2023 COASTAL MASTER PLAN

HABITAT SUITABILITY INDEX MODEL IMPROVEMENT RECOMMENDATIONS

REPORT: VERSION 01
DATE: AUGUST 2019

PREPARED BY: SHAYE E. SABLE, DAVID C. LINDQUIST, LAURA D'ACUNTO, ANN C. HIJUELOS, MEGAN K. LA PEYRE, ANN M. O'CONNELL, & ELIZABETH M. ROBINSON

COASTAL PROTECTION AND
RESTORATION AUTHORITY
150 TERRACE AVENUE
BATON ROUGE, LA 70802
WWW.COASTAL.LA.GOV

COASTAL PROTECTION AND RESTORATION AUTHORITY

This document was developed in support of the 2023 Coastal Master Plan being prepared by the Coastal Protection and Restoration Authority (CPRA). CPRA was established by the Louisiana Legislature in response to Hurricanes Katrina and Rita through Act 8 of the First Extraordinary Session of 2005. Act 8 of the First Extraordinary Session of 2005 expanded the membership, duties, and responsibilities of CPRA and charged the new authority to develop and implement a comprehensive coastal protection plan, consisting of a master plan (revised every six years) and annual plans. CPRA's mandate is to develop, implement, and enforce a comprehensive coastal protection and restoration master plan.

CITATION

Sable, S.E., Lindquist, D.C., D'Acunto, L., Hijuelos, A.C., La Peyre, M.K., O'Connell, A.M., & Robinson, E.M. (2019). 2023 Coastal Master Plan: Habitat Suitability Index Model Improvement Recommendations. Final Report (49 p.) Baton Rouge, Louisiana: Coastal Protection and Restoration Authority.

ACKNOWLEDGEMENTS

This document was developed as part of a broader Model Improvement Plan in support of the 2023 Coastal Master Plan under the guidance of the Modeling Decision Team (MDT):

- Coastal Protection and Restoration Authority (CPRA) of Louisiana – Elizabeth Jarrell, Stuart Brown, Ashley Cobb, Catherine Fitzpatrick, Krista Jankowski, David Lindquist, Sam Martin, and Eric White
- University of New Orleans – Denise Reed

The following experts were responsible for the preparation of this document:

- Shaye E. Sable – Dynamic Solutions, LLC
- David C. Lindquist – CPRA
- Laura D'Acunto – United States Geological Survey (USGS), Wetland and Aquatic Research Center
- Ann C. Hijuelos – USGS, Wetland and Aquatic Research Center
- Megan K. La Peyre – USGS, Louisiana Fish and Wildlife Cooperative Research Unit
- Ann M. O'Connell – University of New Orleans
- Elizabeth M. Robinson – Louisiana State University (LSU) AgCenter

The authors would like to thank Brady Carter, with the Louisiana Department of Wildlife and Fisheries (LDWF), and Erik I. Johnson and Katie Percy, with Audubon Louisiana, for their valuable input on these recommended improvements.

EXECUTIVE SUMMARY

As part of the model improvement effort for the 2023 Coastal Master Plan, the Habitat Suitability Index (HSI) models used during previous master plans were reevaluated to assess how the model relationships could be improved, and to determine what species should be included in the master plan analyses. This process considered the technical reviews, comments, and suggested improvements provided by model developers, advisory groups, and other experts during previous master plans. Reviews were then conducted to determine the availability of data and information that could be used to make model improvements. As a result of this effort, a recommended list of relevant species to model is provided, and HSI model improvements are recommended that are categorized by whether the suitability index (SI) relationship to be improved is statistical-based or literature-based.

The species recommended to be included in the 2023 Coastal Master Plan analyses are: eastern oyster, brown shrimp, white shrimp, blue crab, crayfish, gulf menhaden, spotted seatrout, largemouth bass, American alligator, gadwall, mottled duck, brown pelican, seaside sparrow, and bald eagle. These species were selected because they represent a range of taxonomies, life histories, trophic levels, and habitats, and most are commercially- or recreationally-important in coastal Louisiana. Most of these species were also included in the 2017 Coastal Master Plan analyses, and the models used during that effort should be further improved. Seaside sparrow and bald eagle are new for the master plan, and new models should be developed for the analyses.

The 2017 fish, shrimp, and blue crab HSI models included a water quality SI that was based on statistical analyses of species catch and environmental data collected by the Louisiana Department of Wildlife and Fisheries. As suggested during the 2017 Coastal Master Plan, the modeling approach used to develop the water quality SI was revisited and alternate modeling approaches were explored. Using literature and an evaluation of the general steps of model development, three components for HSI model improvement were identified, including 1) selecting alternative modeling approach(es); 2) detecting and resolving statistical issues; and 3) improving model fit and evaluation. Multiple options for each component were explored, which resulted in a proposed multi-step phased approach for model improvement. This proposed approach entails improving the generalized linear models used for the 2017 water quality SIs and then, if desired, comparing them to alternative model approaches (e.g., generalized additive models) to explore model performance and select the best approach to use for the 2023 Coastal Master Plan HSI models.

All of the existing master plan HSI models include literature-based SIs, which use information from published studies of species-habitat associations to derive suitability relationships. Similar to previous master plans, these literature-based SIs should be updated and improved for the 2023 Coastal Master Plan using recent literature and new ecological knowledge. Preliminary reviews were

conducted and recent information was found that could be used to improve the eastern oyster, crayfish, and potentially brown pelican HSI models; but no appropriate recent literature was located for improvement of the American alligator, gadwall, and mottled duck HSI models. However, it is recommended that the literature reviews and information searches be continued. In addition to the statistical-based water quality SI, the 2017 fish, shrimp, and blue crab HSI models also included a structural habitat SI that was based on literature showing high densities of these species in fragmented marsh. The relationship used for this SI, however, did not account for the effects of other estuarine habitats, such as submerged aquatic vegetation and oyster reefs, which are also important to these species. Therefore, a meta-analysis approach is proposed that would estimate the relative importance of these habitats for each species, and the results of this analysis could be used to calculate a new structural habitat SI for the 2023 Coastal Master Plan.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

AIC ..... AKAIKE'S INFORMATION CRITERION
AUC ..... AREA UNDER THE RECEIVER OPERATING CHARACTERISTIC CURVE
CART ..... CLASSIFICATION AND REGRESSION TREES
CPRA ..... COASTAL PROTECTION AND RESTORATION AUTHORITY
CPUE ..... CATCH PER UNIT EFFORT
DNVB ..... DEEP NON-VEGETATED BOTTOM
GAM ..... GENERALIZED ADDITIVE MODEL
GLM ..... GENERALIZED LINEAR MODEL
HSI ..... HABITAT SUITABILITY INDEX
ICM ..... INTEGRATED COMPARTMENT MODEL
LDWF ..... LOUISIANA DEPARTMENT OF WILDLIFE AND FISHERIES
MDT ..... MODEL DECISION TEAM
ME ..... MARSH EDGE
MI ..... MARSH INTERIOR
PM-TAC ..... PREDICTIVE MODELING TECHNICAL ADVISORY COMMITTEE
PPT ..... PARTS PER THOUSAND
RMSE ..... ROOT MEAN SQUARE ERROR
SAV ..... SUBMERGED AQUATIC VEGETATION
SI ..... SUITABILITY INDEX
SNVB ..... SHALLOW NON-VEGETATED BOTTOM
TSS ..... TRUE SKILL STATISTIC
USFWS ..... UNITED STATES FISH AND WILDLIFE SERVICE
USGS ..... UNITED STATES GEOLOGICAL SURVEY

1.0 INTRODUCTION

Habitat suitability index (HSI) modeling has a long history in water resource and restoration planning for describing the quality or capacity of habitats to support fish and wildlife species (United States Fish and Wildlife Service [USFWS], 1981). HSI models are simple to construct and communicate, and are informed by species life history information along with presence-absence or relative abundance data collected over a range of habitat conditions. HSI models consist of functions that relate key environmental variables to the quality or suitability of the habitat for a species. The individual relationships for each environmental variable are called suitability indices (SI). The SIs are standardized to a 0 to 1 scale, with 0 defined as unsuitable and 1 defined as most suitable.

Habitat suitability index models have been used in previous master plan modeling efforts to evaluate the potential effects of coastal restoration and protection projects on habitat for key coastal fish, shellfish, and wildlife species. For the 2012 Coastal Master Plan, the HSI models were based on SIs derived from the literature and best professional judgement from observations of species-habitat associations in the field (Nyman et al., 2013). For the 2017 Coastal Master Plan, the HSI models included a mix of SIs informed by literature and statistics (Brown et al., 2017). More specifically, for blue crab, brown shrimp, white shrimp, gulf menhaden, bay anchovy, spotted seatrout, and largemouth bass, statistical components of the 2017 HSI models included a water quality SI that related monthly species catch-per-unit-effort data (CPUE) with corresponding salinity and water temperature measurements collected by the Louisiana Department of Wildlife and Fisheries (LDWF) long-term coastwide monitoring program. This water quality SI was then combined with literature-based SIs for structural habitat and chlorophyll a concentration to form the HSI model for each species. However, models for eastern oyster, crayfish, American alligator, gadwall, green-winged teal, mottled duck, and brown pelican continued to be based on literature-derived relationships because of the lack of suitable datasets for development of statistical-based models.

The 2017 Coastal Master Plan HSI models received feedback and review throughout the entire model development process from several entities, including the Predictive Modeling Technical Advisory Committee (PM-TAC), LDWF scientists, and other experts. These reviews provided recommendations for improvement of the modeling approach for future master plans (Callaway et al., 2017). Major comments regarding the 2017 HSI models included:

1. Re-evaluate the fish, shellfish, and wildlife species included in the modeling effort. This evaluation should consider whether there are additional economically- or ecologically-important species that should be included in the effort. New species should be added if warranted and provided there are sufficient resources available (e.g., existing models or data), to develop an HSI model. Conversely, species could be dropped if they are no longer justified or if

model performance cannot be improved.

2. Re-evaluate the Generalized Linear Model (GLM) approach used to develop the statistical-based SIs for the 2017 HSI models. The polynomial functions used in the approach may impose an unrealistic functional form to the CPUE data and may fit poorly in areas of sparse data (Callaway et al., 2017). More recent, updated statistical methods should be investigated for development of the HSI models. It was also recommended that future work investigate the robustness of the HSI models to alternative formulations and data uncertainty.

3. Incorporate new ecological knowledge into the existing HSIs. Suitability indices could be adjusted based on revised understanding and/or additional data from the literature or field studies. For example, suggested revisions include adjusting eastern oyster life history processes such as spawning in relation to seasonal environmental conditions. Another example is to reevaluate how to model suitability for structural habitats, beyond strictly marsh vegetation and open water, for the fish and shellfish species that differentially use these coastal habitats for increased foraging and predation refuge.

As part of the model improvement effort for the 2023 Coastal Master Plan, the HSI models were reevaluated to assess the data and information available to improve existing SIs, as well as to determine whether additional species or life stages should be included (or excluded). To accomplish this effort, the 2023 Coastal Master Plan HSI team was established and tasked to: 1) review the 2017 HSI models, results, and lessons learned from implementation into the master plan modeling framework; 2) consider technical reviews, comments, and suggested improvements provided by model developers, advisory groups, and other experts; and 3) provide a series of HSI model improvement recommendations to the master plan Model Decision Team (MDT). The MDT is responsible for deciding which recommendations to adopt, and then initiating the HSI model improvement activities.

The purpose of this technical memorandum is to document the process the 2023 Coastal Master Plan HSI Team has taken and communicate potential recommendations to the MDT. This technical memorandum is organized into four model improvement activities under Section 2. The first activity (Section 2.1) is to revisit the species included in previous master plan modeling efforts and identify relevant species to include in the 2023 Coastal Master Plan effort. Most of the species identified in this memorandum were also included in the 2017 Coastal Master Plan. Consequently, as with 2017 models, the 2023 HSI models for these species are likely to include a mix of literature-based and statistical-based SIs. The second activity re-evaluates the methods used to develop the statistical-based SIs, and proposes alternative statistical modeling approaches, methods to detect and resolve statistical issues, and methods to improve model fit and evaluation (Section 2.2). The third activity suggests ways in which the literature-based SIs can be updated and improved by incorporating recent literature, data, and different analyses (Section 2.3). The fourth activity includes suggestions for the

development of HSI models for new species (Section 2.4). Lastly, Section 3 summarizes the recommendations (and options for implementing the recommended improvements) to provide CPRA with potential next steps toward implementing the 2023 HSI model improvements.

2.0 MODEL IMPROVEMENT ACTIVITIES

2.1 IDENTIFY RELEVANT SPECIES TO MODEL

Several factors were considered in selecting relevant species to include in the 2023 Coastal Master Plan modeling effort. Species were selected to represent the range of habitats that are likely to be affected by master plan projects, including marshes, swamps, barrier islands, and subtidal water bottoms. In addition, the selected species represent different taxonomic groups, life histories, and trophic levels for a more complete assessment of project effects across faunal communities. Because of their importance to Louisiana's culture and economy, key species supporting commercial and recreational fishing and hunting industries were selected. Lastly, species of conservation concern, as identified by the Louisiana Wildlife Action Plan (Holcomb et al., 2015), were considered and a select few are recommended to be included.

