North Atlantic LCC Aquatic Habitat Assessment 2015

Estuarine Fish Habitat Assessment: A General Framework and Winter Flounder Pilot Studies

Final Report submitted to the North Atlantic Landscape Conservation Cooperative (NALCC) Assessment Project

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North Atlantic LCC
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Abstract

The North Atlantic Landscape Conservation Cooperative (NALCC) contracted Downstream Strategies (DS) to perform aquatic habitat assessments for the Northeast United States. Part of this project included creating predictive models for estuarine areas. Winter flounder were selected as the species to be modeled for this pilot study, beginning with a model of Narragansett Bay. After learning from that effort, a separate predictive habitat model for winter flounder was performed on Long Island Sound.

This document describes the process used to create a modeling framework for these assessments, details of the habitat assessments, and a discussion of the lessons learned that may aid future similar efforts. We created models with predictive accuracy similar to other estuarine predictive habitat models. We also found that the relationships between habitat and winter flounder described by our predictive models were generally corroborated by previous literature. We also note the limitations of each model and suggest possibilities for overcoming these in future efforts.

The data and modeling results from this assessment will be incorporated into a web-based decision support tool. This tool will enable users to visualize and download data and model outputs and establish conservation priorities based on user-defined ranking criteria. Combined, the modeling results contained within this report along with the publically accessible web application will improve public awareness of conditions of the modeled estuaries and empower resource managers to implement scientifically-defensible conservation actions. The web tool can be accessed here: www.fishhabitattool.org.

Acknowledgements

We offer a special thanks to Scott Schwenk, North Atlantic Landscape Conservation Cooperative (NALCC); Emily Greene, Atlantic Coast Fish Habitat Partnership (ACFHP); Julie Devers, US Fish and Wildlife Service (USFWS); and Lisa Havel, ACFHP, for leading this project and coordinating partners.

This project would not have been possible without the invaluable technical assistance, data, and review provided by the following: Kristan Blackhart, National Oceanic and Atmospheric Administration (NOAA); Steven Correia, Massachusetts Division of Marine Fishes (MADMF); Christopher Deacutis, Rhode Island Department of Environmental Management (RIDEM); Mark Gibson, RIDEM; Penny Howell, Connecticut Department of Energy & Environmental Protection (CTDEEP); Dawn McReynolds, New York State Department of Environmental Conservation (NYSDEC); Vincent Manfredi, MADMF; Moe Nelson, NOAA; Chris Powell, RIDEM retired; Michael Scherer, Normandeau Associates; Eric Schneider, RIDEM; George Shuler, The Nature Conservancy (TNC); Caroly Shumway, Merrimack River Watershed Council (MRWC); David Stevenson, NOAA; Howard Townsend, NOAA.

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Project Background

Introduction

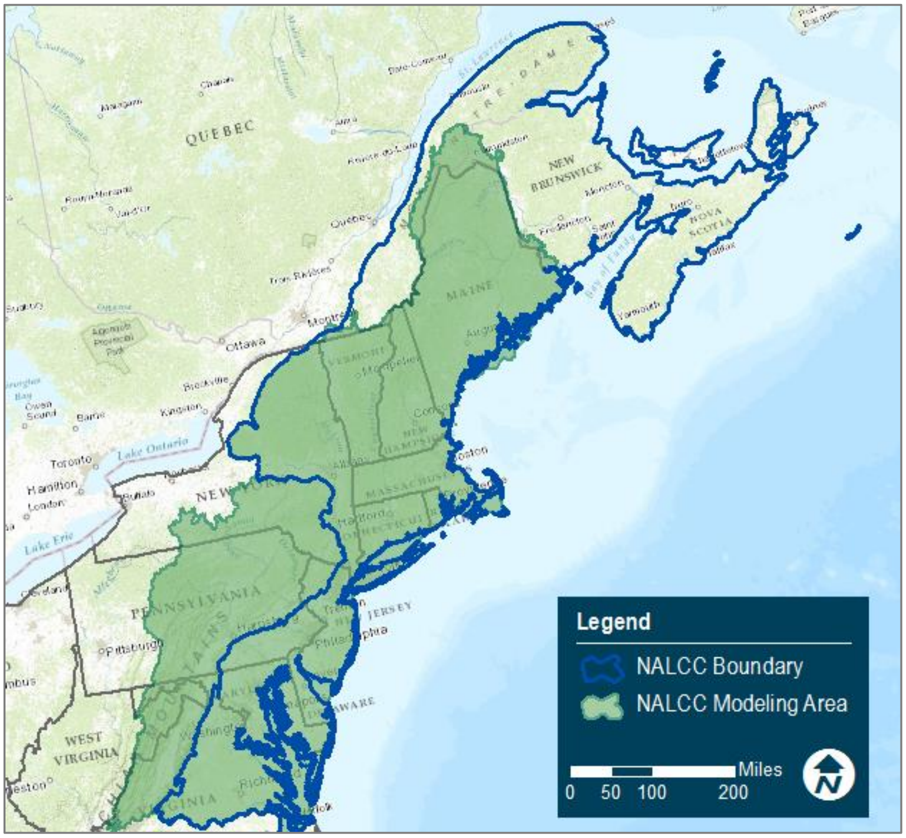
Since 2012, Downstream Strategies (DS) has produced 35 distinct predictive models for several Fish Habitat Partnerships (FHP) across the United States[1]. These models utilized widely-available landscape variables (e.g. land use, geology, precipitation) as predictors for instream aquatic responses such as presence of certain guilds or species of fish. After careful consideration of strengths and weaknesses compared to other statistical methods, Boosted regression tree (BRT) models were selected as the predictive statistical models for these analyses. These models created a broad and unique understanding of the link between terrestrial and aquatic health, and allowed for the quantification of stressors and natural habitat quality for each response.

Based on this work, DS was contracted by the North Atlantic Landscape Conservation Cooperative (NALCC) to perform habitat assessments for inland and estuarine/coastal areas within the NALCC region (Figure 1). The goal of the project was to build from successes in modeling inland aquatic species and to customize the existing modeling framework to be applicable to modeling coastal species. Our approach was driven by collaboration with stakeholders throughout the entire project. Stakeholders determined the endpoint, scale, and area of focus for the models. Stakeholders also reviewed data, methods, and results at all stages of the project and provided feedback—based on local knowledge and expertise—to ensure the project outcomes met the needs of stakeholders.

This report documents the workflow and outcomes from the coastal modeling aspect of the NALCC Aquatic Assessment project. Details of the inland and diadromous modeling efforts will be summarized in separate reports.

[1] Example report: http://www.northatlanticlcc.org/projects/downstream-strategies-project/public-working-documents/example-report-habitat-modeling-report-for-the-ohio-river-basin-and-southeast-aquatic-resources-partnerships

FIGURE 1. STUDY AREA



Pilot Model Overview

The primary goal of these habitat assessment models was to assess habitat for specific biological endpoints in a consistent framework that could be applied to other endpoints developed as part of similar future efforts. It is important to note that these models are dissimilar from traditional marine stock assessments, see Previous Coastal Assessment Efforts section for more details. In addition to the habitat assessment, the team was tasked to produce results that could be integrated into the existing decision support tool. Through contracts with the USFWS, DS has created a web-based decision support tool that allows users to query, rank, and interact with varying levels of data from similar aquatic assessments. The data produced as part of these assessments will be incorporated into this tool.

Care was taken to engage and pursue the proper stakeholders throughout this project. Along with the NALCC project officer, DS worked to coordinate with a team of researchers, planners, scientists, and restoration experts for North Atlantic aquatic species. To begin, a group of core project coordinators were selected. The estuarine/coastal coordinators included Emily Greene, Atlantic Coast Fish Habitat Partnership (ACFHP) Coordinator; Caroly Shumway, Merrimack River Watershed Council; and Julie Devers, USFWS. Following her departure from the position, Emily Greene was replaced with the new ACFHP Coordinator, Lisa Havel.

The project team worked with these stakeholders to develop a methodology that was consistent with the goals of the project and its end-users. DS first examined and researched existing efforts for assessing and modeling coastal and estuarine habitat. Using this information and input, we developed a framework—in collaboration with stakeholders—that built upon existing efforts and precedent to establish the coastal and estuarine methods.

We worked with the NALCC coordinators to rank and prioritize potential species of interest for our modeling efforts. We examined state and federal priority species lists and ranked species based on the number of plans in which they were included. Once a small list of priority species for in-depth modeling was determined, we began analyzing data availability. It was at this point that winter flounder (*Pseudopleuronectes americanus)* was selected as the pilot species to model estuarine environments. Other estuarine species are listed on more state and federal plans, but winter flounder are a well-studied, recreationally- and commercially- important species in the Northeast, resulting in good coverage and quality of available data. After several iterations of stakeholder input, feedback, and review we determined that the pilot model for winter flounder should be carried out in a single data-rich estuary, Narragansett Bay of Rhode Island and Massachusetts (Figure 3).

Following the establishment of these decisions, a technical review team was established. This team consisted of winter flounder researchers and biologists with experience in the North Atlantic, many of whom were intimately familiar with the Narragansett Bay population. Table 1 lists the review team for the Narragansett Bay model.

TABLE 1. NARRAGANSETT BAY TECHNICAL REVIEW TEAM

Review Team	Organization	Position
Kristan Blackhart	NOAA/NFHP	NFHP Habitat Assessment
Steven Correia	MADMF	Environmental Analyst
Christopher Deacutis	RIDEM	Supervisory Environmental Scientist
Julie Devers	USFWS	Fish Biologist, ACFHP Science and Data Committee
Mark Gibson	RIDEM	Deputy Chief of Marine
Emily Greene	ACFHP/NOAA	Former Coordinator/Marine Habitat Outreach Specialist
Lisa Havel	ACFHP	Coordinator
Vincent Manfredi	MADMF	Aquatic Biologist
Moe Nelson	NOAA (NOS)	Marine Biologist, ACFHP Science and Data Committee
Chris Powell	RIDEM	Retired, Vice Chair, ACFHP Steering Committee
Michael Scherer	Normandeau Associates	Vice President
Eric Schneider	RIDEM	Principal Marine Fisheries Biologist
Scott Schwenk	NALCC	Science Coordinator
George Shuler	TNC	Director, Conservation Science and Practice
Caroly Shumway	MRWC	Executive Director, Chair, ACFHP Science and Data Committee
David Stevenson	NOAA (NMFS)	Marine Habitat Resource Specialist, ACFHP Science and Data Committee
Howard Townsend	NOAA (NMFS)	Ecological Modeler

Once the initial model for Narragansett Bay was finalized, there was interest from the coordinators to utilize the lessons learned and apply a similar model to another estuary with abundant data. Long Island Sound (LIS) was chosen for this effort, as there was ample data collected on winter flounder. In addition to many of the reviewers listed in Table 1, Penny Howell, Marine Fisheries Biologist with the CTDEEP and Dawn McReynolds, Marine Habitat Section Head with the NYSDEC provided data and review of the LIS model. The details of this assessment are described below in the section named "Long Island Sound Model."

Previous Coastal Assessment Efforts

Traditionally, stock assessments have been used to examine population trends for coastal fishes. Stock assessments based on recreational and commercial landings and survey catch rates broadly indicate population trends and relative abundance, but are insufficient for drawing inferences about habitat quality or fine-scale spatial distribution. For this habitat assessment we aimed to assess aquatic habitat at a finer scale than has generally been performed using stock assessments, and as such, we examined efforts that focused on estuarine or coastal assessments of fish and data relevant to the North Atlantic.

NOAA compiled information and mapped "Essential Fish Habitat" (EFH) for many coastal fish species by life stage (eggs, larvae, juvenile, adult) within the study area, but this information was very coarse scale (10 minute grid), and was focused on off-shore habitats rather than estuaries (NOAA. 2010). The source documentation for this effort described life history and habitat characteristics of each species (including winter flounder[2]) in detail from existing literature (Pereira et al 1999). Winter flounder move inshore during winter and early spring where they spawn. The newly hatched flounder stay inshore in very shallow waters for up to one year, before migrating offshore with the seasonal adult migration. Migration of adults is generally triggered by temperatures reaching 15° C, but movements have also been tied to food availability, with offshore migrations occurring at lower temperatures if food is scarce, and at higher temperatures if food is abundant. Young of year (YOY) winter flounder are more tolerant of lower salinities and dissolved oxygen levels and are less photonegative than year-one and adult winter flounder. These characteristics allow YOY winter flounder to inhabit shallow, warm inshore areas. As their temperature, salinity, and light tolerances change with age, it likely drives the transition of year one and older fish to deeper and cooler water.

The Nature Conservancy's Northwest Atlantic Marine Ecoregional Assessment[3] (NAMERA) also compiled a great deal of information on coastal communities (Greene et al. 2010). Most of the data described physical habitat, chemistry, and oceanography. Much of these data proved useful as predictor data for our assessment, but detailed information on fish species was not present in the NAMERA assessment. NAMERA did analyze some data on marine fishes to pinpoint critical habitat for selected species, similar to the NOAA Essential Fish Habitat assessment. NAMERA chose to analyze data by season rather than by life stage, but also utilized a 10-minute grid for much of the analysis, and again focused on marine waters rather than inshore estuaries for the fish assessments. The DS assessment goal was to address potential inshore stressors, such as impervious surfaces, outfalls, and/or hardened shoreline at a fine (intra-estuary) scale. By focusing the assessments on estuaries rather than offshore areas, we intended to interrogate and understand processes within estuaries in order to specifically define relationships between fish populations and anthropogenic stressors in the watersheds of the estuaries. While the NAMERA fish assessment was useful for more regional-scale planning and for pinpointing critical offshore habitats, it was not designed in a way to answer our research questions.

The National Fish Habitat Action Plan's Coastal Assessment[4] focused on inshore estuaries nationwide rather than marine habitats (Greene et al. 2015). The initial assessment focused on scoring distinct estuaries by their overall health as defined by existing physical and chemical datasets; it did not directly incorporate biological information into the estuarine health scores. A second pilot study is currently underway in the Northern Gulf of Mexico that incorporates predictive modeling and aquatic species prevalence to further define estuary health (NOAA 2013). This approach more closely resembles the desired product from this project, but the scale of the assessment is still coarse and provides predictions of stressors and conditions at the estuary-wide scale. This methodology is still under development and is intended to be utilized as a framework to be applied regionally for all US estuaries. This regional effort with estuary-wide prioritization is providing useful results, but is still not at a resolution fine enough for intra-estuary assessments, which is the desire for the DS assessment.

Framework Development

This project's goal was to build upon the modeling framework developed by DS for inland aquatic modeling[5]. DS's inland aquatic models were developed for numerous Fish Habitat Partnerships (FHPs) throughout the Midwest and were funded by the United States Fish and Wildlife Service (USFWS). These assessments utilized the National Hydrography Dataset (NHD) and the NHD Plus (Horizon Systems 2010), a supplemental geospatial hydrologic dataset built on top of the NHD. These data include discrete catchment polygons that delineate the local drainage area for each specific stream segment. These catchments were utilized as our modeling unit, and predictor data were summarized within each catchment. Response data were likewise summarized within catchments to create our predictive models, the results of which were extrapolated to all catchments within the defined study areas.

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[2] http://www.nefsc.noaa.gov/nefsc/publications/tm/tm138/tm138.pdf
[3] https://www.conservationgateway.org/ConservationByGeography/NorthAmerica/UnitedStates/edc/Documents/namera-phase1-fullreport.pdf
[4] http://csis.msu.edu/sites/csis.msu.edu/files/NFHAP2014.pdf
[5] http://midwestfishhabitats.org/resources/Report

DS created a working methodology for the winter flounder model that was based on the DS inland aquatic modeling effort and modified to meet the geographic needs of an estuarine model and the requirements defined during several iterations of stakeholder input and research. This methodology was presented to, and accepted by the stakeholder group. This methodology was used as the framework for all coastal and estuarine modeling efforts for the NALCC project. The process utilized to formulate this framework is described below. Details for specific modeling efforts and the data utilized for each will be described in more detail within their respective sections.

DS utilized boosted regression trees (BRT), a machine learning statistical method, in the development of inland assessments. This method was selected after careful review of many statistical methodologies during previous projects for the USFWS. DS staff and partners, along with the stakeholders for the FHP assessments, decided upon BRT over competing methodologies after comparing and contrasting the strengths and weaknesses of each. BRT models combine decision trees and boosting methodologies, which often result in better cross-validated models than other methods (Elith et al., 2006). Decision trees are advantageous because (1) they can incorporate any type of predictor data (binary, numeric, categorical); (2) model outcomes are unaffected by differing scales of predictors; (3) irrelevant predictors are rarely selected; (4) they are insensitive to outliers and non-normalized data; (5) they can accommodate missing predictor data; and (6) they can automatically handle interactions between predictors (Elith et al., 2008). The boosting algorithm used by BRT improves upon the accuracy of a basic regression tree approach by following the idea that averaging many models offers efficiency over finding a single prediction rule that is highly accurate (Elith et al., 2008). BRT also runs quickly compared to other robust methods such as Bayesian modeling, which allows for efficient re-runs of models to forecast scenarios where predictor variables are manipulated. This was a key factor as it also allows for the creation of "on-the-fly" scenario-based decision support tools.

Given the success of the DS inland assessment and the efficiencies of utilizing an existing framework, we proposed to transfer the basic framework from the inland assessment to a marine ecosystem, which the stakeholders ultimately approved. Prior to this, we researched marine modeling and designed a modeling framework that utilized a BRT predictive model with a different geographic foundation for designating modeling units.

