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ARTICLE

Evaluation of species distribution forecasts: a potential predictive tool for reducing incidental catch in pelagic fisheries[1]

Sara M. Turner, Jonathan A. Hare, John P. Manderson, David E. Richardson, and John J. Hoey

Abstract: Nontarget catch restrictions are becoming common in fisheries management. We test a potential tool for reducing nontargeted catch that combines species' distribution models and ocean forecast models. We evaluated our approach for Atlantic herring (*Clupea harengus*), Atlantic mackerel (*Scomber scombrus*), alewife (*Alosa pseudoharengus*), and blueback herring (*Alosa aestivalis*). Catch of the latter two species is capped in commercial fisheries of the former two species. Ocean forecasts were derived from a data-assimilative ocean forecast model that predicts conditions 0–2 days into the future. Observed oceanographic conditions were derived from CTD casts and observed fish presence–absence was derived from fishery-independent bottom trawl collections. Species distribution models were used to predict presence–absence based on observed and forecasted oceanographic conditions, and predictions for both were very similar. Thus, most of the error in predicted distributions was generated by the species distribution models, not the oceanographic forecast model. Understanding how predictions based on forecasted conditions compare with predictions from observed conditions is key to developing an incidental catch forecast tool to help industry reduce nontarget catches.

Résumé : Les restrictions sur les prises d'espèces non visées sont de plus en plus répandues en gestion des pêches. Nous mettons à l'essai un outil potentiel pour réduire les prises d'espèces non visées qui combine des modèles de répartition des espèces et des modèles de prévision océanographique. Nous avons évalué notre approche pour le hareng atlantique (*Clupea harengus*), le maquereau (*Scomber scombrus*), le gaspareau (*Alosa pseudoharengus*) et l'alose d'été (*Alosa aestivalis*), les prises des deux dernières espèces étant limitées dans les pêches commerciales aux deux premières espèces. Des prévisions océaniques ont été obtenues d'un modèle de prévision océanographique avec assimilation de données qui prédit les conditions de 0 à 2 jours dans le futur. Les conditions océanographiques observées ont été tirées de profils de CTD et la présence–absence observée de poissons a été obtenue de prélèvements par chalut de fond indépendants de la pêche. Des modèles de répartition des espèces ont été utilisés pour prédire la présence–absence à la lumière des conditions océanographiques observées et des prévisions de ces conditions, et les prédictions pour les deux cas étaient très semblables. Ainsi, la majeure partie de l'erreur associée aux répartitions prédites était engendrée par les modèles de répartition des espèces et non le modèle de prévision océanographique. La compréhension de la correspondance des prédictions basées sur des prévisions des conditions et des prédictions obtenues à partir de conditions observées est un aspect clé de la mise au point d'un outil de prévision des prises accessoires pour aider l'industrie à réduire les prises d'espèces non visées. [Traduit par la Rédaction]

Introduction

Fisheries management is becoming increasingly concerned with reducing nontarget catches, via many different methods (e.g., time and area closures, gear restrictions, and catch caps for nontarget species; Benaka and Dobrzynski 2004; O'Keefe et al. 2013). Sometimes, shifting effort or modifying gear is sufficient, but when species have similar migration routes or morphology, more flexible strategies are necessary (Bethoney et al. 2013*a*; O'Keefe et al. 2013). Adaptive strategies, such as move-on-rules or fleet communication programs, facilitate changing fishing pressure in response to recent catches (Gilman et al. 2006; Bethoney et al. 2013*b*; O'Keefe et al. 2013). These adaptive strategies, referred to as dynamic management, are becoming more prevalent in marine fisheries management and are facilitated by advances in environmental forecasting and technology (Lewison et al. 2015). Further, dynamic management can improve the ecological effectiveness of management while minimizing the economic impacts on industry (Dunn et al. 2016).

Species' distributions are largely related to habitat distributions, and habitat associations have been modeled for a range of marine species (Maury et al. 2001; Hobday 2010; Hartog et al. 2011; Hare et al. 2012*a*; Turner et al. 2015). Species distribution models have been validated and used to predict distributions over comparable spatial and seasonal scales (Stoner et al. 2001; Manderson et al. 2011; Turner et al. 2015), as well as to forecast future distributions under changing climate conditions (Hare et al. 2012*a*; Lynch et al. 2015). Some applications of species distribution models

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include identifying changes in habitat associations for different life stages, understanding drivers of spatial distributions, and predicting distribution and abundance changes related to changing conditions (Maravelias et al. 2000; Stoner et al. 2001; Lynch et al. 2015).

Oceanographic forecast and hindcast models have been developed and evaluated for a range of spatial and temporal scales, and forecasts can include a wide range of parameters, including water temperature, salinity, and currents (Chen et al. 2006; Moore et al. 2011). Forecast models update regularly and include forecasts for the current day and also predictions for coming days; hindcast models estimate past conditions and have been validated with observed conditions, where available. Ocean forecast and hindcast models, such as the finite volume community ocean model (FVCOM), have been developed over a range of spatial scales, from small coastal regions to entire ocean basins, with forecast spatial resolution varying with environmental complexity (Chen et al. 2006). These models have been used to address issues ranging from understanding seasonal variations in local conditions to understanding the population ecology of fish over a large region (e.g., Boucher et al. 2013; Xue et al. 2014).

Combining species distribution models with oceanographic forecasts could provide commercial fisheries with a proactive tool for reducing nontarget catches. We evaluate distribution forecasts for Atlantic herring (*Clupea harengus*), Atlantic mackerel (*Scomber scombrus*), alewife (*Alosa pseudoharengus*), and blueback herring (*Alosa aestivalis*). The former two species are commercially harvested, and catches of the latter two species (often called river herring) are limited in both fishery management plans (US Department of Commerce 2015). To test the potential utility of these combined models, we use previously developed species distribution and overlap models (Turner et al. 2015) in combination with a publically available oceanographic forecast model to

1. Evaluate the accuracy of the ocean forecast model by comparing with observed salinity and temperature during a fishery-independent trawl survey in the spring of 2015.
2. Evaluate the accuracy of species distribution and overlap models coupled with the ocean forecast model by comparing with distribution and overlap models based on observed conditions during a fishery-independent trawl survey in the spring of 2015.