The species recommended to be included in the 2023 Coastal Master Plan modeling effort are: eastern oyster, brown shrimp, white shrimp, blue crab, crayfish, gulf menhaden, spotted seatrout, largemouth bass, American alligator, gadwall, mottled duck, seaside sparrow, brown pelican, and bald eagle (Table 1). Most of these species were included in the 2017 Coastal Master Plan, and consequently there are well-developed HSI models that can be further refined and improved. For the 2017 Coastal Master Plan, life stage-specific HSI models were developed for brown shrimp, white shrimp, gulf menhaden, and spotted seatrout. These should be maintained to account for the changing habitat requirements that occur for these species during the estuarine phase of their life cycles. Bay anchovy (*Anchoa mitchilli*) and green-winged teal (*Anas crecca*), which were included in the 2017 Coastal Master Plan, should be dropped for the 2023 Coastal Master Plan because they are similar to gulf menhaden and gadwall, respectively, in terms of habitats, trophic guilds, and life histories.

Bald eagles and seaside sparrow are included to increase the diversity of habitats represented in the analyses. These species were selected following the recommendations of scientists from Audubon Louisiana, and after an evaluation of available HSI models by the USFWS and other sources. Many other coastal bird, mammal, and reptile species were considered, but dismissed because either the species are habitat generalists that would not be significantly affected by master plan projects, or the master plan's Integrated Compartment Model (ICM) could not supply the required input data for the species' HSI model. Furthermore, some of the models for shoreline or barrier island nesting bird species are better suited for evaluating existing nesting sites and other small, discrete areas; and thus

are not well-suited for coastwide planning assessments. Wildlife species that were considered but not included in the 2023 Coastal Master Plan modeling effort were: American coot, clapper rail, diamondback terrapin, Forster's tern, great egret, laughing gull, least tern, lesser snow goose, mink, river otter, roseate spoonbill, slider turtle, white ibis, and white-tailed deer.

Table 1. Species included in the 2023 Coastal Master Plan HSI analyses, their ecological or economic significance, and the source of the HSI model used for the model improvement effort. x = separate HSI models for the small and large juvenile life stages have been developed. y = separate HSI models for juvenile and adult life stages have been developed.

SPECIES	SPECIES SIGNIFICANCE	MODEL SOURCE
EASTERN OYSTER (*CRASSOSTREA VIRGINICA*)	• ESTUARINE, SEDENTARY, PLANKTIVOROUS MOLLUSK • PROVIDES VALUABLE ECOSYSTEM SERVICES • SUPPORTS IMPORTANT COMMERCIAL FISHERIES	2012 COASTAL MASTER PLAN
BROWN SHRIMP [X] (*FARFANTEPENAEUS AZTECUS*)	• BENTHIC CRUSTACEAN THAT USES ESTUARIES AS JUVENILE NURSERY HABITAT • SUPPORTS IMPORTANT COMMERCIAL FISHERIES	2017 COASTAL MASTER PLAN
WHITE SHRIMP [X] (*LITOPENAEUS SETIFERUS*)	• BENTHIC CRUSTACEAN THAT USES ESTUARIES AS JUVENILE NURSERY HABITAT • SUPPORTS IMPORTANT COMMERCIAL FISHERIES	2017 COASTAL MASTER PLAN
BLUE CRAB (*CALLINECTES SAPIDUS*)	• BENTHIC CRUSTACEAN FOUND IN ESTUARINE HABITATS THROUGHOUT MOST OF ITS LIFE CYCLE • SUPPORTS IMPORTANT COMMERCIAL FISHERIES	2017 COASTAL MASTER PLAN
CRAYFISH (*PROCAMBARUS CLARKII* AND *P. ZONANGULUS*)	• BENTHIC CRUSTACEAN PRIMARILY ASSOCIATED WITH FRESHWATER HABITATS • SUPPORTS IMPORTANT COMMERCIAL FISHERIES	2017 COASTAL MASTER PLAN
GULF MENHADEN [Y] (*BREVOORTIA PATRONUS*)	• PLANKTIVOROUS FISH THAT USES ESTUARIES AS JUVENILE NURSERY HABITAT • SUPPORTS IMPORTANT COMMERCIAL FISHERIES	2017 COASTAL MASTER PLAN
SPOTTED SEATROUT [Y] (*CYNOSCION NEBULOSUS*)	• PREDATORY FISH FOUND IN ESTUARINE HABITATS THROUGHOUT MOST OF ITS LIFE CYCLE • POPULAR RECREATIONAL FISHERY SPECIES	2017 COASTAL MASTER PLAN

SPECIES	SPECIES SIGNIFICANCE	MODEL SOURCE
LARGEMOUTH BASS (*MICROPTERUS SALMOIDES*)	• PREDATORY FISH PRIMARILY ASSOCIATED WITH FRESHWATER HABITATS • POPULAR RECREATIONAL FISHERY SPECIES	2017 COASTAL MASTER PLAN
AMERICAN ALLIGATOR (*ALLIGATOR MISSISSIPPIENSIS*)	• UPPER TROPHIC LEVEL REPTILE PRIMARILY ASSOCIATED WITH FRESHWATER HABITATS • COMMERCIALLY-HARVESTED SPECIES	2017 COASTAL MASTER PLAN
GADWALL (*ANAS STREPERA*)	• MIGRATORY WATERFOWL THAT USES ESTUARIES AS WINTERING HABITAT • POPULAR RECREATIONALLY-HUNTED SPECIES	2017 COASTAL MASTER PLAN
MOTTLED DUCK (*ANAS FULVIGULA*)	• WATERFOWL THAT IS YEAR-ROUND RESIDENT OF ESTUARIES • STATE-IDENTIFIED SPECIES OF CONSERVATION NEED	2017 COASTAL MASTER PLAN
BROWN PELICAN (*PELECANUS OCCIDENTALIS*)	• UPPER TROPHIC LEVEL COASTAL SEABIRD THAT NESTS PRIMARILY ON COASTAL ISLANDS • STATE-IDENTIFIED SPECIES OF CONSERVATION NEED	2017 COASTAL MASTER PLAN
SEASIDE SPARROW (*AMMOSPIZA MARITIMA FISHERI*)	• YEAR-ROUND RESIDENT OF VEGETATED MARSH HABITATS • STATE-IDENTIFIED SPECIES OF CONSERVATION NEED	NEW MODEL
BALD EAGLE (*HALIAEETUS L. LEUCOCEPHALUS*)	• UPPER TROPHIC LEVEL RAPTOR THAT NESTS PRIMARILY IN WOODED, FRESHWATER HABITATS • STATE-IDENTIFIED SPECIES OF CONSERVATION NEED	NEW MODEL

2.2 IMPROVE STATISTICAL-BASED SUITABILITY INDICES

The 2017 HSI models developed for blue crab, brown shrimp, white shrimp, gulf menhaden, spotted seatrout, and largemouth bass included a statistical-based water quality SI. Review of the models by the PM-TAC (Callaway et al., 2017) indicated that the modeling approach used to develop that SI should be revisited and alternate modeling approaches should be explored. To address this comment, the habitat suitability model development literature (also called species distribution models) was reviewed and each of the general steps of model development was considered, from data preparation and model fitting to model evaluation, while considering the ecological justification and rationalization through every step. In keeping with widely accepted principles of model development (e.g., Guisan &

Thuiller, 2005) and working within the framework of available data, the 2023 Coastal Master Plan HSI team identified three components for model improvement:

- Component 1: Select Alternative Modeling Approach(es)
- Component 2: Detect and Resolve Statistical Issues
- Component 3: Improve Model Fit and Evaluation

For each component, multiple options are presented but are not necessarily mutually exclusive. In instances where they are, the pros and cons of selecting one option over another are summarized, where guidance is well-established in the literature. Furthermore, decisions made in one component will influence the available options in other components. To help clarify, the available options are provided in each of the sections and then it is summarized how these options across components may be paired together in the summary recommendations in Section 3.

Component 1: Select Alternative Modeling Approach(es)

Several statistical approaches are available to model species-environment relationships. The selection of the approach is largely driven by the type of data available and the intended purpose and application of the modeling effort (Guillera-Arroita et al., 2015). The 2017 Coastal Master Plan used the GLM modeling approach for constructing the water quality SI for the fish and shellfish HSI models. Although considered a classical and flexible approach, one important limitation with GLMs is their sensitivity to modeling scale, as is further discussed later in this section. In this section, the use of GLMs is revisited and alternative modeling approaches are discussed. Each of the modeling approaches described herein have pros and cons, but it is important to note that there is no consensus within the current literature on an approach that works best for any given situation.

Commonly used modeling approaches, organized by type of data they require, are presented in Figure 1. Each of these approaches are appropriate to use with the available LDWF data and for evaluating projected spatial changes in species' suitability among the 2023 Coastal Master Plan restoration alternatives. The LDWF collects CPUE (relative abundance) using different gears that target certain species and life stages across coastal Louisiana. Any of the models using presence-only/presence-background (Figure 1) will work with the LDWF data but require the data to be rescaled. This means the CPUE response would be changed to 1s and 0s based on criteria the analyst would decide upon. However, models constructed with relative abundance data are generally more robust than models created with presence/absence data (Howard et al., 2014). As a result, the team decided to focus efforts on those approaches suitable for relative abundance data only: GLMs, Generalized Additive Models (GAM), Classification and Regression Trees (CART), RandomForest, and Ensemble Modeling.

Since the modeling approaches will be used in a predictive application, they have implications for the way they should be fitted and evaluated (Elith & Leathwick, 2009). Under-fit models may not adequately describe observed occurrence-environmental relationships while 'over-fit' models may ascribe patterns to environmental noise and may not be accurately interpreted (Merow et al., 2014). In the following sections, each modeling approach is described as well as important aspects that should be considered, including model fit and evaluation. The level of effort for model development (i.e., relative to the other modeling approaches described herein) is briefly described. These considerations are then summarized in Table 2 for all modeling approaches side-by-side.

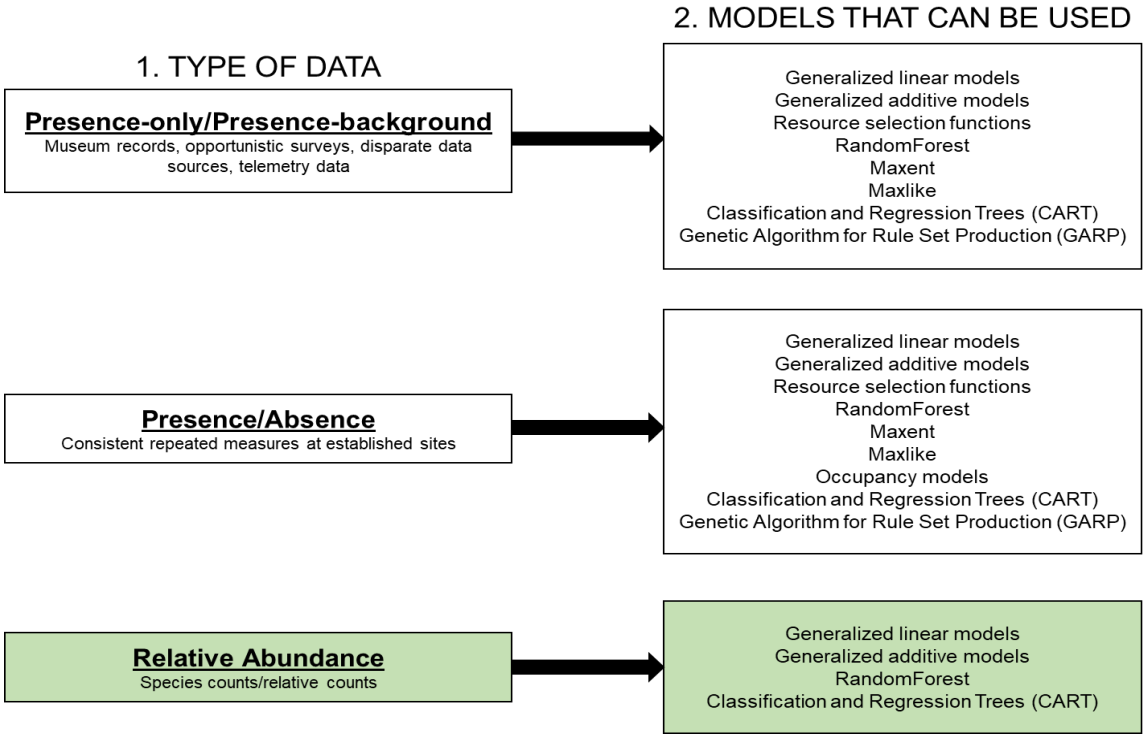


Figure 1. Statistics-based habitat suitability modeling approaches and the data types needed to build them. Green shading indicates modeling approaches that were selected for consideration in the 2023 Coastal Master Plan modeling.

