PRIORITIZING THREATENED SPECIES BY VULNERABILITY TO POTENTIAL HABITAT CHANGE: A MULTI-METHOD APPROACH APPLIED IN COASTAL GEORGIA

by

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(Under the Direction of Nathan P. Nibbelink)

ABSTRACT

Coastal Plain ecosystems in Georgia are vulnerable to future sea level rise (SLR) and urban development; effective wildlife management requires prioritizations of species based on exposure to these stressors. There are two challenges associated with this task: a) understanding the severity and form of potential habitat change species may experience and b) evaluating the interplay between expert-based methods (less time-intensive, more prone to judgement bias) and empirical-based methods (more time-intensive, potentially more accurate) of assessment for prioritizations. I analyzed exposure to potential habitat change due to potential SLR and urbanization for 15 Coastal Plain species using Species Distribution Models and compared prioritizations of species using this empirical method to prioritizations using expert-based methods. Results suggest that SLR results in high exposure to habitat change, and that empirical-based methods may provide lower estimates of vulnerability from both SLR and urbanization than expert-based methods. Results can inform updates to future management plans.

INDEX WORDS: Vulnerability, Sea Level Rise, Urbanization, Wildlife Management, Georgia Coastal Plain, Spatial Ecology, GIS, Threatened and Endangered Species

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DEDICATION

To my parents: thank you for fostering and loving the feral wild-child gene in me.

I still refuse to brush my hair most days.

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CHAPTER I.

INTRODUCTION AND LITERATURE REVIEW

General Introduction and Study Area

In the future, global sea level rise (SLR) is likely to have a dramatic impact on the biological composition of coastal ecosystems and wildlife species in the United States. Estimates for predicted increases in sea level range from 30cm-200cm, which could affect species habitat by increasing the frequency and severity of tidal flooding, reducing available habitat, and fragmenting ecosystems (DeConto & Pollard 2016, Dahl et al. 2017, Sweet et al. 2018, Craft et al. 2009, Leonard et al. 2016). In addition, the National Oceanic and Atmospheric Association estimates that coastal and near-coastal populations will increase by roughly 7.1 million people by 2050, contributing to widespread habitat loss (NOAA 2015, Seto et al. 2012, McKenney 2002). The effect of these continued stressors on coastal and inland-coastal species and their habitat is an issue of growing recognition in the United States, and one that warrants further investigation.

In the Coastal Plain ecoregion of the state of Georgia, USA (**Fig. 2.1**), these events would have a strong impact on natural communities and the species that occupy them. The state's coastal areas account for roughly fifteen percent of current salt marsh habitat on the Atlantic coast (USFWS 2007) as well as the third largest distribution of tidal freshwater swamps in the Southeastern United States (Day et al. 2007), making it a vital resource for species. Inland habitat types such as sandhills, xeric longleaf pine, wiregrass forests and maritime forests provide vital habitat for multiple threatened or endangered species. Previous research has linked long-term declines in these terrestrial habitats to land conversion for agriculture and development, and the loss of Southeastern coastal salt marshes and wetlands due to anthropogenic-related change has been documented since the 1980s (Hefner et al. 1984, Turner et al. 1988). A recent assessment of the habitat vulnerability of 28 species in this region suggested that nearly all species assessed would be exposed to habitat change as a result of sea level rise by 2100 (Hunter et al. 2015). Individual studies on Georgia species also imply that sea level rise and land-use changes will have a significant impact on habitat composition and population dynamics (Valdes et al. 2016, Hunter et al. 2017, Lowery 2016), further suggesting that multiple groups are vulnerable. To effectively manage wildlife in coastal Georgia, it is necessary to assess the factors contributing to species' habitat change, and how this change may contribute to their relative vulnerability in the future.

Vulnerability Assessments

For wildlife agencies seeking to create conservation plans based on vulnerability, resource limitations often require managers to establish top priorities. Species prioritization schemes are a method for ranking species by their perceived vulnerability (Given & Norton 1993). While there is currently no broad scientific consensus regarding the criteria used to assess vulnerability, a framework consisting of three components (exposure to change, sensitivity to change, and relative resilience to change) is commonly used to evaluate species for prioritization (Pacifici et al. 2015, Turner et al. 2003, Williams et al. 2008). Empirical vulnerability assessments that thoroughly address one or more components of vulnerability, e.g., exposure to change, are often centered around the use of Species' Distribution Models (SDMs) (Willis et al. 2015, Rodriguez et al. 2007). This method can provide spatially explicit estimates of habitat suitability across landscapes and allows users to use spatial scenarios of change to quantify exposure to potential habitat change. The primary challenge for researchers utilizing this technique is understanding the severity and form of exposure. Species impacted by one type of stressor (e.g., development) may be unaffected by another (e.g., SLR), or the same groups of species may be heavily impacted by both (Brittain & Craft 2012). Thus, managers utilizing SDMs to evaluate vulnerability to habitat exposure for prioritizations will need to consider multiple types and levels of change.

Alternatively, deductive vulnerability assessments utilizing expert-opinion and literature-based information are a frequently utilized technique used to capture multiple components of vulnerability for numerous species at once, allowing for rapid prioritizations across multiple taxonomic groups (Reece et al. 2014, Hare et al. 2016). This technique relies on the input of species' experts to value multiple elements within the standard vulnerability framework (i.e., species' exposure to change, sensitivity to change, and adaptive capacity to change), as well as other elements related to management efforts. However, deductive vulnerability assessments are often absent of empirical data; that is, results reflect expert judgement on quantitative habitat loss, instead of results based on explicit information. The degree to which empirical-based data regarding quantitative metrics of vulnerability may agree or disagree with expert-based opinion may vary, and a comparison of empirical-based and expert-based results could provide valuable information regarding the contrast between these methods.

Study Objectives

The objectives of this research were twofold. First, I wanted to determine the severity and form of potential exposure to habitat change that threatened or endangered Coastal Plain species may undergo in the future and provide prioritizations of species based on these factors. Second, I was interested in evaluating the contrast between expert-based and empirical-based metrics for valuing exposure to habitat change, and the places where these two methods may or may not agree. The outcomes of this research will address a stated need of the Georgia Department of

Natural Resources' State Wildlife Action Plan (SWAP) for several key planning components: tools and data for assessing and prioritizing the vulnerability of threatened or endangered species to sea level rise and human land-use change, as well as information regarding habitat locations across Georgia. Products will be useful for local and state agencies seeking to consider multiple scenarios of potential change and will ideally assist in informing future management action across the state.

Study Overview

To evaluate long-term exposure to potential habitat change from multiple stressors, I built Species Distribution Models (SDMs) representing suitable habitat, and paired these outputs with spatial models simulating future development and land cover change as a result of SLR to examine change at multiple time points and multiple scenarios. SDMs provide explicit predictions of habitat suitability by relating species' presence and absence data to environmental predictors across space (Elith & Leathwick 2009). The use of SDMs to model species' habitat in Georgia has successfully been applied for several threatened and endangered reptile and amphibian species; this work follows similar protocols and expands on the results (Crawford et al. 2020). I utilized input from wildlife experts at various research institutions, wildlife agencies, and non-profit groups to help choose 15 Coastal Plain species on the basis of their priority for conservation in the state of Georgia, data availability, and available information necessary to build habitat models. I obtained occurrence records from research partners, state wildlife databases, and online citizen science data repositories. I used a suite of environmental predictors describing species' habitat preferences from sources such as the National Land Cover Database, the National Wetlands Inventory, LANDFIRE, and the National Hydrography Dataset, among others. I created my SDMs using generalized linear models (GLMs) in a model selection framework. The use of this technique for SDM application was first documented by Ferrier

(1984, cited in Ferrier et al. 2002), and has been utilized in numerous SDM studies since. To evaluate exposure to different types of change using the outputs of our models, I converted model outputs to binary datasets depicting suitable and unsuitable habitat, and used two datasets representing future SLR and urbanization to calculate the proportion of habitat exposed to change at several time points. To simulate future SLR, I used the Sea Level Affecting Marshes Model (SLAMM) (Clough et al. 2010). SLAMM has previously been successfully applied to evaluate coastal species' habitat vulnerability in Georgia (Hunter et al. 2015, Hunter et al. 2017). For future urbanization, I used the SLEUTH urban growth model. SLEUTH is a cellular automation (CA) model that simulates future urbanization across gridded spatial cells on the basis of five parameters: dispersion (random likelihood of urbanization), breed (likelihood of cells independently becoming urban), infill (regular outward expansion of existing urban growth), slope (resistance of urbanization on steep slopes) and road gravity (attraction of development towards roads) (Clarke et al. 2008). SLEUTH has previously been used in SDM frameworks to examine the impacts of global anthropogenic urbanization on species (Franklin et al. 2014, Conlisk et al. 2012). I calculated the proportion of habitat cells that overlapped with models of SLR and urbanization at several future time points up to 2100 as a representation of exposure to change and used this information to create species ranks.

I compared the results of our SDM study with results from The Standardized Index for Vulnerability and Value Assessment (SIVVA) conducted in Georgia (Reece & Noss 2014). SIVVA utilizes input from species experts and previous assessments to evaluate metrics of species vulnerability and has been used to assess the long-term vulnerability of several taxonomic groups across broad scales in multiple regions (Reece & Noss 2014, Reece et al. 2014, Benscoter et al. 2013). SIVVA is able to capture expert-opinion regarding multiple components of vulnerability (exposure, sensitivity and adaptive capacity), and has the unique advantage of providing additional context-driven criteria that describe species' conservation value as well as the available breadth of information needed to critically evaluate them for management action. The output of SIVVA is a set of species ranks based on vulnerability and other metrics that may be valuable for management decisions. Users are able to evaluate ranks based on individual components (e.g., vulnerability alone) or all components. SIVVA requires user input regarding quantitative measurements of exposure to habitat change (SLR and urbanization). Research comparing SIVVA outputs using empirical-based data for these measurements to results using expert-based judgement has not been conducted and may prove insightful into the advantage of valuing species for ranks using one technique over another.

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CHAPTER II.

ASSESSING CONSERVATION PRIORITIZATION SCHEMES VIA SPECIES VULNERABILITY TO HABITAT CHANGE FROM SEA LEVEL RISE AND URBANIZATION IN GEORGIA'S COASTAL PLAIN[1]

[1]Paulukonis, E., Crawford, B., Wenger, S., Maerz J., Nibbelink, N. To be submitted to Journal of Fish and Wildlife Management.

Abstract

Effective management of threatened wildlife populations in Georgia's Coastal Plain requires prioritizing species by their vulnerability to potential exposure to habitat change from future sea level rise (SLR) and/or urbanization. Few studies have examined how prioritizations may differ between types of stressors. We used species distribution models (SDMs) for 15 species to compare rankings based on habitat exposure under three scenarios of SLR (using the Sea Level Affecting Marshes Model (SLAMM)) and one scenario of urban growth (using the SLEUTH Urban Growth Model) for 4 time points. We also ranked species by Global Rank and amount of protected habitat. Results suggest little overlap between highest ranking species under each stressor (e.g. SLR vs. urbanization). Salt-marsh/beach species had the highest magnitudes of exposure from SLR (25-69%), while inland species averaged between 10-20% from urbanization. Managers may consider prioritizing species based on magnitude of exposure, not Global Rank or protected area status.

Introduction

Future environmental change has the potential to have devastating effects on U.S. coastal ecosystems in the coming century. Predictions for global sea level rise currently suggest an increase of up to 2-meters by the end of the century, which could impact low-lying ecosystem factors such as tidal range, elevation, and proportion of total brackish, freshwater and salt marsh (Craft et al. 2009, Hansen et al. 2016, Kirwan et al. 2013, Watson et al. 2015, Nicholls et al. 2010). For higher coastal habitats less likely to feel the direct brunt of impacts from sea level rise, estimates of future urban growth indicate that coastal development could still threaten ecosystem biodiversity and productivity through habitat loss and shifting land-use (Swenson et al. 2000, Seto et al. 2012). Effective management of wildlife populations in coastal regions requires planning for the relative vulnerability of species to these anthropogenic factors, particularly for threatened or endangered species already at risk of potential extinction (Daniels et al. 1993, Benscoter et al. 2013, Walls et al. 2019). For agencies seeking to create conservation plans addressing future threats, resource limitations mean that managers must often establish top priorities for action (Given & Norton 1993, Miller et al. 2006, Gauthier et al. 2010, Barrett et al. 2014, Walls et al. 2019). Species prioritization schemes, wherein species are ranked by their perceived vulnerability, can aid managers in this task (Kerr & Deguise 2004, Reece & Noss 2014).

In defining criteria used to determine priority rankings, frameworks that include exposure to change, sensitivity to change, and resilience to change can help practitioners integrate multiple dimensions of vulnerability (Turner et al. 2003, Williams et al. 2008). However, data on species' traits needed to support this framework (life history, physiology, adaptive capacity etc.) can be lacking, particularly for rare species (Williams et al. 2008). Species distribution models (SDMs), which provide spatially-explicit predictions of species habitat suitability (and thus potential distribution) by relating presence data to environmental variables across a landscape, can be used to represent exposure to change as an initial indicator of vulnerability (Elith et al. 2006, Elith & Leathwick 2009, Dawson et al. 2011). By quantifying changes in predicted suitable habitat due to sea level rise or urbanization, managers can estimate exposure to potential habitat loss, a metric that can be highly useful for ranking species. The primary challenge in developing rankings based on this factor lies in understanding the severity and form of exposure to potential habitat loss that species may experience. Because species may be impacted by anthropogenic threats in different ways and to different extremes across landscapes, it can be difficult for managers to know how to allocate resources with respect to spatial vulnerability. For example, Brittain & Craft (2012) found that some coastal-dwelling avian species experiencing habitat loss from development were unlikely to experience similar habitat loss from sea level rise. This problem becomes more complicated when considering multiple scenarios for a specific threat, because outcomes for one level of severity (e.g., 1-meter sea level rise) may be different than outcomes for another (2-meter rise) (Bellard et al. 2014). Considering that species' habitat vulnerability can vary widely from threat to threat, managers developing conservation plans will need to identify how prioritizations of species based on exposure to potential habitat loss may shift due to multiple types and levels of change.

While exposure to potential habitat change or loss as a standalone measure can be useful as a first step in identifying priority species, managers will also need to consider the extent to which work has already been done to offset the impacts of anthropogenic threats, as well as the state of the species within a broad ecological context (Joseph et al. 2009, Shi et al. 2005). First, it will be necessary to assess the total amount of habitat within protected lands, where conservation efforts are often primarily directed and where decisions about resources may be most important (Barrett el al. 2014). Species with large amounts of protected habitat may fall lower on priority lists, as managers can choose to prioritize species that are less protected. Management decisions can also account for individual conservation areas that may contain important habitat for certain species, allowing for the enhancement or continued protection of that area. Second, it will be useful to evaluate species' global vs. regional vulnerability status. In other words, when does the need to conserve a species for global conservation outweigh regional goals for management? Species with both high regional vulnerability and high global vulnerability may need to be considered first (Brooks et al. 2006).

Georgia's Coastal Plain ecoregion (**Figure 2.1**), part of the Southeastern U.S., is the largest geographical portion of the state, extending from the Fall Line in the north to the Atlantic

Ocean. The region is marked by a wide variety of habitat types such as well-drained sandhills, xeric longleaf pine and wiregrass forests, salt marsh, bottomland hardwood swamps, and maritime forest. As part of the North American Coastal Plain, the region is recognized as a global biodiversity hotspot, noted for high species endemism coupled with high vulnerability to declines in species richness (Noss et al. 2014, Myers et al. 2000). Since the early 20th century, widespread clearing of natural lands for agriculture and development has modified much of the region, resulting in severe habitat fragmentation and loss, and continued urbanization is likely as human populations in this area are predicted to increase by roughly 30% (Ross et al. 2006, Turner et al. 1988, GIT 2006). Sea level rise is also expected to dramatically influence the severity of habitat loss as a result of heightened tidal inundation in the region (Dahl et al. 2018). Evidence suggests that these factors are likely to negatively impact species' habitat in Georgia throughout the coming century (Craft et al. 2009, Hunter et al. 2015). In response to these and other issues, the state has developed a list of 265 species marked for conservation priority (GADNR State Wildlife Action Plan 2016). Attempts at developing species prioritization schemes via habitat vulnerability have provided information on threats from sea level rise, but thus far the use of multiple types and severities of change scenarios has not been considered (Hunter et al. 2015). In this study, we used SDMs for 15 species of conservation concern to map suitable habitat across the coastal plain. We then assessed vulnerability to multiple threats by projecting the SDMs onto theoretical future landscapes after applying scenarios of urbanization and sea level rise. Finally, we ranked species' vulnerability for each scenario and under multiple ranking schemes considering total exposure to potential habitat change, fractional change, and fraction in protected areas. Our goals were to a) assess species' vulnerability to exposure to potential habitat loss from sea level rise and urbanization, b) evaluate how species' prioritization for regional management action may change under these different scenarios, and c) contextualize prioritization around current available protected habitat and species' global vulnerability.

Methods

Study Area and Species of Interest

In order to support a trend towards developing community-wide standards for species distribution models, we followed guidelines outlined by Araujo et al. 2019 so that all processes and outputs met a standard of bronze or higher (Araujo et al. 2019). First, we consulted with wildlife experts from federal and state agencies, universities, and non-profits to compile an initial list of approximately 50 target species considered to be a priority for conservation in the state. From this list, we used an additional set of criteria to choose 15 avian and reptile species (**Table 2.1**). We first used the state rarity rank (Georgia Conservation Status) to rank all species on the compiled list. Species are ranked from 5 (currently stable) to 1 (critically imperiled), with a letter assigned to denote status at the state level. We eliminated all species with a status of S5, so that all species had a value of S4 (currently stable with concerns about species longevity in the state) or less. Finally, we eliminated species with less than 20 occurrence records (Stockwell & Peterson 2002) or lacked appropriate information on range or habitat preferences. Our study area comprised the combined known range of all 15 species within Georgia's Coastal Plain ecoregion. To better reflect the coastal range of several of our species, we divided the study extent into two parts (**Figure 2.1**). For species found exclusively in the lower Coastal Plain, we restricted the extent to coastally-influenced areas and included the nearshore Atlantic Ocean as a land cover type. For all other species, we included the full extent of the ecoregion, as well as a 2km spatial buffer extended above the Fall Line that encompassed our largest maximum biological window size (detailed below).

Species Data

All spatial analyses were completed using ArcGIS version 10.6.1 (ESRI, Redlands, CA) and R version 3.2 (R Core Team 2016). For 5 selected species, SDMs using similar methods were already available for the region from a complementary project (Crawford et al. 2020). For the remaining 10 species, we collected occurrence records (presence locations) denoting locations where species have been observed from state agency natural heritage programs, research partners, and the eBird citizen science data repository (**Table 2.2**). Records were comprised of a mixture of observations from research and monitoring studies as well as opportunistic sightings. We used occurrence records from the Georgia Department of Natural Resources Element Occurrence (EO) data portal for all but two species. For each EO record, spatial polygon data was used to denote areas where a species or natural community was historically present, ranging in date from early 20th century (historical records) to present day. To avoid potential issues with historical data and representational accuracy, we eliminated all records of collections prior to the year 2000 as well as records with a precision of less than 500m. We converted polygon records to point coordinates by taking the center point to represent the estimated coordinates at which a species was present. For the diamondback terrapin (*Malaclemys terrapin)*, we used abundance data from a multi-year seining and drone survey in Georgia's tidal creeks and streams (Grosse et al. 2011). We randomly selected a single point along creeks that had recorded an abundance ≥ 1 between 2008-2018 to represent the occupancy of each creek (He & Gaston 2000). Data for the seaside sparrow (*Ammodramus maritimus*) came from a multi-year survey of salt marsh bird distributions in coastal Georgia (Hunter et al. 2016).

Our avian datasets were supplemented with records from the eBird citizen science data repository (eBird 2019). eBird is a citizen science data collection program that allows birdwatchers to submit coordinates denoting observations of avian species. Regional filters help reduce the likelihood of misidentifications and double counts, but there is potential for spatial and temporal biases in the datasets. We followed the eBird recommended best practices for additional bias correction (Johnson et al. 2019). To capture observations that reflect recent updates to the eBird filtering protocol, we used only records from 2010 to 2019. For two of our species (the painted bunting (*Passerine ciris*) and the wood stork (*Mycteria americana*), use of Georgia's coastal plain is typically associated with seasonal breeding behavior (Springborn et al. 2006, Gaines et al. 1998). To avoid using eBird sightings that may have occurred during migration (and thus do not necessarily reflect true habitat preferences), we restricted the data to known breeding range and eliminated observations that occurred outside of breeding season for these species. For all species, if two or more observations were located at a single coordinate set, we randomly selected a single observation to eliminate duplicates. As an additional measure of filtering recommended as part of the eBird best practices, hexagonal grids with a 5km spacing between grid centers were used to randomly subsample the remaining points, so that the final output was one observation per cell.

To minimize the potential for spatial bias that can arise from clustered records, we applied a filter over all datasets that randomly removed records occurring within a species-specific biological window of each other (Veloz 2009, Boria et al. 2014). Biological windows (neighborhoods) reflect the relationship between an organism and its surrounding landscape at a certain scale. We based the neighborhood size used to filter records on the average value of each species' core territory obtained from the literature **(Table 2.2)**. Thus, the final set of records for each species had no more than one observation within the specified neighborhood radius of any other observation. Because of a lack of true absence data for the majority of our species, we created sets of pseudo-absence points to compare the environment of known occurences to background environments (Engler et al. 2004, VanDerWal et al. 2009). We randomly generated pseudo-absence points for each species so that all points a) fell outside of the pre-defined neighborhood radius of presence points and b) within the study area appropriate for each species. We generated points at a 1:4 ratio of presence:pseudo-absence points, so that after the removal of points within neighborhood radii, the final output consisted of presence points and pseudo-absence points at an approximate ratio of 1:3 (Crawford et al. 2020).

