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Developing a subseasonal ecological forecast to reduce fisheries bycatch in the Northeast U.S.

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ABSTRACT

Over the past decade, substantial progress has been made in projecting and predicting the spatial distribution of many marine species at seasonal to multidecadal time scales. However, managers and fishers often need to make decisions at much shorter time scales. Subseasonal environmental forecasts, which generate predictions over one to several weeks, can now be combined with species-specific habitat preference data to create ecological forecasts that could facilitate dynamic spatial management. The development of such predictive tools could aid in identifying optimal times and areas for fishers to maximize target catch and avoid nontarget catch. Nontarget catch, or bycatch, can have numerous and potentially severe economic and ecological consequences. Here, we focus on a population of anadromous fish known collectively as river herring (alewife and blueback herring), as they are species of concern and are heavily impacted by bycatch. Using bottom trawl survey data from the Northeast US and subseasonal forecasts of sea surface temperature, we constructed a bycatch risk model to generate probabilistic predictions of river herring distributions in regions frequented by the US mid-water trawl fishery. Assessments of model skill showed that our ecological model performed well in predicting the distribution of river herring and that subseasonal forecasts were effective at 1-week timeframes. There was a clear seasonal effect on forecasted bycatch risk throughout the Northeast US, with particularly high risk in winter and spring months. Importantly, variability in risk was detectable at the weekly timescale and our model identified specific areas and times that fishers should avoid in order to decrease their likelihood of bycatch. The bycatch risk forecast developed in this study is a significant advance from near-real time forecasts and the foundation to build forecast systems by combining species co-occurrence models with subseasonal forecasts. As these subseasonal forecasts are available globally, this approach could be adapted to facilitate the management of other natural resource conflicts around the world.

1. Introduction

At the turn of the century, there was a call for ecological forecasts that could help to anticipate and respond to intensifying anthropogenic pressures (Clark et al. 2001). Ecological forecasts were defined at this time as the “process of predicting the state of ecosystems, ecosystem services, and natural capital, with fully specified uncertainties ...” and relied on scenario planning rather than probabilistic predictions. Since that time, many decadal to multidecadal scale projections for living marine resources have been developed (Payne et al. 2017, Tommasi

et al. 2017, Payne et al. 2022). However, natural resource managers and stakeholders typically need to make decisions at much shorter temporal scales (i.e., daily to multiple months) and only recently have seasonal forecasts been attempted (Brodie et al. 2017, Eveson et al. 2021, Tommasi et al. 2017). In marine resource management, several studies have highlighted the utility of near real-time forecasts that use current or recent environmental data that must be updated daily or monthly (Howell et al. 2008, Eveson et al. 2015, Hazen et al. 2017). While these applications have proven useful, subseasonal forecasts that can predict environmental conditions on the order of weeks to months could provide

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an optimal lead time to inform stakeholders and facilitate planning at these scales to optimize resource use (Dietze et al. 2018).

The dynamic nature of the marine environment triggers rapid species responses such that ecological forecasting has tremendous potential to transform marine spatial planning (Hobday et al. 2011, Hobday et al., 2016, Hazen et al. 2017, Turner et al. 2017b, Thorne et al. 2019). While marine spatial planning is an ancient practice (Lepofsky and Caldwell 2013, Filous et al. 2021), the increasing pressure on marine resource use necessitates innovative approaches to refine the spatial and temporal management of marine resource use. Dynamic (marine) spatial management, defined as ‘management that changes rapidly in space and time in response to the shifting nature of the ocean and its users...’, can better account for shifts in productive habitat and species distributions while maintaining a balance between economic and conservation objectives (Maxwell et al. 2015). The recent improvement of subseasonal forecasting products offers a unique opportunity to inform dynamic spatial management by anticipating future conservation issues (Dietze et al. 2018, Mariotti et al. 2020), particularly at temporal scales relevant for managers. For example, advanced climate models, such as the North American Multi-Model Ensemble (Kirtman et al. 2014) and the Subseasonal to Seasonal (S2S) Prediction research project (Vitart et al. 2017) can now integrate remotely sensed oceanographic data to improve forecasts at the scale of weeks to months. These forecasting products have previously been applied to streamflow forecasting and flood predictions (White et al. 2015), precipitation (de Andrade et al. 2019, Gibson et al. 2021), malaria epidemic forecasting (Landman et al. 2020), and understanding the influence of large-scale, recurring climate patterns on extreme weather phenomena (Vitart et al. 2017). The application of subseasonal forecasts to ecological modeling is still in its infancy, but there have been significant advances in ecological forecasts of individual species that could potentially provide managers and stakeholders with decision support tools weeks in advance instead of seasonal or annual timeframes (Jacox et al. 2020, Stepanuk et al. 2022). Most of these applications are for individual species, but complex conservation challenges arise from the conflict between multiple dynamic processes including the temporary associations between mobile species.

One such quintessential conservation issue that may benefit from subseasonal forecasts is fisheries bycatch, the incidental catch of nontarget species when they co-occur with target species. Bycatch is a persistent global management challenge that affects a wide range of taxa and requires a balance of conservation and resource use (Sims et al. 2008). Bycatch can potentially negatively impact populations of nontarget species and can increase costs to fishers, decrease yield, or even force the closure of a productive fishery if bycatch of non-target species exceeds seasonal or annual limits (O’Keefe et al. 2014, Pons et al. 2022). Recent studies estimate that bycatch and subsequent discards from fisheries globally amounts to approximately 9.1 million tons annually and can irrevocably alter ecosystem structure and processes (Gilman et al. 2020). While varying in degrees of effectiveness, bycatch mitigation strategies include gear restrictions or modifications (Graham et al. 2007, Afonso et al. 2011), deployment of visual or acoustic deterrents (Maree et al. 2014), static closed areas (Smith et al. 2021) and community-based initiatives that engage fishers and their families to facilitate solutions based on local knowledge (Peckham et al. 2007). Bycatch mitigation strategies have also included dynamic spatial management measures that close specific areas on a monthly or seasonal timescale, often referred to as time-area closures (Dunn et al. 2016). In evaluating static vs. dynamic management measures and the impact on fisheries, previous literature has demonstrated that dynamic closures can be 2–10 times smaller while still providing adequate protection to threatened species (Hazen et al. 2018, Smith et al. 2021) and can reduce bycatch by over 50% with minimal disruption or loss to target catches (Pons et al. 2022). As more targeted closures are implemented alongside technological improvements in the collection of environmental data, dynamic management applications can replace static frameworks to improve the sustainability of fisheries (Lewison et al. 2015, Dunn et al.

2016).

Here, we assess whether producing subseasonal forecasts to anticipate future risk of bycatch could provide a means of reducing bycatch of river herring, an anadromous species complex consisting of alewife (*Alosa pseudoharengus*) and blueback herring (*Alosa aestivalis*), both currently considered species of concern in the US. Both species of river herring were petitioned under the Endangered Species Act in 2011 because of severe declines in their abundance coastwide (Limburg and Waldman 2009), but in 2013, the National Oceanic and Atmospheric Administration (NOAA) concluded that a listing of either threatened or endangered was not warranted (NMFS 2019). Instead, an aggressive conservation plan to boost populations was initiated. Despite greater awareness and many dam removals opening freshwater habitat for these anadromous species to spawn, many stocks have not rebounded, especially those in the southern part of their distributional range. Previous research has suggested that bycatch in the Atlantic herring (*Clupea harengus*) and Atlantic mackerel (*Scomber scombrus*) midwater trawl fishery could be impacting the recovery of river herring (Palkovacs et al. 2014, Hasselman et al. 2016), although harvest rates of Atlantic herring have substantially declined in recent years (i.e., 2019–2021) alongside bycatch rates as reported by the NOAA Greater Atlantic Regional Fisheries Office (GARFO 2023). While the Atlantic herring and Atlantic mackerel fisheries are extremely valuable to the US economy, with commercial landings per year jointly averaging about \$10 million in profits (NMFS 2019), bycatch of river herring has previously shut down trawl fisheries in Southern New England in winter and in the Cape Cod region in autumn (GARFO 2023). Quotas of river herring bycatch are provided to trawlers each year to limit this incidental catch (Hare et al. 2021), although their effectiveness is often debated, likely due to misreporting or improperly set catch limits (O’Keefe et al. 2013).