GLMs are commonly used to model habitat suitability of species; this approach was used in the 2017 HSI models. GLMs are a flexible tool which estimates the relationship between predictor variables (environmental covariates) and the response variable (relative abundance) using Maximum Likelihood Estimation. In cases with enough sample size, this estimation method is robust and generally produces adequate predictive ability. All observations within a GLM must be independent, but random effects can be implemented to address non-independence within the data (through time or space). Additionally, predictor variables can be transformed into non-linear relationships using transformations such as quadratic or cubic (sometimes called polynomials) or interactions between

variables can be explored. GLMs can be implemented in any standard statistical software and produce output that can be translated into an equation for prediction (Zar, 2010). One important limitation with GLMs is their sensitivity to the modeling scale: these models often are poor at predicting outside the bounds of the data they are fit to or outside the spatial scale they were fit to (Thuiller et al., 2003). Given that the GLM modeling approach was used for constructing the water quality SI in the 2017 HSI models and this equation has already been integrated into the ICM, the level of effort for incorporating this model into the 2023 HSIs is relatively low (Table 2). However, several other model improvement steps described in the following sections are recommended for this existing model, as discussed in Section 3.0, and this would require a minimal amount of time (3 to 4 months).

GAMs are a special case of GLM which automates the process of identifying the most appropriate transformations of the data to generate a polynomial relationship (Guisan et al., 2002). GAMs allow parametric and non-parametric predictors to be modeled simultaneously, generally leading to a better fit model and a greater ability to predict outside the bounds of the data and at multiple scales (Thuiller et al., 2003). However, this can lead to overfitting and thus great care in the selection of the 'smoother' parameter must be taken (Wood, 2006). GAMs can be implemented in most statistical software and their associated predictive equations extracted, but these equations have the potential to be large and/or complicated. Large or complicated equations may lead to slightly higher computation times in both fitting the model and then predicting the model for new conditions in the future compared to the GLM approach. However, the HSI predictive models implemented within the ICM framework would still run efficiently compared to the other ICM modeling processes; the GAM equations would not be limiting the computation times for the numerical simulations in the master plan. To construct a new water quality SI using the GAM approach, the team estimates a moderate amount of development and testing time (Table 2).

Table 2. Summary of key considerations for each modeling approach. "Distribution assumptions" refers to whether there are limits on the statistical distribution of predictors, "Predictive power" refers to the approach's ability to predict into novel space or time periods, "Development time" is the estimated effort required to build the model, "ease of ICM integration" refers to the level of programming required to code the model into the ICM, and "computation time" refers to how long the model takes to run based on a simulated dataset of 10,000 observations and 2 predictors.

	GLM	GAM	CART	RANDOMFOREST	ENSEMBLE
DISTRIBUTION ASSUMPTIONS	YES	YES, BUT FLEXIBLE	NONE	NONE	N/A
PREDICTIVE POWER	LOW	MODERATE TO HIGH	MODERATE	MODERATE TO HIGH	HIGH
DEVELOPMENT TIME	ALREADY DONE FOR 2017	6-8 MONTHS	6-8 MONTHS	6-8 MONTHS	12+ MONTHS
EASE OF ICM INTEGRATION	ALREADY DONE FOR 2017	EASY TO MODERATE	MODERATE	MODERATE	MODERATE
COMPUTATION TIME	.01 SEC	0.15 SEC	0.05 SEC	36.33 SEC	1 MIN

CARTs are a machine learning technique first introduced in the 1980s to bridge statistics with computer science (e.g., Breiman et al., 1984) for creating predictive models. CARTS (or decision trees, regression trees) are commonly used in data mining with the objective of creating a model that predicts the value of a response variable based on the values of several independent variables. CART models recursively split observation data using identified predictors to find homogenous (i.e., similar) response variable groups (Krzywinski & Altman, 2017). Therefore, CARTs do not produce a predictive equation like GLMs or GAMs, but instead produce rules that can be visualized with a decision tree. These rules can then be used to predict species patterns using new data (i.e., new predictor variables are the future environmental simulated conditions from the ICM). Because CARTs can essentially produce decision trees that are 100% accurate, the models produced with this method can easily be overfit and therefore have low predictive power when used with other data. To address this, the modeler can implement a complexity parameter which limits tree growth based on how well a split improves the relative error in the model (Lever et al., 2016). While there is some guidance on what this value should be, it is generally up to the modeler to determine and justify this value. The model development time using statistical software with the LDWF data would be similar to that for the GAM development and testing (Table 2).

RandomForest is a special kind of CART model that generates multiple classification trees that are then combined into an ensemble classification (Breiman, 2001). As with CART, RandomForest produces a classification tree, not a predictive equation, and are sometimes considered a "black-box" due to the difficulty in examining each individual tree. The algorithm uses an estimate of generalization error called the "out-of-bag" error to determine how strong the classifier is, and the modeler may increase the number of trees produced by the RandomForest algorithm to decrease the error and thus produce a better fit ensemble tree (Breiman, 2001; Peters et al., 2007). Models built using RandomForest are typically highly accurate when tested against data used to build the model (Prasad et al., 2006), but may not necessarily perform any better than other modeling approaches when used in predictive applications with new data (i.e., simulated ICM data inputs). As mentioned, the models are also considered a 'black box' as the algorithm cannot be visualized as a predictive equation. The model development time is similar to that of GAMs and CARTs (Table 2), and the implementation of the resulting RandomForest model as a submodule to be used within the ICM framework would be similar to the GAM and/or CART submodule(s) as well.

Ensemble models are developed by using a consensus method based on output predictions from multiple modeling approaches (Marmion et al., 2008). In this case, the ensemble modeling approach would mean building the four separate models using GLM, GAM, CART, and RandomForest. The predicted suitability outputs from each of these models would then be converted into a weighted average using the modeler's chosen accuracy measure (e.g. area under the receiver operating characteristic curve [AUC] or Cohen's kappa) to produce the ensemble model. Ensemble models have been frequently shown to generate the most accurate and robust habitat suitability models because they incorporate the strengths of all modeling approaches (Grenouillet et al., 2011). However, this approach would require more development time than any of the previous modeling approaches (Table 2), as it requires the modeler to develop each of the above models, and then weigh the predicted responses from each of the four suitability model approaches for the finalized ensemble model.

Component 2: Detect and Resolve Statistical Issues

Prior to running the statistical-based models, there are common data steps that should be conducted to avoid statistical errors and misinterpretation of model output. These include: 1) detecting outliers, 2) testing for heterogeneity of variance, collinearity, and dependence of observations, 3) zero inflation in generalized linear modeling, 4) fitting the correct type of relationships between dependent and independent variables, and 5) using appropriate data transformations (Zurr et al., 2010). The basic principles of data analysis are widely discussed and summarized in the literature (Hilborn & Mangel, 1997; Quinn & Keogh, 2002; Zurr et al., 2010). Although some of these data steps were performed for the 2017 HSI model development (e.g., detecting outliers, testing for collinearity and dependence of observations), they were not documented in the technical reports. Therefore it is recommended that as part of any improvement to the statistical-based models, each of these elements be revisited and

documented to ensure compliance with standard best practices of data analysis.

Component 3: Improve Model Fit and Evaluation

Evaluation of model performance includes assessment of: 1) ecological justification of selected predictor variables; 2) resulting relationships, including the ability to visually interpret the resulting habitat suitability response functions; 3) accuracy of model predictions (Austin et al., 2006; Elith & Leathwick, 2009; Merow et al., 2014). Options for assessing these elements of performance for the statistical-based SIs is discussed below.

In the water quality SI developed for each species in the 2017 HSI models, two predictor variables, salinity and temperature were included because of substantial evidence in the literature that suggest these environmental factors influence habitat suitability for estuarine fish and shellfish life stages (e.g., Adamack et al., 2012; Baker & Minello, 2010; Rozas & Minello, 2010; Flaherty & Guenther, 2011; Patillo et al., 1997; Kupschus, 2003; Froeschke & Froeschke, 2011). Salinity and temperature data collected alongside relative abundance data (i.e., CPUE) were also readily available as part of the existing LDWF fisheries-independent monitoring dataset. Review of the literature revealed that the functional form of the relationship was likely going to be non-linear and interacting, so both linear and quadratic forms of salinity and temperature were included in the model development and selected using stepwise selection procedure ($p \leq 0.05$). This resulted in a relatively simple SI that identified some expected response curves demonstrated by the literature. The same salinity and temperature data were used with the species CPUE data collected by LDWF for the statistical-based water quality SI improvements.

However, additional ecological predictor variables could be considered to increase model complexity and potentially reduce total model error. Predictor variables would be selected that are ecologically relevant and are closely related (i.e., proximal) to the causal factor driving the species CPUE response (Elith & Leathwick, 2009). Tradeoffs exist on the number of variables that should be included. Simple models with few predictors are often capable of identifying key trends while smoothing over noise and variation in the dataset (Figure 2), as is the case with the current water quality SI. Increasing the number of predictors and ultimately increasing the complexity of the model, allows for fitting many features (Figure 2), but can only be done with sufficiently large datasets and care must be taken to avoid over-fitting (Merow et al., 2014).

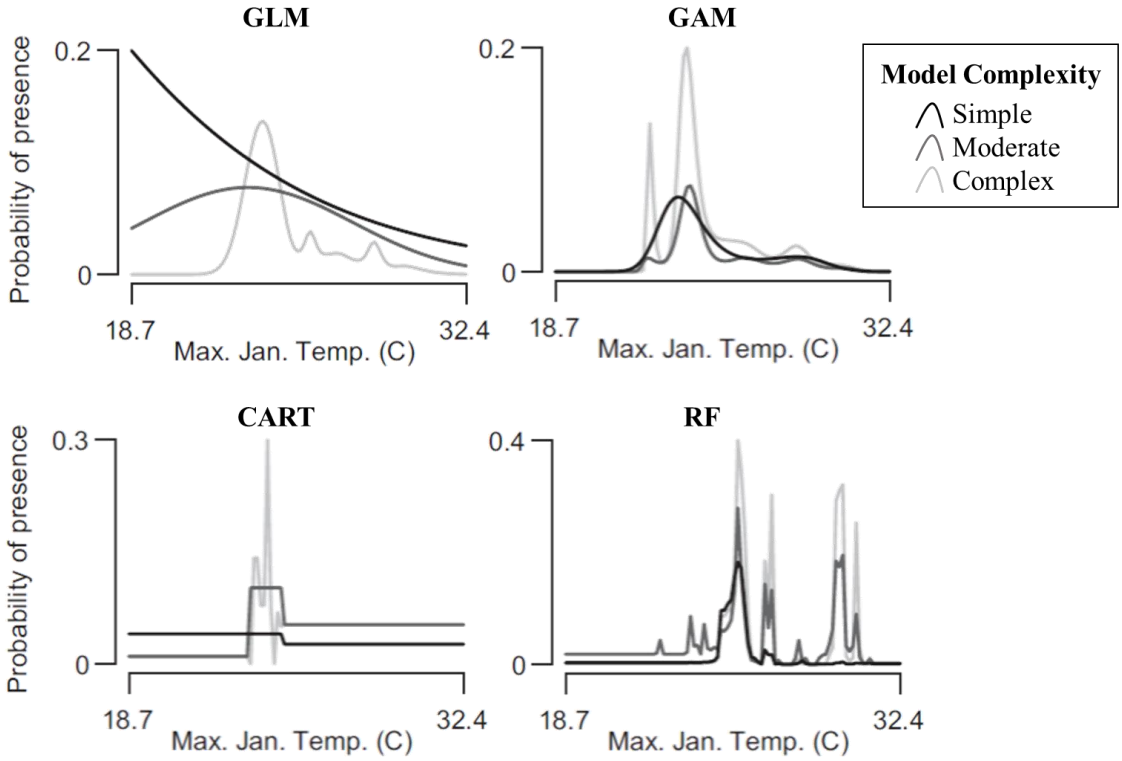


Figure 2. Comparison of response curves among different modeling approaches and with different degrees of control over the complexity of the fitted response curves (from Merow et al., 2014).

Although additional predictor variables related to structural habitat and chlorophyll *a* concentration were included in the fish, shrimp, and blue crab 2017 HSI models as separate SIs (as discussed in Section 2.3), they were developed independently of the water quality statistical-based SI. Another option for improving the statistical-based SI models would be to include additional relevant predictor variables, in addition to salinity and temperature, and reconstruct the SI using one of the modeling approaches described previously. These additional predictor variables would have to come from datasets other than the LDWF fisheries independent monitoring dataset, but that show overlap in space and time with the LDWF dataset. For example, annual land and water spatial data currently exist for the Louisiana coast for 16 years between 1985 and 2016 (Couvillion, 2018) and could be produced for additional years within and around that time period, if needed. Different kinds of predictor variables could be generated from these spatial data, including land-to-water ratios, distance to marsh edge, area of marsh edge, and several fragmentation metrics available within ArcGIS Spatial Analyst. Each of these predictor variables could be calculated within a buffered area around the LDWF sampling location for the years where the datasets overlap. Although multiple buffer sizes could be tested, a literature review may help guide what size buffer is most appropriate for calculating these variables (i.e., at what spatial scale are these variables likely to be important to the species). Although

these data are not currently available for all years of the LDWF data, a reduction in statistical power is not anticipated given that 16 years of data is still a considerably large dataset for habitat suitability modeling. However, if the smaller subset of data does generate concerns or issues, additional land and water datasets could be developed for other years that overlap with the LDWF dataset.

