Using Species Distribution Modeling to Predict River Herring Bycatch in the Atlantic Herring and Atlantic Mackerel Fisheries in the U.S. Atlantic

Abstract

Efforts in restoring river herring populations have not been successful, and part of the reason may be due to river herring bycatch mortality events that occur in other fisheries such as Atlantic herring and Atlantic mackerel. To try to mitigate river herring bycatch events, regulations that include area closures and bycatch caps have been enforced. However, large bycatch events still occur as these three species are highly migratory and their overlap varies throughout space and time. There is also limited knowledge on when and where these species overlap, which can restrict and hurt the Atlantic herring and mackerel fisheries. Therefore, this project created species distribution models for river herring, Atlantic herring, and Atlantic mackerel to try to explain their current migration patterns. These models were then forecasted a week at a time at different dates to analyze if they could accurately predict the presence and absence of these species. Despite data limitations, the accuracy of the models was estimated to be approximately 50-70%, and this project serves as a starting point in helping fishermen minimize river herring bycatch and maximize the landings of their targeted species of Atlantic herring and mackerel.

1. Introduction

Alewife (*Alosa pseudoharengus*) and blueback herring (*Alosa aestivalis*) are two anadromous species that are collectively known as river herring and live along the Atlantic coast of North America (ASMFC, 2024; Lynch et al., 2015). Specifically, blueback herring are distributed from Nova Scotia, Canada south to Florida, and Alewife is mainly distributed from Nova Scotia, Canada south to South Carolina (ASMFC, 2024; Lynch et al., 2015; Reid et al., 2023). As anadromous species, river herring spend most of their lives in the oceans, but they migrate to freshwater in order to spawn, which means they occupy a range of habitats throughout their lifespan including freshwater, estuary, and marine (ASMFC, 2024; Lynch et al., 2015; Reid et al., 2023). The unique life history of river herring allows them to be a conduit for nutrients between fresh and marine environments (Hare et al., 2021). In regulating the food web, river herring is also an important prey item for a myriad of species including other fish, birds, and mammals as well as an important predator (Hare et al., 2021; Kritzer et al., 2022). Commercially, river herring has supported a substantial fishery that peaked in 1958 with a catch of 74.9 million pounds coastwide, but declines in their populations have led to a continual moratorium on the river herring fishery in most states (ASMFC, 2024; Lynch et al., 2015).

The closing of this commercially important species was due to significant declines in the river herring populations, and their stocks remain depleted despite a decade of little to no allowable catch and population restoration efforts (ASMFC, 2024). Several freshwater and marine variables have been thought to contribute to the ongoing issue of river herring low abundances (ASMFC, 2024; Reid et al., 2023). Freshwater drivers that affect river herring populations include the loss of habitat due to dams and water pollution as well as overfishing when their fishery was active (Reid et al., 2023). However, river herring caught as bycatch in marine commercial fisheries is now thought to be the leading cause of river herring mortality and in their inability to recover (ASMFC, 2024). For example, it has been estimated that approximately 5.8 million river herring have been taken as bycatch in other fisheries that have primarily been identified as the Atlantic herring (*Clupea harengus*) and Atlantic mackerel (*Scomber scombrus*) fisheries (ASMFC, 2024; Reid et al., 2023; Turner et al., 2017).

Both Atlantic herring and Atlantic mackerel are highly migratory, pelagic species that inhabit the ocean from as south as North Carolina and as north as Greenland for Atlantic herring and as north as Canada for Atlantic mackerel (Turner et al., 2017). In order to reduce the amount of river herring bycatch in these two fisheries, regulations have been enforced including spatial closures and bycatch caps (ASMFC, 2024). Bycatch caps represent the amount of bycatch allowed for each managed area, and a fishery can be closed early if the bycatch cap is estimated to be exceeded for an area (ASMFC, 2024; Bethoney et al., 2012; Reid et al., 2023). These cap limits are annually variable, and their effectiveness and efficiently reducing bycatch has often been debated (ASMFC, 2024; Hare et al., 2021; Roberts et al., 2023). One reason it has been difficult to reduce bycatch is that river herring, Atlantic herring, and Atlantic mackerel will often school with one another as it is thought that species of similar sizes will school together in order to decrease their predation risk, especially if one species has a small population size (Bethoney et al., 2012; Turner et al., 2017). Another issue with current bycatch mitigation in Atlantic herring and mackerel fisheries is that there is limited understanding of the ecological drivers that might be driving these species distributions including their overlap, which is seen as highly variable throughout the year (ASMFC, 2024; Turner et al., 2017).

Even though there is still a high level of uncertainty where river herring bycatch occurs, several studies have tried to understand the distribution of these species and to reduce bycatch. Lynch et al. (2015) found that river herring are affected by climate change and might change their distributions over time in response to warming waters. Turner et al. (2017) has also analyzed habitat associations of river herring, Atlantic herring, and Atlantic mackerel. A previous river herring bycatch reduction program worked with fishermen to provide almost real-time river herring bycatch information on a spatial and temporal scale in Atlantic herring and mackerel fisheries starting in the winter of 2011 through port sampling and staying in contact with the vessels fishing (Bethoney et al., 2012). Even though the program that was established by Bethoney et al. (2012) was found to be successful in helping fishermen maximize targeted species and minimize bycatch, it was hard to maintain funding and relied on constant communication and updating the model framework. Therefore, Roberts et al. (2023) came up with species distribution models (SDMs) that could forecast the presence and absence of river herring bycatch in the Atlantic herring and Atlantic mackerel fisheries on a weekly basis and found that the model had potential. These studies have created a foundation in establishing that river herring, Atlantic herring, and Atlantic mackerel distributions are dependent on temperature and other environmental factors. These studies also established that the fisheries are willing to change their behavior to avoid river herring bycatch if information is provided for them, and there is potential to be able to find suitable models to forecast these species distributions over the entire year. Therefore, the first objective of this project was to create spatial-temporal SDMs for river herring, Atlantic herring, and Atlantic mackerel along the Atlantic coast of North America. The second objective was to then forecast these models seven days in advance throughout the year. Even though bycatch has been low the past several years due to reduced landing limits of targeted species, these models can help fishermen identify areas where they can maximize their landing quota, while minimizing the risk of incidental landings of depleted river herring populations. This project will create a dynamic model that can be used to spatially manage the Atlantic herring and mackerel species without having to rely fully on static closures and debated catch limits (Dunn et al., 2016).

2. Methods

2.1 Study Area

The study area consists of the continental shelf along the north and middle Atlantic coast of the United States (Figure 1). The specific regions of interest include the Gulf of Maine, Georges Bank, southern New England, and the Mid-Atlantic Bight. This study area was focused on as it is where the majority of Atlantic herring and mackerel fisheries take place and where river herring inhabit for a large portion of their adult life. The spatial scale of the final model will have a resolution of 10' longitude and 5' latitude as it was used in the first river herring reduction program and has received positive feedback from fishermen (Bethoney et al., 2012).

2.2 Data

In order to construct species distribution models for the three targeted species, presence-absence data was used for river herring (alewife and blueback herring), Atlantic herring, and Atlantic mackerel from the fishery independent Northeast Fisheries Science Center (NEFSC) bottom trawl surveys in the winter (https://www.fisheries.noaa.gov/inport/item/22563), spring (https://www.fisheries.noaa.gov/inport/item/22561), summer (https://www.fisheries.noaa.gov/inport/item/22562), and fall (https://www.fisheries.noaa.gov/inport/item/22560). Due to potential distribution changes that could affect the ability to forecast each species, the entire time series during 1963 – 2024 was compared with a reduced time series during 2000 – 2024 to determine what years would be more adequate for forecasting each species distributions into the future (Lynch et al., 2015). Therefore, the winter survey data used were conducted annually around January 30th – March 5th during 1992 – 2007, and the spring survey data used were conducted annually around February 28th – April 27th during 1971 – 2024. In the summer, survey data included were conducted annually around July 18th – August 25th during 1963 – 1995, and the fall survey data used were conducted annually around September 4th – November 9th during 1996 – 2023. Environmental data included sea surface temperature (°C), Julian day calculated from the date of the starting tow, latitude, and longitude. The sea surface temperature was measured using an Expendable Bathythermograph until the 1980s when it was measured using SeaBirdTM conductivity, temperature, and depth profilers (Politis et al., 2014; Reid et al., 1999). Other environmental variables outside of the survey data were depth (m), distance to freshwater (km), bathymetric slope, and bathymetric curvature. These variables were estimated at a spatial scale of 15 arc-seconds with more information at Roberts et al., 2023. A spatial-temporal model was chosen due to all three species being highly migratory, and surface temperature was chosen to be the variable forecasted due to previous studies concluding it to be an important variable in these species distributions (ASMFC, 2024; Boyd et al., 2020; Legett et al., 2021; Roberts et al., 2023; Stephenson et al., 2009; Turner et al., 2017).