In response to this conservation concern, prohibiting fishing in bycatch hotspots has been proposed, but such large closures could have major economic repercussions for fishers. As such, voluntary bycatch reduction programs have been attempted (Bethoney 2012, Bethoney et al. 2017) where bycatch events were communicated amongst fishers. This program coincided with a 60% decrease in total bycatch and 20% decrease in the bycatch ratio (Bethoney et al. 2017). However, success varied greatly in space and it is unclear whether these efforts contributed significantly to increases in the river herring population. Recent work has also demonstrated that species distributions models can predict where river herring will likely overlap with some fishery target species based on environmental conditions (Turner et al. 2016) and how ocean forecasts 0–2 days into the future can be utilized to predict river herring distributions and potential overlap with target species (Turner et al. 2017a). A subsequent study also illustrated how the accuracy of forecast models can be evaluated with fishery-dependent data in a cooperative research framework (Turner et al. 2017b). Therefore, the purpose of this work was to build on these important bycatch avoidance studies by developing an ecological forecast model that combines species distribution modeling with subseasonal forecasting products that target 1–2 weeks into the future to coincide with operational timescales.

Here, we take a habitat modeling approach to estimate bycatch risk combined with state-of-the-art subseasonal forecast products to make spatially and temporally explicit predictions of bycatch risk for river herring. We developed a bycatch forecast for the Northeast US region to: 1) identify areas of high bycatch risk in areas that the midwater trawl fisheries target Atlantic herring and Atlantic mackerel; 2) incorporate uncertainty into models of bycatch risk to provide realistic measures of confidence in model predictions; 3) evaluate application of subseasonal forecasts of sea surface temperature (SST) to the bycatch risk model; and 4) assess changes to forecasted bycatch risk in space and time. The predictive forecast that we develop could inform decision making for fishers by highlighting areas to avoid in order to decrease the likelihood of bycatch and contribute to the development of a proactive tool to support existing dynamic management strategies.

2. Methods

2.1. Study area and data collection

Bottom trawl survey data were obtained from the NOAA Northeast Fisheries Science Center (NEFSC). These surveys have been conducted in federal waters along the Northeast US coast since 1963, and as such this dataset provides information on fish and macroinvertebrate abundance and distribution using a stratified random sampling design. At each survey station, the weight and number of individuals are recorded by species along with spatial coordinates, date and time of trawl, and temperature, salinity, and depth (Politis et al. 2014). While sampling is conducted from North Carolina to the US/Canadian border, representing a large portion of the marine river herring distribution, we constrained our analysis to four subregions that were consistently sampled over the time series similar to previous research on river herring bycatch (Turner et al. 2016). All analyses were performed at the individual trawl scale, which resulted in approximately 600,000 individual trawls. Additionally, we removed any trawls that occurred during the summer months, due a lack of sampling consistency across years. These exclusions amounted to approximately 15% of the data, or 85,000 trawls over 58 years (1963–2020), with 512,345 trawls remaining.

2.2. Environmental variables

To develop predictions of fish distributions, we modeled the co-occurrence of bycaught and target fish species related to environmental covariates. We obtained SST and depth data recorded in-situ via CTD casts at every trawl station within 5 m from the bottom (Politis et al. 2014). These variables have been included in previous modeling efforts to identify relationships between river herring distribution and habitat features (Turner et al. 2016). We were limited to covariates that are currently able to be forecasted and thus had to eliminate variables often used in fisheries models, such as bottom temperature and primary productivity.

We identified three additional environmental static variables that have known or plausible roles in river herring distribution: distance to freshwater bays, seafloor slope and curvature (Hare et al. 2021, Appendix S1: Table A1). Bathymetric features, such as slope and curvature, are known to have an impact on ocean dynamics and are often attributed to areas of increased productivity and demersal fish abundance (Leitner et al. 2021). A spatial layer for the distance to bays (in meters) was derived from GPS coordinates of ocean-accessible freshwater bays along the Northeast US coastline and the Euclidean distance tool in ArcGIS. Bathymetric slope and curvature data layers were derived from a bathymetry layer with a grid spacing of 15 arc-seconds (GEBCO Compilation Group, 2021) and calculated with Benthic Terrain Modeler in ArcGIS (Walbridge et al. 2018).

2.3. Model development

To ensure accurate predictions, all continuous variables were first assessed for collinearity using a Pearson correlation coefficient. A collinearity threshold value of 0.7 was applied to reject the use of two or more highly correlated variables in the same model (Dormann et al. 2013). Individual observations were identified as outliers and removed from subsequent analyses if any explanatory or response variables fell more than two standard deviations away from their mean; these amounted to less than 3% of the dataset. Generalized additive models (GAMs) were then used to establish relationships between fish distributions and the environmental variables. GAMs are particularly useful in ecological studies because they can model non-linear relationships between the response and predictor variables and allow for different assumptions about distribution of the data (Yee and Mitchell 1991, Guisan et al. 2002). GAMs were fit in R Statistical software (Version 4.0.3, R Core Team 2020) using the 'mgcv' package (Wood 2017). The

dataset was first filtered to only include those trawls where a target species (Atlantic herring or Atlantic mackerel) was present, which resulted in 34,610 trawls available for model fitting. Then, a separate presence or absence variable was created for bycatch, resulting in a value of 1 if either or both species of river herring were recorded in the trawl or a value of 0 if neither species was recorded. To predict bycatch risk for each target species, we fit a presence/absence GAM with a binomial error distribution, a maximum of 5 knots to avoid overfitting, and using restricted maximum likelihood (REML). Hereafter, we refer to this component of the analysis as the 'predicted risk' model. We focus the results on the Atlantic herring/bycatch risk model, with further detail and figures for the Atlantic mackerel/bycatch risk model available in Appendix S1.

Cubic regression spline functions were used for each environmental covariate included in the GAMs. Subregion of the study area (Gulf of Maine (GOM), Georges Bank (GB), Southern New England (SNE), and the Mid-Atlantic Bight (MAB)) and season were incorporated as factor variables in order to account for seasonal and spatial variability. For each GAM, we checked the basis dimension values for each smooth term to ensure the correct number of knots were present by comparing the estimated degrees of freedom (edf) to the number of knots used in modeling and the associated p-value (Wood 2017). Pairwise concavity was also analyzed to ensure close relationships did not exist between the smooth terms. We selected the model with the lowest Akaike's Information Criterion (AIC) value to use in forecasts.

2.4. Model evaluation

To evaluate whether model performance varied between years, we used a k-folds cross validation approach by partitioning the dataset by year, resulting in 58 folds. Each fold (i.e., year of data available in the bottom trawl survey) was withheld from the model and then assessed using deviance explained, adjusted R^2 , and area under the curve (AUC) of the receiver operating characteristic (ROC) plot. AUC measures the model's ability to distinguish between classes (i.e., bycatch presence and absence), where values are scaled between 0 and 1, with a value 1 representing a perfect fit, values 0.8 or higher signifying a good fit, and values 0.7–0.8 representing an acceptable fit (Mandrekar 2010). AUC values were plotted for each year of available data and for each predicted risk model (Appendix S1: Figure A2) to assess temporal variability in model performance. We also generated calibration metrics and plots using the 'sdm' package in R to assess agreement between the observations and probabilistic predictions for each bycatch risk model. A well-calibrated model has a resulting value of 1 (Vaughan and Ormerod 2005). Overall model accuracy was then examined using confusion matrices that quantify the proportions of correctly and incorrectly classified bycatch presence. We selected the optimum probability threshold to generate each confusion matrix, where the sensitivity (the percentage of observed positives correctly predicted) equaled the specificity (the percentage of observed negatives correctly predicted) for each model.

To evaluate the predicted risk models spatially, we converted all modeled environmental variables (i.e., in-situ SST, in-situ depth, distance to bays, curvature, slope) into grids at a 0.2 decimal degree resolution to match the forecasting analysis (described below), thereby creating predictive surfaces of bycatch risk. Considering the seasonal variation in risk relative to the target species, we evaluated Northern Hemisphere spring (March-May; all years) and fall (September-November; all years) separately by holding each season (incorporated as a factor) constant when generating spatial predictions. We then quantified the model uncertainty or confidence in the resulting probability estimates using the coefficient of variation (CV), which is the ratio of the standard error to the predicted value per observation, and mapped uncertainty alongside the predictions for spring and fall. We also examined regional variation in predicted risk model uncertainty (Appendix S1: Figure A4) and utilized this spatial distribution of error to focus the

Table 1

Summarized GAM results for each bycatch risk model averaged from the 58-folds cross validation to capture temporal variability across all years of data (1963–2020).

Performance Metrics	Atlantic herring/River herring	Atlantic mackerel/River herring
Proportion of deviance explained	18.7	20.3
R-squared	0.24	0.25
AIC	7757	3615
AUC	0.78	0.79
Sensitivity	0.71	0.73
Specificity	0.69	0.72
Correct positives (%)	44	42
False negatives (%)	12	11
Correct negatives (%)	26	31
False positives (%)	18	16

forecasting analysis only in areas of high model confidence.