Dutil et al. (2013) described a process where the authors used generalized linear models and geospatial analyses to find relationships between three marine fish species in the Gulf of St. Lawrence in order to supplement existing sampling data for the purpose of habitat conservation, management, and recovery. They utilized a square grid pattern to define distinct modeling units within their study area and summarized physical habitat and fish sample information (trawl surveys) within those square modeling units. This methodology was similar to DS's existing inland assessment methodology in that habitat variables within distinct units were summarized and related to existing fish sample data. Although the statistical approach differed, the generalized framework was applicable as a basis for transferring the inland assessment modeling methodology to the marine environment, where a gridded overlay of marine environments would be utilized in place of the catchments used in the inland assessment.

Several other studies have used similar methodologies. Best et al. (2012) utilized a similar approach to create models that would predict probability of occurrence for marine mammals in the Gulf of Mexico and United States' east coast. This approach focused on marine mammals rather than fishes, but nonetheless was an example of utilizing habitat and environmental data to predict the status of mobile animals in marine environments. Young et al. (2010) used variable-sized square grids and generalized linear models (GLM) to predict rockfish probability of occurrence off the coast of California. Juntunen et al. (2012) used Bayesian models to predict species distribution and biomass for multiple marine species in the Baltic Sea using a 2km square grid as the modeling unit. Hardy et al. (2011) utilized several machine learning statistical procedures to predict presence, abundance, and biomass of snow crab (*Chionoecetes opilio*) in Alaskan waters. This is certainly not an exhaustive review of predictive models from marine environments, but does indicate the applicability of several different predictive modeling methods for several types of marine animals in various settings.

Leathwick et al. (2006) used boosted regression trees to predict species richness of demersal marine fish near New Zealand. They also compared boosted regression trees to generalized additive models (GAM), and found that BRT “substantially” outperformed the traditional GAM model, and that using environmental variables as predictors was effective in the prediction of demersal fish richness.

While the efforts above used mainly square grids, hexagonal grids have also been used in marine applications (James et al. 2005, Read et al. 2010). When evaluating hexagons for conservation, they are more effective than squares because they can be arranged in a more spatially compact manner, which results in less superfluous planning units (Nhancale and Smith 2011).

We proposed to the stakeholder group to use the basic statistical methodology (BRT) from the DS inland assessment, coupled with a hexagonal grid to define the individual modeling units within our analysis. This methodology coupled the efficiencies of utilizing an existing framework with the functional advantages of BRT and the spatial efficiency of a hexagonal grid system while not straying from established methodologies used for other predictive models in marine systems. This framework proposal was accepted by the stakeholder group after explanation and review.

A 1km^2 size was chosen by the stakeholders and review team as the smallest unit of area at which estuarine management takes places in inshore areas. Nhancale and Smith (2011) noted that small planning units were more efficient, and as such we opted to utilize a smaller unit rather than larger units because data and results could be aggregated within larger units of management after analyses if so desired. We used “Create Hexagon Tessellation” geoprocessing package[6] within ArcGIS 10 to create 1km^2 hexagons for the entire NALCC modeling area. The tool automatically assigned each hexagon a unique identifier. Habitat data such as depth, substrate, distance to shore, temperature, latitude, etc. were summarized for each hexagon and used as predictor variables.

Response data in the form of trawl surveys and/or seine surveys were used to characterize responses of marine species throughout the defined study areas. These response data were assigned to a discrete hexagon. Details describing the source of response data and how the response data were processed for each effort can be found in the description of each model.

For hexagons where both predictor data and response data were available, those datasets were joined based on the unique hexagon identifier. The resulting dataset was used to create a predictive model that allowed for the characterization of the fish response for **all** hexagons within the study area.

Statistical Approach

Boosted Regression Trees (BRT), a machine-learning statistical technique, average the results from hundreds to thousands of individual decision trees in order to improve model accuracy (Elith et al. 2008). Figure 2, below, adapted from Elith et al. 2008, shows an example tree with two predictor variables (X_1 and X_2), splits points t_1, t_2, etc, and a response Y. The bottom figure illustrates the prediction surface of the example tree.

The BRT output included a list of the predictor variables used in the model ordered and scored by their relative importance. The relative importance values are based on the number of times a variable is selected for splitting, weighted by the squared improvement to the model as a result of each split, and averaged over all trees (Friedman and Meulman, 2003). The relative influence score is scaled so that the sum of the scores for all variables is 100, where higher numbers indicate greater influence.

We utilized the R software package and ‘gbm’ package to create the BRT models , along with source code from Elith et. al’s (2008) supplemental materials. We utilized the default settings for model building for most options, including using a 10-fold cross validation procedure and bag fraction = 0.75. Tree complexity (interaction depth) and learning rate (contribution of each tree added to the model) were set individually for each model, depending on data structure and model performance.

[6] http://www.arcgis.com/home/item.html?id=03388990d32741 60afe240ac54763e57

The BRT output also contained quantitative information on partial dependence functions that was plotted to visualize the effect of each individual predictor variable on the response after accounting for all other variables in the model (see Figure 6). Similar to the interpretation of traditional regression coefficients, the function plots are not always a perfect representation of the relationship for each variable, particularly if interactions are strong or predictors are strongly correlated. However, they do provide a useful and objective basis for interpretation (Friedman, 2001; Friedman and Meulman, 2003, Elith et al. 2008).

Each partial dependence plot illustrates the general relationship between a single predictor variable and the response variable. The method used to create these function plots was described in detail in Friedman (2001). Generally speaking, the influence each variable has on the response is calculated when holding all other variables in the model consistent, or "integrating" them out. The predictor variable is plotted across the x-axis and the marginal effect on the response is plotted on the y-axis. These plots cannot be used to precisely indicate the exact change in the response at varying predictor levels, but is useful to assess the general relationship between predictors and the response, especially for understanding the directionality of each relationship.

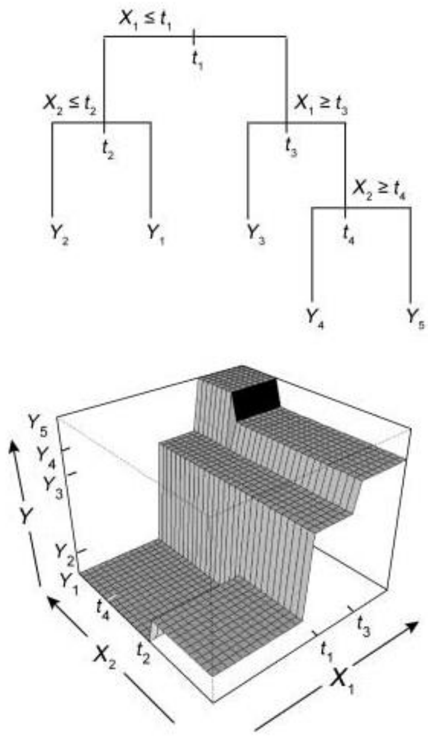


FIGURE 2. EXAMPLE DECISION TREE AND PREDICTION SURFACE (FROM ELITH ET AL. 2008)

Residuals were analyzed to more fully understand the strengths and shortcomings of the model predictions. The residuals are a measure of the difference in the measured and modeled values (measured value *minus* modeled value). Negative residuals indicate overpredictions (predicting higher values than are true), while positive residuals indicate underpredictions (predicting lower values than are true).

We created and examined plots to compare residuals against predictor values and fitted vales. These plots were used to understand the consistency of predictions and to visualize what types of conditions were predicted well, overpredicted, or underpredicted by the model. A dashed line representing a residual value of zero (perfect model fit) is also shown. A loess line was also plotted to show the general trend of the plotted points (solid line). A loess line that closely matched the dashed line would indicate that the model equally over- and under-predicts values across the range of the predictor or fitted value.

Additional plots that show the square root of the absolute value of the residuals were created to visualize the magnitude of predictive error across the range of predictors and fitted values. Residuals were also mapped in order to analyze spatial patterns of omission and commission, which could highlight regions where the model is performing well or poorly or could suggest missing explanatory variables.

Narragansett Bay Model

Introduction

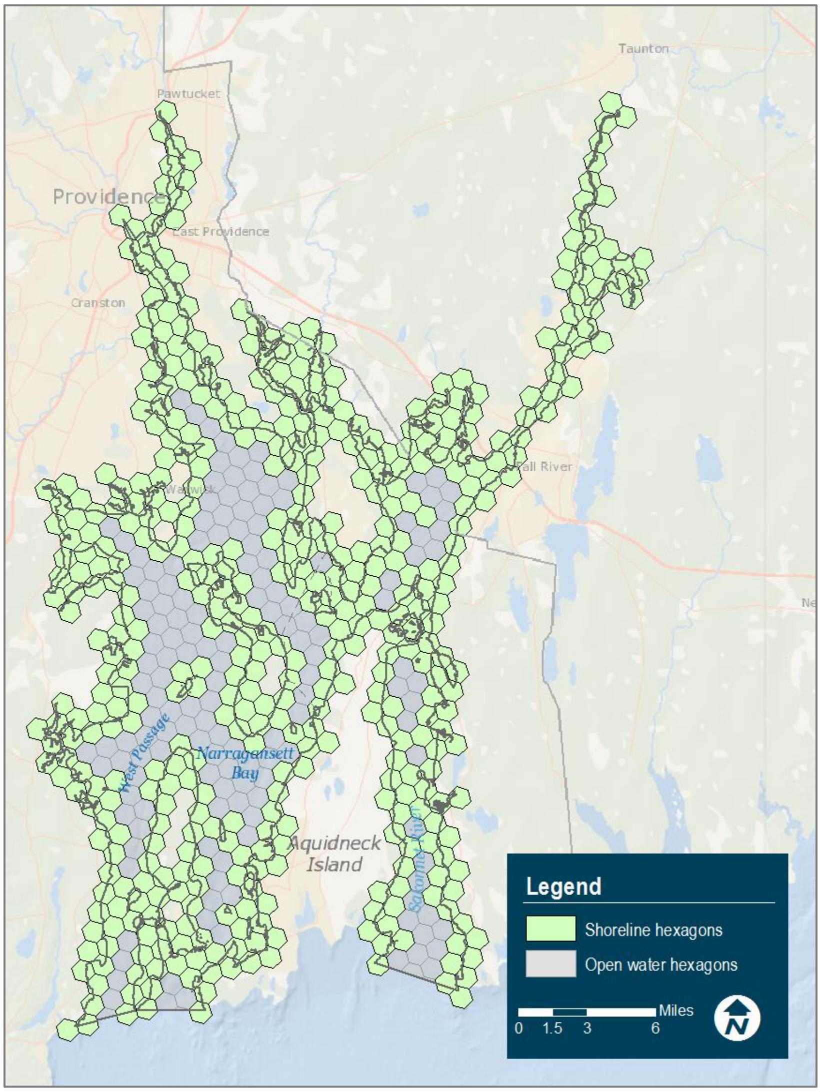
Narragansett Bay is a 380 km^2 estuary within Rhode Island and Massachusetts (Figure 3). Winter Flounder within the bay have declined over recent years and are of importance for both commercial and recreational fisheries. Narragansett Bay is well studied, and there are several datasets containing many decades of seine and trawl data on winter flounder within the bay. For these reasons, it was chosen by the project coordinators as the site for the pilot model and framework development effort.

Methods

Study Area

The modeling hexagons (n = 647) for the Narragansett Bay study area were extracted using NOAA shoreline to delineate the bay. Figure 3 below illustrates the modeling hexagons for Narragansett Bay, and delineates the open water hexagons (the outline of which do not intersect shoreline), and the shoreline hexagons.

FIGURE 3. MODELING HEXAGONS



Response Data

Winter flounder are a migratory species, but are known to stay within Narragansett Bay after hatching until approximately age-1 before their first out-migration to the open ocean. To meet the goals of the stakeholders and partners, we chose to focus on only young-of-year (YOY) and age-1 winter flounder. This would allow for us to find relationships between habitat conditions solely inside of the study area and YOY flounder that have not been exposed to conditions outside of the study area. Assessment or inclusion of adult winter flounder would likely indicate habitat preferences and areas of high value to the population, but may not have been as appropriate to assess anthropogenic stressors to the natal portion of the population.

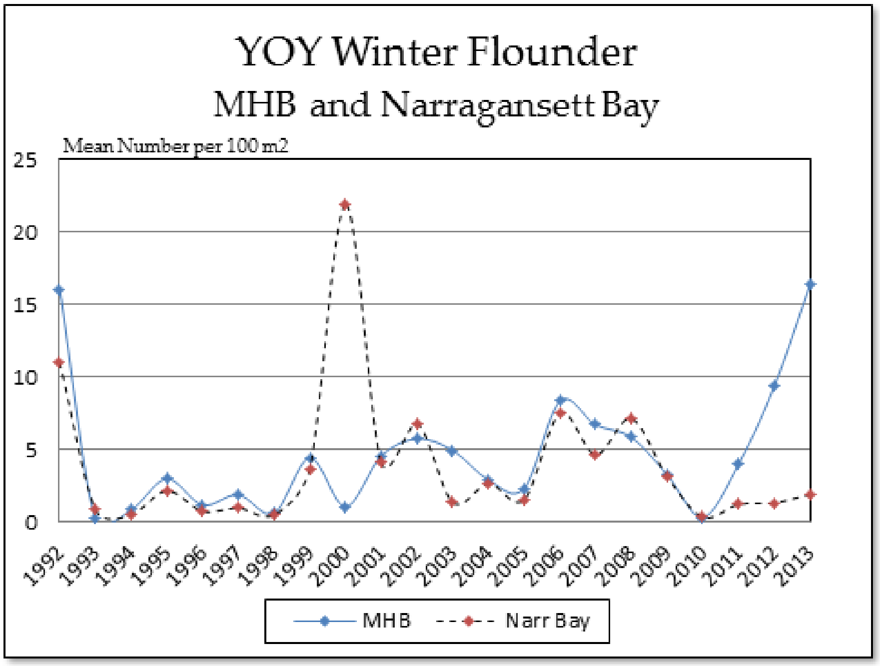
Eric Schneider (RIDEM) performed analysis of seine and trawl survey data to determine length threshold to utilize as an upper criterion for flounder considered within this study. After plotting number at length and proportion of age at length, he determined that an upper length of 220 millimeters (mm) total length was a reasonable threshold to determine fish less than age-2. Age-1 and YOY flounder are assumed to have not yet migrated out of Narragansett Bay where they could have potentially been impacted or influenced by factors outside of the Narragansett Bay study area. Specifically, Eric Schneider found that the threshold of 220 millimeters would include 100% of YOY, 79% of age-1 fish, and only 13% of fish greater than age-1. More details of this analysis can be found in Appendix C.

Data from both seine and trawl surveys were compiled for Narragansett Bay from two main sources, Rhode Island Division of Fish and Wildlife (RIDFW) and Normandeau Associates. The latter was tasked with collecting samples for power plants in the Mount Hope Bay (MHB) portion of Narragansett Bay, while RIDFW provided data for the majority of the remainder of the study area (McNamee, 2008-2013; Powell, 1988-2007). The RIDFW seine samples were concentrated in the upper bay to focus juvenile finfish sampling in closer proximity to the nursery habitat more prevalent in the upper bay.

Initially, all data sources (both seine and trawl) were used to compile winter flounder densities for the response dataset, but due to potential bias and capture efficiency differences between seine and trawl gear, only seine data were utilized for the final model. Trawl data is collected in open water, generally away from shoreline areas. Seine data are collected immediately adjacent to shore. While not quantified specifically for the gear used in this analysis, it is commonly understood that there are differences in capture efficiency and size selectivity between different gear types. Seines generally are more efficient at capturing smaller fish that inhabit shallow areas near shore. Trawls are better at capturing larger fish in deeper habitats. Since seines are generally used to target capture of YOY winter flounder, this model utilized only the seine data as response data for the final model. Additionally, due to the absence of response data from open water hexagons, they were removed from the predictive model, leaving 484 shoreline hexagons that were evaluated for this assessment (Figure 3).

The seine data provided to DS were collected from years 2000 to 2013 for the MHB data and from 1988 to 2013 for the RIDFW data. In order to create a temporal match to predictor variables, which were generally created or compiled within the last decade, DS suggested using only more recent samples from these datasets. Eric Schneider of RIDFW analyzed yearly trends in winter flounder abundance from 1992 – 2013. These trends are shown in Figure 4 for both MHB and Narragansett Bay, with the units of mean sampled YOY winter flounder densities from seine surveys. Based on the trends evident, it was decided by the review team that using sample data from 2001-2013 would create an approximate temporal match with predictor variables and would avoid the abnormally strong year class from 2000, thus gathering data from a time period when estimates of abundance were relatively stable.

