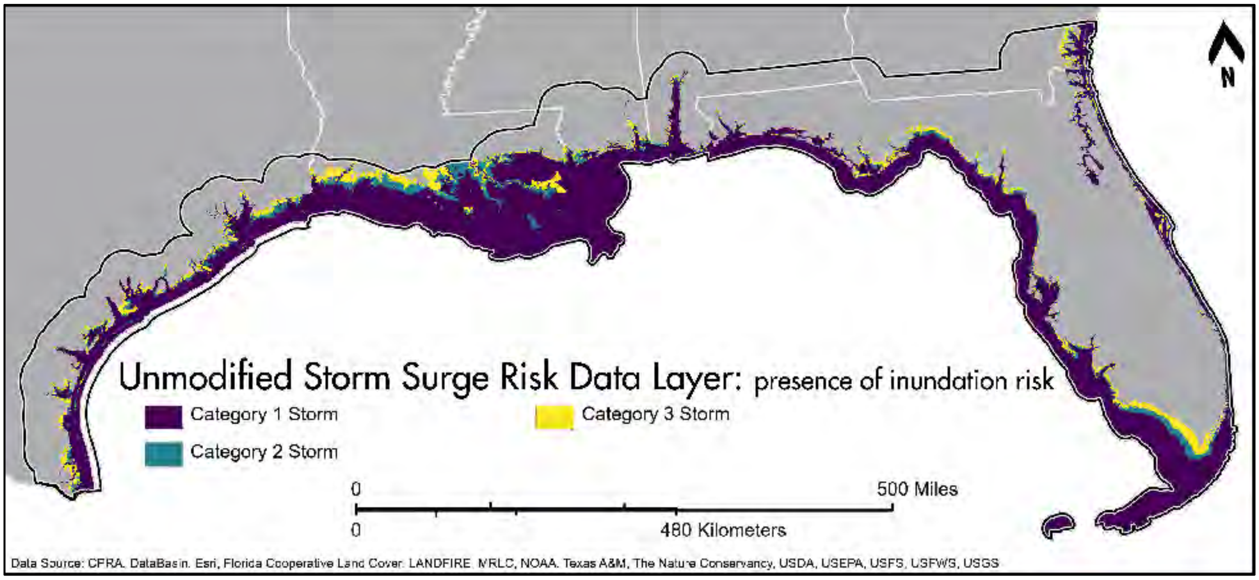


Figure B-22. Unmodified storm surge dataset reflecting inundation risk from category 1, 2, and 3 storms. Cells were resampled to 1,000 m grid cell size and clipped to the ecosystem stressor spatial domain.

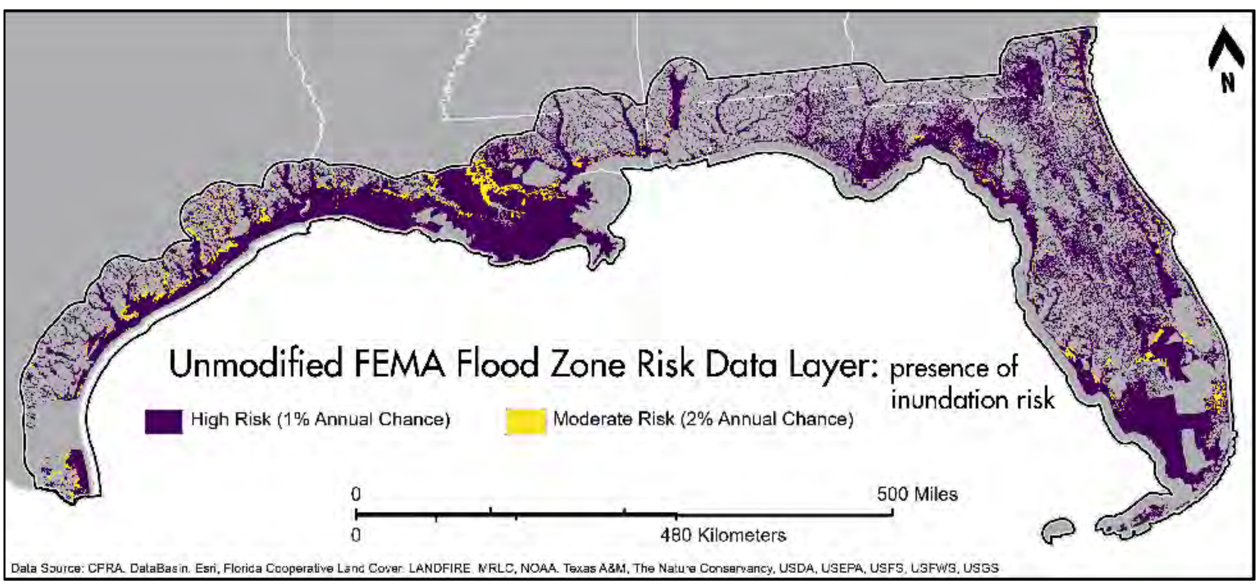


Figure B-23. Unmodified FEMA flood zone dataset reflecting flooding risk (1% and 2% annual risk areas). Cells were resampled to 1,000 m grid cell size and clipped to the ecosystem stressor spatial domain.

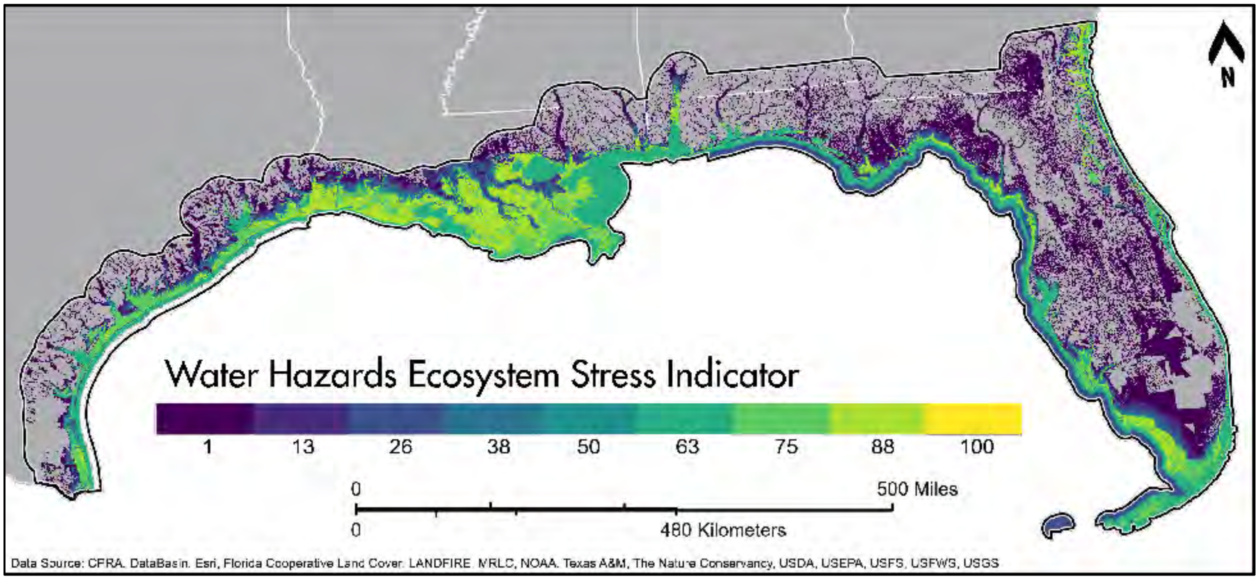


Figure B-24. Water Hazards Ecosystem Stress Indicator layer mapped across the project area. A score of 100 reflects highest ecosystem stress based on applied thresholds, one indicates lowest ecosystem stress from this indicator, and grey areas reflect no threat from this indicator.

Data Gaps and Limitations:

Sea level rise and coastal flood hazards are based on coarse assessments of future potential impact and should be interpreted with caution. Using a static projection of sea level rise provides no indication of timeframe of the threat but does represent the extent of water with an increase in mean sea level of 3 ft above current elevations. Different projections show variations in the specific time it would take to reach this amount, so land managers should investigate the raw data projects for a specific area of interest. The assessment of inland flooding based on FEMA flood maps should also be interpreted with caution. These datasets have data gaps (e.g., data for some areas is only available from original digitized paper forms or some maps may not be officially approved) for the following counties in Texas: Hidalgo and Kenedy.

During late 2021, there is a planned release of an Army Corps of Engineers (USACE) coastal hazard model that will represent water-related habitat loss with modelled projections of sea level rise, storm surge hazard, and other water-related threats across the northern Gulf of Mexico. The USACE is currently working to expand their assessment conducted for the North Atlantic across the entire Gulf of Mexico coast. Future updates of this work intend to incorporate that data, which is known to be far more accurate than the currently used methodology. For more information on what that work will produce, please see the USACE North Atlantic Comprehensive Study documentation (USACE, 2015) and the USACE website (https://www.nad.usace.army.mil/CompStudy/).

Indicator: Drought

Relevance and Context:

Drought is commonly referred to as a time of less-than-normal or expected rainfall resulting in short-term and long-term impacts (Verdi et al., 2006). Drought causes environmental stress on many species (flora and fauna) and has the potential to cause long-term change in ecosystems: species distributions, landscape biodiversity, wildfire, net primary production, to name only a few (Clark et al., 2016). The northern Gulf of Mexico has experienced historical periods of drought that may have contributed to the structure of both ecological and societal characteristics of the region (Cook et al., 2007). For example, the severe statewide drought in Florida from 1998 to 2002 is considered one of the worst ever to impact the state (Verdi et al., 2006), resulting in record-low streamflows in several river basins, increased freshwater withdrawals, and created hazardous conditions for wildfires, sinkhole development, and low lake levels.

Hydrology is a critical component of ecosystem function along the Gulf of Mexico coastal region and disruptions to normal water levels and flow patterns caused by drought can impact a variety of ecosystems. For example, disrupted hydrology can negatively impact the regeneration of bald cypress wetlands and emergent and aquatic coastal marsh communities (Kinney et al., 2014; Lei & Middleton, 2018). Drought is often linked to indicators of climate change due to the consequences of shifting precipitation patterns (Carruthers et al., 2017; Harte Research Institute for Gulf of Mexico Studies, 2019). Climate change can alter patterns of storms, and significant storms (e.g., tropical cyclones) can be an important climatic factor determining drought duration along the Gulf of Mexico (Maxwell et al., 2013). Furthermore, the interacting effects of sea level rise and drought poses a significant threat to coastal forests in the Gulf of Mexico; research by Williams et al., (2003) in Florida illustrates that drought can be the final factor leading to coastal hardwood tree mortality when a tree stand is already significantly threatened by hypersaline conditions caused by sea level rise.

Faunal species that rely closely on available moisture (e.g., salamanders and other amphibians) have been shown to be highly susceptible to drought in the southeastern U.S. (Walls et al., 2013), whereas others may be more resilient to drought conditions. For example, freshwater mussels in the Gulf Coastal Plain of southwestern Georgia can survive under debris during periods of prolonged low stream flow (Golladay et al., 2004), and some fish population assemblages in the southwest U.S. have been shown to recover rapidly post-drought (Matthews & Marsh-Matthews, 2003). Temporal considerations of drought are also important, with some evidence of greater drought resilience in grasslands that experience recurrent mild drought stress compared to grasslands with lower drought stress (Backhaus et al., 2014). These studies highlight the variability of drought impacts on different flora and fauna across the US (Golladay et al., 2004). Drought is highlighted as a threat to ecosystems across the northern Gulf of Mexico in state wildlife action plans (Table B-20).

Table B-20. Summary of the impacts of drought highlighted in US Gulf State Wildlife Action Plans that could pose potential threat to wildlife.

State	Reference	Summarized Statement of Threat
Texas	(Texas Parks and Wildlife Department, 2012a, 2012b)	Associated with climate change, drought can post a highly localized threat particularly for rare species that have few options to adapt under changing climatic conditions. Decreased precipitation can result in habitat shifts, alterations, or disappearance. Shifting temperatures and precipitation may threaten estuarine nursery areas by altering water temperatures and salinity patterns.
Louisiana	(Holcomb et al., 2015)	Climate change, linked to shifts in precipitation regimes, is noted as a threat to forests (bayhead swamp/forest seep and bottomland hardwood habitats) where drought could have negative impacts on habitat. Increased drought could negatively impact species that rely on freshwater flow (i.e., mollusks, crustaceans, inland fishes, amphibians, and reptiles).
Mississippi	(Mississippi Museum of Natural Science, 2015)	Shifts in temperature and precipitation (associated with climate change) noted as a threat to wildlife in Mississippi.
Alabama	(Alabama Department of Conservation and Natural Resources, 2015)	Climate change resulting in altered temperature and precipitation regimes are noted threats to native species (specifically those with highly specialized habitat requirements, species already near temperature limits, isolated/rare populations, pathogen-susceptible populations). Drought is noted as a threat to surface water sources, impacting amphibian breeding sites and formerly permanent streams (impacting fish/mollusk species).
Florida	(Florida Fish and Wildlife Conservation Commission (FWC), 2019)	Changing precipitation patterns are expected to result in creased rainfall in the northern part of the state, and less rainfall (more drought) in the southern portion. Altered climate patterns outside the natural variation, associated with climate change, is a known threat to wildlife in Florida.

Data & Method:

The Drought Ecosystem Stress Indicator is based on information provided by the US Drought Monitor program, an effort produced jointly by the National Drought Mitigation Center (NDMC) in partnership with the University of Nebraska-Lincoln, NOAA, and the US Department of Agriculture (USDA). The NDMC web site (https://droughtmonitor.unl.edu/) hosts a wealth of drought monitoring data and can act as a trigger point for drought disaster declarations. The drought metric used in this assessment is based upon non-consecutive weeks of drought occurrences classified as “D3” (extreme) and “D4” (exceptional). These categories are based on four key indicators (Palmer Drought Severity Index [PDSI], CPC Soil Moisture Model, USGS Weekly Streamflow, Standardized Precipitation Index [SPI]), local condition and impact reports, and other objective indicators. NDMC documentation states that the final drought category is often based on what the majority of the indicators show and on local observation.

Drought data for D3 and D4 classifications was downloaded by county (parish) for each state for the time spanning January 2011 to January 2021. The data was downloaded from Drought Monitor at https://droughtmonitor.unl.edu/Data/DataDownload/WeeksInDrought.aspx on 4/13/2021. The datasets were downloaded separately for each of the Gulf of Mexico states, combined, and then joined to the respective US Census TIGER/line county polygon dataset. The weeks in D3 and D4 were summed together for each county, and then the county polygons were converted to a 30 m raster. The cell values were classified using Equation 1 to maintain a consistent 1 to 100 scale. Zonal statistics were then utilized to resample the 30 m raster into 1 km^2 hexagon grid.

Ecological Threshold:
An ecosystem report card series developed for the United Kingdom details how drought can impact grasslands, woodlands, wetlands, lakes, rivers, and streams in a variety of ways based on multiple biotic and abiotic factors (Acreman et al., 2020; Berry et al., 2020; Dobel et al., 2020a, 2020b; Thompson & Ayling, 2020), and a review by Clark et al., (2016) highlights the multiple interacting effects of drought, insects pests, and fire. These factors made determination of a single ecosystem threshold for drought difficult to ascertain. Drought levels of D3 and D4 explained above were used to assess ecosystem stress caused by drought. To provide context of ecosystem stress caused by these drought conditions, Table B-21provides examples of historic observations of the impacts of these drought conditions in Texas (https://droughtmonitor.unl.edu/Data/StateImpacts.aspx).

Table B-21. Summary of historic impacts of D3 and D4 drought reported for Texas provided by NDMC.

Drought Category	Historical Impact
Impacts of D3 drought	Soil has large cracks; soil moisture is very low; dust and sand storms occur. Row and forage crops fail to germinate; decreased yields for irrigated crops and very large yield reduction for dryland crops. Need for supplemental feed, nutrients, protein, and water for livestock increases; herds are sold. Increased risk of large wildfires. Many sectors experience financial burden. Severe fish, plant, and wildlife loss reported. Water sanitation is a concern; reservoir levels drop significantly; surface water is nearly dry; river flow is very low; salinity increases in bays and estuaries.
Impacts of D4 drought	Exceptional and widespread crop loss is reported; rangeland is dead; producers are not planting fields. Livestock culling continues; producers wean calves early and sell herds due to importation of hay and water expenses. Seafood, forestry, tourism, and agriculture sectors report significant financial loss. Extreme sensitivity to fire danger; firework restrictions are implemented. Widespread tree mortality is reported; most wildlife species' health and population are suffering. Devastating algae blooms occur; water quality is very poor. Exceptional water shortages are noted across surface water sources; water table is declining. Boat ramps are closed; obstacles are exposed in water bodies; water levels are at or near historic lows.

Prolonged drought that leads to sustained water deficit stress is known to cause the performance of a plant or ecosystem to shift (decrease) until it reaches a threshold, or an abrupt nonlinear change in ecosystem condition (Munson et al., 2020). Collins and Xia (2015) and Van Auken (2000) show that over decadal time periods irreversible ecosystem transitions can occur for grasslands in the Southwestern US (from mesic to xeric and from grassland to shrubland). Due to the lack of specific ecological thresholds for drought stress, this assessment was conducted for a decadal timeframe (2011-2021) and evaluated drought stress for the Drought Ecosystem Stress Indicator as a simple linear relationship: more drought imparting more ecosystem stress (Clark et al., 2016); more drought is reflected as the cumulative, non-consecutive number of weeks in which severe (D3 and D4) drought occurred by county within the project area.

Ecosystem stress caused by drought is expressed in continuous values from 0 to 100 for each 1 km^2 hexagon cell (Table B-22). Values of 0 reflect no weeks of reported drought.

Table B-22. Interpretation of cell values for the Drought Ecosystem Stress Indicator.

1 km2 Hex Cell Value	Interpretation (total # of non-consecutive weeks in D3 and D4 drought over 10 years)	1 km2 Hex Cell Value2	Interpretation (total # of non-consecutive weeks in D3 and D4 drought over 10 years)
1	6	33	74
2	8-9	34	77
4	12-13	36	80-82
5	14-15	37	84
6	16-17	38	86
7	18-19	39	88
8	20-22	40	89-90
9	23-23	41	91-92
10	25-26	42	93
11	27	43	95-96
12	29-30	44	98
13	31-32	45	101
14	33-34	47	105
15	35-37	50	111-112
16	38-39	51	113
17	40	52	115-116
18	43	55	122
19	45	56	123-124
21	48	59	130-131
22	50-52	61	134
23	53-53	62	136
24	55-56	68	150
25	57	69	151
26	59-60	72	159
27	62	75	165
28	63	86	188
29	65-66	88	193
30	68-69	90	196
31	70-71	91	198-199
32	73-73	100	218

Current Condition:
First, the draught dataset was resampled to a 1,000 m cell grid and clipped to the ecosystem stress spatial domain. Next, the threshold was applied and the data scaled such that cell values of 0 reflect lowest ecosystem stress and values of 100 reflect maximum stress (Table B-25).

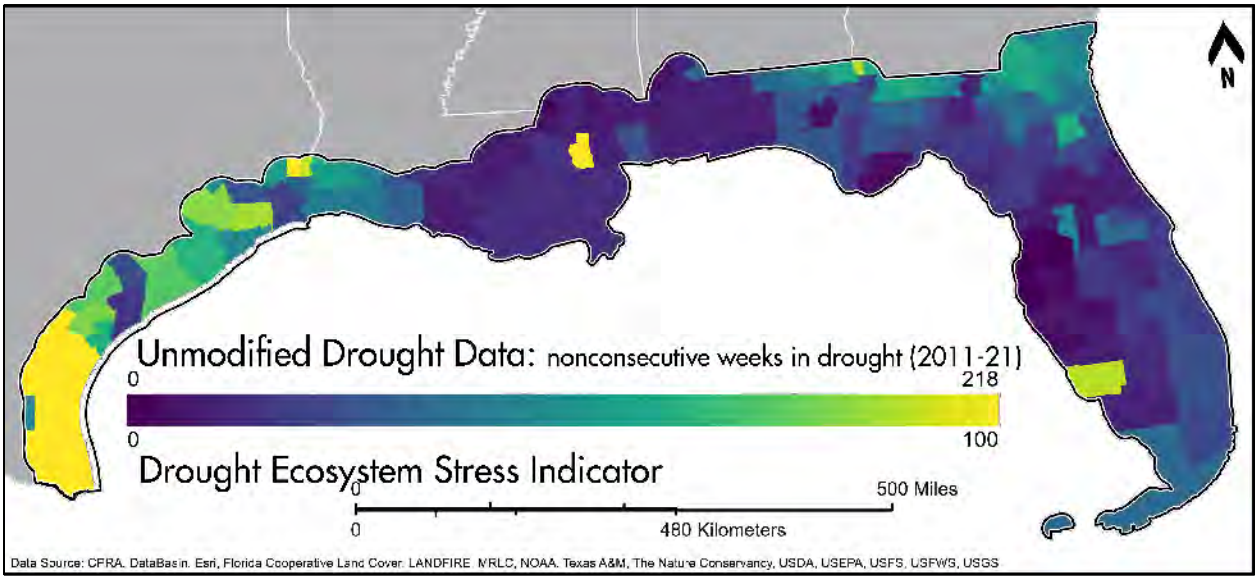


Figure B-25. Unmodified drought data (2011-2021) and the Drought Ecosystem Stress Indicator (non-consecutive weeks in drought) mapped together across the project area.

Data Gaps and Limitations:
Further scientific study is required to understand the impacts of drought on flora and fauna as well as to ascertain an ecologically-relevant threshold to assess drought stress across ecosystems (Clark et al., 2016; Munson et al., 2020). This assessment does not differentiate the impacts between short-term and long-term drought, but rather should be interpreted more broadly as total drought occurrence over a 10-year timespan.

In terms of data and interpretation, NDMC data is meant to provide a consistent big-picture look at drought conditions in the U.S. and it can be used to identify likely areas of drought impacts (including water shortage). However, the developers caution that this dataset should not be used to infer specifics about local conditions and that decision-makers should consult local water systems experts when planning specific projects in an area. Importantly, this assessment is based on historical drought conditions and does not provide an estimate of future drought. Furthermore, although the full NDMC dataset is nationwide, monitoring data for each county in the study area could not be gathered for the entire ten-year timeframe of this assessment; the known data gap in this assessment was for Baldwin County, AL, for which drought data was only available for the years 2011, 2012, and 2016.

Indicator: Wildfire Hazard

Relevance and Context:

Wildfire is a major driver of transformation for a variety of ecosystems. 'Natural' fire regimes are critical for normal ecosystem function (e.g., an essential component of germination and biodiversity), but recent global changes in climate and fire management practices are contributing to shifts in fire severity and fire frequency (Bowman et al., 2009). Projections point to increasing extreme fire weather conditions over the next decades (Krawchuk et al., 2009). Studying and evaluating severe wildfire is increasingly being considered through a socio-ecological lens due to the direct threats to both humans (particularly vulnerable communities) and wildlife (Tedim et al., 2018).

Fires that occur with high frequency or high intensity can result in soil degradation and changes in vegetation composition and biodiversity, impacting key ecosystem services for both humans and natural resources (Chuvieco et al., 2014; Foley, 2005; Harrison et al., 2010). In the southeastern US, forested areas characterized by only slight topographic variability (e.g., Florida) are a patchwork of forest types that are strongly governed by fire: pine flatwoods, hardwood-cypress swamps, and others (Kirkman et al., 1999). These areas also produce the most extreme fire behavior potential in the eastern US (Hough & Albini, 1978; Wade et al., 1989), including large wildfires (Krofcheck et al., 2019). Management and mismanagement of wildfire is of significant concern to those interested in wildlife conservation and management, particularly because heterogeneity within forests across the Southeast and the Gulf of Mexico coast provides habitat for many federally listed faunal species, such as the red-cockaded woodpecker (*Leuconotopicus borealis*), gopher tortoise (*Gopherus polyphemus*), and eastern indigo snake (*Drymarchon couperi*). Wildfire frequency is also related to other key stressors such as drought; Labosier et al., (2015) show a significant correlation between wildfire frequency and periods of dry weather in the central Gulf Coast region.