2.5. Application and assessment of subseasonal reforecasts to predicted risk models

The Subseasonal Experiment (SubX), a NOAA Climate Testbed project, produces climate forecasts from 6 global ensemble models with the goal of providing operational real-time forecast targeting the week 1–4 outlook, quantifying subseasonal predictions in the state-of-the-art modeling systems, and exploring the sources of subseasonal predict-

ability (Pegion et al. 2019, Stepanuk et al. 2022). SST forecasts are provided by all six SubX models: NCEP-GEFS (National Centers for Environmental Prediction Environmental Modeling Center Global Ensemble Forecast System), NASA-GEOS5 (National Aeronautics and Space Administration Global Modeling and Assimilation Office Goddard Earth Observing System), Navy-ESPC (Naval Research Laboratory Navy Earth System Prediction Capability), RSMAS-CCSM4 (Community Climate System Model version 4 run at the University of Miami Rosenstiel School for Marine and Atmospheric Science); ESRL-FIM (Earth System Research Laboratory Flow-Following Icosahedral Model) and NCAR-CESM1 (National Center for Atmospheric Research Community Earth System Model Version 1). The SubX models are initialized once to four times a week with a minimum forecast lead time of 35 days. Details of each model configuration are documented in Pegion et al. (2019). In this study, we focus on developing forecasts with a 1-week lead time (the average of forecast lead day 1 to day 7, Stepanuk et al. 2022); as river herring and Atlantic herring demonstrate strong relationships to SST (Turner et al. 2016), a 1-week lead time could be beneficial to fishers by highlighting areas to avoid due to high probability of bycatch. We utilized the retrospective forecasts (also called reforecasts) for SST, which are available from 1999 to 2015 (17 years). Instead of using direct forecasts of SST output from the models, we apply a bias correction to remove the systematic model biases:

$$SST_{bc}(y, t, \tau) = [SST_f(y, t, \tau) - SST_{f_{lim}}(t, \tau)] + SST_{obs_clim}(t, \tau)$$

where $SST_{bc}(y, t, \tau)$ indicates the bias-corrected SST for forecast year

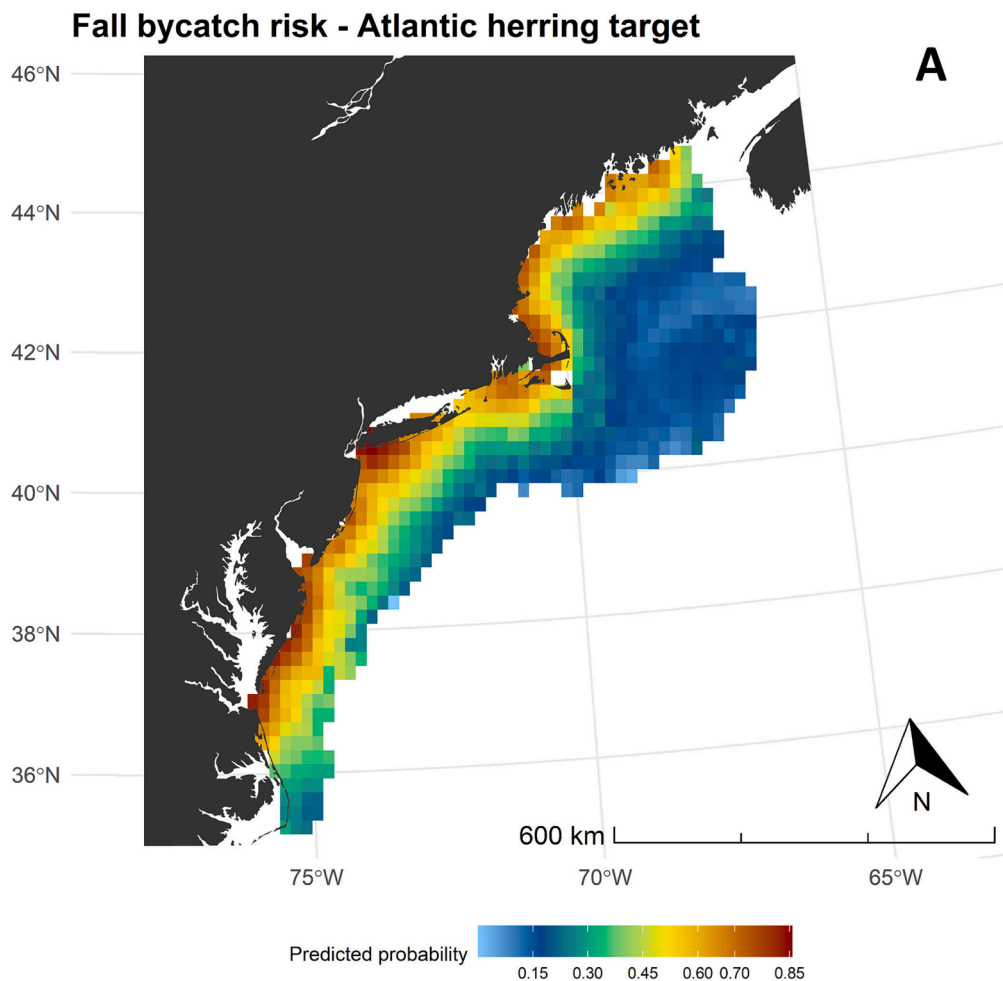


Fig. 1. A) Fall spatial predictions and B) associated model uncertainty (displayed using the coefficient of variation) for the Atlantic herring/bycatch risk model across all years of data.

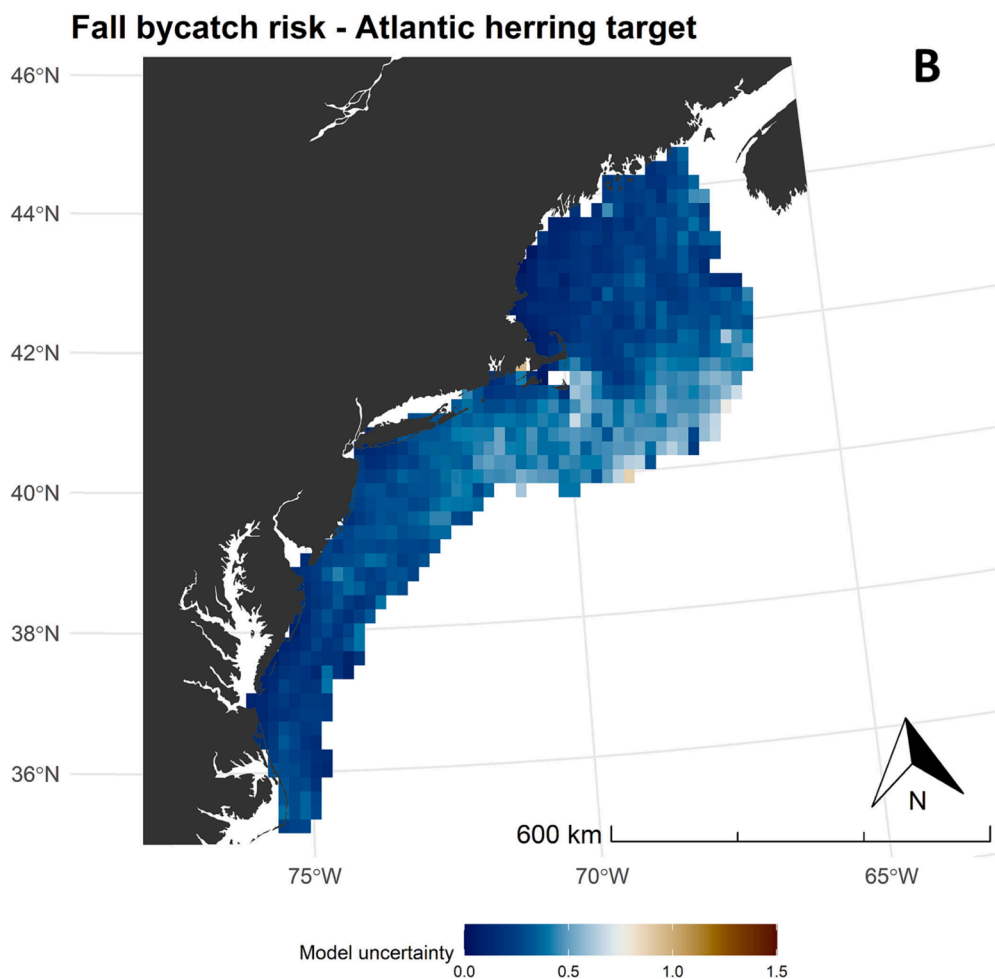


Fig. 1. (continued).

