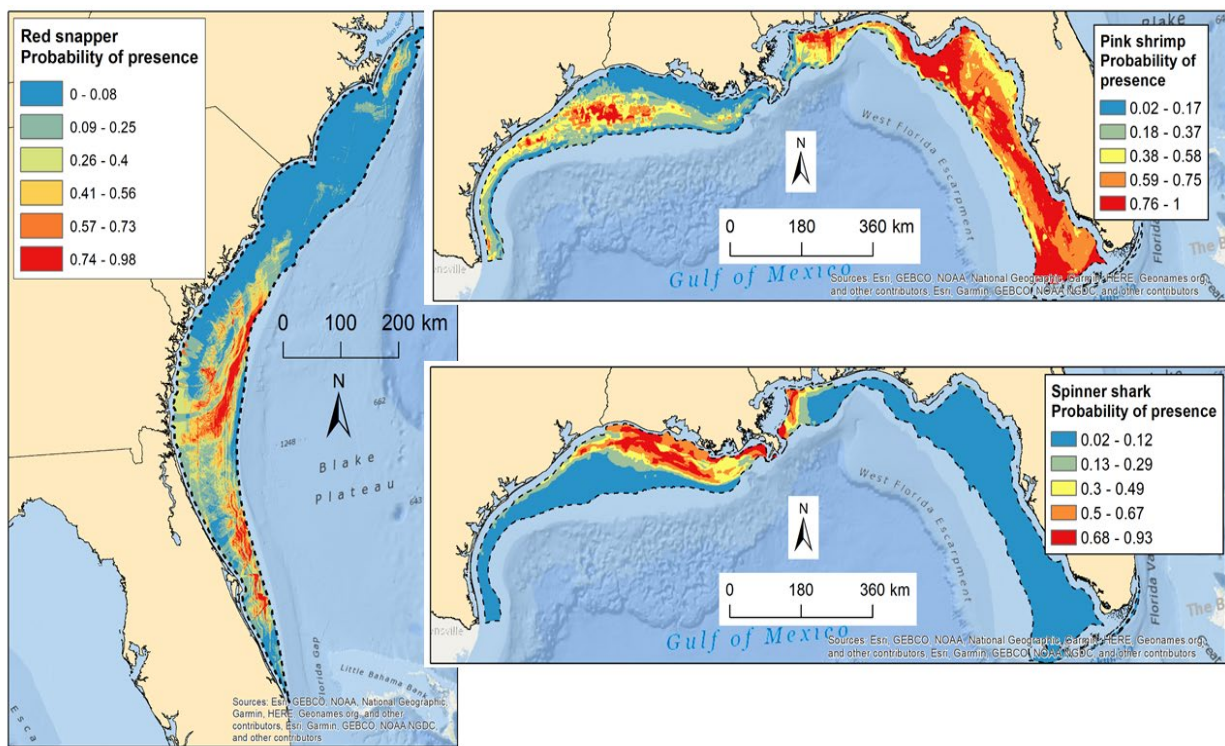


Regional Essential Fish Habitat Geospatial Assessment and Framework for Offshore Sand Features

Volume 3: Predicting the Distribution of Select Fish Species of the Gulf of Mexico, South Atlantic, and Greater Atlantic



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Regional Essential Fish Habitat Geospatial Assessment and Framework for Offshore Sand Features

Volume 3: Predicting the Distribution of Select Fish Species of the Gulf of Mexico, South Atlantic, and Greater Atlantic

January 2020

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By

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List of Abbreviations and Acronyms

AUC	area under the curve statistic
BL	bottom longline
BOEM	Bureau of Ocean Energy Management
BPI	bathymetric position index
BRT	boosted regression trees
CPUE	catch per unit effort
CRM	Coastal Relief Model
CSSP	Congressional Supplemental Sampling Program
CCMA	Center for Coastal Monitoring and Assessment
CV	coefficient of variation
DOI	Department of the Interior
EFH	Essential Fish Habitat
FL	fork length
ft	foot/feet
GAM	generalized additive model
GHRSSST	Group for High Resolution Sea Surface Temperature
GIS	Geographic Information System
IE	interaction effect
IUCN	International Union for Conservation of Nature
kg	kilogram(s)
km	kilometer(s)
km ²	kilometers squared
L	liter(s)
m	meter(s)
min	minute(s)
MLD	mixed layer depth
mg	milligram(s)
mm	millimeter(s)
MODIS	Moderate Resolution Imaging Spectroradiometer
MUR	Multiscale Ultrahigh Resolution
MSLABS	Southeast Fisheries Science Center, NMFS, Mississippi Laboratory
<i>n</i>	sample size
nat TL	natural total length
NCCOS	National Centers for Coastal Ocean Science
NCODA	Navy Coupled Ocean Data Assimilation
NEFSC	Northeast Fisheries Science Center
nGoM	northern Gulf of Mexico
NMFS	National Marine Fisheries Service
NOAA	National Oceanic and Atmospheric Administration
NOS	National Ocean Service
nm	nautical mile(s)
NWI	National Wetlands Inventory
OCS	Outer Continental Shelf
OCSLA	Outer Continental Shelf Lands Act
ppt	part(s) per thousand
psu	practical salinity unit(s)
R _s	Spearman rank correlation
s	second(s)

SDM	species distribution model
SEAMAP	Southeast Area Monitoring and Assessment Program
SERFS	Southeast Reef Fish Survey
SL	standard length
SLA	Submerged Lands Act
SST	sea surface temperature
TL	total length
°C	degree(s) celsius

Abstract

Species distribution models (SDMs) are a state-of-the-art statistical modeling approach that quantifies the relationships between species and spatially explicit environmental data. SDMs work by extending the identified species-habitat relationships to the entire distribution of species under consideration. These predictive modeling results are ideal to inform management decisions. In this volume, we used a variety of fisheries-independent data sources in the Gulf of Mexico and South Atlantic to produce SDMs for select marine fish and shrimp species. Environmental data on habitats included oceanographic conditions, geomorphology, geography, prey, and the nearby ecosystems of wetlands and estuaries. For the Greater Atlantic, we summarize SDMs developed by the Northeast Fisheries Science Center that combined trawl surveys with data on oceanographic conditions, substrate, and zooplankton. Together, these maps and quantified habitat relationships (or lack thereof) add to the information synthesized in *Volume 1: Fish Habitat Associations and the Potential Effects of Dredging on the Atlantic and Gulf of Mexico Outer Continental Shelf*. The analyses evaluated the best habitat predictors of marine species and depicted the distribution of select marine fish and shrimp species. Species' relationships with geomorphology characteristics were limited and of minor importance compared to other habitat predictors. None of the Gulf of Mexico species examined were related to bottom currents, slope, or the heterogeneity of depth. Of minor importance in the models, white shrimp had a higher catch per unit effort (CPUE) farther away from shoals, and pink shrimp were positively related to sand grain sizes. Red snapper age-0 had a higher CPUE in close proximity to shoals and where the bathymetric position index predominately showed a hill topography. In the South Atlantic, none of the five species examined were associated with geomorphology characteristics. Overall, species' distributions were primarily related to oceanographic conditions, nearby wetlands and estuaries, and prey species. When applicable, geomorphology predictors only had minor influence on species distribution.

1 Predicting the Marine Distribution of Three Penaeid Shrimp Species in the Northern Gulf of Mexico

1.1 Introduction

In the northern Gulf of Mexico (nGoM), USA, the Penaeid species of brown shrimp (*Penaeus aztecus*), pink shrimp (*Farfantepenaeus duorarum*), and white shrimp (*Litopenaeus setiferus*) have high economic value. From 2006 to 2015, annual commercial catches of shrimp in the region had an economic value ranging from \$327.6 to \$585.8 million and catches have ranged from 178.9 to 289.0 million pounds (National Marine Fisheries Service 2017). As a specific example of the Penaeid species, 2016 landings included brown shrimp (\$157 million), white shrimp (\$206 million), and pink shrimp (\$24.4 million) (NOAA NMFS Office of Science and Technology 2019). In addition to their economic importance, shrimp are key components of the ecosystem as a common prey for both benthic and pelagic fish (Tarnecki et al. 2016). In particular, brown shrimp have been documented as an integral part of the nGoM food web, as they are described as prey of small pelagic fish, small demersal fish, flatfish, king mackerel, Spanish mackerel, benthic feeding sharks, several snapper and grouper species, black drum, red drum, and others (Tarnecki et al. 2016).

Brown, pink, and white shrimp are estuarine-dependent in their early life stages, which is when they are relatively well studied. Within estuaries, juvenile white and brown shrimp are most abundant at open water-marsh edges, and they respond positively to the amount of time the marsh is flooded (Minello and Rozas 2002; Rozas and Minello 2015; Rozas et al. 2007). As adults, these three Penaeids are demersal and utilize the marine environment. Of the three Penaeids, brown shrimp are the best studied in the nGoM. Of particular importance, research has concentrated on the effects of hypoxia on brown shrimp (Craig 2012; Craig and Crowder 2005; Craig et al. 2005). These studies show that brown shrimp aggregate at the edge of hypoxic zones and may move farther inshore or offshore to avoid hypoxic waters. Since 2007, the development of species distribution models (SDMs) have begun to proliferate for marine species (Melo-Merino et al. 2020). SDMs use statistical species-habitat relationships to predict the spatial distribution of species (Guisan and Zimmermann 2000). Montero et al. (2016) developed an SDM for brown shrimp and found brown shrimp relative abundance was positively related to mud, shallow depths (< 100 m), lower salinities (< 20 ppt), higher bottom temperatures (> 20°C), latitude/longitude, and were uncommon in hypoxic conditions. For pink shrimp, Drexler and Ainsworth (2013) developed an SDM and tested five predictor variables. Their results were initially modeled at a 10-km scale and were aggregated into broad polygons that improved model accuracy (Drexler and Ainsworth 2013). Their model showed pink shrimp were less abundant in waters with mud sediments compared to other grain sizes. Drexler and Ainsworth (2013) also showed pink shrimp abundance declined most in waters > 120 m in depth and with waters < 15°C. They found a negative relationship with chlorophyll and a positive relationship with dissolved oxygen of $\geq 5 \text{ ml}^{-1}$. Concerning adult white shrimp, their habitat use and marine distribution remains poorly documented.

Recent advances in modeling the distribution of brown and pink shrimp have greatly improved our knowledge of the marine distribution of Penaeids. However, even with these species, much remains unknown about their relationships to geomorphology, ocean currents, and the nearby ecosystems on which each species depends. Turner (1977) found a strong positive correlation between coarse measures of inshore brown shrimp landings and emergent wetland area in the nGoM. Diop et al. (2007) found landings of white shrimp over time were positively, but weakly, correlated with late juvenile abundances. Yet, the distribution of Penaeids in the offshore, marine ecosystem has not yet been related to nearby wetlands and estuaries. Overall, testing the relationships of shrimp species' distribution with a

comprehensive suite of habitat variables has the potential to inform management, strengthen environmental impact assessments, and refine our knowledge of important waters for each species.

The need to fill these knowledge gaps is exemplified by marine resource extraction activities like dredging. The demand for offshore marine sand is increasing in the United States (Drucker et al. 2004), and sand is commonly used for beach renourishment, barrier island restoration, and wetland restoration. Throughout this report, we use the term "sand" to broadly characterize sediment resources, and we recognize that sediment dredging may include a variety of grain sizes depending on the application. Sand shoals are often preferred resources because of the quantity of sand per unit area, and the dredging of Outer Continental Shelf (OCS) sand shoals is likely to increase in the future as demand increases due to renourishment cycles for beaches, emergency repairs of beaches after storms, and the projected effects of sea-level rise (Nairn et al. 2004). In particular, the nGoM coast benefits greatly from barrier islands that reduce storm surge (Grzegorzewski et al. 2011), and these islands require regular sediment replenishment. The Bureau of Ocean Energy Management (BOEM), as part of the US Department of the Interior, is responsible for the management and development of mineral resources on the OCS, including sediment resources. As demand for OCS sand increases, BOEM faces complex multi-user interactions, including issues of resource allocation, cumulative impacts from repeated use, fisheries use and potential conflicts, protection of archaeological sites, oil and gas infrastructure, potential renewable energy infrastructure, and impacts on Essential Fish Habitat (EFH) (Michel et al. 2013).

As part of our project, we have identified shoal locations and developed a classification scheme based on expert opinion and shoal characteristics of interest (Volume 2). The classification includes characteristics hypothesized to be related to fish such as bottom current direction and velocity, slope, depth, sediment grain size, rugosity (i.e., depth heterogeneity), and shell presence. In addition to the effect of shoals themselves, these characteristics are largely untested in relation to fish and shrimp species. Here, our objectives were to:

- 1) Test for habitat relationships of brown, pink, and white shrimp with a broad suite of environmental factors, including geomorphology, oceanographic characteristics, and nearby ecosystems
- 2) Model the spatial distribution of white, brown, and pink shrimp with multiscale predictors

1.2 Methods

1.2.1 Study Area

The study area spanned the extent of the nGoM from Texas to Florida, USA. The landward boundary began with federally managed waters (3 nm from the shoreline of Louisiana, Mississippi, and Alabama; 9 nm from the shoreline of Texas and Florida) through the 50-m depth contour. More specifically, we defined the landward boundary of the study area by the 1953 Outer Continental Shelf Lands Act (OCSLA), which distinguishes Federal- and state-managed waters. The oceanic boundary of the study area was defined by a 50-m contour line from National Oceanic and Atmospheric Administration's (NOAA's) Coastal Relief Model (CRM) (NOAA National Centers for Environmental Information 2010). Only waters ≤ 50 m in depth were included in the study because our focus was on the potential impact of sediment dredging and the logistics of dredging limit potential areas to these shallow depths. The study area had a total surface area covered of 162,985 km². The benthic substrate of the area consists of unconsolidated sediments ranging from mud to gravel with natural patches of hard bottom reefs.

1.2.2 Biological Data

We obtained offshore shrimp data from fishery-independent trawl surveys of the Southeast Area Monitoring and Assessment Program (SEAMAP) in the nGoM. With the exception of minor changes in sample selection procedures in 2010 and thereafter, surveys have used similar gear, protocols, and a random stratified sampling design based on depth and shrimp statistical area since 1992 (Craig et al. 2005; Gulf States Marine Fisheries Commission 2017). From these data, we used the years of 2003–2017 because we wanted to depict current conditions as best as possible, and this timeframe still provided us with an adequate sample size. Trawl surveys from the SEAMAP program span the entire nGoM and are conducted in the summer (June–August) and fall (October–December) seasons. Trawl surveys targeted shrimp and groundfish using a 12.8-m net in the central and eastern nGoM and with a 6.1-m net near Texas. Surveys were conducted at all hours of the day. Complete counts of shrimp were conducted in summer surveys. In the fall, complete counts were conducted for samples < 22.7 kg. For larger catches, totals counts were estimated by extrapolating from a subset of the catch. We used the centroid of trawl survey tows to represent survey locations and to calculate environmental variables. We removed extremely long or short tow survey lengths, and subsequently, trawls ranged from 11–52 min and 1.0–5.2 km. We calculated the relative abundance of each shrimp species by calculating catch per unit effort (CPUE) as shrimp km⁻¹ of survey. Because initial relative abundance models showed below-average results for pink shrimp, we used presence/absence data for modeling this species. Prior to analyses, we used Generalized Additive Models (GAMs) (knots=3) to explore the effects of trawl length and duration on the presence/absence or CPUE of species. All tests showed <1% of the deviance was explained by these effects except for the effect of length on white shrimp CPUE, which explained 3% of the deviance. Given these minimal effects, we proceeded with using CPUE and presence/absence data. We used summer (June–August) and fall (October–December) trawl surveys for analyses of shrimp.

Pink shrimp ranged throughout the nGoM, and we used the entire study area for the analysis. We restricted the analyses of white shrimp and brown shrimp to their primary geographic ranges because the inclusion of hundreds, or thousands, of absence points outside a species' range may skew the results towards predictor variables characterizing the species' geographic range rather than their fine-scale distribution and habitat associations. Additionally, our goal was to add to existing knowledge of distributions to aid in management applications. For white shrimp, we excluded trawl surveys east of a longitude of W 87.9°. Only 1 of 1,653 trawl surveys east of this latitude recorded a white shrimp, and this longitude was > 200 km from that presence location. For brown shrimp, we excluded trawl surveys east of a longitude of W 84.5° because only 6 of 1,203 locations (8 of 570,733 individuals) were found east of this longitude. The next nearest brown shrimp in a trawl survey east of this longitude was > 100 km away.

1.2.3 Geographic Information System (GIS) Methods and Environmental Data

We converted all fish survey and environmental GIS data to the North America Albers Equal Area Conic map projection. To calculate environmental variables with focal statistics (e.g., mean depth within a 3-km radius), we initially included a 5-km buffer of the study area. We removed this buffer after final maps were developed. Because we anticipated hierarchical relationships of shrimp with predictor variables (e.g., broad oceanographic factors and fine-scale substrate factors and depth), we predicted all SDMs to a 90-m resolution raster. The 90-m resolution was the same as several, but not all environmental variables. For data initially at a resolution > 90 m, we conducted a bilinear resampling and then aligned the data to the other 90-m datasets.

We developed predictor variables to depict oceanographic conditions, substrate, geography, and nearby ecosystems (**Table 1-1**). For bathymetry, and variables derived from bathymetry, we used the CRM (NOAA National Centers for Environmental Information) for offshore waters of Texas, Louisiana, Mississippi, and Alabama. Offshore of Florida, we observed large errors in depth values that spanned tens of kilometers and were usually observed as rectangular boxes with little variability. Therefore, we used

sounding data developed into a 50-m raster grid by the US Geological Survey (Robbins et al. 2007). To be consistent with the regional analysis, we resampled to a 90-m resolution using bilinear interpolation. To correspond to the approximate length of trawl surveys, we used ArcGIS focal statistics to calculate the CV (coefficient of variation) of depth, mean slope, mean sediment grain size, proportion of area with shoal, and proportion of area with a positive bathymetric position index (BPI) within a 3-km radius.

Table 1-1. Predictor variables developed to predict the distribution of brown, pink, and white shrimp in the nGoM.

Oceanographic predictors were obtained from aggregations of monthly means spanning 2003–2017 unless otherwise noted.

Variable type	Predictor variable (units)	Resolution	Data source
Substrate	CV of depth	90 m	CRM + modifications
Substrate	Distance to shoal (km)	90 m	Pickens and Taylor, NOAA Biogeography Branch, identification of shoals
Substrate	Proportion of area with shoal	90 m	Pickens and Taylor, NOAA Biogeography Branch, identification of shoals
Substrate	Mean sediment grain size (mm)	370 m	Chris Jenkins, University of Colorado, interpolation of usSEABED data
Substrate	Proportion of area with BPI ≥ 1	90 m	CRM + modifications
Substrate	Slope (degrees)	90 m	CRM + modifications
Oceanographic	Mean depth (m)	90 m	CRM + modifications
Oceanographic	Bottom temperature ($^{\circ}\text{C}$)	4.4 km	HYCOM + NCODA
Oceanographic	Chlorophyll-a (mg m^{-3})	5.5 km	Aqua MODIS satellite, 8-day composites
Oceanographic	Bottom salinity (psu)	4.4 km	HYCOM + NCODA
Oceanographic	Bottom current, U- and V-directional velocity (m s^{-1})	9.3 km	HYCOM + NCODA
Oceanographic	Mixed layer thickness (m) (depth where temperature change from surface is 0.2°C)	4.4 km	HYCOM + NCODA
Oceanographic	Hypoxia (mean probability of hypoxia)		North Carolina State University
Geography	East or West of W 88° longitude	90 m	
Geography	Distance to shoreline (km)	90 m	Submerged Lands Act
Nearby ecosystems	Nearby wetlands (km^2)	90 m	National Wetlands Inventory
Nearby ecosystems	Nearby estuaries (km^2)	90 m	National Wetlands Inventory

* HYCOM + NCODA = Hybrid Coordinate Ocean Model + Navy Coupled Ocean Data Assimilation; MODIS = Moderate Resolution Imaging Spectroradiometer

We used the ArcGIS Benthic Terrain Modeler (Wright et al. 2012) to calculate the slope and BPI. The BPI is an index that represents underwater hill and valley topography, with values ≥ 1 indicating a cell is higher than surrounding cells and a BPI ≤ -1 indicating a cell is lower than surrounding cells. We used the BPI to calculate the proportion of area as a topographic high. For mean sediment grain size, we used a data interpolation of usSeabed from NOAA/National Ocean Service (NOS) National Centers for Coastal Ocean Science (NCCOS) (Kinlan et al. 2013). Aspect, BPI classified as a valley, and sediment grain size

classes were initially explored but did not provide further information beyond slope, sediment grain size, and shoal features that were already depicted.

We obtained oceanographic predictor variables by using Duke University's Marine Geospatial Ecology Toolbox (Roberts et al. 2010) within ArcGIS to summarize monthly means. Variables included bottom water temperature, chlorophyll-*a* (chlorophyll), bottom salinity, mixed layer thickness, and bottom current velocity for U and V directions (**Table 1-1**). All measures were averaged monthly over the period extending from January 2003 through December 31, 2017. Monthly measures were then averaged by seasons: spring = March 1–May 31, summer = June 1–Aug 31, fall = Sept 1–Nov 30, and winter = Dec 1–Feb 29. We used only remote sensing data to characterize oceanographic conditions because these measures are consistent across the geography and variables represented a relatively long-term characterization of the water column (i.e., monthly averages rather than a single day of a specific survey). Therefore, oceanographic measures represented spatial tendencies and related ecological processes rather than instantaneous conditions. Data on bottom temperature, bottom salinity, and bottom currents (U- and V- directions) were obtained from the HYCOM + NCODA Gulf of Mexico 1/25 degree analysis (GLMI0.04) (Chassignet et al. 2009). The Marine Geospatial Ecology Toolbox derived values calculated each day from the following datasets that have identical spatial extents and resolutions:

- 1 January 2003–30 April 2009: HYCOM dataset expt_20.1
- 1 May 2009–1 April 2014: HYCOM dataset expt_31.0
- 2 April 2014 and later: HYCOM dataset expt_32.5

The v-directional raster characterized the north (+) and south (-) currents and the u-directional raster characterized the east (+) and west (-) currents.

To quantify hypoxia (≤ 2 mg L⁻¹ dissolved oxygen), we used the results of Matli et al. (2018), who modeled the extent and probability of hypoxic conditions for each year based on three separate data collection efforts. To obtain a relative index of long-term conditions, we used the mean probability of hypoxia for July and August from 2003–2017 as a predictor variable. As the data were initially points, we created an interpolated raster dataset by using ordinary, spherical kriging with calculations including eight adjacent points. Because the dataset ended abruptly at an area of high hypoxia probability, we used the ArcGIS “Expand” tool to extrapolate all values up to 35 km.