All states intersecting with the Gulf of Mexico highlight the importance of fire for ecosystem health and integrity (Table B-23). The Wildfire Hazards Indicator is included as an indicator of ecosystem stress due to the potential of wildfire to become severe and destructive outside the range of long-term burn conditions or frequencies experienced by these ecosystems.

Table B-23. Summary of the impacts of wildfire highlighted in US Gulf State Wildlife Action Plans that could pose potential threat to wildlife.

State	Reference	Summarized Statement of Threat
Texas	(Texas Parks and Wildlife Department, 2012a, 2012b)	Managing wildfire and inappropriate application of fire are noted as threats to native grassland species, citing threat of encroachment by woody shrubs.
Louisiana	(Holcomb et al., 2015)	Fire suppression/mismanagement is a noted threat to calcareous forests habitat, savanna (including eastern longleaf pine flatwoods savanna and eastern upland longleaf pine woodland), grasslands (calcareous prairie, coastal prairie), freshwater floating marshes, ephemeral ponds, and bogs/seeps (due to woody encroachment). Mismanagement of fire can reduce total available/suitable habitat for arthropods, amphibians and reptiles, birds, and mammals.

State	Reference	Summarized Statement of Threat
Mississippi	(Mississippi Museum of Natural Science, 2015)	Altered fire regime is identified as a regional threat impacting East Gulf Coastal Plain and Upper East Gulf Coastal Plain ecoregions. Inappropriate use of fire can also have a negative impact on water, soil, and air quality in Mississippi.
Alabama	(Alabama Department of Conservation and Natural Resources, 2015)	Mismanaged application of fire (or fire exclusion) is cited as detrimental to multiple habitat types in Alabama.
Florida	(Florida Fish and Wildlife Conservation Commission (FWC), 2019)	Fire suppression is a natural system modification that is a threat to Florida ecosystems.

Data & Method:
The Wildfire Hazard Ecosystem Stress Indicator used in this assessment was derived from the USDA Forest Service 2020 Wildfire Hazard Potential map (https://www.firelab.org/project/wildfire-hazard-potential). This geospatial raster tool was developed to help inform evaluations of wildfire risk or prioritization of fuels management needs across large spatial scales (Dillon et al., 2015). This dataset depicts the relative potential for wildfire that would be difficult for suppression resources to contain based on data related to spatial estimates of wildfire likelihood and intensity as well as spatial fuels and vegetation data from LANDFIRE (Dillon et al., 2015). This spatial tool is primarily intended for forest management practitioners to locate areas where vegetation treatments may be needed and does not include information on current or forecasted weather or fuel moisture conditions.

The Wildfire Hazard Potential map data is provided at 270 m spatial resolution, where each cell reflects one of five wildfire hazard potential classes: very low, low, moderate, high, and very high. A cell characterized by having very high wildfire hazard potential indicates that the given area is characterized as having fuels with the highest determined probability of experiencing torching, crowning, and other forms of extreme fire behavior under conducing weather conditions. The 2020 classified raster dataset was downloaded from: https://firelab.org/project/wildfire-hazard-potential on 3/23/2021. The classified Wildfire Hazard Potential raster dataset was resampled from 270 m to 30 m resolution and rescaled using Equation 1 to create a uniform 1 to 100 scale. Zonal statistics were then utilized to resample the 30 m raster into 1 km^2 hexagon grid.

Ecological Threshold:
The Wildfire Hazard Ecosystem Stress Indicator is based on models that integrate potential for fire, fire fuel, and areas susceptible to fire damage (Dillon et al., 2015). Specific ecological thresholds for fire were not available for the northern Gulf of Mexico project area, therefore the thresholds developed for the USDA Wildfire Hazard Potential map were used in this assessment. Ecosystem stress caused by wildfire hazard is expressed in values scored from 1 to 100 for each 1 km^2 (Table B-24). NODATA reflects background value (outside the project's spatial domain).

Table B-24. Interpretation of cell values for the Wildfire Hazard Ecosystem Stress Indicator.

1 km^2 Hex Cell Value	Interpretation (risk of unmanageable fire)
0	Not a burnable area (developed, water)
1	Very low risk
26	Low risk
50	Moderate risk
75	High risk
100	Very high risk

Current Condition:

First, the wildfire hazard risk dataset was resampled to a 1,000 m cell grid and clipped to the ecosystem stressor spatial domain (Figure B-26). Next, the threshold was applied and the data scaled such that cell values of 0 reflect areas that are not burnable (developed areas, water), 1 reflects lowest ecosystem stress, and 100 reflects maximum stress (Figure B-27).

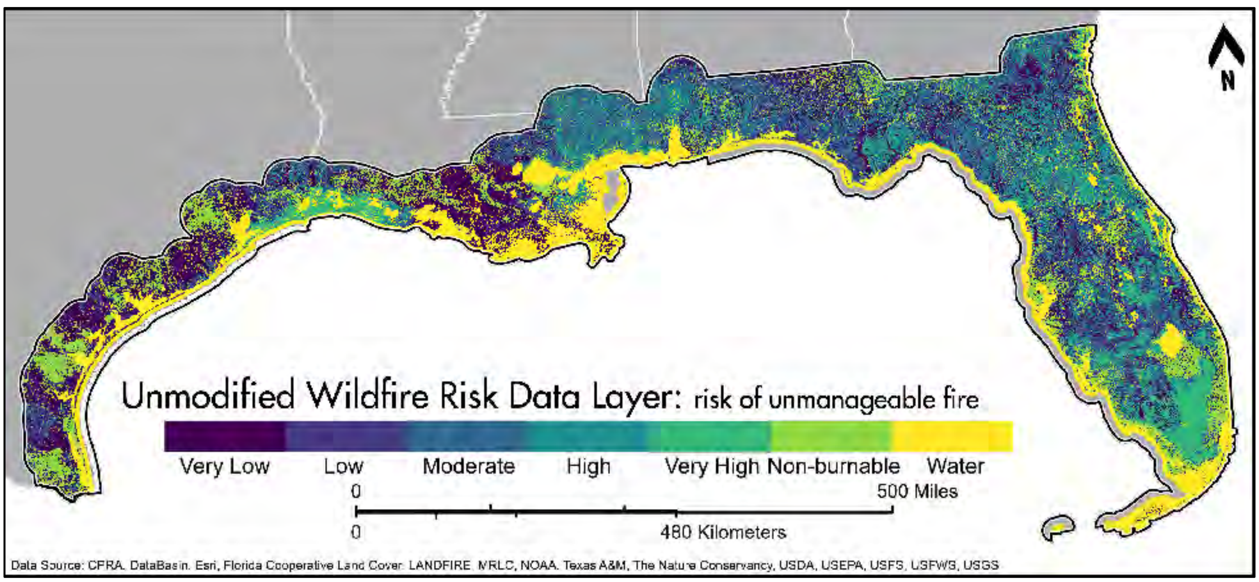


Figure B-26. Unmodified wildfire risk data layer. Cells were resampled to 1,000 m grid cell size and clipped to the ecosystem stressor spatial domain.

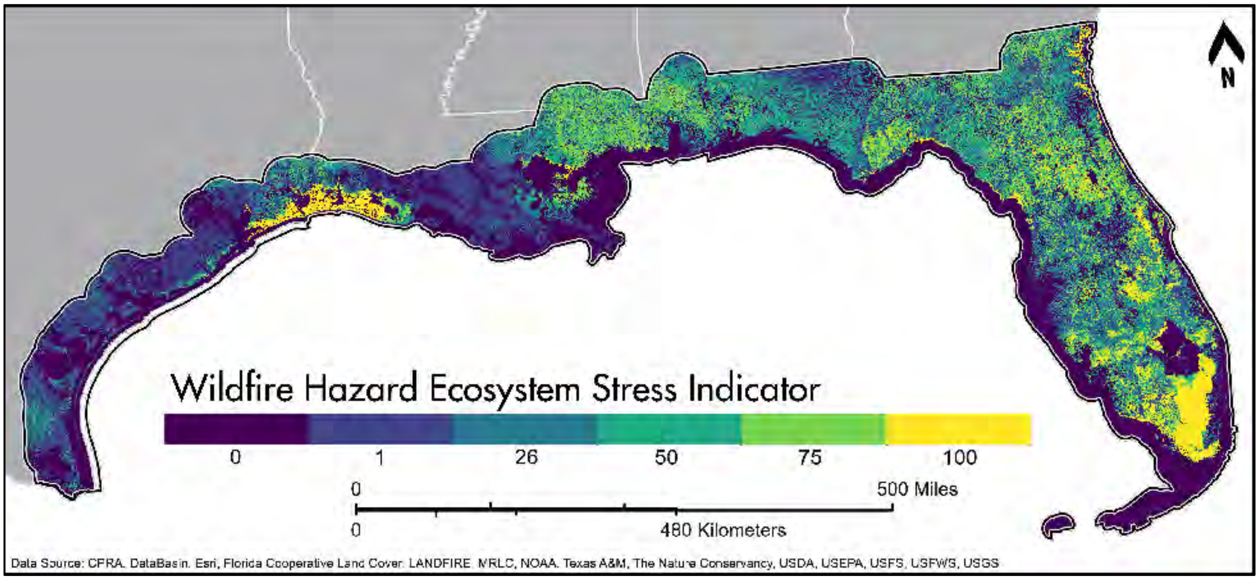


Figure B-27. Wildfire Hazard Ecosystem Stress Indicator layer mapped across the project area. A score of 100 reflects highest ecosystem stress based on applied thresholds, one indicates lowest ecosystem stress from this indicator, and zero reflects no threat from this indicator (non-burnable areas).

Data Gaps and Limitations:

Potential risk of severe wildfire damage reflected in the USDA Wildfire Hazard Potential map does not directly translate to ecosystem stress. This Ecosystem Stress Indicator is included in this assessment because it reflects valuable information related to potential risk that a land manager should consider when planning or managing projects. This data product is one of several factors that should be considered for strategic planning and conservation, and the developers do not recommend that this dataset be used for forecasting wildfire for any specific timeframe.

Indicator: Hydromodification

Relevance and Context:

The structure, function, and dynamics of aquatic ecosystems in riparian zones (including floodplains and adjacent wetlands) are controlled and maintained by the flow of freshwater streams and rivers. Alterations to streamflow can dramatically shift the hydrologic regime that had been present for many thousands of years and upon which organisms have adapted (Anandhi et al., 2018). Dams, culverts, levees, diversions, and drainage ditches are the result of humans altering natural hydrologic patterns for purposes such as flood relief, power generation, and water supply. However, flow alterations are associated with ecological change, and Poff et al., (2010) shows that ecological change increases with increase in the magnitude of flow alteration. Work by Gillespie et al., (2015) highlights that flow modifications result in ecosystem responses among water flow, biota, and water quality

Connectivity for aquatic natural resources is highly valued to USFWS as well as the U.S. states along the northern Gulf of Mexico. Within-stream conditions can directly impact biological processes. For example, crayfish populations in impounded streams in Alabama exhibit restricted gene flow between segments up- and downstream of dams, with evidence of one-directional gene flow (downstream) in dam-obstructed stream segments (Barnett et al., 2020). When rivers meet the ocean, coastal ecosystems depend on periodic freshwater flows for maintaining coastal wetland plant structure and faunal communities which have enormous ecological, environmental, and socio-economic value (Alexander & Dunton, 2002). Coastal wetlands such as those in Louisiana are experiencing habitat loss due to a combination of sea level rise, subsidence, saltwater intrusion, and reduced sediment inflow, in part the result of hydrologic modifications (Day et al., 2000, 2011; Scavia et al., 2002). Water restrictions upstream caused by dams can reduce freshwater flows to coastal systems; the Nueces River Delta near Corpus Christi, Texas, is one example of a freshwater-limited Gulf of Mexico system (Heinsch, 2004). Ecosystem productivity Nueces River system has declined due to reduced freshwater flows, which led to hypersaline and dry conditions in the higher elevation areas of the marsh platform (Alexander & Dunton, 2002; Montagna et al., 2002).

Like point source pollution sources, the ecological stress imparted by dams and other obstructions is highly variable and context-dependent, making regional assessments more difficult. Aquatic obstructions are typically highlighted in state wildlife action plans as a component of urban expansion (see Table B-13). Their inclusion in many ecosystem health reports warrants their inclusion here (America's Watershed Initiative, 2015; Carruthers et al., 2017; Costanzo et al., 2015; Dobel et al., 2020b; Harte Research Institute for Gulf of Mexico Studies, 2019; Harwell et al., 2016; SALCC, 2015).

Data & Method:

Due to the high variability in ecosystem stress imparted by aquatic barriers and hydrologic modifiers, a broader watershed-health index developed by the USEPA Office of Water was used to create the Hydromodification Ecosystem Stress Indicator. The goal of the USEPA Office of Water Healthy Watersheds Program is to bring more emphasis to protecting high quality waters under the Clean Water Act (USEPA, 2012, 2017). One product from that program was a series of integrated assessment reports conducted to assess watershed health for the entire US (https://www.epa.gov/hwp/examples-integrated-assessments-watershed-health#integrated). The product of the preliminary USEPA Healthy Watersheds Project is data that identifies healthy watersheds that may represent good prospects for protection

(USEPA, 2017). The sub-index of geomorphology condition was used in this assessment because it provides a watershed-scale indication of ecosystem stress caused by hydrologic modifications across the study area. The geomorphology sub-index is based on watershed feature indicators with the potential to alter geomorphic processes: dam density (per watershed), artificial drainage ditches (% ditch drainage per watershed), near-stream roads (road density in riparian [hydrologically active] zone), and high intensity land use (% high intensity land cover in riparian [hydrologically active] zone) (USEPA, 2017; Young & Sanzone, 2002). The index is calculated as the mean of its normalized feature indicator values and inverted to be directionally consistent with other USEPA Healthy Watershed indicators.

To create the Hydromodification Ecosystem Stress Indicator layer, the preliminary index data was downloaded by state, and the geomorphology index data normalized by USEPA Level III Ecoregion was used. Data was downloaded from https://www.epa.gov/hwp/download-preliminary-healthy-watersheds-assessments. The geomorphology sub-index values given by HUC12 watershed normalized by USEPA Level III Ecoregion (see USEPA [2017] and [2012] for further information) were extracted from datasets downloaded for each Gulf of Mexico state. Using the NHDPlus High Resolution database, data was merged and joined based on HUC12 identifier. The joined polygon layer was then converted to 30 m raster. The original cell values (scaled 0 to 1) were inverted such that higher values indicate lower watershed health (to align with other stress indicators in this assessment). Those values were then scaled up to reflect a 0 to 100 scale. Zonal statistics were then utilized to resample the 30 m raster into 1 km^2 hexagon grid.

Ecological Threshold:

Ecological thresholds were integrated into the index created by the USEPA Healthy Watersheds Project (USEPA, 2012, 2017; Young & Sanzone, 2002). The geomorphology sub-index of watershed health accounts for watershed features listed above (dams, artificial drainage ditches, near-stream roads, and high intensity land use in the riparian zone). Dams are included specifically due to their ability to alter channel geomorphology by slowing water velocity and increasing sediment deposition above the dam and releasing sediment-deficient water below the dam outfall. The Hydromodification Ecosystem Stress Indicator is expressed in values scored from 0 to 100 on a continuous scale for each 1 km^2 hexagon cell (Table B-25). NODATA reflects background value (outside the project's spatial domain).

Table B-25. Interpretation of cell values for the Hydromodification Ecosystem Stress Indicator.

1 km^2 Hex Cell Value	Interpretation (watershed health score based on inverse geomorphology index)
0	Lowest amount of watershed stress reflected by the USEPA Healthy Watersheds Project (inverse) geomorphology index
100	Highest amount of watershed stress reflected by the USEPA Healthy Watersheds Project (inverse) geomorphology index

Current Condition:

First, the USEPA Watershed Health geomorphology sub-index dataset was resampled to a 1,000 m cell grid and clipped to the ecosystem stressor spatial domain (Figure B-28). Next, the original sub-index the threshold was applied and the data scaled such that cell values of 1 reflect lowest ecosystem stress and values of 100 reflect maximum stress (Figure B-29).

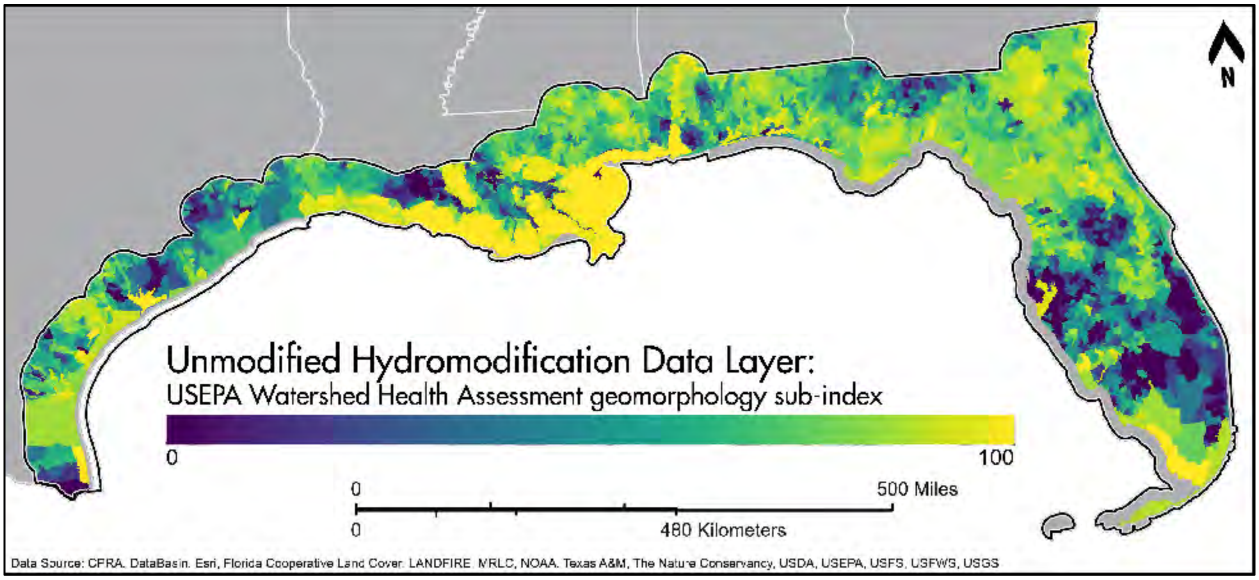


Figure B-28. Unmodified hydromodification (USEPA Watershed Health geomorphology sub-index) data layer. This data layer reflects the original scale of the sub-index, where 100 indicates healthy watersheds. Cells were resampled to 1,000 m grid cell size and clipped to the ecosystem stressor spatial domain.

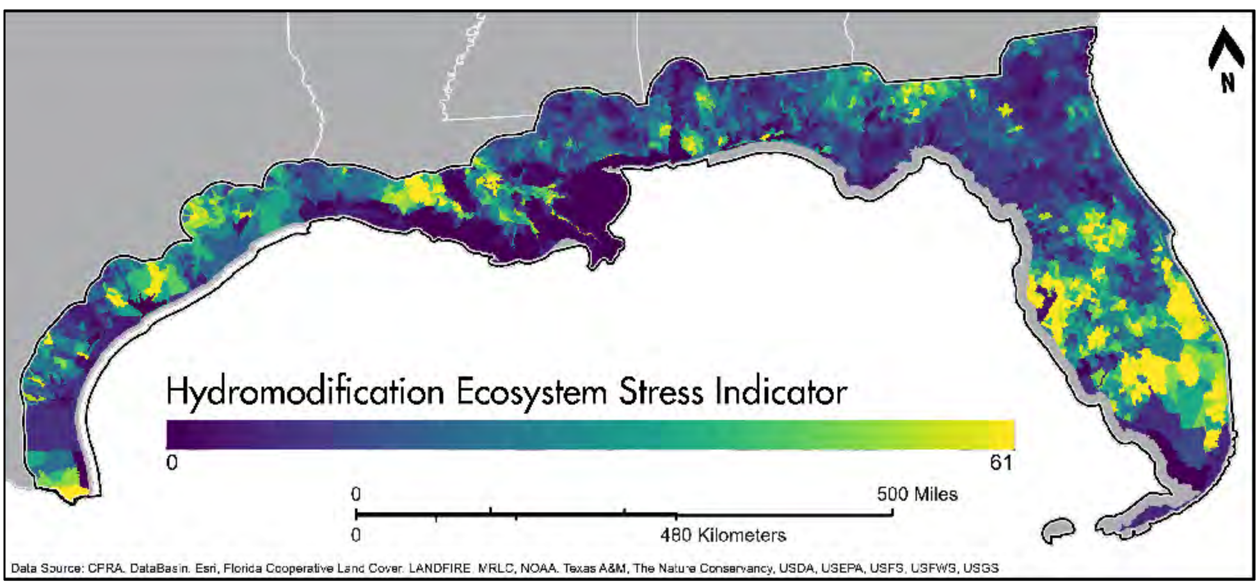


Figure B-29. Hydromodification Ecosystem Stress Indicator layer mapped across the project area, scaled 0-100 based on applied thresholds.

Data Gaps and Limitations:

Although the data used here was derived from *preliminary assessments*, the information is still indicative of ecosystem stress at a broad, geographically consistent scale.

SENSITIVITY ANALYSIS OF ECOSYSTEM STRESS

Several analyses were conducted to determine the sensitivity of the Integrated Ecosystem Stress Indicator layer to the component Ecosystem Stress Indicators and to evaluate if the results were consistent with understanding of the spatial distribution of ecosystem stress in the Gulf of Mexico project area (Figure 1). The Ecosystem Stress Indicators described above were scaled to 1000 m rasters and then exported as ASCII files from ArcGIS to create a format translatable in Matlab. The individual raster layers were then imported into the Mathworks© Matlab software program. The base version of Matlab version 2020B was used with no additional toolboxes; in addition, the following script from the Mathworks file exchange was used: bplot.m (https://www.mathworks.com/matlabcentral/fileexchange/42470-box-and-whiskers-plot-without-statistics-toolbox; Jonathan C. Lansey, 2015). The complete rectilinear grid consisted of 1733490 individual cells, 1358230 of which were outside of the domain of interest (i.e., water cells in the Gulf of Mexico), resulting in 375260 grid cells used in the analysis. Grid cells outside of the domain of interest (Figure 1) were assigned a value of Not a Number (NaN; the flag for NoData within the Matlab environment) for all stressors. Grid cells within the domain tagged as NoData for individual Ecosystem Stress Indicators within the raster files was similar replaced with NaNs. The Integrated Ecosystem Stress Indicator layer was then generated as the unweighted sum of the individual Ecosystem Stress Indicator layers omitting any NaN values (i.e., the sum ignoring the presence of NaNs). NaN values within the domain were excluded from all calculations.