(y), initialized day (t), and forecast lead time (τ). The original SST forecast output ($SST_f(y, t, \tau)$) is subtracted by the 17-year forecast daily climatology ($SST_{f_clim}(t, \tau)$) to remove the mean bias, and then the observed 17-year daily climatology ($SST_{obs_clim}(t, \tau)$) is added. The multi-model ensemble mean (MME) is calculated for the days when more than 4 models overlap on the same initialized date. The forecasted surface temperature is evaluated against the skin temperature from the European Centre for Medium-Range Weather Forecasts (ECMWF) ERA-Interim (Dee et al. 2011) as they provide high spatial and temporal resolution. Reanalysis data is often regarded as ‘observation’.

Evaluation of the predicted risk model highlighted the Gulf of Maine in summer and Southern New England in winter and spring as the regions with highest potential risk of bycatch (described in Results), similar to previous studies (Cournane et al. 2013, Hasselman et al. 2016). For these 2 regions, we therefore generated new spatial predictions of bycatch risk specific for Atlantic herring fishers using the bias-corrected SST reforecasts in place of the in-situ SST used to develop the model. This resulted in weekly forecasts of bycatch risk at a 1-week lead time for all years of available reforecast data (1999–2015). Hereafter, we refer to these models as the ‘forecasted risk’. This process was then replicated for all 6 forecast models available from SubX to determine if seasonal or spatial (Gulf of Maine vs. Southern New England) variation exists in how each forecast model predicts risk of bycatch. Finally, as previous research identified the multi-model ensemble mean (MME) as more skillful than any individual model alone as the model errors from individual forecasts are cancelled out (Pegion et al. 2019), we selected this MME forecasted risk model to generate example spatial outputs for Southern New England and the Gulf of Maine to visualize

change in risk on a weekly scale.

3. Results

3.1. Predicted risk model evaluation

The predicted risk model with the lowest AIC value included smoothing functions of SST, bathymetric curvature, distance to freshwater bays, with region and season incorporated as factor variables. GAM plots demonstrate that high bycatch risk is generally associated with cooler SST (especially in the 4–8°C range), minimal seafloor curvature, and close proximity to freshwater bays (Appendix S1: Figure A1). Winter and spring had elevated bycatch risk, with minimal risk occurring in the fall months. Spatially, the Gulf of Maine had the highest bycatch risk potential, followed by Southern New England. Results from the 58-folds cross validation showed the predicted risk model had an acceptable fit, with a mean AUC of the receiver operator curve at 0.78 across all years of data (Appendix S1: Figure A2). AUC values were either acceptable or excellent for the years that coincide with the forecasting analysis (1999–2015). Low performing years were concentrated between 1968 and 1986 (Appendix S1: Figure A2). The calibration test produced a value of 0.91, reflecting strong agreement between the observations and model predictions (Appendix S1: Figure A3). The mean proportion of deviance explained was 18.7% across the 58-folds (Table 1). The mean proportion of correct positives was 44% using the optimum probability threshold (where model sensitivity equals specificity), while mean proportion of correct negatives was 26% (Table 1).

There were significant seasonal differences in the spatial pattern of

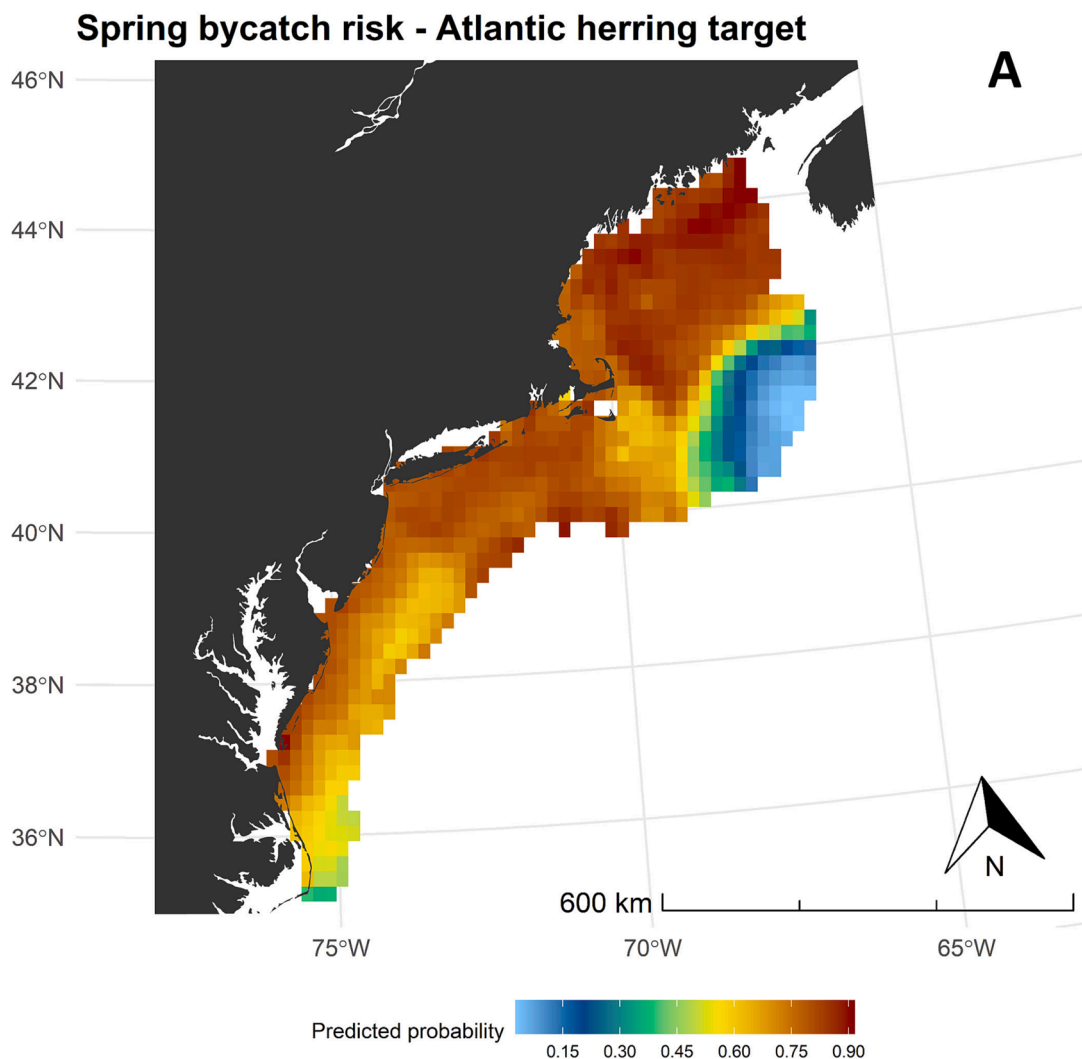


Fig. 2. A) Spring spatial predictions and B) associated model uncertainty (displayed using the coefficient of variation) for the Atlantic herring/bycatch risk model across all years of data.

predicted risk of Atlantic herring and river herring bycatch (Figs. 1 & 2). There was an elevated risk (i.e., greater than 60% predicted probability) directly along the coastline of the Southern New England and Mid-Atlantic Bight regions during the fall months, that lessened further up towards the Gulf of Maine during that time (Fig. 1A). Bycatch risk also steadily declined to less than 15% further offshore (Fig. 1A). Bycatch risk for the spring months, however, was high (i.e., >60%) for the entirety of Southern New England and the Gulf of Maine, including coastal and offshore waters (Fig. 2A). Very low risk (i.e., <less than 20%) was only observed in the Georges Bank region for spring (Fig. 2A). The associated model uncertainty, displayed using the CV, revealed higher confidence in the probability estimates in the spring (Fig. 2B & Appendix S1: Figure A4). Model uncertainty was patchy throughout all regions during the fall, with higher model uncertainty throughout Southern New England and along the edges of the study area (Fig. 1B & Appendix S1: Figure A4). Georges Bank contained the highest degrees of uncertainty in predictions in fall and spring (Figs. 1 & 2). The lowest model uncertainty occurred in the Gulf of Maine in spring.

3.2. Forecasting bycatch risk

An assessment of SubX model skill demonstrated that forecasts were effective at 1-week leadtimes and therefore valuable for this application

(Fig. 3). All 6 SubX models showed close agreement in predicting probability of bycatch for Atlantic herring fishers, regardless of the season or region of the study area being considered (Figs. 4 & 5). While there were some temporal gaps in the MME, which requires the overlap of 4 individual models on the same initialization date, this model also aligned closely with the other 6 models. Forecasts for both regions were seasonally variable with the highest forecasted risk in the spring months (Figs. 4 & 5). Forecasted risk peaked in the Gulf of Maine between the 2nd and 4th week of April, with the exception of 2012 which demonstrated higher risk earlier in the year (Fig. 4). Gulf of Maine forecasted risk also increased steadily during the fall months and into winter (i.e., from 30% in early September to above 70% by mid-January; Fig. 4). Our results suggest that vessels targeting Atlantic herring in the Southern New England region have a more than 70% probability of encountering bycatch from January into early April, with bycatch risk decreasing to below 50% closer to summer (Fig. 5). Overall risk was lower (less than 50%) in the fall months yet showed a steady increase between September and December, similar to the Gulf of Maine (Fig. 5).