One week forecasts were implemented using forecasted sea surface temperature from the European Centre for Medium-Range Weather Forecasts (ECMWF), which is a subseasonal-to-seasonal perturbed model (https://apps.ecmwf.int/datasets/data/s2s/levtype=sfc/type=cf/) and Julian day. Each forecast had ten perturbed models that were averaged to create the ensemble mean across a spatial grid of 0.2 decimal degrees. Since the sea surface temperature is being forecasted from a model (SST_M) for a particular day, the average NOAA satellite daily sea surface temperature during 2007 – 2024 for that day ($\overline{SST_O}$;https://psl.noaa.gov/data/gridded/data.noaa.oisst.v2.highres.html) and hindcast data for the particular day of approximately twenty years from the ECMWF forecast model ($\overline{SST_M}$) was used to help correct for any potential bias (Equation 1).

Equation 1: $(SST_M - \overline{SST_M}) + \overline{SST_O}$

NOAA fishery dependent observer data was also used as an independent testing set to evaluate the predictability of the presence and absence models for each species in diagnostics. These data are from observers that are required to be on a certain percentage of vessels in each fishery to collect data on bycatch, targeted catch, and biological data that is crucial in setting fishing quotas for all fisheries. Fishery dependent observations will only be summarized across years and the whole study area due to confidentiality.

2.3 Statistical Analysis

Binomial generalized additive models (GAMs) were used to create statistical SDMs for river herring, Atlantic herring, and Atlantic mackerel separately with the mgcv package (R Core Team, 2025; Wood, 2017). The binomial distribution was used due to analyzing presence-absence data, and GAMs were used to allow for flexibility and smoothers on environmental variables. All continuous environmental variables had a smoother and the spatial-temporal variable had a tensor product (Pedersen et al., 2019). Environmental variables were evaluated for collinearity using correlation coefficients and the principal component analysis (PCA). One variable was either dropped or both variables were included as an interaction if the correlation coefficient and concurvity was estimated to be consistently greater than 0.5 and would contribute to the model significantly according to the PCA (Kovács, 2022). High collinearity between two or more environmental variables can lead to violations in the assumption that variables are independent, and concurvity analyzes non-linear correlations among variables (Kovács, 2022). The best model was then chosen using the dredge() function from the package MuMln in R to analyze all combinations of variables to find the model with the lowest corrected Akaike information criterion (AICc; Bartoń, 2023). The number of pseudo-absences in the model was causing the model to not be able to predict presences, so the number of pseudo-absences were randomly reduced to equal the number of presences in river herring (n = 5,223), Atlantic herring (n = 5,994), and Atlantic mackerel (n = 5,913; He & Garcia, 2009). Cross validation was used to create a training set (70% of the data randomly selected) and a testing set (30% of the data randomly selected) in order to test the predictability of the model (Pedersen et al., 2019). Diagnostics for each model that was analyzed included sensitivity, specificity, and area under the curve (AUC; Franklin, 2010). The sensitivity is a proportion of how well the model does in predicting presences, and the specificity is a proportion of how well the model does in predicting absences (Franklin, 2010). The threshold in the predicted probabilities to determine presence or absence of each cell was determined by the point of maximum accuracy that balances the trade-offs between specificity and sensitivity determined based on the cross validation of the model. The AUC is a threshold independent analysis that evaluates the true and false positive error rate of the model (Franklin, 2010). An evaluation of the predictability of the model across months was also analyzed with the whole dataset (Thuiller et al., 2009).

The best models were then used to predict the presence and absence of targeted species using one week temperature forecasts from ECMWF. Spatially, the environmental variables will be summarized into grids at 0.2 decimal degrees to match the sea surface temperature forecasts. Dates forecasted were also chosen based on the availability of fishery dependent observer data to evaluate the accuracy of the forecasted species distribution models in ten high river herring bycatch events recorded. The final map of forecast SDMs were summarized over 10’ longitude and 5’ latitude. Fishery dependent observer data was then used to compare the accuracy of forecasts across ten dates that found high levels of river herring abundance. A summary of the model methods are found in the supplementary section.

3. Results

3.1 Evaluation of environmental variables

Environmental variables were tested for independence from one another using the correlation coefficients, PCA, and estimated concurvity (Figures 2-3). The environmental variable of log(depth) was removed due to its positive correlation with longitude and latitude, and the distance to bays variable was also removed due to its positive correlation with longitude. Even though slope and curvature seemed to have a moderate amount of collinearity, both variables were still included due to the estimated concurvity being less than 0.5. The variables Julian day and surface temperature had a high correlation coefficient of 0.8 and concurvity greater than 0.5, but both variables were important for forecasting the model. Therefore, these two variables were included as an interaction term. As expected due to the study area, latitude and longitude were also highly correlated, so these two variables were also included as an interaction term.

3.2 River herring model

The best river herring model with the lowest AICc value included the environmental variables of curvature, slope, longitude, latitude, surface temperature, and Julian day (Figure 4). It was also found that reducing the time series to only include surveys during 2000 – 2024 had a higher predictability of river herring presences across months that were present compared to the full time series (Figure 5). For instance, the months that were surveyed after 2000 had AUC values greater than 0.8, except for March, but the entire time series had the majority of months with AUC values less than 0.8 (Figure 5). Overall, the full model that included both the training and testing data sets had an explained deviance of 51.2%. The cross-validation diagnostics performed relatively well with an AUC of 0.92 and both a specificity and sensitivity around 0.8 (Table 1). The residuals of the river herring SDM did show some trends that might be due to the timing of the seasonal surveys (Figure 6). The distribution of river herring shifted throughout the year as the majority of river herring were predicted to be in the southern portion of the study area in January and shifted throughout the year to be higher north near Maine in June and November (Figure 7). Comparing the observer fisheries catch data and the forecasted maps for ten high bycatch events found that the model accuracy in predicting the presence and absence of river herring was approximately 60.3%.

3.3 Atlantic herring model

The best Atlantic herring model with the lowest AICc included the environmental variables of slope, longitude, latitude, surface temperature, and Julian day (Figure 8). The reduced time series during 2000 – 2024 was chosen compared to the full time series as it generally had slightly higher AUC values for surveyed months, especially for February and November that generally have high bycatch events (Figure 9). The full model with both the training and testing data sets had an explained deviance of 45.4%. Results from the cross-validation analysis found an AUC of 0.89 and the specificity and sensitivity were both around 0.8 (Table 1). The residual plot showed similar trends to the river herring SDM (Figure 10). Also similar to the river herring SDM, Atlantic herring distributions shifted throughout the year (Figure 11). In January, Atlantic herring presences were found close to shore along the continental shelf from Delaware to Maine (Figure 11). Their distribution moved slightly more north and to the Gulf of Maine in June, and they were mainly distributed in the Gulf of Maine in November (Figure 11). Overall, the accuracy of the SDMs based on ten high bycatch events observed by the fisheries was around 53.6%. With these forecasts, the distributions of Atlantic herring and river herring can be compared. For example, vessels targeting Atlantic herring and avoiding river herring should target their efforts in the southern Gulf of Maine and northern region of Georges Bank in November (Figure 16).