The first component of the sensitivity analysis was to evaluate the distribution of data for each of the Ecosystem Stress Indicators individually (Figure B-30). The Invasive Species, Non-Point Source Pollution, and Impervious Surface Ecosystem Stress Indicators have median and mean values above 50, reflecting that their value tends to be high in locations where they are present. Point Source Pollution, Urban Expansion, Drought, Wildfire Hazard, and Hydromodification Ecosystem Stress Indicators have the lowest mean and median values, reflecting that these indicators tend to have low values where they are present. The Disease & Disease Risk Ecosystem Indicator is recorded as presence only (i.e., 100 where disease is detected or where risk is present), therefore there is no spread in the data. All Ecosystem Stress Indicators have a skewed distribution as shown by disparate values of the mean and median and/or the presence of multiple outliers (values outside of the 9th to 91st percentile). Part of this skew is attributable to the discretized nature of some of the indicators, which can be observed in their distribution. For example, the Urban Expansion Ecosystem Stress Indicator is benchmarked against a select set of thresholds that can be observed in the outlier distribution (Figure B-30).

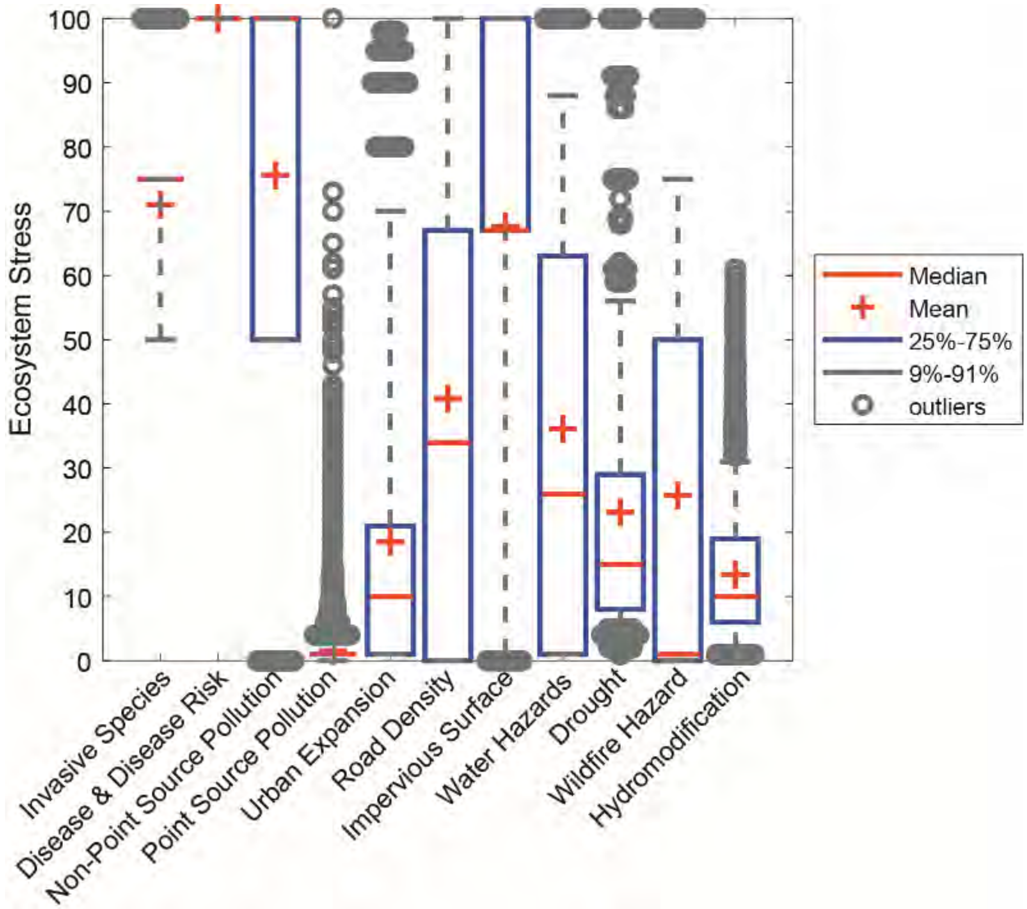


Figure B-30. Boxplot of the distribution of values for each Ecosystem Stress Indicator.

The previously described Ecosystem Stress Indicators were combined as an unweighted sum (the Integrated Ecosystem Stress Indicator layer; Figure B-31), which ranged from 0 to 633 over the project area. Spatial variability in the Integrated Ecosystem Stress Indicator layer can be observed on the scale of 1 km to 100's of km. Some features can be identified within the Integrated Ecosystem Stress Indicator layer, notably a region of reduced ecosystem stress in the vicinity of the Mississippi River delta and around Lake Okeechobee and the Everglades National Park, in coastal Louisiana this is in part due to the large water bodies (such as Chandeleur Sound) that do not have reliable assessments for most indicators. A thin band of low ecosystem stress is found along the coast, most prominently along the west coast of Florida. This band is indicative of the shallow offshore region where the Ecosystem Stress Indicators characterized in this study, which focuses predominantly on terrestrial sources of ecosystem stress, have little or no influence. The predominant contributor to the Integrated Ecosystem Stress Indicator in most of this shallow nearshore band is the Water Hazards Ecosystem Stress Indicator, in this case reflecting risk of future increases in water depth driven by relative sea level rise. Users of the Integrated Ecosystem Stress Indicator layer should be aware that marine ecosystem stress indicators have not been included in this assessment, therefore these data should not be considered a comprehensive analysis of ecosystem stress in shallow nearshore regions. Outside of this coastal band the number of individual Ecosystem Stress Indicators contributing to the Integrated Ecosystem Stress Indicator layer varied in space (Figure B-32) with a mean value of 6.53 and a standard deviation of 1.79.

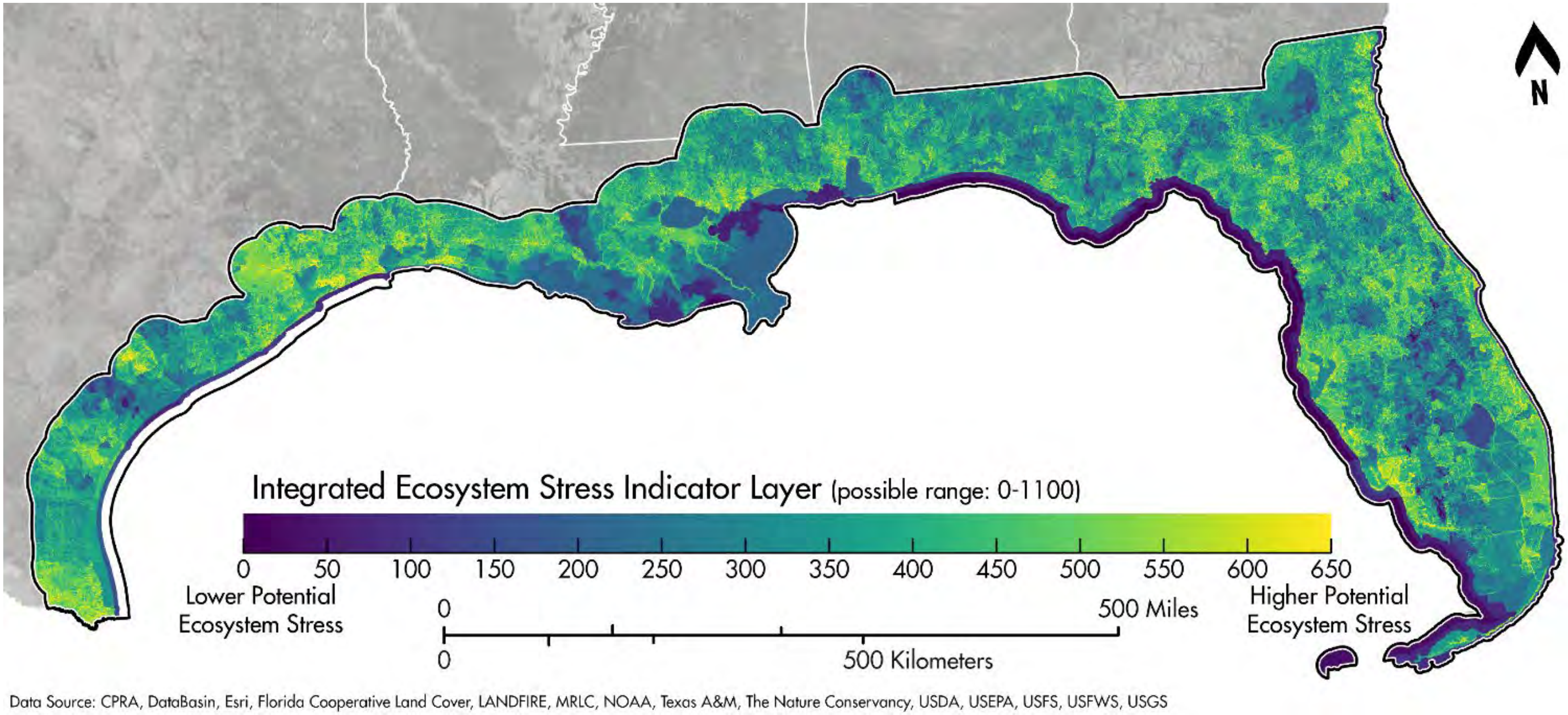


Figure B-31. Map of the Integrated Ecosystem Stress Indicator layer, calculated as the unweighted sum of the 11 Ecosystem Stress Indicators. Scale ranges from 0 (no stress) to a possible 1100 (highest possible combined stress). Highest observed Integrated Ecosystem Stress value across the project area was 650.

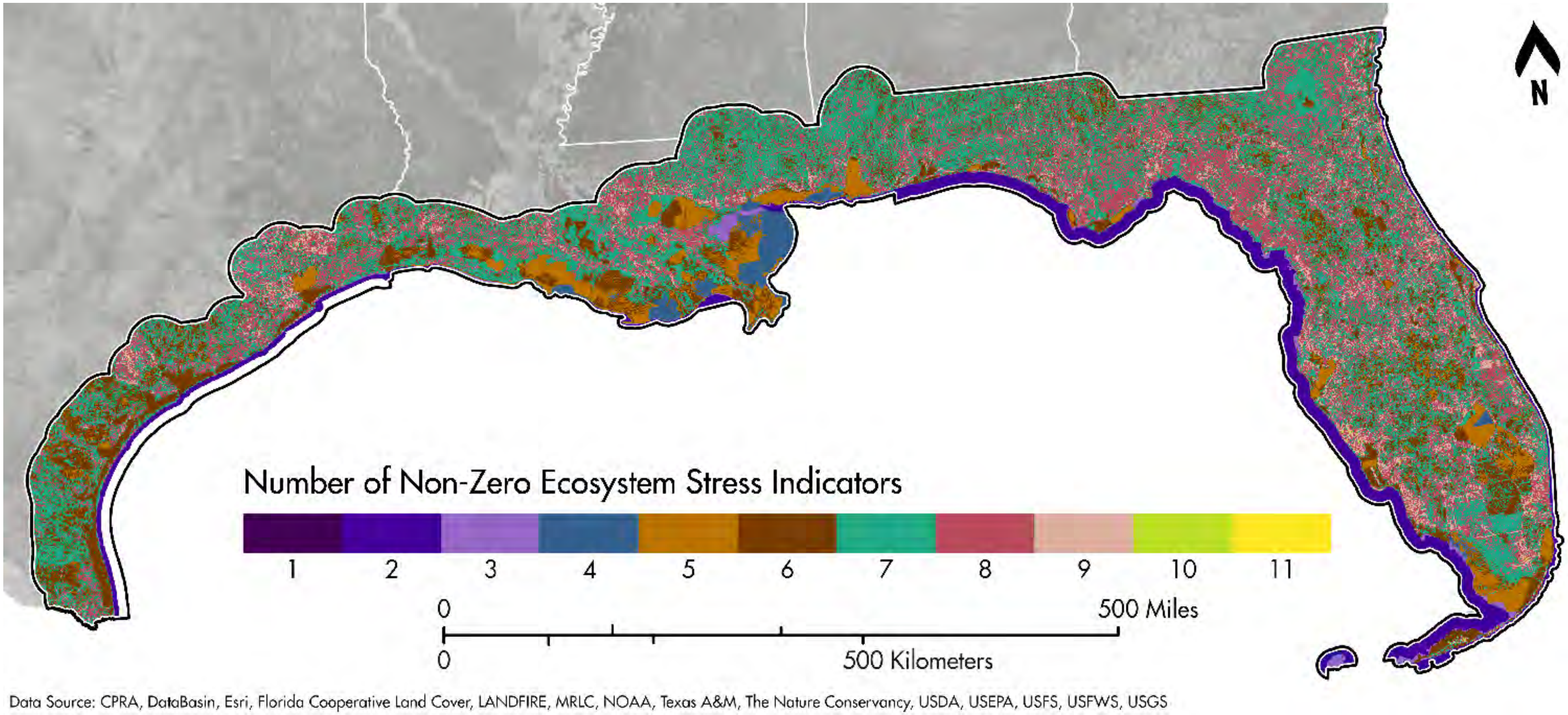


Figure B-32. Count of the number of non-zero Ecosystem Stress Indicators occurring within each 1-km grid cell.

The range of contribution of each Ecosystem Stress Indicator to the Integrated Ecosystem Stress Indicator layer was analyzed to determine if one or more indicator was dominant over the others (Figure B-33). Point Source Pollution, Urban Expansion, Drought, Wildfire Hazard, and Hydromodification Ecosystem Stress Indicators tended to contribute the least to the Integrated Ecosystem Stress Indicator layer, reflecting that these indicators have low values and/or are localized when they occur. The contribution from the other Ecosystem Stress Indicators was well-distributed, with a mean contribution varying from 12-29% of the Integrated Ecosystem Stress Indicator layer.

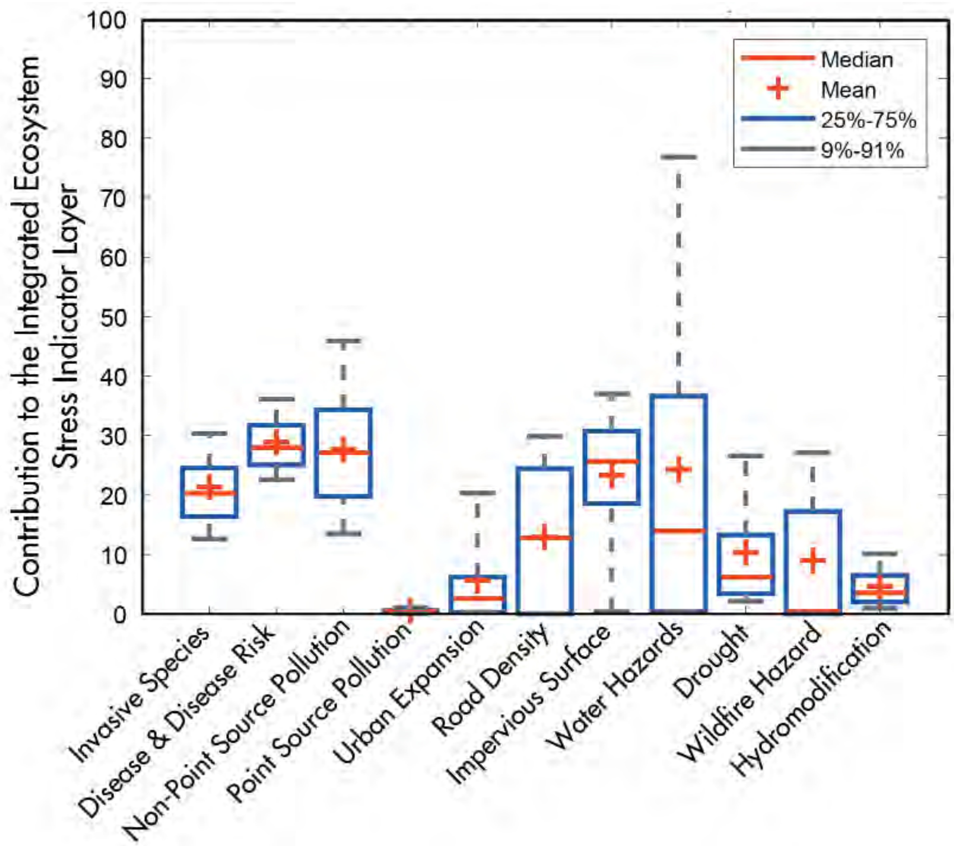


Figure B-33. Statistics of the percentage each Ecosystem Stress Indicator is making to the Integrated Ecosystem Stress Indicator layer.

The Integrated Ecosystem Stress Indicator layer was assessed to identify the major contributing Ecosystem Stress Indicators, i.e., the individual Ecosystem Stress Indicator that contributed the highest fraction of 'combined ecosystem stress' within grid cells (Figure B-34). Non-Point Source Pollution, Road Density, and Impervious Surface Ecosystem Stress Indicators had the highest percentage of grid cells in which they were the sole or shared maximum contributor to the Integrated Ecosystem Stress Indicator layer, whereas Invasive Species, Disease, Urban Expansion, Drought, and Hydromodification Ecosystem Stress Indicators had the lowest percentage of grid cells in which they were the sole or shared maximum contributor. Point Source Pollution and Hydromodification Ecosystem Stress Indicators had the fewest grid cells in which they were the maximum contributor (a single grid cell and 111 cells out of 375260 total cells, respectively). Throughout most of the region, between 1-3 stressors contribute or co-contribute the maximum fraction of the Integrated Ecosystem Stress Indicator layer (Figure B-35). Water

Hazards, Impervious Surface, and Non-Point Source Pollution were the Ecosystem Stress Indicators contributing the most to the Integrated Ecosystem Stress Indicator layer in cases of a sole maximum contributor (

Figure B-34, Figure B-36). The Water Hazard Ecosystem Stress Indicator is the sole maximum contributor to the Integrated Ecosystem Stress Indicator layer in the nearshore band along the coast. In the case of multiple Ecosystem Stress Indicators co-contributing the maximum percentage to the Integrated Ecosystem Stress Indicator layer, the most common groupings were Impervious Surface and Non-Point Source Pollution; Impervious Surface, Road Density, and Point Source Pollution; and Impervious Surface and Road Density (Figure B-37). In cases where multiple Ecosystem Stress Indicators are contributing the same maximum fraction to the Integrated Ecosystem Stress Indicator layer, it is virtually always because both indicators have reached their maximum value of 100.

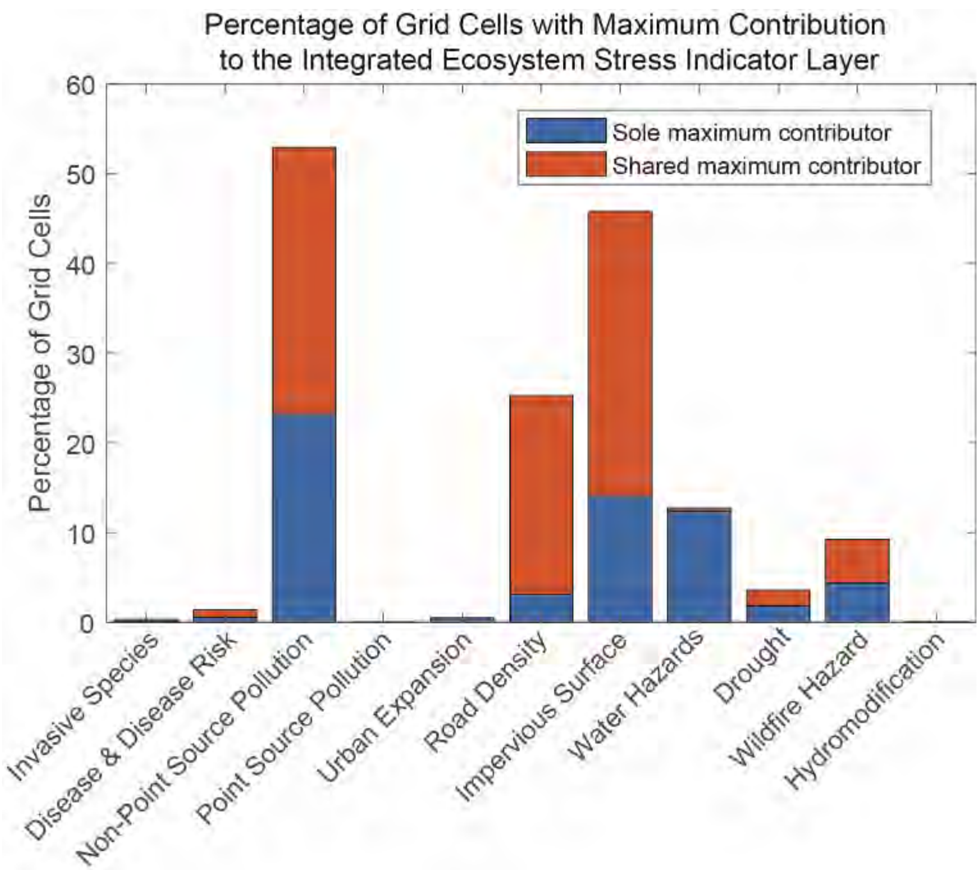
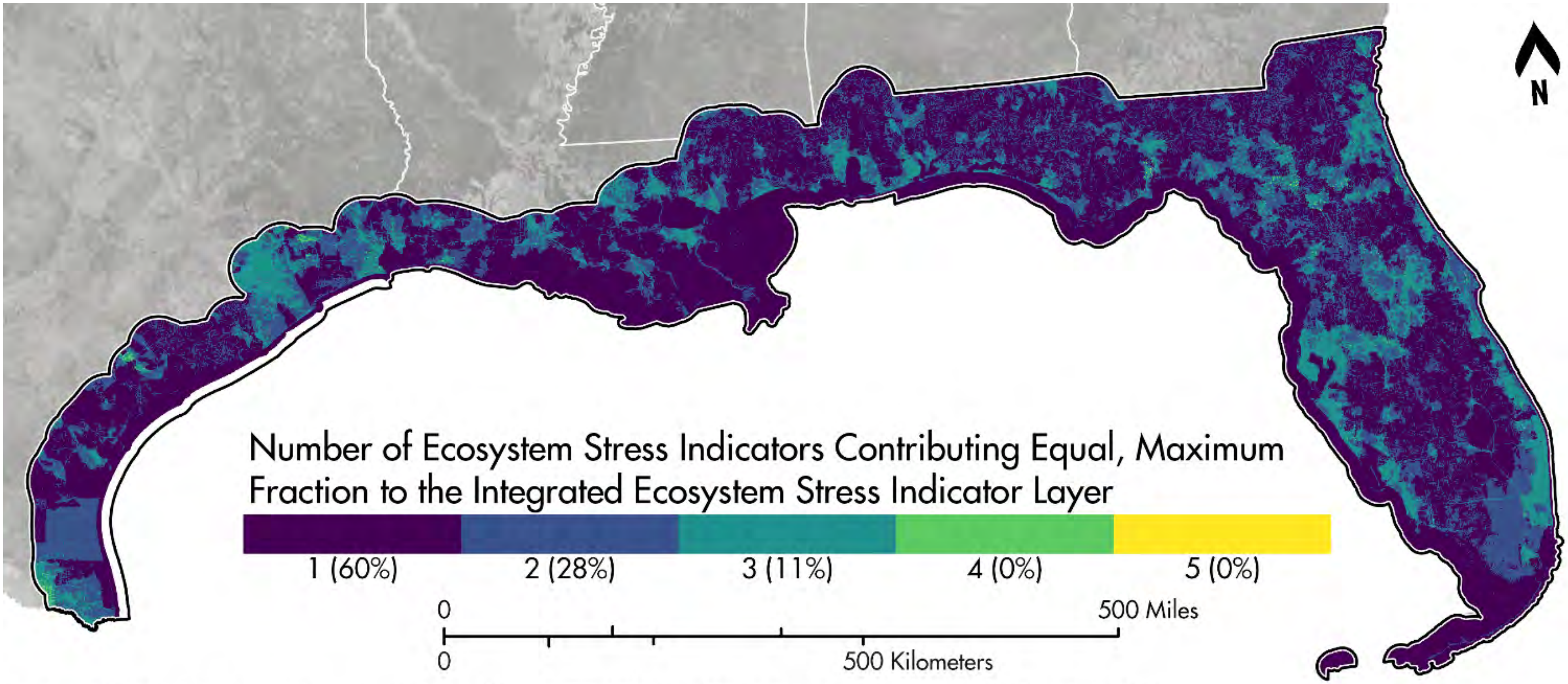
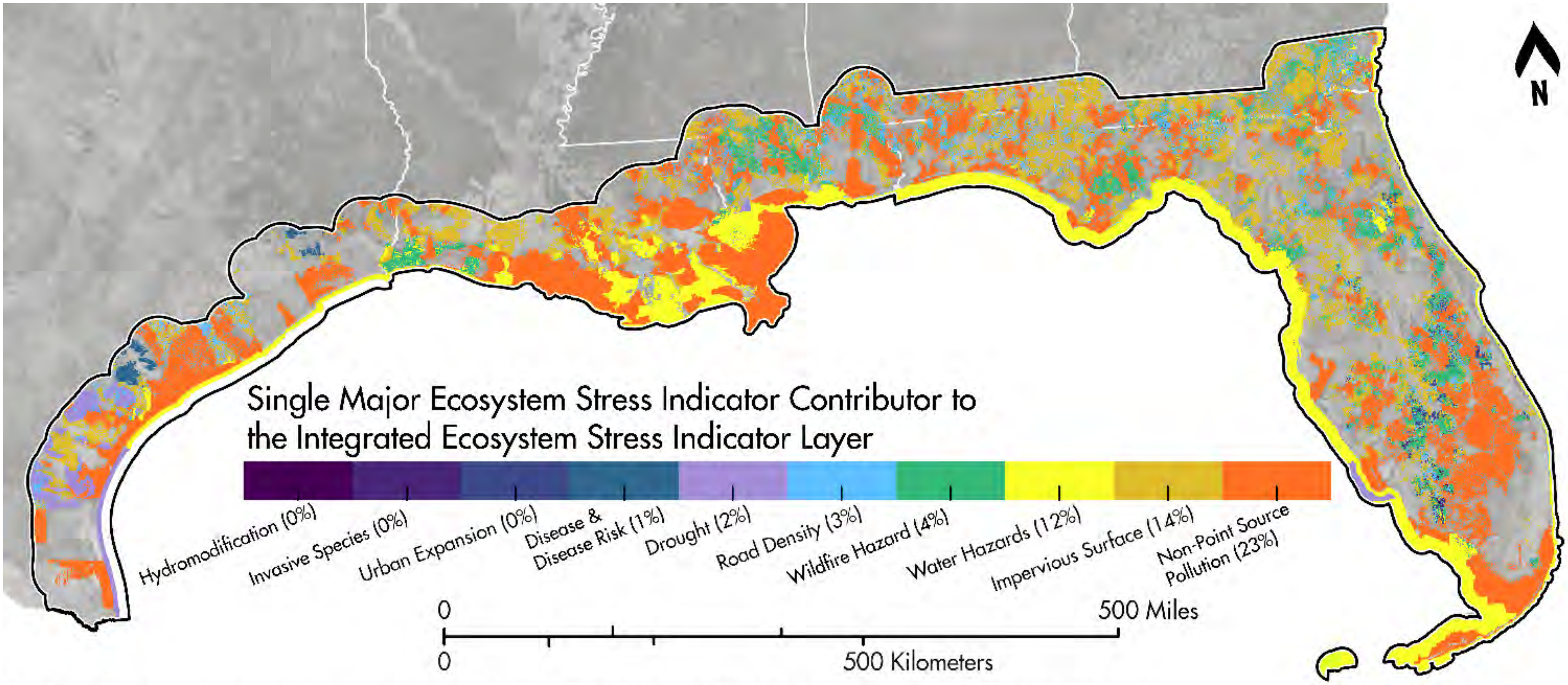