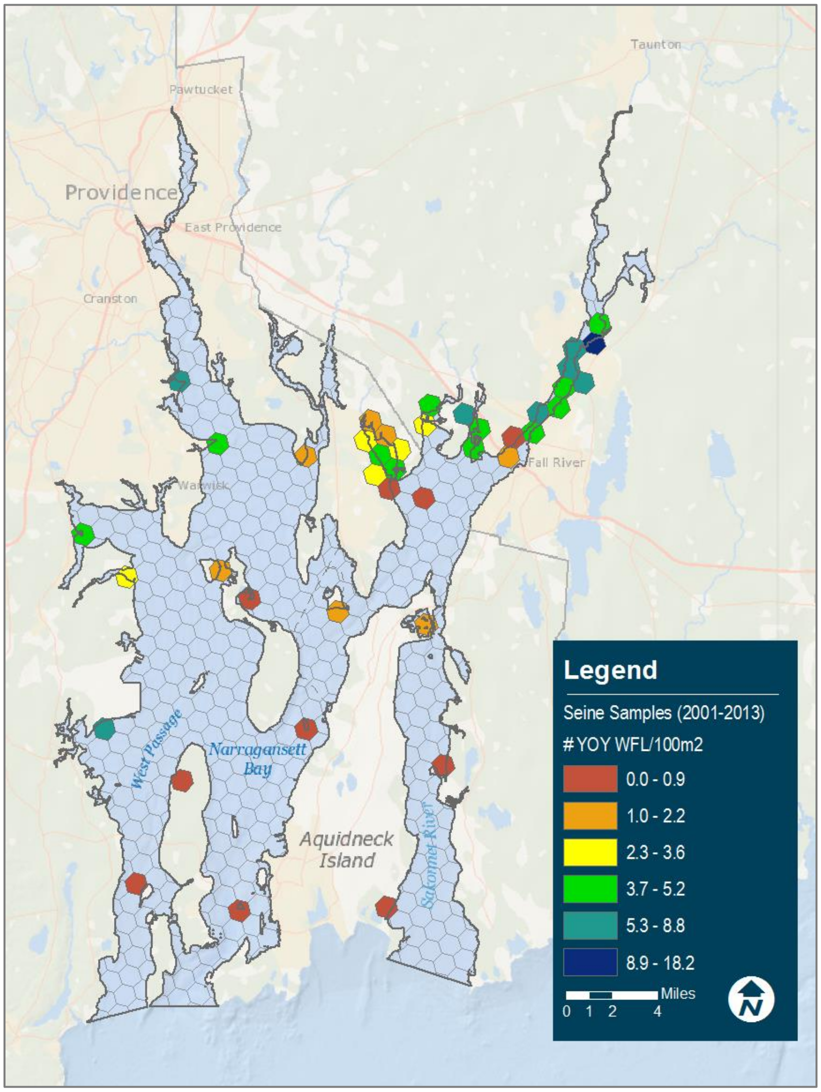
FIGURE 4. WINTER FLOUNDER DENSITY TRENDS



Providers of the seine data provided the number of YOY flounder captured and the estimated area swept per seine haul. This allowed us to calculate an estimated YOY flounder density for each sample. For the predictive model, only a single response value was required for each hexagon that had data. This required DS to summarize the data within hexagons that had more than one sample taken during the 13-year period defined above for the response data. To calculate the 13-year mean winter flounder YOY density within each hexagon, the total number of YOY winter flounder collected in each hexagon was divided by the total area sampled in that hexagon across all sampling events. Figure 5 shows the study area and the mean YOY winter flounder density for the hexagons where seine samples were taken during the specified 13-year time period. There were a total of 41 hexagons with response data (a relatively small sample size), and they were geographically skewed, as the samples were more concentrated in the northeastern portion of the study area.

Before modeling, the calculated densities that were used as the response variables were analyzed for normality, and were show to be non-normally distributed. A log transformation was utilized to create a more normalized distribution of response data. This transformation improved the predictive ability of the BRT when analyzing cross-validated statistics from preliminary models using transformed and untransformed response datasets.

FIGURE 5. RESPONSE DATA



Predictor Data

DS and the review team compiled aquatic and nearshore terrestrial predictor data from multiple sources. Each predictor variable was summarized for each hexagon within Narragansett Bay. Table 2 below shows a summary of all predictor data sources that were utilized. A full list of all processed predictor variables considered in the final model and extracted from the sources listed in Table 2 can be found in Appendix A. Additionally, DS and the review team pursued additional predictor data that were unable to be utilized in the modeling effort, mainly due to the geographic limitations (i.e. the data did not cover the entire study area). A summary of these data sources that were examined, but unable to be used for modeling, can be found in Appendix B .

TABLE 2. PREDICTOR VARIABLES

Predictor Variable	Source
Depth/Bathymetry	NOAA CSC
Eelgrass/SAV	URI
Estuarine habitat type	RIDEM

Hardened shoreline	RIDEM
Impervious surfaces	NLCD
NPDES outfalls	RIDEM
Nutrient levels	NOAA
Salinity zones	NOAA
Substrate composition	Brown University
Substrate composition	TNC NAMERA

Note: Substrate data from Brown University had better resolution, but did not cover the entirety of the study area, and in those areas the TNC data was utilized. Both data sources had the same structure which allowed us to combine them.

Predictive Modeling

The BRT model was created using 100% of the available response data because of the limited amount of response data (n = 41). The resulting model was then extrapolated to all unsampled shoreline modeling hexagons within Narragansett Bay. Because the response variable was log-transformed before the model was run, all extrapolated values were first back-transformed to number of fish per $100m^2$.

Plots of fitted values and predictor variable values versus residual values were created with a loess line plotted for the data points and a dashed line at zero residual. We also mapped residuals for each of the 41 hexagons where residuals were calculated. The values are shown by standard deviation of the residuals, which allows for a quick visual interpretation of areas that contain the most extreme overpredictions (negative residuals) or underpredictions (positive residuals).

Results

Model Details

Predictive Performance

The final model was comprised of 1,450 trees and used a learning rate of 0.005 and tree complexity = 1. The model had a CV correlation statistic of 0.685±0.092 and it explained 60.5% of the deviance in the response data.

Variable Influence Accuracy

Table 3 shows the predictor variables used in the model ordered and scored by their relative importance. The salinity zone variable was the single most important predictor variable in the model with a relative influence of 24.7%. This was a three-zone variable, with each hexagon classified as either being Tidal Fresh Zone, Mixing Zone, or Ocean Zone.

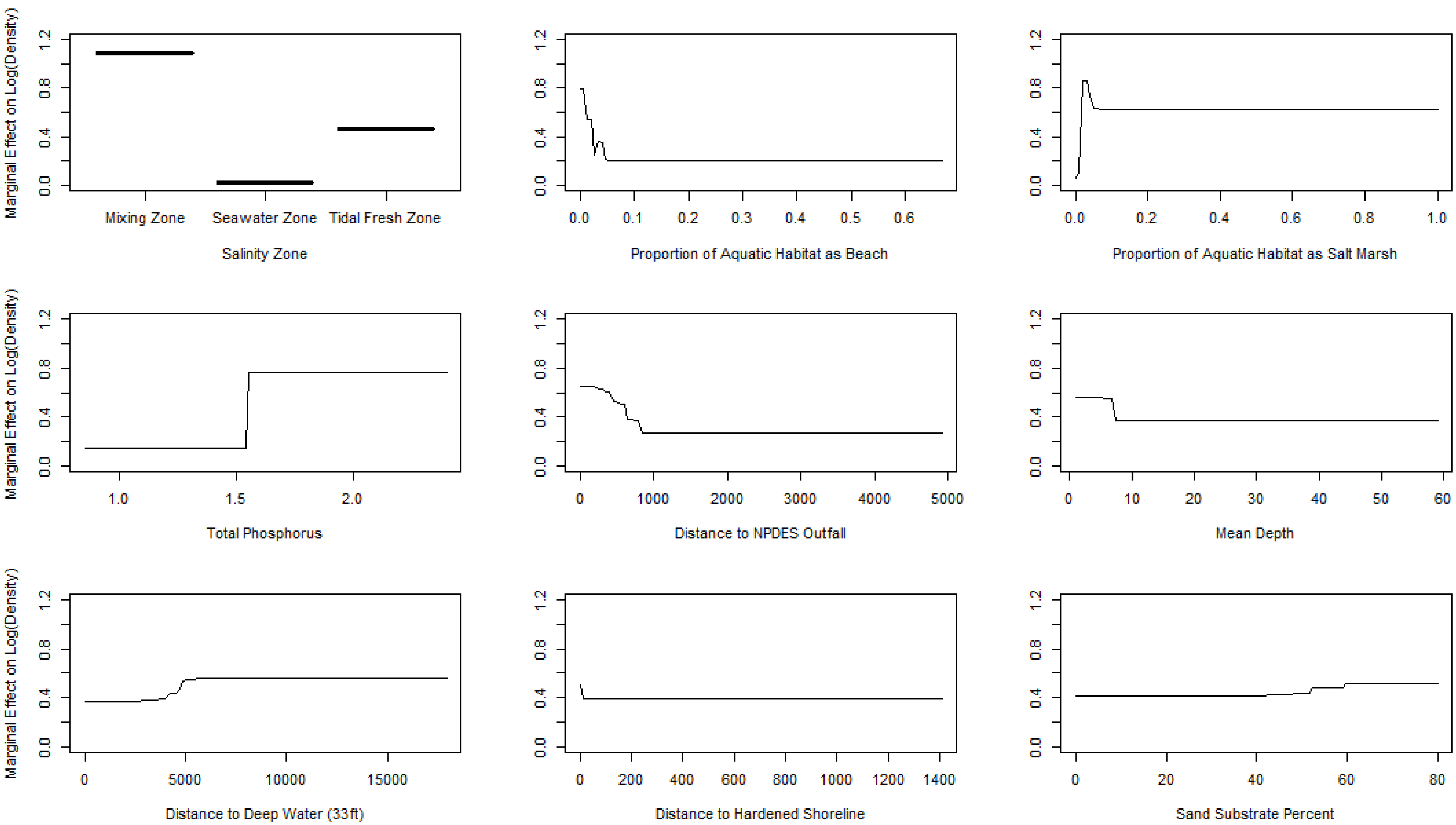
TABLE 3: RELATIVE INFLUENCE OF ALL VARIABLES IN THE FINAL NARRAGANSETT BAY WINTER FLOUNDER MODEL

Variable Description	Relative Influence
Salinity zone	24.7
Percent of aquatic habitat as beach	18.3
Percent of aquatic habitat as salt marsh	17.7
Mean total phosphorus within hexagon	12.7
Distance to nearest NPDES outfall	9.8
Mean water depth within hexagon	7.2
Distance to nearest deep water (> 33 feet)	6.0
Distance to nearest hardened shoreline	2.0
Percent of benthic habitat as sand	1.7

Variable Functions

These plots show the marginal effect on the response variable (log(abundance)) on the y-axis as the predictor variable (x-axis) changes, which is the influence each variable has when holding all other variables in the model constant. It cannot be used to precisely indicate the exact change in the response at varying predictor levels, but is useful to assess the general relationship between predictors and the response, especially for understanding the directionality of each relationship. Additional details about how these plots were created are provided in the Statistical Approach section. The function plots for the nine variables in the winter flounder model (Table 3) are illustrated in Figure 6.

FIGURE 6: FUNCTIONAL RESPONSES OF THE DEPENDENT VARIABLE TO INDIVIDUAL PREDICTORS OF WINTER FLOUNDER

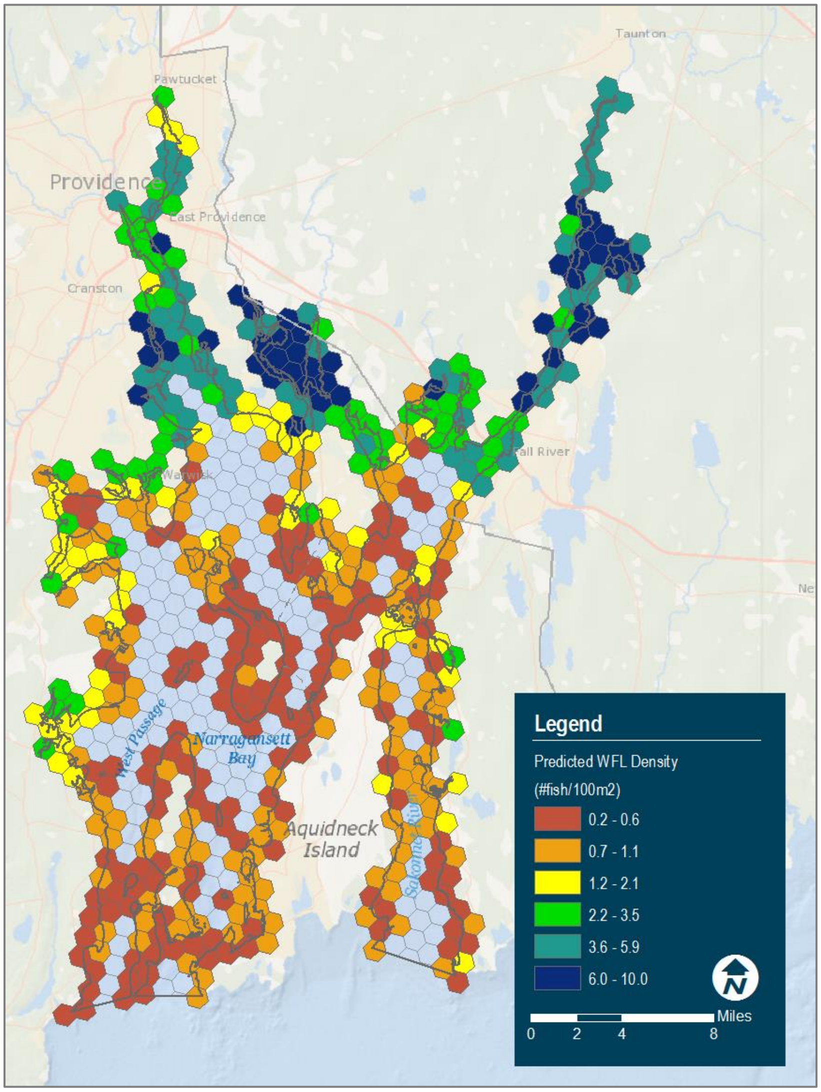


NOTE: SEE APPENDIX A FOR DETAILED DESCRIPTIONS OF VARIABLES.

Predicted Outcomes

Winter flounder abundance was extrapolated for all 484 hexagons that intersected the shoreline using the BRT model. After the values were back-transformed to fish/100m^2, the predicted abundance ranged from 0.22 to 9.95 fish/100m^2. The mean predicted abundance was 2.05 fish/100m^2. There were 229 hexagons with a predicted abundance of greater than 1.00 fish/100m^2, with the majority of these hexagons occurring in the northern portion of the bay. These results are mapped in Figure 7.

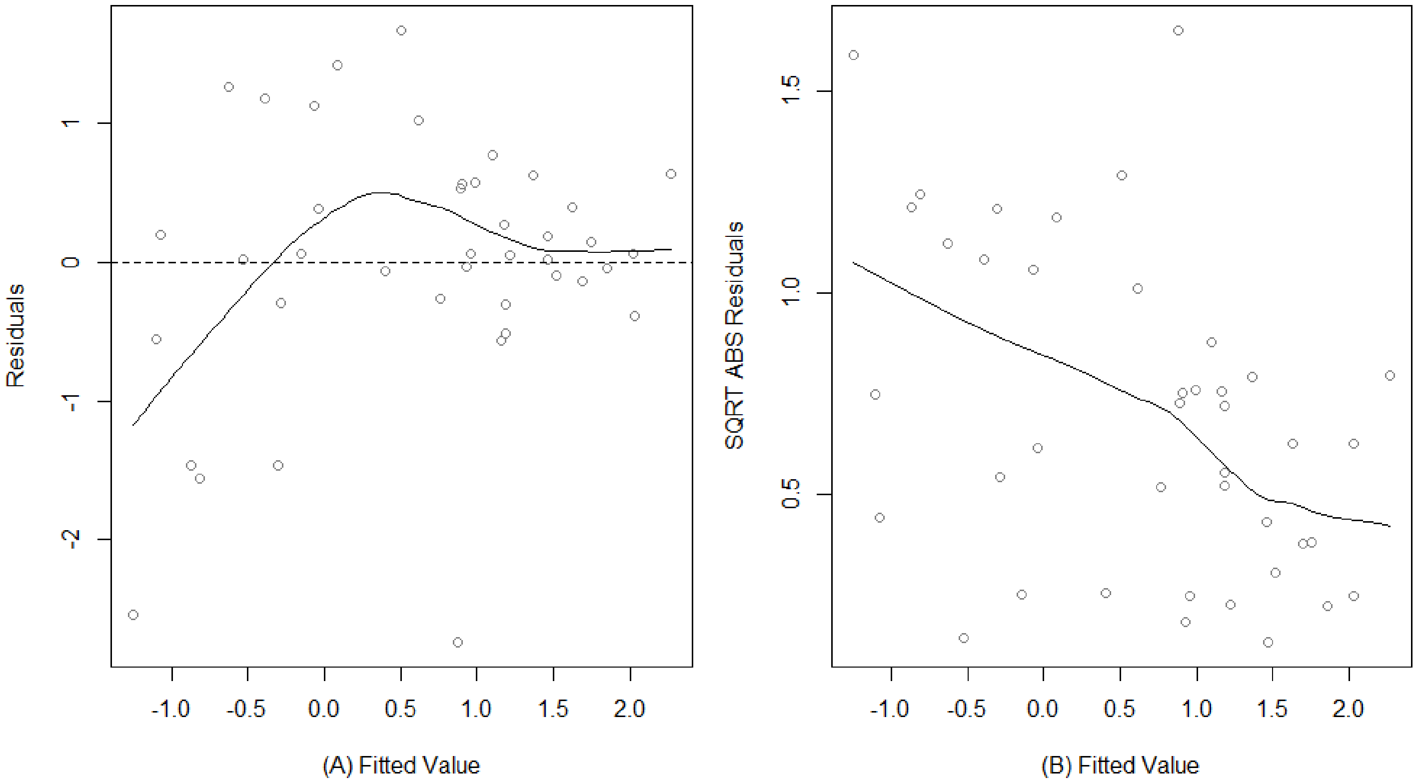
FIGURE 7. PREDICTED YOY WINTER FLOUNDER ABUNDANCE.