Other predictor variables associated with Mississippi and Atchafalaya River discharge, climate, and weather, for example, could also be explored for inclusion, pending available data, ease of accessing data, collinearity with other variables (discussed below), and other considerations determined by the model developers. Although not all of these predictor variables may be available output from the ICM, it is important to include them in the expanded data set because they have the potential to adjust the relationships of other predictor variables. For integration into the ICM, they could be held constant (at their mean, for example) and would not need to vary over time. Discussion of relevant variables with LDWF scientists would assist in refining a list of predictor variables for possible inclusion in the expanded dataset. As part of the model building procedure, variable selection methods (e.g., p-values, 95% confidence intervals) would then be used to select the most appropriate variables for final inclusion in the updated SI.

One potential outcome of this option for incorporating additional predictor variables in the expanded dataset is that none of the variables are ultimately selected for inclusion in the model (i.e., variables are not significant or do not improve model fit). One way to prevent spending too much effort to arrive at this unwanted outcome for this option would be to first conduct some simple data exploratory steps, such as testing for correlation between relative abundance and the new predictor variables first, prior to building the model. If no discernable pattern emerges, the model developers could determine that continuing this expanded data exploration for model building is likely not a promising endeavor.

Whether the expanded dataset option is included for implementation or not, assessment of model biases should be performed and documented for the 2023 water quality SI models. After predictors are selected for the model, model biases such as collinearity among predictors and spatial autocorrelation in model residuals should be assessed. Model biases were not documented in the 2017 Coastal Master Plan and warrant revisiting as part of the model improvement activity. Several diagnostics exist for testing for collinearity (

Table 3). Ignoring collinearity can result in increased error and potential failure to detect significant effects when they exist (i.e. Type II error; Zurr et al., 2010). Where collinearity may be present, one of the predictor variables could be removed.

Table 3. Collinearity diagnostics: indices and their critical values (from Dormann et al., 2013).

Method	Threshold
Absolute value of correlation coefficients (|r|)	> 0.7 high collinearity
Determinant of correlation matrix (D)	Near 0 = high collinearity Near 1 = no collinearity
Condition index (CI)	> 30
Condition number (CN)	> 30
Kappa (K)	5
Variance-decomposition proportions (VD)	> 0.5
Variance inflation factor (VIF)	> 10
Tolerance	< 0.1

Spatial autocorrelation, or the tendency for data closer together in space to be more similar, is a well-known phenomenon in ecology (Legendre, 1993) and may be present in the existing water quality SI. The presence of spatial autocorrelation can both impact the coefficient estimates and the strength of the relationships within a model (Lichstein et al., 2002). In models of habitat suitability or species distribution, accounting for spatial autocorrelation within the observation data can change predictor variable importance and improve the fit (or reduce levels of uncertainty, Dormann, 2007). To address spatial autocorrelation within HSI models, researchers typically employ one of two approaches: 1) spatial thinning of observations or 2) statistical methods that address or account for autocorrelation. Spatial thinning of observations requires knowledge of the species' dispersal ability and using that knowledge to remove observations until there are no observations that are spatially dependent on each other (Fortin & Dale, 2005). Statistically accounting for spatial autocorrelation within the species models can be done by adding environmental covariates such as day of year or geographic region to account for seasonal timing of life stage migrations and species occurrence within the various coastal habitats. To test whether the existing model's output is spatially autocorrelated, the residuals of the existing model can be checked using Moran's I and a decision can then be made on if and how it should be addressed (Dormann et al., 2007). If an autocorrelation variable is added to the model while resolving biases, the variable can be held constant when integrated into the ICM and would not affect or limit the model's use in the master plan.

The second step of assessing model performance is evaluating the interpretability of the response curve (e.g., Figure 2). Once fitted, generating response curves for individual predictor variables, while holding other variables in the model constant (at their mean, for example), can assist in determining whether the predicted response is ecologically reasonable (Austin, 2007). The complexity of the model will have a considerable effect on the generality and interpretability of response curves, as illustrated

in Figure 2. The complexity of the model is a function of the number of predictors, order of interactions, and other features specific to the modeling approaches themselves.

In the existing 2017 water quality SI based on salinity and temperature, the fitted response curves confirmed the species-habitat relationships from other studies in coastal Louisiana and Texas (Adamack et al., 2012; Baker & Minello, 2010; Rozas & Minello, 2010; Patillo et al., 1997). However the fitted polynomial response curves often flipped outside of the data range used to fit the model(s), so the model values were truncated to the values at the data extremes. For example, if the habitat suitability score was equal to 0.2 at a salinity of 2 ppt and a temperature of 10 degrees C, then the suitability score was set to 0.2 at temperatures below 10 degrees when salinity was equal or less than 2 ppt. The other statistical modeling approaches can be evaluated with the current GLM approach to determine if the fits and behavior of the functions are better.

Several data partitioning methods are available to train (fit the model) and validate (estimate prediction error) habitat suitability models. For sufficiently large datasets, like the LDWF dataset, the data can be randomly divided once into training and validation datasets (for example application see Drexler & Ainsworth, 2013). Alternatively, cross-validation (i.e. k-fold partitioning), jackknifing, and bootstrapping can be used to determine which part of the data is used to fit the model and which part to test it, and the procedure is repeated several times providing a mean and variance for validation measures (for example application see Cianfrani et al., 2010). Because the procedure is repeated a number of times for these alternative approaches, they are more time consuming than the training and validation procedure. However, the cross-validation procedures are presented as an option, because if there is interest in implementing the expanded dataset option for potential addition of new predictor variables, the exercise would result in fewer years of data for an overall smaller dataset. Regardless of the approach, care should be taken in splitting the dataset to control for underlying biases such as spatial autocorrelation, as previously discussed (Merow et al., 2014).

Various criteria are available to evaluate the resulting model(s) fit to the data (i.e., original LDWF and/or the expanded data set). Goodness of fit is a measure of the difference between the observed data and predicted values and is typically assessed using the chi-square statistic, coefficient of determination (R^2), examination of model residuals, information criterion such as likelihood or Akaike's Information Criterion (AIC; Akaike, 1973; Thomson & Emery, 2014), or root mean square error (RMSE; Zar, 2010). Model accuracy can also be assessed on the validation dataset by also using RMSE, AUC (Hanley & McNeil, 1982), Cohen's K (Monserud & Leemans, 1992), and/or the true skill statistic (TSS; Allouche et al., 2006). Depending on the statistical modeling approach taken, some of these measures are more appropriate than others. RMSE is commonly reported for assessment of model performance, and is used for all statistical HSI approaches; R^2 is used for GLMs and GAMs; AIC is used for GLMs, GAMs, and CART; AUC, Cohen's K, and TSS are more appropriate for RandomForest. Each of these measures has their own bias, so it is advised to use more than one measure beyond

RMSE when assessing model accuracy. Existing guidelines for assessing some of these measures of model accuracy are provided in Table 4.

Goodness of fit and accuracy of the model predictions were not assessed for any of the water quality SIs during the 2017 Coastal Master Plan effort. Confidence intervals and goodness of fit tests should be calculated for the statistical model(s) to define the degree of certainty in the predictions between a lower and upper bound. Calculation of model accuracy would require an independent dataset to validate the existing model(s). One option would be to use the LDWF dataset beyond 2013 (2014-2019) as a validation data set, if the same data set used for the 2017 HSI models (1986-2013) is used to fit the statistical based SIs. Another option is to divide the full dataset (whether using the original LDWF data set or the proposed expanded data set) into a test and validation dataset to fit and then re-run the model(s). This recommendation is elaborated on in Section 3.0.

Table 4. Guidelines for assessing model accuracy using AUC, Cohen's (Araújo et al., 2005) and TSS statistics (Landis & Koch, 1977; Eskildsen et al., 2013).

Model Accuracy Assessment	**Model Accuracy Statistics**		
	AUC	**Cohen's K**	**TSS**
Excellent	>0.90	>0.75	1
Good	0.80-0.90	0.4-0.75	0.6-0.9
Fair	0.70-0.80	.	0.4-0.6
Poor	0.60-0.70	< 0.40	0.0-0.4
Fail	0.50 - 0.60	.	0.0
No predictive ability	≤0.5	0	< 0

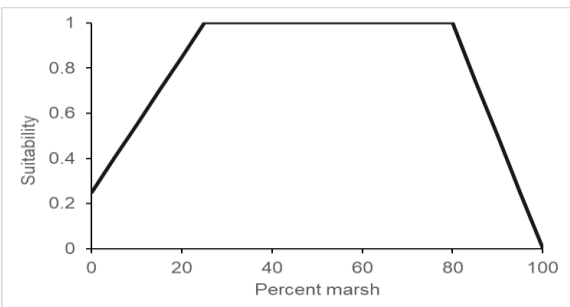
2.3 IMPROVE LITERATURE-BASED SUITABILITY INDICES

All existing master plan HSI models include literature-based SIs. These SIs describe the habitat suitability for a variety of environmental factors, such as water level, vegetation type, marsh-to-open water habitat configuration, and chlorophyll *a* concentration. For the 2012 and 2017 Coastal Master Plan modeling efforts, these SIs were updated with ecological knowledge from recent literature and data. It was hoped that the literature-based SIs could be replaced with statistical-based SIs, similar to

the previously discussed fish and shellfish water quality SIs, but this effort has been hampered by a lack of suitable datasets. As a result, the literature-based SIs for the 2023 Coastal Master Plan should be updated with information from recent studies, beginning with the potential improvements discussed in the respective model reports from the 2017 Coastal Master Plan (Brown et al., 2017 and attachments). Suggested improvements to the literature-based SIs are discussed below for each species or species group.

Fish, Shrimp, and Blue Crab

The 2017 HSI models for blue crab, brown shrimp, white shrimp, gulf menhaden, spotted seatrout, and largemouth bass each included a structural habitat SI based on the areal proportion (presented as a percentage) of marsh vegetation to open water simulated for each grid cell of the ICM. The relationship used for the species' juvenile models was adapted from Minello and Rozas (2002), and represents the observed increase in juvenile fish, shrimp, and crab densities in fragmented marsh habitats (Figure 3). Variations of the marsh-to-open water relationship were also developed for models of older life stages, but were skewed more toward open water having greater suitability.



$SI_2 = (0.03*V_2) + 0.25$, when $V_2 < 25$
1.0, when $25 \leq V_2 \leq 80$
$5.0 - (0.05*V_2)$, when $V_2 > 80$

Figure 3. Graphic and numerical representation of the suitability index function used to describe juvenile species habitat suitability based on the percentage of marsh within a modeled cell.

In addition to marsh and open water, there are other habitat types, such as submerged aquatic vegetation (SAV) and oyster reefs, that are important to estuarine fish and shellfish but are not accounted for in the current HSI models. The classification of these habitat types requires information about the variables that define them. As the ICM generates more of this information, it will allow for the inclusion of these habitats in the SI to better define structural habitat suitability for these species.

The methodology proposed for refining the structural habitat SI has two components. The first component is to refine the SI by adding habitat types beyond the marsh and open water classifications. Based on a preliminary review of recent literature (e.g., Minello, 2017), additional species relative abundance/density data should be used to derive relative suitability scores for six estuarine habitat types. The six habitat types identified from the literature are: interior marsh (MI),

marsh edge (ME), shallow non-vegetated bottom <1 m depth (SNVB), deep non-vegetated bottom ≥1 m depth (DNVB), SAV, and oyster reef (Oyster). The suitability scores of each habitat type can be estimated relative to each other from a meta-analysis of field data available from Louisiana and Texas. Minello (1999) and Minello et al. (2003) have performed similar meta-data analyses for determining which estuarine habitat types support the highest abundances of nekton.

Not all field studies measure the same habitat types or species metrics. A table of the field studies can be constructed to record the catch data by habitat types (see example in Table 5). The catch data by habitat type would then be standardized to the maximum value recorded for each study. For example, if nekton density were highest in SAV, then the SAV suitability score would be 1.0 and the lower-density habitats would be scaled relative to this maximum. Plots of the standardized catch data by habitat type for each study in Table 5 are demonstrated in Figure 4. The relative suitability of each habitat type (0-1) can be determined across the studies using the mean and variation among the standardized scores by habitat type. After the relative SI scores are estimated using the meta-data, they can be coded as a step function as shown in Figure 5. The pattern shown in Figure 5 might be appropriate for juvenile species that prefer vegetated habitats; however, a different pattern would be expected for species or life stages that occur in less structured, open water habitats such as gulf menhaden. Therefore, the relative suitability of each habitat type should be evaluated by species and life stage, and common SI functions could be used across species if similar patterns emerge.