Figure B-34. Distribution of the percentage of 1-km grid cells in which each Ecosystem Stress Indicator makes the maximum contribution to the Integrated Ecosystem Stress Indicator layer.



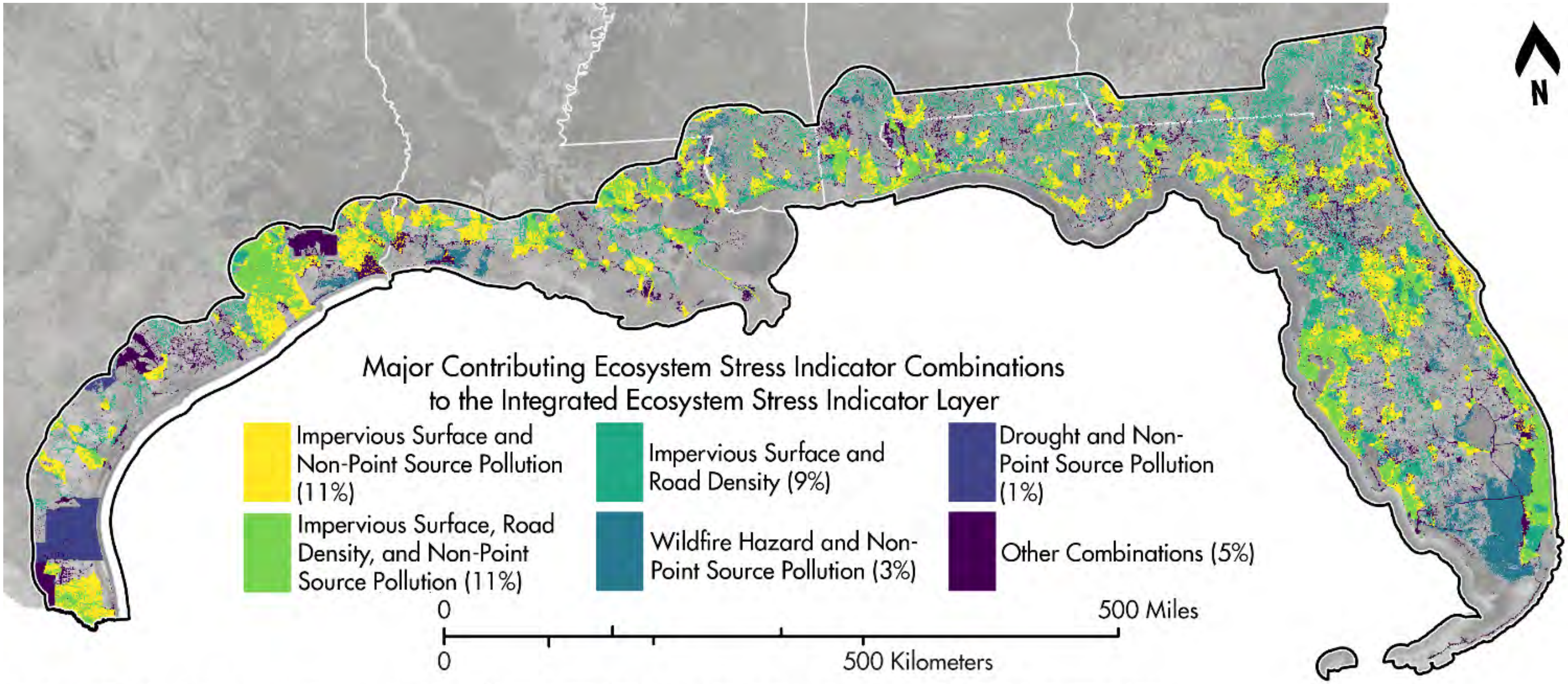
Data Source: CPRA, DataBasin, Esri, Florida Cooperative Land Cover, LANDFIRE, MRLC, NOAA, Texas A&M, The Nature Conservancy, USDA, USEPA, USFS, USFWS, USGS

Figure B-35. Number of Ecosystem Stress Indicators that share the maximum contribution to the Integrated Ecosystem Stress Indicator layer. If two Ecosystem Stress Indicators are both contributing 100 to the Integrated Ecosystem Stress Indicator layer and the other indicators are contributing less than 100, the value shown here would be 2.



Data Source: CPRA, DataBasin, Esri, Florida Cooperative Land Cover, LANDFIRE, MRLC, NOAA, Texas A&M, The Nature Conservancy, USDA, USEPA, USFS, USFWS, USGS

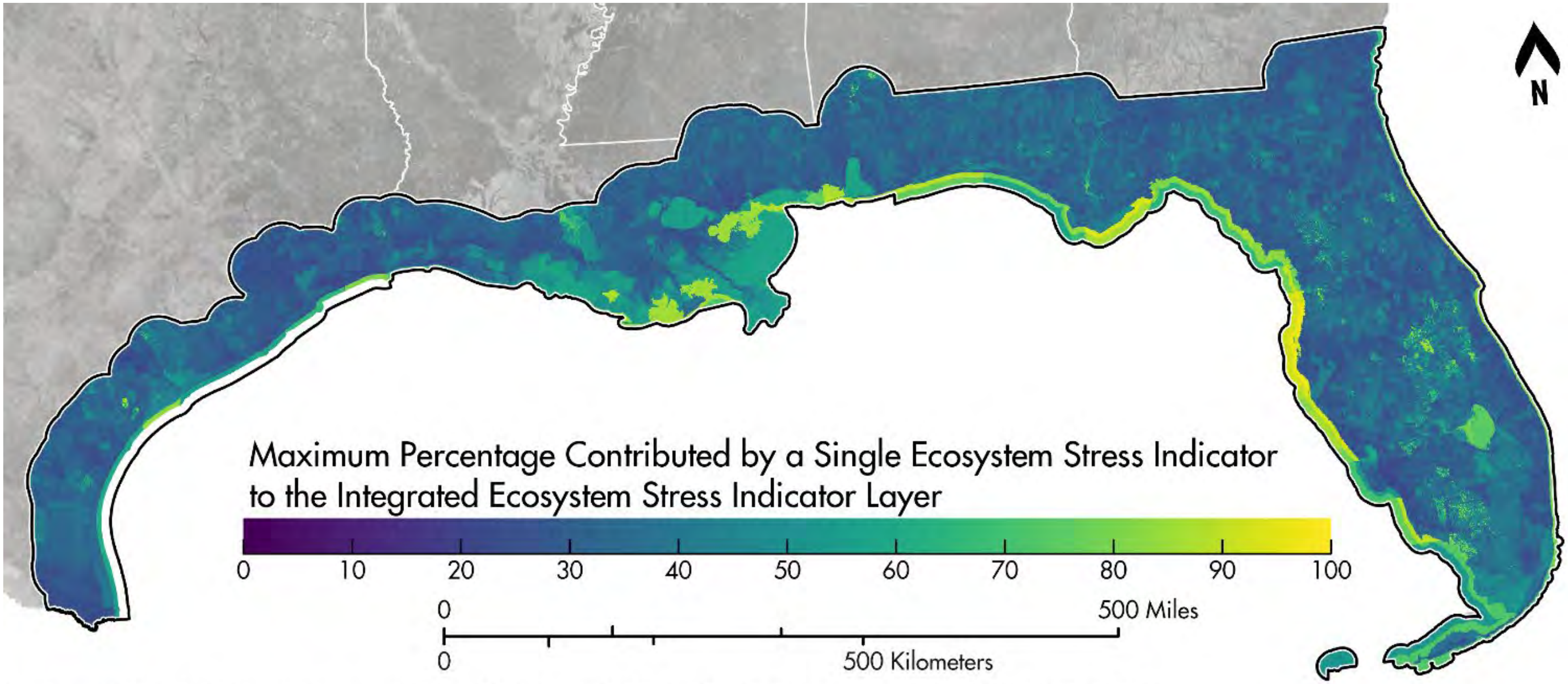
Figure B-36. Sole maximum Ecosystem Stress Indicator contributors to the Integrated Ecosystem Stress Indicator layer. Data represents that a given Ecosystem Stress Indicator is contributing more to the Integrated Ecosystem Stress Indicator layer than any other Ecosystem Stress Indicator.



Data Source: CPRA, DataBasin, Esri, Florida Cooperative Land Cover, LANDFIRE, MRLC, NOAA, Texas A&M, The Nature Conservancy, USDA, USEPA, USFS, USFWS, USGS

Figure B-37. Shared maximum contributors to the combined ecological stress layer. The stressors within each group are contributing the same percentage of the combined layer, which is greater than the percentage of any other stressors.

Consistent with the evaluation of individual Ecosystem Stress Indicator contributions to the Integrated Ecosystem Stress Indicator layer (Figure B-33), the percent contribution of the indicator contributing the most tended to be less than 50% in most cases (Figure B-38). This finding suggests that no single Ecosystem Stress Indicator is dominating the Integrated Ecosystem Stress Indicator layer. The exception was the nearshore coastal band, where the Water Hazards Ecosystem Stress Indicator is dominant because, as previously noted, the terrestrial stressors evaluated in the current study do not generally impact marine areas. This result is also apparent when looking at the distribution of unweighted sum values when each of the Ecosystem Stress Indicators is contributing or co-contributing the maximum fraction of the Integrated Ecosystem Stress Indicator layer (Figure B-39). The overall distribution of values for the Integrated Ecosystem Stress Indicator layer does not vary depending on what indicator(s) are contributing the highest fraction of the unweighted sum, with three exceptions. The Point-Source Pollution Ecosystem Stress Indicator only contributes the highest percentage to the Integrated Ecosystem Stress Indicator layer in one grid cell out of the 375,260 total. It should be noted, however, point-source pollution sources only influence the Indicator layer for 5km from their location. The actual distance over which a point-source pollution source can influence habitat and species is larger than that in some cases. However, there was not enough data to support varying the radius of potential influence for individual point-source pollution sources. Because the Water Hazards Ecosystem Stress Indicator layer dominates in a band along the coast where the terrestrial stress values are low or zero, the total combined ecosystem stress when this indicator is the major contributor tends to be lower than for other indicators. Lastly, the Hydromodification Ecosystem Stress Indicator, a watershed-scale indicator that scores cells that are both aquatic and terrestrial, tended to be the major contributor to the Integrated Ecosystem Stress Indicator layer in areas where the overall combined ecosystem stress was low (e.g., some inland areas). Further analysis is needed to tease apart the correlations between the Hydromodification Ecosystem Stress Indicator and other indicators in inland areas; currently the data suggests that this indicator only becomes dominant in the absence of other indicators.



Data Source: CPRA, DataBasin, Esri, Florida Cooperative Land Cover, LANDFIRE, MRLC, NOAA, Texas A&M, The Nature Conservancy, USDA, USEPA, USFS, USFWS, USGS

Figure B-38. Maximum percentage of the Integrated Ecosystem Stress Indicator layer contributed by any single Ecosystem Stress Indicator.

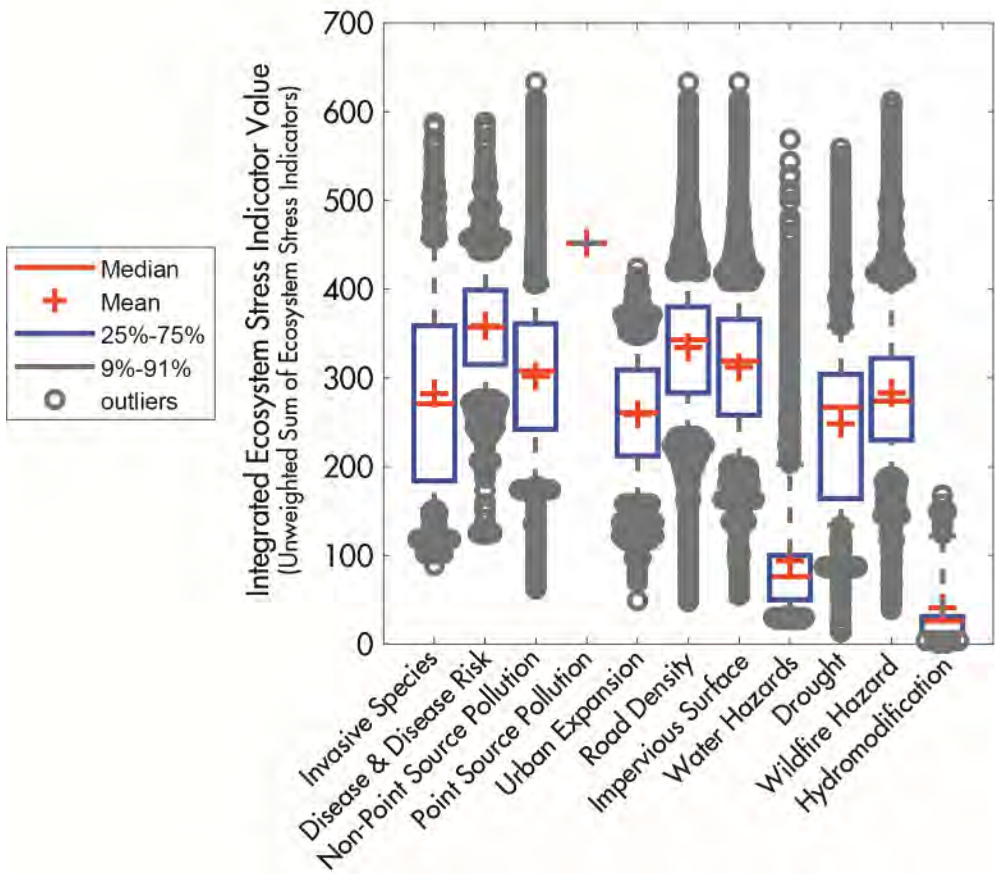


Figure B-39. Statistics of the Integrated Ecosystem Stress Indicator layer when a given Ecosystem Stress Indicator contributed or co-contributed the maximum fraction to the unweighted sum. Point-Source Pollution only contributed the maximum percentage to the Integrated Ecosystem Stress Indicator layer at one location (point) within the project area.

The next analysis applied to the Ecosystem Stress Indicators was to evaluate the correlation between the indicators (Figure B-40). The highest correlation between individual Ecosystem Stress Indicators was between Road Density and Impervious Surface. This reflects that both indicators occur in populated areas and that roads themselves are part of the impervious surface layer. The Hydromodification Ecosystem Stress Indicator layer was also well correlated to both Road Density and Impervious Surface. This result is unsurprising given that roads are factors considered directly in the Hydromodification Indicator. In addition, high intensity land use is included in the Hydromodification Indicator, with populated areas having higher road density and coverage of impervious surface. The Integrated Ecosystem Stress Indicator layer had the highest correlation with Road Density and Impervious Surface Ecosystem Stress Indicators. Negative correlation was found between Water Hazards and the Road Density, Impervious Surface, and Hydromodification Ecosystem Stress Indicators because of the presence of nearshore and unpopulated coastal areas (i.e., wetlands) within the region.

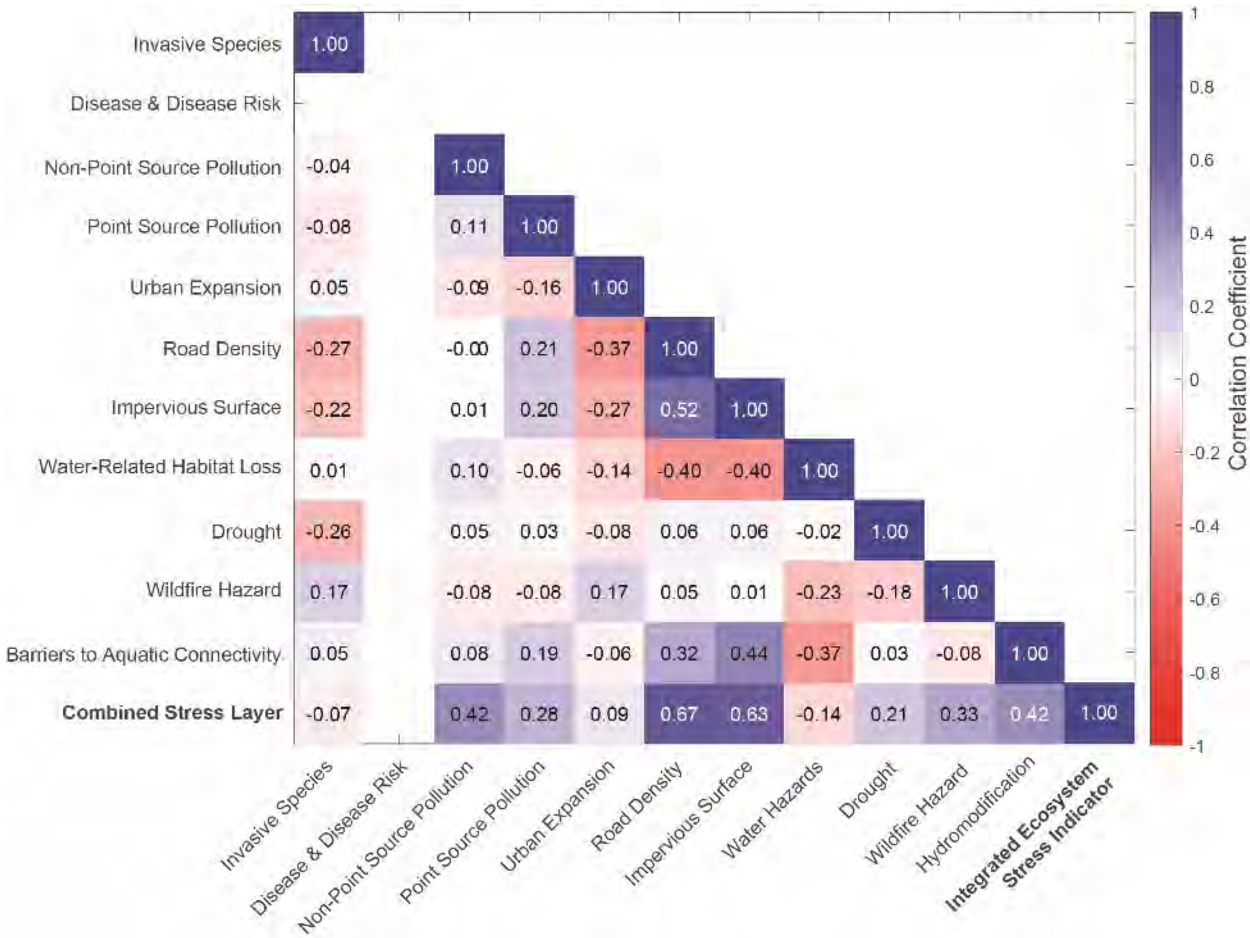


Figure B-40. Correlation between each of the individual Ecosystem Stress Indicators and to the Integrated Ecosystem Stress Indicator layer. Integrated ecosystem stress was calculated as the unweighted sum of the individual Ecosystem Stress Indicators. Disease is a presence only metric (i.e., value of 100 if disease is present) and could not be correlated with the other stressors.

As a final analysis of the Ecosystem Stress Indicators and Integrated Ecosystem Stress Indicator layer, the relative combination of “future stressors” (i.e., the Water Hazards Ecosystem Stress Indicator, which includes the influence of relative sea level rise; and the Urban Expansion Ecosystem Stress Indicator, which projects areas at risk of future urbanization) was evaluated. These indicators were isolated for analysis because they reflect a snapshot of ecosystem stress both currently and anticipated into the future to the associated habitats, whereas Ecosystem Stress Indicators such as Road Density, Drought, etc. reflect stress that is currently impacting an area. For this evaluation, the Integrated Ecosystem Stress Indicator layer was normalized by the maximum unweighted sum to rescale from 0-1. A normalized Integrated Ecosystem Stress Indicator layer was then calculated similarly but excluding the contribution of the Water Hazards and Urban Expansion Ecosystem Stress Indicator layers (i.e., a normalized Integrated Ecosystem Stress Indicator layer was generated by first taking the unweighted sum of all indicators excluding the Water Hazard and Urban Expansion indicators, then normalizing by the maximum value in that unweighted sum). The Integrated Ecosystem Stress Indicator layer excluding the future stressors was then divided by the Integrated Ecosystem Stress Indicator layer including all Ecosystem Stress Indicators (Figure B-41). Consistent with the influence of relative sea level rise, the future stressors contributed the highest fraction of the Integrated Ecosystem Stress Indicator layer along the coast. This evaluation indicates that these areas are those likeliest to be on a trajectory of increasing ecosystem stress over time, whereas combined stress in other areas is likely to be more stable over time.