Geographic and nearby ecosystem predictor variables considered included distance to shoreline, nearby wetland area, nearby estuarine area, and a longitudinal threshold that depicted whether the location was east (1) or west (0) of the W 88° longitude near Mobile Bay, Alabama, USA. Waters west of this longitude are dominated by mud sediments, large river influences, lower salinities, and higher chlorophyll concentrations that extend farther offshore compared to eastward waters. Waters east of this longitude are dominated by sandy substrates and higher salinities. The abundance of brown shrimp (Montero et al. 2016) and juvenile red snapper (Dance and Rooker 2019) have been shown to differ at this longitude threshold. To determine if coastal wetlands contributed to the distribution of shrimp in the marine environment, we used National Wetlands Inventory (NWI) data (U.S. Fish and Wildlife Service 2018) and its classification of “estuarine and marine wetland”. To quantify nearby wetland area (km²), we first calculated the farthest distance from a wetland in the study area. Using the resulting 160 km distance, we then used ArcGIS focal statistics to sum all wetland cells (90 m resolution) within 160 km of a cell in the marine environment. The metric was converted to wetlands km². Unfortunately, we could not use NWI data to define estuaries because of large areas of missing data. Therefore, we defined nearby estuary area from a map of EFH from red drum *Sciaenops ocellatus* (NOAA NMFS n.d.) that characterized all estuaries in the nGoM. As the layer included some nearshore waters, we removed all waters that were seaward of the shoreline position. Similar to nearby wetlands, estuary cells within 160 km of each cell were summarized for the study area. Distance to shoreline was calculated from the boundaries of the Submerged Lands Act (Bureau of Ocean Energy Management 2010; 2012), which depicts a distance of 3

or 9 nm from shoreline, depending on the state. We used the buffer tool to re-create the approximate shoreline boundaries and then calculated the Euclidean distance from the shoreline to each cell in the study area.

1.2.4 Statistical Analysis

We examined predictor variables for multicollinearity, and we removed highly correlated variables ($r > 0.80$) prior to analyses. In an initial analysis of pink shrimp, we found a strong negative relationship with nearby estuaries. This was likely a result of pink shrimp being common on the Florida shelf, which coincides with low estuarine areas. Because this relationship was likely because of other correlates on the Florida shelf (e.g., sand sediments, higher salinity), we did not include nearby estuaries as a predictor of pink shrimp. In addition to environmental predictors, we used season (summer or fall trawl survey) and start time of surveys as predictors. The time at which surveys are conducted can affect the detectability of species and has previously been documented as affecting brown shrimp catch (Craig and Crowder 2005). Regarding seasonality, changes in summer and fall distributions are likely because of species' natural history. We did not use year as an explanatory factor because the primary objective of our research was to determine long-term value of waters and substrates of the nGoM. Therefore, we assume years of high or low abundance are representative of long-term shrimp distribution.

Our trawl survey dataset had a large number of locations, which led to some being in close proximity to others. Individual surveys are likely to be independent over the 15 years of data collection, but we wanted to ensure our models were robust to specific survey locations. Fourcade et al. (2018) found that a purely random split of training and validation data for SDM assessments led to a high validation accuracy assessment for models derived from fake predictors. They found a “checkerboard” approach of aggregated training or validation locations was helpful, and a “block” approach was best at distinguishing models as being poor when they were truly poor (Fourcade et al. 2018). Similarly, we aggregated training and validation data with alternating bands along a longitudinal gradient (**Figure 1.1**). The use of a longitudinal gradient maintained a depth gradient in each block. More specifically, we reclassified a raster of longitude into 70 equal interval divisions, which resulted in 23-km bands across the study area. We then alternated the delineation of training (two bands) and validation (one band) datasets to achieve the desired ratio of training and validation data.

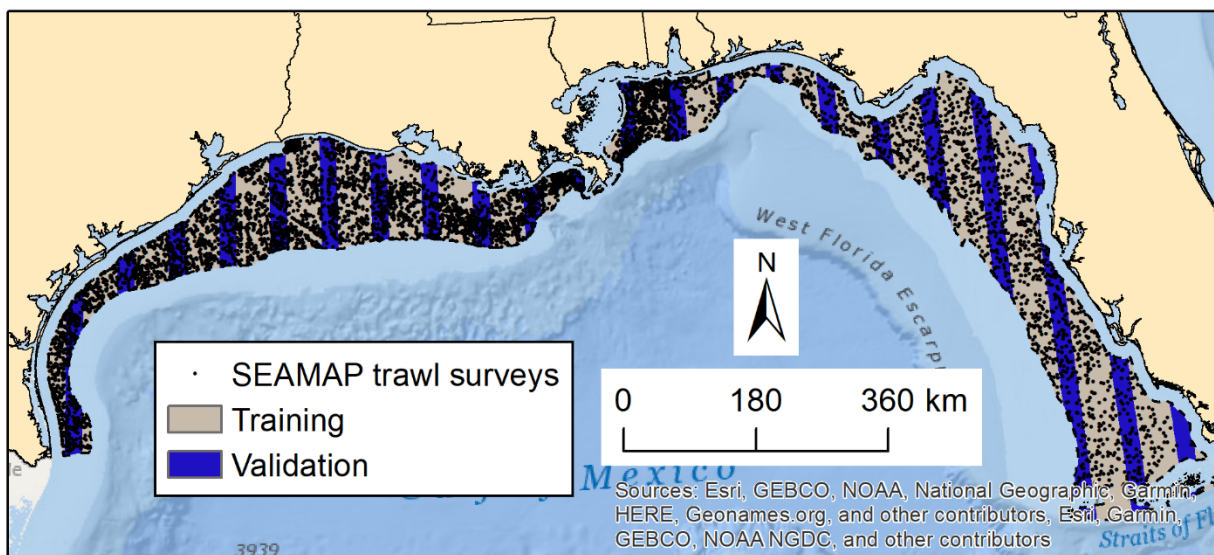


Figure 1.1. The study area with training and validation zones depicted with trawl surveys overlaid.

We used boosted regression trees (BRT) to model species-habitat relationships with the training data. In comparative studies of SDM statistical methods, BRTs and similar techniques have outperformed generalized linear models (GLMs), Maxent, and other techniques (Couce et al. 2012; Rooper et al. 2017; Smolinski and Radtke 2017). Classification and regression decision trees are the basis of BRT. Decision tree analyses are ideal for quantifying nonlinear relationships and complex interactions, which are both inherent in ecological data (De'ath and Fabricius 2000). The predictive power of decision trees are enhanced by boosting, which sequentially adds trees that improve the model; the results are then derived from an ensemble of hundreds of trees (De'Ath 2007; Elith et al. 2008). We followed the general procedures outlined by Elith et al. (2008) to develop BRTs. We iteratively assessed tree complexities of 1–5 and used learning rates that resulted in > 1,000 trees. The tree complexity represents the level of interaction allowed to occur (e.g., 1 = no interaction effects, 2 = interaction between two variables), and the number of trees are iterations. For brown and white shrimp, we used a Poisson log-linear model using CPUE as the dependent variable. For pink shrimp, we used a binomial model to predict probability of presence. We followed the BRT model “simplification” procedure described by Elith et al. (2008). In this procedure, the weakest predictor is dropped sequentially, predictors are ranked in order of importance, and the change in model deviance with each drop is assessed. The inflection point where the model’s deviance sharply increases after a drop defines which variables remain in the model with the goal of having a parsimonious model without losing predictive power. To be consistent, we defined an inflection point as an increase of > 2% of the deviance explained when dropping a single variable and $\geq 3\%$ for multiple dropped variables.

To assess accuracy of relative abundance models, we report the percent deviance explained (similar to an r^2 for Poisson regression) from the cross-validation and validation datasets. A Spearman rank correlation (R_s) was also calculated between observations and predictions of the validation dataset. For the pink shrimp presence/absence model, we used a receiver operator characteristic, area under the curve statistic (AUC). The AUC has been commonly used to test predictive ability of SDMs (Guisan and Zimmermann 2000) and is independent of thresholds. Measures of the AUC range from 0.0 to 1.0 and were interpreted as suggested by Manel et al. (2001) and Swets (1988) as follows: < 0.50 = no discriminatory power; 0.50–0.69 = poor power; 0.70–0.89 = good power; and 0.90–1.0 = excellent discriminatory power. In addition, we report the confusion matrix for the presence/absence model at the probability of presence threshold determined by the maximum Kappa that optimally discriminates presence and absence. We report relative importance of each variable in the model as suggested by Elith (2008). The relative importance of all variables in the model sums to 100%. Likewise, we assessed the strength of interaction, and these results are on a continuous scale with zero showing no interaction effect. We report interaction effect (IE) measures with a score of > 10 because these were most straightforward to interpret.

We used the statistical program R (R Core Team 2018) and the package “dismo” (Hijmans et al. 2017) to implement BRT. To predict models to the extent of the study area, or geographic range of species, we used the R packages “rgdal” (Bivand et al. 2019) and “raster” (Hijmans 2019). We assumed the effect of time of survey represented a detectability effect rather than a change in distribution. Therefore, we applied the models during each species' peak time of detectability: 10:30 for brown shrimp, 02:00 for white shrimp, and 06:00 for pink shrimp.

1.3 Results

Brown and white shrimp models explained a substantial amount of variation in CPUE, and the pink shrimp model was very good at predicting presence/absence (**Table 1-2**). Brown shrimp were present on 76.3% of trawl surveys with a total of 570,725 individuals. Mixed layer depth (MLD) in the spring and summer were most influential in the model with a deeper mixing of water related to a higher brown shrimp CPUE (**Figure 1.2 and Figure 1.3**). Brown shrimp CPUE was lowest from 11:00 through 24:00, and the season effect showed CPUE was greatest during summer. We found a slight positive relationship

of brown shrimp with fall bottom temperature, and nearby wetlands had a positive effect on CPUE. There was a strong interaction between spring MLD and nearby wetlands (IE = 41), which showed the highest predicted CPUE where high nearby wetland area was combined with a relatively deep spring MLD.

Table 1-2. BRT specifications and measures of accuracy for the shrimp species distribution models.

Species	<i>n</i>	Tree complexity	Learning rate	# of trees	Cross-validation	Validation	Validation Spearman correlation
Brown shrimp	4,417	4	0.02	1,850	Deviance explained = 45%	Deviance explained = 37%	0.64
White shrimp	3,967	5	0.01	1,200	Deviance explained = 41%	Deviance explained = 30%	0.55
Pink shrimp	5,620	3	0.01	2,000	AUC = 0.84	AUC = 0.85	NA

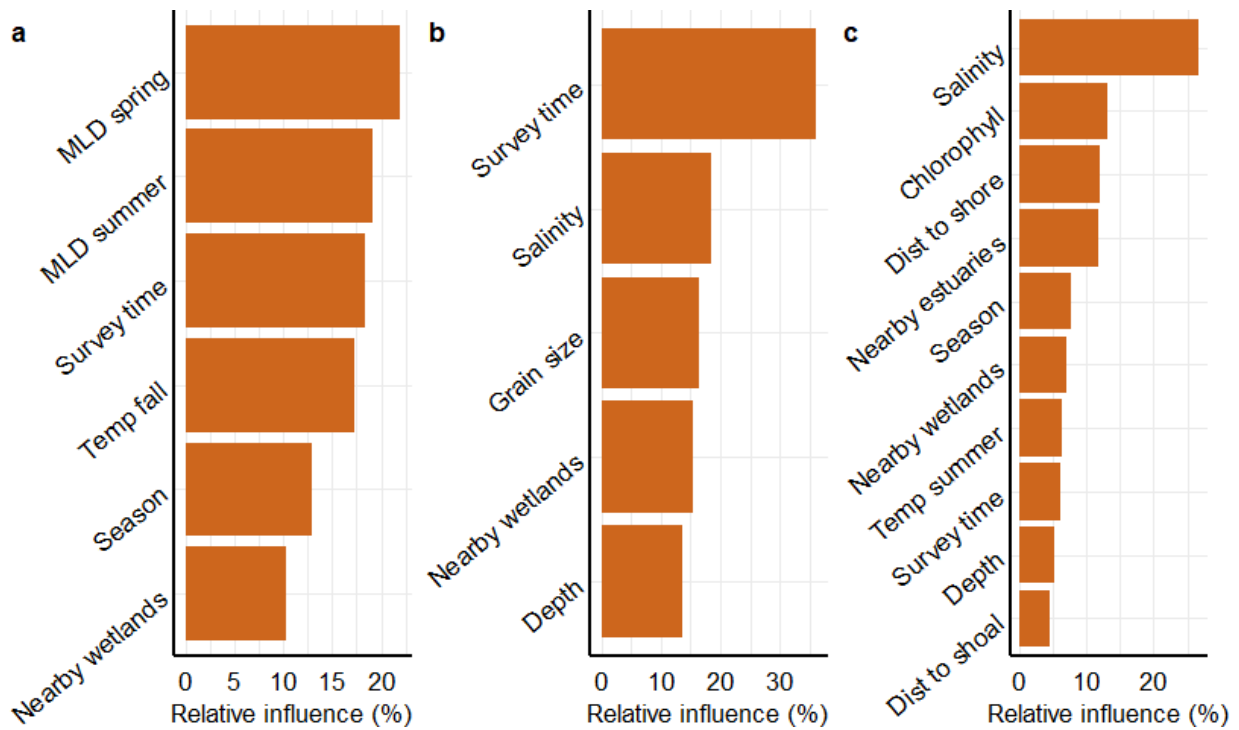


Figure 1.2. Relative importance of variables from the a) brown shrimp, b) pink shrimp, and c) white shrimp SDMs for the nGoM.

MLD = mixed layer depth, Temp = bottom water temperature, Grain size = sediment grain size, Dist = distance

White shrimp were present on 39.1% of trawl surveys, with a total of 44,455 individuals. White shrimp were most abundant with salinities of 22–30 psu, high chlorophyll concentrations, within 30 km of the shoreline, and with greater amounts of nearby estuaries and wetlands (**Figure 1.2 and Figure 1.4**). They had a higher CPUE during the fall season, with higher summer bottom temperatures, and with depths of approximately 15–30 m; they had a lower CPUE near midnight. White shrimp were slightly more abundant farther away from shoals. There was an interaction between salinity and nearby wetland area (IE = 17) that showed CPUE was greatest where high salinity coincided with a high nearby wetland area. The lowest predicted CPUE was at lower salinities with few nearby wetlands. An interaction between chlorophyll and season (IE = 13) showed chlorophyll had a greater influence on CPUE during the fall.

Pink shrimp were present on 22.6% of trawl surveys with a total of 36,015 individuals. Surveys from 11:00 to 23:00 had an extremely low probability of presence (**Figure 1.2 and Figure 1.4**). Pink shrimp presence was associated with salinities spanning 31–36 psu and substrate with sand grain sizes (less likely with silt or granule gravel grain sizes) (see Wentworth 1922). The relationship with nearby wetland area showed substantial variability, but pink shrimp were less likely when wetland area was extremely low and when wetland area was very high. Pink shrimp had the highest likelihood of presence with depths of 18–30 m, although considerable uncertainty existed at shallow depths. Survey time interacted with both salinity (IE = 65) and wetlands (IE = 65). This showed that these habitat variables had the greatest effect during times when pink shrimp were catchable. The pink shrimp model discriminated absence much better than presence (**Table 1-3**), and the overall accuracy represented by the AUC score was very good. The spatial models of the three species showed distinct patterns (**Figure 1.3 to Figure 1.5**).

Table 1-3. Confusion matrix from the validation data of the pink shrimp model at the optimal threshold to distinguish presence/absence, which was with a probability of 0.38.

	Observed absence	Observed presence	User's accuracy (% correct)
Predicted absence	1,323	180	88%
Predicted presence	132	241	65%

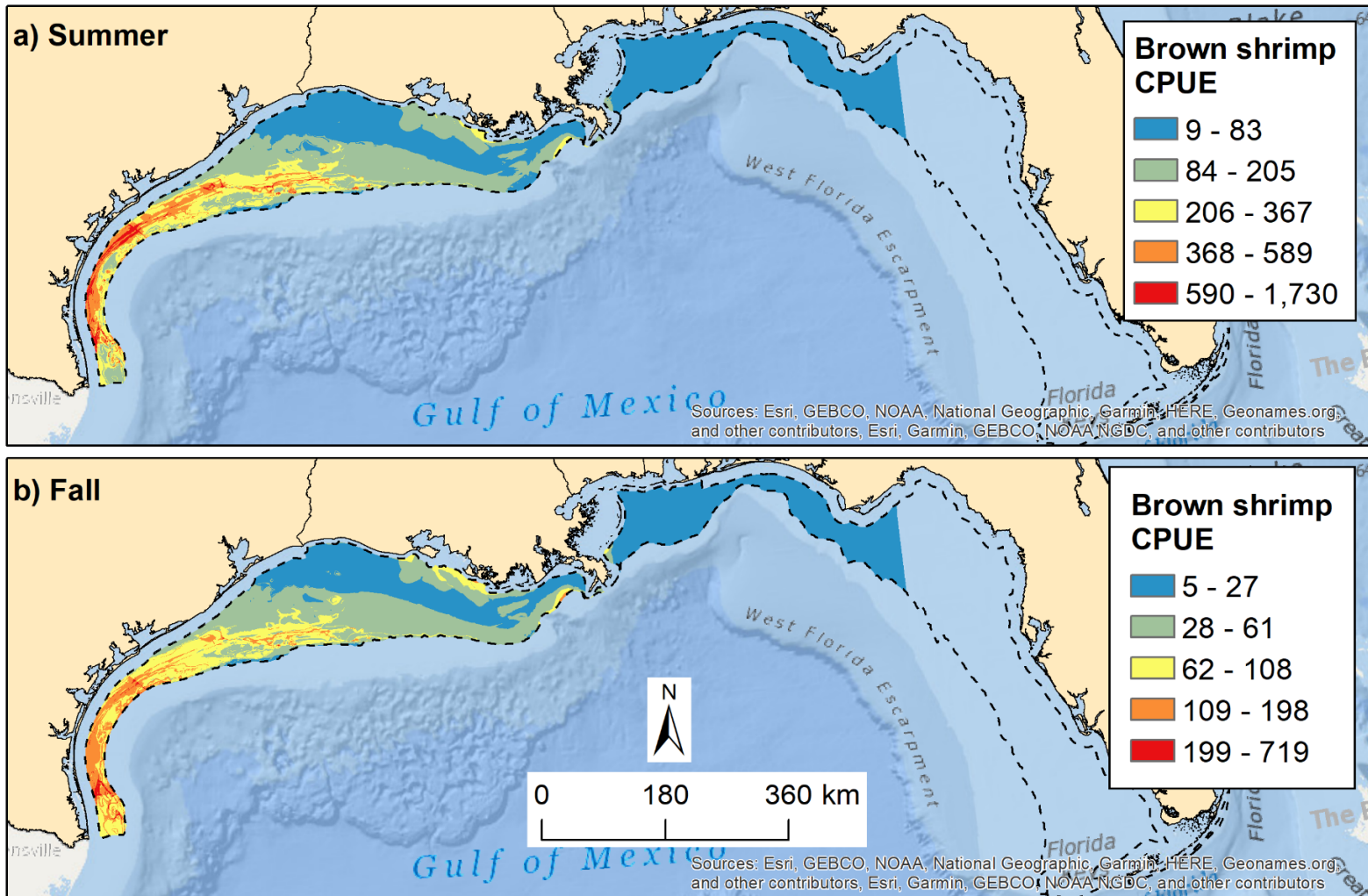


Figure 1.3. Predicted brown shrimp CPUE in the a) summer and b) fall seasons.

The study area is indicated by the dashed line, and CPUE represents the predicted number of shrimp per km of trawl survey.

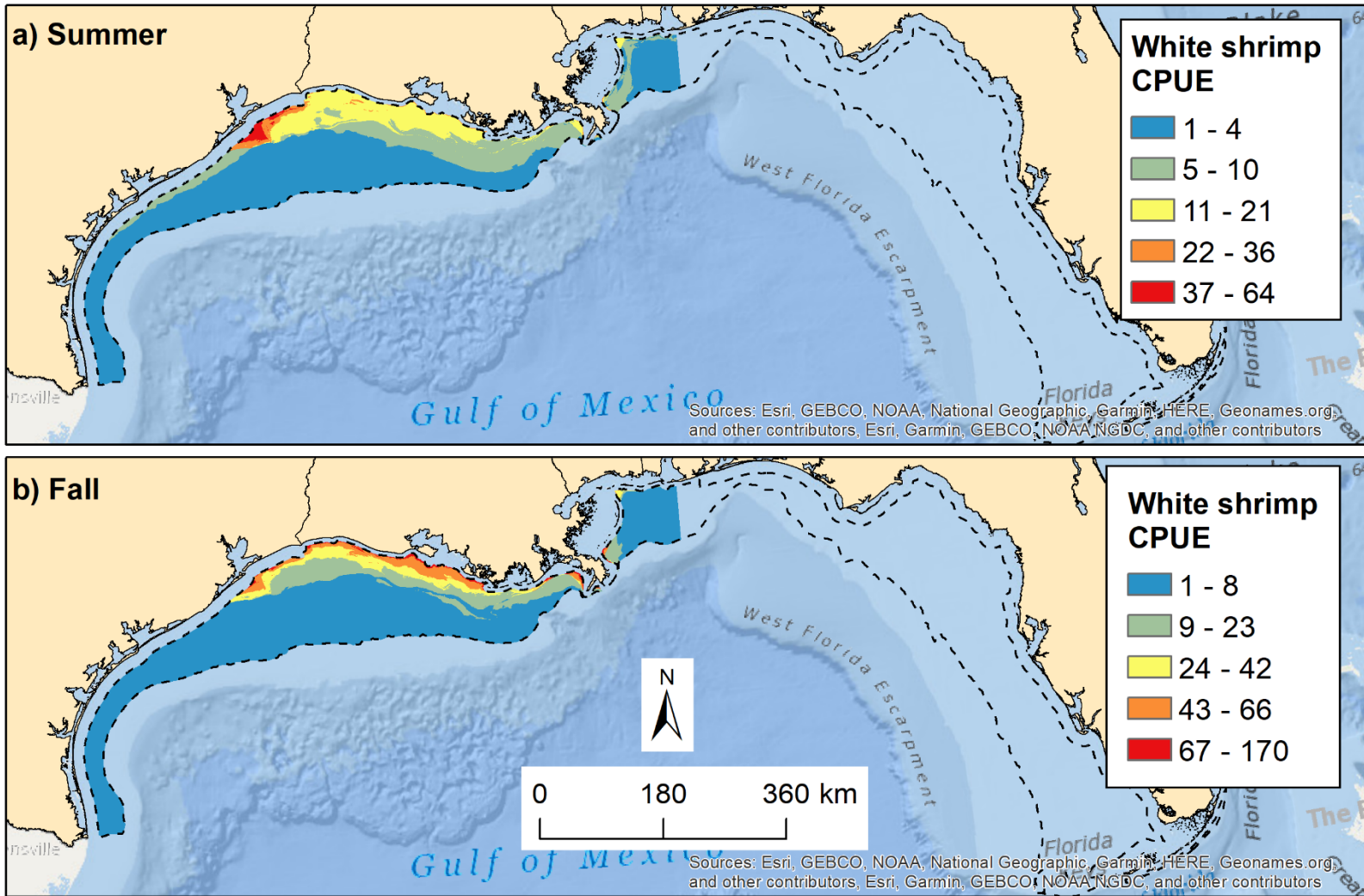


Figure 1.4. Predicted white shrimp CPUE in the a) summer and b) fall seasons.

The study area is indicated by the dashed line, and CPUE represents the predicted number of shrimp per km of trawl survey.