Methods

Study area

The Northeast Fisheries Science Center (NEFSC) bottom trawl survey is conducted throughout the Northeast United States Continental Shelf from Cape Hatteras, North Carolina, through the Gulf of Maine. Alewife, blueback herring, Atlantic herring, and Atlantic mackerel are regularly caught during the spring trawl survey, and the survey area encompasses the majority of the species' ranges in late winter and spring. Alewife and blueback herring are anadromous, spawning in freshwater and estuarine habitats in the late spring (Fay et al. 1983). During their marine migrations, alewife and blueback herring are found in coastal estuaries and shelf habitats to depths of 200 m. Atlantic herring are a marine species, and on the Northeast US Continental Shelf, they spawn in Georges Bank and the Gulf of Maine, overwinter in southern New England and the Mid-Atlantic Bight, and are distributed in the Gulf of Maine in summer (Stevenson and Scott 2005). Atlantic mackerel are also a marine species, and on the Northeast US and Canadian Continental Shelf they spawn near Newfoundland into the Gulf of St. Lawrence and in the Mid-Atlantic Bight (Sette 1950). Atlantic mackerel overwinter from the Mid-Atlantic Bight to Nova Scotia and in the summer are distributed in the Gulf of Maine and near Newfoundland (Sette 1950). Commercial fisheries for Atlantic herring and Atlantic mackerel encounter alewife and blueback herring during the winter and early spring in southern New England and in the Gulf of Maine in the summer (Cournane et al. 2013). Each of these seasonal–regional fisheries is allocated roughly 30% of the total Atlantic herring quota.

Data collection

The NEFSC bottom trawl survey has been conducted at least twice a year since 1968. The survey uses a stratified, random sampling design, and at each station the latitude, longitude, date, time, catch number, and catch mass are recorded. A detailed description of the sampling protocols is given in Politis et al. (2014). Briefly, a standardized Yankee 36 bottom trawl was used through 2008, when the survey switched to a new vessel using a standardized three-bridle, four-seam bottom trawl with a rockhopper sweep. The on-bottom tow duration is 20 min, and the tow speed is 3.0 knots (1 knot = 1.852 km·h^{-1}) (Politis et al. 2014). At each survey station, the conductivity, temperature, and depth (CTD) are recorded within 10 m of the bottom, within 3 h of the trawl start, and within 3 nautical miles (1 n.mi. = 1.852 km) of the midpoint of the trawl path (Politis et al. 2014).

Species distribution models were developed using data from the winter (February) 1993–2007 and spring (March–May) 1991–2013 surveys (Turner et al. 2015). The winter survey only operated from 1993 to 2007; spring data were restricted because consistent environmental data collection with a CTD instrument began in 1991 (Holzwarth-Davis 1993). Seasons were limited because the ranges of environmental variables, and thus potential habitats, vary widely among seasons (Mann 1993); we focused on winter and spring because this is when the majority of mixed catches in commercial fisheries occur (Shepherd 1986; Bethoney et al. 2013*b*; Cournane et al. 2013). Catch and CTD data from the spring 2015 bottom trawl survey (14 March 2015 – 6 May 2015) were used for model evaluation.

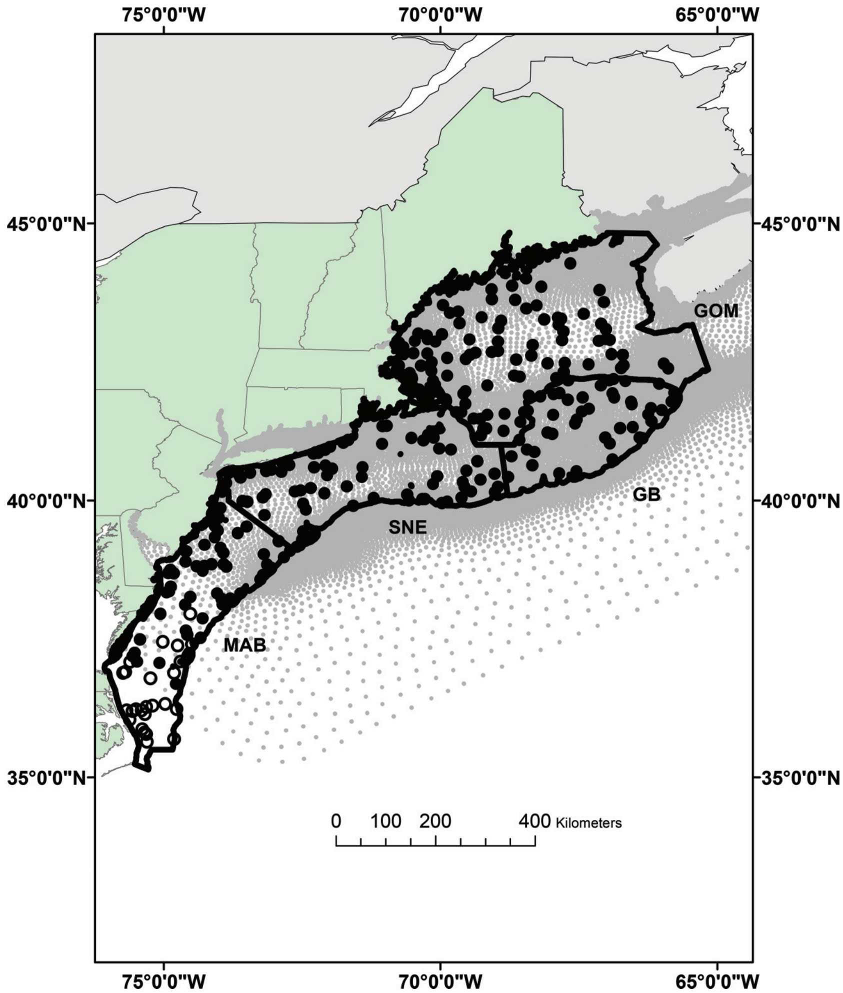
Forecast ocean model

Forecast bottom temperature and bottom salinity were downloaded from FVCOM for the current day (Day 0), 1 day in advance (Day 1), and 2 days in advance (Day 2) for midnight and noon for the entire model domain for each day during the spring 2015 trawl survey (Chen et al. 2006). All six forecasts were downloaded for all but seven of 44 of the survey days (the result of forecast model update computer errors). Trawl survey stations were spatially matched with the nearest three FVCOM forecast model nodes (grid resolution ranges from 0.3 to 15 km) and temporally matched to the closest model time (midnight or noon); stations and nodes more than an average of 10 km apart were excluded. The temporal difference between the station observations and forecasted conditions did not exceed 6 h; during preliminary work we found that forecasts showed little variation over time scales less than a day. Salinity and temperature were averaged for the three nodes. The spatial overlap between the survey area and FVCOM is almost complete, encompassing 82% of the spring 2015 survey stations (Fig. 1); the missing area is Chesapeake Bay and south.

Species distribution model

Habitat associations of alewife, blueback herring, Atlantic herring, and Atlantic mackerel were previously modeled using generalized additive models (GAMs) with the "mgcv" package version 1.8-6 for R (Hastie and Tibshirani 1990; Wood 2006; R Core Team 2014). The response variable was species presence–absence, and a binomial link function was used in model formulation. The final models included smooth functions of bottom temperature, bottom salinity, and depth, a tensor product smooth of solar azimuth and elevation (because they co-vary), and region (Gulf of Maine, Georges Bank, Southern New England, and the Mid-Atlantic Bight) as a factor variable (Turner et al. 2015). Model-predicted species' distribution overlap was quantified by taking the product of the two species occurrence probabilities. See Turner et al. (2015) for a

Fig. 1. Map of the Northeast United States Continental Shelf with regions outlined (GOM = Gulf of Maine; GB = Georges Banks; SNE = southern New England; MAB = Mid-Atlantic Bight). Small grey symbols indicate finite volume community ocean model (FVCOM) forecast grid nodes; large black circles represent Northeast Fisheries Science Center (NEFSC) spring 2015 bottom trawl survey stations (solid circles indicate stations less than 5 km from an FVCOM node; hollow circles indicate stations more than 5 km from FVCOM nodes, which were excluded from our analyses).



detailed description of species distribution model development and evaluation.