Residuals Analysis

Figure 8 shows the fitted values (predicted log(density) value for hexagons that had response data) versus the residual values (8a) and the fitted values versus the square root of the absolute value of the residuals (8b). Figure 8a shows that the model may be overpredicting at very low densities and underpredicting at medium densities. The plot on the right, plot (b), shows that the magnitude of residuals decreases as predicted density increases, and may indicate that the model is less accurate at predicting lower densities.

FIGURE 8. FITTED VALUE RESIDUALS.



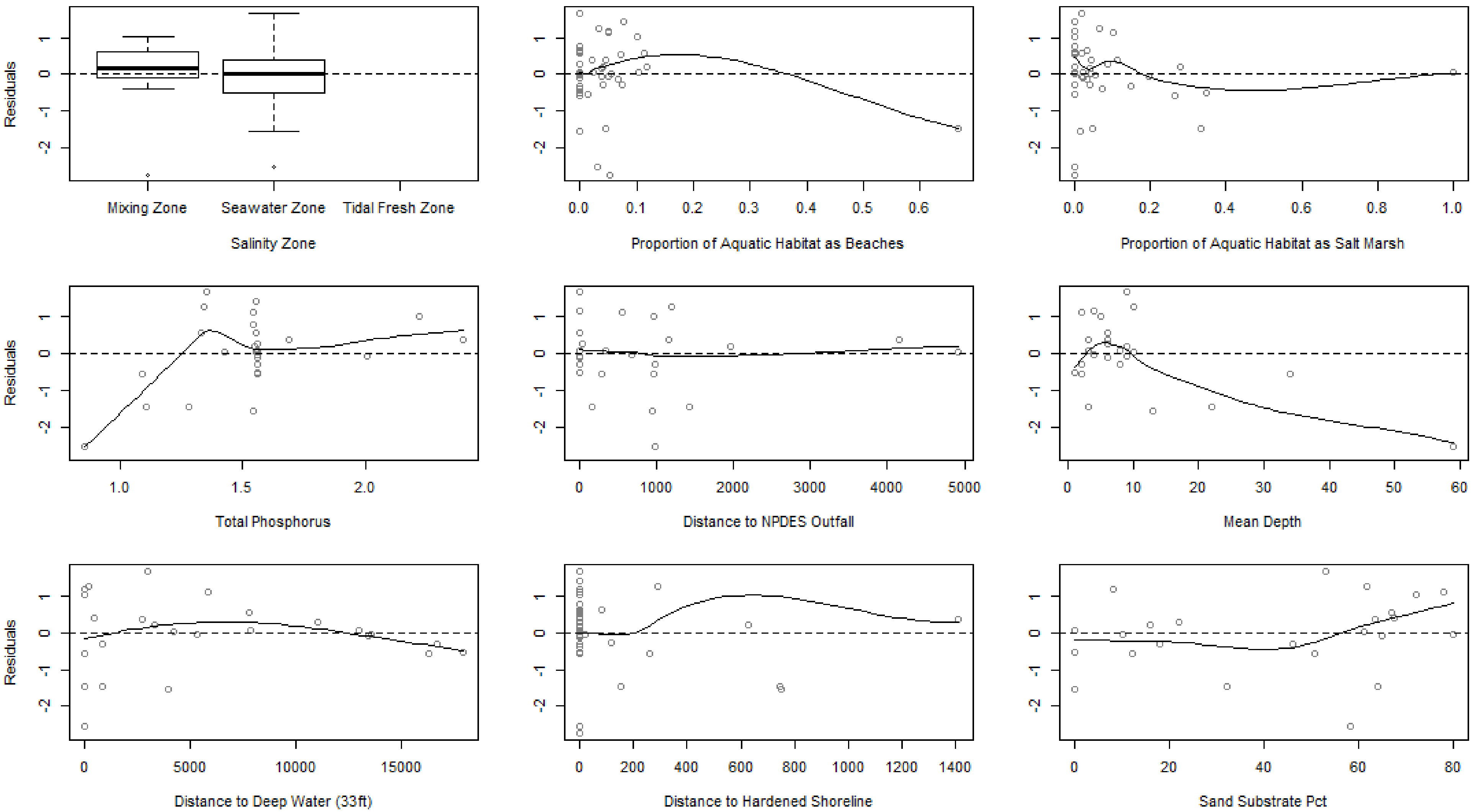
Note: Plot (a) indicates fitted values versus residuals, plot (b) indicates fitted values versus the square root of the absolute value of the residuals.

We plotted the residuals against the predictor variables in a plot similar to Figure 8(a) above. These are shown in Figure 9, and the plots are ordered to correspond to their relative influence within the model (see Figure 6). We also plotted the value of each predictor variable against the square root of the absolute value of the residuals for a comparison similar to Figure 8(b) above. These plots are shown below in Figure 10, and show the magnitude of residuals at differing values of predictor variables. These plots all have a loess line plotted to indicate trends, but with the small sample size available, it is possible that the loess lines are more sensitive to extreme values than the predicted values from the BRT model.

These plots indicate that the model is better at predicting some habitat types than others. Shallow areas in the mixing salinity zone and moderate to high phosphorus levels predicted well, but deep habitats in the ocean salinity zone and low phosphorus levels were all overpredicted. The residual plots also indicate that areas with high levels of sand substrate are underpredicted compared to low and moderate levels of sand substrate. The plot of percent beach habitat has one extreme value that skews the tail of the trend line and would indicate an overprediction at high proportions of sand substrate, but the trend where the majority of data exists doesn't show a strong pattern of over- or under-prediction.

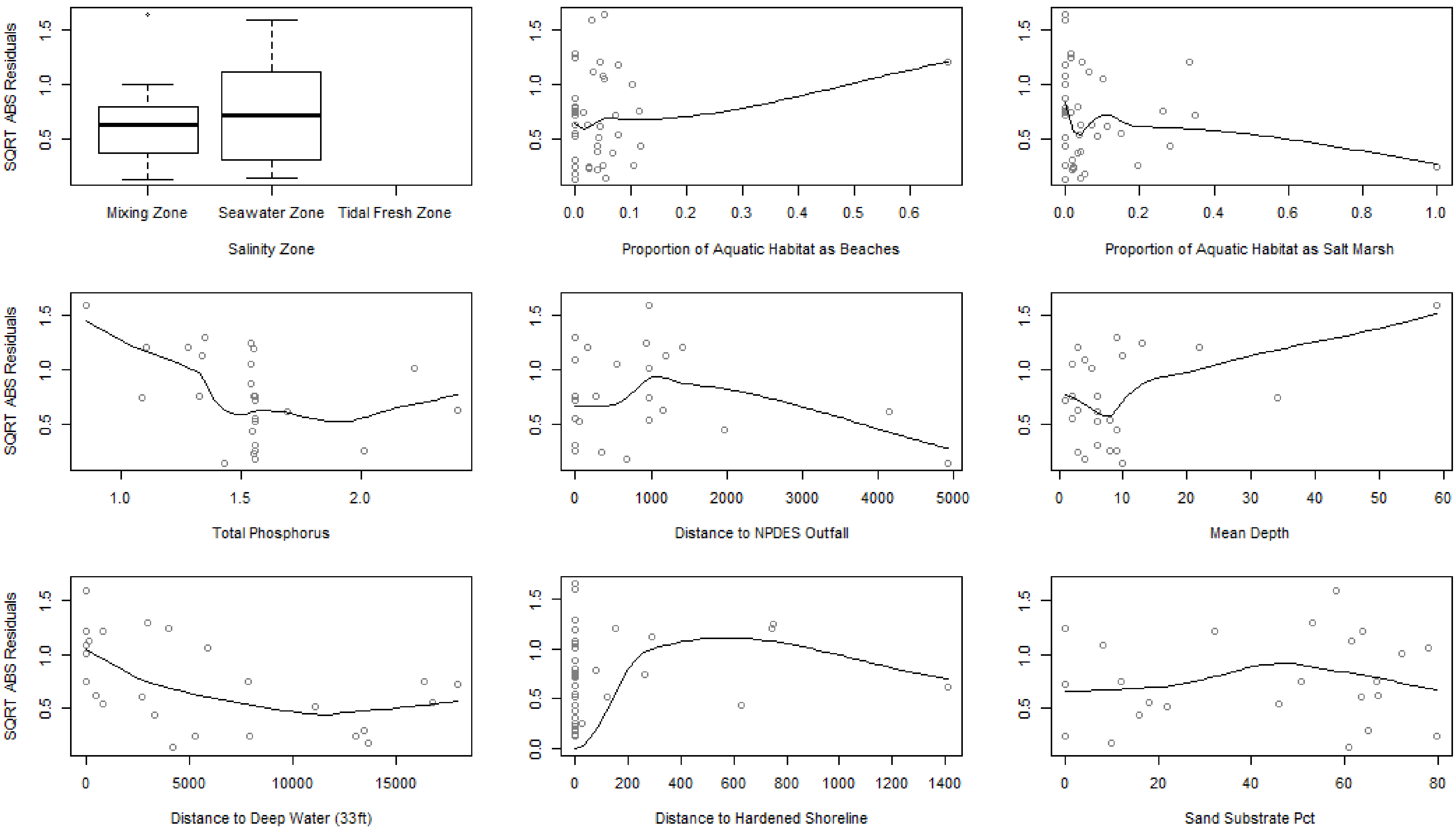
We also mapped residuals for each of the 41 hexagons where residuals were calculated (Figure 11) to assess spatial patterns of prediction errors.

FIGURE 9. RESIDUAL PLOTS FOR PREDICTOR VARIABLES.



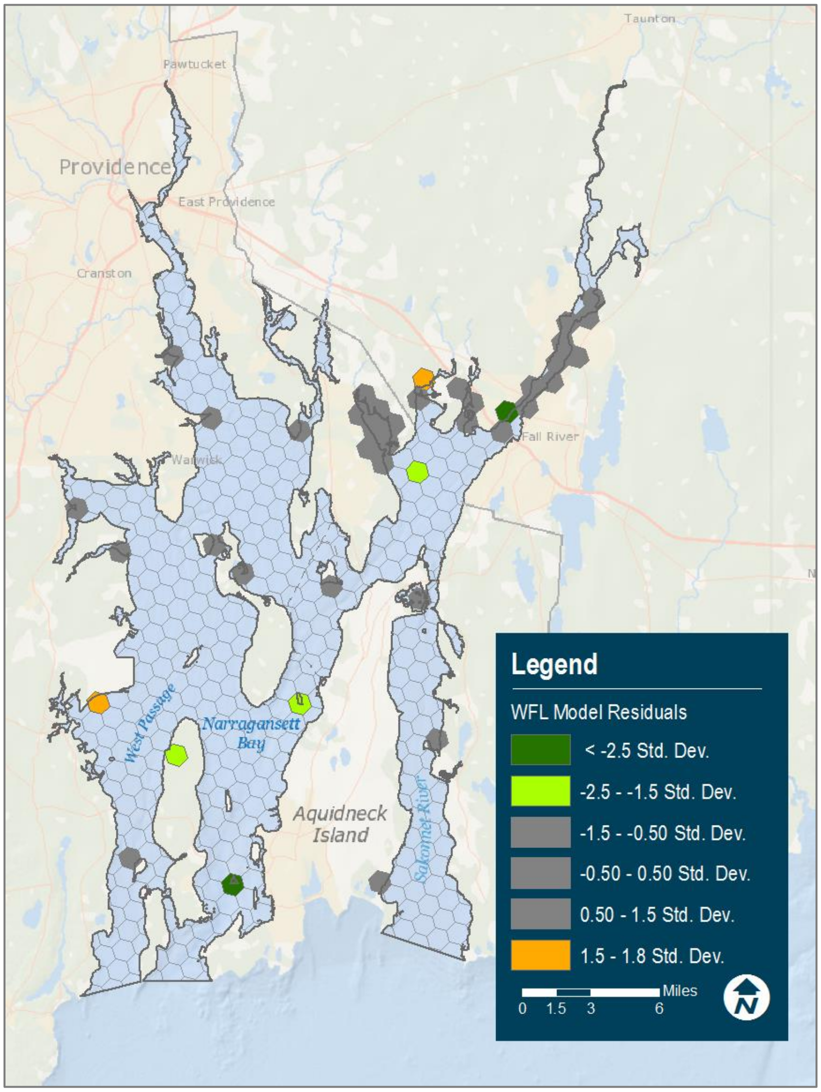
NOTE: SALINITY ZONE IS BASED ON THREE CATEGORICAL CLASSES RATHER THAN CONTINUOUS VARIABLES PLOTTED THROUGHOUT THE REMAINDER OF THIS FIGURE.

FIGURE 10. SQRT ABSOLUTE VALUE RESIDUAL PLOTS FOR PREDICTOR VARIABLES.



Note: SALINITY ZONE IS BASED ON THREE CATEGORICAL CLASSES RATHER THAN CONTINUOUS VARIABLES PLOTTED THROUGHOUT THE REMAINDER OF THIS FIGURE.

FIGURE 11. MAPPED RESIDUALS



Discussion

Generally, the distribution of YOY winter flounder as predicted by this model confirmed existing Narragansett Bay knowledge. In a similar analysis of Narragansett Bay, Meng et al. (2005) found juvenile winter flounder densities to be highest in the upper bay, in areas of high human density and near marsh habitat. These habitat relationships mirror the habitat factors that were relevant to the similar distributional pattern of our model, and each one is discussed in more detail below.

The areas with higher YOY winter flounder densities tend to be within the 'Mixing Zone' or to a lesser extent the 'Tidal Fresh' salinity zones. The mechanism for why YOY tend to be found in areas with lower salinities values is not fully understood. Some research has shown that salinity gradients in estuaries influence the area of habitat available to YOY winter flounder, and that more stenohaline predators such as summer flounder and sea robins are less effective in lower salinities (Mark Gibson, personal communication).

Saucerman and Deegan (1991) found that YOY winter flounder did not move far from likely settlement locations during summer, which could cause habitat associations with areas proximal to spawning habitats rather than with preferred habitats, but since the size class of winter flounder used in our analysis include both newly settled YOY and larger juveniles, it is possible that their distributions represent preferred habitat conditions rather than spawning habitat preference for adult winter flounder. Therefore, it is possible that lower salinities could be actively sought out by the YOY winter flounder in our analysis. Stoner et al. (2001) studied smaller size classes of YOY winter flounder in the Mid-Atlantic (25-55 mm, which overlaps the lower end of our size range) and found that this size class of winter flounder were associated with intermediate salinities (approximately 20 ppt).

The function plots above (Figure 6) indicate that winter flounder are found in areas that are shallow. This fits current knowledge on the habitat preference of YOY winter flounder. The source document for EFH (Pereira et al. 1999) indicates that young winter flounder associate with shallow areas, as does Stoner et al. (2001), which showed association of YOY winter flounder with depths less than two to three meters, depending on the exact size class of fish. Manderson et al. (2004) found that YOY winter flounder likely inhabited shallow habitats as a means of avoiding predation from summer flounder (*Paralychthys dentatus*) and other predators.

Figure 6 also shows a relationship where higher densities of YOY winter flounder are associated with higher percentages of sand substrate. This relationship does not exhibit a high relative influence when compared to other habitat factors in our model, but a trend is visible. Howell et al. (1999) found that juvenile winter flounder associated with mud habitats and that lower densities were observed in sand habitats in Connecticut embayments, which differs from the trends in our habitat relationships. Of note though, Goldberg et al. (2002) found that habitat type associations with YOY winter flounder was more variable from system to system, and even from year to year, so the association with sand substrate within Narragansett Bay may not be expected to carry through to other estuaries, and could be a factor of local habitat and/or prey availability.

The model also indicated a relationship between urbanization/development and YOY winter flounder abundance. The variables indicating mean imperviousness within a 2km buffer of the focal hexagon and distance to nearest hardened shoreline both indicate that the more urbanization/development within Narragansett Bay, the higher the density of YOY winter flounder likely to be encountered. This confirms the habitat relationships found by Meng et al. (2005), where juvenile winter flounder densities in Narragansett bay were in areas of high human population or disturbance. It is important to note that this relationship may not be a cause-effect relationship, but rather that development has occurred in areas proximal to habitats that are more favorable for YOY winter flounder. The relationships indicate that these developed areas are still of importance to winter flounder and should be protected, although they may seem degraded.

Also of note is the relationship between salt marshes and YOY winter flounder indicated by the model. Within Narragansett Bay, salt marshes are a relatively rare habitat type. The relationship between salt marsh and YOY winter flounder abundance indicates that within areas where there is some amount of salt marsh habitat, there is also an increased likelihood of higher YOY winter flounder abundances, even though this relationship breaks down in hexagons with extremely high proportions of salt marsh. The breakdown in that relationship is likely occurring because very high proportions of salt marsh is very rare within the modeled data. While this relationship could be causative, we cannot definitely draw that conclusion from our analysis This relationship does parallel finds from Meng et al. (2005) where they saw highest juvenile winter flounder densities at sites near marshes.

Lastly, the function plots indicate YOY abundance is higher in areas with less beach habitat, and in areas with higher total phosphorus levels. The increased phosphorus may correlate with higher primary productivity, which could result in higher food availability for YOY winter flounder. The reduced density expected in areas with increased beach habitat could be a habitat association or preference that is evident in the Narragansett Bay population of winter flounder, similar to the unique habitat associations described by Goldberg et al. (2002) for distinct systems. Phelan et al. (2001) showed in laboratory studies that prey availability would over-ride sediment choice by YOY winter flounder. It is possible that a lack of prey for YOY winter flounder in Narragansett Bay beach habitat could be contributing to the lower abundances in areas with high beach habitat, but more detailed studies would be needed to confirm that prey availability differences was influencing habitat choice or association.