3.4 Atlantic mackerel model

The best Atlantic mackerel model with the lowest AICc included the environmental variables of slope, longitude, latitude, surface temperature, and Julian day (Figure 12). The full time series was found to be better at predicting the presence and absence of Atlantic mackerel compared to a shorter time series across years (Figure 13). The only month where the reduced time series for years after 2000 had a higher AUC value was November (Figure 13). The full model with both training and testing data sets included had an explained deviance of 23.2%. Results from the cross-validation analysis were slightly lower compared to river and Atlantic herring with an AUC of 0.79 and a specificity and sensitivity around 0.71 (Table 1). Residuals in the Atlantic mackerel GAM were also similar to river and Atlantic herring(Figure 14). Due to the migratory behavior of Atlantic mackerels, their distributions shifted throughout the year when forecasted. They were distributed more south and closer to shore in January, and they were predicted to be distributed more north and offshore in June and November (Figure 15). Analyzing ten high river herring bycatch events recorded in the fisheries found that the forecast model was correct approximately 70.2% in predicting the presence and absence of Atlantic mackerel. Using the November forecast as an example, it was found that vessels targeting Atlantic mackerel and wanting to avoid river herring should concentrate their efforts in Georges Bank and along the outer continental shelf (Figure 16).

4. Discussion

4.1 Similar study comparisons

There have been several studies that have tried to reduce the bycatch of river herring in Atlantic herring and mackerel fisheries with variable success. Previously, Bethoney et al. (2012) implemented a river herring bycatch program that was successful in working with the majority of Atlantic herring and mackerel fishery vessels. Their project continued several years until both Atlantic herring and mackerel populations showed signs of depletion and there was not enough allowable catch to have the program continue. This project also did not forecast the species distributions but provided fishermen with almost real-time bycatch information by continual monitoring of vessel landings and staying in contact with vessel captains (Bethoney et al., 2012). While successful, this project was time extensive for researchers and relied on vessels reporting accurate bycatch information. Due to the extensive work and time to run this program, the Bethoney et al. (2012) also focused mainly on landings in Massachusetts, but my study will focus on the entire spatial scale of both the Atlantic herring and mackerel fisheries. Turner et al. (2017) also attempted a forecast of river herring bycatch in part of the Atlantic herring fishery, but they were only able to forecast one or two days near shore in Rhode Island. Ultimately, this study was not able to find contrasts greater than 20% between low and high presence probabilities (Turner et al. 2017). However, this study did illustrate that using oceanographic forecasts was not the issue as they were able to survey forecasted areas and take environmental samples, but they realized that the model was not correctly modeling the biology of the species

(Turner et al., 2017). Therefore, my study will continue the successful portions of their work in communicating with fishermen on where to focus their effort and develop forecasts that are able to capture the variability in the environment and life histories of the species.

One study started on this work of developing and improving forecasting for these species by including different environmental variables, a larger spatial area, and forecasting more than a few days in advance (Roberts et al., 2023). While Roberts et al. (2023) also had limited success depending on the forecast model and the length, they found that the models were most effective at one week timeframes and that bycatch was associated with cooler temperatures, minimal seafloor curvature, and close to freshwater bays where river herring spawn. This project formed the basis for my own project as I also analyzed bycatch at one-week intervals and found that temperature and curvature were important in predicting the presence and absence of river herring, Atlantic herring, and Atlantic mackerel throughout the year. The only reason I did not include the distance to freshwater as a variable was due to it being heavily correlated with my spatial variables that I found were more important to include. Spatial and temporal variables included within the model helped better explain the biology of these highly migratory species. Similarly, both of our studies found that the Gulf of Maine and the southern New England regions have the highest potential of bycatch (Roberts et al., 2023).

The background information from previous projects helped me build the most informative model at a meaningful spatial and temporal scale (Bethoney et al., 2012; Roberts et al., 2023; Turner et al., 2017). These studies also found important environmental variables that created a starting point for my model.

4.2 Study limitations

While my study illustrated a partly successful SDM in predicting the presence and absence of river herring, Atlantic herring, and Atlantic mackerel on a one-week scale, there were several assumptions and limitations in the model. One assumption was that the ECMWF sea surface temperatures were adequate for the entire study area and that all model biases were removed and accounted for in my standardizations. Sub-seasonal forecasts are still relatively new and constantly being updated to improve their ability and accuracy. My SDMs were also restricted in environmental variables that could be included as only variables that could be forecasted to the future or would stay the same over time could be included in the models. Therefore, it is highly likely that other abiotic and biotic variables are influencing the SDMs of these species throughout the year that could not be accounted for in this study. The biggest limitation in this study was the data. While the NEFSC bottom trawl surveys are extensive and consistent, it has been theorized that bottom trawls are not the most adequate at catching pelagic species that stay within the water column such as river herring, Atlantic herring, and Atlantic mackerel.

4.3 Future research recommendations

The next step to these SDMs for river herring, Atlantic herring, and Atlantic mackerel will be to acquire more data in order to fill in missing months and have more data in areas where the surveys did not consistently survey such as inshore regions. Other surveys might also use more adequate gear methods that have a higher catchability in catching these species such as fishery dependent surveys. In order to add more surveys, the next step will also be to attempt a vector autoregressive spatial-temporal (VAST) model, which is a more complex algorithm compared to GAMs. VAST models will also allow me to predict abundances of species and to incorporate all three species into one model instead of the current separate GAM for each species. Another step will be to continue to make connections with the Atlantic herring and mackerel fisheries to set up a helpful and successful river herring reduction program.

4.4 Conclusion

River herring was once an important commercial fishery with the goal that the populations will one day recover enough to reimplement a commercial fishery. One of the potential reasons that hinder the recovery of river herring is the mass mortality events that occur when river herring is caught as bycatch in the Atlantic herring and mackerel fisheries. Regulations and programs have been implemented to decrease the amount of bycatch in these fisheries, but the knowledge gaps in understanding the spatial and migratory behaviors of these species has made it difficult. Therefore, this project creates SDMs for river herring, Atlantic herring, and Atlantic mackerel forecasted one week ahead to help fisheries avoid areas that potentially have high probabilities of bycatch present. These maps not only help fishermen minimize their risk of encountering bycatch, but it also depicts areas that still have high occurrence probabilities of targeted species. This project has many implications that will not only be beneficial in Atlantic herring and mackerel fisheries, but it can also be used in mitigating bycatch events in other fisheries.

5. References

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6. Tables

Table 1. The diagnostics of threshold, sensitivity, specificity, and area under the curve (AUC) from the cross validation of the best river herring, Atlantic herring, and Atlantic mackerel models.

Diagnostic	River herring	Atlantic herring	Atlantic mackerel
Threshold (specificity = sensitivity)	0.62	0.60	0.53
Sensitivity	0.84	0.80	0.72
Specificity	0.85	0.81	0.71
AUC	0.92	0.89	0.79