Table 5. Example data table showing nekton density by habitat types from four independent studies, where MI = interior marsh, DNVB = deep non-vegetated bottom, SNVB = shallow non-vegetated bottom, ME = marsh edge, SAV = submerged aquatic vegetation, and Oyster = Oyster reef.

Citation	Location	Gear	Season	Species Metric	Species	MI	DNVB	SNVB	Oyster	ME	SAV
Minello & Rozas 2002	Galveston	Drop	Spring 1995	Density (#/m^2)	blue crab		0.2	1.8		2.6	
	Bay	sampler	Fall 1995		blue crab		2.9	5.9		8.1	
			Spring 1995		brown shrimp		0	0.5		3.5	
			Fall 1995		white shrimp		1.7	8.4		39.5	
LaPeyre & Gordon 2012	Calc/Sabine	Throw	Summer 2007	Density (#/m^2)	All					18.5	145.5
	LA	trap	Fall 2007		All					65.3	176.8
			Summer 2008		All					32	98.7
Minello 1999	TX and LA	Enclosure	Sp, Sum, Fall	Density (#/m2)	All	19.263		15.5	89.62	142.18	64.21
	22 studies	samplers	1984-1997								
Castellanos & Rozas 2001	Atchafalaya	Throw	Spring 1995	Density (#/m2)	All			1.4		7.1	13.3
		trap	Summer 1994		All			0		41.9	69.7
			Fall 1994		All			5		96.2	44.7

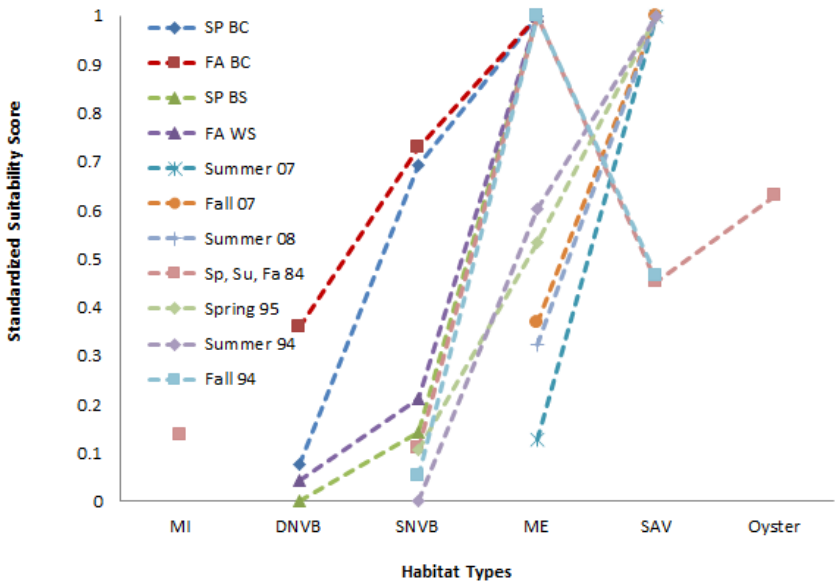


Figure 4. Plots of the standardized suitability scores by habitat type for each of the studies listed in Table 5. The scores are standardized by the maximum habitat value in each row listed by field study in the table. The legend uses abbreviations based on the Season and Species columns in the table. For example, SP BC = Spring 1995 for blue crab from Minello and Rozas (2002) in the first row, FA WS = Fall 1995 for white shrimp in the fourth row. Habitat categories are MI = interior marsh, DNVB = deep non-vegetated bottom, SNVB = shallow non-vegetated bottom, ME = marsh edge, SAV = submerged aquatic vegetation, and Oyster = Oyster reef.

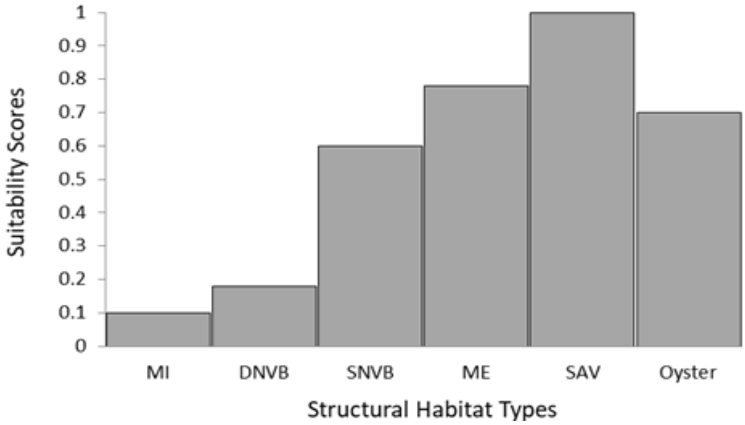


Figure 5. An example demonstration of SI scores for each habitat type estimated from the suggested meta-analysis of field data collected in coastal Louisiana and Texas. Note that the actual suitability scores by habitat types have yet to be determined and may not appear as shown.

The second component to refining the structural habitat SI will require identifying and estimating the areal proportion of MI, ME, SAV, SNVB, DNVB, and oyster reef for each grid cell across the ICM coastwide domain. For each ICM grid cell (500 m resolution in 2017), the six habitat types can be classified (at 30 m resolution in 2017). The current ICM needs improvement in classifying and projecting the probability of occurrence for SAV and potentially oyster reef. The remaining habitats, MI, ME, SNVB, and DNVB can be classified relatively well by the ICM.

Additionally, the monthly proportion of time that the MI and ME habitats are inundated with water, and therefore accessible to the fish and shellfish, can also be estimated using the ICM output. Inundation can affect species marsh use, especially since marsh habitats can vary in steepness (Roth et al., 2008; Minello et al., 2012; Minello et al., 2015; Rozas & Minello, 2015). It is also important to note that the "marsh edge" definition from the ICM output (currently at a 30 m scale; a broad definition) includes what is typically defined as "edge" (~within 5 m of open water) and "inner marsh" (>5 m from open water) habitat from the field studies. Both marsh steepness and the definition of marsh edge from the ICM will be considered carefully when delineating the habitats and determining inundation of MI and ME habitats within the ICM grid. Daily water levels are available from the ICM, and the elevations of the ME and MI habitat types can be subtracted from the daily water levels to determine water depth (i.e., inundation) of the ME and MI habitats. The monthly proportion of time that water levels exceed the ME and MI elevations (e.g., water depths ≥ 0.1 m) can then be determined and used as an estimate of habitat accessibility for the species. Therefore, the refined SI equation describing structural habitat suitability for fish and shellfish species would be:

$$SI = [ScoreMI*(PMI*PInund)] + [ScoreDNVB*PDNVB] + [ScoreSNVB*PSNVB] + [ScoreME*(PME*PInund)] + [ScoreSAV*PSAV] + [ScoreOyster*POyster]$$

Where the relative suitability scores (Score) by habitat type are determined from the meta-data analysis and weighted by the areal proportion (P) of the habitat type in each ICM grid cell. The ME and MI habitats are additionally weighted by the proportion of time (in days) they are inundated with water (PInund) and accessible to the species. The number of habitat types within each ICM grid cell does not matter. That is, any of the habitat types can be missing for a grid cell, because all suitability scores are weighted by the areal proportion of each habitat given the total area of each ICM grid cell.

The 2017 HSI models also included SIs related to chlorophyll a concentration. Chlorophyll *a* concentration was used as a proxy for the planktonic prey of gulf menhaden and bay anchovy (Sable et al., 2017a; Sable et al., 2017b), as well as to represent primary productivity and thus food availability for largemouth bass (Hijuelos et al., 2017a). However, these SIs were inactive during the 2017 Coastal Master Plan analyses due to limitations in the ICM's ability to simulate chlorophyll. For the 2023 Coastal Master Plan, chlorophyll will no longer be an output of the ICM. As a result, it is recommended that the chlorophyll SIs be removed for the 2023 HSI models. Even if chlorophyll remained as an output, the SIs for gulf menhaden and bay anchovy would have to be revised to be

more representative of chlorophyll *a* concentrations in coastal Louisiana.

Eastern Oysters

The existing HSI model for eastern oyster has been unchanged since its development for the 2012 Coastal Master Plan (Soniat, 2012). An attempt was made to develop statistical-based water quality SIs for a 2017 oyster HSI model using LDWF's monitoring data; however, limitations in the dataset impaired the identification of significant statistical relationships, so the decision was made to continue using the 2012 HSI model (Hijuelos et al., 2017b). The oyster monitoring program has recently been expanded, but the increased sampling frequency (3 times per year at select Barataria and Pontchartrain Basin stations) still may be inadequate for evaluating the intra-annual effects of salinity and temperature variability on oysters. The oyster monitoring dataset should be reconsidered for future oyster HSI model improvements, but in the interim the existing literature-based model, with additional improvements, should provide a more robust tool for determining oyster habitat suitability.

After conferring with LDWF scientists and the 2012 oyster HSI model developer (Dr. Tom Soniat), it is suggested that several of the SIs be adjusted to reflect recent studies. The time interval indicated in the SI "Mean salinity during the spawning season May through September" may no longer be accurate because recent research indicates that the oyster spawning season is much longer and recruitment remains high through November (Casas et al., 2015). Therefore, the time interval covered by this SI should be expanded to April through November. The time interval used by the SI representing oyster-killing floods, "Minimum monthly salinity January through December", also may be inappropriate. Recent studies have indicated that oysters can survive periods of low salinities (<3 ppt) when temperatures are low (<25°C; La Peyre et al., 2013; Rybovich et al., 2016; Lowe et al., 2017). Therefore, the HSI model should use two minimum salinity relationships similar to those used by Denapolis (2018; i.e., one relationship for "cold months" and one for "warm months"). Lastly, the cultch map used for calculations of the SI "Percent of bottom covered by cultch" should be updated with recent survey data. This will allow the model to be used to evaluate impacts to current oyster-producing water bottoms.

In addition to adjustments and updates to existing SIs, new suitability indices should be investigated for inclusion in the oyster HSI model. Water temperatures >32°C have been shown to curtail oyster feeding, increase disease occurrence, and increase mortality (La Peyre et al., 2015; Rybovich et al., 2016; Lowe et al., 2017). To account for these effects, a new SI should be explored that considers maximum temperatures, mean monthly summer temperatures, or percentage of days with temperatures >32°C. In addition, burial of oysters by sediment deposition should be explored as an SI, because this has been cited as a main cause of oyster reef failure across a range of settings (Powers et al., 2009; Twichell et al., 2010).

Crayfish

The 2017 crayfish HSI results showed much less suitable habitat than expected, and some areas known to provide good crayfish habitat received low suitability scores. Preliminary investigation suggests that the limiting factor driving these results may be the SI "Water depth from July through September", because >96% of the coastwide ICM output in one simulation year examined had July-September water depths >15 cm, which are unsuitable for summer reproductive activities. Therefore, this function should be reformulated, perhaps by adjusting the time intervals covered by the two water depth SIs, as suggested in the 2017 Coastal Master Plan Crayfish HSI Model report (Romaire, 2017).

Romaire (2017) also suggested improvements to the SI describing the suitability of sediment for crayfish burrowing activity. The existing model uses "percentage of sand in soil substrate" to define this relationship, but the "percent sand" conditions simulated by the ICM were almost always optimal. Romaire (2017) suggested replacing "percent sand" in the model with the soil classification system used in the United States Department of Agriculture's Soil Survey Geographic Database. The suitability of these soil classes for crayfish burrowing should be evaluated based on sand content and other potential unfavorable soil characteristics (Burras et al., 1995; McClain & Romaire, 2004; Chapman, 2014). If it is determined that the dataset can be used to define crayfish habitat suitability, then it should be noted that soil conditions would remain static throughout the analyses because the ICM cannot simulate changes to the soil classes over time or as a result of potential restoration and protection projects. However, if it is determined that nearly all wetland soil classes are suitable for crayfish burrowing, then this SI should be removed from the HSI model.

American Alligator

The 2017 alligator HSI results indicated a large area of suitable habitat and estimated high scores in wetland areas known for high alligator densities. However, there were a few areas (i.e., the Rockefeller Wildlife Refuge) that exhibited lower suitability scores than expected. This was likely due to an incomplete understanding of water depth variability for these areas, many of which are impounded with their water levels actively managed. In general, the "Relative water depth to the marsh surface" SI should be updated by incorporating information from recent literature on the effects of water depth on alligator nesting and foraging behavior in Louisiana (Waddle, 2017). An initial literature review failed to produce any relevant recent studies, however, this effort should be continued and local alligator experts should be consulted for available information. In addition, the model's "Habitat type" SI, which describes the relative suitability of vegetated habitat types, may be improved if it were based on actual alligator abundance, rather than aerial surveys of alligator nests and hunting reports (Waddle, 2017). Again, the literature and local experts should be consulted to determine if there are suitable studies from which a replacement "Habitat type" SI can be developed. If these improvement efforts are unfruitful, then the existing alligator HSI model should be used as is.