Example spatial outputs of forecasted risk using the MME demonstrate that variability was detectable at the weekly stage, and that it was possible to distinguish specific areas and weeks where Atlantic herring fishers have a high probability of encountering bycatch (Figs. 6 & 7). The weekly forecast plots beginning in late October of 2008 and 2014 for

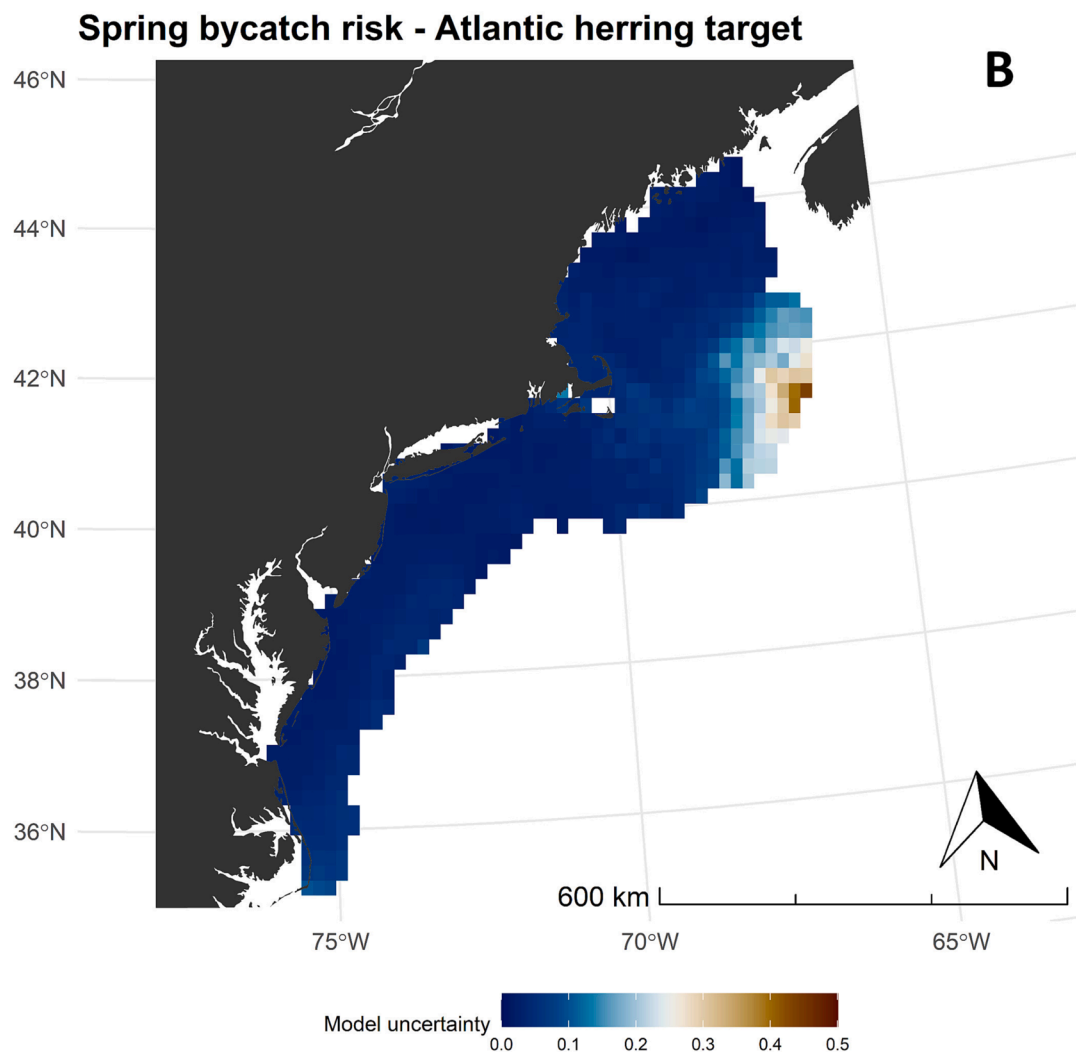


Fig. 2. (continued).

the Gulf of Maine highlighted the increasing bycatch presence along the shoreline (Fig. 6). Winter in the Southern New England region is known for high probability of bycatch, as demonstrated in the forecasted risk plots for February of 2004 and 2010, which shows consistently high predicted values (i.e., >50%) for much of the region (Fig. 7). However, these plots also reveal increasing risk forecasted in each week throughout February, especially off the coast of Long Island, New York. Throughout both regions, the latter years (i.e., 2014 in Figure 6 and 2010 in Fig. 7) appear predisposed to higher bycatch risk earlier in the year.

4. Discussion

To our knowledge, this is the first study to integrate a species co-occurrence model with oceanographic forecasts to generate a sub-seasonal ecological forecast. Previous studies have integrated habitat models with near real-time satellite ocean data on individual species (Howell et al. 2008, Hazen et al. 2017) or made ecological forecasts at the scale of months to decades (Payne et al. 2017). Our model was developed at a timescale relevant to inform fisheries management, a significant advance since the call to develop ecological forecast models was invoked 20 years ago (Clark et al. 2001). If integrated into a potential decision support tool for fishers, this model could be updated weekly based on environmental conditions and adapted to the target/bycatch species of interest. This could allow commercial fishers to

identify areas to avoid in order to decrease the likelihood of bycatch in a highly variable environment or allow managers to close certain areas for short periods of time, providing a 1-week lag time for preparation.

The key novelty provided by this analysis is the feasibility of skillfully forecasting river herring distributions with a 1-week lead time in regions where we know bycatch has the potential to close the target fishery. The use of environmental forecasts in species distribution modeling, rather than relying on near-real-time conditions, has increased significantly over the past decade as managers seek to better anticipate how such broad changes will reshape ecosystems (Spillman and Hobday 2014, Turner et al. 2017a, Tulloch et al. 2020). For example, seasonal forecasts have been applied to monitoring coral bleaching (Spillman 2011), determining habitat preferences for southern bluefin tuna (Eveson et al. 2015), and tracking the migration and distribution of Pacific sardines (Kaplan et al. 2016). For fisheries management in particular, finer-scale ecological predictions are more suited to minimize risks and prevent economic losses than seasonal or annual forecasts that cannot capture the daily or weekly dynamics of a system. Subseasonal forecasts, like SubX, that operate at the weekly scale, can be a powerful tool when integrated with distribution models to provide early warning signals to fishery managers. However, this weekly scale may not adequately capture some environmental conditions that could have a significant impact on species distributions and therefore the potential for bycatch. While the daily forecast scale can be more applicable to commercial fleet dynamics, previous research has demonstrated