Environmental Variables

For each species, we tested a suite of biotic and abiotic predictor variables hypothesized to influence species' distributions, based on a literature search of each species' habitat preferences. We used 30-m raster datasets describing characteristics across the species-appropriate extent (**Table 2.3**). Our hypothesis-based set of variables captured each species' relationship to factors associated with a) land cover, b) vegetation characteristics, c) topography and soil, d) disturbance, and e) climate (**Table 2.5**). Because species may use habitat differently at various spatial scales, it can be useful to investigate relationships between species and landscapes using multiple neighborhood sizes (Addicott et al. 1987, Johnson et al., 2004, Hagen-Zanker 2016). We selected a minimum and maximum neighborhood size for each species based on best available information regarding species habitat use at different scales and calculated the mean value for each variable at each scale.

We created landscape metrics for each variable using FRAGSTATS version 4.2 (McGarigal et al. 2012), the Spatial Analyst Toolbox in ArcMap, and the SpatialEco package in R (Evans 2020). For land cover, we created variables describing appropriate vegetation, barren or urban land, and wetlands or water factors related to each species' habitat preferences using present-day habitat types included in the United States Geographical Service (USGS) 2016

National Land Cover Dataset (NLCD 2016), the Sea Level Affecting Marshes Model [SLAMM; (Clough et al. 2010)], SLEUTH Urban Growth model (Clarke et al. 1997), the USGS National Wetland Inventory database (NWI), LANDFIRE Existing Vegetation Type datasets (LANDFIRE 2013), and National Hydrography Dataset (NHD 2019). Each individual dataset was reclassified as 1, meant to define the variable of interest, or 0, encompassing all other land cover classifications. These datasets were then used to extract metrics such as percent of habitat, mean habitat patch area, number of habitat patches, and habitat edge density within the specified neighborhoods for each species and scale. For certain variables, we defined unique components of the landscape relevant for individual species. For example, to capture the tendency of the Wilson's Plover (*Charadrius wilsonia*) to choose nesting sites closer to marsh vegetation, we created a variable that captured the percent of beach and dry land within 100m of adjacent marsh (Derose-Wilson et al. 2013). Vegetation characteristics were drawn from the LANDFIRE Existing Vegetation Height (EVH) dataset and the NLCD Tree Canopy Cover dataset. EVH was used to describe average heights of vegetation relevant to species. We reclassified heights from 0 (shortest) to 1 (highest) in 0.25 increments, with each increment describing a range of heights. We also included a deciduous index (EVI), which captured the difference in winter and summer greenness. Topography and soil variables captured relevant characteristics of elevation and drainage. We used elevation data from the USGS 30-m Digital Elevation Model (DEM). For several species, a Topographic Position Index (TPI) was used to represent a location's elevation relative to its local surroundings, e.g., components such as sand-hills (positive TPI) and valleys (negative TPI). A soil drainage index from the gridded SSURGO raster from the Natural Resources Conservation Service [NRCS; (Natural Resources Conservation Service 2017)] described poorly-drained to well-drained soils. For disturbance variables, we used a fire frequency dataset representing the percentage of years burned between 2001 and 2016 and a historical land disturbance dataset created from historical land cover data identifying places classified as developed or converted to agriculture between 1938 and 2001 (Crawford et al. 2020). Because air temperature in Georgia's Coastal Plain has limited spatial variability (and thus explanatory power), we did not include gridded temperature data as a covariate. Datasets representing the mean summer and winter precipitation were included for several reptile species. We extracted values from the gridded datasets for each covariate to the presence and pseudo-absence points for model fitting.

Species Distribution Models

We used logistic regression (generalized linear models, GLMs) in a model-selection framework to create our presence and pseudo-absence SDMs (Burnham & Anderson 2002). All models and accompanioning statistical analyses were completed in R. We ranked models using Akaike Information Criterion (AIC_c) weights and selected the model with the highest weight. For each species, we first grouped all variables by their type (e.g., beach/flat for American oystercatcher, **Table 2.5**) and performed model selection to compare neighborhood sizes and choose the scale most appropriate for each variable. We then tested all variables from the first stage of model selection for collinearity by using a Pearson correlation coefficient ≥ 0.7 or ≤ -0.7 to evaluate pairs of variables that were correlated, choosing the best-supported variable of the two. Finally, for each species, we tested all remaining variables at their best-supported scales, including quadratic and 1-way interaction terms for variables where quadratic or interaction relationships were supported by the literature.

We performed model evaluation using several methods (Araujo & Guisan 2006). We used 4-fold cross-validation to evaluate the performance of the best-fitting model for each species. We calculated the area under the curve (AUC) from the receiver-operating characteristic plot (ROC plot) (Fielding and Bell 1997), where values of 0.7 or higher were considered reasonably good at distinguishing presence from pseudo-absence. We evaluated model classification accuracy of presence and pseudo-absence points by calculating the True Skill Statistic (TSS, sensitivity (proportion of true presences) + specificity (proportion of true negatives) – 1), and then using the maximum TSS value to choose the optimal cutoff value (Allouche et al. 2006). We calculated the point biserial correlation coefficient (COR), which is used to measure the strength of the relationship between a continuous variable (predictions) and a dichotomous variable (original presence/pseudo-absences) where 1 indicates a positive relationship and -1 a negative relationship, as an additional measure of accuracy (Liu et al. 2011). We also produced variograms using model residuals to test for spatial autocorrelation. Relative importance of each variable was calculated using hierarchical partitioning, which measures proportion of variance explained by each component of the model (Chevan & Sutherland 1991). We projected the best-fitting models out to the landscape to map continuous habitat suitability ranging from 0 (not suitable) to 1 (highly suitable). To evaluate fraction of potential exposure to habitat loss, it is necessary to select a threshold from this continuous range that denotes habitat as binary classes of suitable/unsuitable (Bean et al. 2012). We converted continuous suitability into binary rasters of 1/0 (suitable/unsuitable) using the optimal cutoff value (the value at which the TSS, e.g., model accuracy, is highest) as our threshold. For agencies interested in identifying higher quality habitat, it can be useful to evaluate suitability using multiple thresholds to capture a range of intended uses (Freeman & Moisen 2008). Therefore, we also used values of 0.4 and 0.6 to create binary rasters of ‘moderate’ and ‘high’ habitat suitability, respectively (Crawford et al. 2020).

To avoid including areas that may unrealistically represent suitable habitat, we converted any predicted suitable cells that overlapped with open water and present-day high intensity urban areas to the unsuitable habitat class. For coastal regions, we defined open water as all classes encompassing inland open water, riverine open water, estuarine open water and open ocean using the SLAMM classes for Georgia's coast. In upland areas where SLAMM data is not available, we used the NLCD Open Water category. To define high intensity urban areas, we used the SLEUTH urban growth model, which denotes current urbanization based on land-cover, transportation, and topography. We created datasets describing currently protected habitat for each species by extracting the binary SDM outputs to the USGS Protected Areas Database (http://www.protectedlands.net/), and the GADNR Conservation Lands Database (https://glcp.georgia.gov/). These databases provide an inventory of federal and state managed lands, including areas that are both publicly and privately owned. We summarized the amount of total available habitat and habitat within protected lands by calculating area (km^2) and percent of habitat. To accurately reflect the extent of coastally-influecned species, we ranked species in two groups: Coastal Plain and lower Coastal Plain.

Scenario Evaluation and Vulnerability Ranking

We used the SLAMM predictions for coastal regions to define inundation from sea level rise and the SLEUTH urban growth model to represent urban growth in the future. We chose four future time points at which to examine impacts of sea level rise and urban growth (2025, 2050, 2075 and 2100). For urbanization, SLEUTH defines raster classes denoting predicted probability of growth based on data describing slope, land-use, exclusion, urbanization, transportation and hill-shade (Clarke 1997). Classes are numbered from 3 (0-2.5% probability of urban growth) to 16 (97.5-100% probability of urban growth). We included all classes greater than or equal to 10 (50-60% probability) and reclassified them to a single class to represent predicted urban growth for each future time point. To predict coastal change from sea level rise, SLAMM uses digital elevation data and National Wetland Inventory data to simulate processes involved in wetland conversion under different scenarios of sea level rise. The result is a dataset representing changed land cover conditions under sea level rise. Due to uncertainty surrounding realistic projections of future sea level, we used datasets for scenarios of 1m, 1.5m and 2m sea level rise. For each scenario, we reclassified SLAMM classes denoting riverine open water, estuarine open water, and open ocean to a single class for inundation. To assess the impact of future sea level rise and urbanization on Coastal Plain species, we used several measures of change in total available habitat and protected area habitat to define potential habitat loss. We first overlaid the binary SDM outputs for the entire extent and within protected areas for each threshold with the binary datasets conveying urban growth and inundation in R. Each SDM cell that overlapped with cells denoting growth or inundation was converted to 'unsuitable', so that the output was a raster with a changed sum of total habitat cells, indicating each species' exposure to potential habitat loss at each future time point. We used these outputs to calculate percent change, percent total, and area of range-wide and protected habitat for each year within each scenario. Because scenarios of urban growth are unlikely to impact habitat that is currently protected, we only evaluated future habitat loss from inundation for protected areas.

To assess several types of prioritization schemes, we created a series of species vulnerability rankings. We first ranked species by their percent change in habitat as a result of sea level rise and urbanization, where ranks of 1 represented highest percent of potential habitat loss or change. We also ranked species by area of total available habitat using 1 to represent least amount of area (and thus top priority). To assess the amount of habitat falling within conservation areas, we also ranked species by the total percent of available habitat within protected lands, where 1 represented the lowest percent of protected habitat. We compared these ranks for urbanization to sea level rise, choosing a 'cutoff' rank of 8 to represent species within distinct categories of vulnerability for each type of change. Finally, we used Global Rank, a metric used for Conservation Status Assessment (CSA) created by national conservation non-profit NatureServe (NatureServe 2019), to convey species' relative global vulnerability to potential extinction. We used a cutoff rank of 3 ('Vulnerable') to represent species above or below high global vulnerability.

Results

Present-Day Habitat

Our filtering methods resulted in no fewer than 49 total presence points for each species, consistent with recommended sample sizes (**Table 2.2**). Best fitting models all exhibited adequate to good model performance (**Table 2.6**). For more information on variable contribution for each model, see **Appendix B**. AUC values ranged from 0.77 (adequate) to 0.95 (excellent). Biserial correlation coefficients were above 0.30 for all models (Elith et al. 2006), with a minimum COR value of 0.44 and a maximum of 0.84. Accuracy (the maximum TSS) was above 65% for all models. Spatial variograms revealed no extreme patterns of range-wide autocorrelation. RCWO and BACS displayed some evidence of spatial structure, but the proportion of the range was small enough so that no bias was expected. Total area of suitable habitat ranged from 343.3-35798.2 km^2, using the optimal cutoff threshold (**Table 2.7**). Habitat falling within protected areas ranged from 107.5-3649.7 km^2, or 7.3-31.3 % of total habitat. For areas of 'moderate' and 'high' habitat suitability, total habitat area varied from 243.4-14567.9 km^2 and 114.6-4527.6 km^2, respectively. Amount of habitat in protected areas for these classes was between 80.6-2490.4 km^2 ('moderate' class) and 21.9-1405.4 km^2 ('high' class), i.e., 8.5-

44.7 % and 14.9-50.5 % of total habitat. Total percent of habitat falling within protected areas decreased as suitability classes become more restrictive (optimal cutoff, ‘moderate’ and ‘high’ habitat suitability threshold values) for 3 out of 4 species whose range is restricted to the lower Coastal Plain. Conversely, all species within the total Coastal Plain as well as the seaside sparrow had higher percentages of habitat falling within protected zones in the more restrictive classes.

Future Habitat and Species Ranks

We present prioritization schemes for species vulnerability to future exposure to potential habitat loss or change, using habitat classified as suitable under the optimal cutoff threshold. Full results from the ‘moderate’ and ‘high’ suitability classes are in **Appendix C**. As trends in rankings for vulnerability to potential sea level rise were similar across scenarios, hereafter we discuss prioritization schemes using the 2-meter sea level rise scenario, with all ranks determined by projections to 2100. Patterns in rank order varied only slightly over time; results for 1-m and 1.5-m ranks are available in **Appendix A**. Species restricted to the lower Coastal Plain ranked highest for exposure to potential habitat loss from sea level rise by 2100, ranging from 7-72%. In contrast, species occupying broader ranges experienced very little exposure to potential habitat loss from sea level rise (0-6%). The highest percent of potential habitat lost by a species via urbanization was 22%, substantially lower than the highest percent of potential habitat lost by a species to sea level rise. Species ranked for high vulnerability to exposure habitat change from sea level rise generally ranked low for vulnerability to change from urbanization, and vice versa (**Figure 2.3, A**). Two exceptions were the painted bunting (PABU) and wood stork (WOST), which ranked moderately high for habitat loss to sea level rise, and high or highest for habitat loss due to urbanization (**Figure 2.3, B**). Several species were ranked moderately low for vulnerability to both components (**Figure 2.3, C)**. Species ranking highest on the basis of percent habitat loss from sea level rise were also ranked highest based on total predicted area, but tended to rank lower based on the amount of habitat currently protected (**Table 2.8**). The top-ranking species under scenarios of urbanization ranked lowest based on total predicted area but tended to have less protected habitat (**Table 2.8**). Species ranked lowest ('Apparently Secure' to 'Secure') for global vulnerability (**Figure 2.4, 1A**), typically had the highest regional vulnerability to sea level rise, while those ranked for higher global vulnerability ('Vulnerable' to 'Imperiled') had the lowest (**Figure 2.4, 1D**). Several species ranked high for global vulnerability also ranked reasonably high for regional vulnerability to urbanization (**Figure 2.4, 2B**). Species ranking low for urbanization vulnerability also ranked low for global vulnerability (**Figure 2.4, 2C**).

Discussion

Our results indicate that all species evaluated are likely to experience some form of habitat loss or change from either sea level rise or urbanization, but that few species will experience significantly high loss from both stressors. The severity of potential habitat loss experienced by species was highly dependent on their range and amount of predicted suitable habitat. Coastally restricted species had less predicted suitable habitat area initially and experienced more severe declines in predicted suitable habitat in the future than those species occupying some portion of the larger Coastal Plain. Given the restricted range of both salt-marsh and coastline habitats in GA, this is unsurprising (USFWS 2007). We found that species utilizing salt-marsh, beach, and other coastal habitat types will be most vulnerable to potential habitat loss from sea level rise, which is consistent with previous evidence suggesting that salt-marsh and beach reliant species will be highly vulnerable to potential habitat loss from sea level rise in the future (Hunter et al. 2015, Hunter et al. 2014, Brittain & Craft 2012, Galbraith et al. 2002). A majority of species occupying some or all of the entire Coastal Plain experienced little habitat loss from sea level rise, averaging loss below 0.5% even under 2m sea level rise scenarios. Instead, results indicate that despite larger estimates of predicted suitable habitat area than lower Coastal Plain species, inland Coastal Plain species will experience substantial habitat exposure (3-20%) to urbanization, which agrees with other studies suggesting development is a major threat to Georgia's inland terrestrial species in the region (Leonard et al. 2016, Breininger et al. 2012, Plentovich et al. 2007, Gibbon et al. 2000).

Because ranks based on fraction of protected habitat were a factor of total available habitat area, assessing the role of protected lands in prioritizing species is difficult. Several of the lowest ranking species for priority on the basis of protected habitat ranked low for vulnerability to habitat loss, yet still ranked moderately high for action based on total available habitat area. For example, the red-cockaded woodpecker (RCWO), Bachman's sparrow (BACS), and gopher frog (GF) all had roughly 1/3 to half of their total habitat falling within protected areas yet ranked within the top 10 for priority based on low total available habitat. Georgia populations of these species have historically been documented in longleaf pine ecosystems (GADNR 2010[a], GADNR 2010[b], Maerz and Terrell 2016). Due to the widespread decline of these ecosystems and the recognition of their importance for multiple regional species, a large portion of longleaf pine habitat in Georgia tends to fall within some protected land. This indicates that while species utilizing these landscapes may have much of their available habitat protected, they still rank relatively high for action based on total available area due to specific habitat requirements. This pattern is consistent for species using salt-mash and beach habitats, which had roughly 1/4-1/3 of their habitat protected along Georgia's coast, yet have little total predicted habitat to begin with (e.g., SESP, AMOY). Further, whether protected or not, these habitat types will be vulnerable to the effects of SLR, whereas inland protected areas will not be vulnerable to encroaching development. This suggests that while managers may be able to use the amount of habitat falling within protected area to offset the impacts of future change, eliminating species for top ranking on the basis of total protected habitat is an ineffective strategy, and managers will instead need to evaluate species for total available habitat.

All species ranking highest for habitat vulnerability to sea level rise were classified as 'Apparently Secure' or 'Secure' globally, indicating these species reportedly have large to medium populations currently showing no extreme declines throughout their range (Clay et al. 2014, NatureServe 2019). The challenge in weighing global status against regional vulnerability is that the magnitude of species' vulnerability to potential habitat loss within a region may outweigh priorities for global conservation, particularly when global priority schemes may be data deficient. For many of our species, population status has not been re-evaluated since 1996. This means that global listings may not be accurate reflections of range and population resiliency, a problem documented in several large-scale global priority systems (Ramesh et al. 2017). This does not necessarily mean that global conservation status should be discounted as a tool for regional management decision, but rather that managers may need to use global conservation status as a secondary measure for final priority ranking if the magnitude of projected regional habitat loss for a species is extremely high (e.g., 35-100% of habitat projected to be lost). Although species ranking high for both global vulnerability and regional vulnerability to habitat loss (e.g., Southern hognose snake, SHS and striped newt, SN) will still likely rank high for priority for conservation action, managers will need to weigh the magnitude of regional vulnerability to habitat loss as a primary factor for those species ranking lower globally.

While all salt-marsh and beach dwelling species ranked high based on potential habitat loss, the seaside sparrow (SESP) was projected to experience particularly high potential habitat loss. Seaside sparrows are considered habitat specialists, relying primarily on salt marsh for both nesting and foraging activities (Hunter et al. 2015). Unlike the other species ranked high for habitat loss to sea level rise, all of which utilize beach habitats in conjunction with salt and brackish marsh, the seaside sparrow is limited by its dependence on this singular habitat type. Under the SLAMM model, salt marsh habitats are degraded substantially, with a conservative estimate of 6% loss by 2100 under 1m SLR. In contrast, the model predicts increases in tidal flats and estuarine beaches, meaning that beach habitats will be surprisingly persistent despite inundation; this likely accounts for the gap between habitat loss values between the seaside sparrow and species ranked directly below it. For upland species, the contribution of urbanization to the conversion of alternative inland habitat types could also inadvertently buffer the impact of habitat loss. Species associated with agricultural, pasture, or even low or moderately developed areas may be able to utilize these land cover types to their advantage, offsetting the full effect of habitat loss of other natural landscapes (Lee & Carroll 2014, Kopachena & Crist 2000). This may be most applicable for species ranked high for vulnerability to both sea level rise and urbanization, as in the case of the painted bunting (PABU) and wood stork (WOST). Both species concentrate around coastal wetlands/swamps (freshwater and brackish/saltmarsh) and shrub-scrub and maritime forest habitats for nesting, but are also found near inland agricultural and riparian areas in and outside of breeding season, consistent with habitat variables used in our top models (Gaines et al. 1998, Kopachena & Crist 2000, Brittain et al. 2010). The use of both generalized inland and coastally adjacent habitat types likely drives the high and moderately high ranks for these species in both categories, suggesting that species occupying habitat along this coastal-inland gradient could be more susceptible to both forms of stressors. However, these habitat generalists could potentially benefit from other habitat types that may arise as a result of anthropogenic change, meaning that managers will need to consider which high ranking species may be habitat specialists vs. habitat generalists.

It should be noted that there are two challenges associated with models simulating future sea level rise and future urbanization in this region. Firstly, we chose to present results using a 2-m sea level rise scenario. There is some debate about the uncertainty associated with predictions of sea level rise, although recent studies have suggested that conservative estimates of sea level rise may be unrealistic, indicating that managers may wish to consider worst-case (i.e., 2-m) scenarios (Kopp et al. 2017, Kulp et al. 2019). Using this justification, we felt our choice of a 2-m scenario was appropriate and that rankings were consistent between severities. However, the magnitude of exposure does vary between scenarios, and agencies may choose to consider more conservative scenarios, potentially resulting in slightly different interpretations of results. Secondly, models for development often fail to account for some human responses to future stressors such as SLR. The SLEUTH model relies on information from current distributions of development and does not presently include information about potential human responses to SLR that may inadvertently impact coastal wildlife populations, therefore potentially underestimating the true impact of future development. For example, the building of sea walls is rapidly becoming a common urban planning technique to address SLR. Sea walls have been shown to have negative impacts on diamondback terrapin habitat, resulting in habitat fragmentation and loss of habitat connectivity (Isdell et al. 2015). While efforts to construct sea walls are presently limited in Georgia, it is reasonable to assume that armoring of shorelines will be a mitigation tactic employed in the future, meaning that SLEUTH is presently unable to capture these relationships. Thus, our estimates of exposure to habitat change from development may be conservative for some coastal species who may be prone to vulnerability from development-related mitigation efforts.