Limitations

Response data was only available for 41 hexagons within Narragansett Bay. While this data was sufficient enough to produce a predictive model with reasonable cross-validated accuracy, the amount and distribution of these sites likely limited the accuracy of the final model. Having additional data to create the model would result in a more complete understanding of the distributional outputs from the model as well as the relationships to habitat.

Response data were also not collected using randomized locations, and as such it is possible that not all habitats available within Narragansett Bay were sampled. This can cause the predictions for habitats outside those represented within the response data to be questionable. The habitats selected for the RIDFW sampling were selected because they were considered good juvenile finfish habitat and in areas where the sample gear could be used effectively.

This model required the use of summarized response data. The dataset averaged conditions over the 13-year period selected, and as such can only be interpreted as indicative of the generalized conditions across that time frame. Yearly variance due to weather, water quality, or cyclical biological interactions is beyond the scope of this analysis.

Likewise, this model used summarized predictor variables to predict the most likely conditions within a 1-km hexagon. Conditions within each hexagon were summarized, so precise conditions at any given location within each hexagon could vary significantly from the summarized conditions. Given the scale at which predictor variables were available, the 1-km hexagon was deemed appropriate by winter flounder biologists as the most fine-scale management unit given current data. As the resolution of predictor variables improves, the scale of analysis can likewise be reduced in order to reduce variability within each modeling unit (hexagon).

Predictor variables were not available or not available at the required resolution for several factors potentially important for YOY winter flounder. Water temperatures are known to be important in structuring distribution of winter flounder, but within Narragansett Bay, there were no reliable measures of temperature interpolated for the entire study area able to be processed in the timeframe necessary for this project. Similarly, salinity is also important to winter flounder, and while we were able to use a zonal (categorical) predictor variable, a continuous representation of salinity was not available for this effort within Narragansett Bay. After this Narragansett Bay modeling effort was completed, salinity and temperature data for the entire northeast was located and acquired. This data came from NECOFS and was utilized for the Long Island Sound model. We recommend future projects prioritize the acquisition or processing of continuous complete interpolated surfaces of annual or seasonal water quality.

Relationships found within any predictive model should be interpreted with the results from existing literature. Relationships between the response and any predictor variable in these types of models indicate correlation, and caution should be used when extrapolating such results as mechanistic or causative.

Long Island Sound Model

Introduction

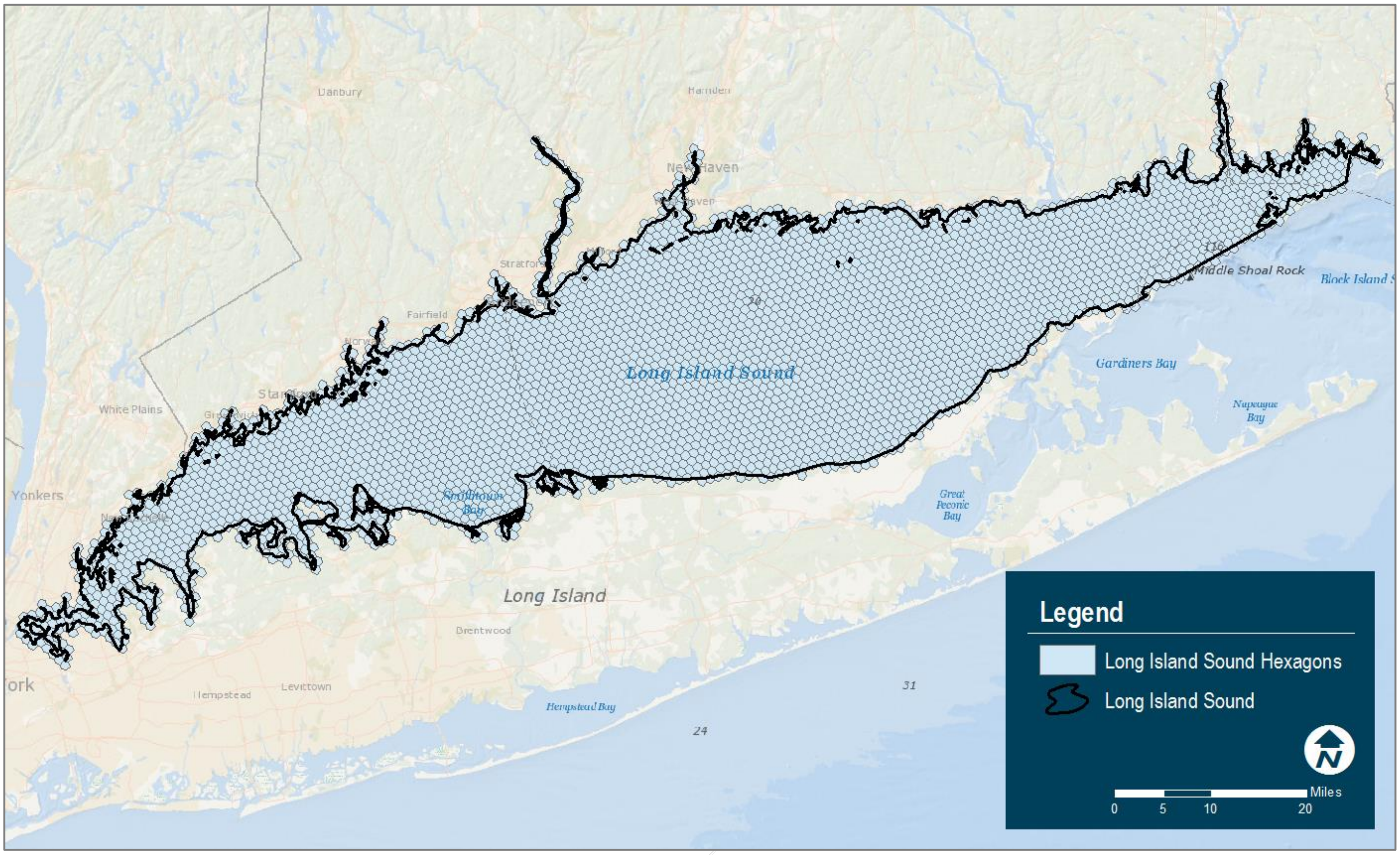
Long Island Sound (LIS) is a 3,367 km^2 estuary that lies between Long Island, New York and Connecticut. (Figure 12). Winter Flounder here are of importance for both commercial and recreational fisheries. LIS is well sampled, and there are several datasets containing many decades of seine and trawl data on winter flounder within the bay. It was chosen to supplement the Narragansett Bay effort because of the data availability and to be able to compare results from the two systems.

Methods

Study Area

The one square kilometer modeling hexagons for the LIS study area were extracted using the estuary boundary defined within the National Fish Habitat Action Plan Coastal Assessment (National Fish Habitat Action Plan, 2010). Figure 12 below shows the 3,756 modeling hexagons for LIS.

FIGURE 12. LONG ISLAND SOUND MODELING HEXAGONS



Response Data

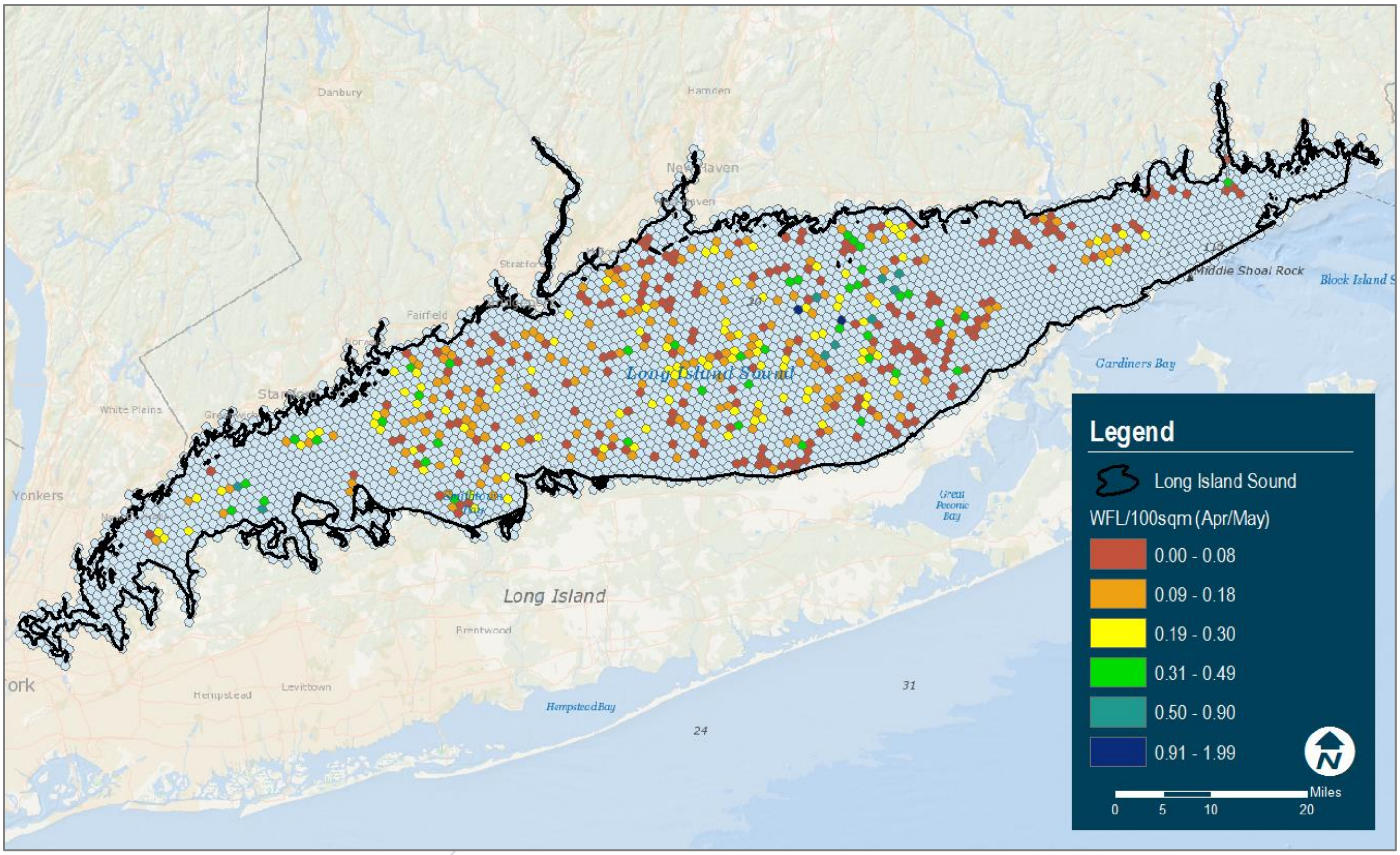
To complement and contrast the response data used during the Narragansett Bay effort, where YOY winter flounder were the focal size class of the response, stakeholders and partners chose to focus on all winter flounder sampled by trawl surveys. Trawl surveys generally do not target YOY winter flounder, and for our effort all winter flounder collected in trawl surveys were used to create the final response dataset. This would allow for us to find relationships between winter flounder and areas of high value to the population as a whole. Partners and biologists indicated that late spring (April and May) would be the most critical time period to analyze flounder density and to also the time period when salinity and temperature may have the most influence on flounder densities.

Trawl survey data were compiled for LIS from Connecticut Department of Energy and Environmental Protection (CTDEEP) for data collected between 2001 – 2013. After removing trawls with potentially erroneous location data (i.e. those trawls that were excessively long, or were indicated as crossing land according to start and end locations) and removing samples taken outside of April and May, there were 994 unique trawls in the dataset that were then associated to the appropriate hexagons. This resulted in a modeling dataset of 525 hexagons, because in many cases multiple trawls were within the same hexagon.

Providers of the trawl data provided the number of flounder captured and the estimated area swept per trawl. This allowed us to calculate an estimated flounder density for each sample. For the predictive model, only a single response value was required for each hexagon that had data. This required DS to summarize the data within hexagons that had more than one sample taken during the 13-year period defined above for the response data. To calculate the 13-year mean late spring winter flounder density within each hexagon, the total number of winter flounder collected in each hexagon was divided by the total area sampled in that hexagon across all sampling events. Figure 13 shows the study area and the mean winter flounder density for the hexagons where samples were taken during the specified 13-year time period.

Before modeling, the calculated densities that were used as the response variables were analyzed for normality, and were show to be non-normally distributed. A log transformation was utilized to create a more normalized distribution of response data. This transformation improved the predictive ability of the BRT when analyzing cross-validated statistics from preliminary models using transformed and untransformed response datasets.

FIGURE 13. LIS RESPONSE DATA



Predictor Data

DS and the review team compiled aquatic and nearshore terrestrial predictor data from multiple sources. Each predictor variable was summarized for each hexagon within LIS. Table 4 below shows a summary of all predictor data compiled for this effort. Some of the variables listed in Table 4 were not utilized within the final predictive model, as some variables were removed from the model for redundancy or lack of variability.

TABLE 4. LIS PREDICTOR VARIABLES

Predictor Variable	Variable Description	Source
Min_depth	Minimum depth within hexagon	NOAA
Max_depth	Maximum depth within hexagon	NOAA
Mean_depth	Mean depth within hexagon	NOAA
Mean_temp	Mean April-May bottom temperature, 2006-2009	NECOFS
Mean_salinity	Mean April-May bottom salinity, 2006-2009	NECOFS
Mean_chlorophyll	Mean chlorophyll-a	TNC

Dist_to_marsh	Distance to emergent marsh	TNC
Pct_gravel	Percent benthic gravel	TNC
Pct_sand	Percent benthic sand	TNC
Pct_silt_mud	Percent benthic silt and mud	TNC
Pct_depression	Percent depression bottom form	TNC
Pct_low_slope	Percent low slope bottom form	TNC
Pct_steep	Percent steep bottom form	TNC
Pct_mid_flat	Percent mid flat bottom form	TNC
Pct_side_slope	Percent side slope bottom form	TNC
Pct_high_flat	Percent high flat bottom form	TNC
Pct_high_slope	Percent high slope bottom form	TNC
Pct_erosion	Percent erosion sediment environment	USGS
Pct_sorting	Percent sorting sediment environment	USGS
Pct_deposition	Percent deposition sediment environment	USGS
Pct_transport	Percent transport sediment environment	USGS
Mean_imperv_2km	Mean imperviousness within 2km buffer	NLCD

Abbreviation Note: NECOFS – Northeast Coastal Ocean Forecast System

Predictive Modeling

The BRT model was created using all of the response data hexagons (n = 525). The resulting model was then extrapolated to all unsampled modeling hexagons within LIS. Because the response variable was log-transformed before the model was run, all extrapolated values were first back-transformed to number of fish per 100m^2.

Plots of fitted values and predictor variable values versus residual values were created with a loess line plotted for the data points and a dashed line at zero residual. We also mapped residuals for each of the 525 hexagons where residuals were calculated. The values are shown by standard deviation of the residuals, which allows for a quick visual interpretation of areas that contain the most extreme overpredictions (negative residuals) or underpredictions (positive residuals).

Results

Model Details

Predictive Performance

The final model was comprised of 1,400 trees and used a learning rate of 0.01 and tree complexity = 1. The model had a CV correlation statistic of 0.357±0.023 and it explained 23% of the deviance in the response data.

Variable Influence Accuracy

Table 5 shows the predictor variables used in the model ordered and scored by their relative importance. The mean salinity variable was the single most important predictor variable in the model with a relative influence of 37.2%, but the next variable in terms of relative influence, maximum depth, was nearly as important, at 32.8%. Water temperature and bottom characteristics are the next most influential variables, and the only anthropogenic factor (mean imperviousness within 2km buffer) included as a predictor was near the bottom of the influential variables, at 2.1% of the relative influence on the final model.