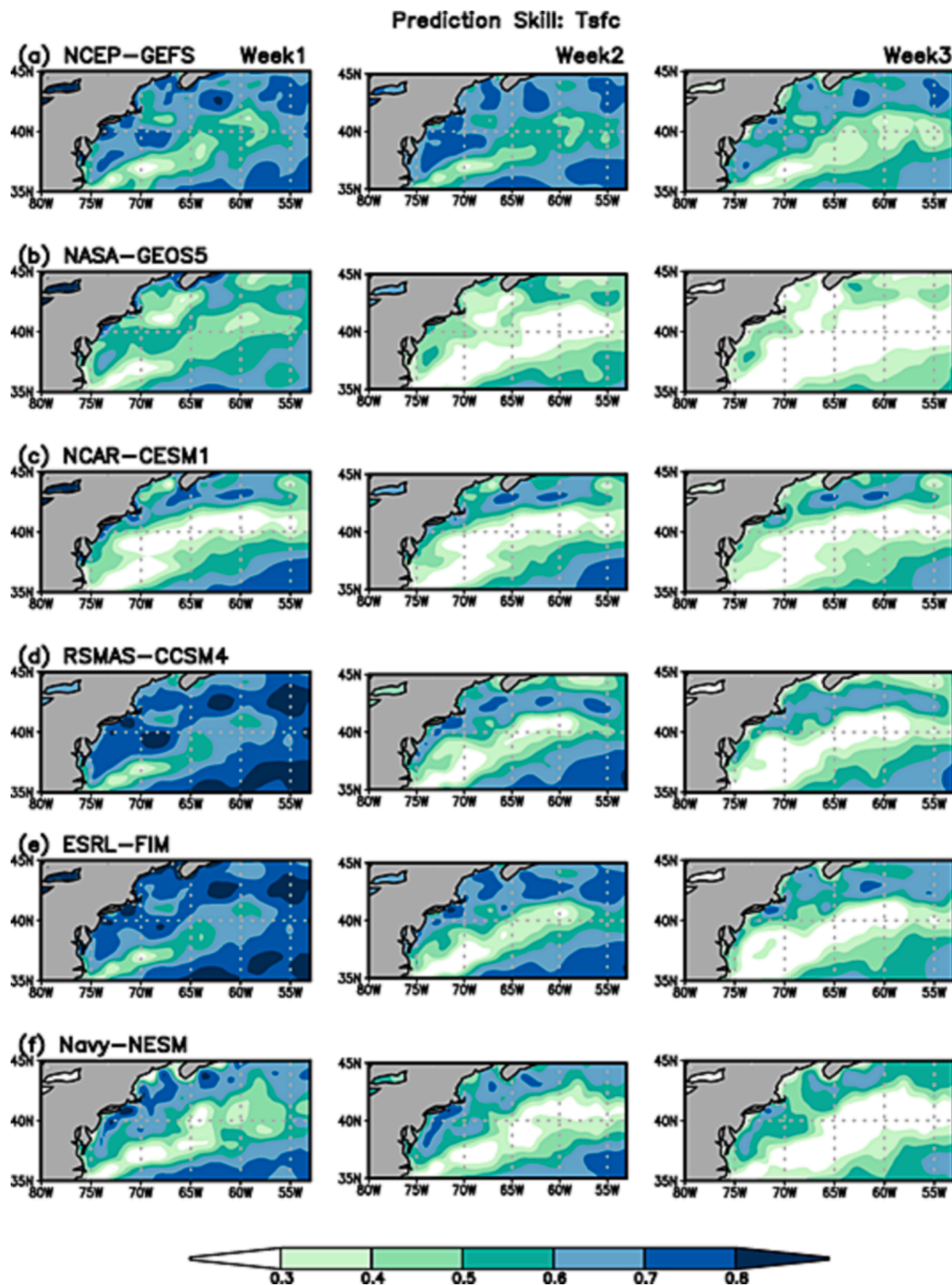


Fig. 3. SST forecast skill measured by anomaly correlation coefficient (ACC) as a function of forecast week 1 to week 3 for (a) NCEP-GEFS, (b) NASA-GEOS4, (c) NCAR-CESM1, (d) RSMAS-CCSM4, (e)ESRL-FIM and (f) Navy-NESM.

that substantial heterogeneity exists at this scale specific to species distributions, which could significantly increase model uncertainty (Turner et al. 2017a, 2017b). The trade-offs associated with forecasting at these shorter timeframes should be strongly considered so the model output matches the decision context.

Previous studies and published reports from independent observer data have identified winter in Southern New England and fall in Cape Cod (Gulf of Maine) as likely high bycatch risk (Hare et al. 2021, GARFO 2016). Similar spatiotemporal variation in predicted risk is generated from our model and seasonally explicit spatial outputs. This context is

particularly significant when considering bycatch mitigation strategies, or restricting area use for trawlers, as different areas of the fishery are more impactful on river herring populations than others (Bethoney et al. 2014). Bycatch in Southern New England, for example, is likely constrained to only a few river herring stocks and more immature size classes relative to the Gulf of Maine, providing further justification for quotas to potentially reduce juvenile bycatch mortality (Bethoney et al. 2014). Accurately identifying regional and seasonal changes to risk is an important step in the development of a tool to predict in detail where bycatch is most likely to occur in the future (Turner et al. 2017a, 2017b).

Gulf of Maine - AH target

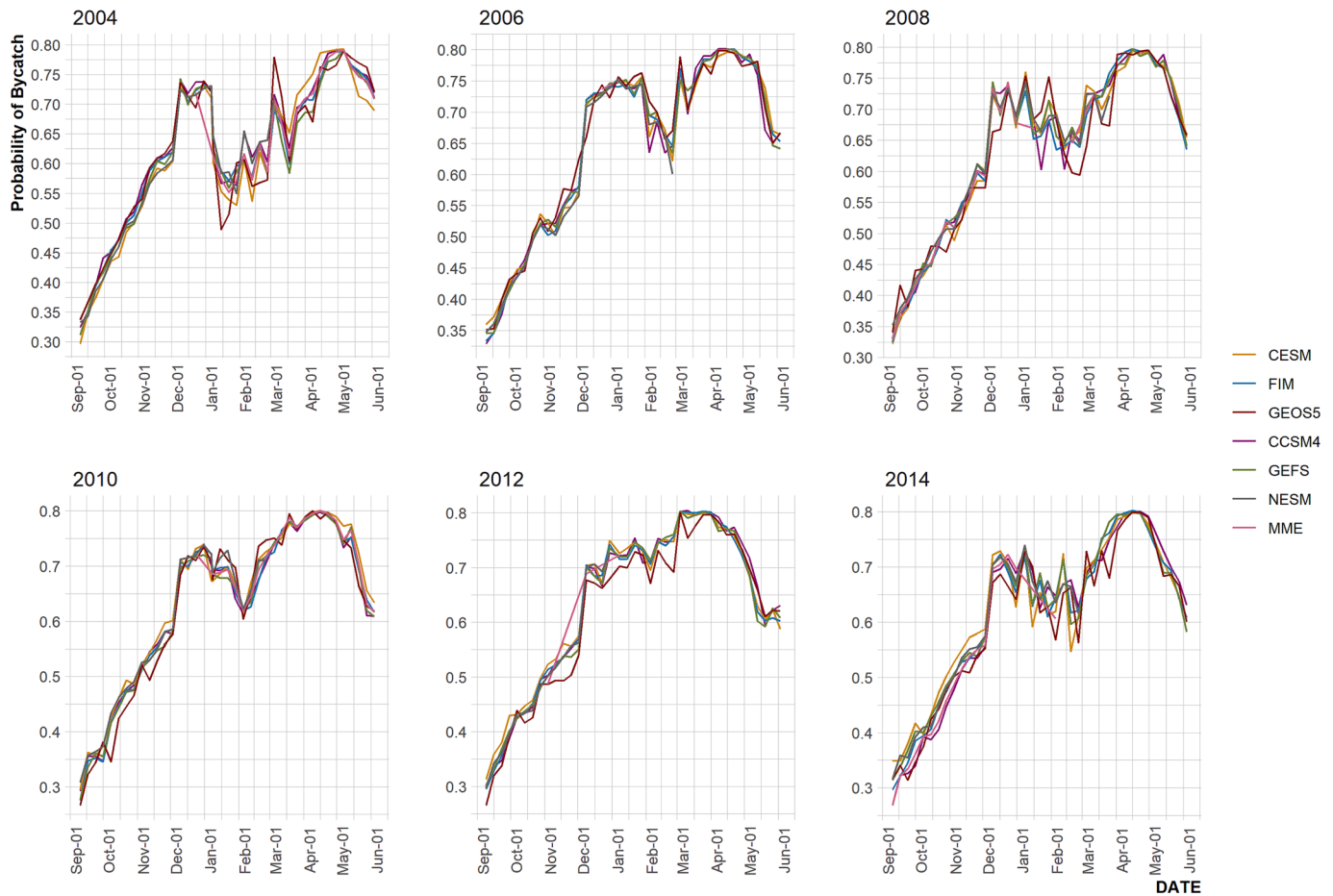


Fig. 4. Predicted probability of bycatch for vessels targeting Atlantic herring in the Gulf of Maine region. Predicted values generated separately for all 6 SubX models and a multi-model ensemble mean (MME).

Future work could also validate the predicted risk models alongside data from the Bycatch Avoidance Program (Bethoney, 2012), with the aim of incorporating the forecasted risk outputs into the program and future development of a predictive tool (Turner et al. 2017b). Our forecasted risk model provides both a seasonal outlook on risk for Atlantic herring fishers as well as examples of selected weeks that coincide with known bycatch potential.

It is increasingly apparent that static management approaches are no longer sufficient as large area closures can cause significant economic hardship to stakeholders (Dunn et al. 2016) and static closed areas may not achieve management goals in light of well-documented species range shifts, reduced recruitment, and increased mortality in response to large-scale warming (Nye et al. 2009, Pershing et al. 2015). Additionally, as a consequence of shifting species and habitats, models that can effectively use environmental drivers of species overlap or co-occurrence are increasingly important, particularly when spatial or temporal overlap involves commercially harvested species (Turner et al. 2016). Previous research has modeled co-occurrence of marine fish by multiplying probabilities from single species distribution models (Turner et al. 2016) or through a Bayesian joint modeling framework (Roberts et al. 2022). Our target/bycatch overlap approach provides an effective method for identifying common spatial habitats relative to environmental attributes rather than independently modeling each target and bycatch species, although it is parameterized to only model where a target species is present. As bycatch reduction plans are becoming integral to fisheries management, this approach can be easily modified to the target/bycatch species of interest at a spatiotemporal

scale relevant to anticipate such interactions and adjust operations accordingly.