To summarize, statistical analysis was conducted to test the sensitivity of the Integrated Ecosystem Stress Indicator layer to the individual Ecosystem Stress Indicators used in its creation and to determine if any unexpected results suggested potential issues with the Indicator calculation methodologies and identified thresholds. Observed correlations between individual Indicators were consistent with understanding of land use and did not suggest potential issues with the Indicator calculation methodology (for example, Road Density, Impervious Surface, and Hydromodifications were well-correlated, reflecting the tendency of roads and paved surfaces to be co-located with modified hydrologic connectivity). The indicators that tended to have the highest values where present and that contributed the most to the Integrated Ecosystem Stress Indicator layer were consistent with expectations. Namely, Invasive Species, Non-Point Source Pollution, and Impervious Surface Ecosystem Stress Indicators had the highest values where they were present and contributed the highest percentage of the Integrated Ecosystem Stress Indicator layer. Invasive Species has a high average value because it is presence only (i.e., always equal to 100); however, Non-Point Source Pollution and Impervious Surface Indicators are widespread throughout the region and contribution to Integrated Ecosystem Stress is expected to be high.

Similarly, a high degree of variability was found in Ecosystem Stress Indicators where wide range is be expected. Namely, Road Density and Water Hazards had the greatest variability and range of contribution to the Integrated value, reflecting differences between rural and urban areas (for Road Density) and variability between coastal and inland areas (for Water Hazards). Road Density, Impervious Surface, and Non-Point Source Pollution contributed the most to the Integrated Ecosystem Stress layer over the largest proportion of the project area, reflecting the prevalence of urban and agricultural land. Similarly, Water Hazards tended to dominate along the coast, as would be expected given relative sea level rise and that the other Ecosystem Stress Indicators used in this analysis were terrestrially focused. However, no single Ecosystem Stress Indicator was dominant across the entire landscape, suggesting that reasonably high thresholds were selected (i.e., no threshold was set so low that an Ecosystem Stress Indicator “maxed out” over widespread regions). Conversely, Point Source Pollution, Urban Expansion, Drought, Wildfire Hazard, and Hydromodification Ecosystem Stress Indicators tended to have lower values and contribute less to the Integrated Ecosystem Stress. Because thresholding is required to calculate these Ecosystem Stress Indicators, low contribution may reflect that a lower threshold should be used and/or that the calculation methodology could be refined. However, additional analysis would be required to differentiate between necessary improvements to the calculation methods and the potential that some of these Ecosystem Stress Indicators may not be major, widespread contributors within the Gulf of Mexico region.

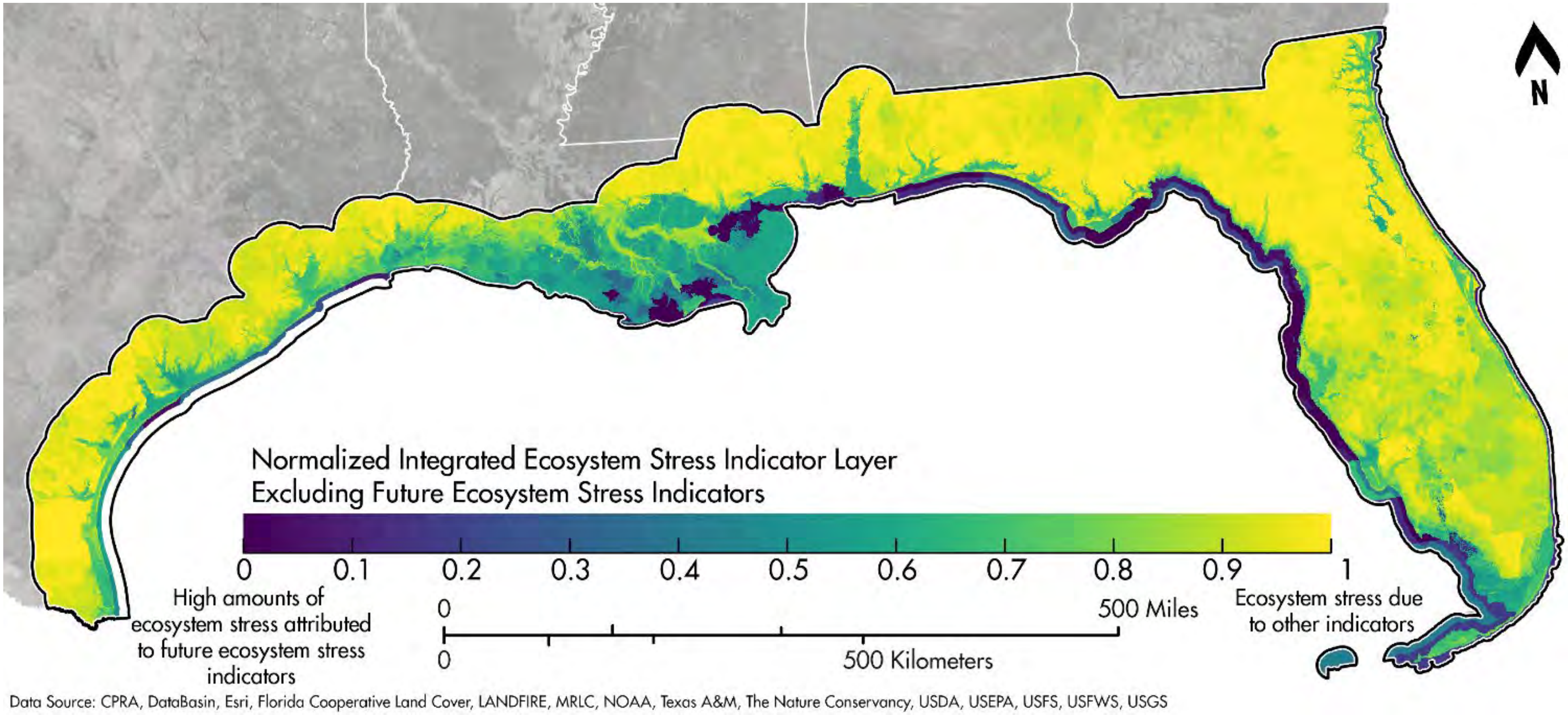


Figure B-41. Ratio of the Integrated Ecosystem Stress Indicator layer excluding future Ecosystem Stress Indicators to the Integrated Ecosystem Stress Indicator layer including all indicators. The ratio was calculated by dividing the Integrated Ecosystem Stress Indicator layer including all indicators by the Integrated Ecosystem Stress Indicator layer excluding future indicators (Water Hazards and Urban Expansion). A value approaching zero indicates that much of the ecosystem stress in an area in the Integrated Ecosystem Stress Indicator is coming from anticipated future ecosystem stress indicators, whereas a value approaching one indicates Integrated Ecosystem Stress is predominantly attributed to indicators that are currently impacting an area. The band along the cost where this ratio is low is indicative of areas that are frequently submerged under current conditions. In these areas, the dominance of the Water Hazards stressor may also occur because most of the other Stress Indicators are terrestrial in nature and will have low values in water or very low-lying coastal areas.

NEXT STEPS AND FUTURE WORK

- Use the upcoming USACE coastal hazards modeling product to better represent the potential threat of sea level rise, storm surge, and hazardous storms to Gulf of Mexico coastal areas. Anticipated release: 2021. Will replace the current Water Hazards Ecosystem Stress Indicator that currently includes static sea level rise and FEMA floodplain designation
- Stakeholder engagement with land managers and project planners to refine this list of Ecosystem Stress Indicators to those that are most impactful across a range of project types in the Gulf of Mexico coastal region
- Engage subject matter experts to develop region-specific and habitat-specific thresholds for each Ecosystem Stress Indicator

REFERENCES

Acreman, M., Dobel, A., & François, E. (2020). *Wetlands report card 2020* (p. 10). UKRI Natural Environment Research Council.

Adams, S., Ryon, M., & Smith, J. (2005). Recovery in diversity of fish and invertebrate communities following remediation of a polluted stream: Investigating causal relationships. *Hydrobiologia*, *542*, 77–93.

Alabama Department of Conservation and Natural Resources. (2015). *Alabama's Wildlife Action Plan, 2015-2025*. Alabama Department of Conservation and Natural Resources Division of Wildlife and Freshwater Fisheries.

Alexander, H. D., & Dunton, K. H. (2002). Freshwater inundation effects on emergent vegetation of a hypersaline salt marsh. *Estuaries and Coasts*, *25*(6B), 1426–1435.

Alves, D. M. C. C., Terribile, L. C., & Brito, D. (2014). The Potential Impact of White-Nose Syndrome on the Conservation Status of North American Bats. *PLOS ONE*, *9*(9), e107395.

America's Watershed Initiative. (2015). *Mississippi River Watershed Report Card* (p. 8). America's Watershed Initiative.

Anandhi, A., Crandall, C., & Bentley, C. (2018). Hydrologic Characteristics of Streamflow in the Southeast Atlantic and Gulf Coast Hydrologic Region during 1939–2016 and Conceptual Map of Potential Impacts. *Hydrology*, *5*(3), 42.

Arnold, C. L., & Gibbons, C. J. (1996). Impervious Surface Coverage: The Emergence of a Key Environmental Indicator. *Journal of the American Planning Association*, *62*(2), 243–258.

Backhaus, S., Kreyling, J., Grant, K., Beierkuhnlein, C., Walter, J., & Jentsch, A. (2014). Recurrent Mild Drought Events Increase Resistance Toward Extreme Drought Stress. *Ecosystems*, *17*(6), 1068–1081.

Baker, B. H., Czarnecki, J. M. P., Omer, A. R., Aldridge, C. A., Kröger, R., & Prevost, J. D. (2018). Nutrient and sediment runoff from agricultural landscapes with varying suites of conservation practices in the Mississippi Alluvial Valley. *Journal of Soil and Water Conservation*, *73*(1), 75–85.

Barnett, Z. C., Adams, S. B., Ochs, C. A., & Garrick, R. C. (2020). Crayfish populations genetically fragmented in streams impounded for 36–104 years. *Freshwater Biology*, *65*(4), 768–785.

Bechtold, T., Havlick, D., & Stockmann, K. (1996). Analysis of Road Densities in Selected Grizzly Bear Management Units in the Northern Rockies. *ESRI Proceedings of User Conference*.

Bellwood, D. R., Hughes, T. P., Folke, C., & Nystrom, M. (2004). Confronting the coral reef crisis. *Nature*, *429*, 827–833.

Belyea, C., & Terando, A. (2013a). Urban Growth Modeling for the SAMBI Designing Sustainable Landscapes Project.

Belyea, C., & Terando, A. (2013b, July). Urban Growth Modeling for the SAMBI Designing Sustainable Landscapes Project.

Bennett, V. J. (2017). Effects of Road Density and Pattern on the Conservation of Species and Biodiversity. *Current Landscape Ecology Reports*, *2*(1), 1–11.

Berry, P., Broadmeadow, M., & Morecroft, M. (2020). *Woodlands report card 2020* (p. 13). UKRI Natural Environment Research Council.

Bowman, D. M. J. S., Balch, J. K., Artaxo, P., Bond, W. J., Carlson, J. M., Cochrane, M. A., D'Antonio, C. M., DeFries, R. S., Doyle, J. C., Harrison, S. P., Johnston, F. H., Keeley, J. E., Krawchuk, M. A., Kull, C. A., Marston, J. B., Moritz, M. A., Prentice, I. C., Roos, C. I., Scott, A. C., Swetnam, T. W., van der Werf, G. R., & Pyne, S. J. (2009). Fire in the Earth System. *Science*, *324*(5926), 481–484.

Brown, C., Andrews, K., Brenner, J., Tunnell, J., Canfield, C., Dorsett, C., Driscoll, M., Johnson, E., & Kaderka, S. (2011). *Strategy for Restoring the Gulf of Mexico (A cooperative NGO report)* (p. 23). Arlington, VA: The Nature Conservancy.

Candau, J., Rasmussen, S., & Clarke, K. (2000). A coupled cellular automaton model for land use/land cover dynamics.

Carruthers, T., Beckert, K., Dennison, B., Thomas, J., Saxby, T., Williams, M., Fisher, T., Kumer, J., Schupp, C., Sturgis, B., & Zimmerman, C. (2011). *Assateague Island National Seashore natural resource condition assessment: Maryland, Virginia* (No. 2011/405). Fort Collins, Colorado: National Park Service.

Carruthers, T., Carter, S., Florkowski, L., Runde, J., & Dennison, W. (2009). *Rock Creek Park natural resource condition assessment, National Capital Region Network* (Natural Resource Report NPS/NCRN/NRR No. 2009/109) (p. 79). Fort Collins, Colorado: National Park Service.

Carruthers, T., Hemmerling, S., Barra, M., Saxby, T., & Moss, L. (2017). *"This is your shield… this is your estuary." Building community and coastal resilience to a changing Louisiana coastline through restoration of key ecosystem functions.* (No. WISR-002-2017) (p. 48). The Water Institute of the Gulf.

Cederholm, C., Reid, L., & Salo, E. (1981). *Cumulative effects of logging road sediment on salmonid populations in the Clearwater River, Jefferson County, Washington* (State of Washington Water Research Centre Report) (pp. 38–74). Pullman, Washington.

CERP. (2019). *2019 Everglades System Status Report: Assessment period of 2012-2017* (p. 175). Comprehensive Everglades Restoration Plan (CERP) REstoration COordination and VERification (RECOVER) program.

Chaudhuri, G., & Clarke, K. C. (2014). Temporal Accuracy in Urban Growth Forecasting: A Study Using the SLEUTH Model: Temporal Accuracy in Urban Growth Forecasting: A Study Using the SLEUTH Model. *Transactions in GIS*, *18*(2), 302–320.

Chen, Q., & Liu, J. (2014). Development process and perspective on ecological risk assessment. *Acta Ecologica Sinica*, *34*(5), 239–245.

Chiari, Y., Glaberman, S., & Elmore, J. (2017). Widespread Occurrence of <i>Batrachochytrium dendrobatidis<i/> in Southern Alabama, USA. *Herpetological Review*, *48*(2), 356–359.

Chuvieco, E., Martínez, S., Román, M. V., Hantson, S., & Pettinari, M. L. (2014). Integration of ecological and socio-economic factors to assess global vulnerability to wildfire: Assessment of global wildfire vulnerability. *Global Ecology and Biogeography*, *23*(2), 245–258.

Clark, J. S., Iverson, L., Woodall, C. W., Allen, C. D., Bell, D. M., Bragg, D. C., D'Amato, A. W., Davis, F. W., Hersh, M. H., Ibanez, I., Jackson, S. T., Matthews, S., Pederson, N., Peters, M., Schwartz, M. W., Waring, K. M., & Zimmermann, N. E. (2016). The impacts of increasing drought on forest dynamics, structure, and biodiversity in the United States. *Global Change Biology*, *22*(7), 2329–2352.

Clarke, K. C., & Johnson, J. M. (2020). Calibrating SLEUTH with big data: Projecting California's land use to 2100. *Computers, Environment and Urban Systems*, *83*, 101525.

Clements, W. H., & Rohr, J. R. (2009). Community responses to contaminants: Using basic ecological principles to predict ecotoxicological effects. *Environmental Toxicology and Chemistry*, *28*(9), 1789–1800.

Cobb, R. C., Ruthrof, K. X., Breshears, D. D., Lloret, F., Aakala, T., Adams, H. D., Anderegg, W. R. L., Ewers, B. E., Galiano, L., Grünzweig, J. M., Hartmann, H., Huang, C., Klein, T., Kunert, N., Kitzberger, T., Landhäusser, S. M., Levick, S., Preisler, Y., Suarez, M. L., Trotsiuk, V., & Zeppel, M. J. B. (2017). Ecosystem dynamics and management after forest die-off: a global synthesis with conceptual state-and-transition models. *Ecosphere*, *8*(12), e02034.

Cohen, J. M., McMahon, T. A., Ramsay, C., Roznik, E. A., Sauer, E. L., Bessler, S., Civitello, D. J., Delius, B. K., Halstead, N., Knutie, S. A., Nguyen, K. H., Ortega, N., Sears, B., Venesky, M. D., Young, S., & Rohr, J. R. (2019). Impacts of thermal mismatches on chytrid fungus *Batrachochytrium dendrobatidis* prevalence are moderated by life stage, body size, elevation and latitude. *Ecology Letters*, *22*(5), 817–825.

Coles, J., McMahon, G., Bell, A., Brown, L., Fitzpatrick, F., Scudder Eikenberry, B., Woodside, M., Cuffney, T., Bryant, W., Cappiella, K., Fraley-McNieal, L., & Stack, W. (2012). *Effects of urban development on stream ecosystems in nine metropolitan study areas across the United States* (US Geological Survey Circular No. 1373) (p. 138).

Collins, S., & Xia, Y. (2015). Long-Term Dynamics and Hotspots of Change in a Desert Grassland Plant Community. *The American Naturalist*, *185*, E30–E43.

Conway, T. M. (2007). Impervious surface as an indicator of pH and specific conductance in the urbanizing coastal zone of New Jersey, USA. *Journal of Environmental Management*, *85*(2), 308–316.

Cook, E. R., Seager, R., Cane, M. A., & Stahle, D. W. (2007). North American drought: Reconstructions, causes, and consequences. *Earth-Science Reviews*, *81*(1–2), 93–134.

Cooke, S. C., Balmford, A., Johnston, A., Newson, S. E., & Donald, P. F. (2020). Variation in abundances of common bird species associated with roads. *Journal of Applied Ecology*, *57*(7), 1271–1282.

Costanzo, S., Kelsey, H., & Saxby, T. (2015). *Willamette River Report Card: Scores and Scoring Methodology*. University of Maryland Center for Environmental Scinece Integration and Application Network.

Day, J. W., Britsch, L. D., Hawes, S. R., Shaffer, G. P., Reed, D. J., & Cahoon, D. (2000). Pattern and process of land loss in the Mississippi Delta: A spatial and temporal analysis of wetland habitat change. *Estuaries*, *23*(4), 425.

Day, J. W., Kemp, G. P., Reed, D. J., Cahoon, D. R., Boumans, R. M., Suhayda, J. M., & Gambrell, R. (2011). Vegetation death and rapid loss of surface elevation in two contrasting Mississippi delta salt marshes: The role of sedimentation, autocompaction and sea-level rise. *Ecological Engineering*, *37*(2), 229–240.

Dillon, G., Menakis, J., & Fay, F. (2015). Wildland Fire Potential: A Tool for Assessing Wildfire Risk and Fuels Management Needs. In *Proceedings of the large wildland fires conference; May 19-23, 2014; Missoula, MT.* (pp. 60–76). Fort Collins, Colorado: US Department of Agriculture, Forest Service, Rocky Mountain Research Station.

Dobel, A., May, L., Gunn, I., Spears, B., & François, E. (2020a). *Lakes and reservoirs report card 2020* (p. 15). UKRI Natural Environment Research Council.

Dobel, A., O'Hare, M., Gunn, I., & François, E. (2020b). *Streams and rivers report card 2020* (p. 16). UKRI Natural Environment Research Council.

Duchardt, C. J., Augustine, D. J., & Beck, J. L. (2020). Anthropogenic and Natural Disturbance Differentially Affect Sagebrush Bird Habitat Use. *The Journal of Wildlife Management*, *84*(7), 1361–1372.

Dueñas, M., Hemming, D., Roberts, A., & Diaz-Soltero, H. (2021). The threat of invasive species to IUCN-listed critically endangered species: A systematic review. *Global Ecology and Conservation*, (e01476).

Florida Fish and Wildlife Conservation Commission (FWC). (2019). *Florida's Wildlife Legacy Initiative: Florida's State Wildlife Action Plan* (p. 254). Tallahassee, Florida.

Foley, J. A. (2005). Global Consequences of Land Use. *Science*, *309*(5734), 570–574.

Gillespie, B. R., Desmet, S., Kay, P., Tillotson, M. R., & Brown, L. E. (2015). A critical analysis of regulated river ecosystem responses to managed environmental flows from reservoirs. *Freshwater Biology*, *60*(2), 410–425.

Glorioso, B., Waddle, J., & Richards-Zawacki, C. (2017). Prevalence of <i>Batrachochytrium dendrobatidis<i/> and <i>B. salamandrivorans<i/> in the Gulf Coast Waterdog, <i>Necturus beyeri<i/>, from Southeast Louisiana, USA. *Herpetological Review*, *48*(2), 360–363.

Golladay, S. W., Gagnon, P., Kearns, M., Battle, J. M., & Hicks, D. W. (2004). Response of freshwater mussel assemblages (Bivalvia:Unionidae) to a record drought in the Gulf Coastal Plain of southwestern Georgia. *Journal of the North American Benthological Society*, *23*(3), 494–506.

Gunderson, L. H. (2000). Ecological resilience - In theory and application. *Annual Review of Ecology and Systematics*, *31*, 425–439.
Hak, J. C., & Comer, P. J. (2017). Modeling landscape condition for biodiversity assessment—Application in temperate North America. *Ecological Indicators*, *82*, 206–216.
Hallac, D. E., Sadle, J., Pearlstine, L., Herling, F., & Shinde, D. (2012). Boating impacts to seagrass in Florida Bay, Everglades National Park, Florida, USA: links with physical and visitor-use factors and implications for management. *Marine and Freshwater Research*, *63*(11), 1117.
Harrison, S. P., Marlon, J. R., & Bartlein, P. J. (2010). Fire in the Earth System. In J. Dodson (Ed.), *Changing Climates, Earth Systems and Society* (pp. 21–48). Dordrecht: Springer Netherlands.
Harte Research Institute for Gulf of Mexico Studies. (2019). *Texas Coast Expanded Report Card 2019* (p. 7). Harte Research Institute for Gulf of Mexico Studies.
Harwell, M. A., Gentile, J. H., McKinney, L. D., Tunnell, J. W., Dennison, W. C., Kelsey, R. H., Stanzel, K. M., Stunz, G. W., Withers, K., & Tunnell, J. (2019). Conceptual Framework for Assessing Ecosystem Health. *Integrated Environmental Assessment and Management*, *15*(4), 544–564.
Harwell, M., Gentile, J., McKinney, L., Tunnell Jr., J., Dennison, W., & Kelsey, R. (2016). *A New Framework for the Gulf of Mexico EcoHealth Metrics* (p. 26). Harte Research Institute for Gulf of Mexico Studies; University of Maryland Center for Environmental Scinece Integration and Application Network.
Haynes, R. W., Graham, R. T., & Quigley, T. M. (1996). *A Framework for Ecosystem Management In the Interior Columbia Basin And Portions of the Klamath and Great Basins* (No. PNW-GTR-374) (p. 75). US Forest Service and US Bureau of Land Management with assistance from the Pacific Northwest Forest Experiment Station.
Heilman, G. E., Strittholt, J. R., Slosser, N. C., & Dellasala, D. A. (2002). Forest Fragmentation of the Conterminous United States: Assessing Forest Intactness through Road Density and Spatial Characteristics: Forest fragmentation can be measured and monitored in a powerful new way by combining remote sensing, geographic information systems, and analytical software. *BioScience*, *52*(5), 411–422.
Heinsch, F. (2004). Carbon dioxide exchange in a high marsh on the Texas Gulf Coast: effects of freshwater availability. *Agricultural and Forest Meteorology*, *125*(1–2), 159–172.
Holcomb, S. R., Bass, A. A., Seymour, M. A., Lorenz, N. F., Gregory, B. B., Javed, S. M., & Balkum, K. F. (2015). *Louisiana Wildlife Action Plan* (No. LA WAP-October 2015). Baton Rouge. LA: Louisiana Department of Wildlife and Fisheries.
Holland, A. F., Sanger, D. M., Gawle, C. P., Lerberg, S. B., Santiago, M. S., Riekerk, G. H. M., Zimmerman, L. E., & Scott, G. I. (2004). Linkages between tidal creek ecosystems and the landscape and demographic attributes of their watersheds. *Journal of Experimental Marine Biology and Ecology*, *298*(2), 151–178.
Hoos, A., & Roland, V., II. (2019). *Spatially referenced models of streamflow and nitrogen, phosphorus, and suspended-sediment loads in the Southeastern United States* (Scientific Investigations Report No. 2019–5135) (p. 87). US Geological Survey.
Hough, W. A., & Albini, F. (1978). *Predicting Fire Behavior in Palmetto- Gallberry Fuel Complexes* (Research Paper No. SE-174) (p. 48). Asheville, North Carolina, USA: USDA, Forest Service, Southeastern Forest Experimentation Station.
IAN UMCES. (2019). *Everglades 2012-2017 Report Card* (p. 6). REstoration COordination and VERification (RESTORE), and the Integration and Application Network, University of Maryland Center for Environmental Science.
Integration and Application Network. (2015). *The Development Process and Methods for the Coastal Georgia Report Card* (p. 24). University of Maryland Center for Environmental Scinece Integration and Application Network.
Jantz, C. A., & Goetz, S. J. (2005). Analysis of scale dependencies in an urban land-use-change model. *International Journal of Geographical Information Science*, *19*(2), 217–241.