Table 5: Relative influence of all variables in the final winter LIS flounder model

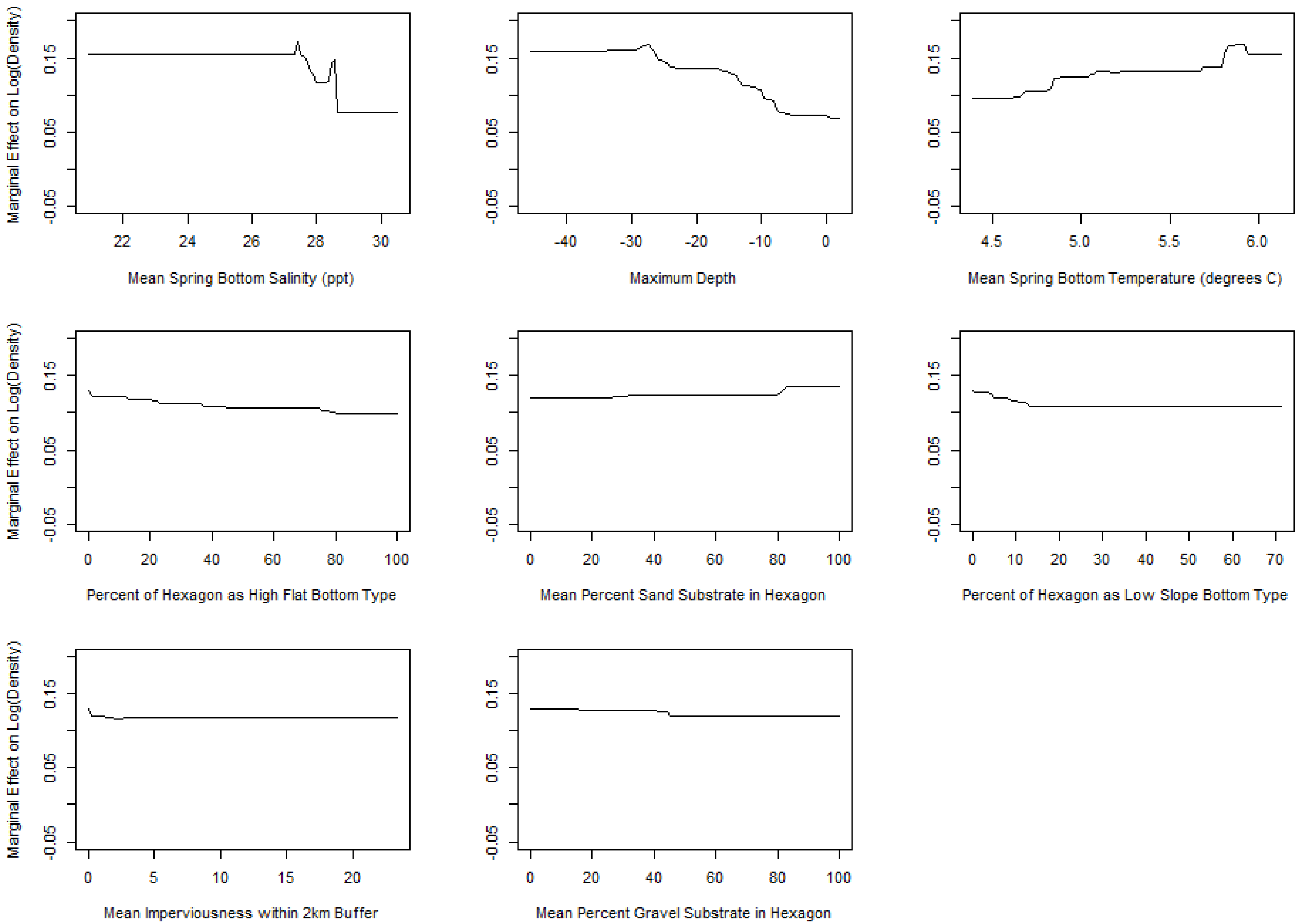
Variable Description	Relative Influence
Mean spring salinity	37.2
Maximum depth	32.8

Mean spring temp	14.1
Percent high flat bottom type	5.0
Percent sand bottom sediment	4.0
Percent low slope bottom type	3.0
Mean imperviousness within 2km buffer	2.1
Percent gravel bottom sediment	1.7

Variable Functions

These plots show the marginal effect on the response variable (log(abundance)) on the y-axis as the predictor variable (x-axis) changes, which is the influence each variable has when holding all other variables in the model consistent. It cannot be used to precisely indicate the exact change in the response at varying predictor levels, but is useful to assess the general relationship between predictors and the response, especially for understanding the directionality of each relationship. Additional details are provided in the Statistical Approach section on how these plots are calculated. The function plots for the eight variables in the winter flounder model (Table 5) are illustrated in Figure 14.

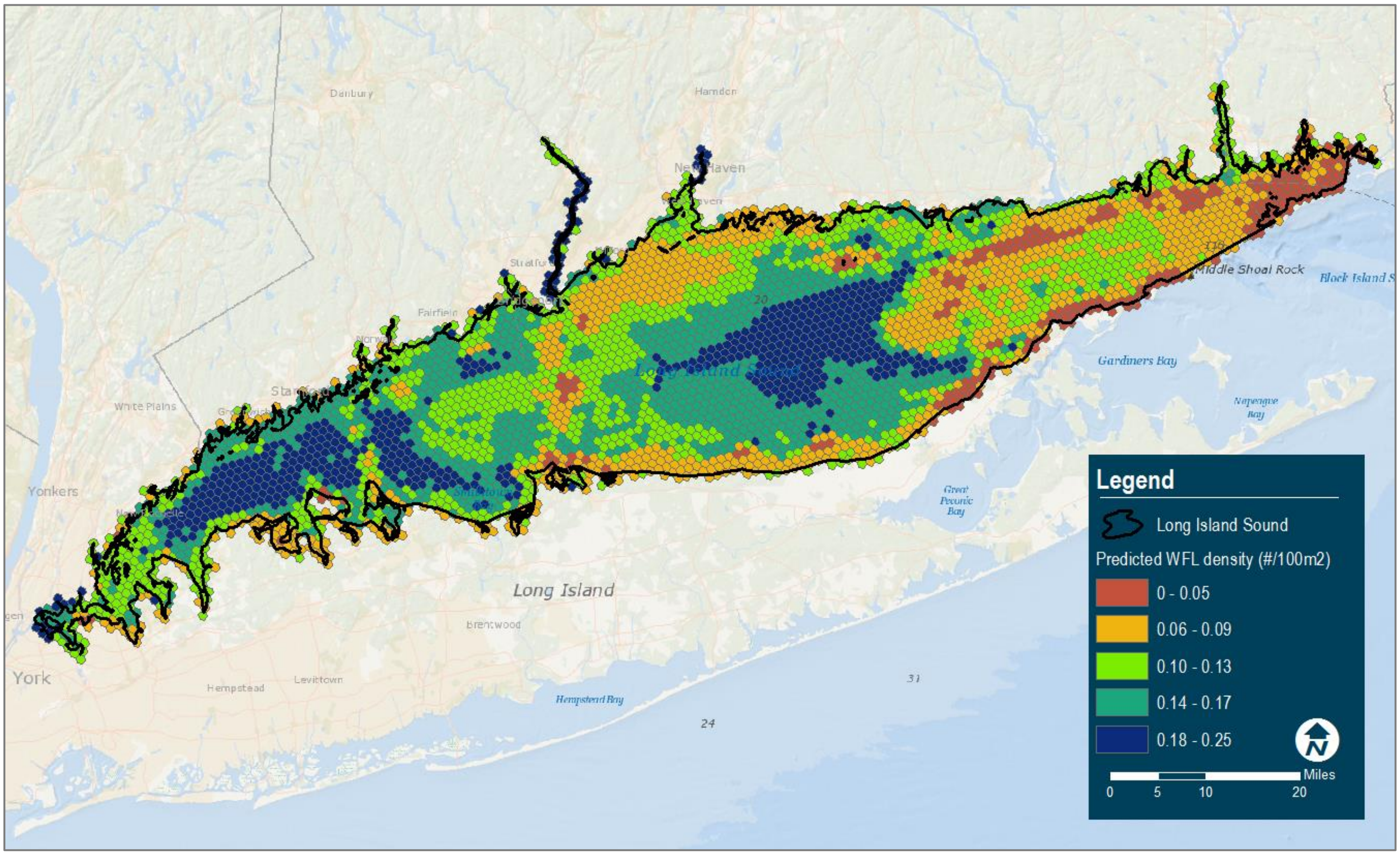
FIGURE 14: FUNCTIONAL RESPONSES OF THE DEPENDENT VARIABLE TO INDIVIDUAL PREDICTORS OF WINTER FLOUNDER IN LIS



Predicted Outcomes

Winter flounder abundance was extrapolated for all 3,756 hexagons within LIS using the BRT model. After the values were back-transformed to fish/100m^2, the predicted densities ranged from 0 to 0.25 fish/100m^2. The mean predicted abundance was 0.12 fish/100m^2. There were 213 hexagons with a predicted abundance of greater than 0.20 fish/100m^2, with the majority of these hexagons occurring in the western or central portion of the bay. These results are mapped in Figure 15.

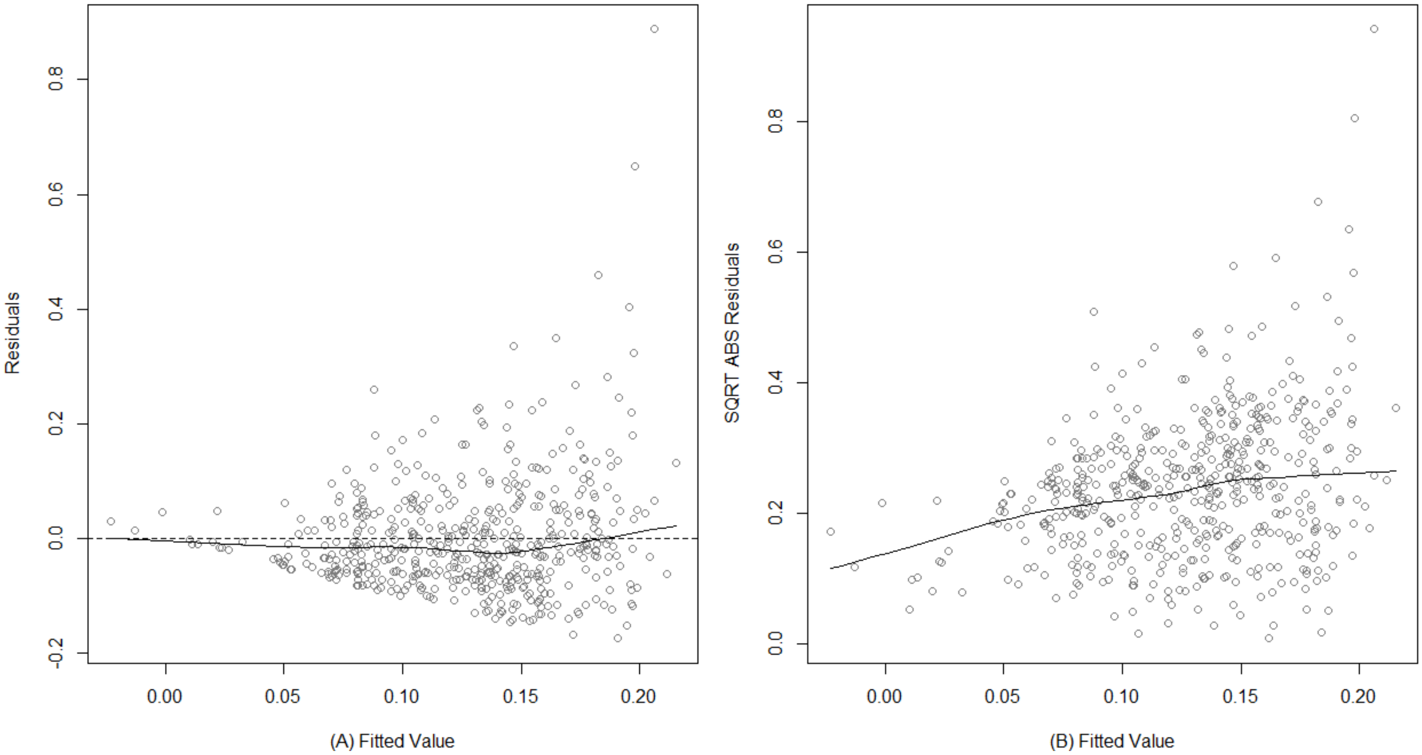
FIGURE 15. PREDICTED WINTER FLOUNDER ABUNDANCE FOR LIS.



Residuals Analysis

Figure 16 shows the fitted values (predicted log(density) value for hexagons that had response data) versus the residual values (16a) and the fitted values versus the square root of the absolute value of the residuals (16b). Figure 16a shows that the model predicts low and moderate densities reasonably well, but indicates that it may underpredict the highest densities. Plot (b) shows that the magnitude of residuals increases as predicted density increases, and may indicate that the model is less accurate at predicting higher densities. This pattern is also evident when examining the maximum densities within the response data map (Figure 13) and the maximum density predicted by the BRT model (Figure 15). It seems that the model is unable to relate habitat characteristics to hexagons that have the highest densities of winter flounder, perhaps due to localized characteristics which are unaccounted for within the predictor data in this analysis.

FIGURE 16. FITTED VALUE RESIDUALS.



NOTE: PLOT (A) INDICATES FITTED VALUES VERSUS RESIDUALS, PLOT (B) INDICATES FITTED VALUES VERSUS THE SQUARE ROOT OF THE ABSOLUTE VALUE OF THE RESIDUALS.

Similarly, we plotted the residuals against the predictor variables in a plot similar to Figure 16(a) above. These are shown in Figure 17, and the plots are ordered to correspond to their relative influence to the model (see Figure 14). We also plotted the value of each predictor variable against the square root of the absolute value of the residuals for a similar comparison to the one in Figure 16(b) above. These plots are shown below in Figure 18, and show the magnitude of residuals at differing values of predictor variables. These plots all have a loess line plotted to indicate trends.

Analysis of Figure 17 reveals an absence of directional bias, where the model drastically over- or underpredicts consistently across the range of predictor variables. The only indication of such predictive bias occurs at low salinity values and at high imperviousness values. In both of these scenarios, which are generally rare in the modeled data, the model tends to overpredict flounder density at the noted ranges.

When analyzing the magnitude of residuals values (Figure 18), we can see there are some habitat types that are predicted more consistently than others, even if there isn't directional bias indicated from the plots in Figure 17. Areas with lower values for low slope, high flat, gravel, and imperviousness all predict comparatively better than other habitat types, while none of the ranges for any of the predictor variables seem to predict especially poorly.

We also mapped residuals for each of the 525 hexagons where residuals were calculated (Figure 19) to assess spatial patterns of prediction errors. This map again indicates the underpredictions of the hexagons containing the highest sampled densities of winter flounder.

FIGURE 17. RESIDUAL PLOTS FOR PREDICTOR VARIABLES.

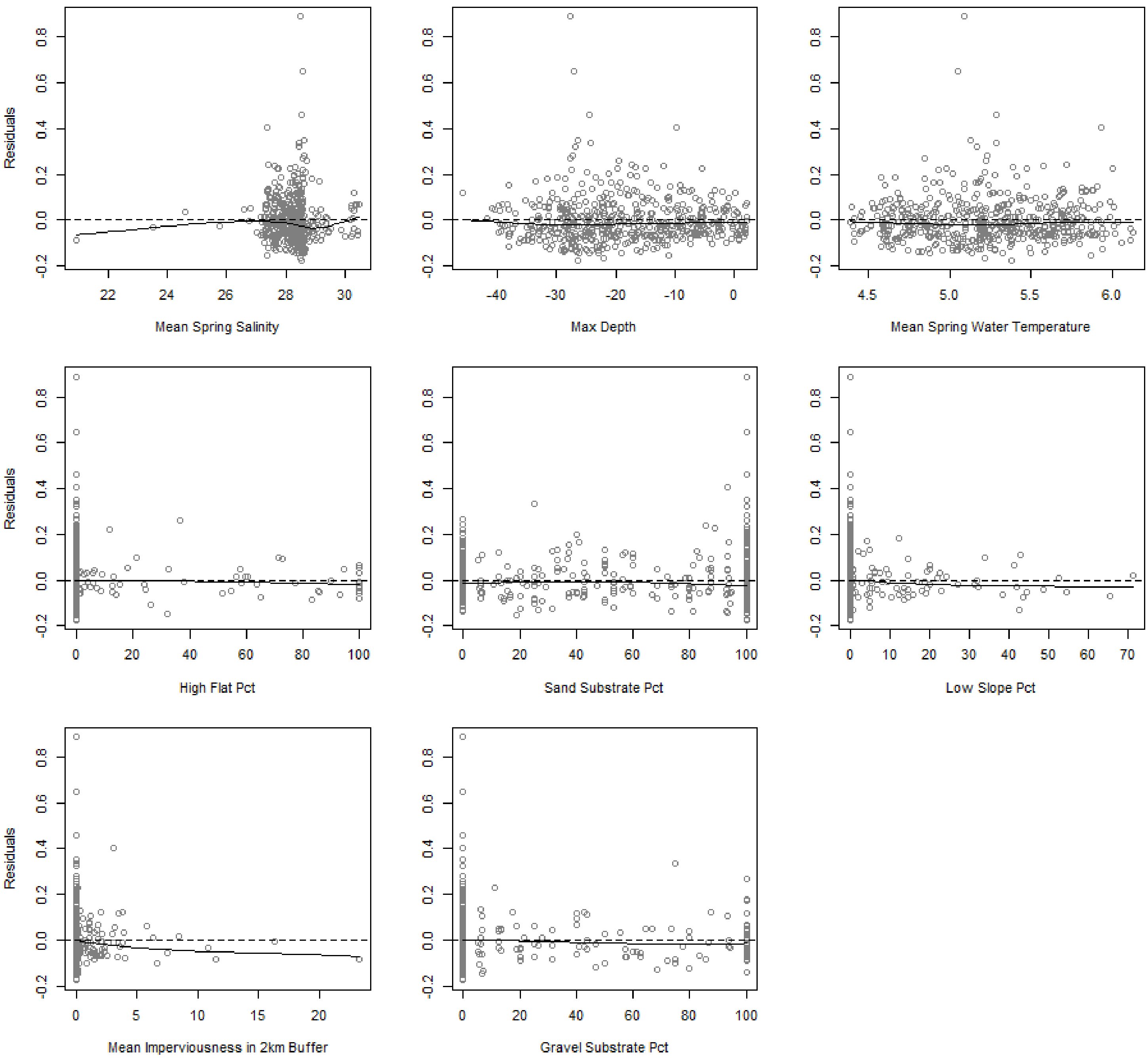


FIGURE 18. SQRT ABSOLUTE VALUE RESIDUAL PLOTS FOR PREDICTOR VARIABLES.