Evaluation of ocean forecast model (objective 1)

Mean forecasted bottom temperatures and bottom salinities were compared with CTD observations using paired t tests, both throughout the survey range and regionally, testing the null hypothesis that the observed and forecasted conditions are the same. The mean absolute difference between observed and mean forecasted temperature and salinity (mean absolute errors; MAEs) were also calculated to evaluate and compare the accuracy of the three forecasts (Day 0, Day 1, and Day 2).

Evaluation of species distribution forecasts (objective 2)

GAMs were used to predict presence–absence and overlap for the spring 2015 survey using the CTD data and FVCOM Day 0, Day 1, and Day 2 forecasts. The probabilities from the species distribution models and modeled overlap based on the observed and forecasted oceanographic conditions were also evaluated with paired t tests and by estimating the MAEs. Confusion matrices, using previously established thresholds (where sensitivity equaled selectivity in model evaluations; Turner et al. 2015), were used to further compare model results. Confusion matrix accuracies were compared by calculating the Kappa statistics for predictions using the observed and forecasted conditions.

Table 1. Mean absolute errors between observed and forecasted oceanographic conditions for all Northeast Fisheries Science Center (NEFSC) trawl survey stations (14 March 2015 – 6 May 2015).

	Region	Day 0 forecast	Day 1 forecast	Day 2 forecast
Bottom temperature (°C)	All	1.62	1.63	1.64
	GOM	0.93	0.92	0.91
	GB	1.46	1.45	1.46
	SNE	1.42	1.41	1.42
	MAB	2.85	2.92	2.94
Bottom salinity (ppt)	All	0.56	0.56	0.56
	GOM	0.33	0.33	0.33
	GB	0.40	0.40	0.40
	SNE	0.73	0.73	0.73
	MAB	0.80	0.80	0.81

Note: GOM, Gulf of Maine; GB, Georges Bank; SNE, southern New England; MAB, Mid-Atlantic Bight.

Results

Ocean forecast evaluation

The averaged bottom temperature forecasts (Day 0, Day 1, and Day 2) were statistically different from the observed bottom temperatures ($4.1 < t < 4.4$, df = 270, $p < 0.001$), and the mean observed temperature was 6.4 °C and the MAEs were 1.6 °C (Table 1; Fig. 2).

Fig. 2. Day 2 FVCOM forecasted bottom temperature against the observed bottom temperature by region of the Northeast US Continental Shelf; the black line is the 1:1 line. GOM = Gulf of Maine; GB = Georges Bank; SNE = southern New England; MAB = Mid-Atlantic Bight.

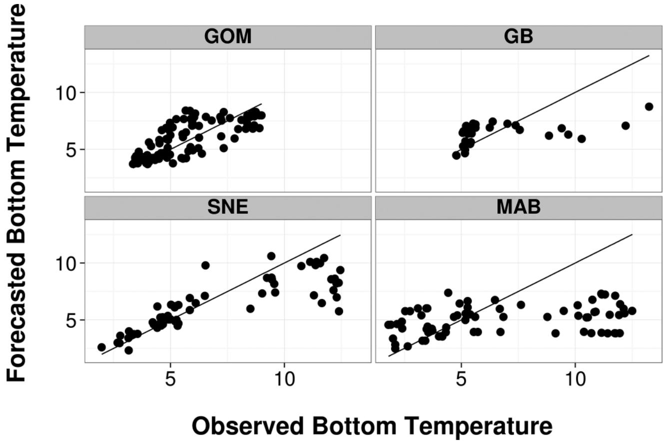


Fig. 3. Map of the direction of error between observed and forecasted bottom temperature for NEFSC 2015 bottom trawl stations on the Northeast US Continental Shelf. Blue circles represent stations where observed temperature was < –0.5 °C cooler than the forecasted temperature; red squares represent stations where the observed temperature was >0.5 °C warmer than the forecasted temperature; black triangles represent stations with temperature deviations < ±0.5 °C. [Colour online.]

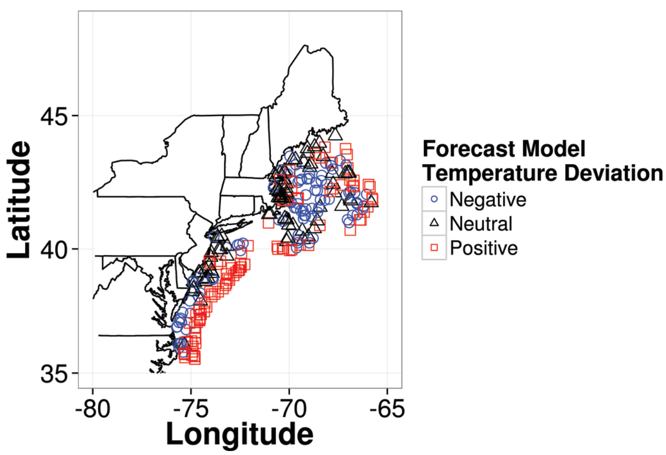


Fig. 4. Day 2 FVCOM forecasted bottom salinity against the observed bottom salinity by region of the Northeast US Continental Shelf; the black line is the 1:1 line. GOM = Gulf of Maine; GB = Georges Bank; SNE = southern New England; MAB = Mid-Atlantic Bight.