Gadwall and Mottled Duck

The 2017 gadwall HSI results were lower than expected, with suitability scores rarely exceeding 0.5. These results were initially attributed to low spatial resolution of the ICM's water depth output (Leberg, 2017a) or the somewhat restrictive water depth SI used in the model. However, neither of these factors affected green-winged teal HSI model, which also had a restrictive water depth relationship but produced much higher scores. Preliminary investigation suggests that the limiting factor driving these results was the SI "Proportion of cell that is water with SAV". Only 5.5% of the coastwide ICM output in one simulation year examined had any SAV coverage, which seems lower than expected based on recent work by DeMarco et al. (2018). Therefore, improvements to the ICM's ability to predict SAV coverage should be explored. If SAV predictions cannot be substantially improved, then the gadwall model should be replaced with the better performing green-winged teal HSI model.

Otherwise, the gadwall and mottled duck HSI models (and the teal model if used) should be updated with recent literature and data, if available, on these species usage of different vegetated habitats and the influence of water depth on habitat utilization (Leberg, 2017a; Leberg, 2017b). An initial literature review did not yield any relevant recent studies, however, this effort should be continued and local waterfowl experts should be consulted for available information. Leberg (2017b) also suggested that the mottled duck HSI model could be improved by incorporating this species' nesting habitat. This would entail expanding the domain of the ICM to include changes to upland areas or non-wetland, elevated habitats immediately adjacent to coastal wetlands. However, after discussions with the ICM model developers, it appears that such refinements to the ICM are unlikely, so mottled duck nesting habitat should not be included in the HSI model at this time.

Brown Pelican

The brown pelican HSI model is only applicable to nesting habitat, and therefore the model should be improved with recent literature and data on environmental factors influencing nesting habitat selection and nesting success (Leberg, 2017c). The ongoing RESTORE Act Center of Excellence research project entitled: "Assessment of coastal island restoration practices for the creation of brown pelican nesting habitat", should provide useful information of how site characteristics, such as vegetation type and elevation, affect pelican use of an island for nesting habitat. The project will also provide information of how proximity to prey resources (primarily menhaden) affects nesting success.

The information provided by the RESTORE Act project should result in a more refined brown pelican HSI model, which would be better able to assess suitability at smaller scales (i.e., a barrier island chain or individual island) to determine how nesting habitat changes with island geomorphology. To enable such assessments, the spatial resolution of the HSI model should be increased to match that of the barrier island digital elevation model under development for the 2023 Coastal Master Plan so

that the HSI model can account for finer-scale changes in island size and elevation. Similar fine-scale vegetation input data may also be required, but this would be dependent on whether the ICM's Vegetation subroutine can effectively simulate barrier island vegetation composition and coverage at finer spatial resolution than a 500 m grid cell. If such ICM refinements and model linkages are not practical at this time, then the brown pelican HSI model can still be used to evaluate coastwide changes in potential nesting habitat.

2.4 DEVELOPMENT OF NEW HSI MODELS

Seaside Sparrow

The seaside sparrow has been identified as a potential new species for inclusion in the 2023 Coastal Master Plan modeling efforts. Seaside sparrows are year-round residents of coastal marshes, and thus represent different habitat requirements relative to the bird species included in the 2017 Coastal Master Plan analyses, which primarily use aquatic habitats. Currently, an HSI model has not been developed for the seaside sparrow. A literature review should inform development of a model for the 2023 Coastal Master Plan, with a focus on populations along the northern Gulf Coast (Louisiana and Mississippi) due to differences in migratory behavior and habitat preferences with sparrows along the Atlantic Coast and south Texas. Scientists from Audubon Louisiana, Louisiana State University, and LDWF should also be consulted on model development.

A preliminary literature review indicates that the HSI model may include the following environmental variables: vegetation type, land area, vegetation cover, elevation, and tidal range. Preferred habitats of seaside sparrows in Louisiana include intermediate, brackish, and saline marshes dominated by Spartina spp. (Stouffer et al., 2013). Within these habitats, it has been observed that sparrows have home ranges averaging in size between 7,500 and 12,500 m^2 (Olin et al., 2017), thus small or extremely fragmented patches of marsh may not be suitable sparrow habitat (Stouffer et al., 2013). Nesting sparrows prefer marshes with vegetation cover between 65.8 and 87.5% (Gabrey & Afton, 2000) and at least 200 m away from habitats with tree cover (Cooper et al., 2016; Lehmicke, 2014) to reduce the threat of nest predation. In addition, nesting sparrows may select areas that reduce the risk of nest flooding. Higher marsh elevations, such as areas >0.09 m that do not flood daily (Cooper et al., 2016; Lehmicke, 2014), and areas with lower tidal range (<1 m; Stouffer et al., 2013) are considered more suitable habitat.

Bald eagle

The bald eagle also has been identified as a potential new species for inclusion in the 2023 Coastal Master Plan modeling efforts. This species was selected for inclusion because it nests primarily in wooded freshwater habitats, as opposed to the brown pelican which nests on isolated coastal islands. An HSI model has been developed for the bald eagle, but it may be outdated and focuses on nesting eagles north of the 37th parallel (i.e., San Jose, CA to Norfolk, VA; Peterson, 1986). Furthermore, eagles in Louisiana exhibit seasonal and migratory behaviors dissimilar to the northern populations. Therefore, the existing model may not adequately represent birds in Louisiana coastal habitats. Audubon Louisiana has been working on a bald eagle nesting habitat model that uses master plan output, which could be further developed for the 2023 Coastal Master Plan. Currently the model only uses vegetated habitat type (bottomland hardwood forest, swamp, fresh marsh, etc.) as a variable, but additional variables could include: distance from nest to open water, proximity to prey resources, and percent land/open water coverage.

3.0 SUMMARY OF RECOMMENDATIONS AND OPTIONS FOR IMPLEMENTATION

The team has provided several recommendations for improvement of the 2023 Coastal Master Plan HSI models for key Louisiana fish, shellfish, and wildlife species. Some recommendations have more than one option, apply to either the statistical-based or literature-based SI (or both), and/or apply to more than one species. An outline of each species and improvement method (i.e., statistical-based or literature-based) is provided in Table 6.

Our review and recommendations for the HSI models do not address model post-processing or model implementation, such as exploring temporal and spatial similarities in projected habitat suitability among species, how the HSI model outputs should be interpreted, how model uncertainty may be visually depicted or considered when interpreting HSI model output, or how model results for multiple species and life stages may be summarized or aggregated in a way to more easily communicate outputs for the master plan. These elements will be considered by the team pending the execution of the recommended options presented in this report.

Recommendation 1: Identify Relevant Species to Model

Fourteen species are recommended for improved HSI modeling and integration into the 2023 Coastal Master Plan (Table 1).

Recommendation 2: Improve Statistical-Based Suitability Indices

Several potential options were identified for improving the statistical-based suitability indices, many of which are interconnected and are dictated by decisions made during the model building process. To add clarity in how these improvements may be executed, the options were compiled into a multi-step, phased approach for model improvement (see below and Figure 6). Key decision points were identified at each step, which provide the opportunity to stop improvements and use the model in its current state or continue with additional model improvement activities.

Step 1. Improve Existing GLM-based SI function.

Review of the literature indicates the existing GLM-based SI function is appropriate to use in predictive applications. Several improvements were identified to the current GLM approach that could provide additional statistical rigor and improve model confidence:

- Revisit the statistical issues identified in Section 2.2 - Component 2 and formally document all findings.
- Assess the accuracy of model predictions, as described in Section 2.2 - Component 3, by examining model residuals and comparing observed and predicted values using the measures previously discussed (R2, chi-square statistic, RMSE).
- Generate upper and lower bound confidence intervals for the SI function. Standardizing the confidence intervals on a 0 to 1 scale (to match the scale of the SI function) would provide an error estimate for each HSI prediction.

In addition to improving the SI function itself, the team recommends comparing the frequency distribution of historical salinity and temperature data (from the LDWF data) to the predicted salinity and temperature conditions generated by the 2017 ICM. This would allow for identification of how frequently the model is predicting outside the range of the historical conditions and could be used to identify potentially sensitive time periods or locations where environmental conditions are in the extreme. If the conditions are frequently outside the bounds of the data, this also supports the use of an alternate modeling approach that is less sensitive to these issues.

Following completion of the GLM model assessment (and the comparison of current and future salinity and temperature conditions), a decision point is reached. The model can be used in its newly improved state or additional improvement activities can be executed. This decision is not strictly driven by model accuracy measures or data limitations. Additional factors will influence the interpretation of the accuracy measures and ultimately influence the decision, such as the desired level of confidence in the model by CPRA, CPRA's need for statistical robustness or rigor given the intended purpose of the HSI models, and time and level of effort required for Step 2. The pros and cons of implementing Step 1 only are summarized below.

	PROS	CONS
IMPLEMENT STEP 1 ONLY	REQUIRES A MINIMAL LEVEL OF EFFORT AND TIME TO IMPLEMENT, RELATIVE TO REMAINING STEPS. IMPROVES MODEL DOCUMENTATION. ESTABLISHES AN ESTIMATE OF ERROR IN THE MODEL, WHICH CAN ASSIST IN APPROPRIATELY COMPARING AND INTERPRETING MODEL OUTPUTS ACROSS DIFFERENT SIMULATIONS. ESTIMATE OF ERROR CAN ALSO HELP GUIDE WHETHER ADDITIONAL MODEL IMPROVEMENT IS WARRANTED.	DOES NOT SYSTEMATICALLY EXPLORE WHETHER MODEL PERFORMANCE CAN BE FURTHER IMPROVED. IS NOT AS STATISTICALLY OR SCIENTIFICALLY RIGOROUS AS HABITAT SUITABILITY MODELS FOUND IN THE PEER-REVIEWED LITERATURE.

Step 2. Implement a Single New Statistical Modeling Approach

As previously discussed, there is no clear consensus within the current literature on the selection of one modeling approach over another and any of the above-mentioned modeling approaches are theoretically suitable for this application. As a result, the team recommends testing each of them incrementally, beginning with a single new modeling approach. The modeler should then select which approach to implement, based on review of the LDWF data to confirm model assumptions will be met and the modeler's knowledge and familiarity with the modeling approach. Implementation of this modeling approach would include:

- All other improvement activities described in Section 2.2 – Components 2 and 3.
- Additional environmental and habitat predictor variables could be incorporated at this time. Data compilation and preliminary exploratory analysis could be performed to determine the likelihood of improved model performance with an expanded dataset.

Once the new model is developed, model predictions and performance can be compared with the GLM developed at the end of Step 1. Where differences may exist in the model predictions, comparison of model performance statistics can help elucidate why (e.g., model with higher unexplained deviance may generate less confidence in the predictions; Elith & Graham, 2009). If the comparison indicates model performance has sufficiently improved (see discussion at the end of Step 1), then the new and improved model could be selected for use in the 2023 Coastal Master Plan. However, if model improvement is minimal or if there is interest in further improving the model, and time and resources are available, additional modeling approaches could be incrementally attempted in Step 3.

	PROS	CONS
IMPLEMENT STEP 1 AND STEP 2	SYSTEMATICALLY EXPLORES WHETHER MODEL PERFORMANCE CAN BE IMPROVED. ENHANCES THE STATISTICAL AND SCIENTIFIC RIGOR OF THE MODEL. PROVIDES AN OPPORTUNITY TO IDENTIFY CONSISTENT PATTERNS BETWEEN APPROACHES, WHICH MAY GENERATE ADDITIONAL CONFIDENCE IN THE PREDICTIONS.	REQUIRES MODERATE LEVEL OF EFFORT AND TIME TO IMPLEMENT, RELATIVE TO STEP 1. DOES NOT NECESSARILY GUARANTEE ANY FURTHER IMPROVEMENT IN THE MODEL.

Step 3: Implement All Modeling Approaches

All remaining modeling approaches would be implemented. After completing the modeling and performance assessment outlined in Step 2 for each modeling approach, the modeler could then compare performance across all models. If one modeling approach is clearly superior (has high accuracy and goodness-of-fit and produces ecologically relevant conclusions), then this model should be chosen as the final, improved SI model. If at the end of the modeling exercise, all models perform similarly, an ensemble modeling approach could be taken. The ensemble model approach involves using a common measure of accuracy or fit to generate a weighted average of all model predictions. Thus, the final model output will combine the strengths of each modeling approach to produce the best possible prediction. This step will take considerably more time than previous steps, but would produce the most statistically rigorous result.