While the nuances of impacts to species from future anthropogenic threats are difficult to completely assess, we present an initial attempt at helping managers consider tradeoffs between prioritization schemes under multiple types of change. Our results suggest that managers may need to prioritize species (or their habitats) based on the regional total amount of available habitat, and the magnitude of habitat loss. We found that species restricted to the lower Coastal Plain were projected to lose up to 40-70% of their habitat due to sea level rise, roughly twice the amount of habitat loss projected for top ranking species under urbanization. Although these species currently rank low for global vulnerability, this result has implications for populations outside of Georgia, as sea level rise may have similar effects on populations along the rest of the Atlantic coast, potentially changing the nature of species' global status (Hayes 1994). We also felt that focusing on results due to change by the end of the century was appropriate, as top-ranking species for early (2025) and mid-century (2050) habitat loss deviated little from results by 2100. However, it may be valuable for managers seeking to develop short-term conservation plans to use priority schemes for timescales closer to mid-century, as several inland species ranked higher for immediate habitat loss due to urbanization by 2025 than species experiencing habitat loss from sea level rise by 2025 (see **Appendix A**). Differing conservation timelines and goals will mean that managers need multiple lines of evidence in order to make informed decisions and appropriately allocate resources. We offer a multi-scenario, broad ranging set of results that may help to contextualize potential management actions and provide a first step for combating species' long-term vulnerability.

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Figures and Tables

Table 2.1. Georgia Coastal Plain Species and their regional conservation status. Conservation status is defined by a state government agency, the Georgia Department of Natural Resources. Type indicates species group. Acronyms are assigned from the U.S. Bird Banding Laboratory (BBL) and from various literature. Highlighted species indicate species restricted within the lower Coastal Plain.

Scientific Name	Common Name	Type	Acronym	State Rank
Ammodramus maritimus	Seaside Sparrow	Av^{P}	SESP	S3
Charadrius wilsonia	Wilson's Plover	Av^{SB}	WIPL	S2
Haematopus palliatus	American Oystercatcher	Av^{SB}	AMOY	S2
Mycteria americana	Wood Stork	Av^{MB}	WOST	S3
Leuconotopicus borealis	Red-cockaded Woodpecker	Av^{WP}	RCWO	S2
Passerina ciris	Painted Bunting	Av^{P}	PABU	S2S3
Peucaea aestivalis	Bachman's Sparrow	Av^{P}	BACS	S2
Lithobates capito	Gopher Frog	Am	GF	S2S3
Notophthalmus perstriatus	Striped Newt	Am	SN	S2
Crotalus adamanteus	Eastern Diamond-backed Rattlesnake	R	EDR	S4
Drymarchon couperi	Eastern Indigo Snake	R	EIS	S2
Gopherus polyphemus	Gopher Tortoise	R	GT	S3
Heterodon simus	Southern Hognose Snake	R	SHS	S1S2
Malaclemys terrapin	Diamondback Terrapin	R	DT	S4
Pituophis melanoleucus	Florida Pine Snake	R	FPS	S3

Type: *Av^{SB}= avian: shorebirds, Av^{MB} = avian: marsh birds, Av^{P} = avian: passerines, Av^{WP} = avian: woodpeckers, Am = amphibian, R = reptile.*
State ranks: *S1 = Critically Imperiled, S2 = Imperiled, S3 = Vulnerable, S4 = Apparently Secure.*

Table 2.2. Sources for presence points, total presence and pseudo-absence points, and filtering scheme used to remove potential bias for 10 species. R&M denotes points gathered from Research and Monitoring studies. Pseudo-absences were generated at a 1:4 ratio, then filtered using the neighborhood size so that the final ratio of presence to pseudo-absence points was 1:3. For more information on data collection for species denoted with *, see Crawford et al. 2020

Species	Neighborhood	NatureServe	eBIRD	R&M	Presence Points	True Absences	Pseudo-Absences	Total
AMOY	100m	187	68	-	255	-	788	1043
BACS	100m	299	239	-	538	-	1649	2187
DT	500m	9	-	40[a]	49	8	157	214
EDR	900m	260	-	-	260	-	774	1034
EIS	900m	224	-	-	224	-	738	962
FPS*	-	-	-	-	-	-	-	-
GF*	-	-	-	-	-	-	-	-
GT*	-	-	-	-	-	-	-	-
PABU	700m	-	269	-	269	-	844	1113
RCWO	100m	163	62	-	225	-	694	919
SHS*	-	-	-	-	-	-	-	-
SN*	-	-	-	-	-	-	-	-
SESP	200m	-	-	99[b]	99	115	190	404
WIPL	100m	35	47	-	82	-	250	332
WOST	2km	26	371	-	248	-	805	1053

[a] Grosse et al. 2011, [b]Hunter et al. 2015, *Crawford et al. 2020

Table 2.3. 30-m raster datasets used to describe habitat variables for 10 species. All variables denoted with * were modified raster datasets borrowed from Crawford et al. 2019.

Predictor	Source
Landcover	2016 National Land Cover Database (NLCD) (https://www.mrlc.gov/nlcd11_data.php) Sea Level Affecting Marshes Model (SLAMM) (http://warrenpinnacle.com/prof/SLAMM/index.html) SLEUTH Urban Growth Model (http://www.ncgia.ucsb.edu/projects/gig/Dnload/download.htm) USGS National Wetland Inventory (NWI) (https://www.fws.gov/wetlands/) LANDFIRE Existing Vegetation Type (EVT) (https://www.landfire.gov/evt.php) National Hydrography Dataset (NHD) https://www.usgs.gov/core-science-systems/ngp/national-hydrography
Vegetation Characteristics	LANDFIRE Existing Vegetation Height (EVH) (https://www.landfire.gov/evh.php) NLCD Canopy Cover Dataset Emergent Vegetation Index (EVI) MODIS (https://modis.gsfc.nasa.gov/data/dataprod/mod13.php)
Topography and Soil	USGS Digital Elevation Model (DEM) (http://eros.usgs.gov/#/Guides/dem) Topographic Position Index (TPI) (http://eros.usgs.gov/#/Guides/dem) NRCS Gridded SSURGO (GSSURGO) Soil Drainage Index (gSSURGO: https://www.nrcs.usda.gov/wps/portal/nrcs/main/soils/survey/)
Disturbance	*MODIS Fire Frequency (https://earthdata.nasa.gov/earth-observation-data/near-real-time/firms/active-fire-data), LANDFIRE (https://www.landfire.gov/) *Historical Land Disturbance USGS / EROS (https://landcover-modeling.cr.usgs.gov/projects.php)
Climate	University of Idaho Gridded Surface Meteorological Data (U of I METDATA)

Table 2.4. Top-performing models describing suitable habitat for 10 species.

Species	Model
AMOY	plandbh100 + edmsh1km + edmsh1km^2 + urb_1km + ow_1km + ow_1km^2
BACS	plandpine800 + plandpine800^2 + fire800 + fire800^2 + herbht800 + shrbht800 + can100 + can100^2
DT	plandmsh500 + landco_800 + landco_800^2 + urb_800 + urb_800^2 + elev500
EDR	can250 + can250^2 + dran250 + dran250^2 + fire900 + landco250 + landco250^2 + plandpine900 + plandpine900^2 + urb250 + urb250^2 + evi250 + evi250^2 + hist900 + hist900^2 + precip + precip^2 + tpi + tpi^2
EIS	rip_900 + can250 + can250^2 + dran250 + dran250^2 + landco900 + landco900^2 + plandpine900 + plandpine900^2 + urb900 + evi250 + evi250^2 + hist900 + hist900^2 + precip + precip^2 + tpi
PABU	plandfor700 + mpashb700 + shrbht700 + plandrip700 + can700 + can700^2 + elev700
RCWO	plandpine800 + plandpine800^2 + fire800 + fire800^2 + herbht800 + shrbht800 + can100
SESP	edmsh200 + edmsh200^2 + plandbrack200 + elev200 + urb_200 + urb_200^2
WIPL	edbh100 + urb_1km + plandco1km + ow_1km
WOST	wat2000 + nwifwd_2000 + nhd_2000 + landco2000 + can2000 + elev2000

Table 2.5. Predictor variables for 10 species.

Species	Variable	Name	Description (unit)	Min./Max. Neighborhood Size[a]	Source
AMOY	Beach/Flat	plandbh	Percent of landscape (%)	100m/1km	SLAMM (10, 11, 12)
		mpabh	Mean patch area (m^2)		
		npbh	Number of patches		
	Salt/Brackish Marsh	plandmsh	Percent of landscape (%)		SLAMM (7, 8, 20)
		edmsh	Edge density (m/ha)		
	Open Water	ow_	Mean distance (m)		SLAMM (15, 16, 17, 19)
	Urbanization	urb_	Mean distance (m)		NLCD (21:24)
	Elevation	elev	Mean elevation (m)		DEM
BACS	Longleaf Pine	pland pine	Percent of landscape (%)	100m/800m	LANDFIRE
		mpapine	Mean patch area (m^2)		
		nppine	Number of patches		
		pine_	Mean distance (m)		
	Herbaceous	plandherb	Percent of landscape (%)		NLCD (71)
		mpaherb	Mean patch area (m^2)		
		npherb	Number of patches		
		herbht	Height of vegetation (m)		LANDFIRE (EVH)
	Canopy/Forest	can	Percent of cover (%)		NLCD
		forht	Mean height of forest (m)		LANDFIRE
	Shrub	shrbht	Mean height of shrub (m)		LANDFIRE
	Fire Frequency	fire	Percent of years burned (0.1 increments)		MODIS,LANDFIRE
DT	Salt/Brackish Marsh	plandmsh	Percent of landscape (%)	500m/800m	SLAMM (7, 8, 20)
		mpamsh	Mean patch area (m^2)		
		edmsh	Edge density (m/ha)		
	Beach/Land near marsh	plandco	Percent (%) beach/dry land w/in 500m marsh		SLAMM (2, 10, 11, 12)
		landco_	Distance (m) beach/dry land w/in 500m marsh		
		mpalandco	Area (m^2) beach/dry land w/in 500m marsh		
	Urbanization	urb_	Mean distance (m)		NLCD (21:24)
	Elevation	elev	Mean elevation (m)		DEM
EDR/EIS	Landcover	landco	Percent of Shrub/Barren/Forested (%)	250m/900m	NLCD (41:43, 52, 71)
	Canopy	can	Percent of cover (%)		NLCD
	Longleaf Pine	pland pine	Percent of landscape (%)		LANDFIRE
	EVI	evi	Difference between summer/winter vegetation		MODIS
	Agriculture	plandag	Percent landscape (%)		NLCD (81,82)
		ag_	Mean distance (m)		
	Historical Land-Use	hist	Historical land-use (1 = used, 0=unused) (%)		USGS,EROS
	Fire Frequency	fire	Percent of years burned (0.1 increments)		MODIS, LANDFIRE
	Drainage	dran	1:well drain, 0.5:mod drain, 0:poor drain (%)		NRCS
	Urbanization	urb	Percent landscape (%)		NLCD (21:24)
		urb_	Mean distance (m)		
	Precipitation	precipsum	Mean Precipitation in Summer (mm)		U of I
		precipwin	Mean Precipitation in Winter(mm)		
EIS	Riparian	plandrip	Percent of landscape (%)	250m/900m	LANDFIRE EVT
		rip_	Mean distance (m)		
		edrip	Edge density (m/ha)		
PABU	Canopy	can	Percent of cover (%)	300m/700m	NLCD
	Salt/Fresh Marsh	plandmsh	Percent of landscape (%)		LANDFIRE (marsh)
		edmsh	Edge density (m/ha)		
		msh_	Mean distance (m)		
		formsh	Sum of distance between forest/marsh		NLCD (41:43), LANDFIRE (marsh)
	Riparian	plandmsh	Percent of landscape (%)		LANDFIRE EVH (riparian)
		edmsh	Edge density (m/ha)		
		msh_	Mean distance (m)		
	Forested	plandfor	Percent of landscape (%)		NLCD (41:43)

		edfor	Edge density (m/ha)		
		npfor	Number of patches		
	Shrub	plandshrub	Percent of landscape (%)		NLCD (52)
		edshb	Edge density (m/ha)		
		mpashb	Mean patch area (m^2)		
	Shrub Height	shrbht	Mean height of shrub (m)		LANDFIRE EVH
	Elevation	elev	Mean elevation (m)		DEM

Predictor variables for 10 species, cont.

Species	Variable	Name	Description (unit)	Min./Max. Neighborhood Size[a]	Source
RCWO	Longleaf Pine	pland pine	Percent of landscape (%)	100m/800m	LANDFIRE
		mpapine	Mean patch area (m^2)		
		nppine	Number of patches		
		pine_	Mean distance (m)		
	Herbaceous	plandherb	Percent of landscape (%)		NLCD (71)
		mpaherb	Mean patch area (m^2)		
		npherb	Number of patches		
		herbht	Height of vegetation (m)		LANDFIRE (EVH)
	Canopy/Forest	can	Percent of cover (%)		NLCD
		forht	Mean height of forest (m)		LANDFIRE
	Shrub	shrbht	Mean height of shrub (m)		LANDFIRE
	Fire Frequency	fire	Percent of years burned (0.1 increments)		MODIS,LANDFIRE
SESP[b]	Salt/Brackish Marsh	plandmsh	Percent of landscape (%)	50m[b]/200m	SLAMM (7, 8, 20)
		edmsh	Edge density (m/ha)		
		mpamsh	Mean patch area (m^2)		
	Brackish Marsh	plandbrack	Percent of landscape (%)		SLAMM (20)
	Forest	ow_	Mean distance (m)		NLCD(41:43)
	Urbanization	urb_	Mean distance (m)		NLCD (21:24)
	Elevation	elev	Mean elevation (m)		DEM
WIPL	Beach/Flat	plandbh	Percent of landscape (%)	100m/1km	SLAMM (10, 11, 12)
		mpabh	Mean patch area (m^2)		
		npbh	Number of patches		
		edbh	Edge density (m/ha)		
		plandco	Percent (%) beach/dry land w/in 100m marsh		
	Salt/Brackish Marsh	plandmsh	Percent of landscape (%)		SLAMM (7, 8, 20)
		edmsh	Edge density (m/ha)		
	Open Water	ow_	Mean distance (m)		SLAMM (15, 16, 17, 19)
	Urbanization	urb_	Mean distance (m)		NLCD (21:24)
	Elevation	elev	Mean elevation (m)		DEM
	Slope	slp	Mean Slope (% rise)		DEM
WOST	Wetlands	plandnwi	Percent of landscape (%)	500m/2km	NWI (forested, emergent, estuarine wetlands), NLCD (11)
		nwifor	Percent (%) wetlands w/in 500m open water		
		nwifwd_	Distance (m) forested wetlands w/in 500m open water		
	Canals/Ditches	nhd_	Mean distance (m)		NHD
	Open Water	wat	Percent of landscape (%)		
		wat_	Mean distance (m)		
	Non-Wetland/Forest Land Cover	landco	Percent of landscape (%)		NLCD (52, 71, 81, 82)
	Canopy/Forest	can	Percent of cover (%)		NLCD
	Forest Height	forht	Mean height of forest (m)		LANDFIRE
	Elevation	elev	Mean elevation (m)		DEM

Table 2.6. Evaluation results for 10 species. Additional evaluation results for 5 species can be found in Crawford et al. 2019. TSS denotes the True Skill Statistics, where TSS = Sensitivity + Specificity - 1. COR represents the point-biserial correlation coefficient.

Species	AUC	Sensitivity	Specificity	TSS	Optimal Cutoff	COR	Accuracy
AMOY	0.928	0.843	0.843	0.686	0.307	0.726	84.2%
BACS	0.882	0.799	0.825	0.624	0.215	0.686	81.8%
DT	0.919	0.878	0.847	0.725	0.303	0.676	84.9
EDR	0.833	0.769	0.744	0.513	0.244	0.536	74.9%
EIS	0.880	0.824	0.779	0.603	0.255	0.636	78.9%
PABU	0.773	0.717	0.673	0.390	0.248	0.440	68.3%
RCWO	0.958	0.902	0.927	0.829	0.248	0.842	91.95%
SESP	0.881	0.828	0.761	0.589	0.289	0.601	77.5%
WIPL	0.909	0.866	0.815	0.681	0.164	0.705	82.5%
WOST	0.822	0.747	0.743	0.490	0.281	0.503	74.3%

Table 2.7. Metrics summarizing characteristics of species habitat across three suitability classes for present day. Total represents the percent and area (km^2) of species' range across the Coastal Plain classified as suitable. Total PA represents the total percent and area of suitable habitat within protected areas. Highlighted species indicate species restricted within the lower Coastal Plain. * indicates species for which a low threshold was not calculated, as the optimal cutoff threshold met the upper limits of 0.40.

Metric	AMOY	DT	SESP	WISP	BACS	EDR	EIS	FPS	GF	GT	PABU	RCWO	SHS	SN	WOST
^{h}Total (%)	1.7	6	1.3	2.8	3.3	3.4	4.2	4.2	3.2	4.5	1.9	2.7	3	2.8	2.9
^{h}Total (km^2)	147.1	523.4	114.6	245.1	3405.7	3416.2	4311.5	4292.2	3288.7	4527.6	1949.4	2784.9	3038.5	2895.1	2983.4
^{h}Total PA (%)	14.9	14.9	35.2	23.5	48.2	23.1	17.6	13.6	38	20.4	15.4	50.5	20	34.6	24.7
^{h}Total PA (km^2)	21.9	78.2	40.3	57.6	1642	790.8	759.9	582.2	1249.7	922	300.8	1405.4	606.8	1001.8	737.6
^{m}Total (%)	6.7	10.4	2.8	4.9	7.3	10.5	11.4	9.2	5.9	7.6	14.3	5.5	5.7	5	10.9
^{m}Total (km^2)	590.3	912.8	243.4	433.1	7446.5	10702.5	11575.1	9313.4	6032.5	7691.3	14567.9	5573.5	5766.6	5116.8	11091.6
^{m}Total PA (%)	18.6	18.1	33.1	26.3	32.6	16.6	13.2	11.3	28.3	17.4	8.5	44.7	16.6	25.5	15.9
^{m}Total PA (km^2)	110	165.5	80.6	114	2425.4	1781.9	1526.3	1054.3	1709.3	1341.6	1243.4	2490.4	956.3	1303.2	1767.3
^{o}Total (%)	9.9	13.2	3.9	12.9	17.5	17.5	21	9.2*	6.9	10.7	35.2	17.5	5.7*	5.8	21.8
^{o}Total (km^2)	870.4	1162.2	343.3	1136.5	17800.3	17816	21407.4	9313.4*	7024.8	10852.4	35798.2	17800.3	5766.6*	5933.8	22165.1
^{o}Total PA (%)	19.3	20.4	31.3	30.1	20.5	13.8	11.2	11.3*	26.2	15.7	7.3	20.5	16.6*	23.4	15.1
^{o}Total PA (km^2)	168.1	236.9	107.5	342.3	3649.7	2458.1	2402.1	1054.3*	1841.9	1706.5	2613.2	3649.7	956.3*	1388.1	3337.2

h denotes 'high' habitat suitability class (0.6 or greater)
m denotes 'moderate' habitat suitability class (0.4 or greater)
o denotes habitat suitability class using the species-specific optimal cut-off value (or greater)

Table 2.8. Species prioritization schemes for scenarios of 2-meter sea level rise (SLR) and future urbanization (50% probability of growth, URB) by 2100. Ranks are meant to convey top priority for each consecutive metric; all metrics are treated independently of each other. Species are ranked first by fraction of exposure to habitat change, with 1 indicating highest percent of habitat change due to the corresponding scenario ($Rank^A$). $Rank^B$ refers to rank for total area (km^2) of habitat available under each separate scenario, with 1 indicating least amount of habitat. $Rank^C$ refers to rank for percent of habitat within protected land, where 1 indicates least amount of protected habitat. Global (G) Rank (as defined by NatureServe) conveys ranks for species' global vulnerability.

	Species	**% Exposure**	**$Rank^A$**	**Area (km^2)**	**$Rank^B$**	**% PA**	**$Rank^C$**	**G Rank**
	SESP	69.32	1	105.34	1	33.93	15	G4
	AMOY	41.37	2	510.35	2	19.48	8	G5
	WIPL	40.02	3	681.64	3	32.69	14	G5
	DT	38.18	4	718.45	4	19.69	9	G4
	WOST	3.09	5	21479.87	14	14.70	5	G4
SLR	PABU	1.83	6	35142.17	15	6.96	1	G5
	EIS	0.38	7	21325.30	13	11.13	2	G3
	EDR	0.15	8	17789.07	10	13.76	4	G4
	SHS	0.05	9	5763.67	5	16.57	7	G2
	GT	0.05	10	10847.30	9	15.72	6	G3
	SN	0.04	11	5931.54	6	23.39	12	G2G3
	FPS	0.03	12	9310.14	8	11.31	3	G4
	BACS	0.00	13	17799.47	11	20.50	10	G3
	GF	0.00	14	7024.54	7	26.22	13	G3
	RCWO	0.00	15	17799.47	12	20.50	11	G3
	Species	**% Exposure**	**$Rank^A$**	**Area (km^2)**	**$Rank^B$**	**% PA**	**$Rank^C$**	**G Rank**
	PABU	19.39	1	28855.79	15	6.96	1	G5
	EDR	19.17	2	14400.96	10	13.76	4	G4
	WOST	18.89	3	17978.1	13	14.70	5	G4
	SHS	18.02	4	4727.311	5	16.57	7	G2
	FPS	17.63	5	7671.677	8	11.31	3	G4
URB	GT	17.09	6	8997.98	9	15.72	6	G3
	SN	14.26	7	5087.582	6	23.39	12	G2G3
	EIS	13.79	8	18455.81	14	11.13	2	G3
	BACS	13.33	9	15427.8	11	20.50	10	G3
	RCWO	9.59	10	15427.8	12	20.50	11	G3
	GF	8.51	11	6426.952	7	26.22	13	G3
	WIPL	5.43	12	1074.758	3	32.69	14	G5
	DT	5.36	13	1099.904	4	19.69	9	G4
	AMOY	3.82	14	837.1674	2	19.48	8	G5
	SESP	0.65	15	341.0793	1	33.93	15	G4

G (Global) Ranks: G2 = Imperiled, G3 = Vulnerable, G4 = Apparently Secure, G5 = Secure.