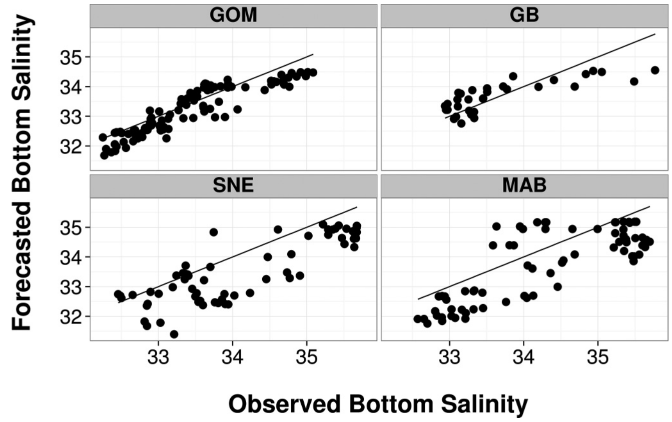
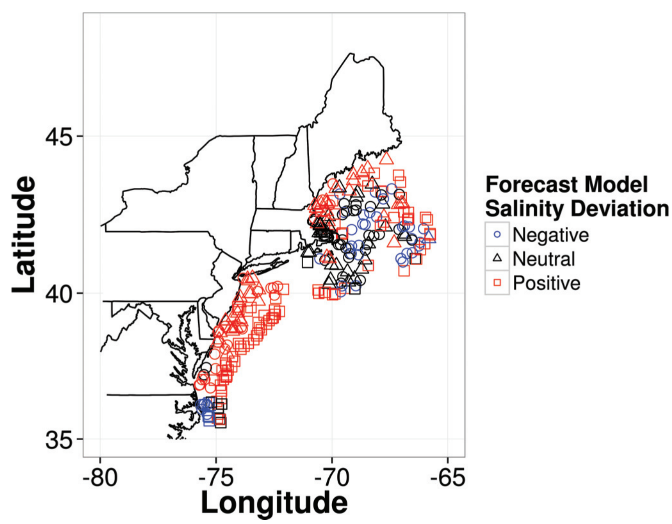


Fig. 5. Map of the direction of error between observed and forecasted bottom salinity for NEFSC 2015 bottom trawl stations on the Northeast US Continental Shelf. Blue circles represent stations where observed salinity was < –0.25 ppt lower than the forecasted salinity; red squares represent stations where the observed salinity was >0.25 ppt higher than the forecasted salinity; black triangles represent stations with salinity deviations < ±0.25 ppt. [Colour online.]



The forecast temperatures were negatively biased when the observed bottom temperature was greater than 8 °C (Fig. 2). Temperature forecast accuracy was consistent across regions, although absolute errors in the Mid-Atlantic Bight were significantly higher than in the Gulf of Maine and southern New England (analysis of variance (ANOVA) with Tukey's honestly significant differences test — $p < 0.05$; Table 1; Fig. 2). Deviations between observed and forecasted bottom temperatures (observed – forecasted) were mapped to identify any spatial patterns in the direction of deviations (Fig. 3). The observed bottom temperatures were generally warmer than the forecasted temperatures at the shelf edge and cooler than forecasted on the shelf. The reason is not clear, but spatial bias may affect use of the forecast, potentially related to finer-scale predictions within a given region.

The averaged forecast bottom salinities were statistically different from the observed bottom salinities ($10.2 < t < 10.5$, df = 270, $p < 0.001$). The mean observed salinity was 33.84 and the MAEs for the forecasted bottom salinities were approximately 0.56, which is not likely to be ecologically significant unless salinity aliases processes such as circulation in the species distribution models (Table 1; Fig. 4). Salinity forecasts were relatively consistent among regions but had a slight negative bias in southern New England and the Mid-Atlantic Bight. The absolute errors were significantly larger in southern New England and the Mid-Atlantic Bight compared with the Gulf of Maine and Georges Banks (ANOVA with Tukey's honestly significant differences test — $p < 0.05$; Table 1; Fig. 4). Spatial patterns in the direction of salinity deviations were also evaluated by mapping deviations between observed and forecasted salinities (Fig. 5). Observed salinities were higher in the southern portion of the study range, and no trends were apparent in the northern portion or between shallow and deep as observed for temperature. The error of lower modeled salinities and lower modeled bottom temperatures may be caused by inaccuracies in modeling water masses distributions and regional-scale circulation patterns.

Table 2. Percentage of stations at which each species (or species overlap) was observed and the mean absolute errors (MAEs) between species distribution model probabilities from observed and forecasted conditions.

	Percent deviance explained*	Percentage of stations observed	MAE Day 0 forecast	MAE Day 1 forecast	MAE Day 2 forecast
Alewife P–A	25.20	83	0.07	0.07	0.07
Blueback herring P–A	16.93	42	0.03	0.03	0.03
Atlantic herring P–A	18.92	69	0.11	0.11	0.11
Atlantic mackerel P–A	20.60	39	0.09	0.09	0.09
Alewife–Atlantic herring	—	64	0.06	0.06	0.06
Blueback herring–Atlantic herring	—	37	0.03	0.03	0.03
Alewife–Atlantic mackerel	—	33	0.04	0.04	0.04
Blueback herring–Atlantic mackerel	—	14	0.02	0.02	0.02

Note: Species distribution models predicted presence–absence (P–A), which was then used to predict overlap (e.g., alewife–Atlantic mackerel).

*From Turner et al. (2015).

The forecasted bottom temperatures and salinities were nearly identical for all three days of the forecast model. The Day 0, Day 1, and Day 2 bottom temperature and salinity forecasts did not differ significantly from each other ($p > 0.05$). The results of the GAM predictions using the different forecasts did not differ significantly either, so only the predictions for the Day 2 forecast model are presented. In the future, 2-day forecasts can be made with very similar accuracy as Day 0 and Day 1 forecasts.

Species distribution forecast

The probabilities of occurrence based on observed oceanographic conditions were similar to those based on the forecasted oceanographic conditions. The forecasted probabilities of occurrence tended to be slightly higher than the probabilities using the observed oceanographic conditions, but the results were generally consistent (Appendix A, Figs. A3–A6). The variability in forecasted and observed temperature and salinity may be partially buffered by the spatial and temporal similarity of observations (included in models as the solar azimuth and elevation and region), because all four species make seasonal migrations to distinct regions, and catchability can vary as a function of the time of day. The differences between model probabilities of species' presence–absence using forecasted and observed oceanographic conditions were statistically significant ($-1.5 < t < -4.8$; df = 270; $p < 0.001$), but the differences in the mean probabilities were all less than 0.1 (alewife mean difference = 0.06; blueback herring mean difference = 0.02; Atlantic herring mean difference = 0.09; Atlantic mackerel mean difference = 0.05; Appendix A, Figs. A7–A10). The MAEs for all species distribution model predictions between the observed and forecast oceanographic conditions were all less than 0.11 (Table 2).

The estimates of presence–absence based on observed oceanographic conditions and forecasted oceanographic conditions were also similar. The confusion matrices for each of the species' distribution models did not differ substantially, but the forecast predictions for alewife, Atlantic herring, and Atlantic mackerel did result in more true positives and fewer true negatives than the predictions from observed oceanographic conditions (Fig. 6). The forecast predictions for blueback herring were roughly the same as the predictions using the observed oceanographic conditions (Fig. 6). The Kappa statistics for model accuracies were relatively low for predictions using both observed and forecasted conditions, although Kappa was slightly higher for the observed conditions for alewife and blueback herring and Atlantic mackerel, and Kappa was the slightly higher for the Atlantic herring forecast model (Table 3). The absolute model skill, or the overall proportion of correct predictions, was always higher for predictions using observed conditions (models with CTD data ranged from 0.67 to 0.73; models with forecasted conditions ranged from 0.63 to 0.69; Table 3).