The development of species distribution models naturally will include elements of uncertainty. However, due to the complexity associated with identifying and interpreting said uncertainty, it is often barely acknowledged or ignored entirely when model results are reported (Beale and Lennon 2012). When practical applications of analyses are addressed, such as the management of marine resources or the impact on a fishing community, uncertainty must be considered. By reporting the model uncertainty alongside the parameter estimates for bycatch risk, we can identify areas of high confidence versus areas of lower interpretability. For example, we found very low uncertainty associated with the probability estimates in the spring compared to the fall (Fig. 1B and 2B). This assessment of model error, for both the bycatch risk and SubX SST models, highlights the dynamic nature of the Gulf Stream region and thus the potential for some grid cells to have lower predictability relative to bycatch risk. With ongoing population assessments of river and Atlantic herring in the Northeast US and concerns over depleting stocks (Hare et al. 2021), it is necessary to improve these predictions and associated uncertainty as a step towards ecosystem-based management.

Our forecasting approach could be used in tandem with existing strategies, such as dam removal and restoration of key habitat, as well as the practical knowledge of fishermen, to mitigate bycatch of river herring, which would contribute both to restoring stocks of river herring and to keeping Atlantic herring fisheries below bycatch thresholds. At the time of publication, Atlantic herring were at very low abundance in

Southern New England - AH target

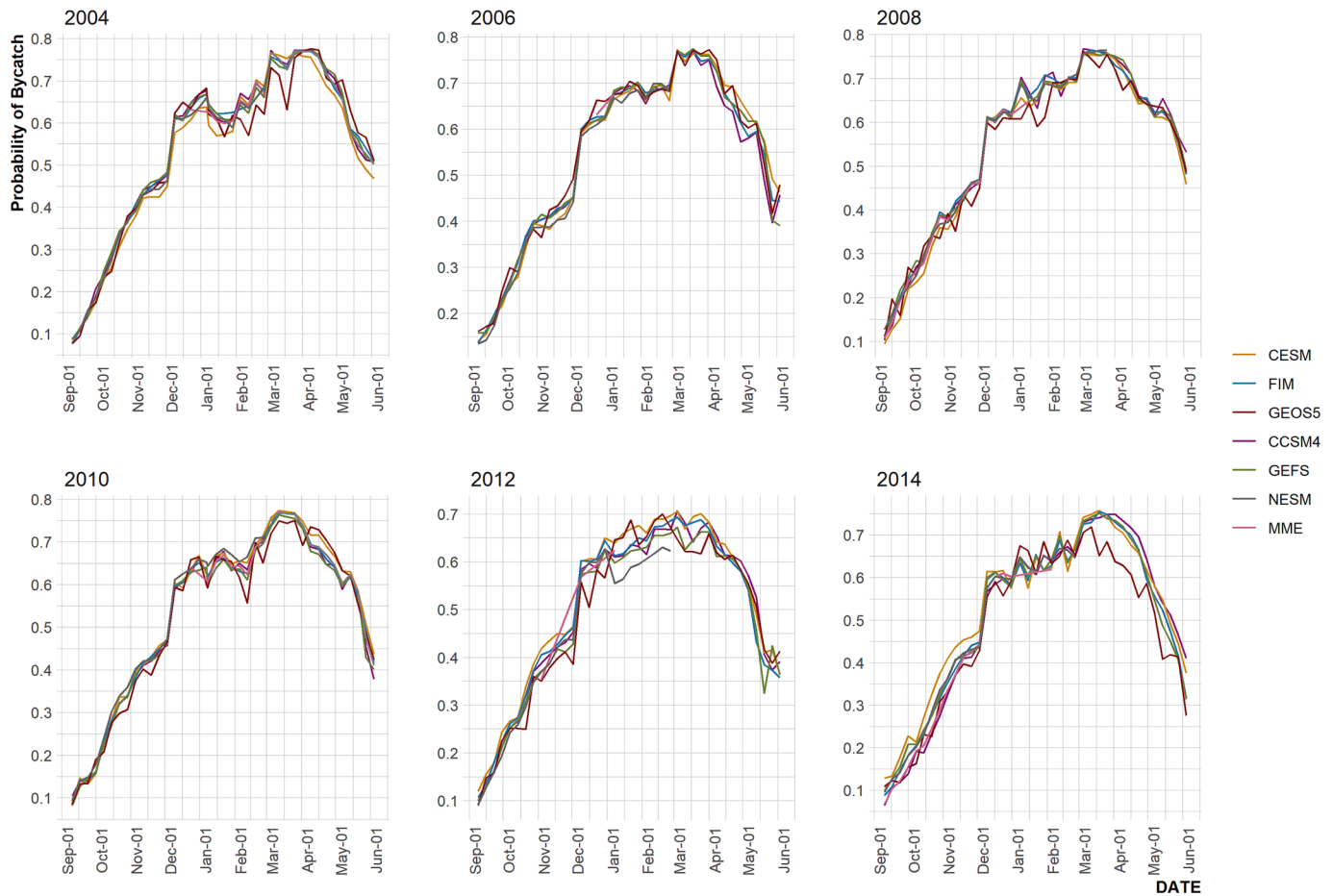


Fig. 5. Predicted probability of bycatch for vessels targeting Atlantic herring in the Southern New England region. Predicted values generated separately for all 6 SubX models and a multi-model ensemble mean (MME).

the US, such that bycatch of river herring was not as much of a concern for river herring recovery as in the past. However, river herring are subject to bycatch in other trawl and gillnet fisheries and bycatch reduction is a key component to the conservation of river herring (Kritzer et al. 2022, Hare et al. 2021). Our modeling approach can be improved and implemented as Atlantic herring recover and can be applied to other species. Area-specific regulations remain in place to both limit the amount of river herring allowed in trawls prior to the closure of a fishery and prohibit vessels within a certain distance from the shoreline (Hasselman et al. 2016). In addition to these regulations, voluntary bycatch avoidance programs have demonstrated positive impacts in fleet behavior that contributes to decreased bycatch (Bethoney et al. 2017). There are multiple ways the bycatch risk forecast could assist managers in optimizing existing strategies and planning procedures. A pressing challenge in fisheries is navigating specific months where target and bycatch species co-occur extensively (Hastings et al. 2017). Use of this forecast can better position vessels in these months by identifying in advance specific weeks that are more conducive to maximizing target catch while minimizing bycatch. As our model does not arbitrarily distinguish low, medium, or high-risk areas, fishers could independently select what risk thresholds they deem acceptable each week. Use of this information can therefore help to ease the financial hardships experienced by fishermen in recent years due to unintended closures and enhance economic efficiency. Ultimately, this analysis could inform the development of a long-term bycatch risk tool for fishers to use directly that can be presented in a live format and regularly updated.

The development of a river herring bycatch risk tool could follow previous accomplishments in forecasting distributions of marine turtles, southern bluefin tuna, and other marine megafauna. The ongoing TurtleWatch project utilizes environmental data to quantify loggerhead turtle interactions with the pelagic longline fishery in Hawaii and provides a daily mapping product of predicted turtle locations to reduce bycatch (Howell et al. 2008). A similar daily product is available in Australia using habitat preference models and seasonal forecasts to contribute to the dynamic spatial management of southern bluefin tuna (Hobday et al. 2011, Eveson et al. 2015). The effectiveness of such conservation tools is attributed to an online framework designed with participation from key stakeholders as well as accessibility. The forecasting tool for southern bluefin tuna, for example, has produced tangible outcomes in the adjustment of fishing operations, particularly as climate change accelerates shifts in habitat and distribution of commercially important fish species (Eveson et al. 2021). In addition to demonstrating the application of subseasonal forecasting to fisheries bycatch, building on similar research utilizing 0–2 day oceanographic forecasts (Turner et al. 2017a), our approach utilized 6 climate forecasting models and found negligible spatiotemporal variability once the forecasts were integrated with the ecological model. This provides even more flexibility and justification for transitioning this model to a web-based tool where managers could preemptively select the forecast model that best fits their objectives for fisheries management (i.e., a model initialized every 5 days, every 7 days, or multiple forecasts generated each week). Furthermore, as numerical weather/climate models and operational forecasting systems are frequently upgraded and