7. Figures

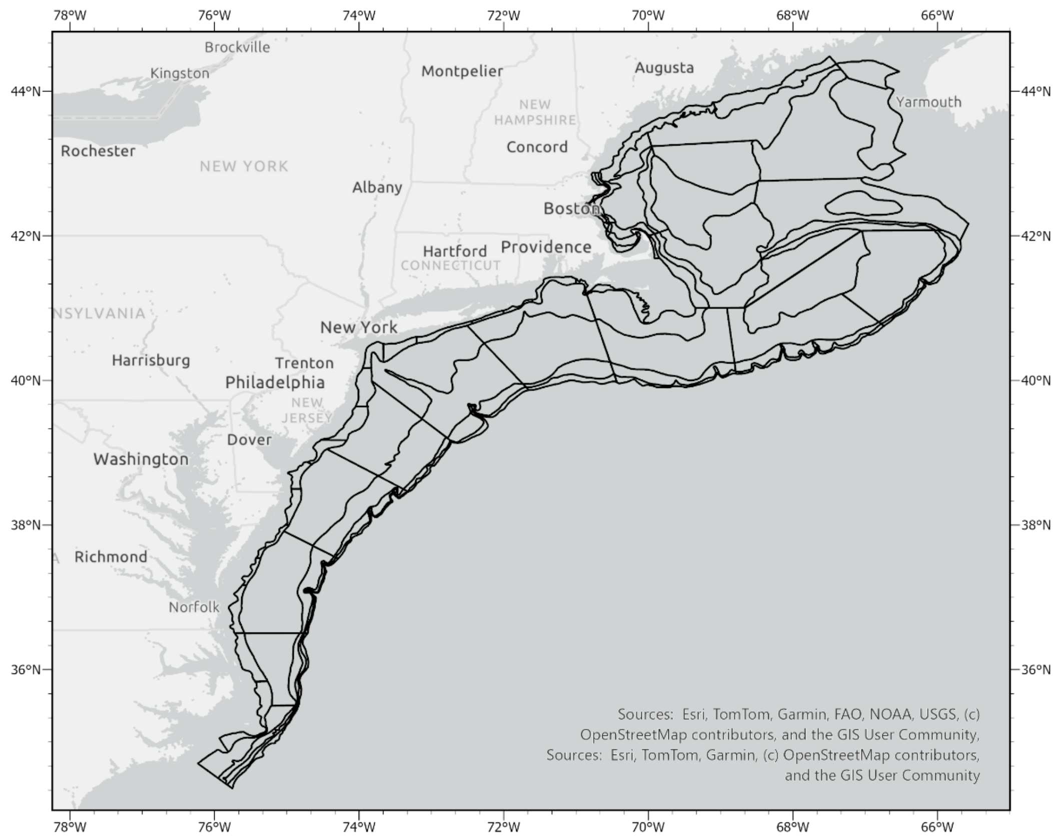

Figure 1. Study Area that encompasses the continental shelf along the Atlantic coast of the U.S. The black lines represent the strata that are sampled annually by the Northeastern Fisheries Science Center (NEFSC) bottom trawl survey.

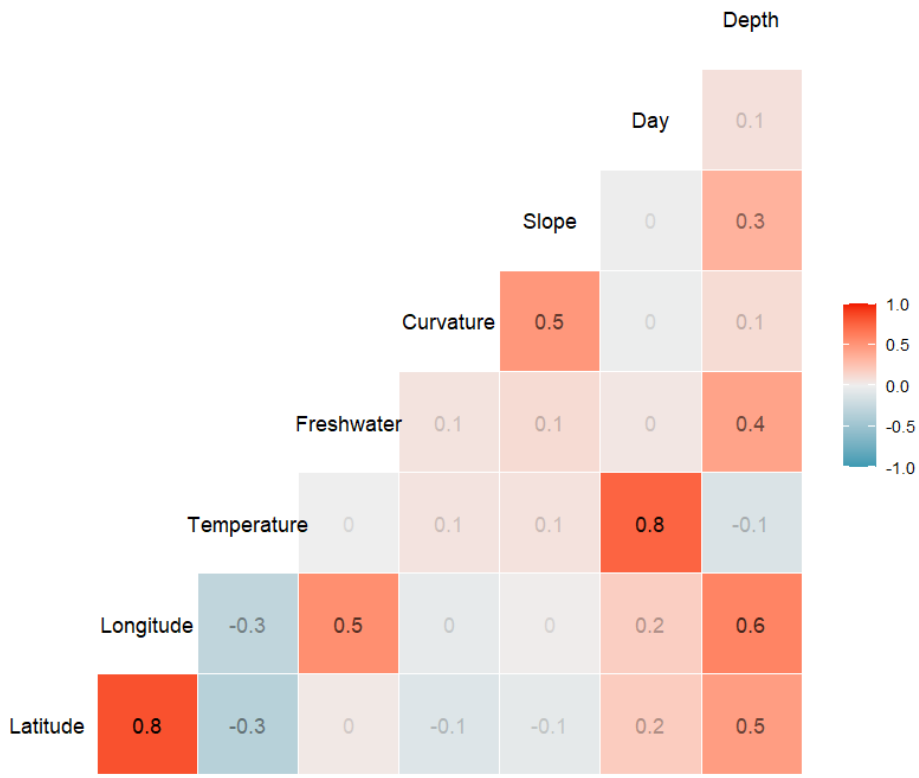

Figure 2. The correlation coefficients between the environmental variables considered in the river herring, Atlantic herring, and Atlantic mackerel SDMs. Red represents variables that are positively correlated with each other, and blue represents variables that are negatively correlated with each other.

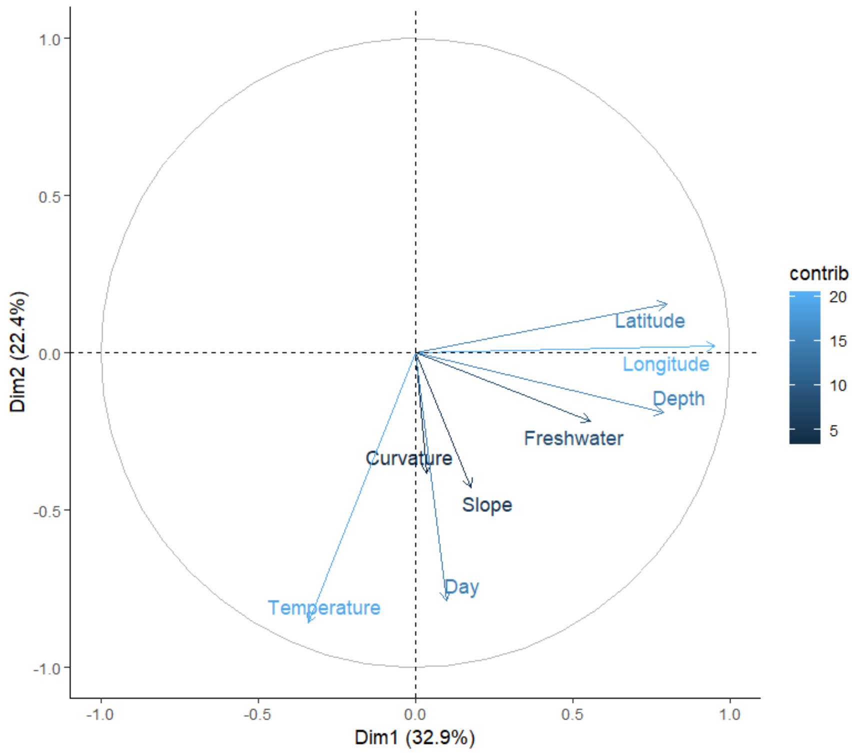

Figure 3. Principal component analysis (PCA) that includes the environmental variables considered for the river herring, Atlantic herring, and Atlantic mackerel SDMs. The colors represent the contribution (contrib) of each variable to the orientation of the PCA. The light blue represents variables with a high contribution, and the darker blue represents low contribution.