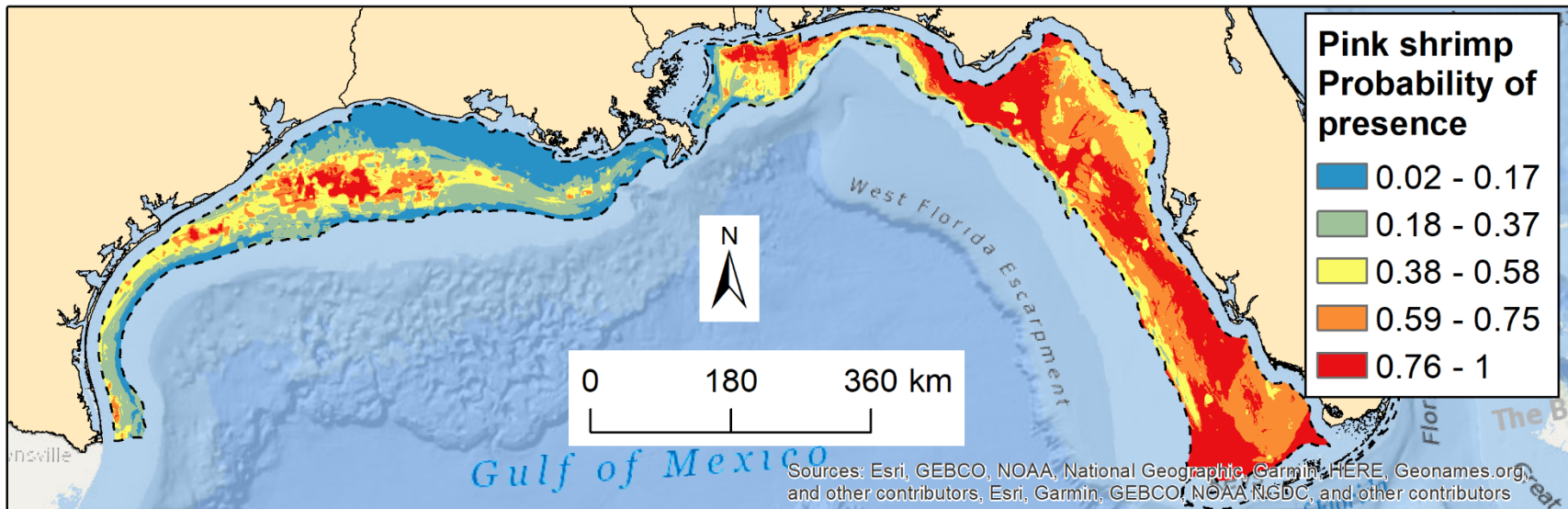


Figure 1.5. Predicted pink shrimp probability of presence in the summer and fall combined.

The study area is indicated by the dashed line, and probability of presence represents the probability of capture given a trawl survey.

1.4 Discussion

Few studies have linked marine and terrestrial ecosystems despite important linkages such as between coastal estuaries and offshore marine habitats (Beger et al. 2010). By analyzing three Penaeid species, we found a consistent pattern that the distributions of these species in the offshore, marine environment were positively related to the amount of nearby coastal wetlands and estuaries. In fact, brown and white shrimp both had interaction effects that included nearby wetlands and an oceanographic factor (MLD and salinity, respectively). These interactions directly demonstrate the linkages between these two ecosystems. Wetland loss and the loss of open water-marsh edges have been independently identified as contributors of shrimp declines in estuarine (Rozas et al. 2007) and marine environments over time (Diop et al. 2007). However, the relationships we quantified further suggest that wetland loss is likely to lead to changes in shrimp distribution in the marine environment.

None of the three Penaeid species' distributions were related to bottom currents or geomorphology metrics of slope, BPI, or CV of depth. Of the geomorphology variables, only distance to shoal and sediment grain size were selected as predictors, and the importance of these variables were relatively minor. Predicted white shrimp CPUE was less in close proximity to shoals and pink shrimp were positively associated with sand grain sizes. Similar to findings of Drexler and Ainsworth (2013) and a qualitative assessment by Mulholland (1984), we found pink shrimp occurred with sand substrates and had a lower probability of occurrence with mud, silt, or gravel substrates. In contrast to Montero et al. (2016), we did not find brown shrimp were associated with mud and silt sediments. However, we excluded trawl data offshore of Florida because it appeared to be outside of the geographic range of the species. If we had included the hundreds of absence locations in those eastern nGoM waters with sand substrates, then the results may have been similar to Montero et al. (2016). By analyzing the three Penaeid species separately, we observed the spatial distinctions among species. Brown shrimp had the highest CPUE in the western nGoM, while pink shrimp were most common east of the W 88° longitude near Mobile Bay, Alabama. White shrimp mostly occurred near the shoreline of the central nGoM.

1.4.1 Brown Shrimp

A greater CPUE of brown shrimp in summer coincides with their peak spawning season in the nGoM (Gulf of Mexico Fishery Management Council 1981). Notably, there was no direct relationship with the high frequency hypoxic zone. Nonetheless, the predicted CPUE of brown shrimp was extremely low in the hypoxic zone. This is likely because brown shrimp had a higher CPUE with a deeper MLD, and these waters tended to occur outside of the high frequency hypoxic zone. The association with fall bottom temperature is also associated with farther offshore habitats. Craig et al. (2005) found brown shrimp move both farther inshore and offshore when hypoxia is severe (i.e., leaving the intermediate depth zone), and this spatial pattern is observed in our model of brown shrimp distribution. We note that our data describes the long-term average brown shrimp distribution rather than annual events that other studies have considered. Harvest strategies for shrimp also do differ in Louisiana and Texas. In Louisiana, shrimp trawlers work in the most shallow waters (< 20 m depth) near estuaries earlier in the year. For Texas, harvest does not occur until later and shrimp trawlers use areas > 20 m in depth (Craig et al. 2005).

1.4.2 Pink Shrimp

The time of day for surveys was influential for pink shrimp and brown shrimp, as CPUE was far higher from approximately midnight to 11:00 for these species. In a lab study, pink shrimp buried themselves in response to daylight and were active in dark conditions (Hughes 1968). Hughes (1968) also found individuals synchronized emergence within a 20–30 minute timeframe. Studies of other Penaeids worldwide have also documented this phenomenon (Wassenberg and Hill 1994). Our pink shrimp model

showed the association with salinity resulted in a distribution skewed towards Florida, although pink shrimp were also predicted to be in other parts of the central nGoM where sand sediments were present. The interaction effects among habitat variables and the time of surveys suggests that surveys at ineffective times are likely to complicate the quantification of species-habitat relationships. The confusion matrix for pink shrimp showed absence can be more accurately predicted compared to presence. This result is expected given that species are detected imperfectly in surveys (see MacKenzie et al. 2002 for details on the topic), and our results depict the predicted catch in a trawl survey. In essence, a species may be present even though a single survey did not detect that species. Applications of these SDMs should consider the results as relative rather than absolute numbers. Waters with a greater probability of occurrence or relative abundance (CPUE) of species should be interpreted in the context of waters with lower probability of occurrence or relative abundance.

1.4.3 White Shrimp

White shrimp CPUE was much higher in the coastal zone where salinity was < 30 psu. White shrimp selected waters closer to the shoreline, with a greater chlorophyll-*a* concentration, and depths of 12–30 m. White shrimp also had a positive association with summer bottom temperatures that were > 28°C. Research on the temporal dynamics of white shrimp in Louisiana coastal waters showed greater water temperatures related to higher abundances of early juveniles, and to a lesser extent, more adult white shrimp. A greater CPUE of white shrimp in the fall coincides with their peak spawning season in the nGoM (Gulf of Mexico Fishery Management Council 1981).

1.4.4 Conclusions and Implications for Dredging

In summary, we have identified habitat associations and modeled the distribution of three federally managed Penaeid shrimp species. Nearby wetlands and oceanographic characteristics, such as bottom temperature, salinity, MLD, and chlorophyll drove the majority of the spatial patterns for these species. Bottom currents, slope, and depth heterogeneity were not associated with species' distributions. In the cases where sediment grain size and distance to shoal were associated with species, the variables explained only a small portion of the variance compared to other variables. We do caution that fishery-independent trawl surveys typically sample ~3 km tows, and microhabitats within these areas were not assessed by our study. Shoals themselves are poorly sampled because of their depth, and, therefore, samples near shoals were assumed to represent those areas. Importantly, the spatial models do show strong spatial patterns that will help inform the identification of important waters for Penaeid species, and their predators, in the nGoM. Broad spatial patterns typical of oceanographic predictors as well as habitat associations with grain size and distance to shoal will help guide impact assessments at a local level, such as at individual dredge sites.

2 Predicting the Marine Distribution of Snappers and Sharks in the Northern Gulf of Mexico

2.1 Introduction

SDMs and similar methods of spatial modeling have proliferated in the last two decades as GIS technologies, remote sensing, availability of spatial data, and computation capacity have rapidly improved. Recent distribution models within marine ecosystems have been applied to ecosystem-based management (Gruss et al. 2018), marine spatial planning (Hattab et al. 2013), scenario assessments (Delevaux et al. 2018), stock assessments (Saul et al. 2013), and climate change (Morley et al. 2018; Su et al. 2013). SDMs can illuminate habitat relationships as well as map the spatial patterns of species' distributions. In turn, mapping is critical for the identification of EFH (Moore et al. 2016; Pennino et al. 2016), defined as those waters and substrates required for a species to spawn, breed, feed, or grow to maturity (US Sustainable Fisheries Act, 1996, Public Law 104-297). EFH is inclusive of prey species, although we are not aware of EFH mapping that explicitly includes the distribution of prey species.

A decade after Robinson et al. (2011) declared that marine ecosystems provide a prime opportunity to test the influence of prey on species' distributions, few studies have explored this possibility (see Volume 2). The nGoM presented an opportunity to test predator-prey relationships with data on a variety of trophic levels. Food webs in the nGoM have been summarized by Tarnecki et al. (2016), including common linkages among Penaeid shrimp, menhaden, squid, and other small demersal and pelagic fish. In particular, the abundance of Gulf menhaden has been shown to have major effects on fisheries (Geers et al. 2016; Robinson et al. 2015). Estuaries, subaquatic vegetation, oyster reefs, and coastal wetlands in the nGoM also contribute towards offshore marine productivity by providing habitat for estuarine-dependent life stages and producing common prey species of the marine environment (e.g., menhaden, shrimp, crabs) (Spies et al. 2016). Much like the effect of prey distribution, the effect of such nearby ecosystems has rarely been considered in SDMs.

In addition to these knowledge gaps, we previously have documented biases towards testing particular habitat variables for particular fish guilds (Volume 1). More specifically, there has been a trend to test numerous substrate predictor variables—but few oceanographic variables—with reef fish, such as snapper. Conversely, the trend for sharks is to test more oceanographic variables, but few substrate variables. Therefore, testing a comprehensive suite of habitat variables has the potential to test these biases and lead to an improved understanding of EFH.

We selected snapper and shark species to study based on their breadth of designated EFH, overlap of a species' EFH with our study area (Federal waters, ≤ 50 m), socio-economic importance, data availability, and potential vulnerability to sand dredging (i.e., demersal species with an affinity to soft sediments). Below, we outline characteristics of each of the selected species:

Sharks:

- Blacktip shark is a large coastal shark that prey on teleost fishes (Cortés 1999) and is listed as globally “vulnerable” by the International Union for Conservation of Nature (IUCN) (Burgess and Branstetter 2000). In the nGoM, juvenile blacktip shark diet is dominated by Gulf menhaden (Betha et al. 2004). Blacktip shark is the second most valuable shark to commercial fisheries of the southeastern US (Castro 1996).
- Spinner shark is listed as globally “near threatened” by the IUCN (Burgess 2009) and is a common target by commercial fisheries. Spinner shark primarily prey on teleost fishes (Cortés 1999), particularly Gulf menhaden (Betha et al. 2004).

- Atlantic sharpnose shark is a relatively small, demersal shark that feeds on crustaceans and teleost fishes (Cortés 1999). In the nGoM, Atlantic sharpnose are regularly caught in recreational and commercial fisheries.

Snappers:

- Red snapper juveniles are demersal before inhabiting natural and artificial reefs as adults (Gallaway et al. 2009). In 2016, commercial landings totaled \$26.5 million in the nGoM (NOAA NMFS Office of Science and Technology 2019); the species is also important for recreational fisheries.
- Lane snapper is a subtropical, reef-associated species that has a demersal juvenile life stage that inhabits shallow waters with sand/mud bottoms, including shoal habitats (Mikulas and Rooker 2008; Wells et al. 2009). Commercial landings of lane snapper are modest, primarily in Florida, where landings totaled \$86,219 in 2016 (NOAA NMFS Office of Science and Technology 2019). They are a regular recreational catch offshore of Florida as well.

The objectives of our study were the following:

- 1) Test for habitat relationships of snapper and coastal shark species with a broad suite of environmental factors, including prey, nearby ecosystems, geomorphology, and oceanographic characteristics.
- 2) Model the spatial distribution of snapper and shark species.

2.2 Methods

2.2.1 Study Area

The study area is described in Section 1.2.1.

2.2.2 Biological Data

Fish data were derived from fishery-independent surveys of SEAMAP and the National Marine Fisheries Service (NMFS) Mississippi Laboratories, which included regular surveys as well as a 1-year survey from the Congressional Supplemental Sampling Program (CSSP) (**Table 2-1**). From these data, we only used data from 2003 and later because we wanted to depict current conditions as best as possible, and this timeframe still provided us with an adequate sample size.

Trawl surveys from the SEAMAP program span the entire nGoM and are conducted in the summer (June–August) and fall (October–December). With the exception of minor changes in sample selection procedures in 2010 and thereafter, surveys have consistently used similar gear and protocols, and a random stratified sampling design based on depth and shrimp statistical area (Craig et al. 2005; Gulf States Marine Fisheries Commission 2017). Trawl surveys targeted shrimp and groundfish using a 12.8-m net in the central and eastern nGoM and a 6.1-m net near Texas. Trawls were conducted consistently during day and night hours. For processing, complete counts were conducted for samples < 22.7 kg, and a sample was taken and the count extrapolated for most species if the sample was larger. Snapper in summer surveys were counted in their entirety. In the fall, only a portion of the biological catch was measured for large samples (> 22.7 kg). For those surveys, the full trawl catch was projected based on a measured sample (e.g., when only half catch was sampled, the number of individuals for each species was doubled). We assumed that this proportionate extrapolation applied to each age group.

Table 2-1. Sources of fisheries-independent survey data spanning 2003–2015.

Sample sizes are provided for waters within our study area.

Data source	Acronym for dataset	Dates	Gear used for survey (<i>n</i> = sample size)	Species modeled
Southeast Fisheries Science Center, NMFS, Mississippi Laboratory (MSLABS)	MSLABS-BL	2003-2017; 8 April–16 Nov	Bottom longline; <i>n</i> = 1,014	Atlantic sharpnose shark, blacktip shark, and spinner shark
Congressional Supplemental Sampling Program (CSSP)	CSSP-BL	2011; 7 April–25 Oct	Bottom longline; <i>n</i> = 498	Atlantic sharpnose shark, blacktip shark, and spinner shark
SEAMAP-trawl	SEAMAP trawl	2003-2017; 30 May–19 Dec	Trawl; <i>n</i> = 5,620	Red snapper (age 0 & age 1), lane snapper (age 0)

We removed extremely long or short trawl survey lengths, and subsequently, trawls ranged from 11–52 min and 1.0–5.2 km. We transformed trawl survey counts to CPUE, calculated as fish km⁻¹ of survey. Prior to analyses, we used GAMs (knots=3) to explore the effects of trawl length and duration on the presence/absence or CPUE of species. All tests showed <2% of the deviance was explained by these effects except for a negative association with red snapper age-0 (2.7%) and a positive association with lane snapper age-1 (4.5%). Given these mixed effects, we proceeded with using CPUE and presence/absence data. We used summer (June–August) and fall (October–December) trawl surveys.

Surveys from the CSSP-Bottom Longline (CSSP-BL) and MSLABS-BL programs used the same sampling methodology. The methods are described in detail by Driggers III et al. (2012) and are outlined here. All bottom longline surveys used a 15/0 circle hook baited with Atlantic mackerel. The MSLABS-BL and CSSP-BL surveys were randomly placed throughout the nGoM. For BL surveys, gear soak times were targeted to be 1 hour, as defined by the time elapsed between completion of deployment and initiation of retrieval. We used the centroid of trawl tows and bottom longline surveys to depict fish survey locations. For bottom longline surveys, we removed extreme survey efforts of ≥134 min, and survey effort ranged from 37–107 min. We also removed surveys with low hook counts (<80 hooks); the remaining surveys had 86–104 hooks per survey. Fish from bottom longline surveys were measured as count 100 hooks⁻¹ hr⁻¹. We used GAMs (knots=3) to explore the effects of survey length (km) and duration (min) on each species. All tests showed < 2% of the deviance were explained by these factors.

2.2.3 Fish Age Classification

The age of red and lane snapper were distinguished for the analysis because these species undergo ontogenetic shifts between early juvenile stages and the adult stage, when they inhabit reefs. The vast majority of sharks were juveniles and adults, both of which occur in similar habitats. Therefore, we did not distinguish age for sharks, but simply had the goal to estimate the proportion of each life stage present. During trawl surveys, fish lengths were measured as total length (TL), fork length (FL), or standard length (SL). We converted all lengths to TL for age classification. For lane snapper, we used the conversion equations from the species' stock assessment (SEDAR 2016). We categorized age classes based on a Bermuda study of lane snapper because the study measured numerous juveniles (Luckhurst et al. 2000), which were not well described elsewhere. Luckhurst et al. (2000) found a minimum length of 185 mm FL (199 mm TL) for age-1 individuals. Based on this finding, we defined lane snapper age-0

(< 199 mm TL) and age-1 or greater (\geq 199 mm TL). Given the dramatic reduction in growth after age one (Luckhurst et al. 2000), we did not distinguish further age groups.

For red snapper length conversions, we used equations from the Gulf of Mexico red snapper stock assessment report (SEDAR 2018). Red snapper of 19–50 mm TL are distinguished as post-settlement juveniles (Gallaway et al. 2009), and their prey items differ from older age classes that begin to prey on fish (Szedlmayer and Lee 2004). Because only 0.01% of red snapper captured by trawl were <50 mm TL, we discarded this age class from the analysis. Red snapper < 172 mm TL have mostly been found in open habitats, whereas the majority of those \geq 172 mm inhabit reef habitats (Szedlmayer and Lee 2004). This threshold is further supported by Powers et al. (2018), who aged red snapper captured in trawl surveys and found age-0 red snapper = 30–170 mm, age-1 = 175–297 mm, and age-2 = 320–360 mm TL. Therefore, we categorized red snapper into the following juvenile age classes (range of catch 18–893 mm TL):

Age-0 = 51–172 mm TL ($n = 25,528$)

Age-1 = 173–300 mm TL ($n = 5,670$)

The majority of sharks were measured by natural total length (nat TL). When only FL was measured, we converted it to nat TL using equations derived from available MSLABS-BL data. For Atlantic sharpnose, the conversion equation was: nat TL mm = $57.308 + 1.118$ (FL mm); $r^2 = 0.952$. For blacktip shark, the equation was nat TL mm = $44.129 + 1.162$ (FL mm); $r^2 = 0.954$. For spinner shark, the equation was TL mm = $25.811 + 1.170$ (FL mm); $r^2 = 0.972$). To further classify the age classes of sharks surveyed, we investigated the literature on length-age class associations. For Atlantic sharpnose shark, we followed the classifications used by Drymon et al. (2012) and Hoffmayer and Parsons (2003), who used the following age classes: Young-of-year = 330–590 mm nat TL, Juvenile = 600–840 mm nat TL, Adults \geq 850 mm nat TL. Castro (1996) reported blacktip shark neonates ranged from 530–660 mm nat TL offshore of Florida, and we used 660 mm nat TL as the maximum length to classify young-of-year blacktip shark. To distinguish juveniles from adults, we classified adults as those \geq 1,407 mm nat TL. This is the median length reported for female blacktip sharks at maturity (Carlson et al. 2006). Carlson et al. (2006) showed male median length at maturity was slightly lower (1,246 mm TL); therefore, our estimate is likely to be slightly biased towards juveniles rather than adults. However, not all sharks were sexed, so detailed evaluation could not be conducted. With an approximation based on Carlson's study (Carlson and Baremore 2005), we defined those spinner shark < 70 cm as young-of-year, 70–116 cm as juvenile, and those > 116 cm as adults.

Of the sexed blacktip sharks, 54% were females and 46% were males. Blacktip shark lengths ranged 656–2,466 mm nat TL with a median of 1,350 mm nat TL in MSLABS-BL data and 1,252 mm nat TL in CSSP surveys. Of blacktip sharks with an age classification, 0.002% (3 individuals) were classified as young-of-year, 65% were juvenile, and 35% were adults. Of the sexed Atlantic sharpnose sharks, 49% were males and 51% were females. Atlantic sharpnose shark length ranged 340–1,223 mm nat TL with a median of 920 mm nat TL in MSLABS-BL surveys and 895 mm nat TL in CSSP surveys. Of Atlantic sharpnose sharks with an age classification, 2% were young-of-year, 27% were juvenile, and 71% were adults. Of sexed spinner shark, 49% were female and 51% were male. Spinner shark age classification showed 3% as young-of-year, 43% as juvenile, and 54% as adults.

2.2.4 GIS Methods and Environmental Data

All GIS analysis procedures and data collection methods were followed as described in **Section 1.2.3** with the exceptions described below. Overall, we developed predictor variables to depict oceanographic conditions, geomorphology, nearby ecosystems, geography, and prey species (**Tables 2-2, 2-3**). Natural reef locations were mapped during SEAMAP reef fish video surveys and were acquired through several mechanisms, including available charting, historical knowledge from fishermen, and bathymetric mapping (i.e., side-scan sonar and multi-beam sonar) (pers. communication, Matthew Campbell and

Brandi Noble, NOAA National Marine Fisheries). The point density of and distance to artificial structures, including artificial reefs as well as oil and gas platforms, were calculated for the study area. Sea surface temperature (SST) variables were obtained as predictors using the same methods as used for other oceanographic data (**Section 1.2.3**). We used SST data processed from GHRSSST (Group for High Resolution Sea Surface Temperature) version 4.1 of the Multiscale Ultrahigh Resolution Level 4 analysis, which obtains high resolution data via a blend of satellite measures (JPL MUR MEaSUREs Project 2015).

Prey species were first identified from the literature. Then, we developed predictor variables for prey that were either readily sampled by the SEAMAP trawl surveys or were available from models developed during our project (**Table 2-3**). We derived data on menhaden (primarily Gulf menhaden), croaker, spot croaker, mantis shrimp, and squid from SEAMAP trawl data. The SEAMAP survey locations were interpolated to create a continuous surface. We synthesized data on prey species from 2003–2017 and conducted ordinary kriging with a spherical semivariogram model. Eight points were used for analysis within a maximum distance of 10 km. The ArcGIS expand tool was used to further extrapolate prey distributions when trawl surveys were > 10 km from a location in the study area.

Table 2-2. Environmental variables developed to predict snappers and sharks in the nGoM.

Oceanographic predictors were obtained from aggregations of monthly means spanning 2003–2017.