	PROS	CONS
IMPLEMENT STEPS 1, 2, AND 3	SYSTEMATICALLY EXPLORES WHETHER MODEL PERFORMANCE CAN BE IMPROVED. FURTHER ENHANCES THE STATISTICAL AND SCIENTIFIC RIGOR OF THE MODEL TO A LEVEL IN LINE WITH THE PEER-REVIEWED LITERATURE.	REQUIRES ADDITIONAL LEVEL OF EFFORT AND TIME TO IMPLEMENT. DOES NOT GUARANTEE ANY FURTHER IMPROVEMENT IN THE MODEL.

Recommendation 3: Improve Literature-Based Suitability Indices

The team recommends refining the structural habitat SI that defines suitability of marsh vegetation to open water for brown shrimp, white shrimp, blue crab, gulf menhaden, spotted seatrout and largemouth bass (Table 6) to include additional habitats such as shallow and deep non-vegetated bottoms (SNVB, DNVB), SAV, and oyster reef.

The team recommends literature-based HSI improvements for several species including the eastern oyster, crayfish, American alligator, gadwall and mottled duck, and the brown pelican. The recommended improvements to these species' HSIs include adding new SI functions, and adjusting existing SI functions, based on updated literature reviews and existing data.

Recommendation 4: Develop New HSI Models

The team recommends developing new HSI models for the seaside sparrow and bald eagle based on a preliminary data review to identify potential environmental variables, and in meeting with Audubon Louisiana to review their bald eagle nesting habitat model.

Table 6. Summary of recommendations that will be implemented for each of the species. Blue checks in the first column of the literature based SI are for species that may be able to use some or all of the additional structural habitats defined for the refined SI proposed for shrimp, blue crab, and fish.

Identify Relevant Species to Model (1)	Improve Statistical Based SI (2)	Improve Literature Based SI (3)		Develop New HSI Model (4)
Eastern Oyster		✔	✔	
Brown Shrimp	✔	✔		
White Shrimp	✔	✔		
Blue Crab	✔	✔		
Crayfish			✔	
Gulf Menhaden	✔	✔		
Spotted Seatrout	✔	✔		
Largemouth Bass	✔	✔		
American Alligator		✔	✔	
Gadwall		✔	✔	
Mottled Duck		✔	✔	
Seaside Sparrow		✔		✔
Brown Pelican			✔	
Bald Eagle				✔

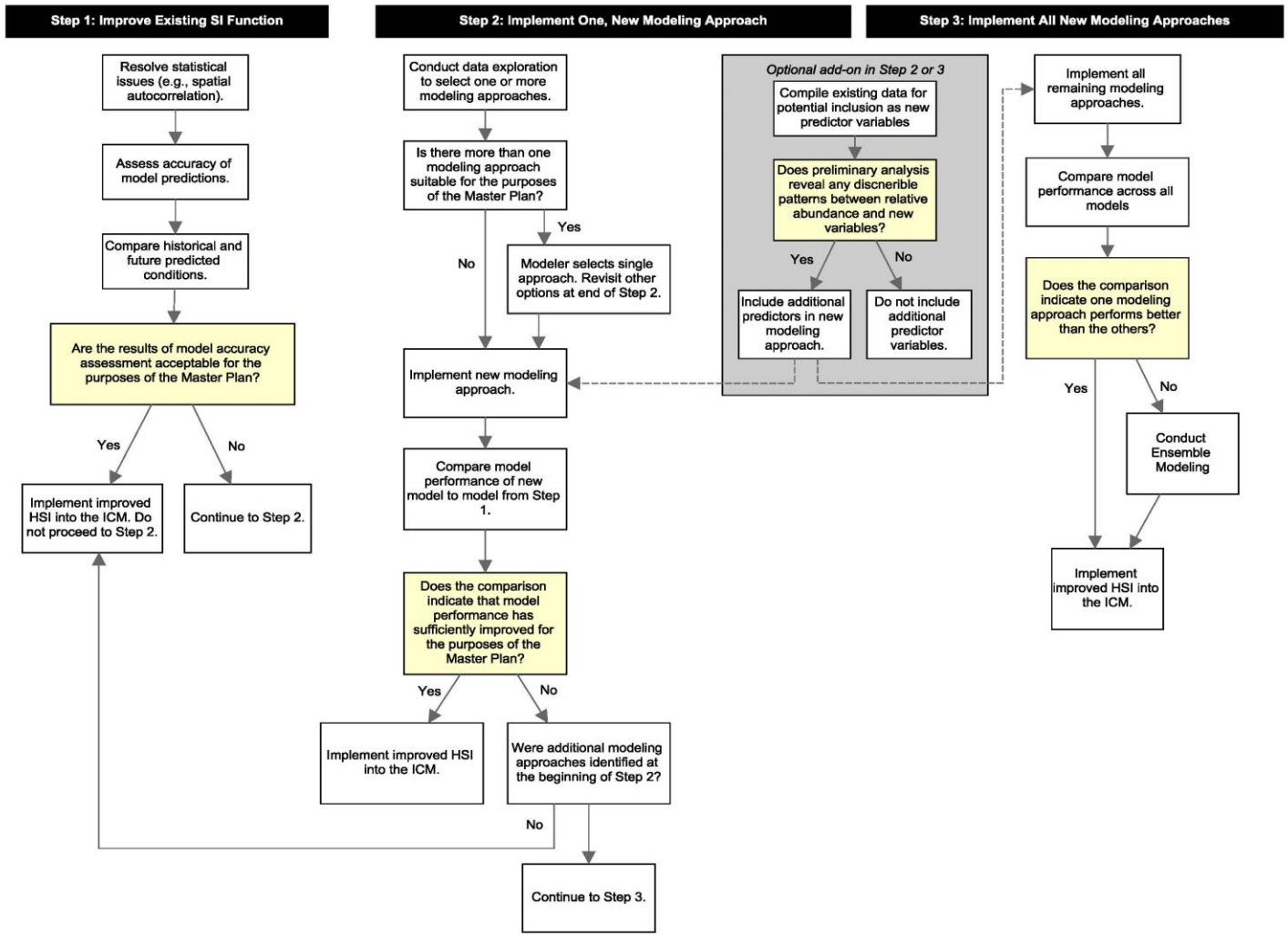


Figure 6. Decision tree for recommended improvements to the statistical-based suitability indices.

4.0 REFERENCES

Adamack, A.T., Stow, C.A., Mason, D.M., Rozas, L.P. & Minello, T.J. (2012). Predicting the effects of freshwater diversions on juvenile brown shrimp growth and production: a Bayesian-based approach. Marine Ecology Progress Series, 444, 155–173.

Akaike, H. (1973). Information theory as an extension of the maximum likelihood principle. In B.N. Petrov & F. Csaki, (Eds), pp. 267-281. Second international symposium on information theory. Budapest, Akaemiai Kiado.

Allouche, O., Tsoar, A., & Kadmon, R. (2006). Assessing the accuracy of species distribution models: prevalence, kappa and the true skill statistic (TSS): Assessing the accuracy of distribution models. Journal of Applied Ecology, 43, 1223–1232.

Araújo, M.B., Pearson, R.G., Thuiller, W., & Erhard, M. (2005). Validation of species-climate impact models under climate change. Global Change Biology, 11, 1504–1513.

Austin, M. (2007). Species distribution models and ecological theory: A critical assessment and some possible new approaches. Ecological Modelling, 200, 1–19.

Austin, M.P., Belbin, L., Meyers, J.A., Doherty, M.D. & Luoto, M. (2006). Evaluation of statistical models used for predicting plant species distributions: Role of artificial data and theory. Ecological Modelling, 199, 197–216.

Baker, R., & Minello, T.J. (2010). Growth and mortality of juvenile white shrimp *Litopenaeus setiferus* in a marsh pond. Marine Ecology Progress Series, 413, 95–104.

Breiman, L. (2001). Random forests. Machine Learning, 45, 5–32.

Breiman, L., Friedman, J. H., Olshen, R. A. & Stone, C. J. (1984). Classification and Regression Trees. New York, NY: Chapman & Hall

Brown, S., Couvillion, B., Conzelmann, C., de Mutsert, K., Fischbach, J., Hunnicutt, C., McKelvy, M., ... White, E. (2017). 2017 Coastal Master Plan: Appendix C: Modeling Chapter 3 - Modeling Components and Overview. Version Final. Coastal Protection and Restoration Authority, Baton Rouge, Louisiana. 72 pp.

Burras, L., Blakewood, G., Richard, T., & Huner, J.V. (1995). Laboratory observations on burrowing in different soils by commercially important procambarid crayfish. Freshwater Crayfish, 10, 427-434.

Callaway, J., Hagen, S., Harris, C., Kimmerer, W., & Waldon, W. (2017). 2017 Coastal Master Plan: Attachment C5-1: Predictive Models Technical Advisory Committee Report. Version Final. Coastal Protection and Restoration Authority, Baton Rouge, Louisiana.

Casas, S., La Peyre, J., & La Peyre, M. (2015). Restoration of oyster reefs in an estuarine lake: population dynamics and shell accretion. Marine Ecology Progress Series, 524, 171-184.

Chapman, A. (2014). The cascading impacts of vegetation on peat soil properties and crayfish survival in the Florida everglades. Master of Science Thesis. Florida Atlantic University, Boca Raton, Florida. 52 pp.

Cianfrani, C., Le Lay, G., Hirzel, A.H., & Loy, A. (2010). Do habitat suitability models reliably predict the recovery areas of threatened species? Journal of Applied Ecology, 47, 421–430.

Cooper, R.J., Lehmicke, A.J., & Woodrey, M.S. (2016). Testing habitat model assumptions for seaside sparrows (*Ammodramus maritimus*) in northern Gulf Coast tidal marsh: final report. Retrieved from Gulf Coast Joint Venture: http://gcjv.org/documents.php

Couvillion, B.R. (2018). Land area in coastal Louisiana (1932 to 2016) - land area spatial data - multi-date composites for specific years: U.S. Geological Survey data release, https://doi.org/10.5066/P99LJJZZ

DeMarco, K., Couvillion, B., Brown, S., & La Peyre, M. (2018). Submerged aquatic vegetation mapping in coastal Louisiana through development of a spatial likelihood occurrence (SLOO) model. Aquatic Botany, 151, 87-97.

Denapolis, T. (2018). Legacy habitat suitability of eastern oysters (*Crassostrea virginica*) in Louisiana: a prelude to Mississippi River Delta freshwater diversions. Master's Thesis. University of New Orleans, New Orleans, Lousiana.

Dormann, C.F. (2007). Effects of incorporating spatial autocorrelation into the analysis of species distribution data. Global Ecology and Biogeography, 16, 129-138.

Dormann, C.F., McPherson, J.M., Araújo, M.B., Bivand, R., Bolliger, J., Carl, G., Davies, R.G. ....Wilson, R. (2007). Methods to account for spatial autocorrelation in the analysis of species distributional data: a review. Ecography, 30, 609-628.

Dormann, C.F., Elith, J., Bacher, S., Buchmann, C., Carl, G., Carré, G., Marquéz, J.R.G. ...Lautenbach, S. (2013). Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. Ecography, 36, 27–46.

Drexler M., & Ainsworth, C. H. (2013). Generalized Additive Models Used to Predict Species Abundance in the Gulf of Mexico: An Ecosystem Modeling Tool. PLoS ONE 8(5): e64458. https://doi.org/10.1371/journal.pone.0064458

Elith, J., & Leathwick, J.R. (2009). Species distribution models: Ecological explanation and prediction across space and time. Annual Review of Ecology, Evolution, and Systematics, 40, 677–697.

Eskildsen, A., Le Roux, P.C., Heikkinen, R.K., Høye, T.T., Kissling, W.D., Pöyry, J., Wisz, M.S., & Luoto, M. (2013). Testing species distribution models across space and time: high latitude butterflies and recent warming. Global Ecology and Biogeography, 22, 1293–1303.

Flaherty, K.E., & Guenther, C.B. (2011). Seasonal distribution and abundance of blue crabs (*Callinectes sapidus*) in the Tampa Bay estuary. Gulf of Mexico Science, 2, 91–110.

Fortin, M.J., & Dale, M.R.T. (2005). Spatial analysis—a guide for ecologists. Cambridge University Press, Cambridge.

Froeschke, J.T., & Froeschke, B.F. (2011). Spatio-temporal predictive model based on environmental factors for juvenile spotted seatrout in Texas estuaries using boosted regression trees. Fisheries Research, 111, 131–138.

Gabrey, S.W., & Afton, A.D. (2000). Effects of winter marsh burning on abundance and nesting activity of Louisiana Seaside Sparrows in the Gulf Coast Chenier Plain. The Wilson Journal of Ornithology, 112, 365-372.

Grenouillet, G., Buisson, L., Casajus, N., & Lek, S. (2011). Ensemble modelling of species distribution: the effects of geographical and environmental ranges. Ecography, 34, 9–17.

Guillera-Arroita, G., Lahoz-Monfort, J.J., Elith, J., Gordon, A., Kujala, H., Lentini, P.E., McCarthy, M.A., ... Wintle, B.A. (2015). Is my species distribution model fit for purpose? Matching data and models to applications. Global Ecology and Biogeography, 24, 276–292.