Jantz, C. A., Goetz, S. J., Donato, D., & Claggett, P. (2010). Designing and implementing a regional urban modeling system using the SLEUTH cellular urban model. *Computers, Environment and Urban Systems*, *34*(1), 1–16.

Johnson, L. R., Trammell, T. L. E., Bishop, T. J., Barth, J., Drzyzga, S., & Jantz, C. (2020). Squeezed from All Sides: Urbanization, Invasive Species, and Climate Change Threaten Riparian Forest Buffers. *Sustainability*, *12*(4), 1448.

Karnauskas, M., Kelble, C. R., Regan, S., Quenée, C., Allee, R., Jepson, M., Freitag, A., Craig, J. K., Carollo, C., Barbero, L., Hanisko, D., & Zapfe, G. (2017). *2017 Ecosystem status report update for the Gulf of Mexico* (NOAA Technical Memorandum No. NMFS-SEFSC-706) (p. 51). NOAA.

Kaufman, L. H. (1982). Stream aufwuchs accumulation: Disturbance frequency and stress resistance and resilience. *Oecologia*, *52*, 57–63.

Kiffney, P. M., & Clements, W. H. (1996). Effects of Metals on Stream Macroinvertebrate Assemblages from Different Altitudes. *Ecological Applications*, *6*(2), 472–481.

Kinney, E. L., Quigg, A., & Armitage, A. R. (2014). Acute Effects of Drought on Emergent and Aquatic Communities in a Brackish Marsh. *Estuaries and Coasts*, *37*(3), 636–645.

Kirkman, L. K., Golladay, S. W., Laclaire, L., & Sutter, R. (1999). Biodiversity in Southeastern, Seasonally Ponded, Isolated Wetlands: Management and Policy Perspectives for Research and Conservation. *Journal of the North American Benthological Society*, *18*(4), 553–562.

Koch, E. W., Barbier, E. B., Silliman, B. R., Reed, D. J., Perillo, G. M., Hacker, S. D., Granek, E. F., Primavera, J. H., Muthiga, N., Polasky, S., Halpern, B. S., Kennedy, C. J., Kappel, C. V., & Wolanski, E. (2009). Non-linearity in ecosystem services: temporal and spatial variability in coastal protection. *Frontiers in Ecology and the Environment*, *7*(1), 29–37.

Koehnken, L., Rintoul, M. S., Goichot, M., Tickner, D., Loftus, A.-C., & Acreman, M. C. (2020). Impacts of riverine sand mining on freshwater ecosystems: A review of the scientific evidence and guidance for future research. *River Research and Applications*, *36*(3), 362–370.

Krawchuk, M. A., Moritz, M. A., Parisien, M.-A., Van Dorn, J., & Hayhoe, K. (2009). Global Pyrogeography: the Current and Future Distribution of Wildfire. *PLoS ONE*, *4*(4), e5102.

Krichbaum, R. S., & Horvath, M. A. (2001). *Influences of Roads in the Hells Canyon Complex Area on Wildlife and Botanical Species of Concern* (Technical Report No. Appendix E.3.2-43 Hells Canyon Complex FERC No. 1971) (p. 100). Idaho Power Company.

Krist, F. J. Jr., Ellenwood, J. R., Woods, M. E., McMahan, A. J., Cowardin, J. P., Ryerson, D. E., Sapio, F. J., Zweifler, M. O., & Romero, S. A. (2014). *2013-2027 National Insect and Disease Forest Risk Assessment* (No. FHTET-14-01) (p. 209). United States Department of Agriculture, United States Forest Service, Forest Health Technology Enterprise Team.

Krofcheck, D. J., Loudermilk, E. L., Hiers, J. K., Scheller, R. M., & Hurteau, M. D. (2019). The effects of management on long-term carbon stability in a southeastern US forest matrix under extreme fire weather. *Ecosphere*, *10*(3), e02631.

Labosier, C. F., Frauenfeld, O. W., Quiring, S. M., & Lafon, C. W. (2015). Weather type classification of wildfire ignitions in the central Gulf Coast, United States: WEATHER TYPE CLASSIFICATION OF WILDFIRE. *International Journal of Climatology*, *35*(9), 2620–2634.

Lamb, C. T., Mowat, G., Reid, A., Smit, L., Proctor, M., McLellan, B. N., Nielsen, S. E., & Boutin, S. (2018). Effects of habitat quality and access management on the density of a recovering grizzly bear population. *Journal of Applied Ecology*, *55*(3), 1406–1417.

LDEQ. (2007). Recommended Best Management Practices: Nonpoint source pollution sand & gravel mining industry. Louisiana Department of Environmental Quality, Concrete and Aggregates Association of Louisiana, Louisiana Geological Survey.

Lei, T., & Middleton, B. A. (2018). Repeated Drought Alters Resistance of Seed Bank Regeneration in Baldcypress Swamps of North America. *Ecosystems*, *21*(1), 190–201.

Liu, Z., He, C., & Wu, J. (2016). The Relationship between Habitat Loss and Fragmentation during Urbanization: An Empirical Evaluation from 16 World Cities. *PLOS ONE*, *11*(4), e0154613.

Longstaff, B. J., Nauman, E., & University of Maryland Center for Environmental Science. (2010). *Integrating and applying science: a practical handbook for effective coastal ecosystem assessment*. Cambridge, MD: IAN Press.

Lowe, M. R., & Peterson, M. S. (2014). Effects of Coastal Urbanization on Salt-Marsh Faunal Assemblages in the Northern Gulf of Mexico. *Marine and Coastal Fisheries*, *6*(1), 89–107.

Lussier, S. M., da Silva, S. N., Charpentier, M., Heltshe, J. F., Cormier, S. M., Klemm, D. J., Chintala, M., & Jayaraman, S. (2008). The influence of suburban land use on habitat and biotic integrity of coastal Rhode Island streams. *Environmental Monitoring and Assessment*, *139*(1–3), 119–136.

Mallin, M. A., Williams, K. E., Esham, E. C., & Lowe, R. P. (2000). Effects of human development on bacteriological water quality in coastal watersheds. *Ecological Applications*, *10*(4), 10.

Marcy, D., Brooks, W., Draganov, K., Hadley, B., Haynes, C., Herold, N., McCombs, J., Pendleton, M., Ryan, S., Schmid, K., Sutherland, M., & Waters, K. (2011). New Mapping Tool and Techniques for Visualizing Sea Level Rise and Coastal Flooding Impacts. In *Solutions to Coastal Disasters 2011* (pp. 474–490). Anchorage, Alaska, United States: American Society of Civil Engineers.

Marshall, T. L., Baca, C. R., Correa, D. T., Forstner, M. RJ., Hahn, D., & Rodriguez, D. (2019). Genetic characterization of chytrids isolated from larval amphibians collected in central and east Texas. *Fungal Ecology*, *39*, 55–62.

Matthews, W. J., & Marsh-Matthews, E. (2003). Effects of drought on fish across axes of space, time and ecological complexity: *Effects of drought on fish across axes of space, time and ecological complexity*. *Freshwater Biology*, *48*(7), 1232–1253.

Maxwell, J. T., Ortegren, J. T., Knapp, P. A., & Soulé, P. T. (2013). Tropical Cyclones and Drought Amelioration in the Gulf and Southeastern Coastal United States. *Journal of Climate*, *26*(21), 8440–8452.

McDonald, R. I., Mansur, A. V., Ascensão, F., Colbert, M., Crossman, K., Elmqvist, T., Gonzalez, A., Güneralp, B., Haase, D., Hamann, M., Hillel, O., Huang, K., Kahnt, B., Maddox, D., Pacheco, A., Pereira, H. M., Seto, K. C., Simkin, R., Walsh, B., Werner, A. S., & Ziter, C. (2020). Research gaps in knowledge of the impact of urban growth on biodiversity. *Nature Sustainability*, *3*(1), 16–24.

McLellan, B. N., & Hovey, F. W. (2001). Habitats Selected by Grizzly Bears in a Multiple Use Landscape. *The Journal of Wildlife Management*, *65*(1), 92.

Mississippi Museum of Natural Science. (2015). *Mississippi State Wildlife Action Plan*. Jackson, Mississippi: Mississippi Department of Wildlife, Fisheries, and Parks, Mississippi Museum of Natural Science.

Mitsch, W. J., Day, J. W., Wendell Gilliam, J., Groffman, P. M., Hey, D. L., Randall, G. W., & Wang, N. (2001). Reducing Nitrogen Loading to the Gulf of Mexico from the Mississippi River Basin: Strategies to Counter a Persistent Ecological Problem. *BioScience*, *51*(5), 373.

Montagna, P. A., Kalke, R. D., & Ritter, C. (2002). Effect of restored freshwater inflow on macrofauna and meiofauna in upper Rincon Bayou, Texas, USA. *Estuaries*, *25*(6), 1436–1447.

Munson, S. M., Bradford, J. B., & Hultine, K. R. (2020). An Integrative Ecological Drought Framework to Span Plant Stress to Ecosystem Transformation. *Ecosystems*.

NOAA. (date unavailable). NOAA Coastal High Tide Flooding - Mapping Methodology. NOAA Office for Coastal Management.

NOAA. (2017, January). Method Description: Detailed Method for Mapping Sea Level Rise Inundation. NOAA Office for Coastal Management.

Olson, D. H., Aanensen, D. M., Ronnenberg, K. L., Powell, C. I., Walker, S. F., Bielby, J., Garner, T. W. J., Weaver, G., Group, T. B. M., & Fisher, M. C. (2013). Mapping the Global Emergence of Batrachochytrium dendrobatidis, the Amphibian Chytrid Fungus. *PLOS ONE*, *8*(2), e56802.

Paine, R. T., Tegner, M. J., & Johnson, E. A. (1998). Compounded Perturbations Yield Ecological Surprises. *Ecosystems*, *1*, 535–545.

Patrick, D. A., & Gibbs, J. P. (2010). Population structure and movements of freshwater turtles across a road-density gradient. *Landscape Ecology*, *25*(5), 791–801.
Peterson, M. S., & Lowe, M. R. (2009). Implications of Cumulative Impacts to Estuarine and Marine Habitat Quality for Fish and Invertebrate Resources. *Reviews in Fisheries Science*, *17*(4), 505–523.
Poff, N. L., Richter, B. D., Arthington, A. H., Bunn, S. E., Naiman, R. J., Kendy, E., Acreman, M., Apse, C., Bledsoe, B. P., Freeman, M. C., Henriksen, J., Jacobson, R. B., Kennen, J. G., Merritt, D. M., Oâ™KEEFFE, J. H., Olden, J. D., Rogers, K., Tharme, R. E., & Warner, A. (2010). The ecological limits of hydrologic alteration (ELOHA): a new framework for developing regional environmental flow standards: Ecological limits of hydrologic alteration. *Freshwater Biology*, *55*(1), 147–170.
Preston, S. D., Alexander, R. B., & Wolock, D. M. (2011). Sparrow Modeling to Understand Water-Quality Conditions in Major Regions of the United States: A Featured Collection Introduction1. *JAWRA Journal of the American Water Resources Association*, *47*(5), 887–890.
Proctor, M. F., McLellan, B. N., Stenhouse, G. B., Mowat, G., Lamb, C. T., & Boyce, M. S. (2020). Effects of roads and motorized human access on grizzly bear populations in British Columbia and Alberta, Canada. *Ursus*, *2019*(30e2), 16–39.
Quigley, T., Haynes, R., & Graham, R. (1996). *Integrated scientific assessment for ecosystem management in the interior Columbia Basin and portions of the Klamath and Great Basins* (General Technical Report No. PNW-GTR382) (pp. viii–197). US Department of Agriculture, Forest Service.
Quigley, T. M., Haynes, R. W., & Hann, W. J. (2001). Estimating ecological integrity in the interior Columbia River basin. *Forest Ecology and Management*, *153*(1–3), 161–178.
Rabalais, N. N., & Turner, R. E. (2001). Hypoxia in the northern Gulf of Mexico: description, causes and change. In N. N. Rabalais & R. E. Turner (Eds.), *Coastal Hypoxia: Consequences for Living Resources and Ecosystems* (pp. 1–36). Washington, D.C.: Coastal and Estuarine Studies No. 58, American Geophysical Union.
Rabalais, N. N., Turner, R. E., Díaz, R. J., & Justić, D. (2009). Global change and eutrophication of coastal waters. *ICES Journal of Marine Science: Journal Du Conseil*, *66*, 1528–1537.
Rieman, B. E., Lee, D. C., & Thurow, R. (1997). Distribution, Status, and Likely Future Trends of Bull Trout within the Columbia River and Klamath River Basins. *North American Journal of Fisheries Management*, *17*, 1111–1125.
Robertson, D., & Saad, D. (2019). *Spatially referenced models of streamflow and nitrogen, phosphorus, and suspended-sediment loads in streams of the Midwestern United States* (Scientific Investigations Report No. 2019–5114) (p. 74). US Geological Survey.
SALCC. (2015). *State of the South Atlantic 2015: Understanding our living landscapes* (p. 16). South Atlantic Landscape Conservation Cooperative.
Scavia, D., Field, J. C., Boesch, D. F., Buddemeier, R. W., Burkett, V., Cayan, D. R., Fogarty, M., Harwell, M. A., Howarth, R. W., Mason, C., Reed, D. J., Royer, T. C., Sallenger, A. H., & Titus, J. G. (2002). Climate change impacts on U. S. coastal and marine ecosystems. *Estuaries*, *25*(2), 149–164.
Schueler, T. (1994). The Importance of Imperviousness. *Watershed Protection Techniques*, *1*(3), 100.
Tedim, F., Leone, V., Amraoui, M., Bouillon, C., Coughlan, M., Delogu, G., Fernandes, P., Ferreira, C., McCaffrey, S., McGee, T., Parente, J., Paton, D., Pereira, M., Ribeiro, L., Viegas, D., & Xanthopoulos, G. (2018). Defining Extreme Wildfire Events: Difficulties, Challenges, and Impacts. *Fire*, *1*(1), 9.
Texas Parks and Wildlife Department. (2012a). *Texas Conservation Action Plan 2012-2016: Gulf Coast Prairies and Marshes Handbook*. Austin, Texas: Texas Parks and Wildlife Department.
Texas Parks and Wildlife Department. (2012b). *Texas Conservation Action Plan 2012-2016: Western Gulf Coastal Plain Handbook*. Austin, Texas: Texas Parks and Wildlife Department.

Thompson, J., & Ayling, S. (2020). *Grasslands report card 2020* (p. 13). UKRI Natural Environment Research Council.

Tian, H., Xu, R., Pan, S., Yao, Y., Bian, Z., Cai, W., Hopkinson, C. S., Justic, D., Lohrenz, S., Lu, C., Ren, W., & Yang, J. (2020). Long-Term Trajectory of Nitrogen Loading and Delivery From Mississippi River Basin to the Gulf of Mexico. *Global Biogeochemical Cycles*, *34*(5).

United Nations Population Division. (2018, May 16). 2018 Revision of World Urbanization Prospects.

Uphoff, J. H., McGinty, M., Lukacovic, R., Mowrer, J., & Pyle, B. (2011). Impervious Surface, Summer Dissolved Oxygen, and Fish Distribution in Chesapeake Bay Subestuaries: Linking Watershed Development, Habitat Conditions, and Fisheries Management. *North American Journal of Fisheries Management*, *31*(3), 554–566.

US Environmental Protection Agency. (2009). Fact Sheet: Introduction to Clean Water Act (CWA) Section 303(d) Impaired Waters Lists. USEPA Office of Water.

US Environmental Protection Agency. (2011). *Gulf of Mexico Regional Ecosystem Restoration Strategy. Gulf Coast Restoration Task Force*. New Orleans, Louisiana: Gulf Coast Ecosystem Restoration Council.

US Environmental Protection Agency. (2019). EJSCREEN Technical Documentation.

USACE. (2015). *North Atlantic Coast Comprehensive Study: Resilient Adaptation to Increasing Risk*. US Army Corps of Engineers.

USEPA. (2000). *Ambient Water Quality Criteria Recommendations: Information supporting the development of state and tribal nutrient criteria. Rivers and Streams in Nutrient Ecoregion XII* (No. EPA 822-B-00-021) (p. 80). US Environmental Protection Agency.

USEPA. (2012). *Identifying and Protecting Healthy Watersheds: Concepts, Assessments, and Management Approaches* (No. EPA 841-V-11-002). Washington, D. C.: US Environmental Protection Agency.

USEPA. (2015, November 25). Level III and IV Ecoregions of the Continental United States [Data and Tools].

USEPA. (2017). *Overview of the preliminary healthy watersheds assessment project: Evaluating relative health and vulnerability of conterminous US watersheds*. US Environmental Protection Agency, Office of Water, Healthy Watersheds Program.

USEPA. (2020, September 9). Summary Table for the Ecoregional Nutrient Criteria Documents [Reports and Assessments].

Van Auken, O. W. (2000). Shrub Invasions of North American Semiarid Grasslands. *Annual Review of Ecology and Systematics*, *31*(1), 197–215.

Verdi, R. J., Tomlinson, S. A., & Marella, R. L. (2006). *The drought of 1998-2002: impacts on Florida's hydrology and landscape*. Reston, Va: US Dept. of the Interior, US Geological Survey.

Villamizar Gulf of Mexicoez, A., Suriyamongkol, T., Forstner, M., & Forks, K. (2016). Prevalence of <i>Batrachochytrium dendrobatidis<i/> in two sympatric treefrog species, <i>Hyla cinerea<i/> and <i>Hyla versicolor<i/>. *Herpetological Review*, *47*(4), 601–605.

Vinebrooke, R., Schindler, D., Findlay, D., Turner, M., Paterson, M., & Mills, K. (2003). Trophic Dependence of Ecosystem Resistance and Species Compensation in Experimentally Acidified Lake 302S (Canada). *Ecosystems*, *6*, 0101–0113.

Wade, D., Lunsford, J., Dixon, M., & Mobley, H. (1989). *A guide for prescribed fire in southern forests* (Technical Publication No. R8- TP- US). Atlanta, Georgia, USA: USDA, Forest Service, Southern Region.

Walls, S. C., Barichivich, W. J., Brown, M. E., Scott, D. E., & Hossack, B. R. (2013). Influence of Drought on Salamander Occupancy of Isolated Wetlands on the Southeastern Coastal Plain of the United States. *Wetlands*, *33*(2), 345–354.

Walsh, C. J., Booth, D. B., Burns, M. J., Fletcher, T. D., Hale, R. L., Hoang, L. N., Livingston, G., Rippy, M. A., Roy, A. H., Scoggins, M., & Wallace, A. (2016). Principles for urban stormwater management to protect stream ecosystems. *Freshwater Science*, *35*(1), 398–411.

Weidlich, E. W. A., Flórido, F. G., Sorrini, T. B., & Brancalion, P. H. S. (2020). Controlling invasive plant species in ecological restoration: A global review. *Journal of Applied Ecology*, *57*(9), 1806–1817.

Wheeler, A. P., Angermeier, P. L., & Rosenberger, A. E. (2005). Impacts of New Highways and Subsequent Landscape Urbanization on Stream Habitat and Biota. *Reviews in Fisheries Science*, *13*(3), 141–164.

Williams, K., MacDonald, M., & Sternberg, L. da S. L. (2003). Interactions of Storm, Drought, and Sea-Level Rise on Coastal Forest: A Case Study. *Journal of Coastal Research, 19*(4), 1116–1121.

Wilson, M. C., Chen, X.-Y., Corlett, R. T., Didham, R. K., Ding, P., Holt, R. D., Holyoak, M., Hu, G., Hughes, A. C., Jiang, L., Laurance, W. F., Liu, J., Pimm, S. L., Robinson, S. K., Russo, S. E., Si, X., Wilcove, D. S., Wu, J., & Yu, M. (2016). Habitat fragmentation and biodiversity conservation: key findings and future challenges. *Landscape Ecology*, *31*(2), 219–227.

Wise, D., Anning, D., & Miller, O. (2019). *Spatially referenced models of streamflow and nitrogen, phosphorus, and suspended-sediment transport in streams of the southwestern United States (ver. 1.1, June 2020)* (No. 2019–5106). US Geological Survey.

Young, T. F., & Sanzone, S. (2002). *A Framework for Assessing and Reporting on Ecological Condition* (SAB Report No. EPA-SAB-EPEC-02-009) (p. 142). Washington, D.C.: US Environmental Protection Agency.

APPENDIX C SOCIAL VULNERABILITY INDEX

METHODOLOGY

Selecting Social Vulnerability Indicators

Vulnerability is a function of local socioeconomic conditions and the nature of the hazard to which the human population is exposed (Adger et al., 2004). Overall vulnerability is dependent on exposure to specific hazards. Social vulnerability, on the other hand, reflects the inherent characteristics of a community or population group that impact their ability to respond to and recover from any number of natural, technological, and social hazards. There are many factors that contribute to a community's ability to respond adaptively to changing conditions and these factors can be represented by an assortment of indicator variables (hereafter simply variables). Variables can be quantitative or qualitative measures derived from observed facts that simplify the reality of complex situations (Cutter et al., 2010). To derive the Social Vulnerability Index (SoVI), this project utilized 43 key variables (as described below), directly linked to the vulnerability factors. These variables were selected based on a review of existing literature, including the work of Cutter (2003), the State of Texas (Peacock et al., 2011), the State of Louisiana (Hemmerling et al., 2020; Hemmerling & Hijuelos, 2016) and U.S. Army Corps of Engineers (Dunning & Durden, 2011) and were adapted to include factors specific to coastal environments (Hijuelos & Hemmerling, 2015; Jepson & Colburn, 2013).