The estimated overlap probabilities were also similar between those based on observed oceanographic conditions and forecasted oceanographic conditions. Species distribution overlap was quantified as the product of the probabilities of two individual species' presence, and overlap probabilities were compared between species distribution models using observed and forecasted oceanographic conditions. The overlap probabilities from the forecast models differed significantly from the modeled probabilities when the observed oceanographic conditions were used ($-10.7 < t < -6.5$; df = 270; $p < 0.0001$; Appendix A, Figs. A11–A14). The differences in the mean probabilities were all below 0.06 (alewife – Atlantic herring = 0.05; blueback herring – Atlantic herring = 0.02; alewife – Atlantic mackerel = 0.03; blueback herring – Atlantic mackerel = 0.01). As observed for the individual species' models, the MAEs for the overlap forecasts compared with the observed oceanographic predictions were slightly higher than the differences in the mean probabilities (Table 2).

The confusion matrices for modeled overlap probabilities using the observed oceanographic conditions were similar to the probabilities when the forecast models were used, although the observed conditions resulted in slightly lower rates of true positives and slightly higher rates of true negatives (Fig. 7). The Kappa statistics for overlap predictions were generally comparable to those for individual species models. Kappas were slightly higher for the observed condition predictions for overlap between alewife and Atlantic herring and between blueback herring and Atlantic herring; Kappa was higher for forecast predictions for overlap between alewife and Atlantic mackerel and between blueback herring and Atlantic mackerel (Table 3). Absolute model skill for overlap models was similar to individual species predictions, with higher skill for observed conditions (models with CTD data ranged from 0.72 to 0.78; models with forecasted conditions ranged from 0.67 to 0.73; Table 3).

Discussion

As fisheries management undergoes a shift from single species to multispecies and ecosystem focuses, strategies to minimize catches of nontarget species, while maximizing catches of target species, need to be developed. Adaptive methods of redistributing effort over finer spatial and temporal scales have proven effective, but most of these are reactive, not proactive (O'Keefe et al. 2013; Little et al. 2015; Lewison et al. 2015). Some studies have used atmosphere–ocean global circulation models to predict how climate change will affect species distributions (e.g., Hare et al. 2010, 2012*a*; Lynch et al. 2015), but combined species distribution and

Fig. 6. Histograms showing the percentages of stations sampled during the NEFSC 2015 spring bottom trawl survey where habitat models using observed conditions (conductivity, temperature, and depth (CTD), solid bars) and FVCOM forecasted conditions (FVCOM, hollow bars) correctly predicted species presence (true positives) and absence (true negatives) and incorrectly predicted species observations (false negatives) and where species were not observed (false positives).

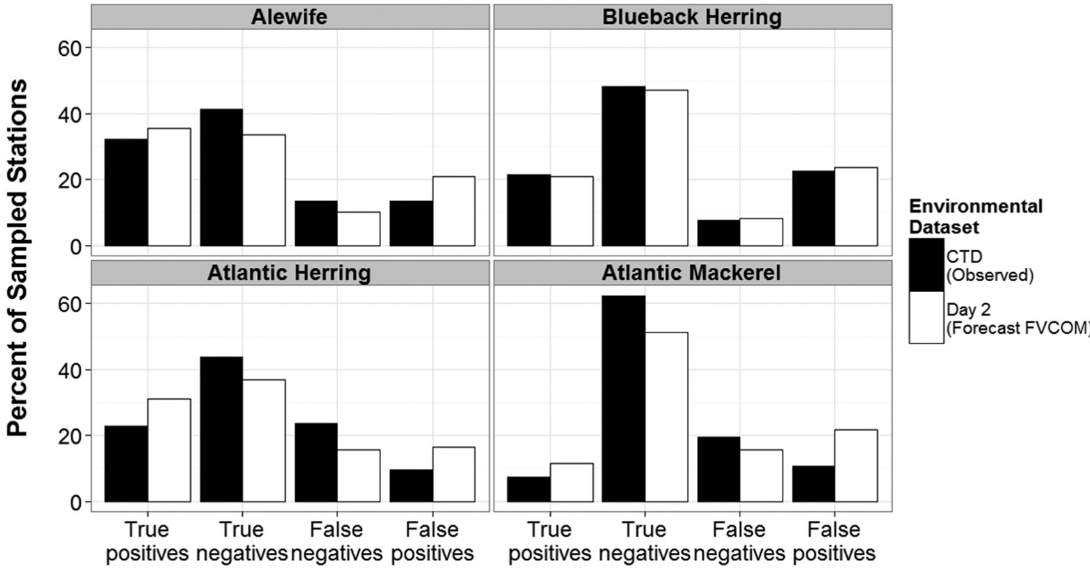


Table 3. Cohen's Kappa statistic for confusion matrices evaluating species' distribution model predictions using observed environmental conditions (conductivity, temperature, and depth, CTD) and forecasted environmental conditions (finite volume community ocean model, FVCOM).

Species	Environmental data	Kappa	Absolute model skill (%)
Alewife	CTD	0.46	73.4
	FVCOM	0.39	69.0
Blueback herring	CTD	0.36	69.7
	FVCOM	0.34	68.2
Atlantic herring	CTD	0.32	66.8
	FVCOM	0.36	67.9
Atlantic mackerel	CTD	0.14	69.8
	FVCOM	0.12	62.7
Alewife–Atlantic herring	CTD	0.45	74.5
	FVCOM	0.45	72.7
Blueback herring–Atlantic herring	CTD	0.39	73.1
	FVCOM	0.33	66.8
Alewife–Atlantic mackerel	CTD	0.09	72.3
	FVCOM	0.21	72.0
Blueback herring–Atlantic mackerel	CTD	−0.05	78.2
	FVCOM	0.06	72.0

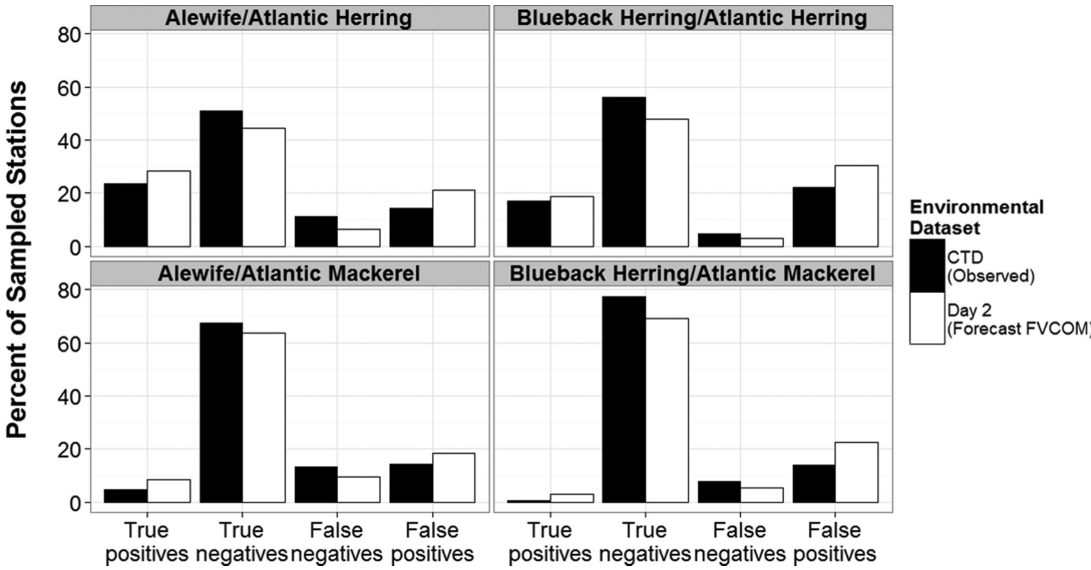
Note: A value of 1 indicates perfect agreement, and values approaching zero suggest any agreement is due to chance. The absolute model skill (the total percentage of correct predictions) is reported for models using observed and forecasted conditions.