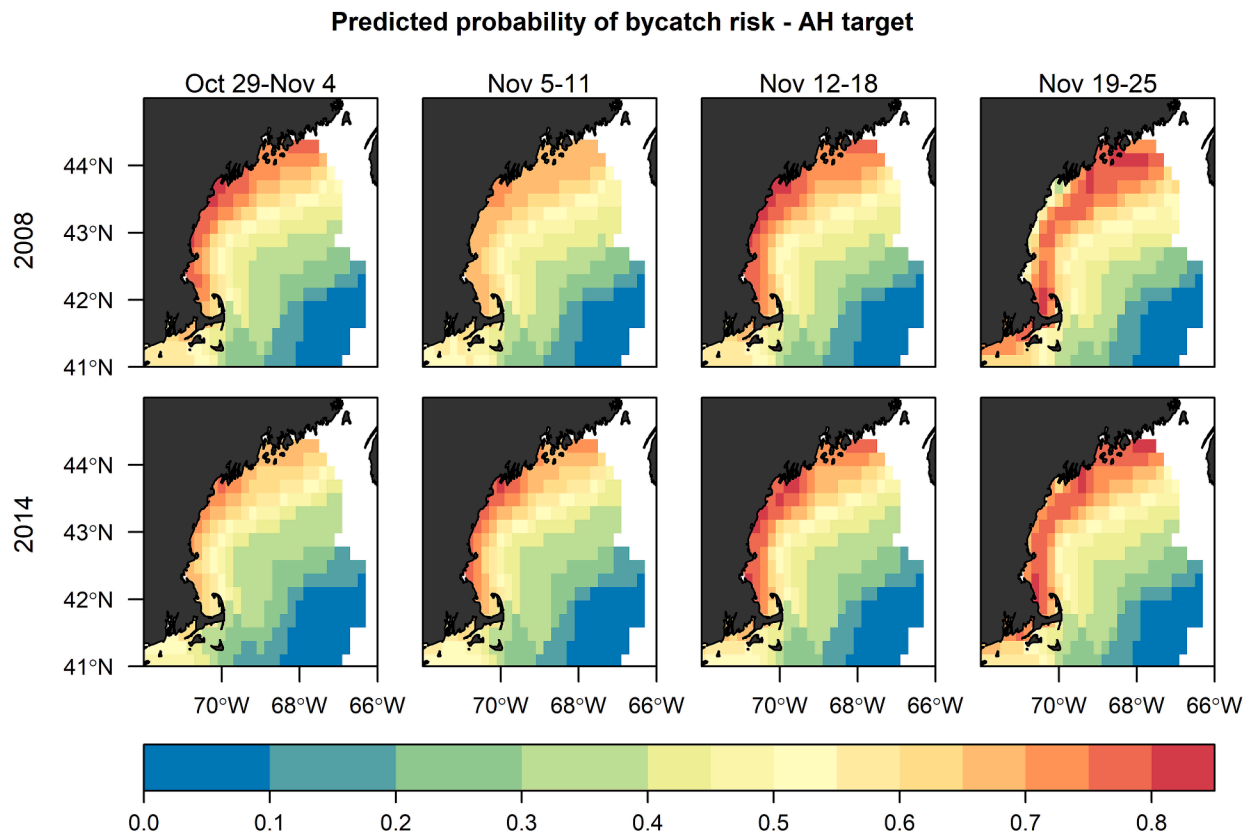


Fig. 6. Spatial output of forecasted risk predictions generated with the SubX MME for vessels targeting Atlantic herring in the Gulf of Maine region.

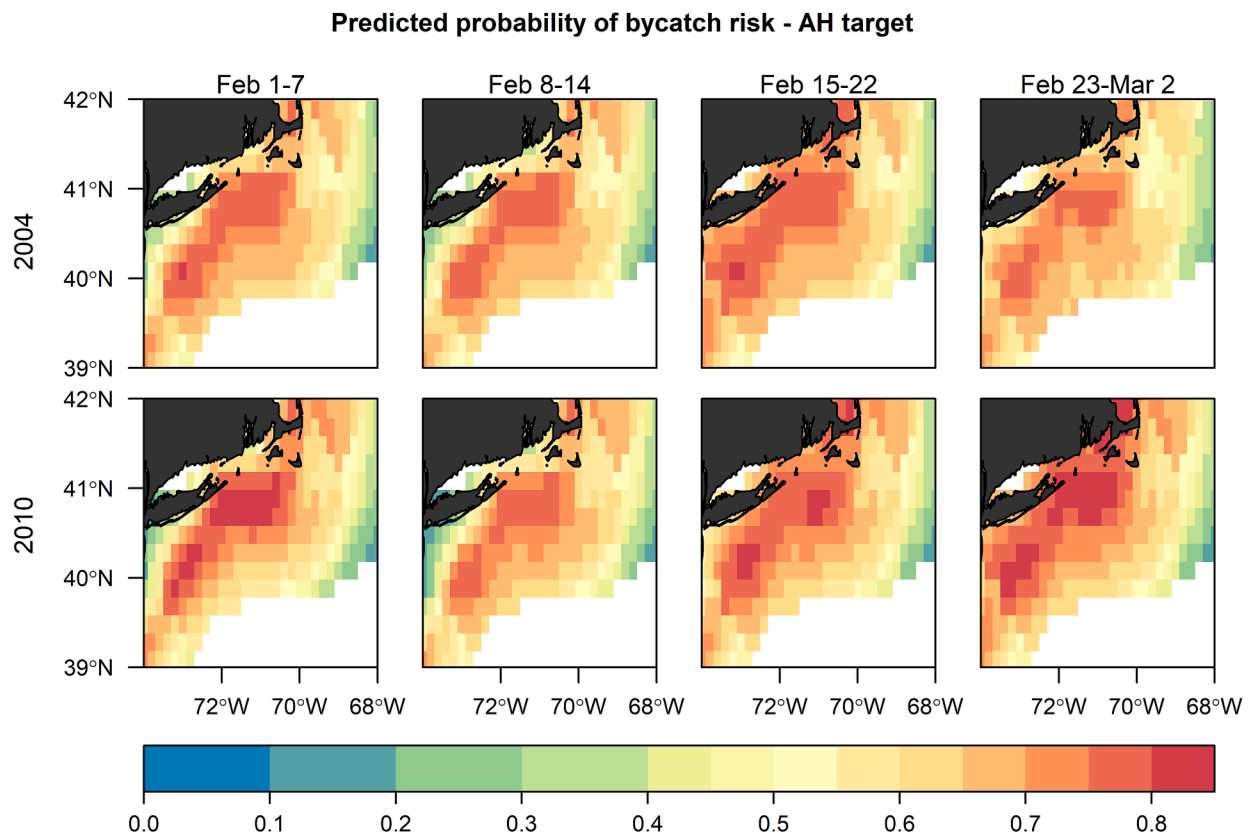


Fig. 7. Spatial output of forecasted risk predictions generated with the SubX MME for vessels targeting Atlantic herring in the Southern New England region.

improved, forecast skill is expected to increase. Better representation of key processes through higher model resolution will provide even more accurate identification of high bycatch risk areas. Previous attempts in bycatch avoidance programs had grid cells of 5 nmi × 8 nmi (10 longitude × 5 latitude) and these approaches had some success (Bethoney, 2012, Bethoney et al., 2017). Our forecast approach could be integrated with such bycatch avoidance programs to improve upon past efforts and enable dynamic spatial management at smaller spatial scales than the current management areas.

5. Conclusions

Defining areas that fishers should avoid at fine spatial and temporal scales presents a unique and multidimensional challenge, both from an ecological and social perspective. Foremost, fishing locations are often based on a suite of considerations beyond just environmental conditions. Secondly, temperature associations are very similar for many target and nontarget species and consequently, fisheries optimized for a target species can have disastrous implications on the sustainability of nontarget species (Hastings et al. 2017). To avoid severe cutbacks to the harvest of target species, or the closure of a fishery altogether, managers require forward-looking planning tools that better position the industry to compensate for shifting environmental conditions at relevant time-scales. Our analysis demonstrates that subseasonal forecasts can be used to predict fisheries bycatch, and could be integrated into fisheries management to mediate target/bycatch species interactions and thus improve decision-making in a dynamic spatial management context. While there will naturally be competing objectives surrounding management frameworks, an increased understanding of fish and fisher's interactions can lead to more effective, integrated approaches to managing the ocean.

Data availability statement.

Bottom trawl survey data are publicly available. [NOAA's National Marine Fisheries Service (NMFS) Northeast Fisheries Science Center (2005). Northeast Fisheries Science Center Bottom Trawl Survey Data. NOAA's National Marine Fisheries Service (NMFS) Northeast Fisheries Science Center, Ecosystems Survey Branch. Woods Hole, Massachusetts, United States of America. <http://www.nefsc.noaa.gov/esb/>]. SubX forecast and reforecast data are publicly available at <http://cola.gmu.edu/subx/>.

Uncited references.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

All data is publicly available and citations are provided.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.pocan.2023.103021>.

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