Guisan, A., & Thuiller, W. (2005). Predicting species distribution: offering more than simple habitat models. Ecology Letters, 8, 993–1009.

Guisan, A., Edwards Jr., T.C., & Hastie, T. (2002). Generalized linear and generalized additive models in studies of species distributions: setting the scene. Ecological Modelling, 157, 89–100.

Hanley, J.A., & McNeil, B.J. (1982). The meaning and use of the area under a receiver operating characteristic (ROC) curve. Radiology, 143, 29–36.

Hilborn, R., & Mangel, M. (1997). The Ecological Detective. Princeton, NJ: Princeton University Press.

Hijuelos, A.C., Moss, L., Sable, S.E., O'Connell, A.M., & Geaghan, J.P. (2017a). 2017 Coastal Master Plan: Attachment C3-18: Largemouth Bass, *Micropterus salmoides*, Habitat Suitability Index Model. Version Final. Coastal Protection and Restoration Authority, Baton Rouge, Louisiana. 25 pp.

Hijuelos, A.C., Sable, S.E., O'Connell, A.M., & Geaghan, J.P. (2017b). 2017 Coastal Master Plan: Attachment C3-12: Eastern Oyster, *Crassostrea virginica*, Habitat Suitability Index Model. Version Final. Coastal Protection and Restoration Authority, Baton Rouge, Louisiana. 23 pp.

Holcomb, S.R., Bass, A.A., Reid, C.S., Seymour, M.A., Lorenz, N.F., Gregory, B.B., Javed, S.M., & Balkum, K.F. (2015). Louisiana Wildlife Action Plan. Louisiana Department of Wildlife and Fisheries, Baton Rouge, Louisiana. 661 pp.

Howard, C., Stephens, P.A., Pearce-Higgins, J.W., Gregory, R.D., & Willis, S.G. (2014). Improving species distribution models: the value of data on abundance. Methods in Ecology and Evolution, 5, 506–513.

Krzywinski, M., & Altman, N. (2017). Classification and regression trees. Nature Methods, 14, 757–758.

Kupschus, S. (2003). Development and evaluation of statistical habitat suitability models: an example based on juvenile spotted seatrout *Cynoscion nebulosus*. Marine Ecology Progress Series, 265, 197–212.

La Peyre, M., Eberline, B., Soniat, T., & La Peyre, J. (2013). Differences in extreme low salinity timing and duration differentially affect eastern oyster (*Crassostrea virginica*) size class growth and mortality in Breton Sound, LA. Estuarine, Coastal and Shelf Science, 135, 146-157.

La Peyre, M.K., Geaghan, J., Decossas, G., & La Peyre, J.F. (2015). Analysis of environmental factors influencing salinity patterns, oyster growth, and mortality in lower Breton Sound Estuary, Louisiana, Using 20 Years of Data. Journal of Coastal Research, 32, 519-530.

Landis, R.J., & Koch, G.G. (1977). The measurement of observer agreement for categorical data. Biometrics, 33, 159–174.

Leberg, P. (2017a). 2017 Coastal Master Plan: Attachment C3-6: Gadwall, *Anas strepera*, Habitat Suitability Index Model. Version Final. Coastal Protection and Restoration Authority, Baton Rouge, Louisiana.

Leberg, P. (2017b). 2017 Coastal Master Plan: Attachment C3-8: Mottled duck, *Anas fulvigula*, Habitat Suitability Index Model. Version Final. Coastal Protection and Restoration Authority, Baton Rouge, Louisiana.

Leberg, P. (2017c). 2017 Coastal Master Plan: Attachment C3-9: Brown Pelican, *Pelecanus occidentalis*, Habitat Suitability Index Model. Version Final. Coastal Protection and Restoration Authority, Baton Rouge, Louisiana.

Legendre, P. (1993). Spatial autocorrelation: trouble or new paradigm? Ecology, 74, 1659-1673.

Lehmicke, A.J. (2014). Breeding ecology of the seaside sparrow (*Ammodramus maritimus*) in Northern Gulf of Mexico tidal salt marshes. PhD Dissertation, University of Georgia, Athens, Georgia.

Lever, J., Krzywinski, M., & Altman, N. (2016). Regularization. Nature Methods, 13, 803-804.

Lichstein, J.W., Simons, T.R., Shriner, S.A., and Franzreb, K.E. (2002). Spatial autocorrelation and autoregressive models in ecology. Ecological Monographs, 72, 445-463.

Lowe, M., Sehlinger, T., Soniat, T., & La Peyre, M. (2017). Interactive effects of water temperature and salinity on growth and mortality of eastern oysters, *Crassostrea virginica*: a meta-analysis using 40 years of monitoring data. Journal of Shellfish Research, 36, 683-698.

Marmion, M., Parviainen, M., Luoto, M., Heikkinen, R.K., & Thuiller, W. (2008). Evaluation of consensus methods in predictive species distribution modelling. Diversity and Distributions, 15, 59-69.

McClain, W.R. & Romaire, R.P. (2004). Effects of simulated drought on crayfish survival and reproduction in experimental burrows: A preliminary study. Freshwater Crayfish, 14,106-115.

Merow, C., Smith, M.J., Edwards, T.C., Guisan, A., McMahon, S.M., Normand, S., Thuiller, W.,.....Elith, J. (2014). What do we gain from simplicity versus complexity in species distribution models? Ecography, 37, 1267–1281.

Minello, T. J. (1999). Nekton densities in shallow estuarine habitats of Texas and Louisiana and the identification of essential fish habitat. American Fisheries Society Symposium, 22, 43-75.

Minello, T.J. (2017). Fishery habitat in estuaries of the Gulf of Mexico: reflections on geographical variability in salt marsh value and function. Gulf and Caribbean Research, 28, ii-xi.

Minello, T. J. & Rozas, L. P. (2002). Nekton in gulf coast wetlands: fine-scale distributions, landscape patterns, and restoration implications. Ecological Applications, 12, 441-455.

Minello, T.J., Able, K.W., Weinstein, M.P., & Hays, C.G. (2003). Salt marshes as nurseries for nekton: testing hypotheses on density, growth and survival through meta-analysis. Marine Ecology Progress Series, 246, 39-59.

Minello, T.J., Rozas, L.P., & Baker, R. (2012). Geographic variability in salt marsh flooding patterns may affect nursery value for fishery species. Estuaries and Coasts, 35, 501-514.

Minello, T.J., Rozas, L.P., Hillen, S.P., & Salas, J.A. (2015). Variability in salt marsh flooding patterns in Galveston Bay, Texas. NOAA Technical Memorandum NMFS—SEFSC—678, NOAA, Washington, DC.

Monserud, R.A., & Leemans, R. (1992). Comparing global vegetation maps with the Kappa statistic. Ecological Modelling, 62, 275–293.

Nyman. J.A., Baltz, D.M., Kaller, M.D., Leberg, P.L., Parsons Richards, C., Romaire, R.P., & Soniat, T.M. (2013). Likely changes in habitat quality for fish and wildlife in coastal Louisiana during the next 50 years. Journal of Coastal Research, Special Issue 67, 60-74.

Olin, J.A., Bergeon Burns, C.M., Woltmann, S., Taylor, S.S., Stouffer, P.C., Bam, W., Hooper-Bui, L. & Turner, R.E. (2017). Seaside Sparrows reveal contrasting food web responses to large-scale stressors in coastal Louisiana saltmarshes. Ecosphere, 8, 10.1002/ecs2.1878.

Patillo, M.E., Czapla, T.E., Nelson, D.M., & Monaco, M.E. (1997). Distribution and abundance of fishes and invertebrates in Gulf of Mexico estuaries, Volume II: Species life history summaries. 11. NOAA's Estuarine Living Marine Resources Program. U.S. Department of Commerce, National Oceanic and Atmospheric Administration, National Ocean Service.

Peters, J., De Baets, B., Verhoest, N.E.C. Samson, R., Degroeve, S., De Becker, P., & Huybrechts, W. (2007). Random forests as a tool for ecohydrological distribution modelling. Ecological Modelling, 207, 304-318.

Peterson, A. (1986). Habitat suitability index models: bald eagle (breeding season). U.S. Fish Wildlife Service. Biological Report 82 (10.126). 25 pp.

Powers, S.P., Peterson, C.H., Grabowski, J.H., & Lenihan, H.S. (2009). Success of constructed oyster reefs in no-harvest sanctuaries: implications for restoration. Marine Ecology Progress Series, 389, 159-170.

Prasad, A., Iverson, L.R., & Liaw, A. (2006). Newer classification and regression tree techniques: bagging and Random Forests for ecological prediction. Ecosystems, 9, 181-199.

Quinn, G.P., & Keough, M.J. (2002). Experimental design and data analysis for biologists. Cambridge University Press, Cambridge, UK ; New York.

Romaire, R.P. (2017). 2017 Coastal Master Plan: Attachment C3-19: Crayfish, *Procambarus clarkii* and *P. zonangulus*, Habitat Suitability Index Model. Version Final. Coastal Protection and Restoration Authority, Baton Rouge, Louisiana.

Rozas, L.P., & Minello, T.J. (2010). Nekton density patterns in tidal ponds and adjacent wetlands related to pond size and salinity. Estuaries and Coasts, 33, 652–667.

Rozas, L.P., & Minello, T.J. (2015). Small-scale nekton density and growth patterns across a saltmarsh landscape in Barataria Bay, Louisiana. Estuaries and Coasts, 38, 2000-2018.

Roth, B.M., Rose, K.A., Rozas, L.P., & Minello, T.J. (2008). Relative influence of habitat fragmentation and inundation on brown shrimp *Farfantepenaeus aztecus* production in northern Gulf of Mexico salt marshes. Marine Ecology Progress Series, 359,185-202.

Rybovich, M., La Peyre, M., Hall, S., & La Peyre, J. (2016). Increased temperatures combined with lowered salinities differentially impact oyster size class growth and mortality. Journal of Shellfish Research, *35*, 101-114.

Sable, S.E., Hijuelos, A.C., O'Connell, A.M., & Geaghan, J.P. (2017a). 2017 Coastal Master Plan: Attachment C3-15: Gulf Menhaden, *Brevoortia patronus*, Habitat Suitability Index Model. Version Final. Coastal Protection and Restoration Authority, Baton Rouge, Louisiana. 30 pp

Sable, S.E., Hijuelos, A.C., O'Connell, A.M., & Geaghan, J.P. (2017b). 2017 Coastal Master Plan: Attachment C3-17: Bay Anchovy, *Anchoa mitchilli*, Habitat Suitability Index Model. Version Final. Coastal Protection and Restoration Authority, Baton Rouge, Louisiana. 31 pp

Soniat, T. (2012). Appendix D3 Eastern Oyster Habitat Suitability Index Technical Report. In: Louisiana's Comprehensive Master Plan for a Sustainable Coast. Baton Rouge, Louisiana

Stouffer, P.C., Taylor, S.S., Woltmann, S., & Bergeon Burns, C.M. (2013). Staying alive on the edge of the Earth: response of seaside sparrows (*Ammodramus maritimus*) to salt marsh inundation, with implications for storms, spills, and climate change. In T.F. Shupe & M.S. Bowen, (Eds), pp 82–93. Proceedings of the 4th Louisiana Natural Resources Symposium. Louisiana State University, Baton Rouge, Louisiana, USA.

Thomson, R.E., & Emery, W.J. (2014). Statistical Methods and Error Handling. pp 219-311. In: Data Analysis Methods in Physical Oceanography. Amsterdam, The Netherlands, Elsevier Science.

Thuiller, W., Araújo, M.B., & Lavorel, S. (2003). Generalized models vs. classification tree analysis: Predicting spatial distributions of plant species at different scales. Journal of Vegetation Science, 14, 669-680.

Twichell, D., Edmiston, L., Andrews, B., Stevenson, W., Donoghue, J., Poore, R., & Osterman, L. (2010). Geologic controls on the recent evolution of oyster reefs in Apalachicola Bay and St. George Sound, Florida. Estuarine, Coastal and Shelf Science, 88, 385-394.

United States Fish and Wildlife Service. (1981). Standards for the development of habitat suitability index models. ESM 103. Division of Ecological Services, U.S. Fish and Wildlife Service, Department of Interior, Washington D.C.

Waddle, H. (2017). 2017 Coastal Master Plan: Attachment C3-10: Alligator, *Alligator mississippiensis*, Habitat Suitability Index Model. Version Final. Coastal Protection and Restoration Authority, Baton Rouge, Louisiana.

Wood, S. (2006). Generalized Additive Models: An Introduction with R. Boca Raton, Florida, Chapman and Hall/CRC Press.

Zar, J. (2010). Biostatistical Analysis, 5th edition. Upper Saddle River, New Jersey, Prentice-Hall, Inc.

Zuur, A.F., Ieno, E.N., & Elphick, C.S. (2010). A protocol for data exploration to avoid common statistical problems: Data exploration. Methods in Ecology and Evolution, 1, 3–14.