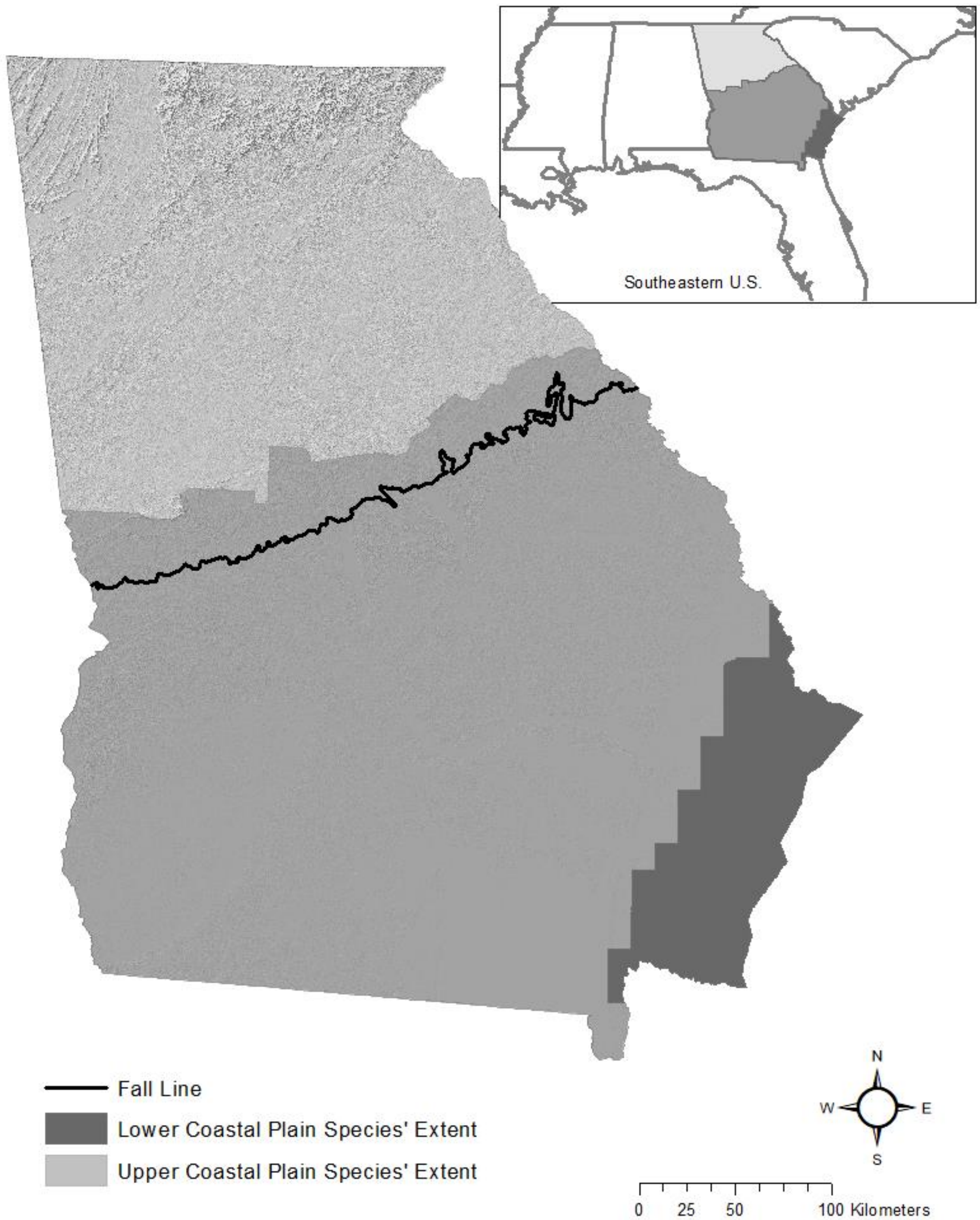

Figure 2.1 Map denoting study area extents for upper Coastal Plain species and lower Coastal Plain species, as well as the Fall Line.

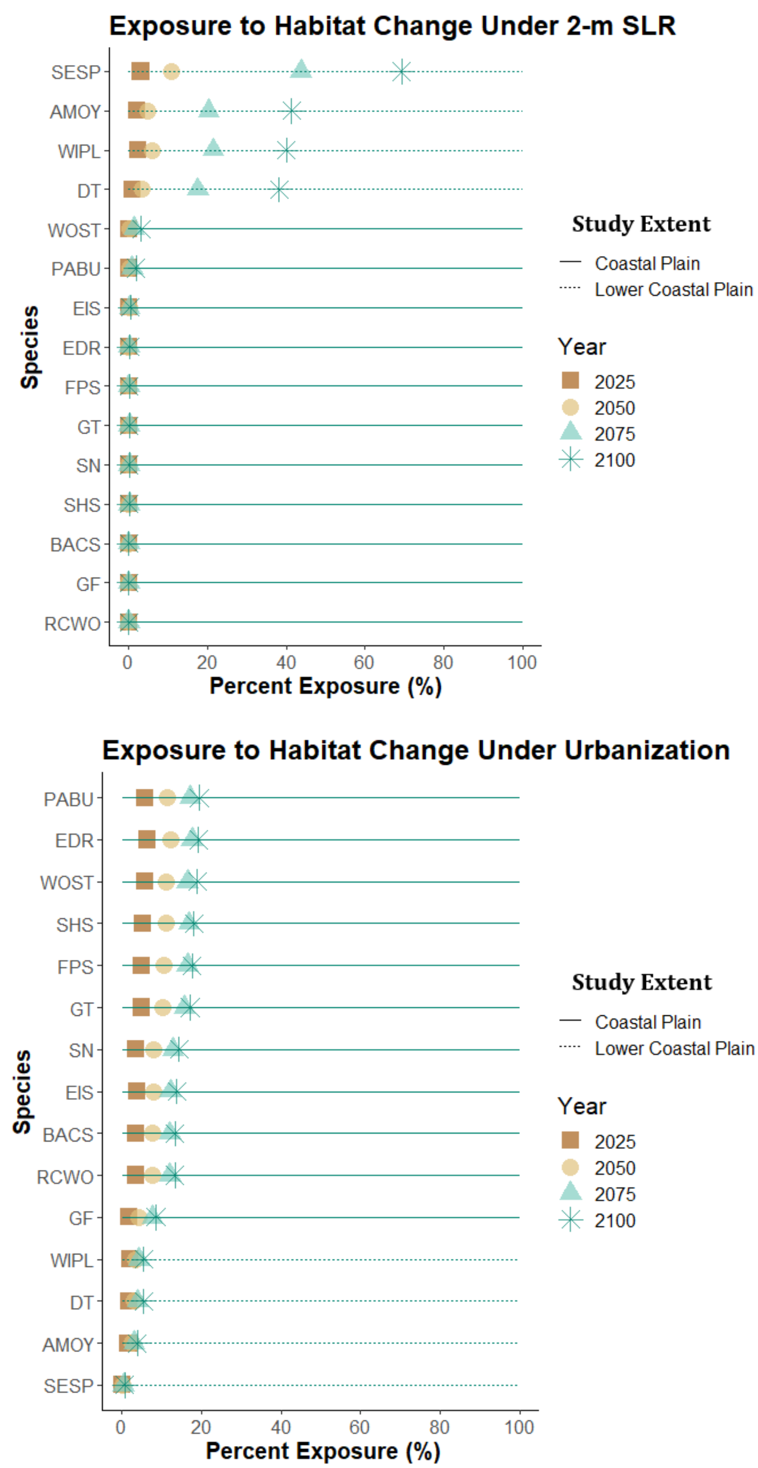

Figure 2.2: Species ranked by percent of exposure to potential habitat change under 2-meter sea level rise (SLR) and 50% probability of urbanization by 2100.

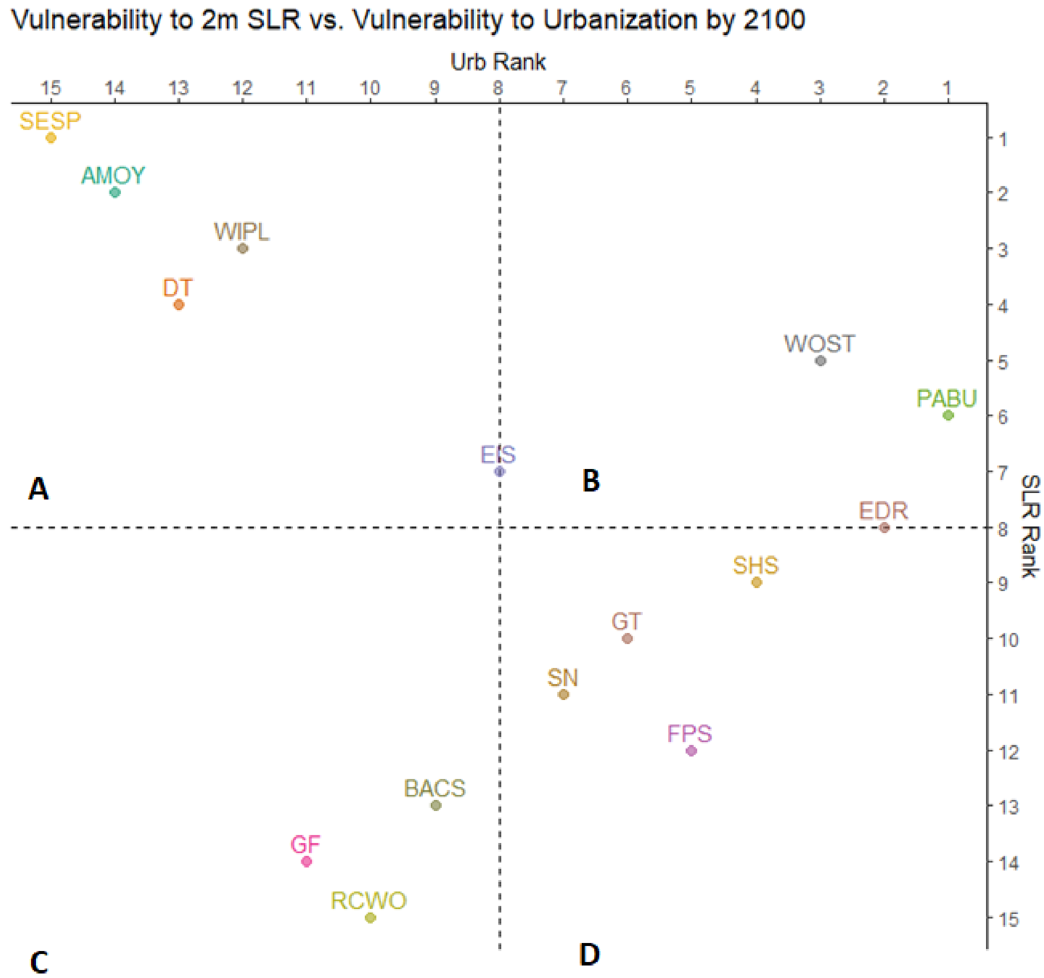

Figure 2.3: Ranks for vulnerability to 2-meter SLR versus ranks for vulnerability to 50% probability of urbanization by 2100. Ranks are based on percent exposure to potential habitat change. Lines indicate framework for evaluating sea level rise vs. urbanization vulnerability.

A: Low Global Vulnerability, High Regional Vulnerability,
B: High Global Vulnerability, High Regional Vulnerability
C: Low Global Vulnerability, Low Regional Vulnerability
D: High Global Vulnerability, Low Regional Vulnerability

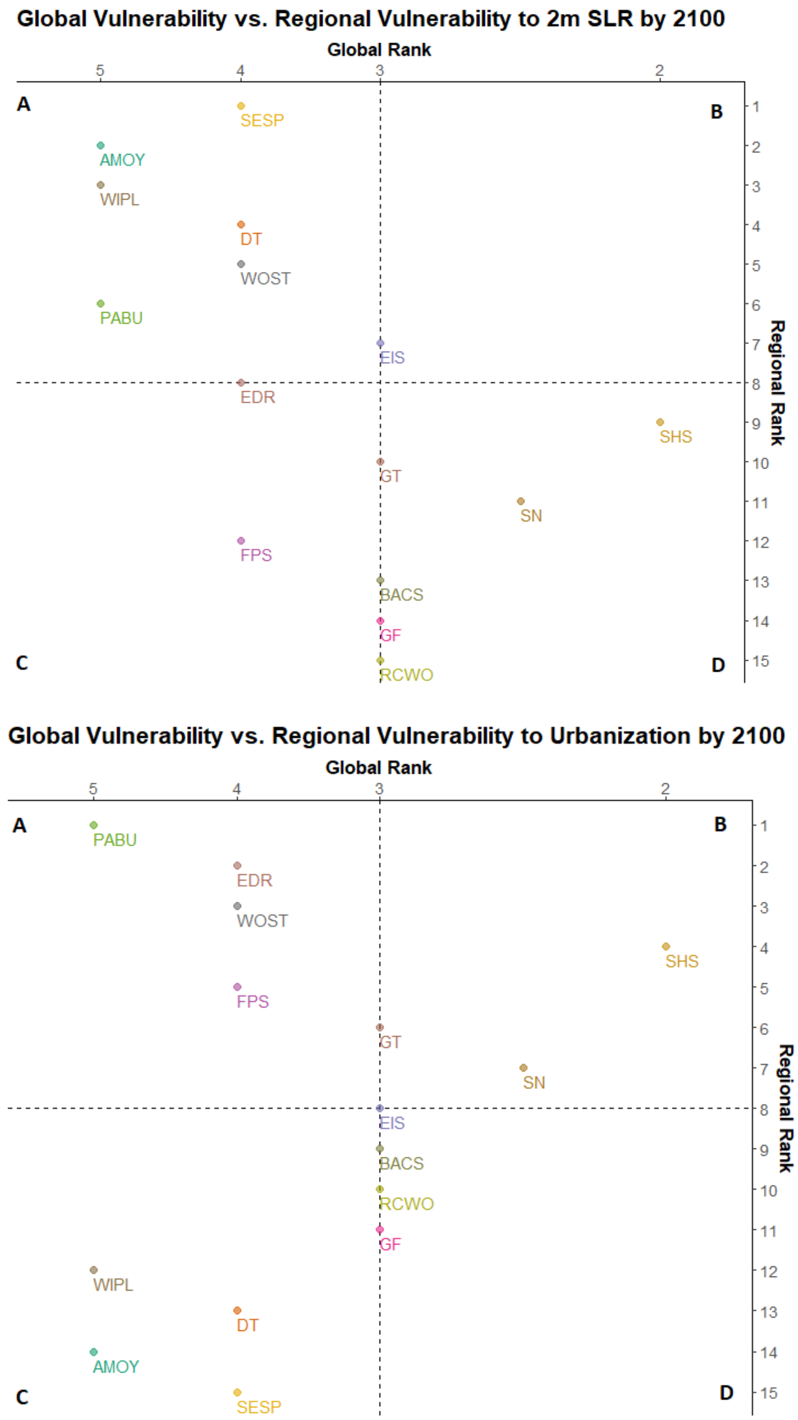

Figure 2.4: Ranks for Global Vulnerability versus ranks for regional vulnerability to SLR (top) and urbanization (bottom). Ranks are based on percent exposure to potential habitat change. Lines indicate framework for evaluating global vs. regional vulnerability.
A: Low Global Vulnerability, High Regional Vulnerability,
B: High Global Vulnerability, High Regional Vulnerability
C: Low Global Vulnerability, Low Regional Vulnerability
D: High Global Vulnerability, Low Regional Vulnerability

CHAPTER III.

USING EMPIRICAL DATA TO INFORM EXPERT-BASED VULNERABILITY ASSESSMENTS IN GEORGIA'S COASTAL PLAIN: A COMPARISON OF SPECIES PRIORITIZATION SCHEMES[2]

[2]Paulukonis E., Reece J., Nibbelink N. To be submitted to Natural Areas Journal.

Abstract

Expert-based vulnerability assessments are commonly used to rank species by multiple components of vulnerability (i.e., exposure, sensitivity, and resilience to change), often when empirical-based data is unavailable for prioritization schemes. Little work has been done to examine how the inclusion of empirical-based data for certain components of these expert-based assessments may change overall rankings. We worked with species experts to conduct a Standardized Index for Vulnerability and Value Assessment (SIVVA) for 15 Coastal Plain species in Georgia. We substituted empirical data for two SIVVA metrics representing habitat exposure to sea level rise and urbanization to compare how metric scores and overall ranks differed between methods. Results suggest a divergence in the two methods, as vulnerability scores for expert-based methods (0.625 - 0.884) were higher than scores for empirical-based methods (0.532-0.688). While the seaside sparrow (*Ammodramus maritimus*) ranked highest for both methods, other coastal species were demoted under the empirical-based method.

Introduction

Coastal ecosystems and the species they support are vulnerable to changes from both sea level rise and urban development in the future. Sea level is predicted to increase between 1-2 meters by the end of the century, and U.S. coastlines are projected to host an additional 7 million people by mid-century (Craft et al. 2009, Dahl et al. 2018, Seto et al. 2012, NOAA 2015). Fish and wildlife agencies need to consider the ways in which biodiversity may be affected by these changes. While ecosystem-based management is ideal, resource limitations often mean that agencies that are tasked with developing conservation plans must choose priority species on which to focus their efforts and resources (Noss 1996, Benscoter et al. 2013, Walls et al. 2019). Vulnerability assessments are commonly used to inform this process. Typically, pre-defined criteria are used to rank species by their vulnerability to future change, and top-ranking species are prioritized for conservation action (Given & Norton 1993, Gauthier et al. 2010). At present, there is no broad consensus regarding the criteria used to establish a definition of species vulnerability (Pacifici et al. 2015). What is acknowledged is that vulnerability is multi-dimensional and involves both intrinsic and extrinsic factors (e.g., sensitivity, resilience, and exposure to change); thus, a prioritization framework that includes these factors is ideal for assessment (Williams et al. 2008, Turner et al. 1993). However, we lack detailed empirical data on many species (e.g., population demographics, genetic and physiological traits, extinction risk), limiting our ability to consider all three factors affecting vulnerability, particularly for rare species.

In situations where data deficiencies prevent the inclusion of quantitative vulnerability criteria, expert opinion is often substituted for information gaps in species assessments (Donlan et al. 2010, McBride et al. 2012, Hare et al. 2016). Expert knowledge can be useful for characterizing the impacts of change scenarios on vulnerability when empirical data is lacking, and is often timelier and less costly than relying on empirical data, two factors that can be crucial when rapid response for management action is need (O'Neill et al. 2008, Gardali et al. 2012). A major reservation about this technique is the concern that experts may be inherently biased, or the results poorly calibrated, leading to over or under estimation of variables commonly used in species assessments (Martin et al. 2011, Tversky & Kahneman 1974). For example, Seguardo (2011) suggested that classifications of Mediterranean freshwater fish species tolerance for disturbance using expert judgement vs. empirical data may differ due to experts failing to account for natural variability in tolerance in their judgement (Seguardo et al. 2011). Further exploration of the interplay between empirical data and expert judgement in vulnerability assessments will be useful to understand the advantage of one method over another, and help to clarify when expert-based methods may be insufficient substitutes for more intensive empirical methods (Martin et al. 2011).

The Standardized Index for Vulnerability and Value Assessment (SIVVA) is an expert-based species' vulnerability assessment and prioritization tool that has been successfully employed across Florida and the Gulf Coast (Reece et al. 2013, Reece & Noss 2014, Reece et al. 2018). SIVVA relies on experts to score species on multiple intrinsic and extrinsic criteria related to species vulnerability, with criteria customized to groups of species. Scores for each criterion are then combined to form a final overall 'rank' for a species. SIVVA explicitly accounts for species vulnerability to sea level rise (SLR), an aspect often missing from prior tools (Reece & Noss 2014). When scoring components of vulnerability related to both SLR and urbanization, the tool requires experts to estimate several quantitative factors in their evaluation of anthropogenic-related vulnerability criteria. Specifically, the tool asks experts to consider the total amount of habitat loss likely to be experienced by species as a result of both SLR and urbanization in the future. However, the degree to which final species rankings may change when empirical data for habitat loss is substituted for expert judgement of habitat loss has not been explored.