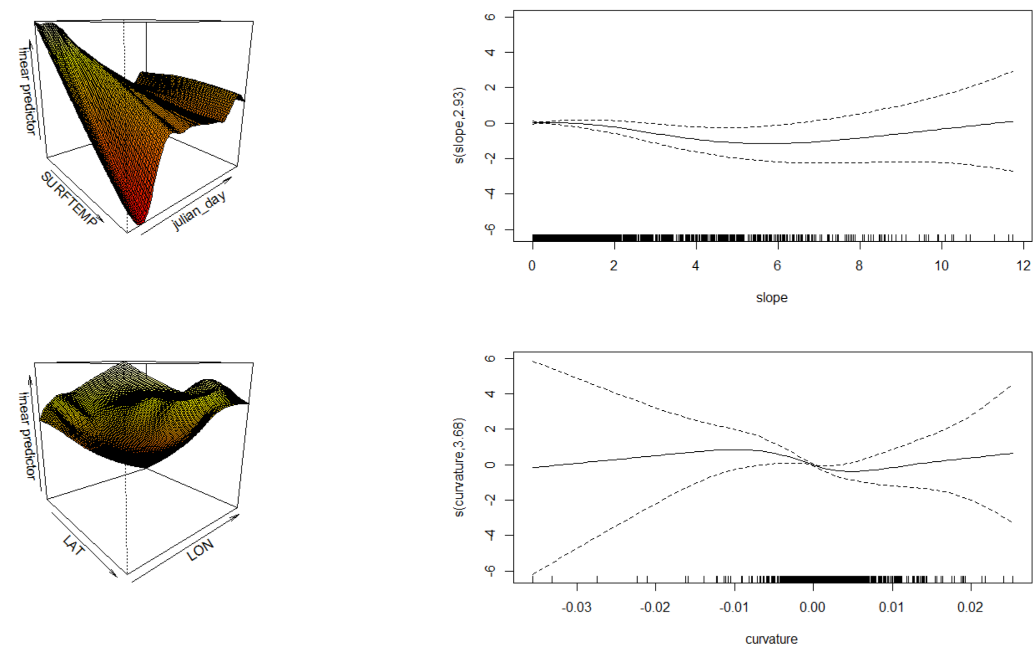

Figure 4. The best river herring generalized additive model (GAM) summary plots, excluding the spatial-temporal tensor product, of the environmental variables including an interaction between surface temperature (SURFTEMP) and day (julian_day), slope, an interaction between latitude (LAT) and longitude (LON), and curvature.

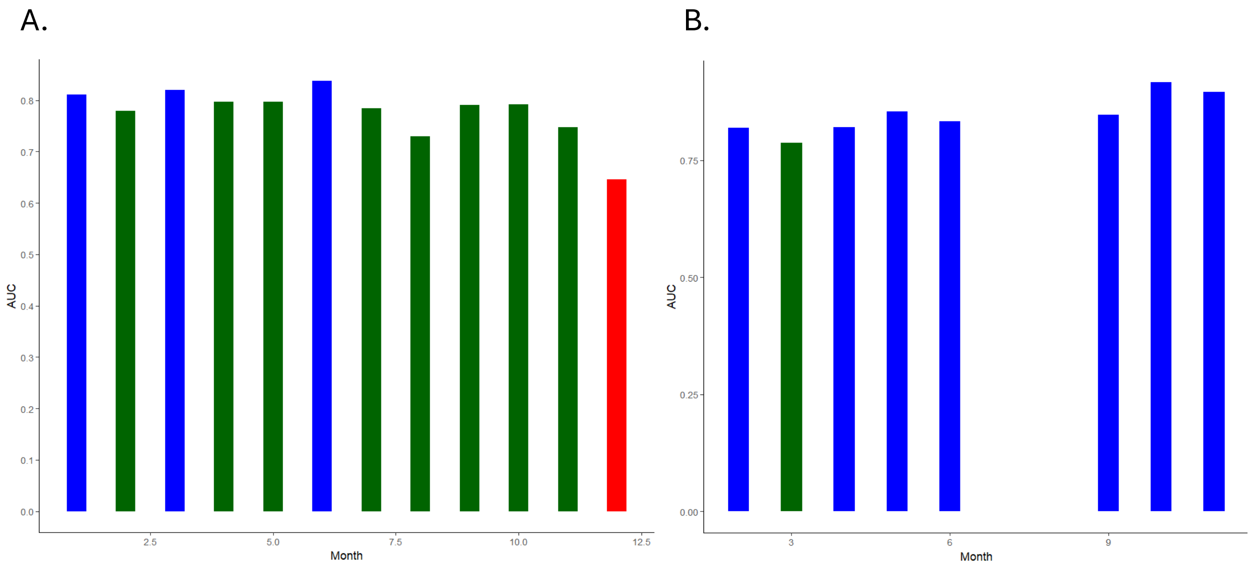

Figure 5. The area under the curve (AUC) for the temporal testing of the best river herring model for A. all survey years and B. surveys that occurred during 2000 – 2024. The blue represents AUC values that were excellent (above 0.80), green represents values that were acceptable (between 0.80 and 0.70), and red represents values that were low (below 0.70).

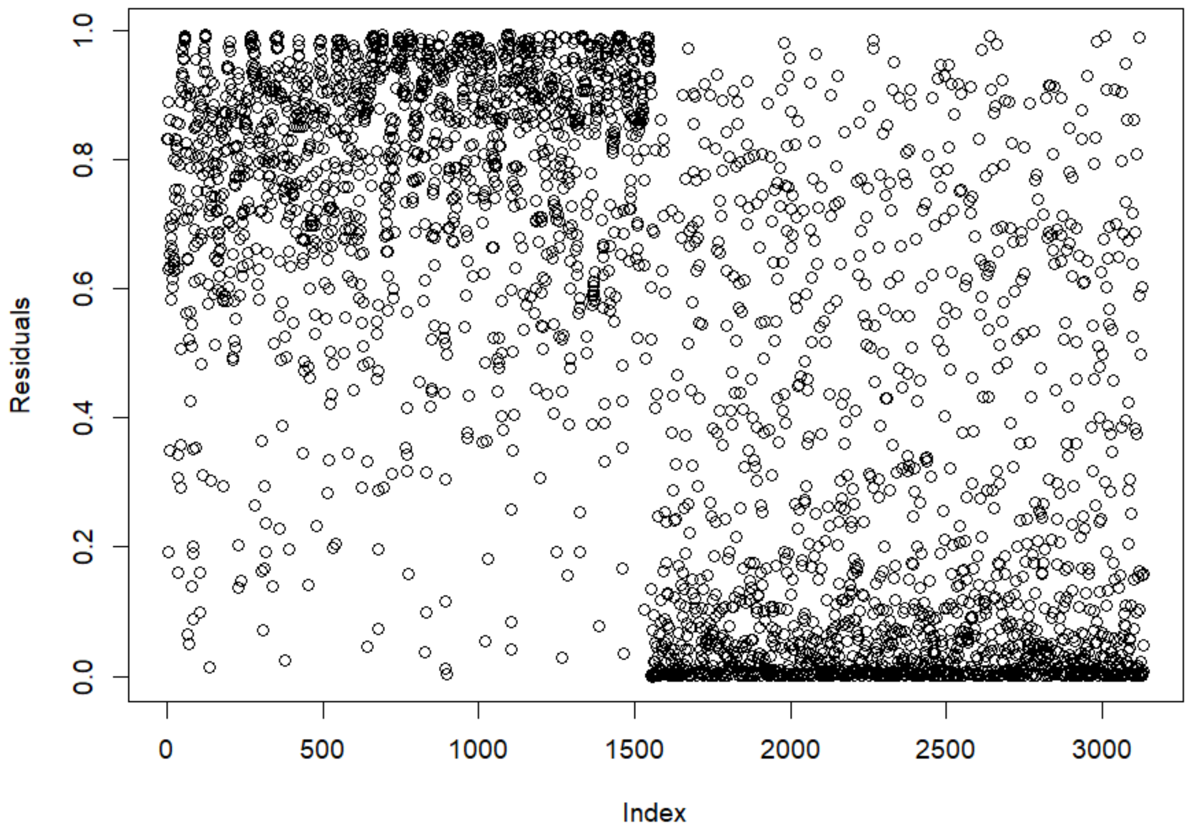

Figure 6. The residuals from the best river herring generalized additive model (GAM).