Variable type	Variable (units)	Radius of analyses (km)	Resolution of data	Data source
Substrate	CV of depth	3	90 m	CRM + modifications
Substrate	Density of oil platforms & artificial reefs (structures km ⁻²)	5	90 m	BOEM, Marine Cadastre
Substrate	Distance to oil platforms & artificial reefs (km)	NA	90 m	BOEM, Marine Cadastre
Substrate	Distance to natural reef (km)	NA	90 m	Matthew Campbell, NOAA National Marine Fisheries
Substrate	Distance to shoal (km)	NA	90 m	Pickens and Taylor, NOAA Biogeography Branch, identification of shoals
Substrate	Proportion of area with shoal	3	90 m	Pickens and Taylor, NOAA Biogeography Branch, identification of shoals
Substrate	Mean sediment grain size (mm)	3	370 m	Chris Jenkins, University of Colorado, interpolation of usSEABED data
Substrate	Proportion of area with BPI ≥ 1	3	90 m	CRM + modifications
Substrate	Slope (degrees)	3	90 m	CRM + modifications
Oceanographic	Mean depth (m)	3	90 m	CRM + modifications
Oceanographic	Sea surface temperature (°C)	NA	1.2 km	GHRSSST blend of satellite measures, MUR-JPL_L4-GLOB-v4.0, NASA Jet Propulsion Lab
Oceanographic	Bottom temperature (°C)	NA	4.4 km	HYCOM + NCODA
Oceanographic	Chlorophyll- <i>a</i> (mg m ⁻³)	NA	5.5 km	Aqua MODIS satellite, 8-day
Oceanographic	Bottom salinity (psu)	NA	4.4 km	HYCOM + NCODA
Oceanographic	Mixed layer thickness (m) (depth where temperature change from surface is 0.2°C)	NA	4.4 km	HYCOM + NCODA
Oceanographic	Bottom current velocity—U & V directions(m s ⁻¹)	NA	9.3 km	HYCOM + NCODA
Oceanographic	Hypoxia (mean probability of hypoxia)	NA	90 m	North Carolina State University
Geography	East or west of longitude W 88°	NA	90 m	-
Geography	Distance to shoreline (km)	NA	90 m	-
Nearby ecosystems	Nearby wetlands	NA	90 m	NWI
Nearby ecosystems	Nearby estuaries	NA	90 m	NWI

* HYCOM + NCODA = Hybrid Coordinate Ocean Model + Navy Coupled Ocean Data Assimilation; GHRSSST = Group for High Resolution SST Level 4 analysis, Multiscale Ultrahigh Resolution (MUR) based on nighttime; MODIS = Moderate Resolution Imaging Spectroradiometer; CRM = Coastal Relief Model; NWI = National Wetlands Inventory

Table 2-3. Biological predictor variables developed to predict the distribution of snappers and sharks.

Species	Prey species predictor variables	Justification for prey inclusion
Red snapper age-0	Brown shrimp (fall), pink shrimp, mantis shrimp (<i>Squilla</i> spp.), squid (<i>Loligo</i> spp.)	(Bradley and Bryan 1975; Szedlmayer and Lee 2004; Wells et al. 2008a)
Red snapper age-1	Searobin (<i>Prionotus</i> spp.), lizardfish (<i>Synodus</i> spp.), squid	(Szedlmayer and Lee 2004; Wells et al. 2008a)
Lane snapper age-0	Brown shrimp (fall) & pink shrimp	(Franks and VanderKooy 2000)
Lane snapper age-1	None identified	NA
Atlantic sharpnose shark	Menhaden (<i>Brevoortia</i> spp.), croaker (<i>Micropogonias undulatus</i>), pink shrimp, brown shrimp (summer)	(Bethea et al. 2004; Drymon et al. 2012; Harrington et al. 2016)
Blacktip shark	Menhaden, croaker	(Barry et al. 2008; Bethea et al. 2004)
Spinner shark	Menhaden	(Bethea et al. 2004; Cortés 1999)

2.2.5 Statistical Analysis

We examined predictor variables for multicollinearity, and we removed highly correlated variables ($r > 0.80$) prior to analyses. In addition to environmental predictors, we used season (summer or fall) for trawl surveys of snappers, day-of-year for shark species, and start time of surveys as predictors. The time at which surveys are conducted can affect the detectability of species and has previously been documented as affecting shark catch (Driggers III et al. 2012). Seasonality of trawls represented changes in summer and fall distributions because of species' natural history. We did not use year as an explanatory factor because the primary objective of our research was to determine long-term value of waters and substrates of the nGoM. Therefore, we assume years of high or low abundance are representative of long-term fish distribution.

Because improving our understanding of species-habitat relationships was one of our objectives, the variables in shark and snapper models differed by a few variables. We excluded variables with no hypothesized relationship to particular fish species to help in minimizing issues with moderately correlated variables. Chlorophyll-*a*, nearby wetlands, and nearby estuaries were tested only for sharks. SST variables were only tested for blacktip shark and spinner shark, as the other species have demersal habits. We only used density of artificial structures, distance to artificial structures, and distance to natural reefs to test with snappers. To summarize predictor variable results, we calculated the frequency of each variable type as depicted in **Table 2-2**.

Training (70%) and validation (30%) data were selected by the same process as used with the statistical analyses of Penaeid shrimp (**Section 1.2.4**). The BRT analysis procedures outlined in **Section 1.2.4** were used to quantify species-habitat relationships, relative importance of predictors, and interaction effects for snappers and sharks. We also assessed the accuracy of models using the same procedures. We assumed the effect of survey time represented a detectability effect for blacktip shark and applied the model at the

peak time of 02:00. For Atlantic sharpnose shark, day-of-year was a factor in the model, and we predicted at the peak time of year in the model (9 April).

2.3 Results

The frequency of species ranged from red snapper age-1 on 18.7% of trawl surveys to Atlantic sharpnose shark on 58.6% of bottom longline surveys (**Table 2-4**). The relative abundance models for red snapper age-0 and Atlantic sharpnose shark explained 41–43% of the deviance in the validation data with an R_s of 0.59–0.60 in their respective models (**Table 2-5**). All species modeled with presence/absence data had an AUC value of ≥ 0.80 in the validation data, indicating the models were very good at discriminating presence and absence (**Table 2-4**). The confusion matrices showed that absence was consistently predicted more accurately than presence (**Table 2-6 to Table 2-10**).

Across all snapper and shark models, 45 variables were selected across the following variable types: oceanographic (22 variables selected), prey (6), substrate (6), geographic (4), temporal variables (4), and nearby ecosystems (3). Of the 22 oceanographic predictors, the most common variables were MLD (6), bottom temperature (5), and salinity (5). Of the substrate variables, three were related to artificial or natural reefs; sediment grain size, BPI, and distance to shoal were each selected one time. Variable importance varied considerably among variables, though sediment grain size, BPI, and distance to shoal were of relatively minor importance (**Figures 2-1, 2-2**).

Table 2-4. Frequency of select snapper and shark species in the trawl and bottom longline surveys from 2003–2017.

Common name	Number of fishery-independent surveys (n)	Type of modeling	Percent of surveys with presence	Total count of species
Red snapper (age 0)	5,620	Count	36	23,076
Red snapper (age 1)	5,620	Presence/absence	18.7	4,753
Lane snapper (age 0)	5,620	Presence/absence	25.7	9,784
Lane snapper (age 1)	5,620	Presence/absence	20.3	1,143
Atlantic sharpnose shark	1,506	Count	58.6	8,765
Blacktip shark	1,506	Presence/absence	28.2	1,831
Spinner shark	1,506	Presence/absence	12.6	872

Table 2-5. BRT specifications and percent deviance explained for marine SDMs of snappers and sharks.

Species	Tree complexity	Learning rate	# of trees	Cross-validation	Validation	Validation Spearman correlation
Red snapper (age 0)	5	0.01	1,400	Deviance explained = 50%	Deviance explained = 41%	0.59
Red snapper (age 1)	2	0.01	1,550	AUC = 0.83	AUC = 0.80	NA
Lane snapper (age 0)	3	0.01	1,950	AUC = 0.84	AUC = 0.83	NA
Lane snapper (age 1)	2	0.02	2,550	AUC = 0.91	AUC = 0.89	NA
Atlantic sharpnose shark	5	0.005	1,900	Deviance explained = 45%	Deviance explained = 43%	0.60
Blacktip shark	1	0.02	1,250	AUC = 0.84	AUC = 0.80	NA
Spinner shark	2	0.005	1,400	AUC = 0.90	AUC = 0.87	NA

Table 2-6. Confusion matrix from the validation data of the red snapper age-1 model at the optimal threshold to distinguish presence/absence, which was with a probability of 0.31.

	Observed absence	Observed presence	User's accuracy (% correct)
Predicted absence	1,323	174	88%
Predicted presence	172	207	55%

Table 2-7. Confusion matrix from the validation data of the lane snapper age-0 model at the optimal threshold to distinguish presence/absence, which was with a probability of 0.37.

	Observed absence	Observed presence	User's accuracy (% correct)
Predicted absence	1,185	200	86%
Predicted presence	201	290	59%

Table 2-8. Confusion matrix from the validation data of the lane snapper age-1 model at the optimal threshold to distinguish presence/absence, which was with a probability of 0.44.

	Observed absence	Observed presence	User's accuracy (% correct)
Predicted absence	1,379	154	90%
Predicted presence	104	238	70%

Table 2-9. Confusion matrix from the validation data of the blacktip shark model at the optimal threshold to distinguish presence/absence, which was with a probability of 0.47.

	Observed absence	Observed presence	User's accuracy (% correct)
Predicted absence	323	61	84%
Predicted presence	34	67	66%

Table 2-10. Confusion matrix from the validation data of the spinner shark model at the optimal threshold to distinguish presence/absence, which was with a probability of 0.33.

	Observed absence	Observed presence	User's accuracy (% correct)
Predicted absence	333	76	81%
Predicted presence	24	52	68%

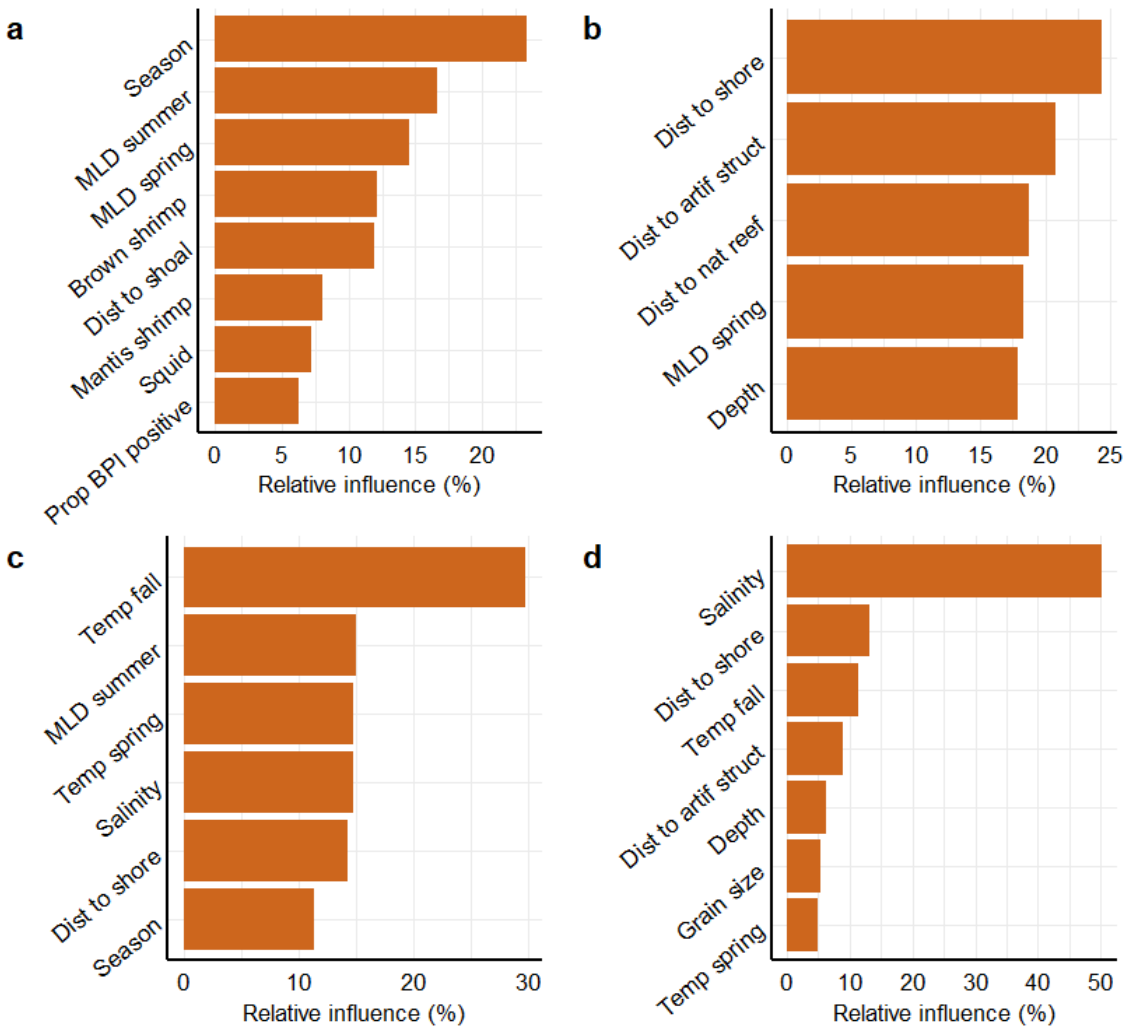


Figure 2.1. Relative importance of variables in models of a) red snapper age-0, b) red snapper age-1, c) lane snapper age-0, d) lane snapper age-1.

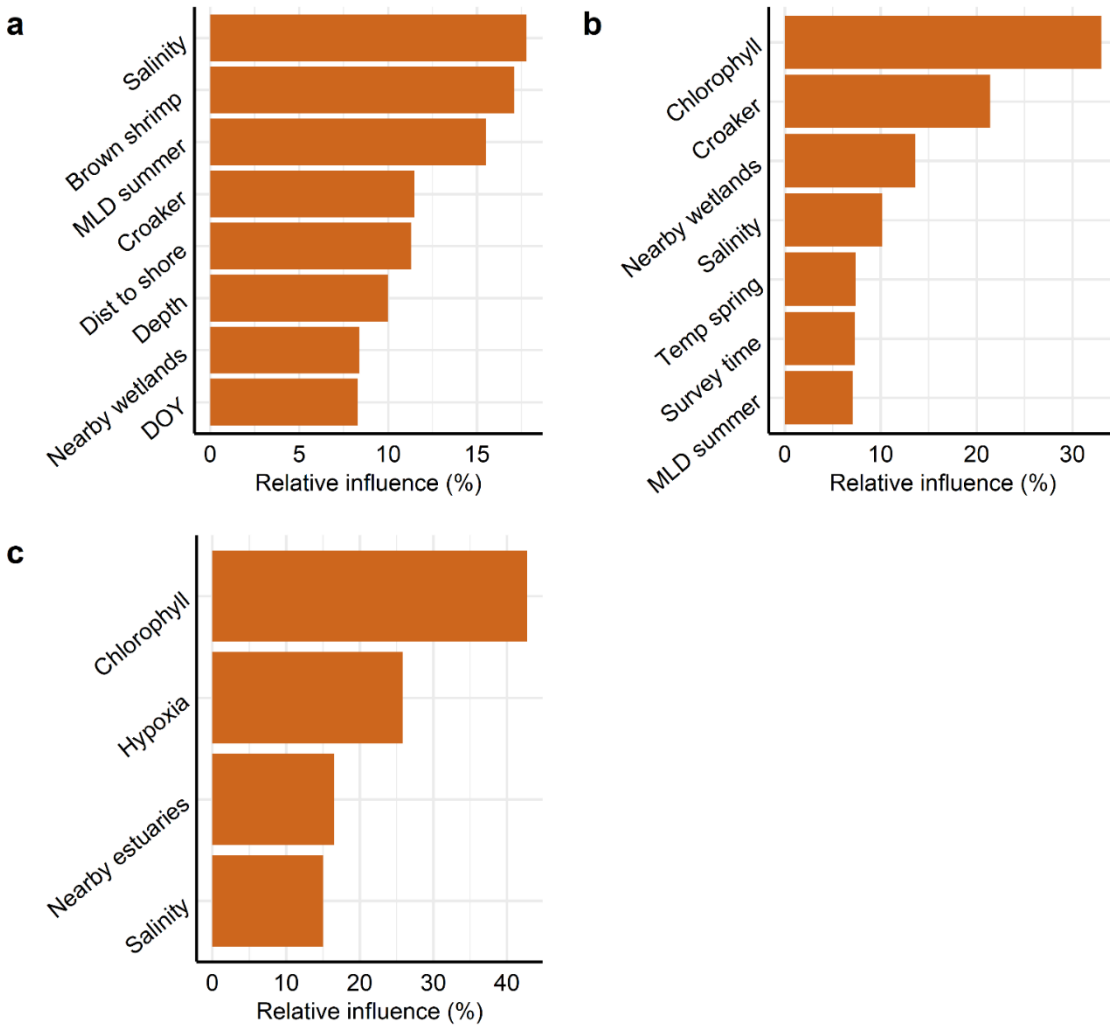


Figure 2.2. Relative importance of variables in models of a) Atlantic sharpnose shark, b) blacktip shark, c) spinner shark.

2.3.1.1 Red Snapper Age-0

As expected, red snapper age-0 (**Figure 2.3**) were more abundant in the fall as individuals become large enough to be captured by trawl sampling. MLD in the spring and fall had strong, positive relationships with red snapper. These young juveniles were positively associated with prey species of brown shrimp, mantis shrimp, and squid. In regard to geomorphology, red snapper age-0 had a higher CPUE within the first few km of shoals and with a high proportion of area with a positive BPI. An interaction between BPI and distance to shoal (IE = 49) showed red snapper had a high CPUE within a few km of a shoal regardless of BPI. At greater distances from shoals, the BPI had a linear, positive effect when the BPI had a positive value positive for > 40% of the surrounding area. MLD in summer primarily affected red snapper during the fall season (IE = 31), and CPUE was highest when a deeper MLD in spring was coincided with a higher brown shrimp CPUE (IE = 19).

2.3.1.2 Red Snapper Age-1

Red snapper age-1 (**Figure 2.4**) shifted farther offshore compared to age-0, but still had a positive association with spring MLD. Individuals moved closer to artificial structures (often within 25 km) and natural reefs (often within 75 km). In regard to interactions, red snapper age-1 moved farther offshore when artificial structures were within 20–40 km (IE = 44). Interpreting these distance from mapped variables, we observed that this meant red snapper age-1 moved farther offshore near Alabama, Mississippi, Louisiana, and Texas (where oil platforms and other artificial reefs were common), but individuals did not move farther offshore in Florida shelf waters. Distance to shoreline interacted with MLD spring (IE = 32) and showed MLD spring had the strongest effect farther from the shoreline. Red snapper age-1 had the highest probability of presence at greater depths up to a 50 m depth.

2.3.1.3 Lane Snapper Age-0

As expected, lane snapper age-0 (**Figure 2.5**) were more abundant in the fall as individuals become large enough to be captured by trawl sampling. Lane snapper age-0 had a higher probability of presence with higher fall and spring bottom temperatures. They had a higher probability of presence farther from the shoreline, with more shallow MLD, and with salinities in the range of 20–34 psu compared to salinities > 34 psu. An interaction between salinity and spring bottom temperature (IE = 61) showed low probability of occurrence at higher salinities (> 32 psu) except where spring bottom temperatures were > 22°C. Probability of occurrence was highest where a shallow MLD in summer coincided with high fall bottom temperatures (IE = 61).

2.3.1.4 Lane Snapper Age-1

Lane snapper age-1 (**Figure 2.6**) had a greater probability of presence in waters < 40 m in depth and with cooler spring bottom temperatures. They were less common with mud and silt substrates (particularly, < 0.03 mm grain size) and when grain sizes became larger than granule gravel (see Wentworth 1922). No interactions were observed.

2.3.1.5 Blacktip Shark

Blacktip shark (**Figure 2.7**) were positively related to chlorophyll and nearby wetlands; they had the highest probability of occurrence with low salinity waters spanning 27–34 psu. Blacktip shark were positively related to croaker prey, but did not directly select for their primary prey of menhaden. The species had a higher probability of occurrence where MLD in summer was relatively deep, and they were more likely to be caught from 00:00–03:00. Interactions were minimal.

2.3.1.6 Spinner Shark

Spinner shark (**Figure 2.8**) had the highest probability of occurrence with salinities of ≤ 30 psu, and they were positively related to chlorophyll and nearby estuaries. Spinner shark had a positive relationship with hypoxia, as probability of occurrence was highest in waters with 20–40% probability of hypoxia. We examined the hypoxia map, and the 20–40% range corresponded well with the edge of highest probability hypoxic zone. Spinner shark had a moderate interaction between hypoxia and nearby estuaries (IE = 38), showing that spinner shark selected waters with 20–40% hypoxia probability that coincide with a relatively high amount of nearby estuaries.

2.3.1.7 Atlantic Sharpnose Shark

Atlantic sharpnose shark CPUE (**Figure 2.9**) was positively related to the prey species of brown shrimp and croaker as well as the amount of nearby wetlands. Atlantic sharpnose shark CPUE was highest in the spring, farther from the shoreline, and at greater depths up to our 50-m maximum in the study area.

Bottom salinity showed a dichotomy where salinities of 27.5–30 psu and 33.5–36 psu had the highest CPUE, but intermediate salinities had fewer Atlantic sharpnose shark. Interaction effects were minimal.