ocean forecast models for short-term, applied purposes are only recently being evaluated and used (Hobday and Hartmann 2006; Eveson et al. 2015; Kaplan et al. 2016). We found that species' distributions and overlap could be predicted using oceanographic forecast models, and the accuracy of predictions using the forecast models was similar to predictions using observed oceanographic conditions. This study demonstrates that most of the error in species distribution forecasts results from the biological species distribution model and not the oceanographic forecast model. Thus, improvements in the oceanographic forecasts will likely yield minimal improvement in the species distribution forecasts at the spatial (tens of kilometres) and temporal (12–24 h) scale of sampling described here. The effects of temperature and salinity forecast errors on species' distribution predictions may be mediated by variables that are not forecasted (i.e., bottom depth, solar azimuth and elevation, and region). Also, false negatives are of greater concern, because they indicate problems with model fit, while false positives suggest suitable, but unoccupied, habitats and can be related to population abundance. Similar results have been found in evaluating the uncertainties in species distribution models coupled with climate models (Hare et al. 2012*b*).

Ocean forecast evaluation

While the observed and predicted temperatures and salinities differed statistically, the average differences are not likely to have significant ecological effects, based on previously modeled habitat associations (Turner et al. 2015). Temperature forecasts were generally more accurate than salinity, especially in cold water below 8 °C. Variability in forecasted salinities was highest in southern New England and the Mid-Atlantic Bight. Some of the variability between observed and predicted conditions likely result from spatial and temporal differences between the trawl stations and the averaged ocean forecast nodes (up to 10 km) and the limited forecast times included in this study. Conditions are not likely to differ drastically over the time scales tested here; spatial variations are the probable source of most variation. Differences are further complicated because the observed conditions are derived from average conditions within 10 km, despite the fine-scale habitat gradients (Rudnick and Ferrari 1999) being sampled over the spatial scale encompassed in a given tow (the area swept for a trawl survey tow is ~24 000 m²). Conversely, the forecast model presents the average across a grid cell (cell size in the FVCOM model varies with greater resolution near shore and near the shelf break and lower resolution mid-shelf). Errors between observed and forecasted temperatures and salinities were relatively small in the areas within southern New England (off Rhode Island) where the winter Atlantic herring fishery is focused; forecasts were more variable in the Mid-Atlantic Bight where the Atlantic mackerel fishery predominantly occurs during winter and early spring. The increased availability of bottom temperature observations for model assimilation would likely improve the bottom temperature forecasts.

Fig. 7. Histograms showing the percentages of stations sampled during the NEFSC 2015 spring bottom trawl survey where habitat models using observed conditions (CTD, solid bars) and FVCOM forecasted conditions (FVCOM, hollow bars) correctly predicted species overlap (true positives) and nonoverlap (true negatives) and incorrectly predicted species overlap (false negatives) and where species did not overlap (false positives).



Species distribution forecast

The differences between the probabilities of species' presence–absence from models using observed versus forecasted oceanographic conditions were statistically significant, but were (on average) relatively small and therefore not likely to be ecologically significant. Also, the model predictions were similar across all three forecasts (Day 0, Day 1, and Day 2), and no regions had substantially better or worse species distribution forecasts using the forecasts versus the observed oceanographic conditions. Given the consistency among the probabilities based on observed conditions and the three forecast models, as an operational forecast tool, industry could be provided with 2-day forecasts. However, the Atlantic mackerel species distribution models exhibited the worst fit of the four (Cohen's Kappa statistics: Atlantic mackerel = 0.12; alewife = 0.39; blueback herring = 0.34; Atlantic herring = 0.36), limiting the utility of the approach described here for the Atlantic mackerel fishery. Despite the relatively low Kappa statistics, absolute model skill was greater than 0.60 for all models using both observed and forecasted conditions; skill values observed here were similar to those estimated by Spillman and Hobday (2014) for seasonal water temperature forecasts. Our results, especially those for models including Atlantic mackerel, were influenced by very low survey encounter rates (39% of survey stations).

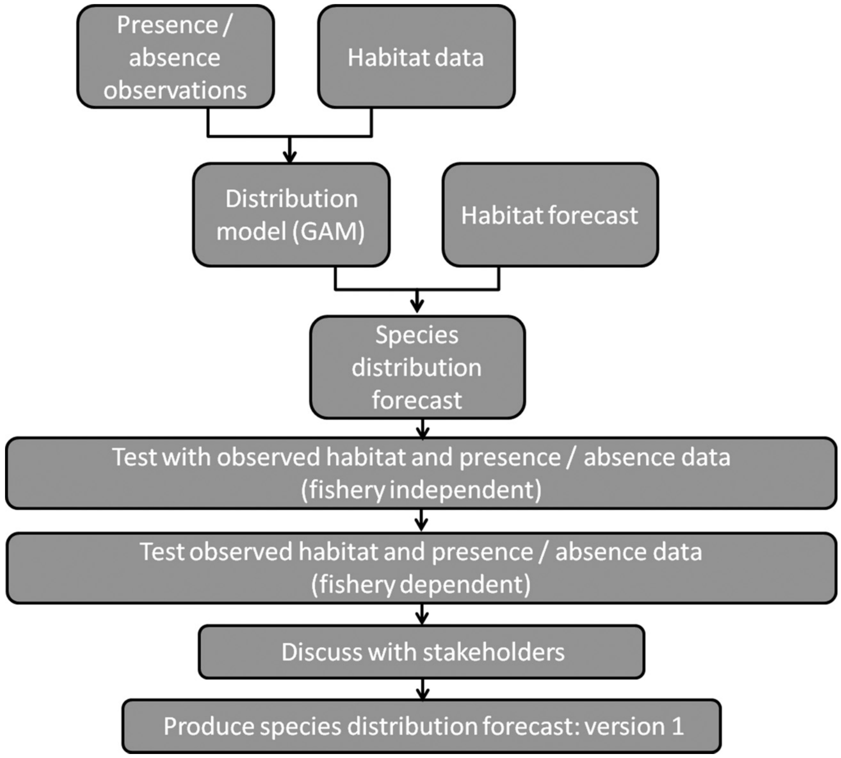
While previous studies have evaluated methods of modeling bycatch–incidental catches and discussed the utility of an online tool to inform industry where areas of high or low probability of mixed catches are, to our knowledge very few of these tools have been made operational (Hobday and Hartmann 2006; Žydelis et al. 2011; Bethoney et al. 2013*a*; Vilela and Bellido 2015). But, most short-term, mixed catch tools developed for industry use are "reactive", reporting to the fleet where mixed catches have recently occurred so these areas can be avoided (Gilman et al. 2006; Bethoney et al. 2013*a*; Dunn et al. 2013). The species included in this study were selected because incidental catch caps were recently implemented for alewife and blueback herring in the Atlantic herring and Atlantic mackerel fisheries. Unfortunately, limited knowledge of the spatial and temporal migrations of alewife and blueback herring, or their overlap with commercially harvested species, makes it difficult for industry to avoid them until after mixed catches occur (Bethoney et al. 2013*a*). Our work provides an important step towards developing a "proactive" mixed catch forecast for industry use by combining species distribution models with ocean forecast models.