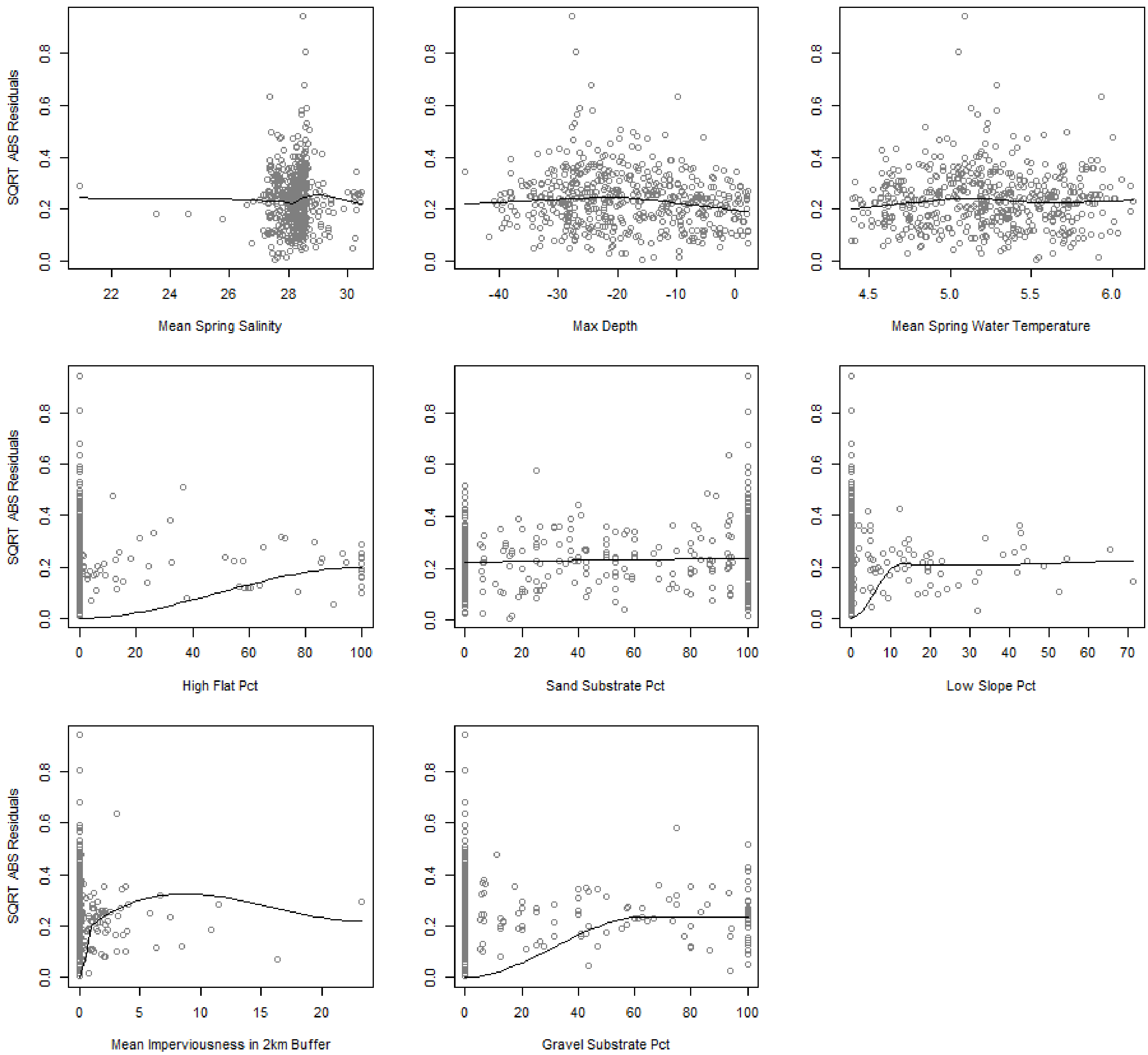
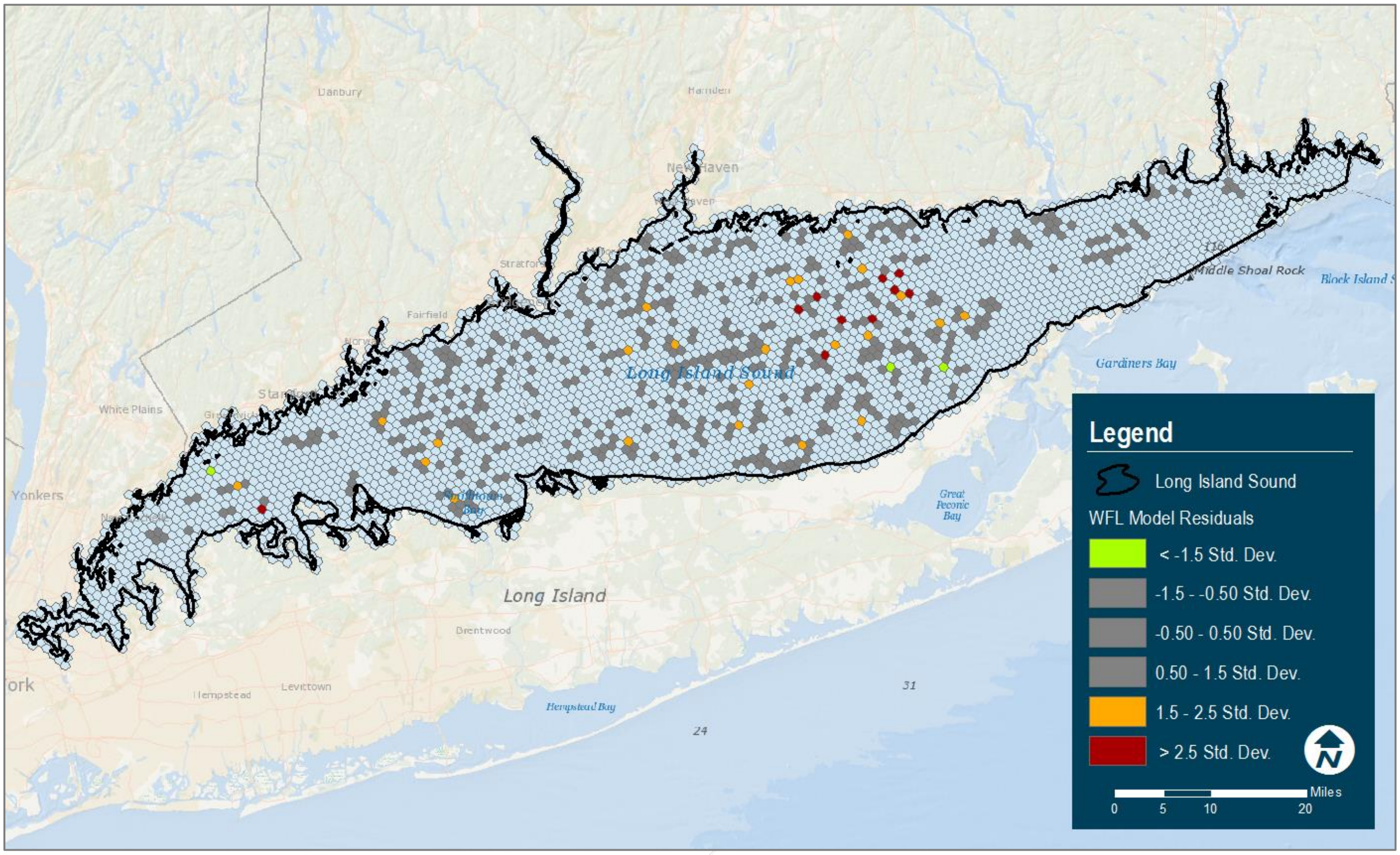


FIGURE 19. MAPPED RESIDUALS FOR LIS MODEL



Discussion

A document by USFWS (2001) synthesized data from multiple research studies on habitat suitability for adult winter flounder. They found that adult winter flounder preferred finer-grain bottom habitats, ranging from mud to gravel, with the most preferred type being a combination of sand and mud. They also found depth suitability for adult winter flounder was best between depths of 0 and 46 meters, while shallower habitats were more suitable for juveniles. Finally, they ranked habitat suitability based on salinity and found that the highest suitability for adult winter flounder occurs at 25-35 ppt, but that salinities ranging from 5-25 ppt were also acceptable.

Our model shows that higher densities of winter flounder are associated with salinities between 21 – 29 ppt, depths of 15-40 meters, and in hexagons with higher percentages of sand substrate and less gravel substrate. These associations within our model fit the associations described in the USFWS (2001) report.

Bottom temperature was also a strong predictor variable in our analysis, and generally warmer temperatures were associated with higher densities of winter flounder. Given that temperatures within the study area are all within the preferred range of winter flounder at the time modeled (April – May), it is possible that associations with warmer temperatures may correlate to food availability. Pereira et al (1999) summarized existing literature by noting that "if water temperatures are not limiting over a wide area, winter flounder will move in response to availability of food." Food availability in warmer portions of LIS during early spring could explain the association seen within our model to warmer temperatures.

Our analysis also showed a weak association with imperviousness, with more imperviousness within a two kilometer buffer being associated with lower flounder densities. This is contrary to the findings in Narragansett Bay, both from our analysis and from Meng et al. (2005). Since areas of high imperviousness occur only in close proximity to shoreline habitats that are generally shallower, the association may not be an indictment of imperviousness as a stressor for adult winter flounder. It is possible that preferred habitat for adult winter flounder in LIS naturally occurs in areas away from shoreline areas that are susceptible to high development and imperviousness.

Lastly, our model showed weak associations with certain bottom forms. Flounder density was higher in areas with less "low slope" and less "high flat" bottom habitats. Other habitat-association studies have generally focused on substrate type rather than bottom form, but it is likely that these have interactive qualities that make interpretation of the associations with bottom form difficult.

Limitations

It is possible that not all habitats available within LIS were sampled. This can cause the predictions for habitats outside those represented within the response data to be questionable. Predictions for habitats that are unable to be sampled by trawl gear are likely to have higher error rates than habitat that were represented within the response data.

This model required the use of summarized response data. The dataset averaged conditions over the 13-year period selected, and as such can only be interpreted as indicative of the generalized conditions across that time frame. Yearly variance due to weather, water quality, or cyclical biological interactions is beyond the scope of this analysis.

Likewise, this model used summarized predictor variables to predict the most likely conditions within a 1-km hexagon. Conditions within each hexagon were summarized, so precise conditions at any given location within each hexagon could vary significantly from the summarized conditions. Given the scale at which predictor variables were available, the 1-km hexagon was deemed appropriate by winter flounder biologists as the most fine-scale management unit given current data. As the resolution of predictor variables improves, the scale of analysis can likewise be reduced in order to reduce variability within each modeling unit (hexagon).

We compiled the best available predictor data available, but data were not available or were not available at the required resolution for all factors potentially important to winter flounder. Water quality factors and sediment contamination could not be directly accounted for given available data. The impact from the presence of predators, fishing harvest or other biological impacts were also unable to be accounted for in this analysis. The addition of these types of factors into future analysis would likely improve their accuracy.

The model produced here performs poorly when predicting the highest densities of winter flounder. The highest densities present in the response data are greater than one fish per 100 square meters. The highest prediction from the model is only 0.25 fish per 100 square meters. The factors contributing to the highest densities are likely unaccounted for within our set of predictor variables, or the summarization of predictor data to a one square kilometer hexagon is causing variability to be lost. The model seems to be more accurate at predicting the difference between very low to moderate densities (Figure 16), but because of the inability of the model to pinpoint the associations between habitat and the highest densities of winter flounder, care should be used in interpreting the predicted results.

Relationships found within any predictive model should be interpreted with the results from existing literature. Relationships between the response and any predictor variable in these types of models indicate correlation, and caution should be used when extrapolating such results as mechanistic or causative.

Framework Discussion/Lessons Learned

Throughout this process, we found that utilizing habitat data to predict winter flounder densities was feasible. The majority of the habitat-flounder associations we found were corroborated by previous research. Data limitations and the time necessary to identify and acquire all available datasets (both predictor and response data) seemed to be the biggest limiting factor to model development. Engaging a broad team of stakeholders and researchers to identify and compile proper data is essential to a smooth and efficient modeling process. Careful consideration of the data availability and structure for future efforts will ensure that resulting predictions will be accurate and useful for resource managers.

Both assessment models were performed for a single estuary. For previous inland habitat assessments, we found this general process to be applicable to large regional scale model as well as smaller, more localized models given sufficient data, where the more localized models were an improvement when analyzing data within a focal watershed. Based on the results from these estuarine studies, it is less clear if a certain scale may improve model results. The relatively data-limited YOY model for the smaller Narragansett Bay (n = 41) described more of the variability than the model for LIS which contained 525 data points. Since these models were based on different responses and utilized slightly different predictor variables, it is unclear how extent of the model and number of data points impacts estuarine models. Given the proper data structure, a habitat assessment using a similar framework should still be feasible at much larger regional extents, along with the smaller extent models described here.

Generally, the use and size of the hexagons we used as modeling units seemed acceptable and compatible with the data availability and resolution for both the predictor and response data. Smaller units would result in issues with response data, where individual trawl surveys intersect numerous hexagons. Using the one square kilometer hexagons, most trawls crossed a maximum of two to three hexagons. The resolution of the predictor datasets spanned from several meters to several kilometers, and given this range of the predictor variable resolution, we found that the one kilometer hexagon worked well to summarize both the higher- and lower-resolution variables.

Through this process, we compiled and attempted to create models for seine and trawl survey data, both separately and combined. An important lesson learned is that despite the ability to convert seine and trawl survey information into consistent units, we found that it is best to utilize only one source of data for each distinct modeling effort. The inconsistencies between sampling methodologies introduce bias and error into the model. It is also important to ensure the sample data can properly represent the response of interest, since not all sampling methodologies are efficient at capturing all size classes of fish or sampling all possible locations and habitat types. To evaluate YOY winter flounder, we utilized seine survey data, but to evaluate adult winter flounder, we relied on trawl surveys, as each methodology sampled the respective size class of fish more efficiently.

Predictor variables for water quality were the most difficult to acquire. Information on salinity and temperature are important to most estuarine species, and data exists in great quantities in newer file formats (NetCDF) for certain areas, but time and substantial computational power is necessary to process this data to be used within the predictive models. Data that relates to contaminates and other water quality measures are seemingly less available for wide extents. For any future modeled response that would be greatly impacted by water quality factors, significant time should be allocated to acquire or produce continuous estimates for these types of predictor data.

Given the mobility of fish in these environments and the tidal and seasonal variability in habitat conditions within estuaries, we would expect lower predictive accuracy from habitat models compared to stream-based models which are much more discrete and static in nature. Despite the inherent variability, we found that the habitat associations were mostly confirmed by other research methods, and that our models explain as much or more variation as other predictive habitat models performed in estuarine environments (Meng et al., 2005). Predictive accuracy for future efforts should continue to improve as data resolution and availability improves.

An important benefit of this particular study is the web-based decision support tool. This tool will enable resource managers and the general public to visualize and download data and model outputs and evaluate conservation priorities based on user-defined ranking criteria. This tool will provide the functionality to evaluate model results alongside other existing data pertinent to protection or restoration priorities. The web tool can be accessed at: www.fishhabitattool.org.

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Appendix A: Predictor Variables for Narragansett Bay Model

Predictor Variable	Description	Source
hexagonID	Hexagon unique identifyer	NALCC 1km2 hexagon grid, Downstream Strategies
AREA_WATER	Area of water within each hexagon (square meters)	NOAA coastline, calculated
DIST_SHORE	Distance to nearest shoreline from each hexagon (meters)	NOAA coastline, calculated
DIST_SAV12	Distance from each hexagon to nearest submerged aquatic vegetation area, 2012 survey (meters)	University of Rhode Island, Environmental Data Center, 2013
AREA_SAV12	Area within each hexagon of submerged aquatic vegetation, 2012 survey (square meters)	University of Rhode Island, Environmental Data Center, 2013
PCT_SAV12	Percent of water area in each hexagon of submerged aquatic vegetation, 2012 survey	University of Rhode Island, Environmental Data Center, 2013
DIST_SAV06	Distance from each hexagon to nearset submerged aquatic vegetation area, 2006 survey (meters)	University of Rhode Island, Environmental Data Center, 2013
AREA_SAV06	Area within each hexagon of submerged aquatic vegetation, 2006 survey (square meters)	University of Rhode Island, Environmental Data Center, 2013
PCT_SAV06	Percent of water area in each hexagon of submerged aquatic vegetation, 2006 survey	University of Rhode Island, Environmental Data Center, 2013
DIST_SAV_ALL	Distance from each hexagon to nearest submerged aquatic vegetation area, 2006 and 2012 surveys combined (meters)	University of Rhode Island, Environmental Data Center, 2013
AREA_SAV_ALL	Area within each hexagon submerged aquatic vegetation area, 2006 and 2012 surveys combined (square meters)	University of Rhode Island, Environmental Data Center, 2013
PCT_SAV_ALL	Percent of water area in each hexagon of submerged aquatic vegetation, 2006 and 2012 surveys combined	University of Rhode Island, Environmental Data Center, 2013
NEAR_DIST	Distance from each hexagon to nearest stormwater outfall (meters)	Rhode Island Office of Water Resources
DIST_MAJ_O	Distance from each hexagon to nearest waste water treatment plan outfall (meters) (-1 equals greater than 3000 meters)	Rhode Island Office of Water Resources
PERVIOUS_BUF	Area of pervious land cover within a 2 km buffer of each hexagon (square meters)	Rhode Island Department of Environmental Management
IMPERV_BUF	Area of impervious land cover within a 2 km buffer of each hexagon (square meters)	Rhode Island Department of Environmental Management
PERVIOUS	Area of pervious land cover within each hexagon (square meters)	Rhode Island Department of Environmental Management
IMPERVIOUS	Area of impervious land cover within each hexagon (square meters)	Rhode Island Department of Environmental Management
MEAN _PER	Mean imperviousness within hexagon	NLCD 2006
MEAN_PER_BUFF	Mean imperviousness within a 2 km buffer of hexagon	NLCD 2006
LENGTH_HAR	Length of hardened shoreline within each hexagon (meters)	Rhode Island DEM, 1996
DIST_HARDS	Distance to nearest hardened shoreline for each hexagon (meters)	Rhode Island DEM, 1996
OPEN_WATER	Area of open water habitat within each polygon (square meters)	LIS Estuarine Habitat, RI Dept. of Environmental Management, LIS Estuary Program; Rhode Island Coastal Resources Management Council; RI Department of Environmental Management, 1996
BRACKISH_M	Area of brackish marsh habitat within each polygon (square meters)	LIS Estuarine Habitat, RI Dept. of Environmental Management, LIS Estuary Program; Rhode Island Coastal Resources Management Council; RI Department of Environmental Management, 1996
SALT_MARSH	Area of salt marsh habitat within each polygon (square meters)	LIS Estuarine Habitat, RI Dept. of Environmental Management, LIS Estuary Program; Rhode Island Coastal Resources Management Council; RI Department of Environmental Management, 1996
BEACHES	Area of beach habitat within each polygon (square meters)	LIS Estuarine Habitat, RI Dept. of Environmental Management, LIS Estuary Program; Rhode Island Coastal Resources Management Council;