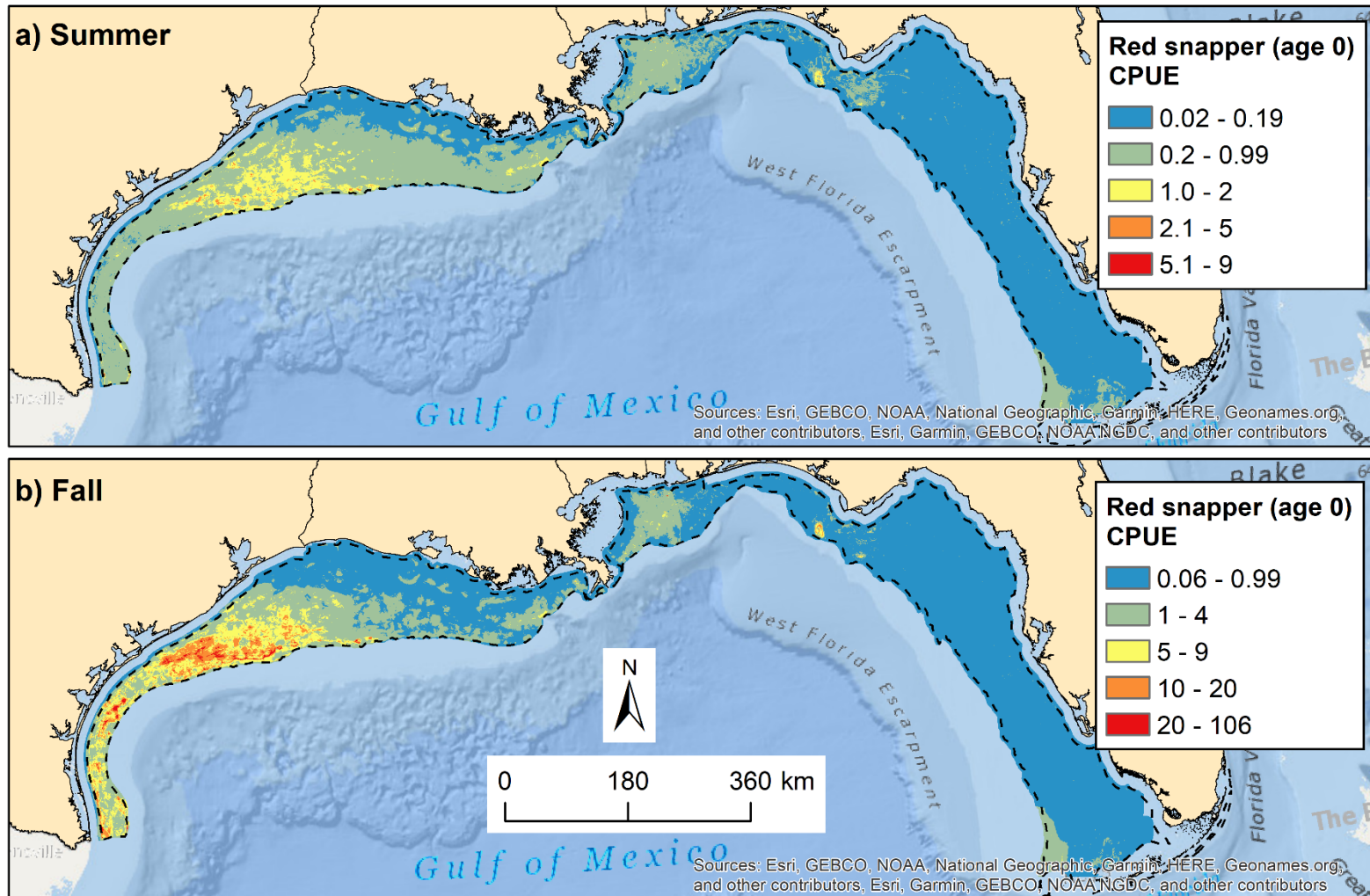


Figure 2.3. Predicted red snapper age-0 CPUE in the a) summer and b) fall seasons.

The study area is indicated by the dashed line, and CPUE represents the predicted number of red snapper per km of trawl survey.

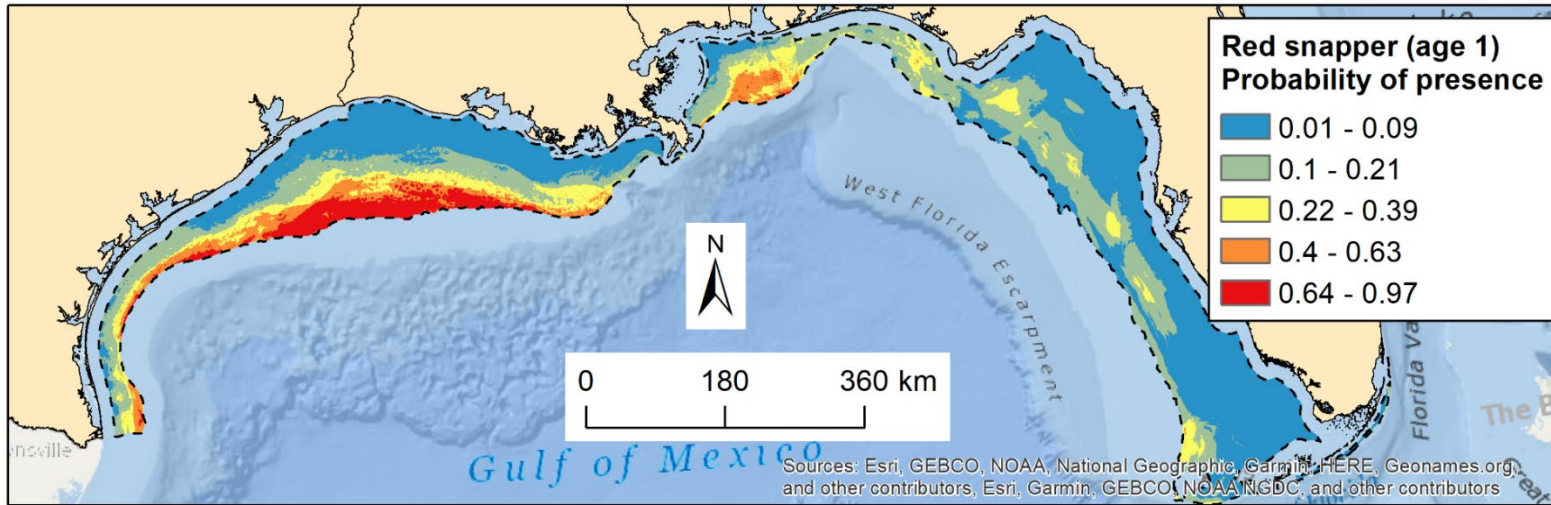


Figure 2.4. Predicted red snapper age-1 probability of presence in the summer and fall seasons combined.
The study area is indicated by the dashed line, and CPUE represents the predicted number of red snapper per km of trawl survey.

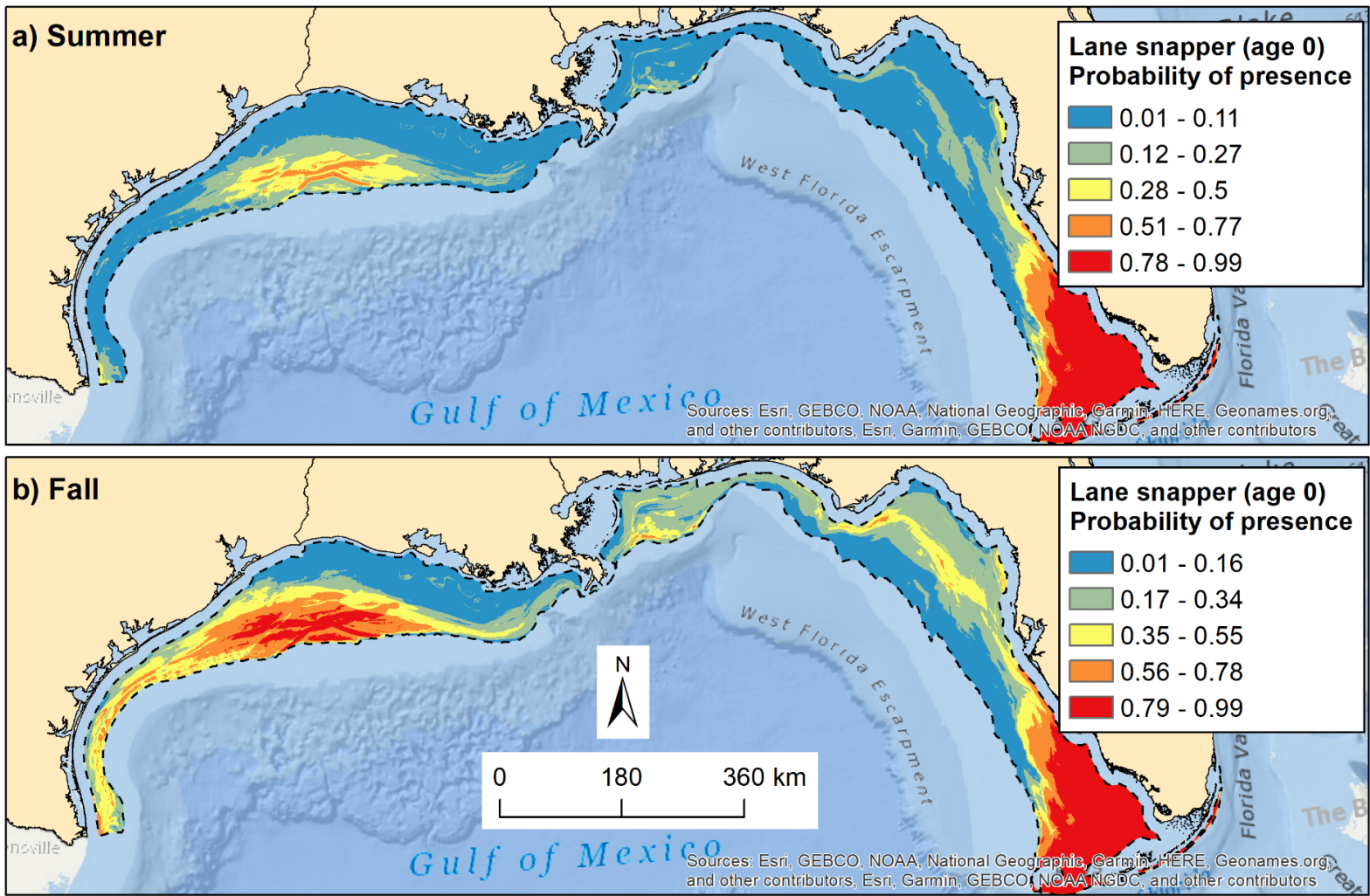


Figure 2.5. Predicted lane snapper age-0 probability of presence in the a) summer and b) fall seasons.
 The study area is indicated by the dashed line, and CPUE represents the predicted number of lane snapper per km of trawl survey.

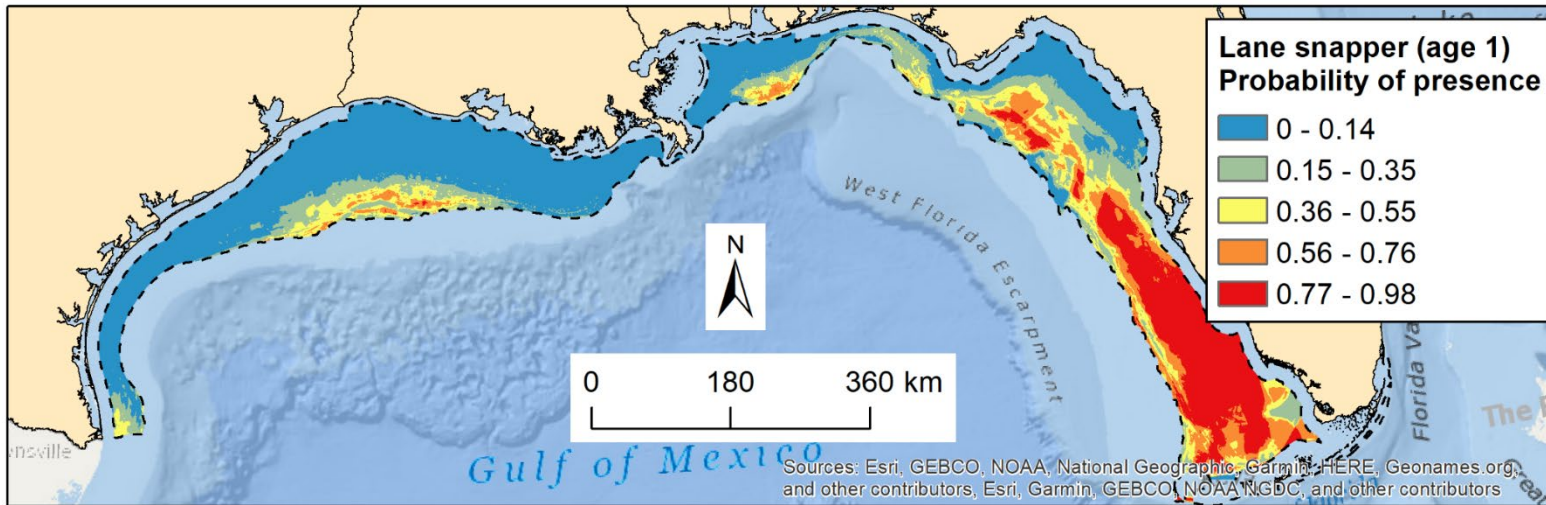


Figure 2.6. Predicted lane snapper age-1 probability of presence in the summer and fall seasons combined.
The study area is indicated by the dashed line, and probability of presence represents the probability of capture given a trawl survey.

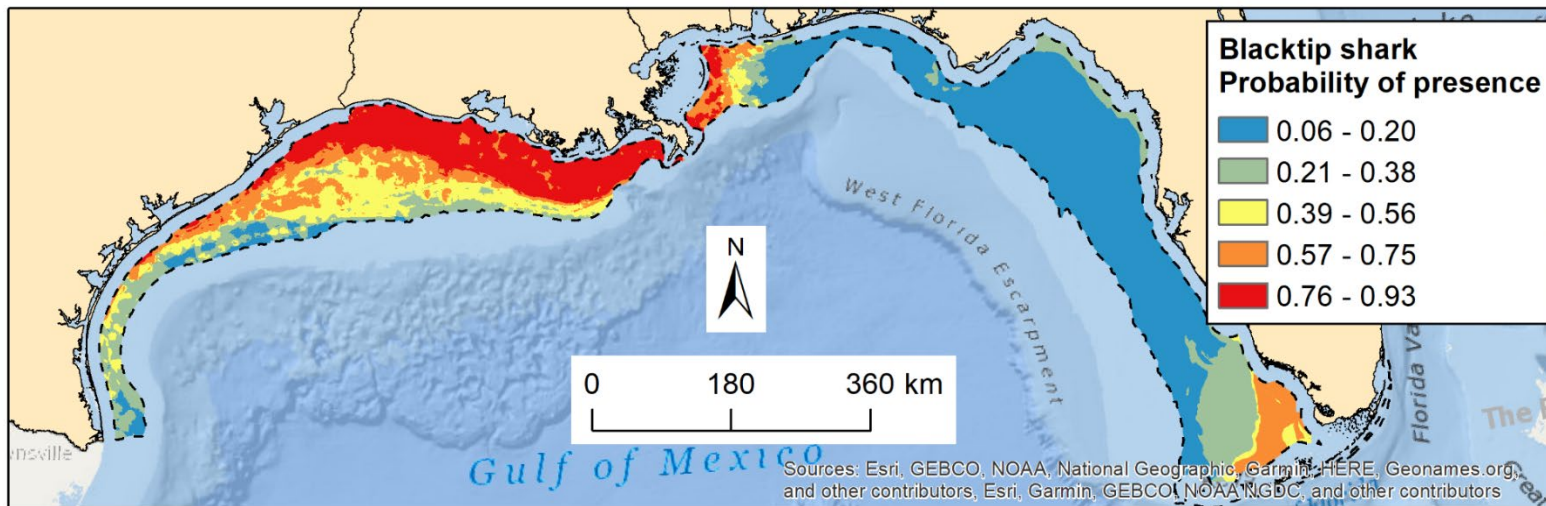


Figure 2.7. Predicted blacktip shark probability of presence in the spring–fall seasons.

The study area is indicated by the dashed line, and probability of presence represents the probability of capture given a bottom longline survey.

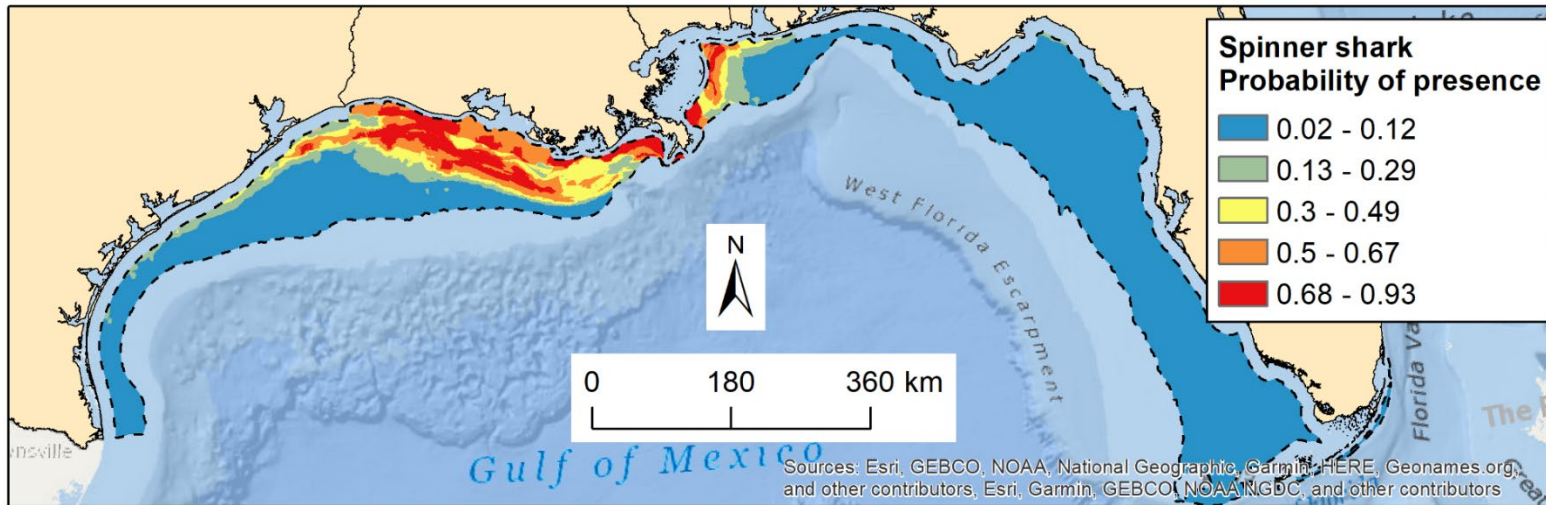


Figure 2.8. Predicted spinner shark probability of presence in the spring–fall seasons.

The study area is indicated by the dashed line, and probability of presence represents the probability of capture given a bottom longline survey.

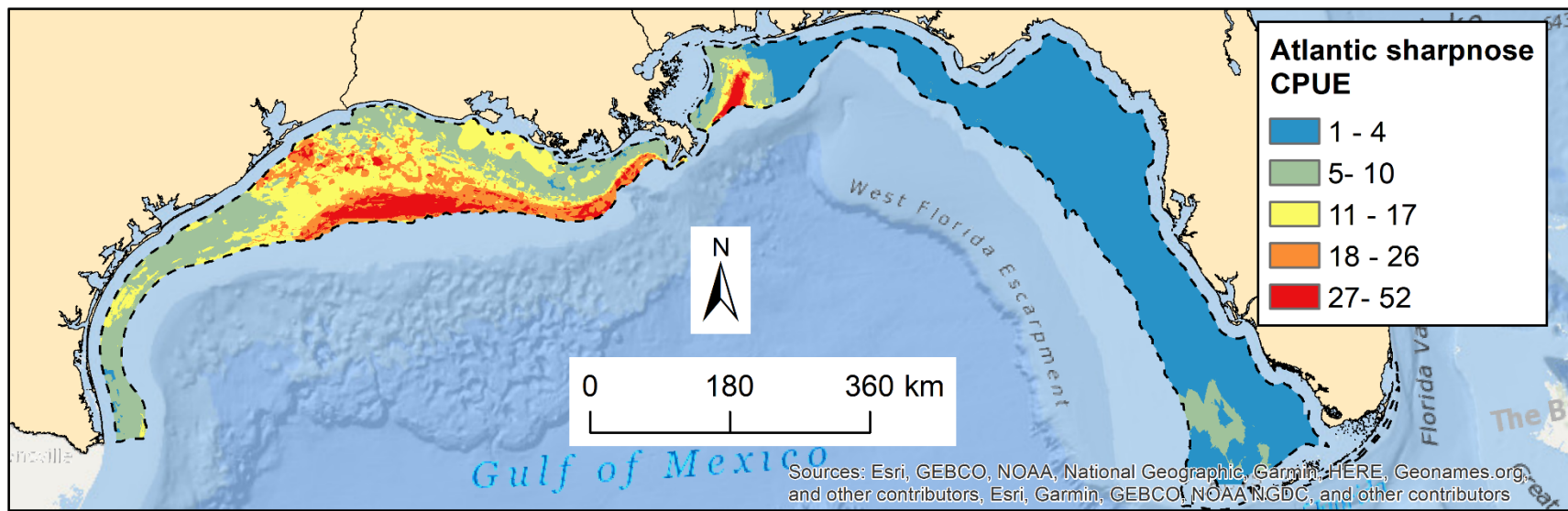


Figure 2.9. Predicted Atlantic sharpnose shark CPUE in the spring–fall seasons.

The study area is indicated by the dashed line, and CPUE represents the predicted number of sharks hooks⁻¹⁰⁰ hr⁻¹ of bottom longline survey.

2.4 Discussion

By testing a comprehensive set of predictors, we discovered new species-habitat relationships with MLD, the area of nearby wetlands and estuaries, prey species, and substrate characteristics. Across all species considered, oceanographic variables were the most commonly selected predictors, and they often scored high in variable importance. Although distance to artificial or natural reefs were important predictors in the red snapper age-1 model, the other geomorphology predictors had low variable importance. Geomorphology predictors only appeared to refine fish distributions where oceanographic characteristics were already suitable for fish. For example, red snapper age-0 had a higher CPUE in close proximity to shoals and where the BPI predominately showed a hill topography. Yet, their spatial distribution was highly skewed towards the western GoM, where MLD was deeper and brown shrimp prey were most common. This inference of variable influence across spatial scales is supported by Mannocci et al. (2017), who shows that oceanographic features operate at intermediate scales of 1–100 km and factors such as prey operate at a scale of 10 m–1 km. We further suggest that geomorphology also affects species at this local scale. We acknowledge that prey species may be also be correlated with geomorphology, oceanography, and nearby ecosystems characteristics. SDMs are correlative models, but the species-habitat relationships we quantified here provide for refined distributions of species, reveal patterns of important habitat factors, and provide a basis for future hypothesis testing concerning EFH. As with the shrimp results (above), no species analyzed here was associated with benthic characteristics of bottom current velocity, slope, or depth heterogeneity.

We discovered MLD was an influential predictor of red snapper age-0 and age-1, lane snapper age-0, blacktip shark, and Atlantic sharpnose shark. MLD was also a predictor of brown shrimp CPUE (Section 1.3.), which were related to red snapper age-0 and Atlantic sharpnose shark. Measures of MLD have rarely been included as predictor of marine fish SDMs (Volume 1). In the nGoM, MLD appears to be influenced by the Loop Current, eddies, and wind stress. The Loop Current enters the Gulf of Mexico through the Yucatan Channel, goes northward in the basin, and then exits via the Straits of Florida. Importantly, the Loop Current produces large spin-off eddies that often take a westward path originating near the Mississippi Delta (Johnson et al. 2017). To a lesser extent, wind influences water vertical structure and contributes to the vorticity of eddies (Ohlmann et al. 2001). The end result is an exchange of shelf waters and deeper waters (Johnson et al. 2017; Ohlmann et al. 2001), and upwelling or downwelling can contribute towards biological productivity (Spies et al. 2016). Therefore, the relationships with MLD and shrimp, snapper, and sharks may be the result of enhanced productivity in these waters.