The prior research examined the relationship between social vulnerability and coastal storm events by identifying structural weaknesses of certain populations that highlight their specific vulnerabilities (Table C-1). Often the core cause of these vulnerabilities (lack of financial resources, special medical needs, political disempowerment, etc.) are independent of any specific hazard, they can be adapted and considered across a range of disruptive events. For coastal storms and other acute events, issues related to immediate evacuation are important. With gradual onset events, like sea level rise and coastal land loss, immediate evacuation may not be needed, but population relocation issues become important. Regardless of the hazard type or the speed of onset, the same structural weaknesses exist in vulnerable populations.

Poverty, minority status, and age are frequent indicators used across a wide range of hazards, but there are other factors that make communities more vulnerable to certain types of hazards. In resource dependent communities, for example, disruption of livelihoods can result from the loss of land and animals for farmers, or boats and nets for fishers (Wisner, 2004). As a result, elevated levels of natural resource employment can be an important determinant in the social vulnerability of a coastal community to impacts from land loss, sea level rise, and tropical storm events.

Table C-1. Social Vulnerability Factors and Their Implications During and After Coastal Storm Events (Adapted from Dunning & Durden, n.d.).

Vulnerability Factor	Response During Event	Recovery
Low income/poverty level	Lack of resources may complicate evacuation.	Lack of financial resources may hinder ability to recover
Elderly/very young	Greater difficulties in evacuation, increased health and safety issues, potential for higher loss of life.	May lack ability to rebound
Disabled/special needs	Greater difficulties in evacuation, increased health and safety issues, potential for higher loss of life.	Lack of facilities and medical personnel in aftermath may make it difficult to return
Single parent/female-headed households	Lack of resources and special needs relative to child care may complicate evacuation.	Lack of resources may hinder ability to recover
Minorities	Lack of influence to protect interests, politically disempowered	Lack of influence to protect interests, lack of connections to centers of power or influence
Occupants of mobile homes/renters	Occupy more vulnerable housing	Potential displacement with higher rent
Natural resource dependence	Delays in evacuation to protect assets, resulting in health and safety issues, including potential for higher loss of life	Potential loss of property and assets may hinder ability to recover, livelihood deterioration

For this project, the key socioeconomic variables were derived from the 2010 Census and the 2015-2019 American Community Survey (ACS) at the census block group level[1]. A block group is a census unit having approximately 1,000 people and is the smallest unit that moderately complete socioeconomic data is available. Vulnerability can vary on smaller scales, like household, but the block group unit can be reliably quantified and is the standard used by local officials and public agencies. It is a best practice when assessing resilience or vulnerability to include point-level or block group level data, since these levels allow easy aggregation to larger scales depending on the specific study needs. Principal component analysis (PCA) requires a large sample size, so this project utilized all census block groups within the Gulf-wide project domain (Figure 1) to ensure the underlying assumptions of the PCA were met. Generally, PCAs require sample sizes ranging from 5 to 10 samples per variable (Bryant & Yarnold, 1995; MacCallum et al., 2001; Nardo et al., 2005).

All input variables were normalized as percentages, per capita values, or density functions and then standardized using z-score standardization. Calculating z-scores allows for comparison of dissimilar data sets on a common scale, generating variables with a mean of 0 and standard deviation of 1. After all the

[1] The American Community Survey is an ongoing survey conducted by the U.S. Census Bureau that regularly gathers data previously gathered in the decennial census. At small census geographies, such as the census block group, data gathered by the American Community Survey exhibit high levels of sampling error. Sampling error is reduced when the data is aggregated into larger groupings (Hijuelos & Hemmerling, 2015).

data were transformed into the units required for analysis of each category, PCA was run on the variables to reduce the observed variables into a smaller number of significant components that represent broader categories of socioeconomic vulnerability.

Conducting Principal Component Analysis

PCA is a multivariate statistical technique generally used to extract the most important information from a large dataset, simplify the description of the dataset, and analyze the structure of the observations and the variables (Abdi & Williams, 2010). PCA analyzes inter-correlated dependent variables and creates new variables, called principal components that are linear combinations of the original variables. These components are surrogate variables that serve to simplify a large number of correlated variables. The analysis produces a correlation matrix in which each original variable is assigned a loading (i.e., weight) as a measure of the variable's correlation to each component. The loadings inform the relative importance of each of the original variables to the components identified in the PCA. In this analysis, variables were deemed important if the PCA resulted in a loading greater than or equal to 0.3. A value of 0.3 or above indicates multicollinearity, meaning that the predictor variables are highly correlated with one another (Hair, 2010). Variables that did not meet the threshold for any component were eliminated from the analysis and a new PCA was performed. Once it was determined that all variables met the loading threshold, the number of components to retain in the analysis for interpretation was decided. This decision was largely based on the total amount of variance accounted for by each component, as reported in the component's eigenvalue. In a PCA, the first component always accounts for the greatest amount of variation in the original variables. The second component is uncorrelated with the first and accounts for the maximum variation that is unexplained by the first component. Each subsequent component likewise accounts for the maximum variation not accounted for in the previous components, such that explained variation is additive with each successive component. Although the total number of possible components is equal to the total number of variables, only meaningful components that explain the majority of the variance are retained in a PCA. In this analysis, the Kaiser-Guttman criterion was used to select the number of components retained in the PCA, such that components with eigenvalues greater than 1 were considered meaningful and retained (O'Rourke & Hatcher, 2014). Because an eigenvalue is a measure of the amount of variance accounted for by a component and because the constituent variables are standardized, any component with an eigenvalue greater than 1 accounts for a greater amount of variance than any of the original variables.

Using the results of the PCA, variables with the highest loadings (> 0.3) within a component were identified as the most important, and these variables were then used to assign a descriptive label to the component. When necessary, a directional adjustment was applied to the entire component to assure that positive values indicated a tendency to increase vulnerability and negative values indicated a tendency to decrease vulnerability (Cutter et al., 2003b). If a component exhibited positive high loadings for variables that would contribute to decreased vulnerability, the component value was multiplied by -1. Components in which the signs of the high loading variables were consistent with their contribution to social vulnerability (a positive sign if they increased vulnerability or a negative sign if they decreased vulnerability) required no adjustment. For components where the influence of the variables was ambiguous or bifurcated, the absolute value was used (Hemmerling & Hijuelos, 2017).

Calculating Overall Social Vulnerability

While understanding the distribution of individual social vulnerability components can be useful, it is often helpful to assess overall social vulnerability if the multidimensional components can be combined into a single index (Rygel et al., 2006). Using the results from the PCA, the components were combined to derive a social vulnerability index (SVI) for all populated census block groups within the study area. Indices are theoretical constructs in which two or more components of are combined to form a single summary value. Such indices have been used in hazards research to generate new information that can be used to comparatively assess differences in social vulnerability in given geographical units (Clark et al., 1998; Colburn et al., 2016; Cutter et al., 2003b; Hemmerling & Hijuelos, 2016; Peacock et al., 2011; Wu et al., 2002).

The directionally-adjusted components in this study were assigned the percentage of their respective eigenvalues, or variance explained, as weights using the following equation:

Equation 1. Weight Assigned to Each Component

$Wi = li\Sigma li$ (1)

where Wi is the weight assigned to each component, and li is the eigenvalue, or variance explained, of each component.

Assigning weights to each component based on the variance explained is reasonable because a larger eigenvalue represents a larger share of the total variance and a more important component (Wang, 2009). Thus, the first component explains the most variance and each successive component contributes less to the variance explained. The final SVI value was calculated using the following equation:

Equation 2. Final SVI Value

$Fs = \Sigma(Fi * Wi)$ (2)

where Fs is the census block group level SVI value, Fi is the component value for each component, and Wi is the weight assigned to each respective component (1).

The resultant social vulnerability values represent a relative measure of social vulnerability and not an absolute measure (Cutter et al., 2011). To graphically represent the relative nature of the metric, the weighted social vulnerability values were normalized by z-scores and mapped by census block group to form a distribution with a mean of 0 and standard deviation of 1. Census block groups with SVI values greater than one standard deviation from the mean have previously been classified as vulnerable (Cutter et al., 2003b). For this analysis, seven categories of vulnerability were identified: very low, low, medium low, medium, medium high, high, and very high. Medium values are within one standard deviation of the mean, medium low values are between -1 and -1.96 standard deviations, medium high values are between 1 and 1.96 standard deviations, and high and low values are those greater than 1.96 or less than -1.96 standard deviations from the mean, respectively. A z-score of 1.96 indicates that the respective index value is significantly above or below the mean value (alpha = 0.05). Finally, the census block level values were aggregated (Hemmerling & Hijuelos, 2017).

RESULTS

Principal Component Analysis

The 43 variables were analyzed using PCA. Five variables (the percent Native American population, percent Hawaiian population, percent of population employed in manufacturing, percent of households receiving public assistance, and percent of population in nursing facilities) did not load significantly on any of the components and was not included in the final PCA run. The final 37 variables representing social vulnerability were grouped into six components based on the Kaiser-Guttman criterion. In total, most of the variance explained was captured by economic status (26%), educated professionals (22%), and elderly population (21%). The remainder of the variance explained by each component can be found in Table C-2.

There are six variables that have split loadings, meaning that they load onto more than one factor. As each of these variables has loadings greater than 0.3, they can be interpreted as contributing to more than one factor. These split loadings (sometimes referred to as complex structures) are not uncommon in the PCA and are not a problem if the components are interpretable. The percentage of adult population disabled is one item that has a split loading. It loads onto four components 1 “Low Economic Status,” component 2 “elderly population,” component 4 “Educated, Professional Workers,” and component 5 “Population Stability.” This is explained by the fact that renter occupied units are often either elderly or disabled, two groups that are at times mutually exclusive. Similarly, the percent of renter-occupied housing units loads on component 1 “Low Economic Status,” component 2 “elderly population,” and component 5 “Population Stability.” Here, for example, the percent of renters in areas with high unemployment or areas where the population may be under employed or a single parent households. In other locations, however, households receiving social security income and age of householder is more indicative of lower economic standing.

Directional adjustments were made on several components, as shown in Table C-2. For the elderly population component, the five constituent variables (per capita income in dollars, percent of adult population that is disabled, percent of households receiving Social Security income, median age, and percent of population over 65 years of age) had negative loadings. Because the signs of the high loading variables must be consistent with their contribution to social vulnerability, with positive values indicating increased vulnerability, the overall component score was multiplied by -1.

Although general descriptive component labels are applied during the interpretation of each component, more variables load highly onto those components than the labels can express (Rygel et al., 2006). For example, the first component was interpreted as “low economic status” because the percent households making less than $35,000 and percent of households that have no vehicle loaded highest on it. This component also included high percentages of residents without internet, living in poverty, and the number of single parent households, categories that were statistically correlated with economic status. Similarly, the percentage of mobile homes and those employed in fisheries, construction, or oil and gas industries were strongly correlated with rural populations. Each of the other components was similarly interpreted. The non-English speaking, migrant component included the percentage of the population speaking little or no English, population born outside of the United States, households without insurance, employment in construction, and rental units. Within the study area, these populations also correlated closely with the Hispanic population.

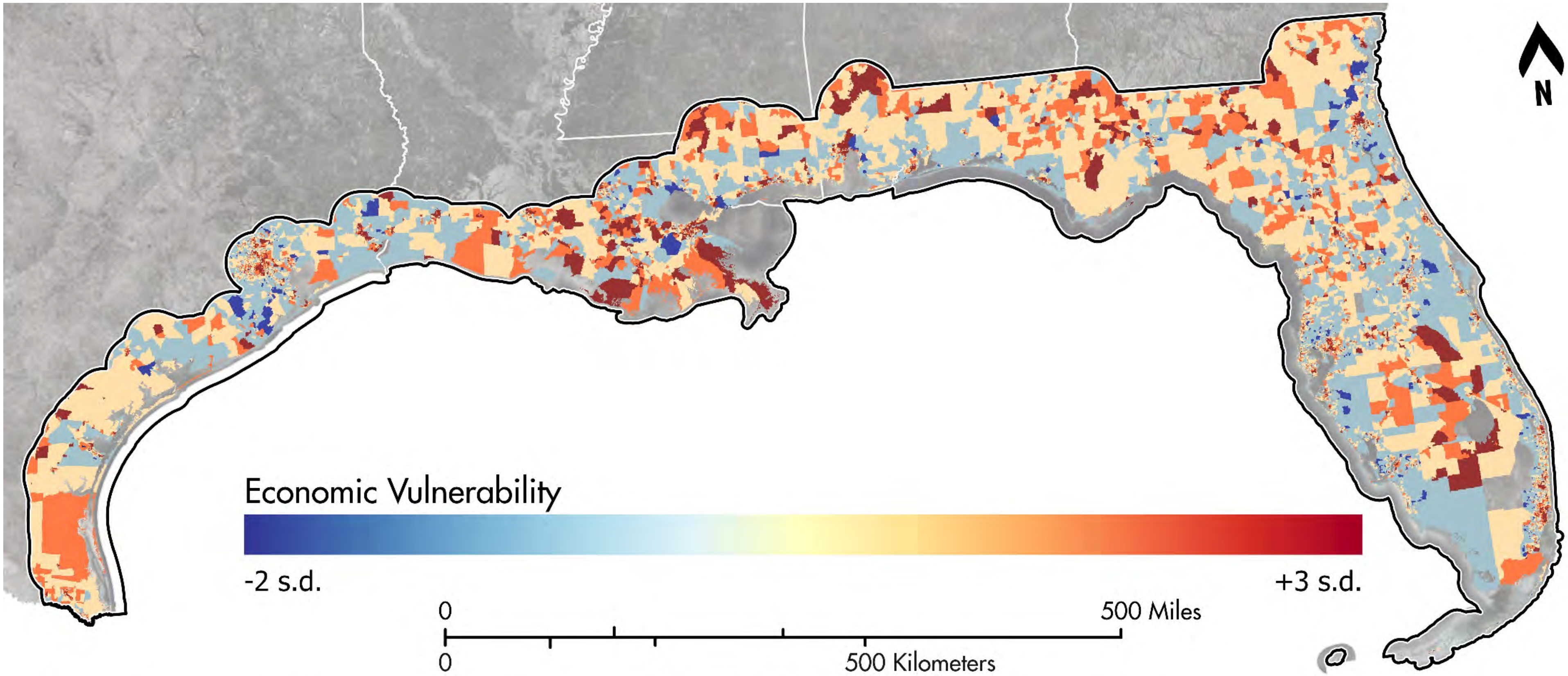
The percent African American population loaded strongly on four components. In two instances, the percent African American population loaded negatively for the components representing migrant workers and rural populations. In three components (low economic status, elderly population, and rural populations), percent African American population was closely correlated to percent single parent household, with both loading high in the low economic status component. The percent of households that have no insurance correlated with percent renter housing units in three components (low economic status, elderly population, and migrant workers). This correlation suggests a lack of insurance is tied to both income and employment in construction industries.

Table C-2. Weight Assigned to Each Component Table.

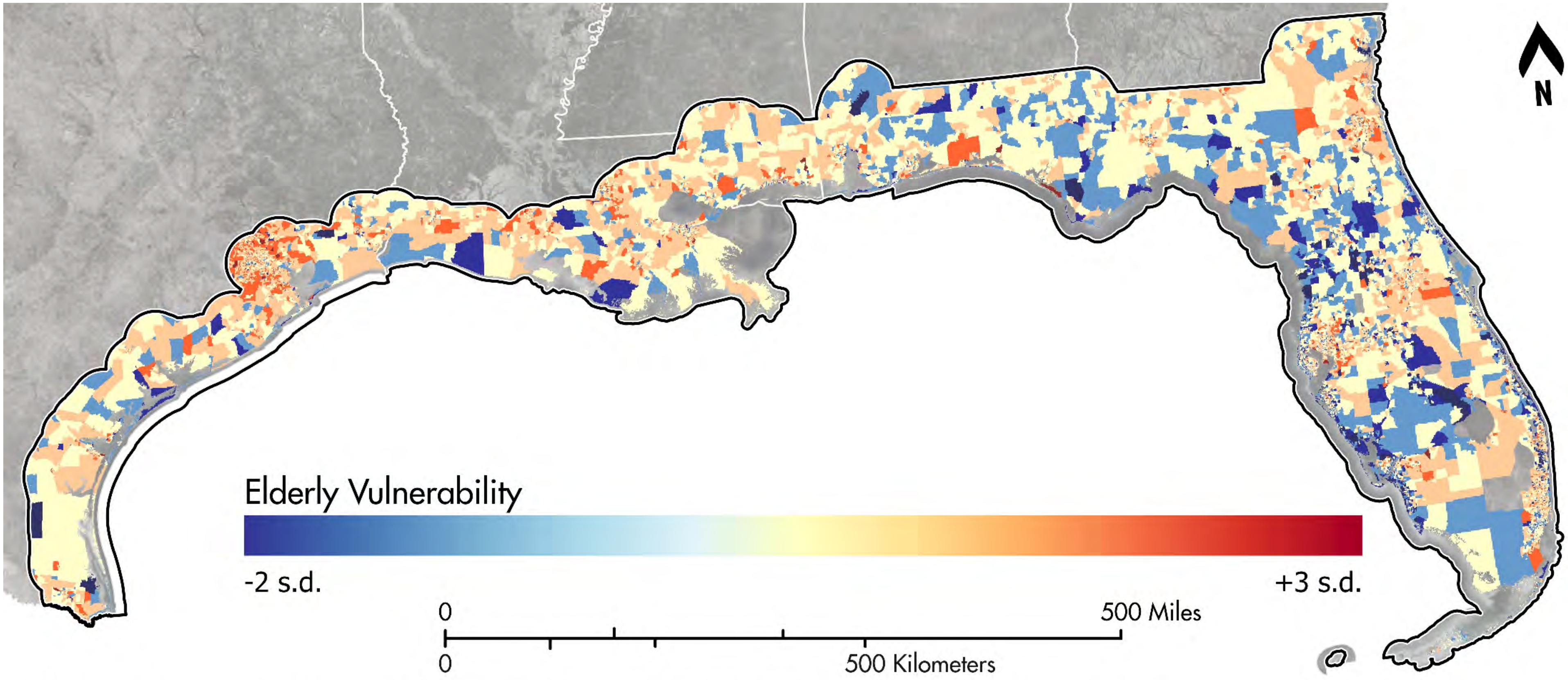
Component	Directional Adjustment	Variance Explained	Component Interpretation	Dominant Variables	Component Loading
1 +	24.00%	Low Economic Status		Percent households making less than $35,000	0.8
				Percent of households that have no vehicles	0.8
				Percent of population living in poverty	0.7
				Percent of households that have no internet	0.7
				Percent single parent households	0.7
				Percent African American population	0.6
				Percent renter-occupied housing units	0.6
				Percent of households receiving Supplemental Social Security income	0.5
				Percent of labor force that is unemployed	0.4
				Percent of adult population that is disabled	0.3
				Percent of households that have no phone	0.3
				Hospital density, number of households per square mile	0.3
				Percent of households that have no insurance	0.3
				Percent of population participating in civilian labor force	-0.3
				Percent of population that vote	-0.3
				Per capita income in dollars	-0.4
				Percent of population with college degree	-0.4
				Median income	-0.5
				Percent households making more than $100,000	-0.5
2 –	21.00%	Elderly Population		Percent of population participating in civilian labor force	0.7
				Percent of population under 18 years of age	0.7
				Percent of population under 5 years of age	0.6
				Percent single parent households	0.3
				Percent renter-occupied housing units	0.3
				Percent of households that have no insurance	0.3
				Percent African American population	0.3
				Per capita income in dollars	-0.3
				Percent of adult population that is disabled	-0.4
				Percent of households receiving Social Security income	-0.8
				Median age	-0.9
				Percent of population over 65 years of age	-0.9
3 +	16.00%	Migrant Workers		Percent of population with limited english	0.9
				Percent Hispanic population	0.8
				Percent of population born outside of the United States	0.8
				Percent of households that have no insurance	0.6
				Percent of population employed in construction	0.4
				Percent renter-occupied housing units	0.3
				Percent African American population	-0.3
				Percent of population that vote	-0.6
				Percent of population with limited english	0.9
				Percent Hispanic population	0.8

Component	Directional Adjustment	Variance Explained	Component Interpretation	Dominant Variables	Component Loading
				Percent of population born outside of the United States	0.8
				Percent of households that have no insurance	0.6
				Percent of population employed in construction	0.4
				Percent renter-occupied housing units	0.3
				Percent African American population	-0.3
4	+	22%	Educated, Professional Workers	Median value of owner-occupied housing in dollars	0.8
				Per capita income in dollars	0.8
				Percent of population with college degree	0.7
				Percent households making more than $100,000	0.7
				Median income	0.7
				Hospital density, number of households per square mile	0.4
				Percent Asian population	0.3
				Percent of households that have no internet	-0.3
				Percent rural population	-0.3
				Percent of households that have no insurance	-0.3
				Percent of population employed in construction	-0.3
				Percent households making less than $35,000	-0.4
				Percent mobile homes	-0.4
				Percent of adult population that is disabled	-0.4
				Percent of population with high school diploma	-0.7
5 +	8%	Population Stability		Percent of population that is native and born in same county	0.7
				Percent of population under 18 years of age	0.3
				Percent of adult population that is disabled	0.3
				Percent of population employed in service industries	-0.4
				Percent renter-occupied housing units	-0.5
6 +	9%	Rural Population		Percent rural population	0.7
				Percent mobile homes	0.6
				Percent of population employed in fisheries industries	0.5
				Percent homes built after 2000	0.4
				Percent of population employed in mining and petroleum extraction industries	0.3
				Percent single parent households	-0.3
				Percent African American population	-0.3

Figure C-1 through Figure C-6 depict each of the significant principal components for each census block group in the study area. The 1,647 census block groups were sorted into five categories of vulnerability by standard deviations above or below the mean, as previously described.