		RI Department of Environmental Management, 1996
SCRUB_SHRU	Area of scrub shrub wetlands habitat within each polygon (square meters)	LIS Estuarine Habitat, RI Dept. of Environmental Management, LIS Estuary Program; Rhode Island Coastal Resources Management Council; RI Department of Environmental Management, 1996
PHRAGMITES	Area of phragmites marsh habitat within each polygon (square meters)	LIS Estuarine Habitat, RI Dept. of Environmental Management, LIS Estuary Program; Rhode Island Coastal Resources Management Council; RI Department of Environmental Management, 1996
STREAMBED	Area of streambed habitat within each polygon (square meters)	LIS Estuarine Habitat, RI Dept. of Environmental Management, LIS Estuary Program; Rhode Island Coastal Resources Management Council; RI Department of Environmental Management, 1996
OYSTER_REE	Area of oyster reef habitat within each polygon (square meters)	LIS Estuarine Habitat, RI Dept. of Environmental Management, LIS Estuary Program; Rhode Island Coastal Resources Management Council; RI Department of Environmental Management, 1996
DUNE	Area of dune habitat within each polygon (square meters)	LIS Estuarine Habitat, RI Dept. of Environmental Management, LIS Estuary Program; Rhode Island Coastal Resources Management Council; RI Department of Environmental Management, 1996
ROCKY_SHOR	Area of rocky shore habitat within each polygon (square meters)	LIS Estuarine Habitat, RI Dept. of Environmental Management, LIS Estuary Program; Rhode Island Coastal Resources Management Council; RI Department of Environmental Management, 1996
PANNES__PO	Area of pannes, pools, and tidal flat habitat within each polygon (square meters)	LIS Estuarine Habitat, RI Dept. of Environmental Management, LIS Estuary Program; Rhode Island Coastal Resources Management Council; RI Department of Environmental Management, 1996
AQUATIC_BE	Area of aquatic beds (eelgrass) habitat within each polygon (square meters)	LIS Estuarine Habitat, RI Dept. of Environmental Management, LIS Estuary Program; Rhode Island Coastal Resources Management Council; RI Department of Environmental Management, 1996
OPEN_WATER_PCT	Percentage of open water habitat within each polygon	LIS Estuarine Habitat, RI Dept. of Environmental Management, LIS Estuary Program; Rhode Island Coastal Resources Management Council; RI Department of Environmental Management, 1996
BRACKISH_M_PCT	Percentage of brackish marsh habitat within each polygon	LIS Estuarine Habitat, RI Dept. of Environmental Management, LIS Estuary Program; Rhode Island Coastal Resources Management Council; RI Department of Environmental Management, 1996
SALT_MARSH_PCT	Percentage of salt marsh habitat within each polygon	LIS Estuarine Habitat, RI Dept. of Environmental Management, LIS Estuary Program; Rhode Island Coastal Resources Management Council; RI Department of Environmental Management, 1996
BEACHES_PCT	Percentage of beach habitat within each polygon	LIS Estuarine Habitat, RI Dept. of Environmental Management, LIS Estuary Program; Rhode Island Coastal Resources Management Council; RI Department of Environmental Management, 1996
SCRUB_SHRU_PCT	Percentage of scrub shrub wetlands habitat within each polygon	LIS Estuarine Habitat, RI Dept. of Environmental Management, LIS Estuary Program; Rhode Island Coastal Resources Management Council; RI Department of Environmental Management, 1996
PHRAGMITES_PCT	Percentage of phragmites marsh habitat within each polygon	LIS Estuarine Habitat, RI Dept. of Environmental Management, LIS

		Estuary Program; Rhode Island Coastal Resources Management Council; RI Department of Environmental Management, 1996
STREAMBED_PCT	Percentage of streambed habitat within each polygon	LIS Estuarine Habitat, RI Dept. of Environmental Management, LIS Estuary Program; Rhode Island Coastal Resources Management Council; RI Department of Environmental Management, 1996
OYSTER_REE_PCT	Percentage of oyster reef habitat within each polygon	LIS Estuarine Habitat, RI Dept. of Environmental Management, LIS Estuary Program; Rhode Island Coastal Resources Management Council; RI Department of Environmental Management, 1996
DUNE_PCT	Percentage of dune habitat within each polygon	LIS Estuarine Habitat, RI Dept. of Environmental Management, LIS Estuary Program; Rhode Island Coastal Resources Management Council; RI Department of Environmental Management, 1996
ROCKY_SHOR_PCT	Percentage of rocky shore habitat within each polygon	LIS Estuarine Habitat, RI Dept. of Environmental Management, LIS Estuary Program; Rhode Island Coastal Resources Management Council; RI Department of Environmental Management, 1996
PANNES__PO_PCT	Percentage of pannes, pools, and tidal flat habitat within each polygon	LIS Estuarine Habitat, RI Dept. of Environmental Management, LIS Estuary Program; Rhode Island Coastal Resources Management Council; RI Department of Environmental Management, 1996
AQUATIC_BE_PCT	Percentage of aquatic beds (eelgrass) habitat within each polygon	LIS Estuarine Habitat, RI Dept. of Environmental Management, LIS Estuary Program; Rhode Island Coastal Resources Management Council; RI Department of Environmental Management, 1996
Sand_MEAN	Percent of sand seafloor within each hexagon	Brown University 2007
Grav_MEAN	Percent of gravel seafloor within each hexagon	Brown University 2007
Mud_MEAN	Percent of mud seafloor within each hexagon	Brown University 2007
Pct_sand	Percent of each hexagon that has sand seafloor	Nature Conservancy 2010
Pct_grav	Percent of each hexagon that has gravel seafloor	Nature Conservancy 2010
Pct_mud	Percent of each hexagon that has mud seafloor	Nature Conservancy 2010
Sand_PCT_comb	Percent of each hexagon that has sand seafloor	Brown University 2007, Nature Conservancy 2010
Gravl_PCT_comb	Percent of each hexagon that has gravel seafloor	Brown University 2007, Nature Conservancy 2010
Mud_PCT_comb	Percent of each hexagon that has mud seafloor	Brown University 2007, Nature Conservancy 2010
TN_MEAN	Average total nitogen value for each hexagon	NOAA, Jason Krumholtz
TP_MEAN	Average total phosphorus value for each hexagon	NOAA, Jason Krumholtz
PO4_MEAN	Average phophate value for each hexagon	NOAA, Jason Krumholtz
DIN_MEAN	Average total nitrate+nitrite+ammonium value for each hexagon	NOAA, Jason Krumholtz
MIN_depth	Minimum depth within each hexagon (ft)	NOAA CSC, Narragansettbay.org
MAX_depth	Maximum depth within each hexagon (ft)	NOAA CSC, Narragansettbay.org
RANGE_depth	Range of depth within each hexagon (ft)	NOAA CSC, Narragansettbay.org
MEAN_depth	Mean depth within each hexagon (ft)	NOAA CSC, Narragansettbay.org
Min_dist_to_33ft_depth	Minimum distance to 33 feet depth from each hexagon (feet)	NOAA CSC, Narragansettbay.org

SZ_NAME	Salinity zone the majority of each hexagon falls within (tidal fresh, mixing, ocean zones)	NOAA

Appendix B: Unused Data for Narragansett Bay Model

The table below shows the data sources examined by DS and the review team for the LIS Winter Flounder model that were unable to be processed or used as predictors in the final model. The column to the far right briefly describes the reasoning behind the choice not to use these data.

Predictor Variable	Source	Reasoning
Chlorophyll	NERR	Limited number of points, no continuous interpolated surface.
Dissolved Oxygen	Multiple	Limited number of points, no continuous interpolated surface.
Impervious surfaces	RIDEM	Only available for RI, lacked coverage in MA. Utilized NLCD data instead.
Salinity	Multiple	Limited number of points, no continuous interpolated surface.
Turbidity	NERR	Limited number of points, no continuous interpolated surface.
Wastewater treatment facilities	RIDEM	Only available for RI, lacked coverage in MA.
Water temperature	TNC NAMERA	Very coarse scale with very little differentiation within study area.
Water temperature	Multiple	Limited number of points, no continuous interpolated surface.

NOTE-SOURCES FOR SALINITY AND WATER TEMPERATURE WERE IDENTIFIED DURING THE LONG ISLAND SOUND MODELING EFFORT THAT HAD COVERAGE FOR THE ENTIRE NORTHEAST, BUT WERE NOT DISCOVERED UNTIL AFTER THE LIS ASSESSMENT WAS FINALIZED.

Appendix C: Narragansett Bay Age-at-length Analysis

Eric Schneider, RIDEM

Purpose: To assess the distribution of catch at length and age captured by the Rhode Island Division of Fish and Wildlife (RIDFW) Narragansett Seine Survey (NB Seine) and Coastal Trawl Survey (Trawl) and determine the size for fish < Age-2 that are caught by both surveys , and thus likely to have not migrated out of LIS.

Objective: (1) Determine if the NB Seine and Trawl surveys capture YOY and Age 1 winter flounder and (2) Provide a min and max length that maximizes catch b/w 2 surveys and minimizes the proportion of WFL being > Age 1.

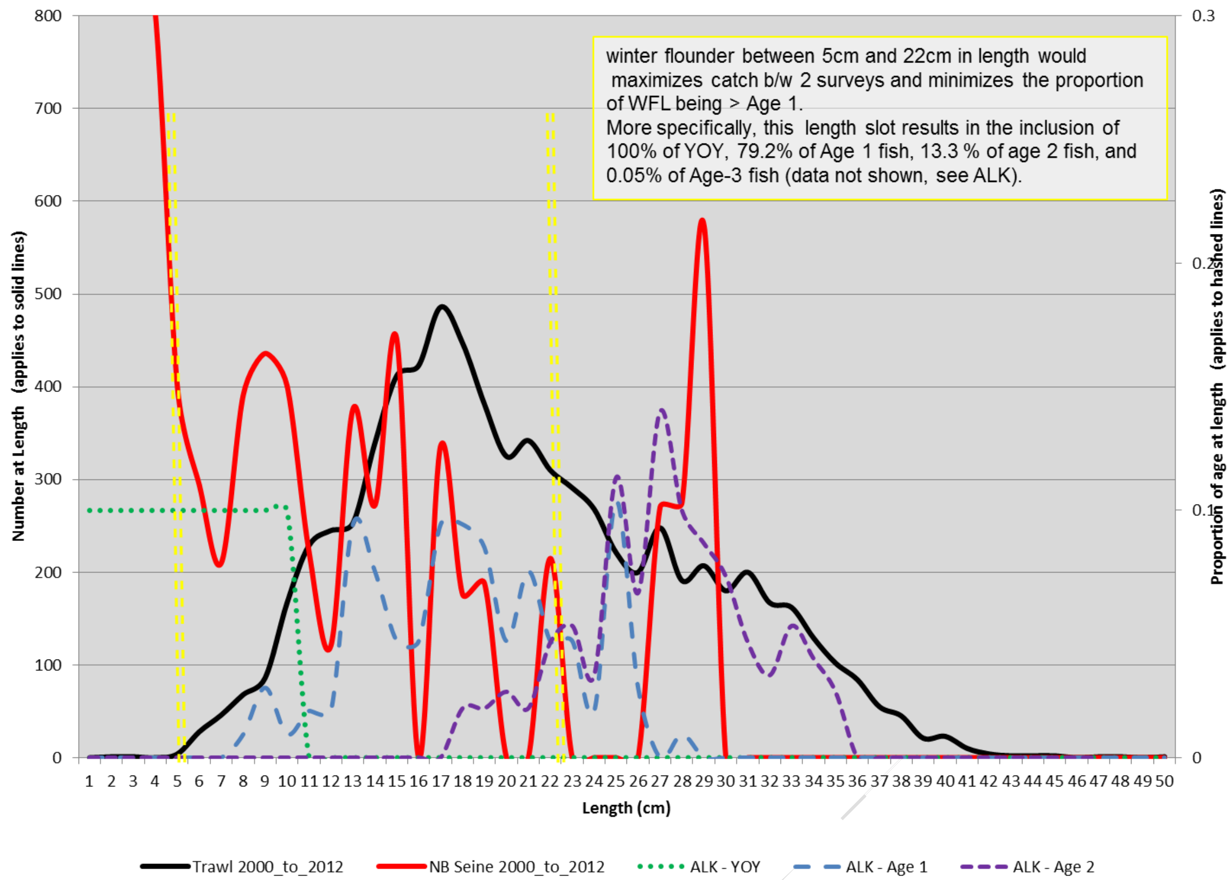
Methods: Numbers of winter flounder at length caught between 2000 and 2012 in the (1) NB Seine and (2) Trawl survey were plotted and compared to the portion at length of Age - YOY, Age-1, and Age-2 fish. For details about data used - see below

Results: Both the NB Seine and Trawl surveys capture YOY and Age 1 winter flounder. It's hypothesized that the NB Seine survey likely only captures Age 2 + early in the spring prior to these fish moving to deeper water. Similarly the Trawl most likely captures YOY late summer to fall when fish are seeking deeper water. The trawl will also capture fish > Age 1.

This following figure, combined with the data in the corresponding table suggests that including winter flounder between 5cm and 22cm in length would maximizes catch between 2 surveys and minimizes the proportion of WFL being > Age 1. More specifically, this results in the inclusion of 100% of YOY, 79.2% of Age 1 fish, 13.3 % of age 2 fish, and 0.05% of Age-3 fish (data not shown, see Age Length Key (ALK)). Note this result is influenced by the fact that only one ALK was referenced, thus in a given year there will be error assoc. with using a static cut off (22cm).

Data used:

Data Label	Description
Trawl_2000-2012	Numbers at length of winter flounder caught in the trawl survey at fixed and random stations in Narr Bay sampled b/w 2000 and 2012
NB_Seine_2000-2012	Numbers at length of winter flounder caught in the NB Seine survey at fixed stations in Narr Bay sampled b/w 2000 and 2012
ALK - YOY	The portion at length (YOY) based on the combined (Spring and Fall) Age Length Key produced by the NEFSC from winter flounder captured by the Bigelow during 2012
ALK - Age 1	The portion at length (Age-1) based on the combined (Spring and Fall) Age Length Key produced by the NEFSC from winter flounder captured by the Bigelow during 2012
ALK - Age 2	The portion at length (Age-2)based on the combined (Spring and Fall) Age Length Key produced by the NEFSC from winter flounder captured by the Bigelow during 2012



Summary: Eric Schneider suggests using fish captured by the Trawl and NB Seine survey between 5cm and 22cm in length will result in the majority of fish being YOY and Age-1. Based on the data used in this analysis, 13% will be Age-2 and 0.05% will be Age-3; This "cut-off" seems like a reasonable, conservative estimate that will provide >85% probability that fish are < Age 2 and likely have not yet migrated (I think this results in 85%, but might be wrth double checking). If a more conservative estimate is needed, the cut-off could be pared back to 19cm (e.g. 96% of all fish < Age 2); however, I think 85% is a reasonable threshold.

Appendix D: Predictor Variables for Long Island Sound

Variable Name	Variable Description	Source
hexagonID	Hexagon Identifier	Downstream Strategies
Min_depth	Minimum depth within hexagon	NOAA
Max_depth	Maximum depth within hexagon	NOAA
Mean_depth	Mean depth within hexagon	NOAA
Mean_temp	Mean April-May bottom temperature, 2006-2009	NECOFS
Mean_salinity	Mean April-May bottom salinity, 2006-2009	NECOFS
Mean_chlorophyll	Mean chlorophyll a	TNC
Dist_to_marsh	Distance to emergent marsh	TNC
Pct_gravel	Percent benthic gravel	TNC
Pct_sand	Percent benthic sand	TNC
Pct_silt_mud	Percent benthic silt and mud	TNC
Pct_depression	Percent depression bottom form	TNC
Pct_low_slope	Percent low slope bottom form	TNC
Pct_steep	Percent steep bottom form	TNC
Pct_mid_flat	Percent mid flat bottom form	TNC
Pct_side_slope	Percent side slope bottom form	TNC
Pct_high_flat	Percent high flat bottom form	TNC
Pct_high_slope	Percent high slope bottom form	TNC
Pct_erosion	Percent erosion sediment environment	USGS
Pct_sorting	Percent sorting sediment environment	USGS
Pct_deposition	Percent deposition sediment environment	USGS
Pct_transport	Percent transport sediment environment	USGS
Mean_imperv_2km	Mean imperviousness within 2km buffer	NLCD