We found prey species and nearby ecosystems were common predictors of species. In our review of spatial distribution models, prey were only considered in 4% of studies (Volume 1). Of these, none were studies of sharks or reef fish. Because SDMs are correlative models, we do not have direct evidence of drivers of species' distributions. However, the statistical models suggest that prey species can be better predictors than other environmental attributes. There are two probable reasons for these results: 1) fish-prey relationships represent a causal relationship, or 2) prey species represent a combination of environmental conditions, which are better correlated to species compared to single predictor variables. Future studies could further test predator-prey relationships to determine their applicability to EFH and ecosystem-based management. The productivity of nearby ecosystems, such as wetlands and estuaries, are usually ignored in marine fish research. Only a few studies have linked offshore marine fish or shrimp distribution to the proximity of mangroves (Barbier and Strand 1998) or estuaries (Beger and Possingham 2008). Nonetheless, interactions among coastal and marine ecosystems have been cited as important areas for conservation (Pickens et al. 2017), and trophic energy exchanges are thought to be important among these ecosystems (Zuercher and Galloway 2019).

As with pink shrimp (**Section 1.3**), the confusion matrices showed predictions of absences were consistently more accurate than predicted presences. Given that detectability is imperfect during surveys (MacKenzie et al. 2002), the SDMs presented here should be considered as relative rather than absolute numbers. Waters with a greater probability of occurrence or relative abundance (CPUE) should be interpreted in comparison to waters with lower probability of occurrence or relative abundance.

2.4.1 Red Snapper

Research on juvenile red snapper in the nGoM has focused on geomorphology, including the chronological selection of sand, shell, low-relief shell, and high-relief shell (Lingo and Szedlmayer 2006; Szedlmayer and Howe 1997; Wells et al. 2008b). Our study adds to these known associations with substrate complexity by quantifying topography at a landscape scale in the form of high relief (i.e., a positive BPI) and the proximity of sand shoals. Observational evidence has suggested a role between juvenile red snapper and sediment grain size (Powers et al. 2018; Szedlmayer and Mudrak 2014); however, we did not find evidence of such an association at the scale of our study area. Spatial patterns of red snapper age-0 were primarily determined by MLD and the predicted CPUE of brown shrimp, with minor contributions from other prey species and substrate complexity. A distinct ontogenetic shift occurred from age-0 to age-1 red snapper. Age-1 red snapper were still associated with spring MLD, but they moved to greater depths, farther offshore, and closer to natural and artificial structures. Our spatial models have similar patterns as Dance and Rooker's (2019) results, though we validated our model and took a more mechanistic approach, rather than testing variables like latitude and longitude.

Switzer et al. (2015) found the abundance of juvenile red snapper near Louisiana were reduced during years with severe hypoxia, and juveniles moved to deeper, cooler waters during those years. Although hypoxia was not selected as a variable for red snapper age-0 in our study, the model showed a low predicted CPUE in waters with a high frequency of hypoxia. The brown shrimp prey species is well known to avoid hypoxic waters (Craig 2012; Craig et al. 2005), and the correlation between brown shrimp and red snapper age-0 may have indirectly resulted in the low predicted CPUE in waters prone to hypoxia. Furthermore, the correlations between brown shrimp and predatory species provides evidence that hypoxia could affect fish farther up the food chain. We caution that trawl surveys were near shoals, but shoals themselves are usually too shallow to survey. Therefore, our habitat models do not account for fine-scale variation directly at the shoal. Dubois et al. (2009) does present evidence that Ship Shoal offshore of Louisiana is a hypoxia refuge for benthic invertebrates.

2.4.2 Lane Snapper

We found both age groups of lane snapper were strongly associated with oceanographic variables, particularly bottom temperature and salinity. They shifted from using salinities of ≤ 34 psu at age-0 to waters with > 34 psu at age-1. Given their subtropical / tropical range, the relationship with bottom temperature was not surprising. However, we expected more relationships with geomorphology. Juvenile lane snapper had been associated with sand shoals offshore of Louisiana (Brooks et al. 2005) and Texas (Mikulas and Rooker 2008; Wells et al. 2009). Our findings of juvenile lane snapper age-1 did show an association sandy sediments, but an association with shoals was lacking.

2.4.3 Blacktip, Spinner, and Atlantic Sharpnose Shark

Spinner and blacktip shark were not correlated with their main prey, menhaden, but bottom trawl surveys may not sample menhaden very well. Both shark species were associated with factors that indirectly describe menhaden habitat. Gulf menhaden utilize estuary and nearshore waters of moderate salinity, where they prey directly on phytoplankton and zooplankton (Olsen et al. 2014). These prey are likely correlated with chlorophyll-*a* measures. Gulf menhaden use estuaries and open water-marsh edges (Costanza et al. 1989; Rozas and Minello 2015; Rozas et al. 2007); therefore, a shark association with

these habitats is expected. Drymon et al. (2013) found the distribution of blacktip shark was best explained by crustacean biomass, but noted these sharks eat small fish. Here, we infer that wetland productivity likely leads to greater blacktip shark CPUE. Spinner shark have previously been found in waters with relatively low dissolved oxygen (Drymon et al. 2013). We found a positive relationship between spinner shark and hypoxia with a peak probability of occurrence with a 25-40% chance of hypoxia. These results suggest that spinner shark may feed on prey that either aggregate at the edge of hypoxic zones (e.g., Craig 2012) or aggregate towards the surface (e.g., Hazen et al. 2009). In lab experiments, Atlantic menhaden (*B. tyrannus*) have been shown to avoid waters with low dissolved oxygen (Wannamaker and Rice 2000), but the specific behavior of menhaden due to hypoxia in the nGoM needs further study.

For Atlantic sharpnose shark, we found habitat relationships that differed from studies that found positive correlations with chlorophyll concentration (Drymon et al. 2013) and depths < 30 m (Drymon et al. 2010). Similar to red snapper, the association with brown shrimp and greater depths meant that low CPUEs of Atlantic sharpnose shark were predicted for frequently hypoxic waters. Harrington et al. (2016) found juvenile Atlantic sharpnose shark fed heavily on Penaeid shrimp offshore of Texas, and other studies in the nGoM have shown they feed on a wide range of species (Bethea et al. 2006; Drymon et al. 2012). The lack of a relationship with chlorophyll in our results may be because salinity, croaker, and nearby wetlands better explained Atlantic sharpnose shark distribution in nearshore waters where chlorophyll is high.

2.4.4 Conclusions and Implications for Dredging

In our wide-ranging study, we can conclude that not all shoals have equal value to fish. This is supported by the fact that Rutecki et al. (2014) reported lane snapper and red snapper in the GoM were either frequent, common, or rare, depending on the shoal. Oceanographic factors, prey species, and nearby wetlands and estuaries all play key roles in determining species' distributions. Evidence shows geomorphology only plays a minor or localized role in determining fish species' distributions. We caution that our analyses were based on fish surveys that typically span 3 km in length and microhabitat selection within this range may have been missed. Yet, our models showed a high predictive ability and were able to quantify suspected relationships between red snapper and substrate complexity. SDMs can illuminate habitat relationships as well as map the spatial patterns of species' distributions. We have demonstrated that modeling the distribution of species can be accomplished at a relatively fine scale. These spatial patterns can be applied to make management decisions and apply a strategic, regional perspective on natural resource use in the nGoM.

3 Predicting the Marine Distribution of Red Snapper, Black Seabass, and Shark Species in the South Atlantic

3.1 Introduction

The US Southeast Atlantic OCS (hereby South Atlantic) supports a diverse assemblage of fishes that provide high economic value to commercial and recreational fisheries. Fisheries economic impact in recent years has exceeded \$4.4 billion annually and supports more than 77,000 jobs (National Marine Fisheries Service 2017). Geographically identified along the coastlines of the states of North Carolina, South Carolina, Georgia, and Florida, the region is bounded by prominent geographic features of Cape Hatteras and Cape Canaveral and oceanographically by the Gulf Stream current to the east. The region is home to species that use an array of seafloor and oceanographic habitats dominated by unconsolidated sediments forming sheets, ridges, and shoals, with interspersed emergent rocky reefs and other hard structures like artificial reefs and shipwrecks. Managed fish species are grouped into complexes based upon their general habitat preference (e.g., “snapper-grouper complex” that use reef and rocky habitats), migratory behaviors (“coastal pelagics” transient predators that seasonally migrate along the coastline), and migratory top predators (sharks).

Fishery-independent surveys have assessed managed species to derive indices of abundance that contribute to stock assessments for managing the populations. However, details on habitat selection and drivers of the broader distribution patterns remain poorly understood for the vast majority of species, including members of the snapper-grouper complex that are surveyed around rocky reefs throughout the region. For the snapper-grouper complex, there is evidence that some species are likely to be observed over soft sediments, though those sediment habitats may be adjacent to structured habitats (Bacheler et al. 2014). Studies of shark distributions are rare in the South Atlantic and mostly focus on seasonality, size and ages in coastal waters and estuaries (Thorpe et al. 2004; Ulrich et al. 2007).

Improvements in species distribution information and a greater understanding of relationships of fish to seafloor characteristics are needed to guide planning and permitting for ocean activities that may impact fish and their habitats. The demand for offshore marine sands is increasing in the United States (Drucker et al. 2004), and sand is commonly used for beach renourishment, barrier island restoration, and wetland restoration. Sand shoals are often preferred sand resources because of the quantity of sand per unit area, and the dredging of OCS sand shoals is likely to increase in the future as demand increases due to renourishment cycles for beaches, emergency repairs of beaches after storms, and the projected effects of sea-level rise (Nairn et al. 2004). BOEM is part of the US Department of the Interior and is responsible for the management and development of mineral resources on the OCS, including sediment resources. As demand for OCS sand increases, BOEM faces complex multi-user interactions, including issues of resource allocation, cumulative impacts from repeated use, fisheries use and potential conflicts, protection of archaeological sites, oil and gas infrastructure, potential renewable energy infrastructure, and impacts on EFH (Michel et al. 2013).

For this paper, we focus on two primary objectives:

- 1) Test for habitat relationships of red snapper, black seabass, and selected shark species with a broad suite of environmental factors, including geomorphology, oceanographic characteristics, and nearby ecosystems
- 2) Model and predict the spatial distribution of five species of hard bottom fish and sharks to identify overlap with sand shoals that may be targeted for dredging activities

3.2 Methods

3.2.1 Study Area

The study area depicted the South Atlantic region of the United States spanning from Cape Hatteras, North Carolina through the South Atlantic Bight. The landward boundary of the study area was defined by OCSLA, which distinguishes Federal- and state-managed waters. The oceanic boundary of the study area was defined by a 50-m contour line from NOAA's CRM (NOAA National Centers for Environmental Information). This particular area was the focus because sand dredging operations authorized by the BOEM for beach and barrier island restoration does not exceed 50 m. The study area had a total surface area of 84,924 km². The benthic substrate of the area consists of fine to coarse sand sediments with patchy areas of hard bottom reefs. The most prominent feature of the South Atlantic is the Gulf Stream current, which creates a cross-shelf mixing of waters and strong water stratification (Castelao 2011). Surface and bottom water intrusions from the Gulf Stream are most frequent in the summer months, are influenced by wind stress, interact with salinity, and are more frequent at the extreme northern and southern waters of the South Atlantic Bight (Castelao 2011).

3.2.2 Biological Data

Fish data were derived from fishery-independent surveys of SEAMAP, the Southeast Reef Fish Survey (SERFS) and the NOAA Southeast Fisheries Science Center, Mississippi Laboratories (**Table 3-1**). From these data, we only used data from 2004 and later because we wanted to depict current conditions as best as possible, and this timeframe still provided us with an adequate sample size. The vast majority of surveys were conducted from spring through fall, and, therefore, our SDMs do not represent snapper or shark distributions in the winter.

Surveys from the MSLABS-BL program used the methodology outlined in detail by Driggers III et al. (2012), with details briefly outlined here. All bottom longline surveys used a 15/0 circle hook baited with Atlantic mackerel. Surveys were randomly placed throughout the study area. Gear soak times were targeted to be 1 hr, as defined by the time elapsed between completion of deployment and initiation of retrieval. We used the centroid of bottom longline surveys to depict fish survey locations. For MSLABS-BL data, we removed extreme survey lengths. More specifically, we removed one survey that was 25 km in length and one that was 0.08 km. The remaining surveys ranged from 0.50–3.7 km. Additional bottom longline data were obtained from the SEAMAP program; however, the survey methodology differed, so these data were only used as presence data for validation purposes. Of the SEAMAP data, we only used surveys offshore of Florida, Georgia, and South Carolina for analysis because waters in our study area were not sampled offshore of North Carolina. The SEAMAP bottom longline methods offshore of Florida and Georgia included using either a 15/0 or a 12/0 circle hook baited with squid. For South Carolina, SEAMAP used a 15/0 circle hook and had a soak time target of 30 min, but they used Atlantic mackerel and striped mullet as bait.

The SERFS program surveys hard bottom locations in the South Atlantic with Chevron traps, and, since 2010, video attached to Chevron traps (Bacheler et al. 2014). The determination of sampling locations and details of both methods are provided by Bacheler et al. (2014), with a brief outline given here. Chevron traps were baited with 24 menhaden, and traps were deployed in groups of six, with each > 200 m from each other. The soak time for traps was targeted for 90 min. Since 2010, video cameras have been mounted over the mouth of traps with a view of approximately 60° from the trap. Video frames were read to identify fish at 30 second intervals over 20 min, which resulted in 41 frames read per sampling effort. For SERFS video surveys, we removed any video surveys that had < 41 frames read. For SERFS trap surveys, we removed traps with a duration of < 10 min and those > 150 min, because they had a much lower catch rate in preliminary models.

Table 3-1. Sources of fisheries-independent survey data. Sample sizes are provided for waters within our study area.

Data source	Acronym for dataset	Dates	Gear used for survey (<i>n</i> = # of surveys)	Species modeled
Southeast Fishery-Independent Survey	SEFIS video	2010–2017; 21 Apr–27 Oct	Video; <i>n</i> = 6,264	Red snapper Validation only for sandbar shark, tiger shark
Southeast Area Monitoring and Assessment: reef fish traps	SEAMAP traps	2010–2017; 23 Apr–26 Oct	Chevron traps; <i>n</i> = 5,210	Black sea bass
Southeast Fisheries Science Center, NMFS, Mississippi Laboratory	MSLABS-BL	2004–2017; 21 Apr–25 Sep	Bottom longline; <i>n</i> = 386	Blacknose shark, sandbar shark, tiger shark
Southeast Area Monitoring and Assessment: bottom longline	SEAMAP longline	2006–2016; 22 Apr–29 Dec	Bottom longline	Validation only for blacknose shark, tiger shark

3.2.3 GIS and Environmental Data Sources

All GIS analysis procedures and data collection methods were followed as described in **Section 1.2.3**, with the following modifications and additions. We developed predictor variables to depict oceanographic conditions, geomorphology, nearby ecosystems, and geography (**Table 3-2**). We used a bathymetry dataset derived as part of the South Atlantic Marine Bight Assessment (Conley et al. 2017). Despite these data being the best available for the South Atlantic, a few notable errors persisted. We updated a 1,600 km² and a 400 km² region offshore of northeastern North Carolina with sounding points acquired in 2016 (NOAA National Centers for Environmental Information 2016). To be consistent, we used the same kriging methods as the South Atlantic Marine Bight Assessment (Conley et al. 2017). To describe aspect, we calculated the aspect cosine and sine. We calculated depth, CV depth, slope, sediment grain size, proportion of area with shoal, slope, aspect, and the BPI within a 3-km radius using ArcGIS focal statistics.

Hard bottom habitats were depicted by three datasets that were combined. A predictive model (developed by Matthew Poti, NOAA Biogeography Branch) depicting probability of hard bottom occurrence was converted into a presence/absence model by representing areas with $\geq 36.3\%$ probability of occurrence as hard bottom presence locations. This threshold was derived as the maximum AUC value, which is the threshold that corresponds with the model’s optimal discrimination ability. We then added polygon data from South Atlantic Marine Bight Assessment mapping of hard bottom features. With this dataset, we removed the classifications of “possible” and “potential” hard bottom or hard bottom slope; these low confidence areas depicted seabed features > 2 km from known hard bottom locations and had substantial uncertainty. All “probable” hard bottom locations (≤ 2 km from known hard bottom), “high confidence” (≤ 1 km from known hard bottom), and very confident (mapped) locations were added to the spatial model. The probable and high confidence locations often depicted polygons where hard bottoms were known to be present along the periphery. The third dataset was the original synthesis of hard bottom point locations that were used as input into NOAA’s predictive model. We removed point locations already classified as hard bottom (from above) and those within 90 m of hard bottom. These adjacent points often surrounded areas depicted as hard bottom. These restrictions resulted in 687 additional points. Because these were often isolated points, we calculated a 1 km buffer around these locations to add to the hard bottom model.

Table 3-2. Environmental variables developed to predict fish species in the South Atlantic.

Oceanographic predictors were from aggregations of monthly means spanning 2003-2017.

Variable type	Variable	Resolution of data	Source data
Substrate	Mean depth (m)	90 m	CRM plus modifications
Substrate	CV of depth	90 m	CRM plus modifications
Substrate	Density of artificial reefs (reefs km ⁻¹)	90 m	BOEM, Marine Cadastre
Substrate	Distance to artificial reef (km)	90 m	
Substrate	Distance to shoal (km)	90 m	Pickens and Taylor, NOAA Biogeography Branch, identification of shoals
Substrate	Proportion of area with shoal	90 m	Pickens and Taylor, NOAA Biogeography Branch, identification of shoals
Substrate	Mean sediment grain size (mm)	90 m	The Nature Conservancy, South Atlantic Marine Bight Assessment, substrate data
Substrate	Proportion hills (with BPI ≥1)	90 m	CRM plus modifications
Substrate	Slope (°)	90m	CRM plus modifications
Substrate	Proportion hard bottom	90 m	Matt Poti, NOAA Biogeography Branch + The Nature Conservancy- SAMBA
Substrate	Distance from hard bottom (km)	90 m	Matt Poti, NOAA Biogeography Branch + The Nature Conservancy- SAMBA
Substrate	Aspect (cosine)	90 m	CRM plus modifications
Substrate	Aspect (sine)	90 m	CRM plus modifications
Oceanographic	Bottom temperature (°C)	9.8 km	HYCOM + NCODA
Oceanographic	Chlorophyll-a (mg m ⁻³)	5.1 km	Aqua MODIS satellite, 8-day composites
Oceanographic	Surface current direction- U (eastward water velocity, m s ⁻¹)	8.9 km	HYCOM + NCODA
Oceanographic	Surface current direction- V (northward water velocity, m s ⁻¹)	8.9 km	HYCOM + NCODA
Geography	Distance to shoreline	90 m	-
Nearby ecosystems	Nearby wetlands (km ²)	90 m	NWI
Nearby ecosystems	Nearby estuaries (km ²)	90 m	NWI

* HYCOM + NCODA = HYbrid Coordinate Ocean Model + Navy Coupled Ocean Data Assimilation; MODIS = Moderate Resolution Imaging Spectroradiometer. CRM = Coastal Relief Model; NWI = National Wetlands Inventory

Salinity data were initially explored, but were excluded because there was minimal variation in our study area. To define the Gulf Stream, and subsequently the distance to the Gulf Stream, we examined summer U- and V- current velocity (m s⁻¹) for the summer season. The mean current velocity was highest during this season. We visually examined the data in 0.5 m s⁻¹ increments and classified waters averaging ≥ 0.5 m s⁻¹ for either the U or V direction as part of the Gulf Stream. This classification created a unified Gulf Stream current in our study area. We used Euclidean distance to calculate distance to the Gulf Stream.

To determine if coastal wetlands contributed to the distribution of fish in the marine environment, we used the classification of “estuarine and marine wetland” to depict estuarine wetlands and “estuarine and marine deepwater” to depict estuaries from the NWI dataset (U. S. Fish and Wildlife Service 2018). First,

we calculated the maximum distance to wetlands within our study area, which was approximately 130 km in the South Atlantic. Then, we summed the number of 90-m cells depicting wetlands, and estuaries, within a radius of 130 km of each cell. The metric was converted to wetland km² and estuaries km² within each 130-km cell. Distance to shoreline was calculated by back-transforming boundaries of the Submerged Lands Act (SLA). The boundaries of the SLA represent a distance of 3 nm from the shoreline of South Atlantic states. We used the buffer tool to re-create the approximate shoreline boundaries (3–9 nm from SLA), and then calculated the Euclidean distance from the shoreline to the entirety of the study area.

3.2.4 Statistical Analysis

We investigated predictor variables for multicollinearity and removed highly correlated variables ($r > 0.80$) prior to analyses. Of note, we removed summer bottom temperature because of a strong correlation with depth ($r = -0.83$). In regard to temporal predictors, we used day-of-year and start time as variables in all models. The time at which surveys are conducted can affect the detectability of species and has previously been documented affecting shark catch (Driggers III et al. 2012). We did not use year as an explanatory factor because our primary objective was to determine long-term use of waters and substrates of the South Atlantic. Therefore, we assume years of high or low abundance are representative of long-term fish distribution.

Because improving our understanding of species-habitat relationships was one of our objectives, the variables in species models differed by a few variables. We excluded variables with no hypothesized relationship to species to help minimize issues with moderately correlated variables. We used chlorophyll as predictor of species except for red snapper. Red snapper are usually farther offshore than a relationship with chlorophyll would suggest. In the Gulf of Mexico (section 2), red snapper were found to be related to shrimp distribution, so we did include nearby wetlands in the South Atlantic models of red snapper. In models of demersal species (red snapper, black sea bass, blacknose shark), we did not test SST. Given the nGoM results (**Sections 1 and 2**), we did not test bottom current velocity. Instead, we tested surface current velocities because of the observed association between surface currents and MLD in the Gulf of Mexico. Data on MLD was not available for the South Atlantic.

For reasons described in **Section 1.2.4**, we aggregated training (70%) and validation (30%) data with alternating bands along a latitudinal gradient (Error! Reference source not found.). The use of a latitudinal gradient maintained a depth gradient in each block. More specifically, we reclassified latitude into 70 equal interval divisions, which resulted in 15-km bands across the study area. We then alternated the delineation of training (two bands) and validation (one band) datasets to achieve the desired ratio of training and validation data. The BRT analysis procedures outlined in **Section 1.2.4** were used to quantify species-habitat relationships, the relative importance of predictors, and interaction effects for snappers and sharks. We also assessed the accuracy of models using the same procedures as described from presence/absence modeling. For blacknose shark, the threshold obtained from the maximum Kappa statistic provided an extremely small sample size of predicted presences. Therefore, we used the presence/absence threshold obtained from minimum distance on the receiver operating characteristic plot. We assumed the effect of time of survey represented a detectability effect of tiger shark. Therefore, we applied the model at their peak time of detectability, which was 23:00.