By mid-century, Southeastern coastal ecosystems are projected to undergo severe changes as a result of encroaching SLR and urbanization. Consequently, the state of Georgia, U.S.A is predicted to experience habitat loss and potential biodiversity declines, and the state has expressed the need to rapidly prioritize species most at risk from these factors in order to develop adequate conservation plans (Craft et al. 2011, Hunter et al. 2015, GADNR SWAP 2015). We used an expert-based vulnerability assessment (SIVVA) in conjunction with outputs from empirical-based Species' Distribution Models (SDMs) to evaluate the effect of differing approaches to quantifying future vulnerability for species' prioritization schemes in Georgia. We substituted SDM data describing species exposure to potential habitat loss as a result of 1-meter SLR and urbanization by 2030 and 2060 for metrics describing expert estimates of potential habitat loss under the same conditions in SIVVA for 15 species in Georgia's Coastal Plain. Our aim was to evaluate the differences between results using expert-based judgement and results using empirical-based metrics for quantitative metrics, and to assess the advantages or disadvantages of one technique over another.

Methods

Expert-Based Metrics

Species Selection

We enlisted experts from universities, federal and state agencies, and non-profit wildlife conservation groups to assist in the process of choosing an initial list of approximately 50 species from the Georgia Department of Natural Resources' State Wildlife Action Plan list of 265 priority species. The species chosen by experts are considered to be a priority for conservation action on the basis of their economic and ecological importance for the state of Georgia. From this list, we chose 15 species for which to create fine-scale SDMs. We chose species that had a minimum of 20 occurrence points as well as adequate information regarding range and general habitat characteristics (Stockwell & Peterson 2002). The Georgia Conservation Status state rarity rank (ranging from 5 (currently stable in state) to 1 (critically imperiled in state)) was used to rank the remaining species. We selected species with a value of 4 or less, and chose the top 15. Our final species list consisted of 7 avian species, 2 amphibian species, and 6 reptile species (**Table 3.1**). Our study area comprised the combined known range of all 15 species within Georgia's Coastal Plain ecoregion.

SIVVA Development and Qualitative Analysis

The SIVVA framework is based on sets of criteria that encompass the three components of species vulnerability (exposure, sensitivity, and adaptive capacity) as well as their conservation value and the amount of information available to inform opinion (Reece & Noss 2014). SIVVA contains four sets of criteria with a range of 5-12 metrics in each set: (1) Vulnerability (includes metrics that describe exposure and sensitivity), (2) Lack of Adaptive Capacity, (3) Conservation Value and (4) Information Availability (**Table 3.2**). Within each criterion, experts are asked to assign metric scores for their species of specialty. Although scores typically range from 0-6, users are able to apply any numerical score applicable for their interest. We used the original 0-6 scale for the purposes of this study, where a score of 0 indicates insufficient information available to assess the metric, scores of 1-2 typically indicate a positive or neutral impact, 3 corresponds to no effect, and scores from 4-6 depict increasingly negative impacts from the metric in question. For example, experts scoring a species for the metric 'Proportion of habitat inundated by or lost to SLR at X m by 2100' for the future time point 2060 under a 1-meter SLR scenario could score the metric for that species as 0 (not enough information on SLR impacts to this species), 1-2 (substantial and moderate increases in habitat as a result of 1-meter SLR by 2060, respectively), 3 (no impact of SLR), or 4-6 (up to 25%, 50%, or 100% loss in habitat as a result of 1-meter SLR by 2060). The exception to this is the criterion 'Information Availability', which assigns higher scores for species with more available information; this is done to indicate that species ranking top for this criterion are those that can be adequately addressed on the basis of knowledge about conservation measures necessary to prevent extirpation. Experts are given the option to assign scores on a one decimal point range, e.g., 3.1, 3.2, etc. Assignments of decimal values are left to the discretion of each expert, although explanations for values are required. In addition, each metric is also given a ‘weight’ that corresponds to an estimation of relative importance of that metric to the overall criteria (**Table 3.2**). Weights are assigned at 0.5, 1.0, 2.0, 4.0, with 4.0 being the strongest importance.

For each species, summary scores for each criterion are calculated as the total number of metric ‘points’ (weight of metric times the score from 0-1), divided by the total possible number of points. In addition, users can choose final summary scores averaged equally across all 4 criteria (arithmetic mean of all criterion scores) or choose to weight one or more criterion more heavily (i.e., total vulnerability contributing a certain percentage (50%, 70%, etc.) to the final score) (Reece & Noss 2014). While the final score for each criterion ranges from 0-1, the interpretation of scores varies slightly by individual criterion. For the Vulnerability criterion, scores closer to 0 indicate low vulnerability, while scores closer to 1 indicate high vulnerability. For Adaptive Capacity, scores close to 0 indicate higher adaptive capacity, while scores close to 1 indicate that the species is less likely to adapt well to future changes. Species with Conservation Value scores near 0 are species classified as having low conservation value, while scores close to 1 indicate high value. Finally, species with scores near 0 for Information Availability indicate less information about the species, with scores near 1 indicating that more information with which to make informed decisions is available for the species in question.

Each of our species was assessed by at least 2 and up to 7 species experts. We identified experts who had authored studies on target species, participated or directed management efforts for target species, or were familiar with the available information on target species. To provide additional context for certain metrics, we provided supplemental material for expert referral. Experts were provided with a bibliography and synopsis of known material related to each species. For metrics involving SLR, we provided maps of predicted inundation (using the Sea

Level Affecting Marshes Model, SLAMM, described below) (Clough et al. 2010). For metrics involving urbanization, we provided maps depicting probability of urban growth using the SLEUTH urban growth model, which simulates urban growth on a scale from 0-100% probability of development (described below) (Clarke 2008). We asked experts to evaluate metrics in the Vulnerability criterion while considering a scenario of 1-meter SLR and moderate-high ($\geq$ 50%) probability of urban development by 2100 for two time points: 2030 (near time point) and 2060 (far time point). All other criteria are evaluated under a single present-day time point (scores are not contingent on future scenarios). The final set of scores for each species was an average of all expert evaluations.

Empirical-Based Metrics

Species Distribution Models and Quantitative Analysis

Empirically-derived measures of SLR and urbanization were created using best available Species Distribution Models for the 15 species (**Table 3.1**). Species Distribution Models (SDMs) provide spatially-explicit predictions of species habitat suitability (and thus supposed distribution) by relating presence (occurrence) data to environmental variables across a landscape (Elith et al. 2006). We created our SDMs using logistic regression (generalized linear models, GLMs) in a model selection framework, and converted the continuous raster outputs from our SDMs to binary datasets of raster cells representing ‘suitable’ (classified as 1) and ‘unsuitable’ (classified as 0) habitat (Burnham and Anderson 2002). For more information on this process see Chapter 2, and Crawford et al. 2020.

For our scenarios of future change, we used spatial models depicting potential SLR and urbanization at future time points in Georgia. The Sea Level Affecting Marshes Model (SLAMM) uses digital elevation data and National Wetland Inventory data to simulate the processes involved in wetland conversion under scenarios of SLR. The model redefines land cover classes as a product of alterations in wetland elevation due to SLR at future time points, resulting in a final dataset representing changed land cover conditions. In Georgia, readily available SLAMM outputs exist for future time points in 25-year increments. We used SLAMM outputs from a 1-m SLR scenario for the years 2025 and 2050 to represent time points 2030 and 2060, respectively. We converted all land-cover classes denoting riverine open water, estuarine open water, and open ocean to a single class of 1 representing inundation. The SLEUTH urban growth model defines raster classes of future urban growth on a scale from 0-100% probability of growth at decadal future time points based on data denoting slope, land-use, exclusion, urbanization, transportation and hill-shade (Clarke 2008). Classes range from 3 (0-2.5% probability of urban growth) to 16 (97.5-100% probability of urban growth). We included all classes greater than or equal to 10 (50-60% probability) and reclassified them to a single class of 1 to represent predicted urban growth for 2030 and 2060.

To substitute quantitative values for our SIVVA vulnerability metrics (**Table 3.2**), we created a value representing the fraction of species' exposure to potential habitat change under each stressor. We overlaid our binary SDM habitat datasets with our single class datasets representing inundation from sea level rise and urbanization. For each species, wherever a raster cell representing predicted 'suitable' habitat (1) overlapped with cells representing inundation (1) or urbanization (1) at each future time point, we used that overlap as a representation of exposure to habitat change, converting each original cell to 'unsuitable' (0). The final output was the change (Δ) in total 'suitable' habitat cells at the two future time points (2030, 2060) divided by the original total 'suitable' habitat to get the fraction of potential exposure to habitat change. Fraction of habitat exposed to change was then used to score metrics describing SLR and urbanization (detailed below).

Metric Comparison

To evaluate the impact of empirical data on the final vulnerability score and overall rank of each species, we chose two metrics in the 'Vulnerability' criterion that had scores based on quantitative habitat loss. We used metric 1, 'Proportion of habitat inundated by or lost to SLR at 1m by 2100' to represent vulnerability to habitat change from future SLR, and metric 3, 'Vulnerability of current distribution or 'escape paths' to current or future barriers' to represent vulnerability to habitat change from urbanization. We kept all other metrics as originally scored by experts in the final comparison of ranks, so that the only components of the two types of assessments (expert-based and empirical-based) that differed were those metrics for SLR and urbanization. We use the term 'non-quantitative' to describe metrics that did not involve experts using their best judgement for numerical estimates of a score.

'Proportion of habitat inundated by or lost to SLR at 1m by 2100' represents the fraction of species' habitat that will be inundated via SLR at future time points, ranging from 0 (no information) to 6 (50-100% of habitat inundated) (**Table 3.3**). This metric is also assigned a weight of 4, meaning that the score for this metric has a high influence on overall vulnerability in Georgia. We used our values representing fraction of potential exposure to habitat change under SLR to input new scores for the empirical-based assessment. To assign scores using fraction of exposure to change, we used a two-step process (**Table 3.4**). In the first step, we evaluated the single digit score for each species using the quantitative fraction exposure to habitat values from our SDM outputs. Because our empirical measurements were not able to capture potential increases in habitat, all empirical-based scores ranged from 3-6. For species having some fraction of exposure to habitat change greater than 0 (no effect, 3) but below 25% fraction of exposure (4), we assigned a single digit score of 3. For species having above some fraction of habitat exposed to change between 25-50%, we assigned a score of 5, and between 50-100%, a score of 6. In the second step, we used decimal values to represent exact measurements of inundation for each species. For each 1/10th increase in decimal place (i.e., 3.1, 3.2), we assigned decimal scores based on a 2.5% or 5% increment range. For example, if our analysis resulted in an estimated fraction of 7% exposure to potential habitat change, we assigned a final score of 3.2, as the value fell between a 5-7.5% range. For any scores falling between 5 and 6, we used a 5% increment range.

'Vulnerability of current distribution or 'escape paths' to current or future barriers' represents the fraction of species habitat blocked by encroaching development at future time points, i.e., removal of accessible habitat due to future development (**Table 3.3**). The metric ranges from 0 (no information) to 6 (100% of habitat blocked); no potential increases in habitat are allowed under this metric. We first assigned a single digit score based on our empirical metrics, ranging from 1-6 (**Table 3.4**). For species having some fraction of exposure to habitat above 1 (distribution/habitat has no encroachment from development) and below 2 (up to 25% of distribution/habitat blocked by encroaching development), we assigned a score of 1, and followed the same 2.5% increment range to assign decimal values indicating some exposure to habitat change from urbanization. For fractions ≥ 25% and < 50%, we assigned a score of 2. The original metric uses values of 3 to indicate 50%, and 4 to indicate ≥ 50%; we used 3 to denote an exact metric of 50% exposure to habitat change, and values of 4 with decimal places to indicate fractions between 50% and 75%. Fractions between 75% and 99% were given a score of 5 (with decimal values), and 100% a score of 6.

For each future time point, we calculated the final Vulnerability criterion score for both our expert-based assessment and empirical-based assessment and ranked each set of species by ascending total vulnerability score. We calculated summary scores for Adaptive Capacity, Conservation Value, and Information Availability. We also created a final summary score for each of our two assessments by computing an average score across all criterion, holding each criterion at equal weight, and ranked species based on this overall summary statistic. Finally, we calculated the mean across scores for Vulnerability metrics 1 and 3 to assess differences in expert-based vs. empirical-based valuation of species' vulnerability to exposure to habitat change from SLR and development.

Results

Metric and Criteria Results

Summary scores from the Vulnerability (VUL) criterion of our expert-based assessment ranged from 0.602-0.881 (2030) and 0.625-0.883 (2060), indicating relatively high vulnerability for all species (**Table 3.5**). Adaptive Capacity (AC) scores ranged from 0.437-0.885, suggesting moderate to low adaptive capacity for our set of species. Conservation Value (CV) scores were relatively low to moderate, falling between 0.245-0.643. Information Availability (IA) ranged from low to high (0.307-0.904). Overall summary scores (average across all four criteria) were between 0.495-0.758 (for 2030) and 0.498-0.759 (for 2060). Experts tended to score metrics for SLR (metric 1) and urbanization (metric 2) similarly for both time points. For 2030, expert-based scores averaged around 4.15 for SLR (4: up to 25% of habitat inundated), and 4.40 for urbanization (4: 50-75% of habitat blocked by encroaching development or natural barriers). At 2060, scores averaged 4.27 for SLR, and 4.51 for urbanization (**Table 3.6**). Summary scores for the Vulnerability criterion from our empirical-based assessment ranged from 0.522-0.682 for 2030, and 0.532-0.688 for 2060 (**Table 3.5**). Overall summary scores using the empirical-based metrics were between 0.458-0.7148 for 2030 and 0.498-0.715 for 2060 (**Table 3.5**). Empirical-based metrics for SLR averaged around 3.09 and 3.12 for 2030 and 2060, respectively (3: no effect of inundation) (**Table 3.6**). Metrics for urbanization averaged 1.19 and 1.31 for 2030 and 2060 (1: no barrier to distribution).

Comparison of Ranks

We present species ranks using summary scores from each single criterion as well as the average summary score across all 4 criteria. For Vulnerability and the average summary score, we detail ranks at both 2030 and 2060. In the Vulnerability criteria, the top-ranking species for both time points using the original expert-based method was the seaside sparrow (*Ammodramus maritimus*). This pattern was consistent for rankings using the empirical-based method for metrics 1 and 3 (**Table 3.5**). For both time points, 4 of the top 5 species ranked highly using the expert-based method for Vulnerability tended to be species utilizing marsh or beach habitats. Using the empirical-based methods, 3-4 of the top 5 (4 for 2030, 3 for 2060) were reptile or amphibian species using upland habitats (**Table 3.7**). In the Adaptive Capacity criteria, the top-ranking species (lowest adaptive capacity) was the diamondback terrapin (*Malaclemys terrapin*). The gopher tortoise (*Gopherus polyphemus*) ranked highest for Conservation Value. For Information Availability, the wood stork (*Mycteria americana*) ranked highest (**Table 3.5**). Using the evenly-weighted average across all 4 criteria (overall summary score), the top-ranking species for both 2030 and 2060 in the expert-based assessment was the seaside sparrow. For the empirical-based assessment, the top-ranking species for 2030 was also the seaside sparrow, but shifted to the gopher tortoise for 2060 (**Table 3.5**). The top 4 species for both empirical and expert methods were consistent at both time points (**Table 3.8**).

Discussion

Our study suggests a disparity between expert-based and empirical-based prioritizations based on SIVVA Vulnerability scores for quantitative SLR and urbanization metrics, indicating that the use of expert judgement for valuing certain components of vulnerability assessments may diverge from results compiled using empirical-based methods. The outcomes of this study provide additional context to previous work centered around the use of expert-based assessments for species prioritization and demonstrates some of the discrepancies between valuations using expert and empirical information, which in turn has implications for funding and research efforts assigned on the basis of prioritizing vulnerability.

For both time points under the expert-based method (based on Vulnerability summary scores alone), 4 of 5 top-ranking species were species utilizing either salt-marsh, estuarine or beach habitat, consistent with recent studies showing that salt-marsh and beach-dwelling species will be vulnerable to the effects of sea level rise and coastal development (Hunter et al. 2015, Brittain & Craft 2012). However, the expert-based metric scores for both SLR and urbanization for these top-ranking species were 2.4 or more points higher than empirical-based scores for the same species, suggesting that the magnitude of exposure to habitat change from these stressors as estimated by species experts is much higher than indicated by empirically-based results. The consequence of this differing magnitude in estimated vulnerability between types of methods is shown in the shift in several top-ranking species for the empirical-based method at both 2030 and 2060, as inland-dwelling reptile and amphibian species that had been ranked just below the top 4 marsh and beach species moved into 2nd-4th place. Reptiles and amphibians are widely recognized as two of the most at-risk groups of vertebrates, primarily as a result of human development resulting in widespread habitat loss and fragmentation (Gibbons et al. 2000, Cushman et al. 2006). Our top ranking inland-dwelling reptiles and amphibians were also valued higher than top beach and marsh-dwelling for the impacts of other types of Vulnerability (fragmentation, lack of protected area). Yet, because beach and marsh species were scored between 5.5-6 for exposure to SLR (near maximum or maximum exposure), they were ranked highest for the expert-based assessment. Expert judgement that overvalues the impact of quantitative habitat change may be associated with particular habitat types; previous studies have noted that experts may be more inclined to infer higher threats in particular ecosystems or on species with particular traits, including marine intertidal habitats (Trull et al. 2018). This trend is not surprising given the two-fold pressure of SLR and urbanization on these coastal habitats, but the degree to which expert opinion may overestimate impacts in certain habitat types, particularly from SLR, warrants further investigation. We also discuss potential motivational and/or cognitive bias contributing to this phenomenon below.

The seaside sparrow was the top-ranked species for Vulnerability across both types of methods at both time points. This is consistent with evidence suggesting that the seaside sparrow will be highly vulnerable to habitat change and/or loss as a result of 1-m SLR (Hunter et al. 2017, also see Chapter 2). Seaside sparrows are habitat specialists, utilizing predominantly salt-marsh habitats for activities (Hunter et al. 2017). Although our estimates for exposure to habitat change were relatively conservative for both SLR at 2030 and 2060 for all species including the seaside sparrow (<25%), more extreme scenarios of SLR (1.5-2-m) indicate that the seaside sparrow and other beach or marsh utilizing species could be facing a loss of roughly 38-81% of suitable habitat (Hunter et al. 2017, also see Chapter 2). However, it should be noted that our use of empirical methods did not include an examination of potential habitat increases, which are possible as part of the SLAMM model. For example, the model predicts relative increases in habitats associated with tidal flats and estuarine beaches that could offset the impact of inundation for several beach species. While this may benefit some top or medium ranking species under the expert-based method (e.g, the American oystercatcher, Wilson's plover), given that these species already rank lowest under the empirical-method, this information may not be crucial to provide further context. In addition, SLAMM predicts an overall decrease in salt marsh of 6% at the lowest scenario (1-m), suggesting that the high ranking of the seaside sparrow and relatively high ranking of other salt marsh species (diamondback terrapin, wood stork) in both methods is accurate.

Interestingly, prioritization results using the equal weighting scheme (average across all 4 criteria) revealed few differences between top rankings under both methods, contrary to rankings using the Vulnerability criteria alone. The top 4 species (the seaside sparrow (*Ammodramus maritimus*), diamondback terrapin (*Malaclemys terrapin*), gopher tortoise (*Gopherus polyphemus*), and the wood stork (*Myceteria Americana*)) for both time points using both methods were consistent, and were also each ranked highest across a single criterion. However, the empirical-based method resulted in a slight shift in the top rank between 2030 and 2060, as the gopher tortoise shifted to rank 1 over the seaside sparrow the later time point (the seaside sparrow ranked highest for both time points for expert-based methods). The gopher tortoise is a keystone species that has been shown to heavily influence biodiversity in Southeastern ecosystems, particularly longleaf pine habitat (Ashton 2008, Catano & Stout 2015). The species is currently a candidate for federal listing under the Endangered Species Act in the Eastern portion of its' range, primarily as a result of human-related habitat loss and fragmentation (Daly et al. 2019). While the species ranked last or second to last for Vulnerability under the expert-based method, and low to medium under the empirical-based method (with relatively similar scores for both SLR and urbanization under both methods), the species scored top for overall

Conservation Value as scored by experts, and relatively high for Adaptive Capacity (indicating low ability to adapt to change) and Information Availability (indicating good information on life history). The advantage of SIVVA's ability to capture multiple dimensions of species' vulnerability as well as information availability and conservation value is that managers are able to evaluate species within a broader context that provides additional information about the potential worth and ease of investing in a top ranking species. In the case of the gopher tortoise, singularly valuing the species' exposure to vulnerability from change would result in low to near-low considerations for management action. Although the empirical-based scores for exposure did result in slightly higher Vulnerability rankings for the gopher tortoise, allowing the impact of other forms of vulnerability as well as the species' conservation value and the amount of information necessary to inform the overall ranking dramatically altered the species' position in the final prioritization. While using empirical-based scores can help to better represent the nature of exposure to habitat, having additional information will be crucial for determining final ranks and providing full context in which to make decisions.