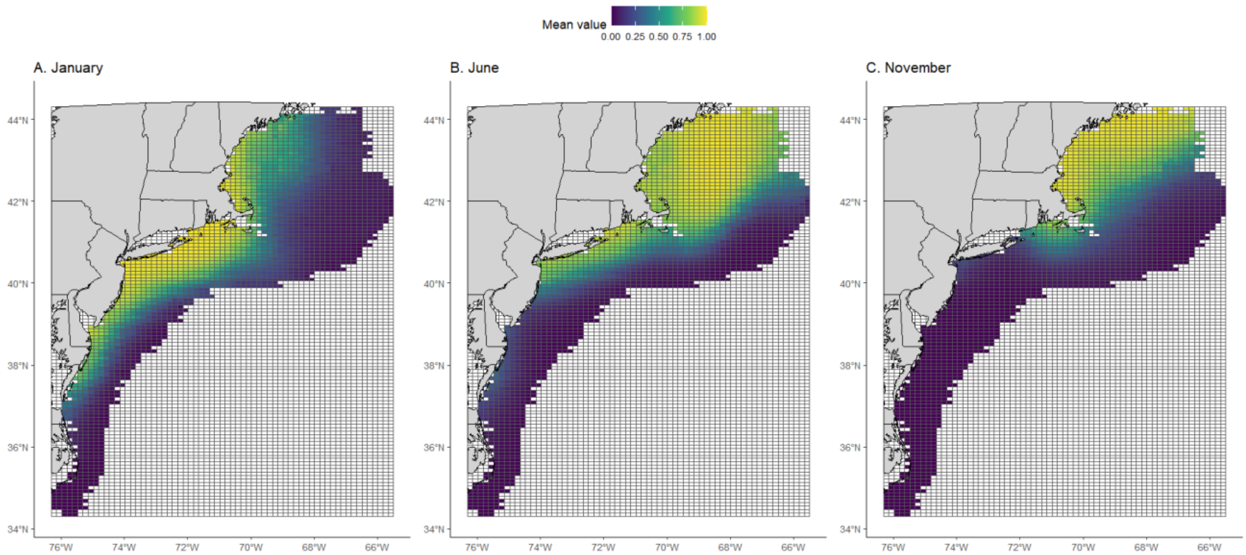

Figure 7. River herring generalized additive model (GAMs) forecasts for a particular day and year in January, June, and November. The colors represent the probability of encountering a river herring in grid cells that are 10’ longitude x 5’ latitude. Warmer colors like yellow represent a high probability of river herring being present, and cooler colors like purple represent a high probability of river herring being absent.

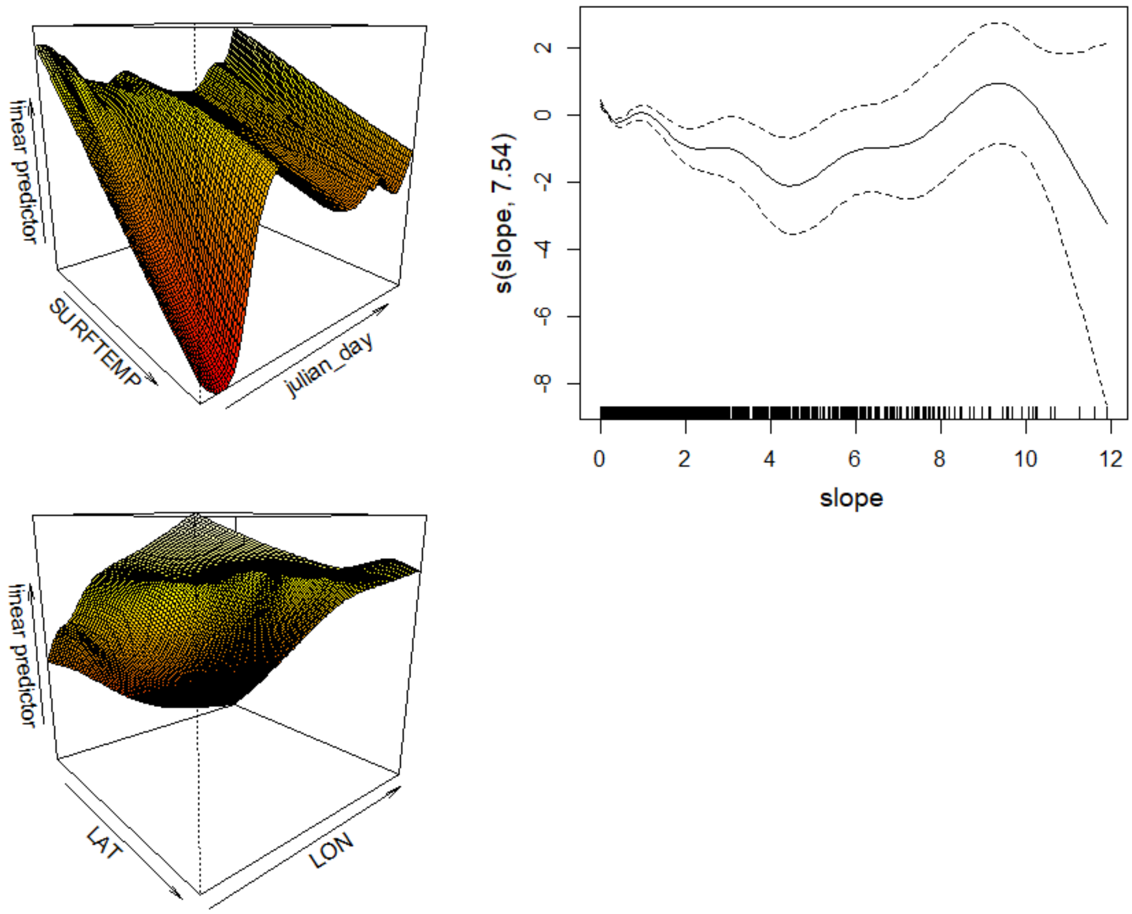

Figure 8. The best Atlantic herring generalized additive model (GAM) summary plots, excluding the spatial-temporal tensor product, of the environmental variables including an interaction between surface temperature (SURFTEMP) and day (julian_day), slope, and an interaction between latitude (LAT) and longitude (LON).

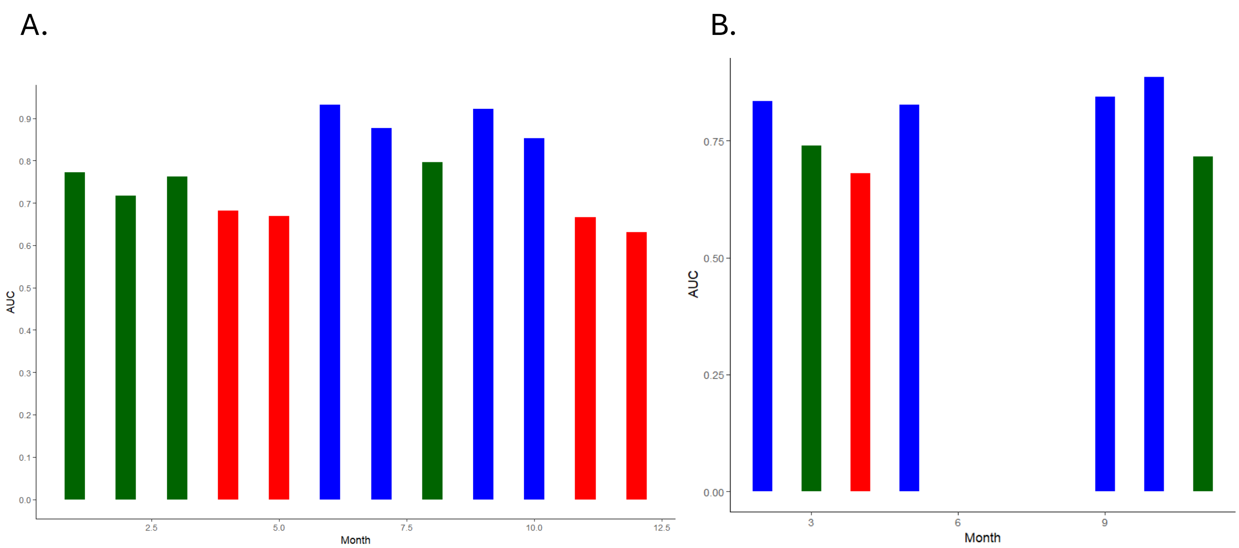

Figure 9. The area under the curve (AUC) for the temporal testing of the best Atlantic herring model for A. all survey years and B. surveys that occurred during 2000 – 2024. The blue represents AUC values that were excellent (above 0.80), green represents values that were acceptable (between 0.80 and 0.70), and red represents values that were low (below 0.70).