Potential issues and future work

To develop a useful species distribution and overlap forecast, a series of scientific and practical evaluations need to be completed (Fig. 8). Once an accurate tool for reducing bycatch–incidental catches has been developed, the most important factor for success is ensuring industry buy-in and involvement and application of the tool (Cox et al. 2007; Hall and Mainprize 2005; O'Keefe et al. 2013). While the lead time of 2 days using this forecast might not be adequate in some fisheries, it is suitable for the Atlantic herring fishery because the existing bycatch avoidance program has already developed methods for communicating maps to vessels while they are fishing and also given the relatively small spatial scales at which differences in overlap occur (Bethoney et al. 2013*a*). Further, the majority (if not all) of the fleet participating in the area and season in which the mixed catches are an issue must participate for effective reductions of nontarget species catches (Bethoney et al. 2013*a*; O'Keefe et al. 2013; Stram and Ianelli 2014). When a new tool is being developed, involving industry from the first stages of brainstorming is ideal; here, our goal is to develop a forecast that can be integrated with the existing bycatch avoidance program, which was developed in collaboration with industry (Bethoney et al. 2013*a*). We plan to involve industry in fishery-dependent model evaluations and development of the forecast tool by working with existing collaborations between researchers and industry. As more fishery-dependent data are collected, we will also evaluate if using fishery-dependent data for the habitat models is more accurate, given the different spatial and temporal resolutions of the trawl survey and the commercial fisheries. We initially attempted modeling abundance as a function of habitat, which would be more informative for industry, but it had poor skill using the fishery-independent data; we will evaluate modeling abundance again when sufficient fishery-dependent data are collected.

The next step for our forecast models is to test them via directed sampling with commercial vessels. This will allow us to evaluate the effectiveness of the models for industry as well as evaluate the most effective spatial scale at which to make the forecasts available to industry. To meet these objectives, current members of the fleet will be involved in the testing and consulted for ways to

Fig. 8. Flow diagram illustrating the inputs and steps required for developing species distribution and overlap forecasts.



refine and improve the models as well as the tools to provide the forecasts to industry. The current "river herring bycatch avoidance" program (developed for the Atlantic herring midwater trawl fishery) reports recent mixed catches by grid cells ~5 n.mi. × 8 n.mi. (Bethoney et al. 2013*a*). The forecasting capabilities described here could be combined with other efforts to improve industry's ability to avoid incidental catch; distribution forecast resolution will likely be converted to a coarser grid system, similar to what is currently used by the bycatch avoidance program. In general, developing cooperation among stakeholders is an effective way to meet management objectives (Hartley and Robertson 2006; Johnson and van Densen 2007). When developing new dynamic ocean management applications, four key factors have been identified for success: existing regulatory framework, which is established here; incentive structure, in this case the risk of fishery closure; technological and analytical requirements, currently under evaluation and development; and stakeholder participation, which is well established via ongoing collaborations (Bethoney et al. 2013*a*; US Department of Commerce 2015; Lewison et al. 2015). Thus, with further model evaluation and refinement, this tool has a high likelihood of further reducing river herring incidental catches while minimizing economic impacts to the industry.

Acknowledgements

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Appendix A

Appendix Table A1 and Figs. A1–A14 appear on the following pages.

Table A1. Summary of confusion matrices for (*a*) predictions using observed conditions and (*b*) predictions using forecasted conditions.

Species	True positives	False negatives	True negatives	False positives
(*a*) Predictions using observed conditions				
Alewife	32.1%	13.3%	41.3%	13.3%
Blueback herring	21.4%	7.7%	48.3%	22.5%
Atlantic herring	22.9%	23.6%	43.9%	9.6%
Atlantic mackerel	7.4%	19.6%	62.4%	10.7%
(*b*) Predictions using forecasted conditions				
Alewife	35.4%	10.0%	33.6%	21.0%
Blueback herring	21.0%	8.1%	47.2%	23.6%
Atlantic herring	31.0%	15.5%	36.9%	16.6%
Atlantic mackerel	11.4%	15.5%	51.3%	21.8%

Note: Threshold values were determined in Turner et al. (2015) and were set where the sensitivity equaled the specificity. Percentage of all trawl stations is reported.

Fig. A1. Boxplots of the absolute errors between observed and forecasted temperatures by regions. Box hinges correspond with the first and third quartiles, the center line indicates the median, whiskers extend to the values within 1.5 times the interquartile range, and points represent outliers.

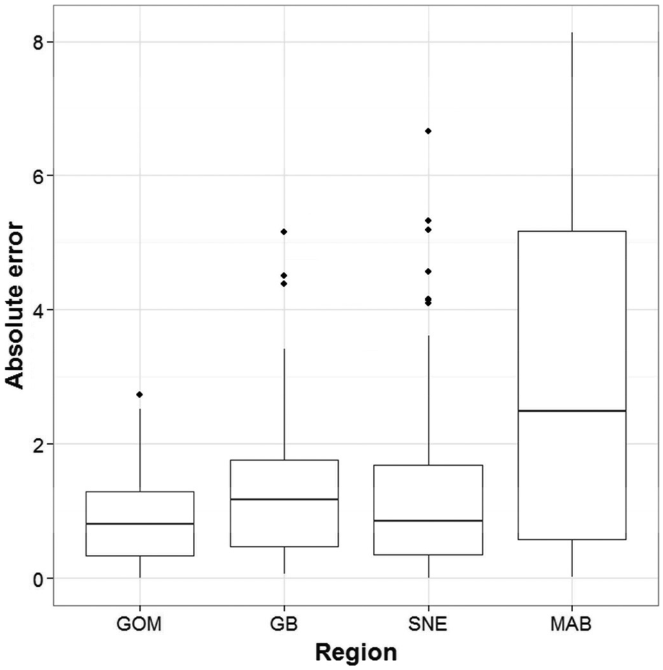

Fig. A2. Boxplots of the absolute errors between observed and forecasted salinities by regions. Box hinges correspond with the first and third quartiles, the center line indicates the median, whiskers extend to the values within 1.5 times the interquartile range, and points represent outliers.