A challenge for any expert-based species vulnerability assessment is that while scores are ideally assigned in an objective manner based on facts, opinion and personal choice may influence scores, likely as a result of either motivational or cognitive bias. Motivational or cognitive bias arises when an expert's responses are 'motivated by his [sic] perceived system of personal rewards for various responses' (McBride & Burgman 2011). In other words, experts likely have an inherent understanding of what is to be gained or lost as a result of their valuation that may unconsciously bias their input (Burgman 2004). Evidence of this may potentially be seen in the discrepancy between expert and empirical scores for exposure to habitat change under our presented scenario (1-m by 2100) of sea level rise. Recent studies suggest that previous models of 1-2m SLR may underestimate the realistic impacts from inundation and flooding to coastal regions, particularly as the latest IPCC estimates suggest higher increases in global temperatures impacting sea level (Kulp et al. 2016, Kulp et al. 2019, DeConto & Pollard 2016). We also acknowledge that the data used for describing inundation from 1-m SLR in Georgia was the most recent available information but did not necessarily reflect newer information about impacts. We did not ask experts to disclose whether or not they had knowledge of this information, yet most experts scored beach and marsh-dwelling species on the extreme end of projected habitat impacts in the next 40 years. Given the uncertainty surrounding the true magnitude of impacts from SLR, experts may recognize the need for overvaluing threats for species that are already faced with challenges to their longevity. In addition, Burgman (2004) suggests that experts may overvalue threats as a result of funding or their own personal interest in a species or set of species, which may further influence valuations towards extreme ends. The question of whether or not this influenced expert opinion in our study warrants further investigation, but it does suggest that a) experts may unconsciously (or consciously) recognize uncertainty surrounding risks and account for it in their valuation of species' vulnerability because of the consequences of undervaluation, and/or b) experts may gravitate towards overvaluing species they have a vested interest in.

Our work addresses a series of needs for managers seeking to fill informational gaps regarding future coastal and coastal plain management in the state of Georgia. First, little research has been done to assess and compile information about the impacts of multiple stressors on Georgia non-game coastal plain species' long-term vulnerability. Second, having expert opinion on elements outside of the framework of vulnerability (conservation value and information availability) is useful for providing managers with other ways of valuing species.

Finally, this work provides an important first step for evaluating the tradeoff between expert-driven and empirical-driven methods for valuing certain components of vulnerability. Understanding the conditions under which expert-based data and empirical-based data can be used in tandem to best assess species for conservation is crucial for effective management and restoration efforts.

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Tables

Table 3.1. Georgia Coastal Plain species and their conservation status regionally (as defined by a state government agency, the Georgia Department of Natural Resources). Type indicates species group. Highlighted species indicate species restricted within the lower Coastal Plain. Reference indicates the reference paper for each SDM.

Scientific Name	Common Name	Type	State Rank	Reference
Ammodramus maritimus	Seaside Sparrow	Av^{P}	S3	a
Charadrius wilsonia	Wilson's Plover	Av^{SB}	S2	a
Haematopus palliatus	American Oystercatcher	Av^{SB}	S2	a
Mycteria americana	Wood Stork	Av^{MB}	S3	a
Leuconotopicus borealis	Red-cockaded Woodpecker	Av^{WP}	S2	a
Passerina ciris	Painted Bunting	Av^{P}	S2S3	a
Peucaea aestivalis	Bachman's Sparrow	Av^{P}	S2	a
Lithobates capito	Gopher Frog	Am	S2S3	b
Notophthalmus perstriatus	Striped Newt	Am	S2	b
Crotalus adamanteus	Eastern Diamond-backed Rattlesnake	R	S4	a
Drymarchon couperi	Eastern Indigo Snake	R	S2	a
Gopherus polyphemus	Gopher Tortoise	R	S3	b
Heterodon simus	Southern Hognose Snake	R	S1S2	b
Malaclemys terrapin	Diamondback Terrapin	R	S4	a
Pituophis melanoleucu[a]	Florida Pine Snake	R	S3	b

Type: AvSB = avian: shorebirds, AvMB = avian: marsh birds, AvP = avian: passerines, AvWP = avian: woodpeckers, Am = amphibian, R = reptile.
State ranks: S1 = Critically Imperiled, S2 = Imperiled, S3 = Vulnerable, S4 = Apparently Secure.
Reference: a = Paulukonis et al. Chapter 2, b = Crawford et al. 2020.

Table 3.2. SIVVA criteria and metrics within each criterion, as well as metric weights. Highlighted metrics indicate metrics used for comparison between expert and empirical-based evaluations.

Criteria	Weight
Vulnerability	
1. Sea Level Rise	4
2. Erosion	0.5
3. Barriers to Movement/Distribution	4
4. Temperature	3
5. Precipitation	1
6. Portion of Range Protected	4
7. Population Fragmentation	0.5
8. Increasing Salinity	0.5
9. Storm surge run-off	2
10. Biotic Interactions	4
11. Synergistic Threats	1
12. Disturbance Regime	1
Lack of Adaptive Capacity	
13. Migration	4
14. Phenotypic Plasticity	4
15. Genetic Diversity	4
16. Adaptive Rate	0.5
17. Demographic Capacity	2
18. Colonization Potential	4
Conservation Value	
19. Level of Endemism	0.5
20. Disjunct Population	3
21. Keystone Species	3
22. Phylogenetic Distinctiveness	2
23. Economic Value	3
24. State or Federal Listing	4
25. Probability of Recovery	0.5
Information Availability	
26. Published Literature	1
27. Demographic/Niche Models	3
28. Population Genetic Studies	0.5
29. Response to Sea Level Rise	4
30. Response to Climate Change	2

Table 3.3. Vulnerability metric scores describing quantitative measurements of habitat change due to human-related stressors (SLR and urbanization (URB)). Experts are asked to assign scores using best judgement as well as provided maps of projected inundation due to SLR and future scenarios of urbanization.

SLR (Metric 1)	URB (Metric 3)
0: Not enough information available	0: Not enough information available
1: Substantial increase in habitat	1: Species' distribution is surrounded by undeveloped habitat lacking natural barriers to dispersal
2: Moderate increase in habitat	2: up to 25% of distribution or 'escape path' from SLR is blocked by encroaching development or natural barriers
3: No effect	3: Half of their distribution or 'escape path' from SLR is blocked by encroaching development or natural barriers
4: up to 25% habitat inundated	4: 50-75% of their distribution or 'escape path' from SLR is blocked by encroaching development or natural barriers
5: 25-50% habitat inundated	5: More than 75% of their distribution or 'escape path' from SLR is blocked by encroaching development or natural barriers, but it is unlikely that these barriers are completely insurmountable.
6: 50-100% of known habitat is lost to inundation	6: Virtually all of their distribution or escape path is blocked and escape from inundation is virtually impossible

Table 3.4. Scoring system for empirical-based metrics based on fraction (in percent) of exposure to potential habitat change from SLR and urbanization (URB). Scores are based on the values between the minimum and up to the maximum of each range. For example, species estimated to have roughly 5.5% of their habitat exposed to potential change from SLR would be assigned a score of 3.3 NIA indicates No Information Available, NA indicates a score representing potential increases in habitat not captured here.

SLR (1)						**URB (3)**							
NIA/NA/NA	0/1/2					NIA	0						
0%	**3**	25%	**4**	50%	**5**	0%	**1**	25%	**2**	50%	**4**	75%	**5**
0-2.5%	**3.1**	25-27.5%	**4.1**	50-55%	**5.1**	0-2.5%	**1.1**	25-27.5%	**2.1**	50-52.5%	**4.1**	75-77.5%	**5.1**
2.5-5%	**3.2**	27.5%-30%	**4.2**	55-60%	**5.2**	2.5-5%	**1.2**	27.5%-30%	**2.2**	52.5-55%	**4.2**	77.5-80%	**5.2**
5-7.5%	**3.3**	30-32.5%	**4.3**	60-65%	**5.3**	5-7.5%	**1.3**	30-32.5%	**2.3**	55-57.5%	**4.3**	80-82.5%	**5.3**
7.5-10%	**3.4**	32.5-35%	**4.4**	65-70%	**5.4**	7.5-10%	**1.4**	32.5-35%	**2.4**	57.5-60%	**4.4**	82.5-85%	**5.4**
10-12.5%	**3.5**	35-37.5%	**4.5**	70-75%	**5.5**	10-12.5%	**1.5**	35-37.5%	**2.5**	60-62.5%	**4.5**	85-87.5%	**5.5**
12.5-15%	**3.6**	37.5-40%	**4.6**	75-80%	**5.6**	12.5-15%	**1.6**	37.5-40%	**2.6**	62.5-65%	**4.6**	87.5-90%	**5.6**
15-17.5%	**3.7**	40-42.5%	**4.7**	80-85%	**5.7**	15-17.5%	**1.7**	40-42.5%	**2.7**	65-67.5%	**4.7**	90-92.5%	**5.7**
17.5-20%	**3.8**	42.5-45%	**4.8**	85-90%	**5.8**	17.5-20%	**1.8**	42.5-45%	**2.8**	67.5-70%	**4.8**	92.5-95%	**5.8**
20-22.5%	**3.9**	45-47.5%	**4.9**	90-95%	**5.9**	20-22.5%	**1.9**	45-47.5%	**2.9**	70-72.5%	**4.9**	95-97.5%	**5.9**
22.5-25%	**4**	47.5-50%	**5**	95-100%	**6**	22.5-25%	**2**	47.5-50%	**3|4**	72.5-75%	**5**	97.5-100%	**6**

Table 3.5. Summary scores for the Vulnerability criterion (VUL) and average across all criteria (ALL) at two time points for both expert-based (EXP) and empirical-based (EMP) methods, as well as summary scores for Adaptive Capacity (AC), Conservation Value (CV), and Information Availability (IA). Species are listed in alphabetical order, and unranked. Scores closer to 1 indicate higher vulnerability for VUL, less adaptive capacity for AC, higher conservation value for CV, and greater amounts of information for IA. * denotes top ranking species for that score category.

Species	VUL (EXP)		VUL (EMP)	
	EXP 2030	EXP 2060	EMP 2030	EMP 2060
American Oystercatcher	*0.742*	*0.743*	*0.531*	*0.536*
Bachman's Sparrow	*0.620*	*0.625*	*0.570*	*0.576*
Diamondback Terrapin	*0.789*	*0.802*	*0.585*	*0.601*
E. Diamondback Rattlesnake	*0.698*	*0.724*	*0.604*	*0.614*
Eastern Indigo Snake	*0.657*	*0.663*	*0.560*	*0.571*
Florida Pine Snake	*0.696*	*0.711*	*0.573*	*0.593*
Gopher Frog	*0.709*	*0.742*	*0.603*	*0.618*
Gopher Tortoise	*0.603*	*0.634*	*0.545*	*0.577*
Painted Bunting	*0.641*	*0.667*	*0.561*	*0.579*
Red-cockaded Woodpecker	*0.639*	*0.649*	*0.565*	*0.570*
Seaside Sparrow	***0.881****	***0.884****	***0.682****	***0.688****
Southern Hognose Snake	*0.695*	*0.713*	*0.605*	*0.623*
Striped Newt	*0.676*	*0.680*	*0.593*	*0.599*
Wilson's Plover	*0.680*	*0.690*	*0.522*	*0.532*
Wood Stork	*0.721*	*0.759*	*0.575*	*0.602*

Species	***AC***	***CV***	***IA***
American Oystercatcher	*0.836*	*0.490*	*0.627*
Bachman's Sparrow	*0.541*	*0.380*	*0.446*
Diamondback Terrapin	***0.885****	*0.484*	*0.763*
E. Diamondback Rattlesnake	*0.712*	*0.276*	*0.693*
Eastern Indigo Snake	*0.626*	*0.609*	*0.500*
Florida Pine Snake	*0.705*	*0.396*	*0.307*
Gopher Frog	*0.874*	*0.409*	*0.689*
Gopher Tortoise	*0.832*	***0.634****	*0.816*
Painted Bunting	*0.586*	*0.398*	*0.582*
Red-cockaded Woodpecker	*0.734*	*0.625*	*0.556*
Seaside Sparrow	*0.787*	*0.500*	*0.865*
Southern Hognose Snake	*0.659*	*0.245*	*0.602*
Striped Newt	*0.810*	*0.285*	*0.307*
Wilson's Plover	*0.437*	*0.531*	*0.333*
Wood Stork	*0.752*	*0.573*	***0.904****

Table 3.5. continued.

Species	ALL (EXP)		ALL (EMP)	
	EXP 2030	**EXP 2060**	**EMP 2030**	**EMP 2060**
American Oystercatcher	*0.674*	*0.674*	*0.621*	*0.622*
Bachman's Sparrow	*0.497*	*0.498*	*0.484*	*0.486*
Diamondback Terrapin	*0.730*	*0.734*	*0.679*	*0.683*
E. Diamondback Rattlesnake	*0.595*	*0.601*	*0.571*	*0.574*
Eastern Indigo Snake	*0.598*	*0.600*	*0.574*	*0.577*
Florida Pine Snake	*0.526*	*0.530*	*0.495*	*0.500*
Gopher Frog	*0.670*	*0.679*	*0.644*	*0.648*
Gopher Tortoise	*0.721*	*0.729*	*0.707*	***0.715****
Painted Bunting	*0.552*	*0.558*	*0.532*	*0.536*
Red-cockaded Woodpecker	*0.638*	*0.641*	*0.620*	*0.621*
Seaside Sparrow	***0.758****	***0.759****	***0.709****	*0.710*
Southern Hognose Snake	*0.550*	*0.554*	*0.528*	*0.532*
Striped Newt	*0.520*	*0.521*	*0.499*	*0.500*
Wilson's Plover	*0.495*	*0.498*	*0.456*	*0.458*
Wood Stork	*0.737*	*0.747*	*0.701*	*0.708*

Table 3.6. Average summary scores for VUL metrics 1 (SLR) and 3 (URB) using both types of methods at two future time points.

	2030 $\bar{X}$		**2060 $\bar{X}$**	
VUL Metric Scores	SLR (1)	URB (3)	SLR (1)	URB (3)
Empirical-Based	**3.09**	**1.19**	**3.12**	**1.31**
Expert-Based	**4.15**	**4.40**	**4.27**	**4.51**

Table 3.7. Species ranks based on the summary score describing Vulnerability for 2030 and 2060. Colors under the 'Expert-based' method convey rank change under the 'Empirical-based' method.

2030 Vulnerability (VUL)		
Expert-based	RANK	Empirical-based
Seaside Sparrow	1	Seaside Sparrow
Diamondback Terrapin	2	Southern Hognose Snake
American Oystercatcher	3	Eastern Diamond-backed Rattlesnake
Wood Stork	4	Gopher Frog
Gopher Frog	5	Striped Newt
Eastern Diamond-backed Rattlesnake	6	Diamondback Terrapin
Florida Pine Snake	7	Wood Stork
Southern Hognose Snake	8	Florida Pine Snake
Wilson's Plover	9	Bachman's Sparrow
Striped Newt	10	Red-cockaded Woodpecker
Eastern Indigo Snake	11	Painted Bunting
Painted Bunting	12	Eastern Indigo Snake
Red-cockaded Woodpecker	13	Gopher Tortoise
Bachman's Sparrow	14	American Oystercatcher
Gopher Tortoise	15	Wilson's Plover
2060 Vulnerability (2060)		
Expert-based	RANK	Empirical-based
Seaside Sparrow	1	Seaside Sparrow
Diamondback Terrapin	2	Southern Hognose Snake
Wood Stork	3	Gopher Frog
American Oystercatcher	4	Eastern Diamond-backed Rattlesnake
Gopher Frog	5	Wood Stork
Eastern Diamond-backed Rattlesnake	6	Diamondback Terrapin
Southern Hognose Snake	7	Striped Newt
Florida Pine Snake	8	Florida Pine Snake
Wilson's Plover	9	Painted Bunting
Striped Newt	10	Gopher Tortoise
Painted Bunting	11	Bachman's Sparrow
Eastern Indigo Snake	12	Eastern Indigo Snake
Red-cockaded Woodpecker	13	Red-cockaded Woodpecker
Gopher Tortoise	14	American Oystercatcher
Bachman's Sparrow	15	Wilson's Plover

Table 3.8. Species ranks based on the average across all criteria for 2030 and 2060. Colors under the 'Expert-based' method convey rank change under the 'Empirical-based' method.

	ALL 2030	
Expert-based	RANK	Empirical-based
Seaside Sparrow	1	Seaside Sparrow
Wood Stork	2	Gopher Tortoise
Diamondback Terrapin	3	Wood Stork
Gopher Tortoise	4	Diamondback Terrapin
American Oystercatcher	5	Gopher Frog
Gopher Frog	6	American Oystercatcher
Red-cockaded Woodpecker	7	Red-cockaded Woodpecker
Eastern Indigo Snake	8	Eastern Indigo Snake
Eastern Diamond-backed Rattlesnake	9	Eastern Diamond-backed Rattlesnake
Painted Bunting	10	Painted Bunting
Southern Hognose Snake	11	Southern Hognose Snake
Florida Pine Snake	12	Striped Newt
Striped Newt	13	Florida Pine Snake
Bachman's Sparrow	14	Bachman's Sparrow
Wilson's Plover	15	Wilson's Plover
	ALL 2060	
Expert-based	RANK	Empirical-based
Seaside Sparrow	1	Gopher Tortoise
Wood Stork	2	Seaside Sparrow
Diamondback Terrapin	3	Wood Stork
Gopher Tortoise	4	Diamondback Terrapin
Gopher Frog	5	Gopher Frog
American Oystercatcher	6	American Oystercatcher
Red-cockaded Woodpecker	7	Red-cockaded Woodpecker
Eastern Diamond-backed Rattlesnake	8	Eastern Indigo Snake
Eastern Indigo Snake	9	Eastern Diamond-backed Rattlesnake
Painted Bunting	10	Painted Bunting
Southern Hognose Snake	11	Southern Hognose Snake
Florida Pine Snake	12	Striped Newt
Striped Newt	13	Florida Pine Snake
Bachman's Sparrow	14	Bachman's Sparrow
Wilson's Plover	15	Wilson's Plover

CHAPTER IV.

CONCLUSIONS

Threatened and endangered species in the State of Georgia and throughout the U.S. face an uncertain future. The results from this work suggest that salt marsh and beach dwelling species will likely be exposed to dramatic habitat change by the end of the century, and exposure to change for these species is unlikely to be insignificant at near time points. While inland species were not projected to be as dramatically exposed to habitat change as coastally adjacent species, even small shifts in the amount of available habitat on short term scales has the potential to influence populations towards or away from long-term stability. Decisions involving these species are made more complicated by the fact that the impacts to species' habitat from these stressors will take significantly different forms, meaning that management approaches to these stressors will not be universal. Urbanization will likely result in the abrupt complete loss of habitat, which may be mitigated by targeting suitable habitat that is not currently protected, or by identifying high richness areas crucial for multiple species. In contrast, sea level rise will likely result in longer, more insidious habitat fragmentation or conversion, which can be challenging to mitigate; the reconstruction of wetlands may be a more appropriate response to this issue.

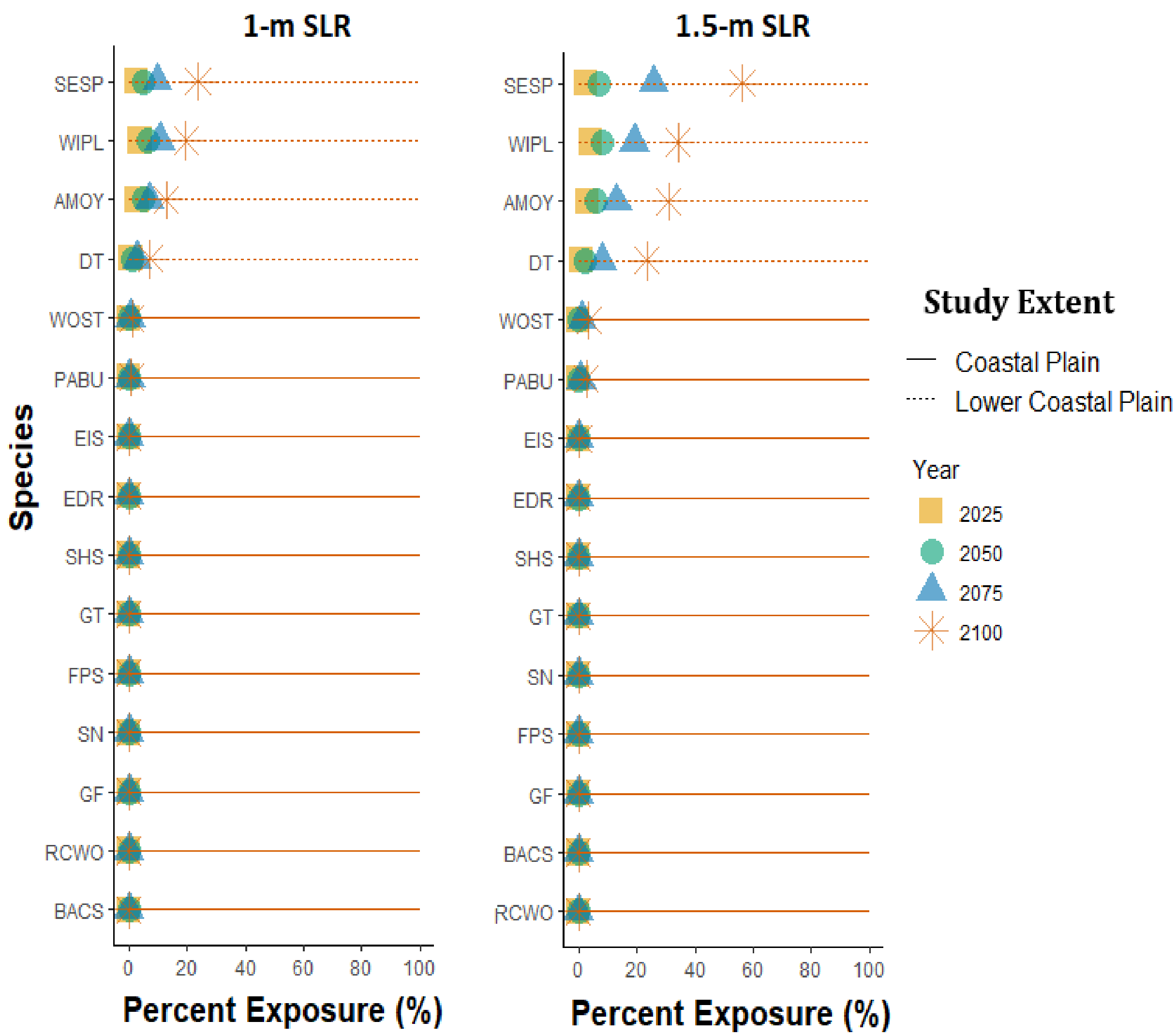
Under all methods and scenarios, the top-ranking species (*Ammodramus maritimus*, or the seaside sparrow) was consistent. Although individual management actions for each species will differ depending on long-term goals for the state of Georgia and the agency responsible for management, the results of this work suggest that consideration of the seaside sparrow for major management action is appropriate. Currently, the species is listed at a rank of S3 (vulnerable) in the state, likely because of its dependence on salt-marsh, an imperiled habitat throughout Georgia and the Atlantic coast. Results from this work and from other studies suggesting severe declines in available habitat for the seaside sparrow in Georgia indicate that fish and wildlife agencies may wish to consider reviewing the species for lower state status or developing long-term conservation plans for this species.