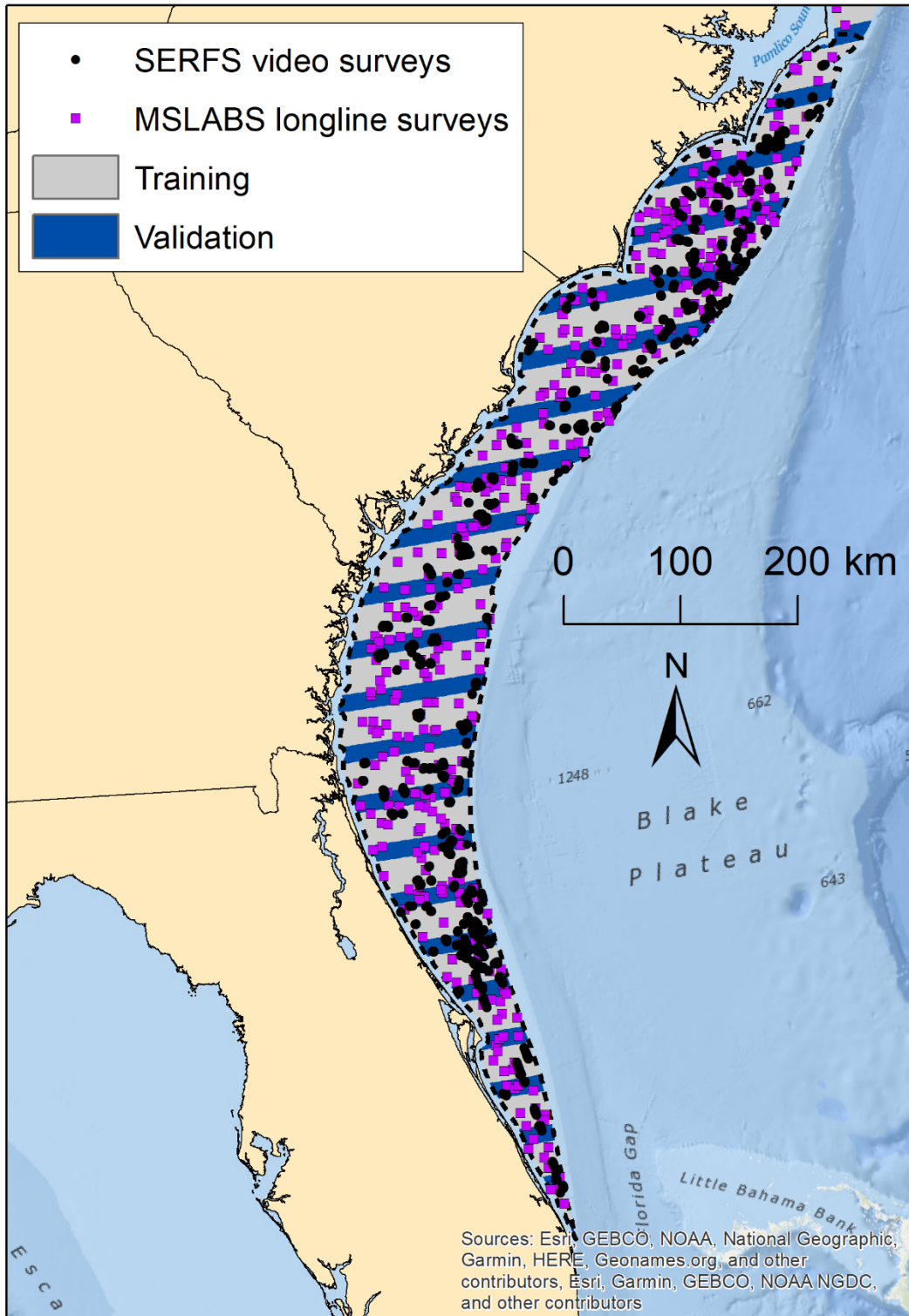


Figure 3.1. The study area with training and validation zones depicted with surveys overlaid. SERFS trap surveys were often at video survey locations.

3.3 Results

The validation results showed AUC statistics ranged from 0.73–0.89, which indicated a good or very good ability of models to discriminate present and absent locations of species (**Table 3-3**). The confusion matrices (**Table 3-4** to **Table 3-8**) showed absences were better predicted than presences for blacknose shark and red snapper. Tiger and sandbar shark models had similar abilities to discriminate presence and absence. For the most common species, black sea bass, presence was predicted better than absences. No geomorphology variables were selected by species, and variable importance measures showed a mixed of oceanographic condition, nearby estuaries and wetlands, and depth all contributed to the SDMs (**Figure 3.2**).

3.3.1 Red Snapper

Red snapper (**Figure 3.3**) were present on 24% of reef video surveys. Red snapper were positively related the amount of nearby wetlands and had the highest probability of occurrence with a depth range of 25–38 m. Red snapper were more likely to occur within approximately 45 km of the Gulf Stream and with westward surface currents. Interaction effects were particularly strong. Red snapper were more likely to occur with a combination of a high amount of nearby wetlands and a greater depth (IE = 212). A combination of westward currents and a depth range of approximately 25–35 m also had a strong positive effect on red snapper occurrence (IE = 82).

3.3.2 Black Sea Bass

Black sea bass (**Figure 3.4**) were present on 66% of reef trap surveys. Black sea bass had a strong, positive relationship with chlorophyll and primarily a positive relationship with nearby estuaries. However, they had a negative relationship with very high amounts of nearby estuaries (> 7,000 km²), which only occurred offshore of North Carolina. Black sea bass had a particularly low probability of occurrence > 75 km from the shoreline (**Figure 3.4**). They had a greater likelihood of occurrence either near the Gulf Stream (< 25 km) or much farther away from the Gulf Stream (> 85 km). Strong interactions occurred among variables. Distance to shoreline had a minimal effect where nearby estuaries were > 7,000 km² (near North Carolina) (IE = 126). For waters with > 7,000 km² of nearby estuaries, the Gulf Stream had a greater effect on black sea bass probability of occurrence (IE = 116).

3.3.3 Blacknose Shark

Blacknose shark (**Figure 3.5**) were present on 10% of MSLABS-BL bottom longline surveys. An additional 56 blacknose shark presence locations from SEAMAP bottom longline surveys were used for validation. The blacknose shark had positive relationships with chlorophyll and the amount of nearby estuaries. They had a higher probability of occurrence with a higher velocity of U-direction surface currents, particularly westward currents; however, eastward currents also had a positive effect. Interactions were not present.

3.3.4 Sandbar Shark

Sandbar shark (**Figure 3.6**) were present on 25% of MSLABS-BL surveys. An additional 50 sandbar shark presence locations from SERFS video were used for validation. For sandbar shark, probability of presence was highest with water depths of 42–50 m and probability declined steadily at more shallow depths. Sandbar shark were related to higher fall bottom temperatures with a sharp increase in their predicted occurrence with temperatures > 24.5°C. Interactions were not present.

3.3.5 Tiger Shark

Tiger shark (**Figure 3.7**) were present on 42% of MSLABS-BL surveys. An additional 37 tiger shark presence locations from SERFS video surveys and 16 SEAMAP bottom longline survey presence locations were used for validation. Tiger shark presence was associated with a greater amount of nearby wetlands and with greater water depths. Peak tiger shark occurrence was predicted with depths of 25–50 m. Survey time also affected the presence of tiger sharks in surveys, as 11:00–23:00 was predicted to have the highest probability of occurrence. There was an interaction with nearby wetlands and survey time (IE = 10). This interaction showed that depth did not have as much of an effect during low probability survey times.

Table 3-3. BRT specifications and AUC statistics for marine species distribution models of snappers and sharks.

Species	Tree complexity	Learning rate	# of trees	Cross-validation AUC	Validation AUC
Red snapper	5	0.02	1,850	0.86	0.79
Black sea bass	4	0.03	1,150	0.86	0.81
Blacknose shark	5	0.001	4,300	0.85	0.88
Sandbar shark	1	0.03	4,950	0.83	0.73
Tiger shark	2	0.002	1,700	0.73	0.73

Table 3-4. Confusion matrix from the validation data of the red snapper model at the optimal threshold to distinguish presence/absence, which was with a probability of 0.41.

	Observed absence	Observed presence	User's accuracy (% correct)
Predicted absence	1,501	331	82%
Predicted presence	135	168	55%

Table 3-5. Confusion matrix from the validation data of the black sea bass model at the optimal threshold to distinguish presence/absence, which was with a probability of 0.58.

	Observed absence	Observed presence	User's accuracy (% correct)
Predicted absence	274	153	64%
Predicted presence	239	1,157	83%

Table 3-6. Confusion matrix from the validation data of the blacknose shark model at the optimal threshold to distinguish presence/absence, which was with a probability of 0.15.

	Observed absence	Observed presence	User's accuracy (% correct)
Predicted absence	101	7	94%
Predicted presence	24	61	72%

Table 3-7. Confusion matrix from the validation data of the sandbar shark model at the optimal threshold to distinguish presence/absence, which was with a probability of 0.33.

	Observed absence	Observed presence	User's accuracy (% correct)
Predicted absence	73	34	68%
Predicted presence	21	59	74%

Table 3-8. Confusion matrix from the validation data of the tiger shark model at the optimal threshold to distinguish presence/absence, which was with a probability of 0.42.

	Observed absence	Observed presence	User's accuracy (% correct)
Predicted absence	52	25	68%
Predicted presence	34	79	70%

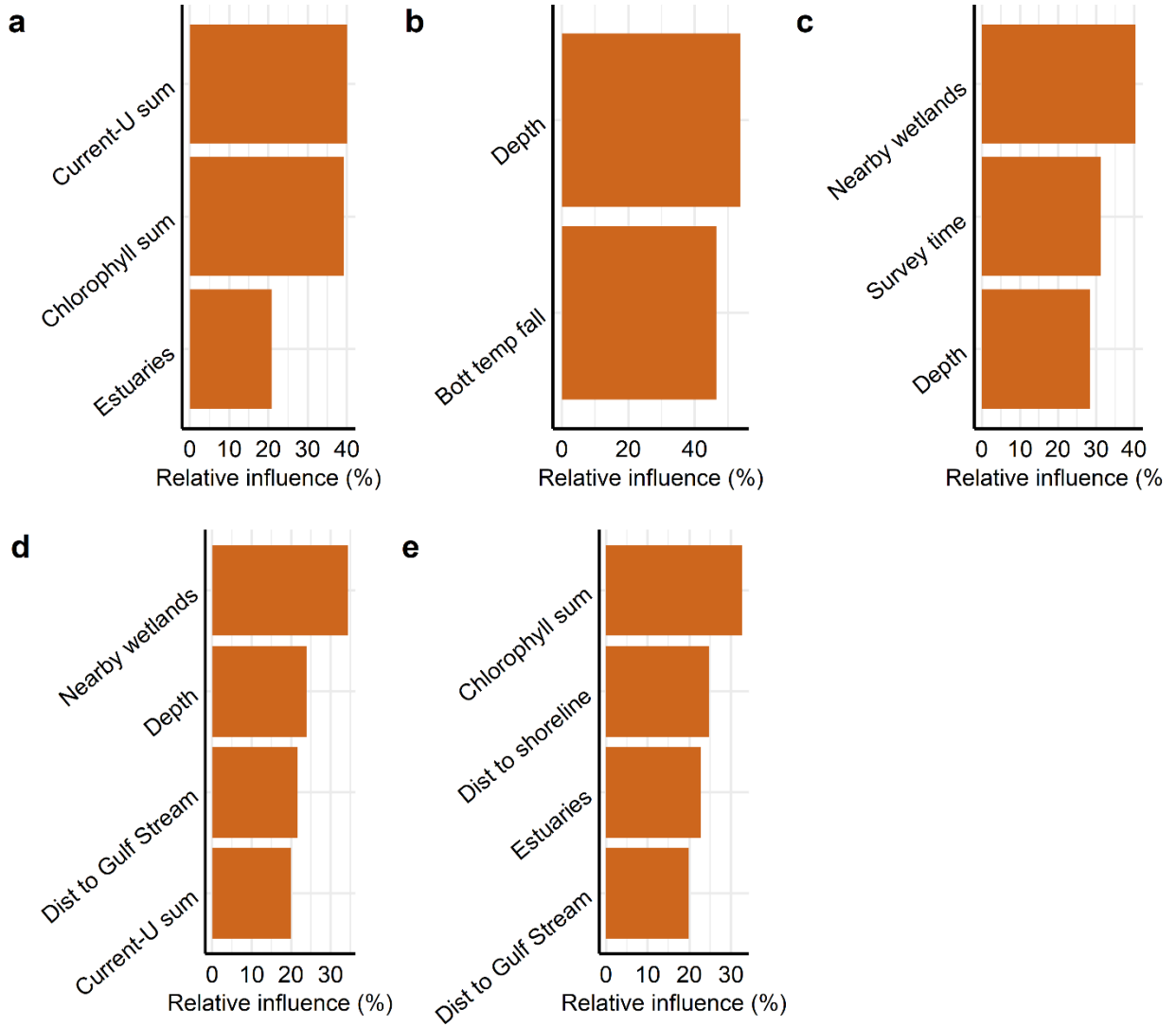


Figure 3.2. Relative importance of variables in models of a) blacknose shark, b) sandbar shark, c) tiger shark, d) red snapper, and e) black sea bass.

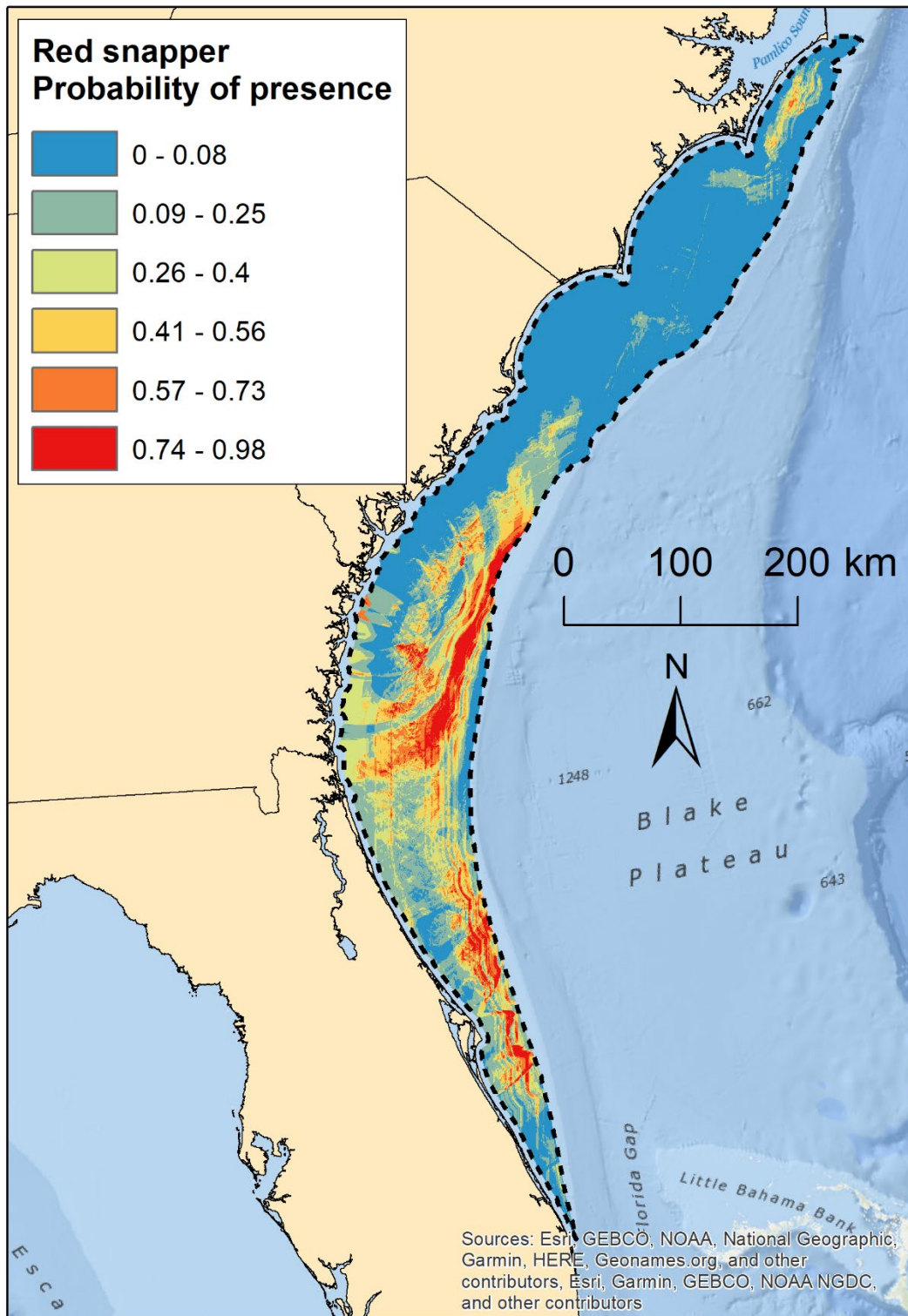


Figure 3.3. Predicted red snapper probability of presence in spring–fall seasons.

The study area is indicated by the dashed line, and probability of presence represents the probability of capture given a video survey at a hard bottom location.

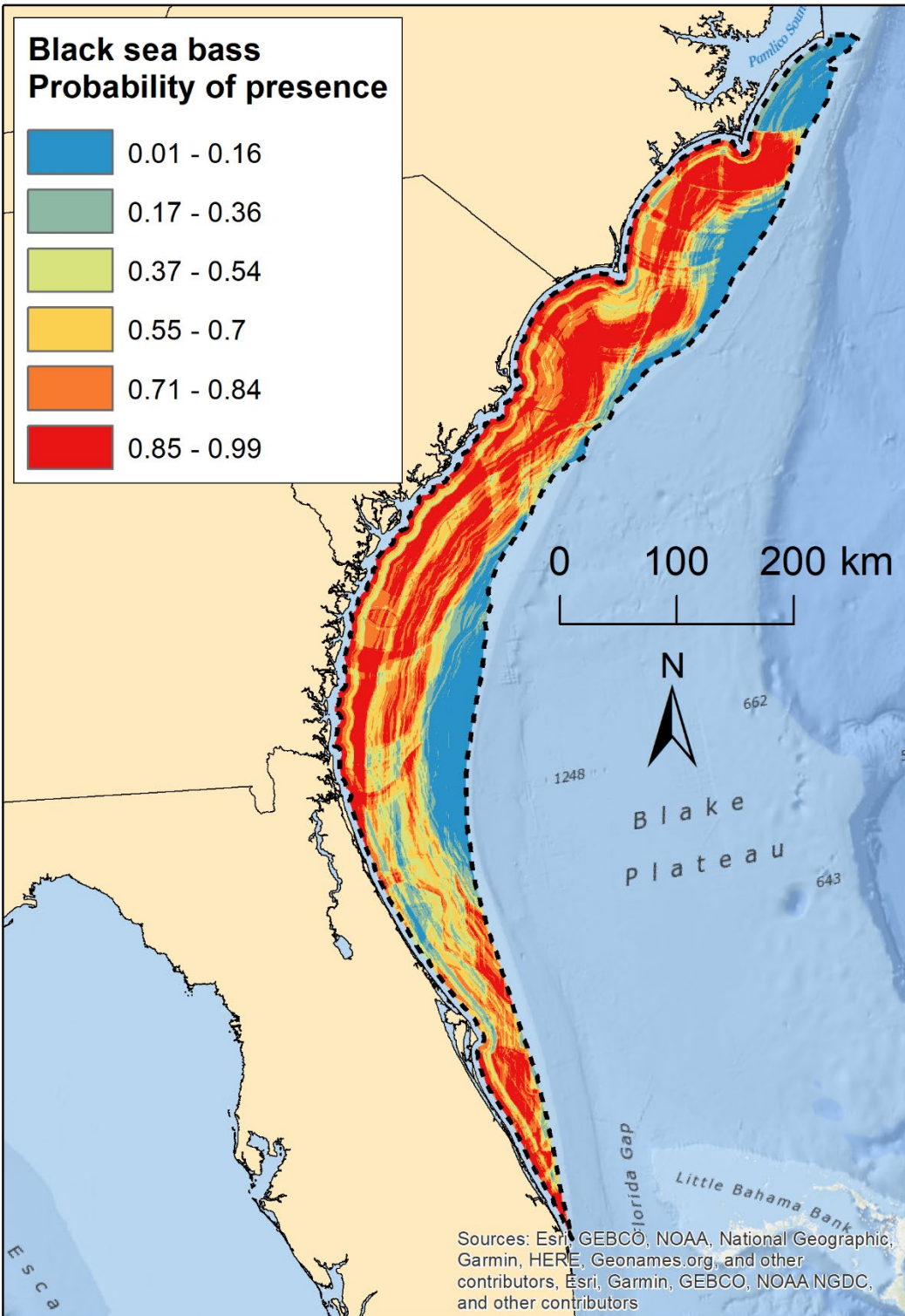


Figure 3.4. Predicted black sea bass probability of presence in spring–fall seasons.

The study area is indicated by the dashed line, and probability of presence represents the probability of capture given a trap survey at a hard bottom location.

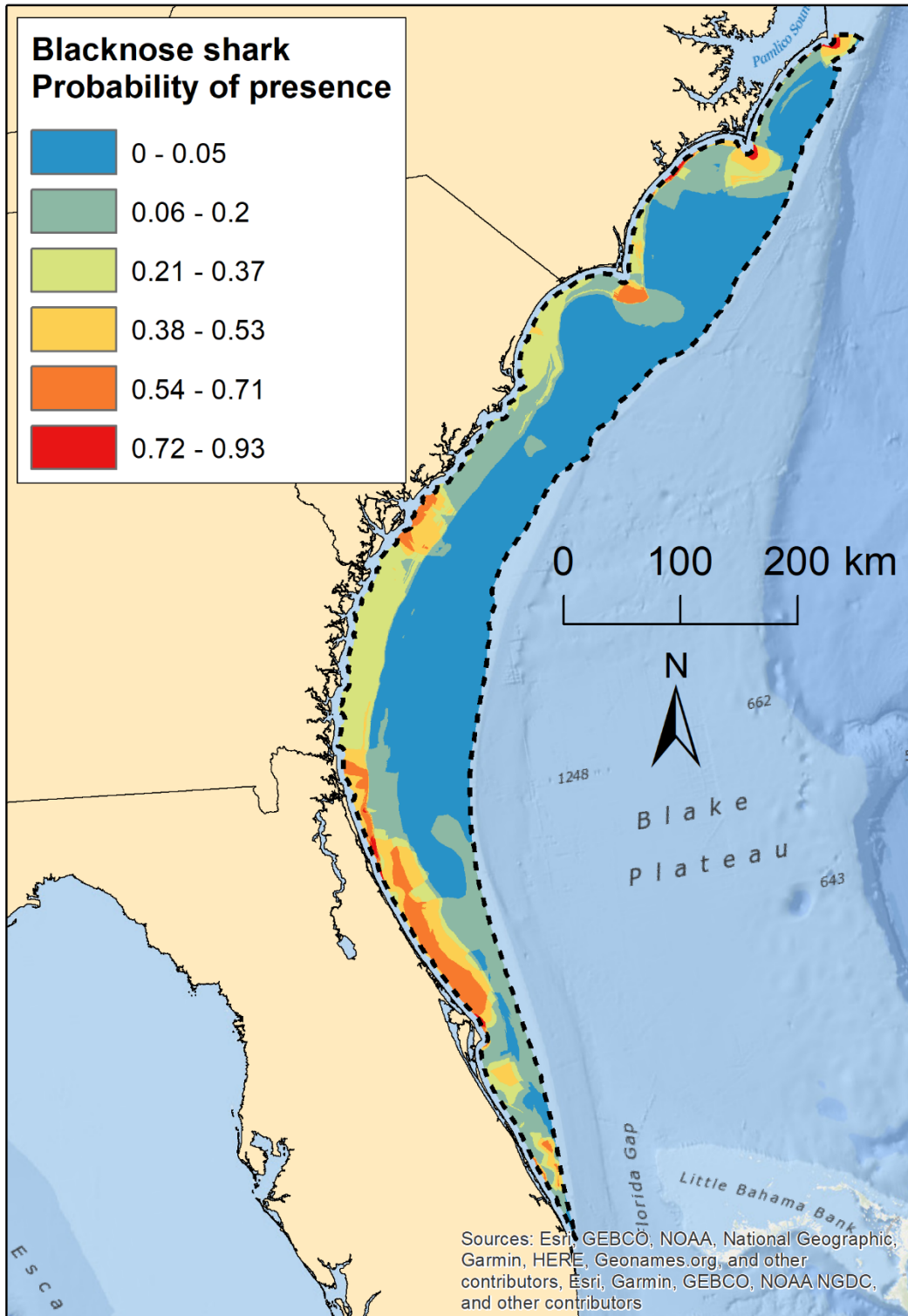


Figure 3.5. Predicted blacknose shark probability of presence in spring–fall seasons.