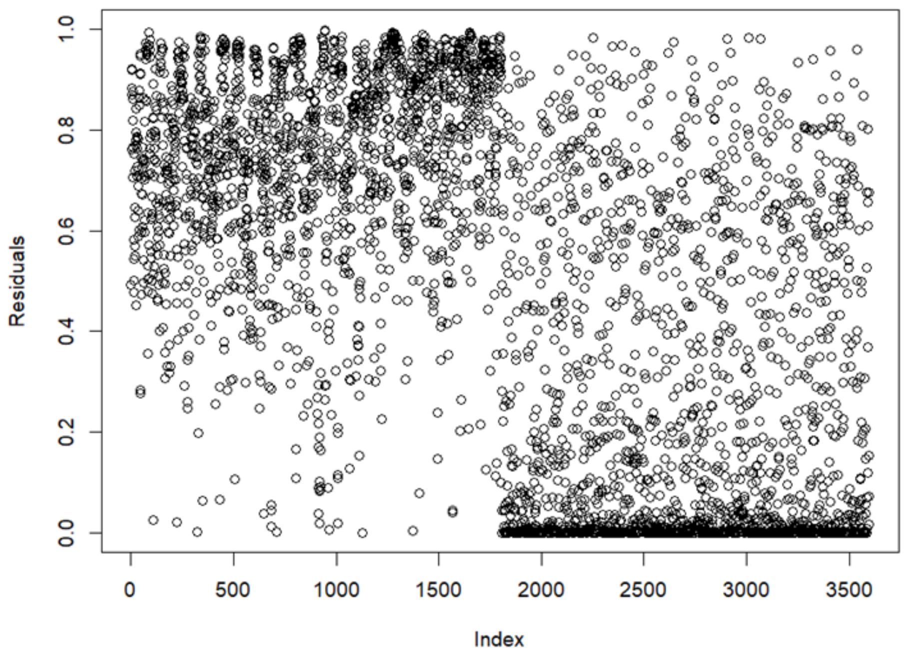

Figure 10. The residuals from the best Atlantic herring generalized additive model (GAM).

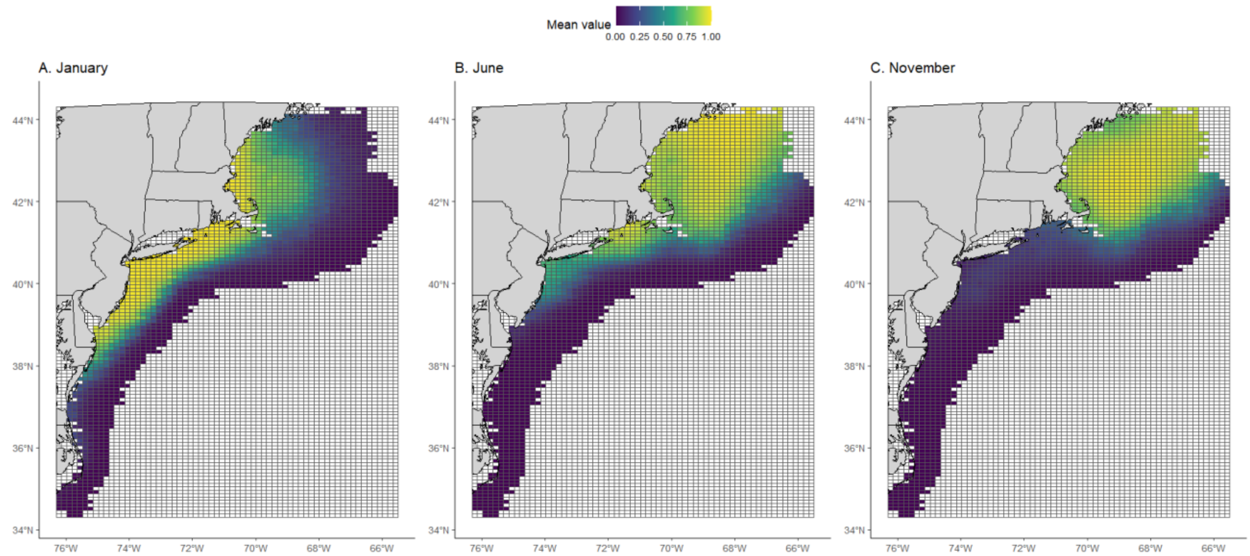

Figure 11. Atlantic herring generalized additive model (GAMs) forecasts for a particular day and year in January, June, and November. The colors represent the probability of encountering a river herring in grid cells that are 10’ longitude x 5’ latitude. Warmer colors like yellow represent a high probability of river herring being present, and cooler colors like purple represent a high probability of river herring being absent.

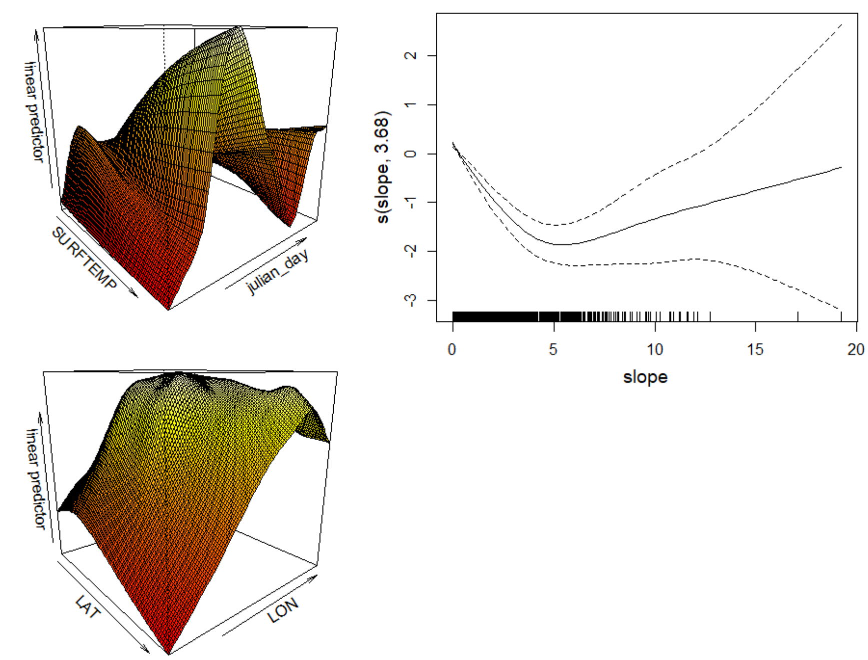

Figure 12. The best Atlantic mackerel generalized additive model (GAM) summary plots, excluding the spatial-temporal tensor product, of the environmental variables including an interaction between surface temperature (SURFTEMP) and day (julian_day), slope, and an interaction between latitude (LAT) and longitude (LON).

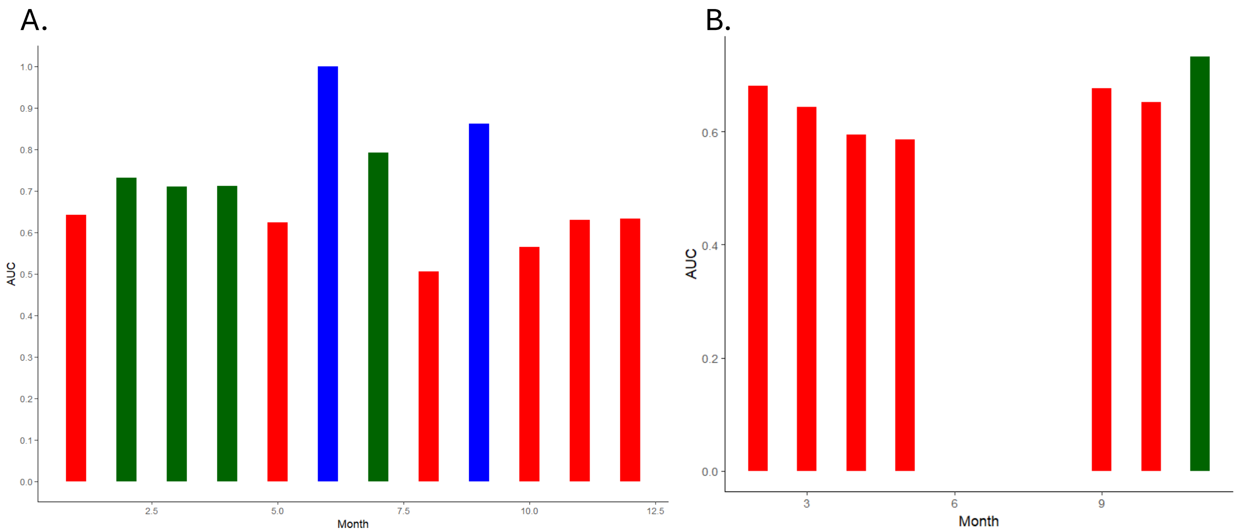

Figure 13. The area under the curve (AUC) for the temporal testing of the best Atlantic mackerel model for A. all survey years and B. surveys that occurred during 2000 – 2024. The blue represents AUC values that were excellent (above 0.80), green represents values that were acceptable (between 0.80 and 0.70), and red represents values that were low (below 0.70).