Future wildlife studies in this region could choose to focus on SIVVA analyses covering additional scenarios and time points to better understand the disparity between vulnerability results using expert and empirical based judgement. Experts presented with later time points as well as scenarios with higher severities may value metrics differently when presented with alternatives beyond one to two time points and one scenario. Efforts to model habitat for additional species in this region may also choose to elicit experts to inform the modeling process, making use of experts to offer hypotheses or knowledge regarding appropriate habitat predictors, as done in Crawford et al. (2020). This could also allow experts to be more closely involved with the process of comparison between methods, which may result in shifts in the way experts approach their SIVVA analysis.

While species vulnerability is a complex and multi-dynamic subject, the inclusion of multiple dimensions of information when evaluating the risks to the long-term prosperity of threatened or endangered wildlife provides managers with a more complete framework in which to make decisions. This work attempted to provide that information by allowing for spatially-explicit results that wildlife managers could use to pinpoint areas of particular interest, as well as multiple time points, scenarios, and thresholds to inform planning at a range of temporal scales and potential change severities. In addition, information about expert judgement regarding the conservation value and information availability of species as well as the global importance of species allows for agencies to incorporate multiple factors pertaining to decision analysis.

APPENDICES

APPENDIX A – SPECIES RANKS FOR 1-M AND 1.5-M SLR



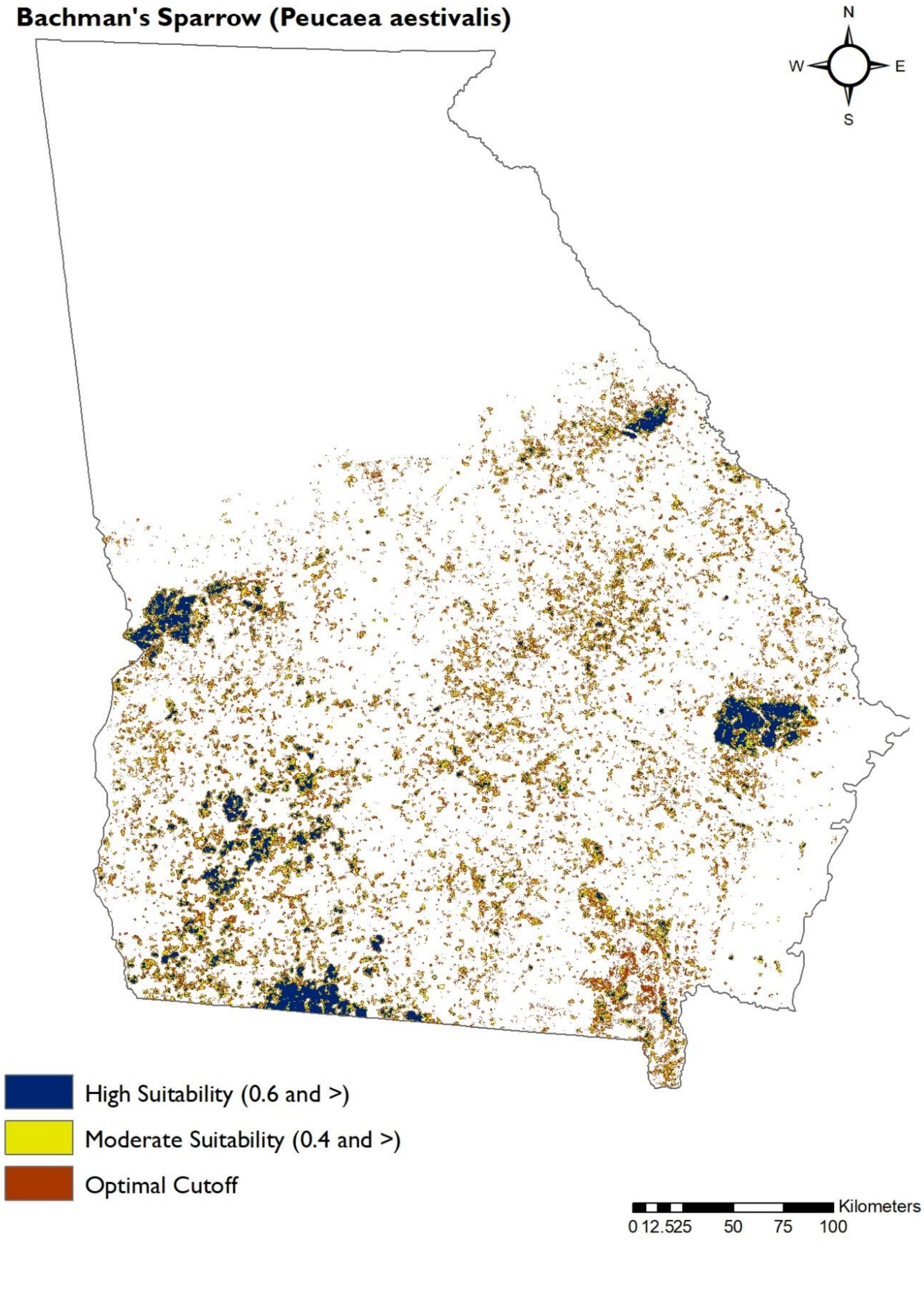
APPENDIX B – PROPORTION OF VARIANCE EXPLAINED BY INDIVIDUAL PREDICTORS

Species	Predictors	% Contribution
AOC	ow_1kmf	47.59
	plandbh100	33.47
	urb_1kmf	12.67
	edmsh1km	6.26
BACS	fire800	48.16
	plandpine800	35.83
	herbht800	7.31
	shrbht800	6.57
	can100	2.13
DT	plandmarsh500	48.52
	elev500	23.43
	landco_800	18.14
	urb_800	9.92
EDR	dran250	24.28
	plandpine900	18.36
	landco250	16.85
	hist900	11.10
	evi250	9.47
	tpi	8.06
	fire900	4.08
	can250	3.88
	precip	3.29
	urb250	0.63
EIS	hist900	17.94
	evi250	16.67
	rip_900	14.67
	pine900	12.96
	dran250	12.53
	landco900	9.25
	precip	8.41
	can250	4.20
	tpi	2.07
	urb900	1.30
PABU	elev700	44.02
	can700	18.02
	plandfor700	17.83
	plandrip700	10.32
	shrbht700	6.20
	mpashb700	3.61

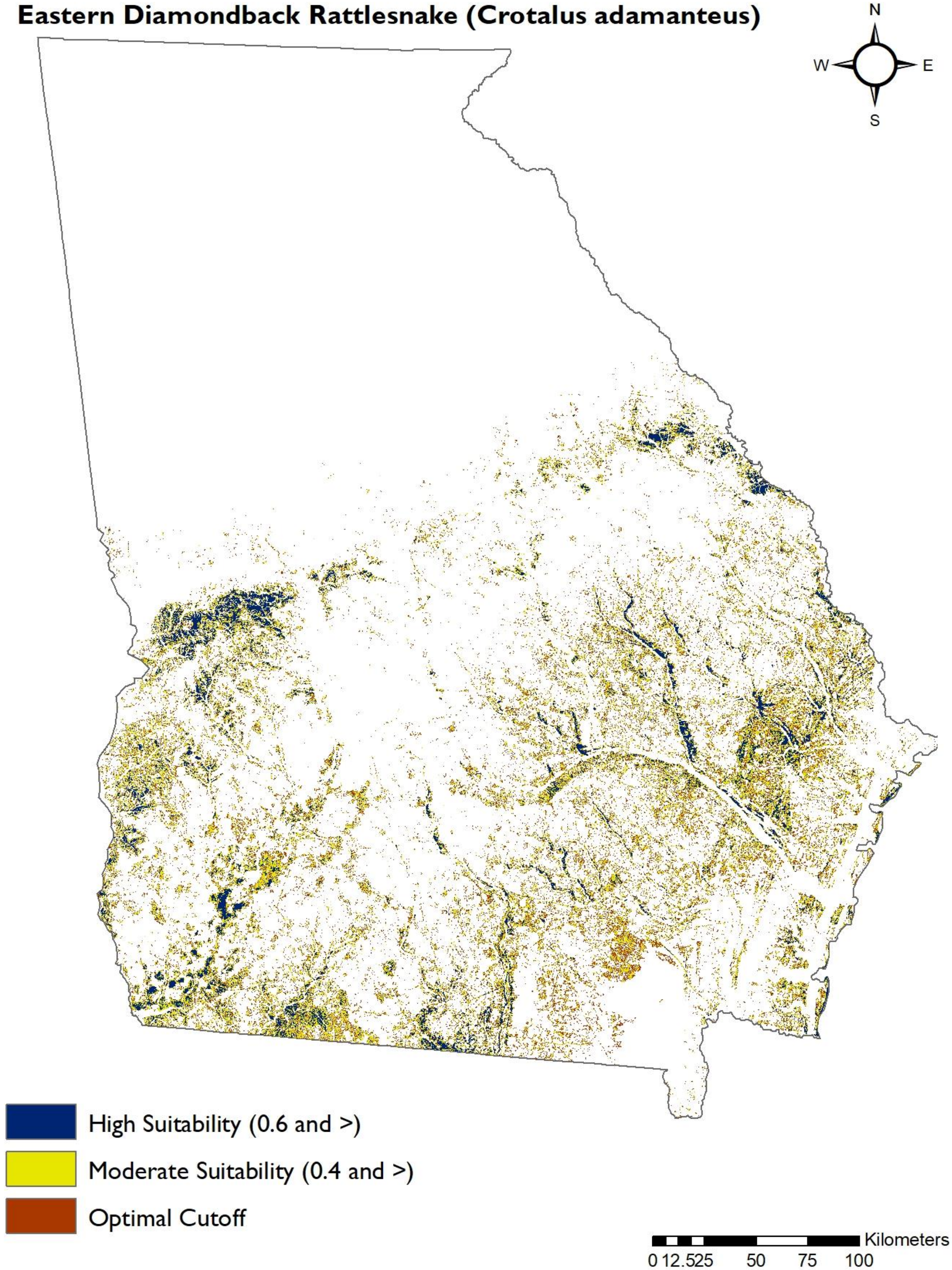
APPENDIX B CONTINUED.

Species	Predictors	% Contributed
RCWO	plandpine800	38.62
	fire800	37.11
	herbht800	8.87
	shrbht800	8.31
	can800	7.09
SESP	edmsh200	43.87
	elev200	38.35
	urb_200	14.62
	plandbrack200	3.16
WIPL	plandco1km	42.73
	edbh100	29.86
	ow_1kmf	20.32
	urb_1kmf	7.08
WOST	elev2000	52.90
	can2000	18.74
	nhd_2000	16.60
	wat2000	4.83
	landco2000	4.22
	nwifwd_2000	2.71

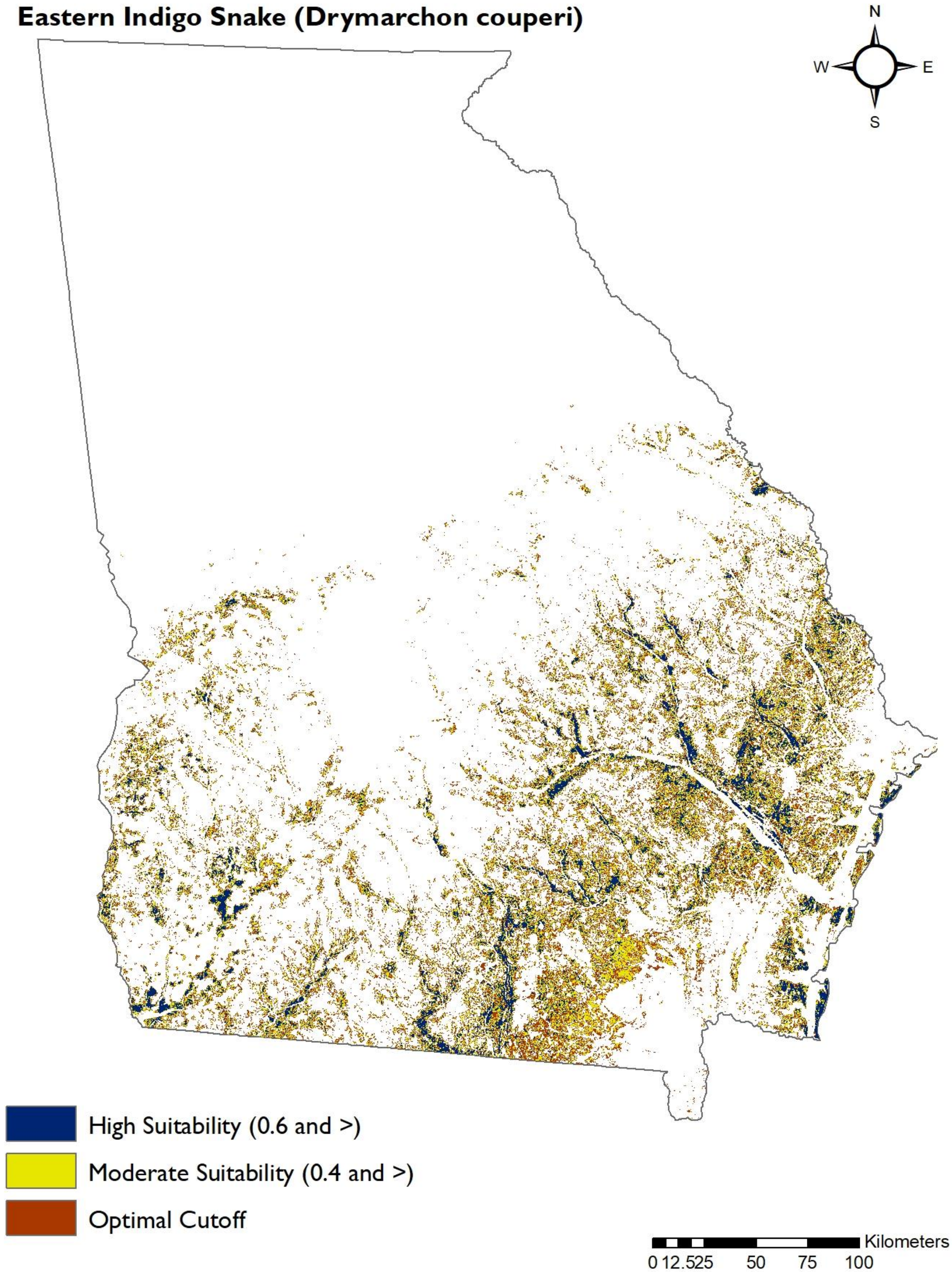
APPENDIX C – SPECIES DISTRIBUTION MODEL OUTPUTS FOR OPTIMAL CUTOFF, MODERATE, AND HIGH THRESHOLDS FOR ALL SPECIES

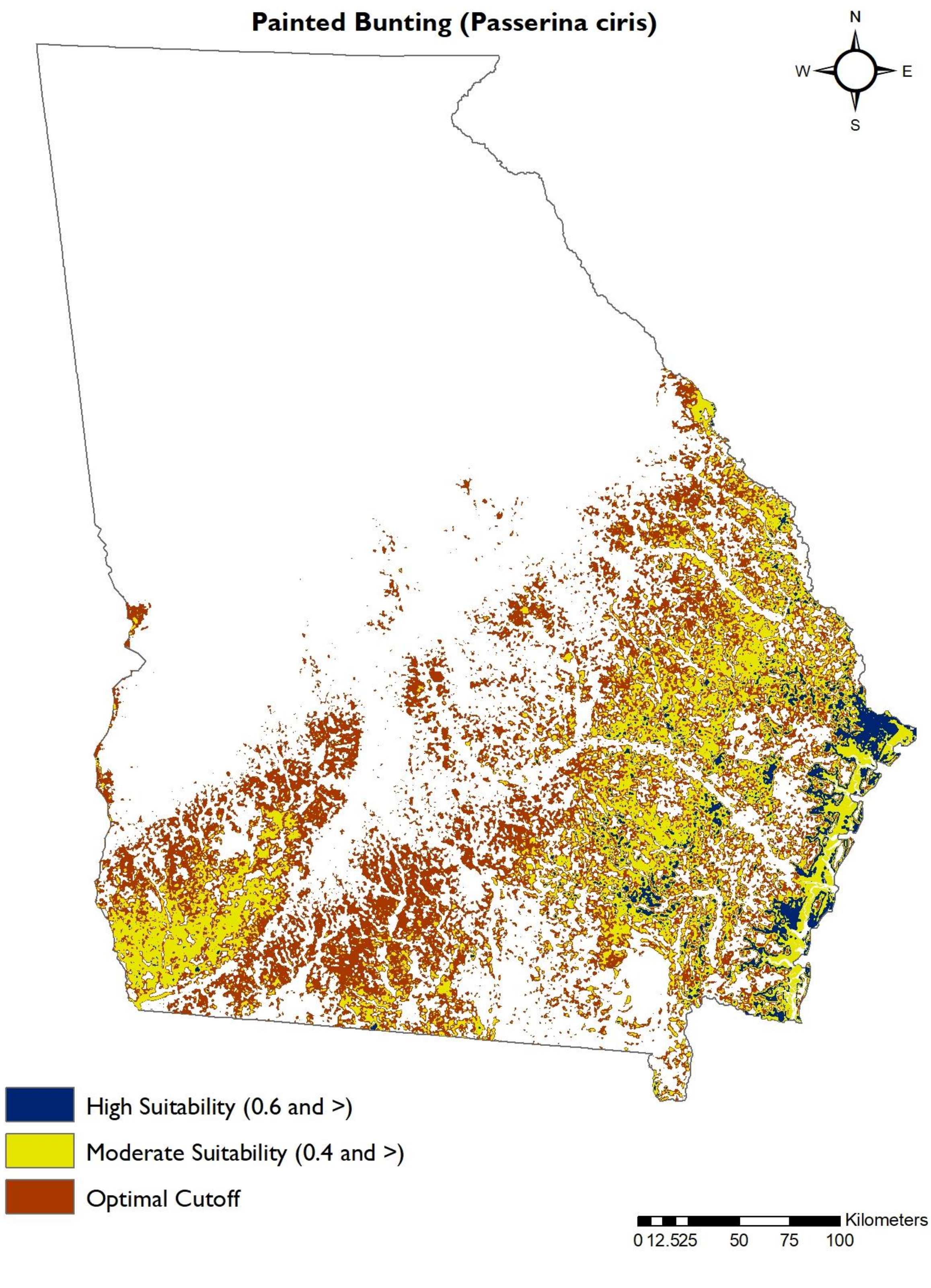


Eastern Diamondback Rattlesnake (Crotalus adamanteus)