Data Source: CPRA, DataBasin, Esri, Florida Cooperative Land Cover, LANDFIRE, MRLC, NOAA, Texas A&M, The Nature Conservancy, USDA, USEPA, USFS, USFWS, USGS



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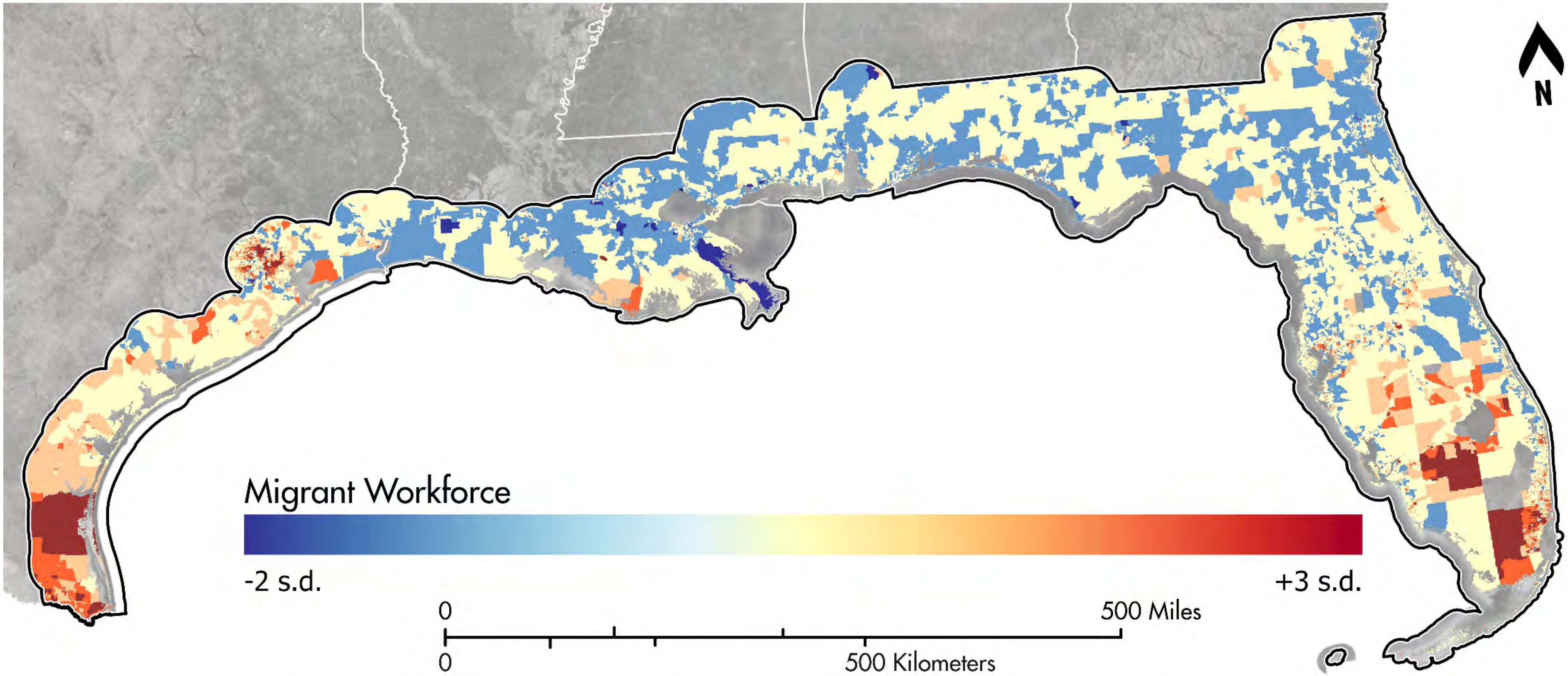

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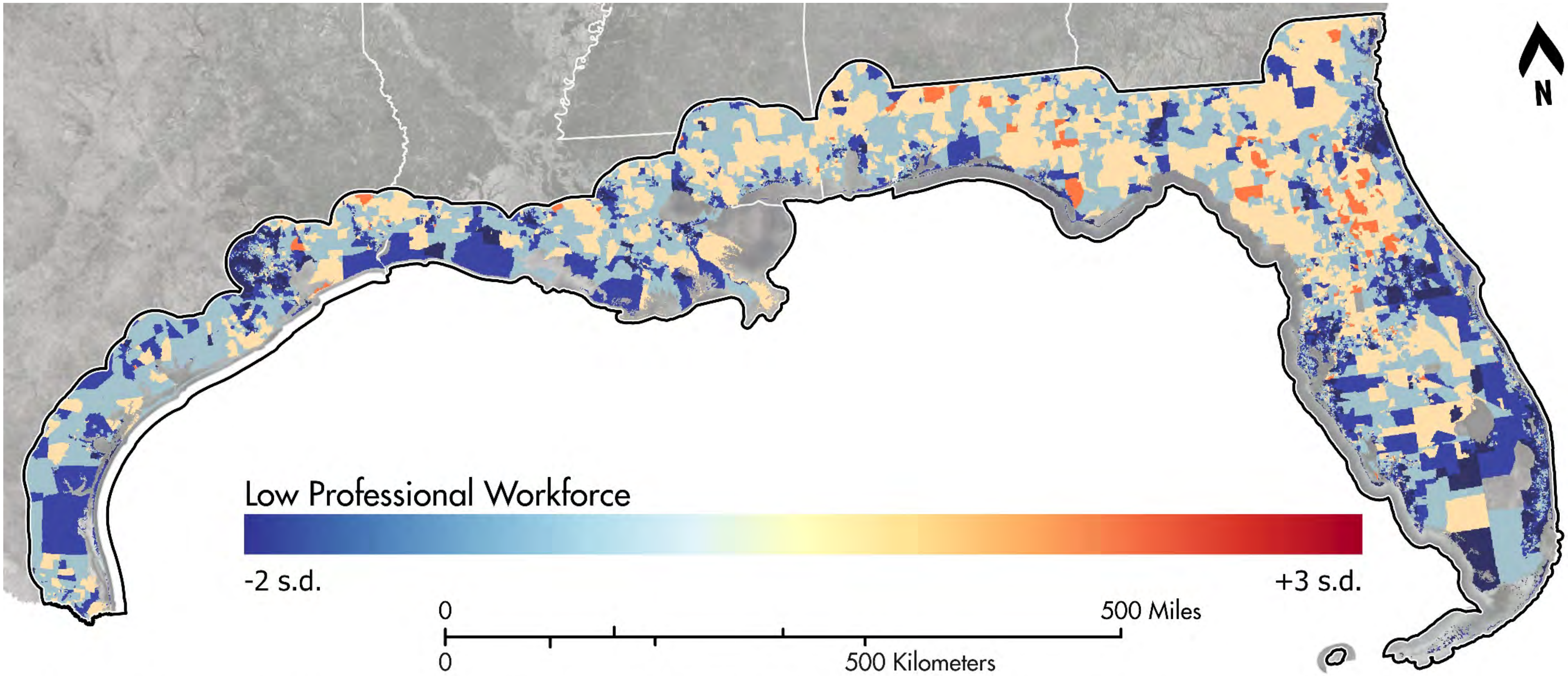

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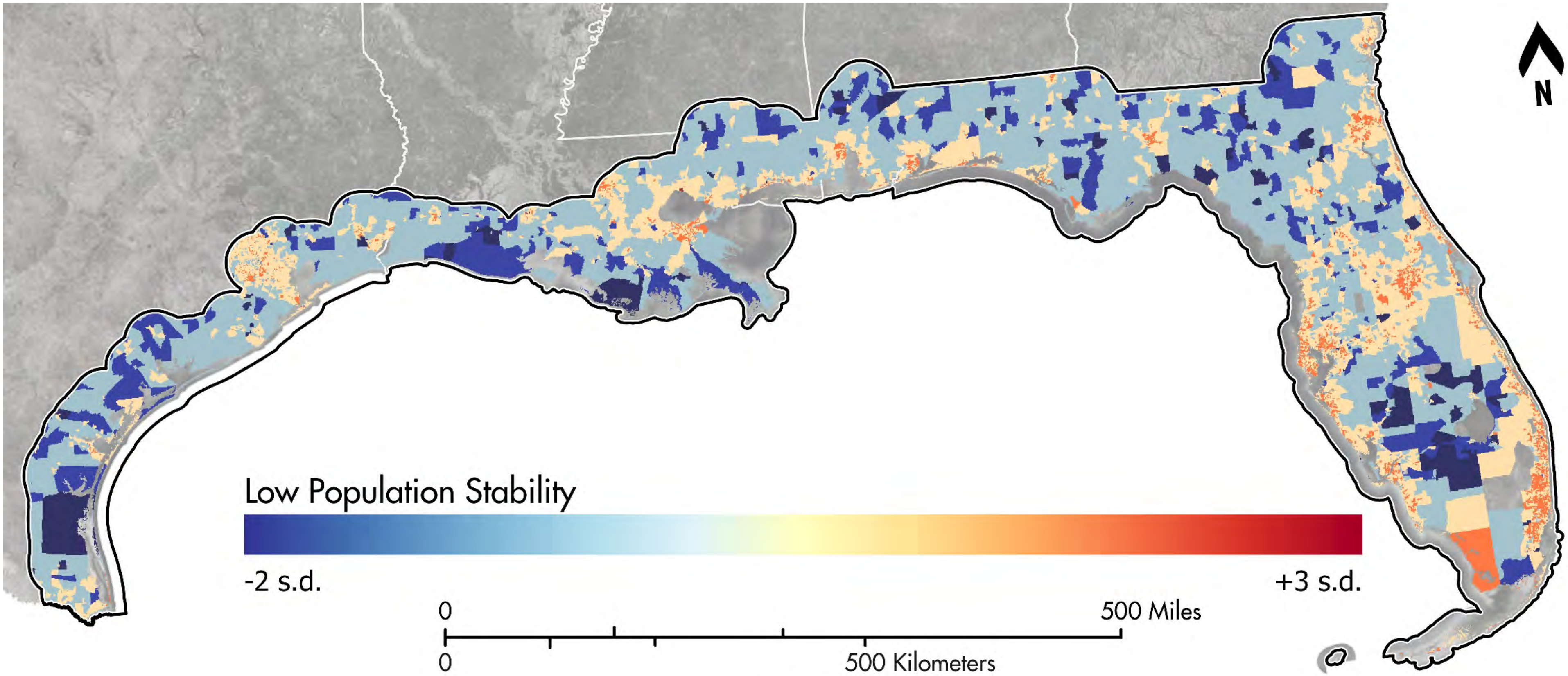
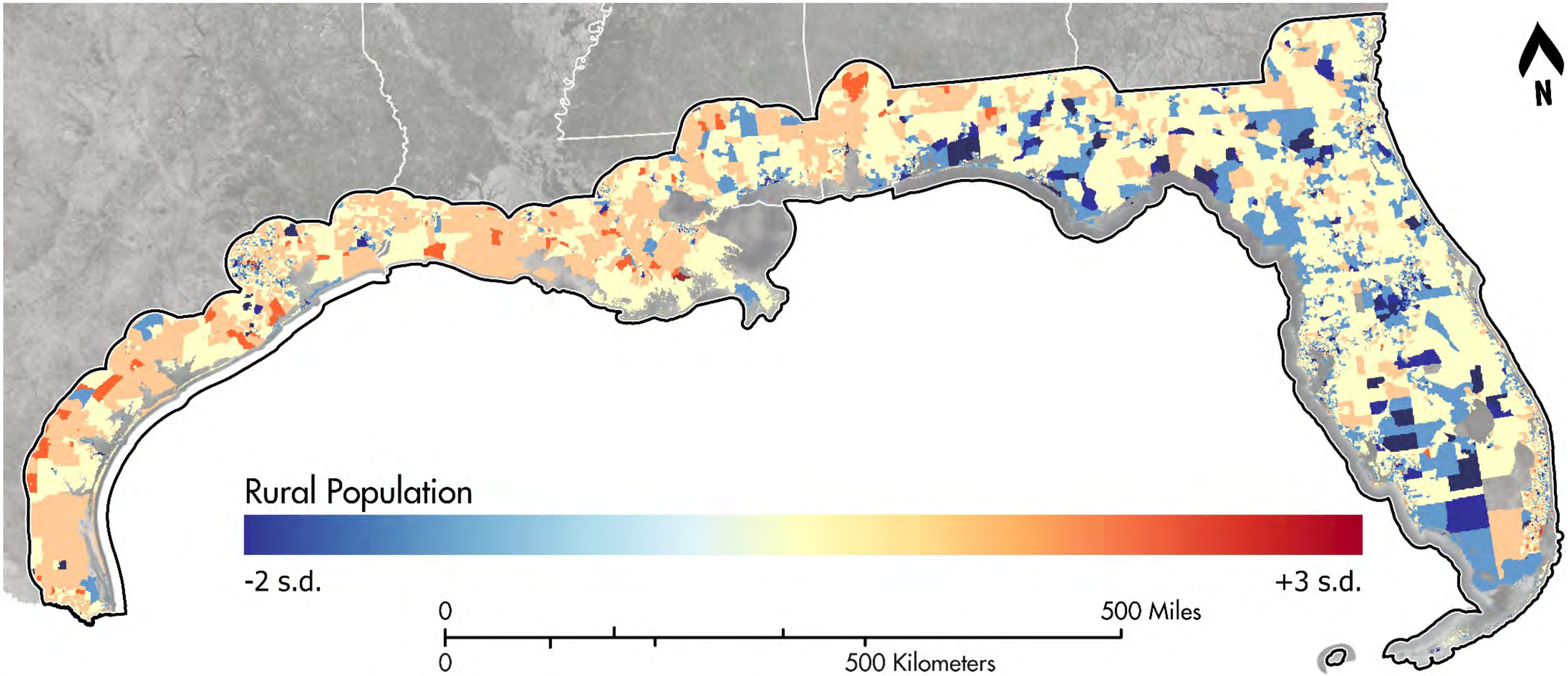


Data Source: CPRA, DataBasin, Esri, Florida Cooperative Land Cover, LANDFIRE, MRLC, NOAA, Texas A&M, The Nature Conservancy, USDA, USEPA, USFS, USFWS, USGS



Data Source: CPRA, DataBasin, Esri, Florida Cooperative Land Cover, LANDFIRE, MRLC, NOAA, Texas A&M, The Nature Conservancy, USDA, USEPA, USFS, USFWS, USGS

Social Vulnerability Index Values

The results of the PCA assigned a component value for all 6 principal components to each census block group in the study area. These values were adjusted for cardinality and weighted (1). The final additive model (2) was used to derive the overall social vulnerability value for each census block group, F_S, as follows:

Equation 3. Overall Socio-economic Vulnerability Value

$$Fs=(F1*W1) - (F2*W2) - (F3*W3) + (F4*W4) - (F5*W5) + (F6*W6)$$

As with the individual components, the Composite Coastal SoVI values were mapped and areas ranging from high to low vulnerability were identified across the coast (Figure C-7). The urban cores, Miami, Tampa Bay, Orlando, Jacksonville, New Orleans, and Houston, as well as the extensively developed shoreline in Florida, show a bifurcation of social vulnerability, with areas of both high and low vulnerability in close proximity[2]. Given the expanse of the study area, the primarily rural areas display a patchwork of moderately low to moderately high.

There are two areas outside of urban areas that cluster moderate and high vulnerability. In Texas, Brownsville and Cameron County along with the rural block groups in Kenedy and Willacy counties to the north exhibit consistently high vulnerability. High vulnerability is consistent with certain household variables, such as only 55 percent having broadband internet, 77 percent speak a language other than English at home, 29 percent of people do not have insurance, having a median household income ($37,772) 60 percent lower than the national average, and having a percentage of persons in poverty (24.9%) 42 percent lower than the national average ("U.S. Census QuickFacts," 2021). In Alabama, the northern portion of the study area, which includes southern Clarke and Monroe counties, eastern/southeastern Washington County, and a small portion of northern rural Baldwin county[3], was another high vulnerability area. High vulnerability is consistent with certain household variables, such as 53 percent not having broadband internet in the home, 13 percent of people do not have insurance, only 45 percent of people are in the work force, having a median household income ($36,405) 57 percent lower than the national average, and having a percentage of persons in poverty (20.1%) 52 percent lower than the national average ("U.S. Census QuickFacts," 2021).

[2] This analysis presented here did not include detailed assessments of specific cities, neighborhoods, and other local geographical areas. The inclusion of these data into analytical tools such as the SCA Conservation Prioritization Tool would allow for a more localized analysis.

[3] Northern Baldwin County QuickFacts were not included in the demographic analysis because southern Baldwin County includes highly developed and vacation destinations (Gulf Shores, Orange Beach, and Fairhope). The overall values would skew the percentages for the other three predominately rural counties.

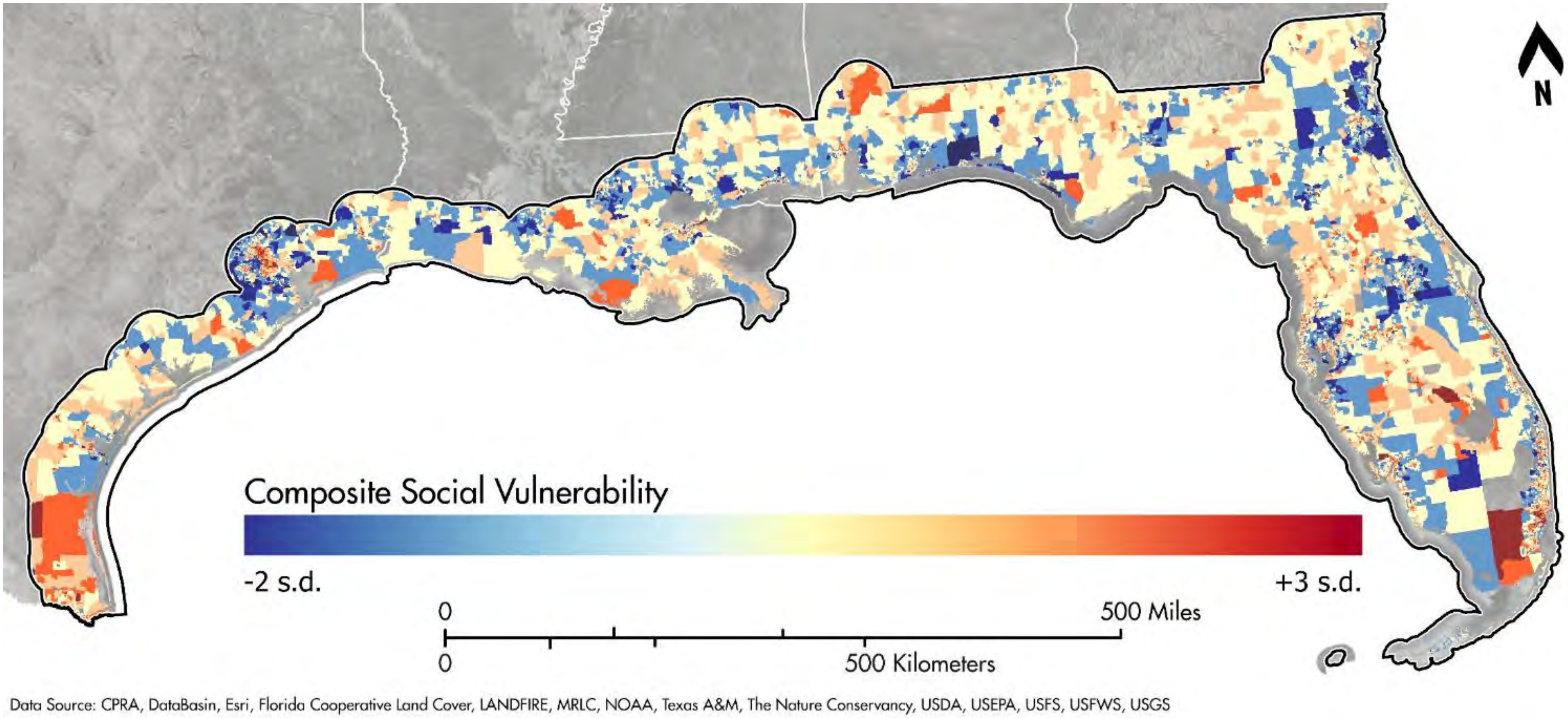


Figure C-7. Composite Social Vulnerability Score, displayed as standard deviations from the mean.

REFERENCES

Abdi, H., & Williams, L. J. (2010). Principal component analysis: Principal component analysis. *Wiley Interdisciplinary Reviews: Computational Statistics*, *2*(4), 433–459.

Bryant, F., & Yarnold, P. R. (1995). Principal-components analysis and exploratory and confirmatory factor analysis. In *Reading and understanding multivariate statistics* (pp. 99–136). American Psychological Association.

Clark, G. E., Moser, S. C., Ratick, S. J., Dow, K., Meyer, W. B., Emani, S., Jin, W., Kasperson, J. X., Kasperson, R. E., & Schwarz, H. E. (1998). Assessing the Vulnerability of Coastal Communities to Extreme Storms: The Case of Revere, MA., USA. *Mitigation and Adaptation Strategies for Global Change*, *3*(1), 59–82.

Colburn, L. L., Jepson, M., Weng, C., Seara, T., Weiss, J., & Hare, J. A. (2016). Indicators of climate change and social vulnerability in fishing dependent communities along the Eastern and Gulf Coasts of the United States. *Marine Policy*, *74*, 323–333.

Cutter, S. L., Boruff, B. J., & Shirley, W. L. (2003a). Social vulnerability to environmental hazards. *Social Science Quarterly*, *84*(2), 242–261.

Cutter, S. L., Boruff, B., & Shirley, W. L. (2003b). Social Vulnerability to Environmental Hazards. *Social Science Quarterly*.

Cutter, S. L., Burton, C. G., & Emrich, C. T. (2010). Disaster Resilience Indicators for Benchmarking Baseline Conditions. *Journal of Homeland Security and Emergency Management*.

Cutter, S. L., Emrich, C. T., & Morath, D. (2011). Appendix C: Social Vulnerability and Place Vulnerability Analysis Methods and Application for Corps Planning: Technical Analyses. In *Social Vulnerability Analysis Methods for Corps Planning* (pp. 74–88). Alexandria, VA: Institute for Water Resoures, U.S. Army Corps of Engineers.

Dunning, C. M., & Durden, S. (2011). *Social vulnerability analysis methods for Corps planning*. Alexandria, VA: U.S. Army Corps of Engineers Institute for Water Resources.

Hair, J. F. (Ed.). (2010). *Multivariate data analysis* (7th ed.). Upper Saddle River, NJ: Prentice Hall.

Hemmerling, S. A., & Hijuelos, A. C. (2016). *Coastal Louisiana Social Vulnerability Index (SVI). Version I.* (p. 27). Baton Rouge, LA: Coastal Protection and Restoration Authority.

Hemmerling, S. A., & Hijuelos, A. C. (2017). *2017 Coastal Master Plan: Attachment C4-11.2: Social vulnerability index* (Version Final) (pp. 1–28). Baton Rouge, LA: Coastal Protection and Restoration Authority.

Hemmerling, S. A., McHugh, C. M., DeMyers, C., Bienn, H. C., DeJong, A., Parfait, J., & Kiskaddon, E. (2020). *A community-informed framework for quantifying risk and resilience in southeast Louisiana*. Baton Rouge, LA: The Water Institute of the Gulf.

Hijuelos, A. C., & Hemmerling, S. A. (2015). *Coastwide and Barataria Basin Monitoring Plans for Louisiana's System-Wide Assessment and Monitoring Program (SWAMP)*. Baton Rouge, LA: The Water Institute of the Gulf.

Jepson, M., & Colburn, L. L. (2013). *Development of Social Indicators of Fishing Community Vulnerability and Resilience in the US Southeast and Northeast Regions* (NOAA Technical Memorandum No. NMFS-F/SPO-129) (p. 64). US Dept Commerce.

MacCallum, R. C., Widaman, K. F., Preacher, K. J., & Hong, S. (2001). Sample Size in Factor Analysis: The Role of Model Error. *Multivariate Behavioral Research*, *36*(4), 611–637.

Nardo, M., Saisana, M., Saltelli, A., & Tarantola, S. (2005). Tools for Composite Indicators Building. Italy: European Commission Joint Research Centre, Institute for the Protection and Security of the Citizen Econometrics and Statistical Support to Antifraud Unit.

O'Rourke, N., & Hatcher, L. (2014). *A step-by-step approach to using SAS for factor analysis and structural equation modeling, second edition*. Cary, N.C.: SAS Institute Inc.

Peacock, W. G., Grover, H., Mayunga, J., Van Zandt, S., Brody, S. D., Kim, H. J., & Center, R. (2011). *The status and trends of population social vulnerabilities along the Texas Coast with special attention to the Coastal Management Zone and Hurricane Ike: The Coastal Planning Atlas and Social Vulnerability Mapping Tools*. A report prepared for the Texas General Land Office and The National Oceanic and Atmospheric Administration. College Station, TX: Texas A&M University.

Rygel, L., O'Sullivan, D., & Yarnal, B. (2006). A Method for Constructing a Social Vulnerability Index: An Application to Hurricane Storm Surges in a Developed Country. *Mitigation and Adaptation Strategies for Global Change*, *11*(3), 741–764.

Wisner, B. (2004). At Risk: Natural Hazards, People's Vulnerability and Disasters. New York, Ny.: Routledge.

Wu, S., Yarnal, B., & Fisher, A. (2002). Vulnerability of coastal communities to sea-level rise: a case study of Cape May County, New Jersey, USA. *Climate Research*, *22*, 255–270.