The study area is indicated by the dashed line, and probability of presence represents the probability of capture given a bottom longline survey.

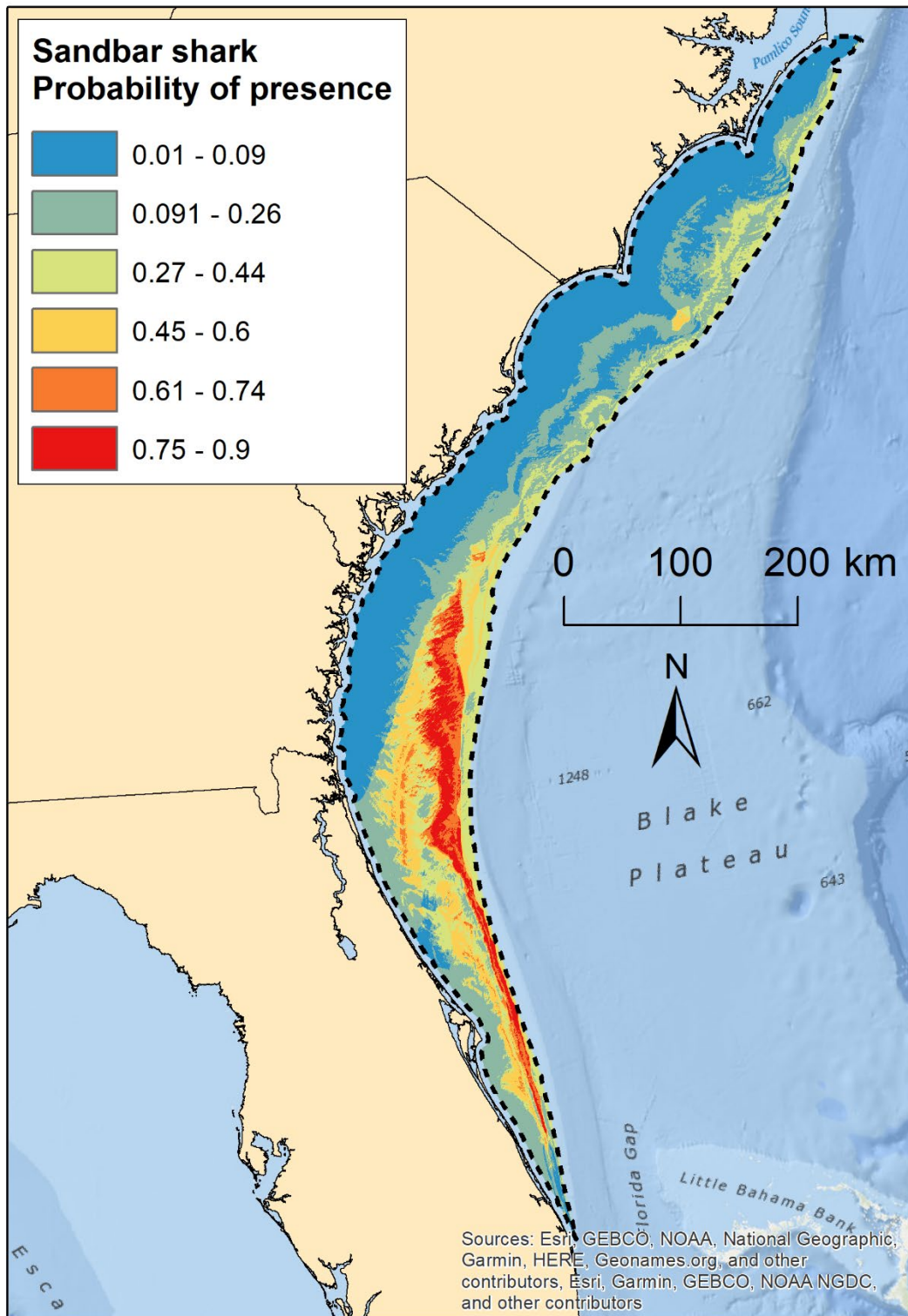


Figure 3.6. Predicted sandbar shark probability of presence in spring–fall seasons.

The study area is indicated by the dashed line, and probability of presence represents the probability of capture given a bottom longline survey.

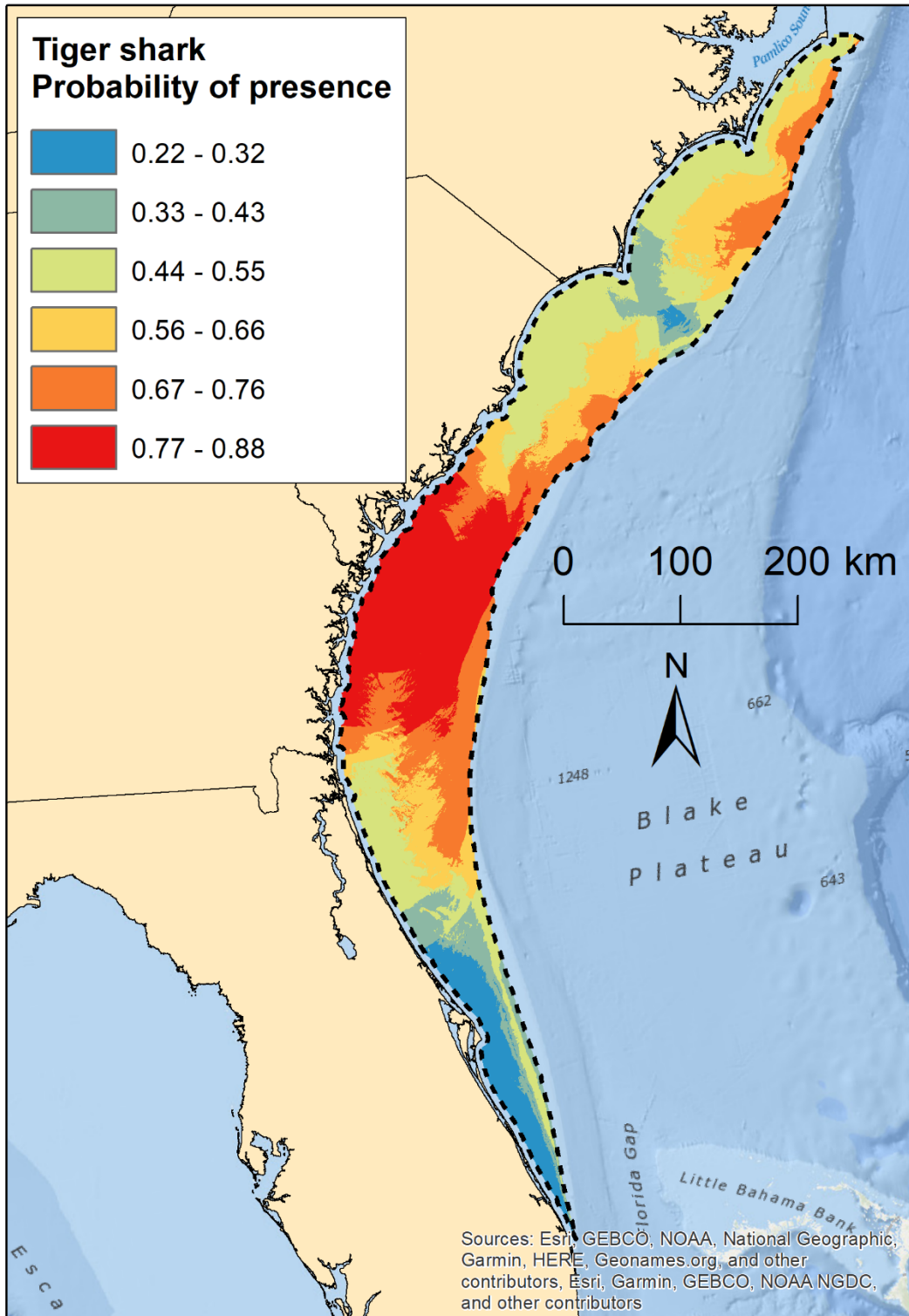


Figure 3.7. Predicted tiger shark probability of presence in spring–fall seasons.

The study area is indicated by the dashed line, and probability of presence represents the probability of capture given a bottom longline survey.

3.4 Discussion

Overall, we discovered new species-habitat relationships that incorporated the nearby ecosystems of wetlands and estuaries along with the most prominent oceanographic feature, the Gulf Stream. Concerning geomorphology, our results with the five South Atlantic fish species analyzed here are consistent with the results from analyses of nGoM shrimp, snapper, and sharks (**Sections 1 and 2**). Oceanographic conditions and nearby ecosystems are the dominant correlates with fish distribution, and the value of shoals as fish habitat is highly variable based on those factors (rather than geomorphology characteristics). In the South Atlantic, none of the five species were associated with the benthic characteristics of slope, aspect, BPI, depth heterogeneity, distance to shoal, or proportion of area as shoal.

3.4.1 Red Snapper and Black Sea Bass

We discovered the proximity to the Gulf Stream was an influential predictor of red snapper and black sea bass. The Gulf Stream is a prominent feature of the South Atlantic, and it creates a cross-shelf mixing of waters as well as strong water stratification (Castelao 2011). Surface and bottom water intrusions are most frequent in the summer months, are influenced by wind stress, interact with salinity, and are more frequent at the extreme northern and southern waters of the South Atlantic Bight (Castelao 2011). These characteristics of Gulf Stream water intermixing with shelf waters is consistent with the red snapper habitat relationships we observed here. Red snapper presence was most likely within approximately 40 km of the Gulf Stream and with a relatively strong western surface current. In the nGoM, we observed a positive relationship with red snapper and a deeper MLD. In the Gulf of Mexico, surface currents and the Loop Current were correlated with deeper MLD (unpublished data). Data sources for MLD were lacking in the South Atlantic, but the surrogates of distance to Gulf Stream and surface current velocity demonstrate the importance of this process. Black sea bass had a greater probability of presence both within 20 km of the Gulf Stream and much farther from the Gulf Stream (> 80 km). The association with the latter probably characterizes their affinity towards high chlorophyll concentrations and being closer to the shoreline. Red snapper were associated with more nearby wetlands, which is consistent with their association with shrimp prey species in the nGoM, whereas the association black sea bass and estuaries may be a result of their use of estuaries as juveniles (Mercer and Moran 1989).

3.4.2 Blacknose, Sandbar, and Tiger Shark

Studies conducted in the shallow waters offshore of North Carolina (Thorpe et al. 2004) and South Carolina (Ulrich et al. 2007) found blacknose shark were common in waters of 3-15 m depths. Our results support these observations, however, we identified more refined habitat characteristics that contributed to their presence within shallow waters. In the nGoM, Drymon et al. (2013) quantified habitat associations of blacknose shark and found depth (or temperature as a correlate) supported a depth preference of 10–30 m. Here, a positive association with chlorophyll meant that blacknose shark were in a close proximity to the shoreline. The positive association with the amount of nearby estuaries and a relatively high velocity of U-direction surface currents resulted in a predicted distribution near many inlets and sounds in the South Atlantic. This finding builds on a previous study that observed blacknose shark near inlets in South Carolina waters (Ulrich et al. 2007). These inlets may be particularly important habitats for blacknose shark.

Our model of sandbar shark showed they primarily used waters ≥ 35 m in depth. In support of this result, observations of sandbar shark in the Gulf of Mexico showed they are rarely encountered at shallow depths but have been recorded in depths of > 30 m (Drymon et al. 2010). We emphasize that we did not analyze data from nearshore, state-managed waters where juveniles may be found (e.g., Ulrich et al. 2007). Seasonal differences in sandbar shark depth use also appear to exist. Conrath and Musick (2008) reported that 80% of summer sandbar shark locations were in depths of < 12 m (range of 0–24 m) in the water column, but winter observations ranged 0–172 m. Total depth of the water column itself was not reported

in this study. In our study, depth was negatively related to bottom temperature. Therefore, the selection for depths up to 50 m is also indicative of sharks using relatively cooler water temperatures in the spring and summer. Additionally, we found an association between sandbar shark and fall bottom temperature, which were the lowest temperatures of the year. Sandbar shark are known to leave waters that get too cold. For example, Conrath and Musick (2008) tracked sharks offshore of eastern Virginia during the summer, and all seven individuals wintered offshore of North Carolina. The authors suggest that this is because of North Carolina's proximity to the warm Gulf Stream.

For tiger shark, we found a greater probability of presence with higher amounts of nearby wetlands. Worldwide, tiger sharks are known to use nearshore habitats (e.g., seagrasses) and to prefer shallow waters; presumably, these preferences characterize waters with a high prey density (Heithaus et al. 2006). Similarly, coastal wetlands of the South Atlantic likely are productive waters for tiger shark prey species.

3.4.3 Conclusions and Implications for Dredging

In our wide-ranging study, we can conclude that not all shoals have equal value to fish in the US Southeast Atlantic. Oceanographic factors, such as distance to Gulf Stream, and surface currents play a substantial role, as well as the amount of nearby wetlands and estuaries. Evidence shows geomorphology only plays a minor role in the distribution of hard bottom fish and sharks. We caution that our analyses were based on fish surveys that typically span 3 km in length, and microhabitat selection within this range may have been missed. Yet, our models showed a high predictive ability. For example, three of five of our models had an AUC of ≥ 0.79 . We have demonstrated that modeling the distribution of species can be accomplished at a relatively fine scale. These predicted spatial patterns can be used in decision support tools to identify potentially sensitive habitats, and relative hotspots for species, and allow for a strategic, regional perspective on natural resource use in the South Atlantic.

4 Predicting the Marine Distribution of Demersal Species in the Greater Atlantic

4.1 Introduction

SDMs are state-of-the-art statistical models that predict the distribution of species based on species-habitat relationships (Guisan and Zimmermann 2000; Robinson et al. 2011). Extending survey samples across the complex habitat mosaics allow for determination of relative hotspots for species and can identify particularly sensitive areas to avoid when planning offshore uses that potentially impact benthic habitats. The Northeast Fisheries Science Center (NEFSC) has recently developed SDMs for the Greater Atlantic (personal communication and unpublished data, Kevin Friedland, NEFSC). They had the objective of modeling the spatial distribution of North Atlantic species for the spring and fall seasons. Their work also examined the broad importance of predictor variables categorized as the following: physical (e.g., depth, temperature), primary production, secondary production (i.e., zooplankton), and benthic habitat complexity (i.e., substrate measures). The NEFSC provided us with a subset of species models derived from the last decade of fishery-independent trawl data, while their broader work covers over 30 years of fishery and oceanographic survey data.

The multispecies spatial modeling effort led by Kevin Friedland (NEFSC) is in the preparation phase for a peer-reviewed manuscript; therefore, we only provide a brief overview here. Currently, there is a manuscript concerning American lobster that is in review, and this manuscript will describe more detailed methodology for the species described here and included in the ShoalMATE tool (see Volume 4). Here, we provide a brief overview of the modeling data sources, methodology, and results.

4.2 Methods

The NEFSC used the following components to build SDMs for the Greater Atlantic:

- Fishery-independent trawl survey data from 2009–2018 were used for statistical modeling. The NEFSC has a longstanding trawl survey program, and the latest decade of data were used for modeling. All species with an adequate sample size from trawl surveys were modeled.
- Predictor variables sampled during trawl surveys included remote sensing data on oceanographic conditions, substrate descriptors, zooplankton abundance, and *in situ* measures of depth, water temperature, and salinity. Oceanographic predictor variables, such as chlorophyll concentration, were summarized on a monthly basis, and each month was tested as a predictor.
- The NEFSC used Random Forest (Cutler et al. 2007) for statistical models. Similar to BRT (Sections 1, 2, and 3), Random Forest is a machine-learning method that uses an ensemble of regression trees to make predictions. Random Forest has been demonstrated as an effective predictive modeling method (Rooper et al. 2017). Model variables were reduced using the model selection criteria of Murphy et al. (2010). Individual models often had > 20 predictor variables. Further details on the modeling methodology will be provided by Friedland et al. (2020).
- The predictive models quantify the probability of occurrence for each species by season (spring and fall), and the accuracy of models were tested with a cross-validation procedure. With this method, species were assessed with a receiver operating characteristic, AUC. The AUC has been commonly used to test the predictive ability of SDMs (Guisan and Zimmermann 2000), and the

analysis is independent of thresholds. Measures of the AUC range from 0.0 to 1.0 and were interpreted as suggested by Manel et al. (2001) and Swets (1988) as follows: < 0.50 = no discriminatory power; 0.50–0.69 = poor power; 0.70–0.89 = good power; and 0.90–1.0 = excellent discriminatory power.

4.3 Summary of Model Outputs

Thirty-four federally managed species were modeled for the spring and fall seasons, and these 68 models all had > 70% accuracy based on the AUC statistics for each season (**Table 4-1**). Overall, the models showed inshore-offshore movements of species were common, so distributions were often strikingly different between seasons. Importantly, these models do not depict summer and winter seasonal distributions of species.

A few inferences can be drawn from all the species modeled by the NEFSC (EFH species and other species) with the longer timeframe of modeling results. Among the categories of predictors, benthic substrate variables were selected least often, and measures of variable importance showed these substrate variables had less importance in models compared to other categories of predictor variables. Secondary production, primary production, and physical variables had varying importance depending on season and type of species (e.g., benthivore vs. planktivore).

Table 4-1. Federally managed species and the accuracy of models provided by the NEFSC.

Common name	Fall AUC	Spring AUC	Common name	Fall AUC	Spring AUC
Acadian redfish	0.94	0.92	Scup	0.91	0.9
American plaice	0.94	0.91	Sea scallop	0.84	0.84
Atlantic cod	0.89	0.84	Silver hake	0.82	0.81
Atlantic herring	0.9	0.76	Smooth skate	0.88	0.89
Black sea bass	0.86	0.86	Spiny dogfish	0.8	0.79
Bluefish	0.86	0.88	Summer flounder	0.9	0.84
Butterfish	0.77	0.86	White hake	0.88	0.87
Clearnose skate	0.92	0.92	Windowpane	0.85	0.83
Goosefish	0.77	0.76	Winter flounder	0.87	0.88
Haddock	0.84	0.85	Winter skate	0.88	0.81
Little skate	0.86	0.83	Witch flounder	0.9	0.84
Longfin squid	0.85	0.89	Yellowtail flounder	0.88	0.87
Northern shortfin squid	0.81	0.88	Atlantic mackerel	0.77	0.77
Offshore hake	0.93	0.91	Barndoor skate	0.88	0.86
Red hake	0.82	0.8	Ocean pout	0.82	0.79
Rosette skate	0.93	0.93	Pollock	0.86	0.82
Scup	0.91	0.9	Atlantic angel shark	0.91	0.92

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Appendix A: Common and Scientific Names Cited in the Text

Common Name	Scientific Name	Common Name	Scientific Name
Acadian redfish	<i>Sebastes fasciatus</i>	Lizardfish	<i>Synodus spp.</i>
American plaice	<i>Hippoglossoides platessoides</i>	Longfin squid	<i>Loligo pealeii</i>
Atlantic cod	<i>Gadus morhua</i>	Mantis shrimp	<i>Squilla spp.</i>
Atlantic herring	<i>Clupea harengus</i>	Menhaden	<i>Brevoortia spp.</i>
Atlantic mackerel	<i>Scomber scombrus</i>	Northern shortfin squid	<i>Illex illecebrosus</i>
Black sea bass	<i>Centropristis striata</i>	Ocean pout	<i>Macrozoarces americanus</i>
Bluefish	<i>Pomatomus saltatrix</i>	Offshore hake	<i>Merluccius albidus</i>
Butterfish	<i>Peprilus triacanthus</i>	Pollock	<i>Pollachius virens</i>
Croaker	<i>Micropogonias undulatus</i>	Red drum	<i>Sciaenops ocellatus</i>
Flounder, summer	<i>Paralichthys dentatus</i>	Searobin	<i>Prionotus spp.</i>
Flounder, windowpane	<i>Scophthalmus aquosus</i>	Sea scallop	<i>Placopecten magellanicus</i>
Flounder, winter	<i>Pseudopleuronectes americanus</i>	Scup	<i>Stenotomus chrysops</i>
Flounder, witch	<i>Glyptocephalus cynoglossus</i>	Shark, Atlantic angel	<i>Squatina dumeril</i>
Flounder, yellowtail	<i>Limanda ferruginea</i>	Shark, Atlantic sharpnose	<i>Rhizoprionodon terraenovae</i>
Goosefish	<i>Lophius americanus</i>	Shark, blacknose	<i>Carcharhinus acronotus</i>
Haddock	<i>Melanogrammus aeglefinus</i>	Shark, blacktip	<i>Carcharhinus limbatus</i>
Hake, red	<i>Urophycis chuss</i>	Shark, sandbar	<i>Carcharhinus plumbeus</i>
Hake, silver	<i>Merluccius bilinearis</i>	Shark, spinner	<i>Carcharhinus brevipinna</i>
Hake, white	<i>Urophycis tenuis</i>	Shark, spiny dogfish	<i>Squalus acanthias</i>
Shark, tiger	<i>Galeocerdo cuvier</i>	Skate, little	<i>Leucoraja erinacea</i>
Shrimp, brown	<i>Farfantepenaeus aztecus</i>	Skate, clearnose	<i>Raja eglanteria</i>
Shrimp, pink	<i>Farfantepenaeus duorarum</i>	Skate, smooth	<i>Malacoraja senta</i>
Shrimp, white	<i>Litopenaeus setiferus</i>	Snapper, lane	<i>Lutjanus synagris</i>
Skate, barndoor	<i>Dipturus laevis</i>	Snapper, red	<i>Lutjanus campechanus</i>



Department of the Interior (DOI)

The Department of the Interior protects and manages the Nation's natural resources and cultural heritage; provides scientific and other information about those resources; and honors the Nation's trust responsibilities or special commitments to American Indians, Alaska Natives, and affiliated island communities.



Bureau of Ocean Energy Management (BOEM)

The mission of the Bureau of Ocean Energy Management is to manage development of U.S. Outer Continental Shelf energy and mineral resources in an environmentally and economically responsible way.

BOEM Environmental Studies Program

The mission of the Environmental Studies Program is to provide the information needed to predict, assess, and manage impacts from offshore energy and marine mineral exploration, development, and production activities on human, marine, and coastal environments. The proposal, selection, research, review, collaboration, production, and dissemination of each of BOEM's Environmental Studies follows the DOI Code of Scientific and Scholarly Conduct, in support of a culture of scientific and professional integrity, as set out in the DOI Departmental Manual (305 DM 3).