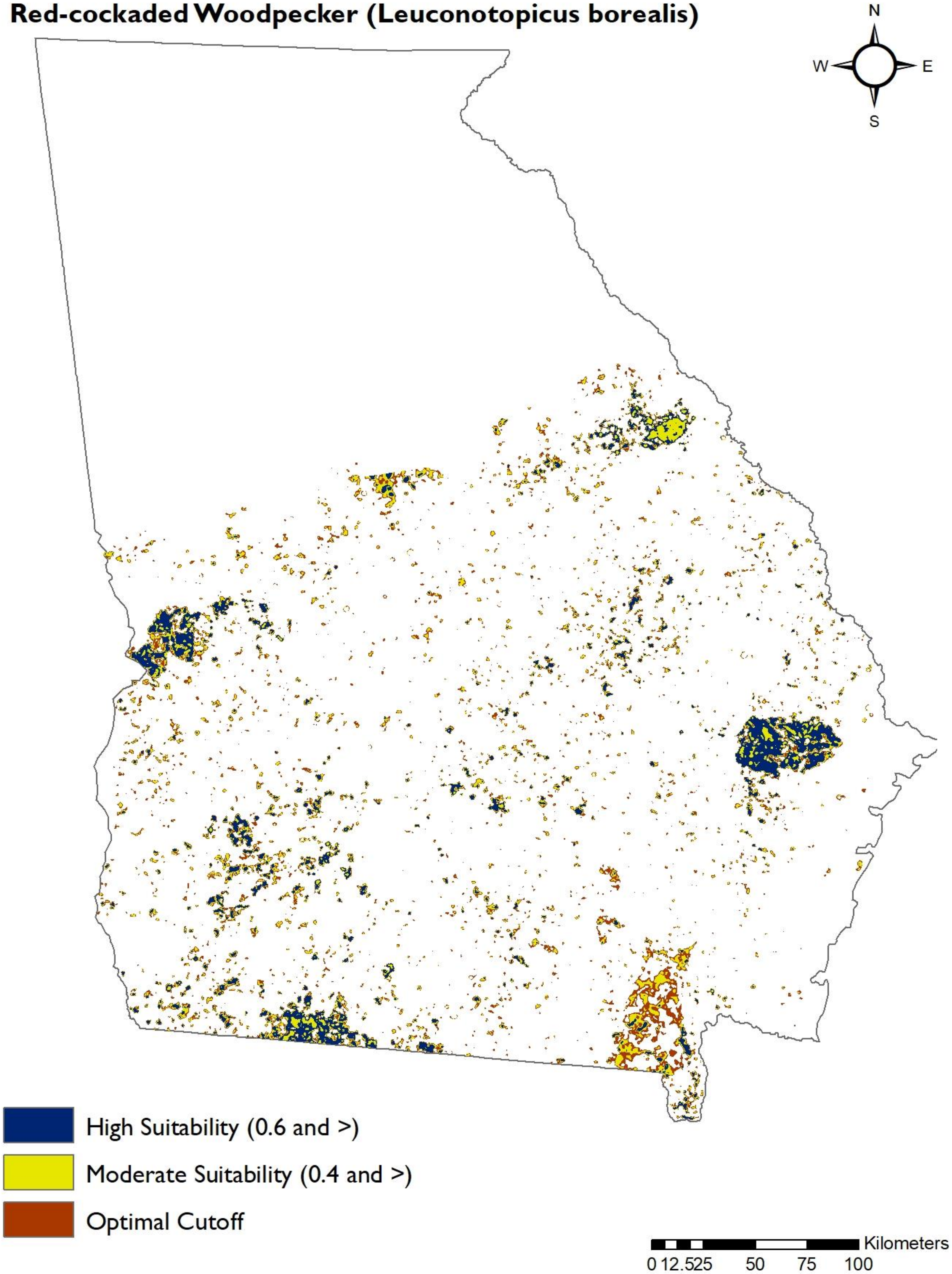


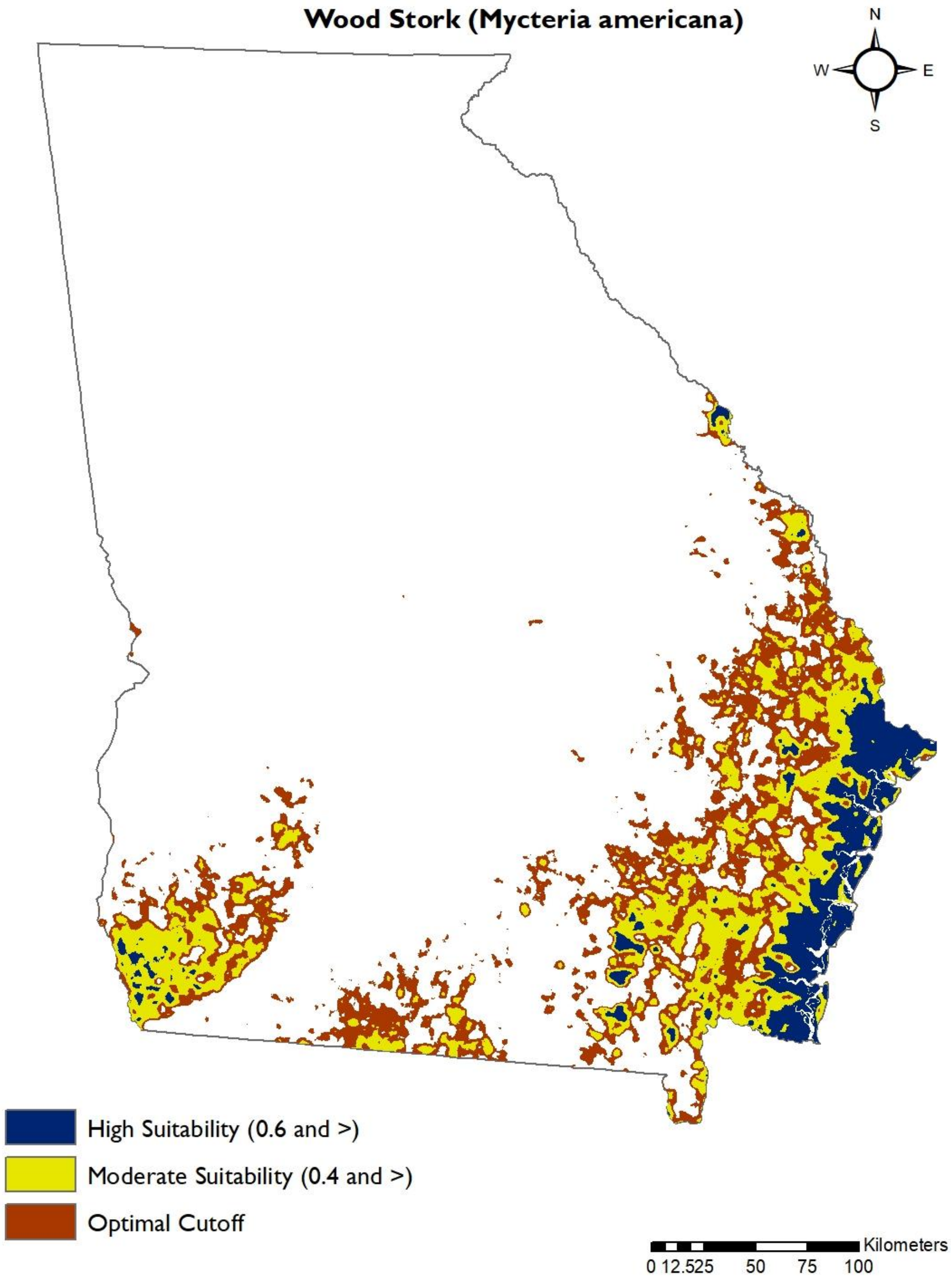
Eastern Indigo Snake (Drymarchon couperi)

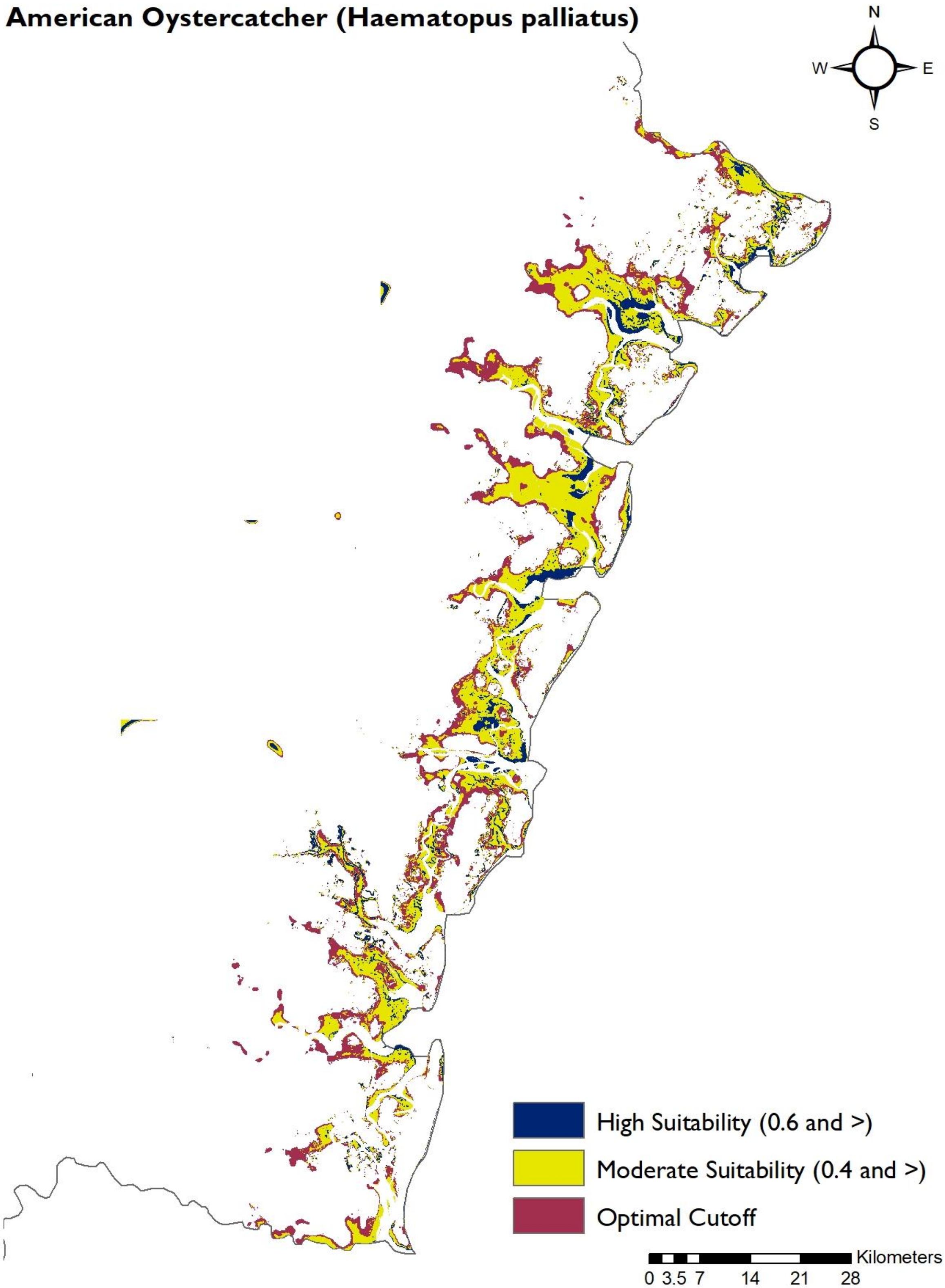



Painted Bunting (Passerina ciris)
N
W
E
S
High Suitability (0.6 and >)
Moderate Suitability (0.4 and >)
Optimal Cutoff
Kilometers
0 12.525 50 75 100

Red-cockaded Woodpecker (Leuconotopicus borealis)

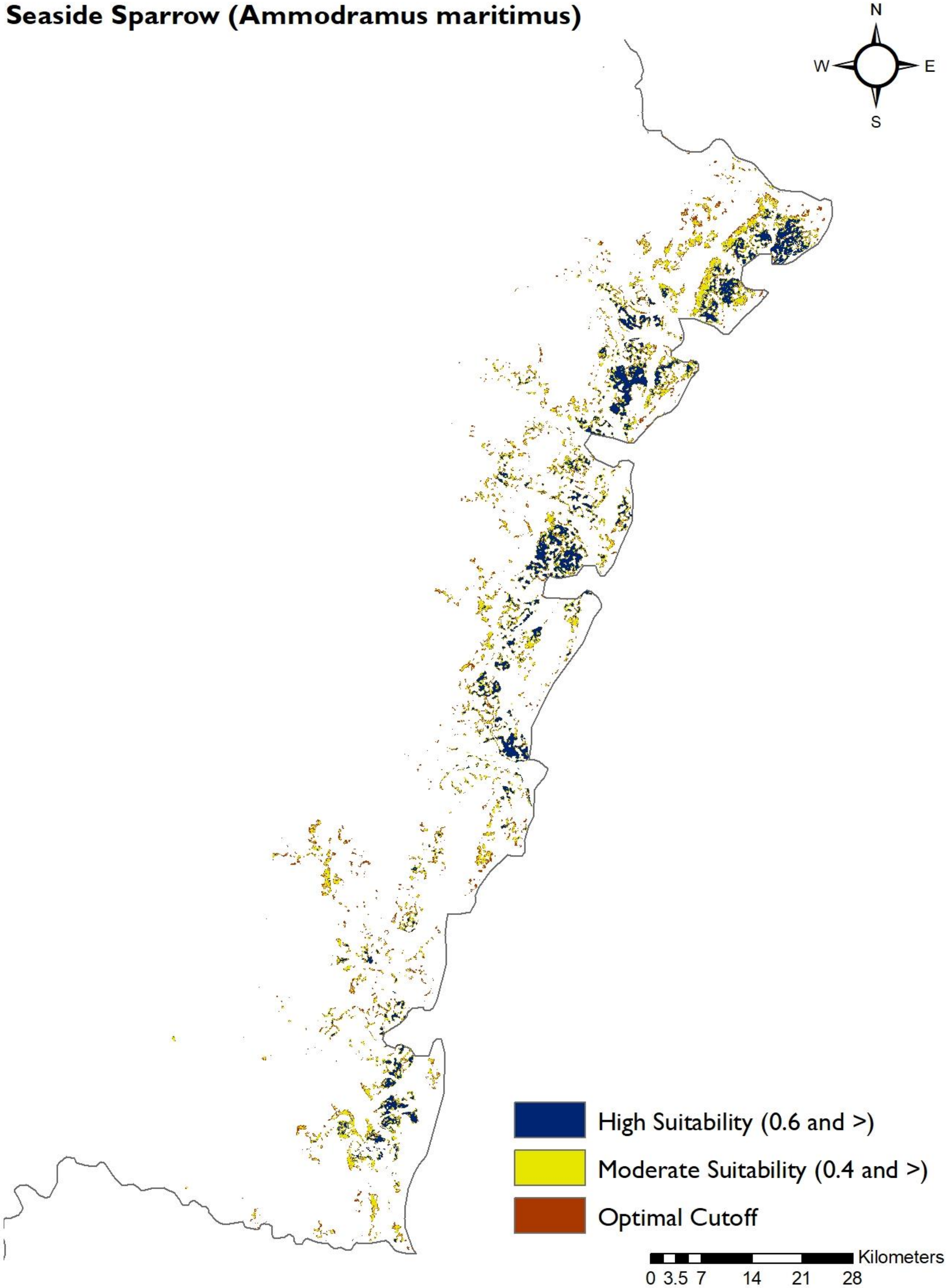



Wood Stork (Mycteria americana)
N
W
E
S
High Suitability (0.6 and >)
Moderate Suitability (0.4 and >)
Optimal Cutoff
Kilometers
0 12.525 50 75 100


American Oystercatcher (Haematopus palliatus)
N
W
E
S
High Suitability (0.6 and >)
Moderate Suitability (0.4 and >)
Optimal Cutoff
Kilometers
0 3.5 7 14 21 28

Diamondback Terrapin (Malaclemys terrapin)

Seaside Sparrow (Ammodramus maritimus)



Wilson's Plover (Charadrius wilsonia)

APPENDIX D: SPECIES DISTRIBUTION MODEL COEFFICIENTS

Model estimates of predictor effects for all species, with confidence intervals

AOC Main Effects		2.5% CI	97.5% CI
Intercept	*-1.189*	*-1.905*	*-0.494*
pland_bh100	*0.140*	*0.095*	*0.189*
pland_bh100^2	*-0.001*	*-0.002*	*-0.001*
ed_msh1km	*0.067*	*0.044*	*0.091*
ed_msh1km^2	*-0.001*	*-0.001*	*-0.001*
urb1kmf	*0.001*	*0.00*	*0.002*
ow1kmf	*-0.007*	*-0.009*	*-0.005*
ow1kmf^2	*0.003*	*0.001*	*0.005*
BASP Main Effects		**2.5% CI**	**97.5% CI**
Intercept	*-2.817*	*-3.346*	*-2.311*
plandpine800	*9.236*	*6.743*	*11.74*
plandpine800^2	*-9.704*	*-13.886*	*-5.395*
fire800	*32.829*	*27.187*	*38.606*
fire800^2	*-79.459*	*-101.389*	*-57.58*
herbht800	*-7.766*	*-10.372*	*-5.272*
shrbht800	*-17.793*	*-27.981*	*-8.671*
can100	*0.024*	*0.007*	*0.041*
can100^2	*0.002*	*-0.001*	*0.003*
DT Main Effects		**2.5% CI**	**97.5% CI**
Intercept	*-0.127*	*-1.640*	*1.406*
marsh500	*3.579*	*1.931*	*5.501*
landco_800	*0.004*	*0.001*	*0.007*
landco_800^2	*-0.001*	*-0.002*	*0.003*
urb_800	*-0.003*	*-0.005*	*-0.002*
urb_800^2	*0.001*	*-0.001*	*0.003*
elev500	*-0.674*	*-1.315*	*-0.178*
EDR Main Effects		**2.5% CI**	**97.5% CI**
Intercept	*-30.038*	*-42.827*	*-18.070*
can250	*0.022*	*-0.010*	*0.054*
can250^2	*0.002*	*-0.001*	*0.004*
dran250	*2.228*	*-0.269*	*4.769*
dran250^2	*0.366*	*-2.097*	*2.857*
fire900	*1.542*	*-2.033*	*5.110*
landco250	*3.422*	*0.956*	*5.963*
landco250^2	*-2.631*	*-4.953*	*-0.358*
pine900	*3.886*	*-0.711*	*8.565*

$pine900^2$	*-5.013*	*-14.788*	*4.440*
urb250	*11.277*	*4.667*	*18.153*
$urb250^2$	*-19.978*	*-37.428*	*-5.854*
evi250	*12.221*	*1.389*	*24.391*
$evi250^2$	*-16.179*	*-30.601*	*-3.521*
hist900	*-2.482*	*-4.976*	*-0.007*
$hist900^2$	*-0.188*	*-2.804*	*2.410*
precip_raw	*0.127*	*0.068*	*0.191*
$precip\_raw^2$	*0.001*	*0.001*	*0.002*
tpi_raw	*0.234*	*0.034*	*0.449*
tpi_raw^2	*-0.085*	*-0.163*	*-0.023*
EIS			
Main Effects		**2.5% CI**	**97.5% CI**
Intercept	*-53.299*	*-71.075*	*-36.977*
rip_900	*-0.005*	*-0.008*	*-0.003*
can250	*0.036*	*0.001*	*0.071*
$can250^2$	*-0.001*	*-0.001*	*0.000*
dran250	*4.756*	*2.163*	*7.423*
$dran250^2$	*-2.192*	*-4.826*	*0.415*
landco900	*1.486*	*-2.953*	*6.141*
$landco900^2$	*-0.687*	*-5.201*	*3.702*
pine900	*3.528*	*-2.757*	*9.746*
$pine900^2$	*-5.241*	*-18.837*	*8.896*
urb900	*0.242*	*-5.004*	*4.594*
evi250	*12.904*	*1.785*	*25.623*
$evi250^2$	*-22.852*	*-38.976*	*-8.865*
precip_raw	*0.253*	*0.173*	*0.340*
$precip\_raw^2$	*0.001*	*0.000*	*0.000*
tpi_raw	*-0.176*	*-0.404*	*0.050*
hist900	*-3.783*	*-6.738*	*-0.854*
$hist900^2$	*0.041*	*-3.257*	*3.267*
PB			
Main Effects		**2.5% CI**	**97.5% CI**
Intercept	*0.337*	*-0.319*	*0.996*
plandfor700	*-2.333*	*-3.558*	*-1.130*
patmshb700	*0.001*	*0.001*	*0.002*
shrbht700	*6.823*	*1.798*	*11.722*
plandrip700	*-3.521*	*-5.121*	*-2.001*
can700	*0.048*	*0.017*	*0.079*
$can700^2$	*-0.001*	*-0.001*	*0.000*
elev700	*-0.019*	*-0.023*	*-0.014*
RCW			
Main Effects		**2.5% CI**	**97.5% CI**
Intercept	*-5.559*	*-7.382*	*-3.961*

plandpine800	*0.713*	*-5.663*	*6.884*
plandpine800^2	*15.816*	*2.237*	*31.133*
fire800	*52.803*	*41.858*	*64.695*
fire800^2	*-138.895*	*-179.920*	*-101.079*
herbht800	*-11.404*	*-18.585*	*-4.788*
shrbht800	*-20.992*	*-45.944*	*-1.067*
can800	*0.019*	*0.001*	*0.038*
SSS			
Main Effects		**2.5% CI**	**97.5% CI**
Intercept	*-6.789*	*-9.080*	*-4.821*
ed_msh200	*0.073*	*0.052*	*0.097*
ed_msh200^2	*0.001*	*0.000*	*0.002*
brack200	*-2.259*	*-3.547*	*-1.062*
elev200f	*-0.483*	*-1.348*	*0.101*
urb_200	*0.001*	*0.000*	*0.001*
WP			
Main Effects		**2.5% CI**	**97.5% CI**
Intercept	*-2.182*	*-3.098*	*-1.290*
ed_bh100	*0.010*	*0.006*	*0.015*
urb1kmf	*0.000*	*0.000*	*0.001*
landco1km	*11.433*	*7.587*	*15.992*
ow1kmf	*-0.002*	*-0.004*	*0.000*
WS			
Main Effects		**2.5% CI**	**97.5% CI**
Intercept	*3.558*	*2.508*	*4.651*
wat2000	*-2.147*	*-5.223*	*0.793*
nwifwd_2000	*-0.001*	*-0.001*	*0.000*
nhd_2000	*0.000*	*0.000*	*0.000*
landco2000	*-0.878*	*-2.131*	*0.379*
can2000	*-0.045*	*-0.059*	*-0.031*
elev2000	*-0.029*	*-0.036*	*-0.023*