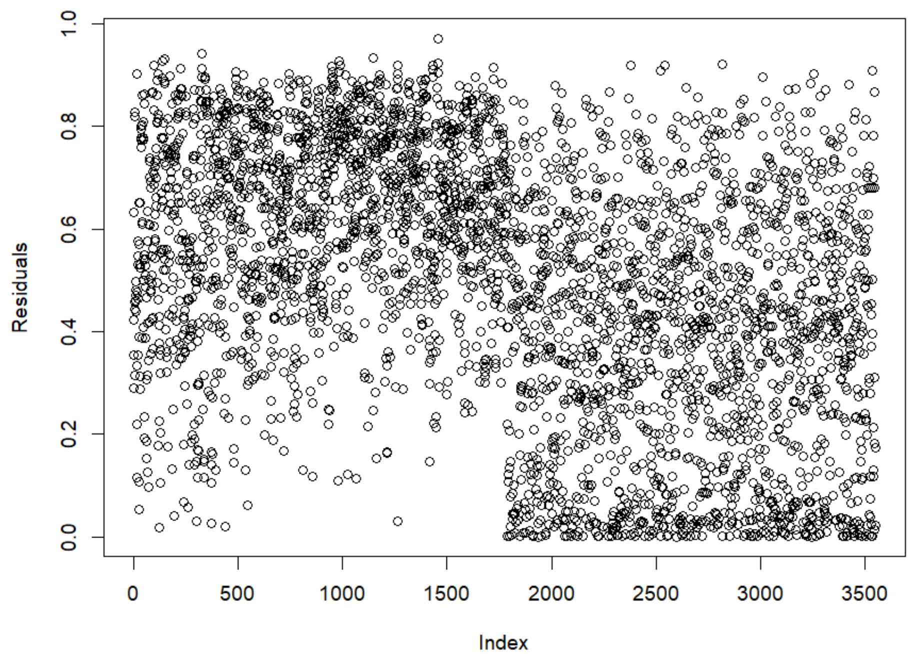

Figure 14. The residuals from the best Atlantic mackerel generalized additive model (GAM).

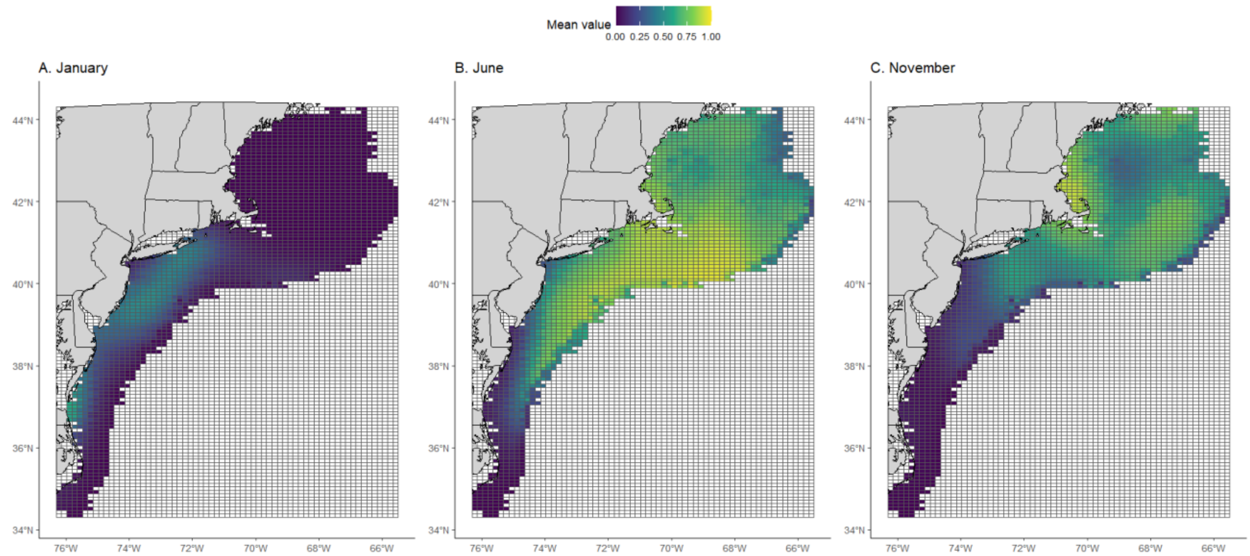

Figure 15. Atlantic mackerel generalized additive model (GAMs) forecasts for a particular day and year in January, June, and November. The colors represent the probability of encountering a river herring in grid cells that are 10’ longitude x 5’ latitude. Warmer colors like yellow represent a high probability of river herring being present, and cooler colors like purple represent a high probability of river herring being absent.

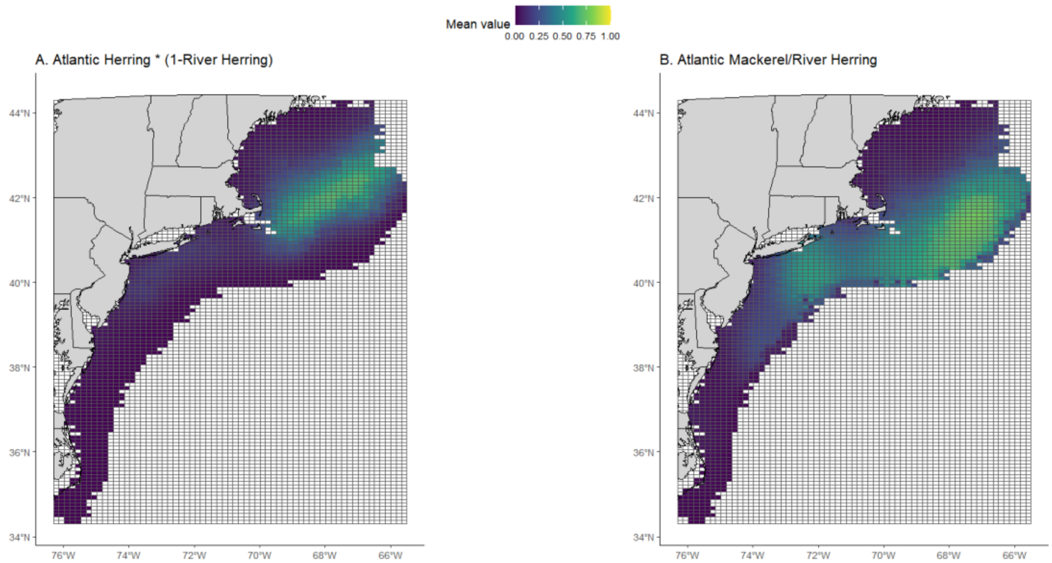

Figure 16. Joint probability likelihood that shows areas where the probability of encountering A. Atlantic herring increases and river herring decreases or B. Atlantic mackerel increases and river herring decreases. The warmer colors like yellow represent areas that maximize the probability of encountering targeted species and minimize the probability of encountering river herring. Cooler colors like purple represent areas that have a high probability of encountering river herring or a high probability that both species are absent.