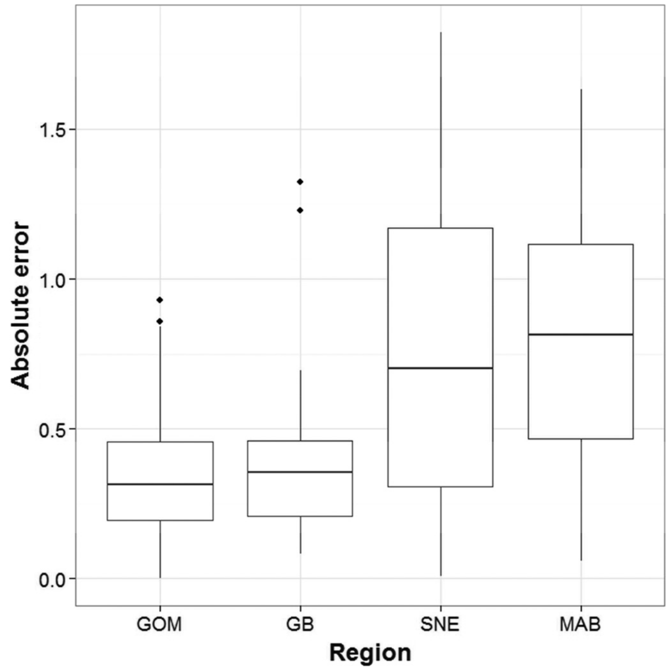

Fig. A3. Model-predicted probability of alewife presence using ocean forecasts models plotted against modeled probability using observed conditions; solid line indicates 1:1. Panels represent regions of the Northeast US Continental Shelf (GOM = Gulf of Maine; GB = Georges Banks; SNE = southern New England; MAB = Mid-Atlantic Bight).

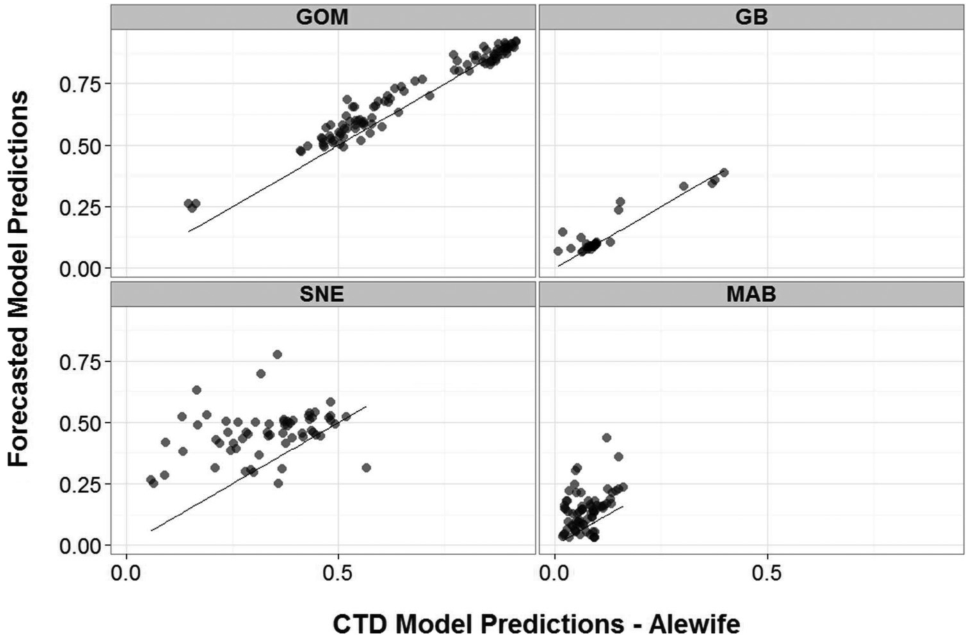

Fig. A4. Model-predicted probability of blueback herring presence using ocean forecasts models plotted against modeled probability using observed conditions; solid line indicates 1:1. Panels represent regions of the Northeast US Continental Shelf (GOM = Gulf of Maine; GB = Georges Banks; SNE = southern New England; MAB = Mid-Atlantic Bight).

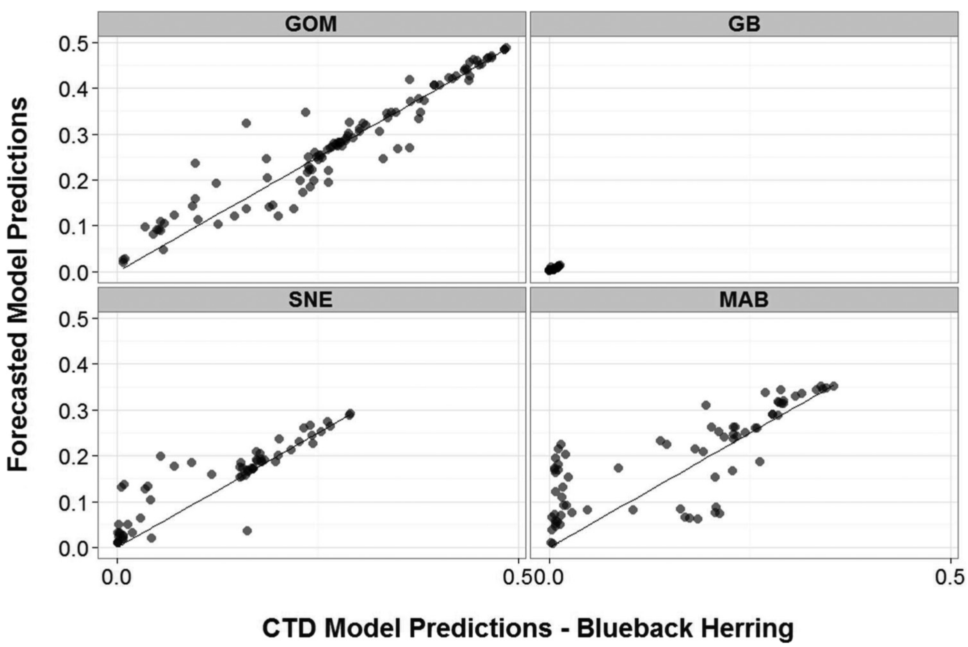

Fig. A5. Model-predicted probability of Atlantic herring presence using ocean forecasts models plotted against modeled probability using observed conditions; solid line indicates 1:1. Panels represent regions of the Northeast US Continental Shelf (GOM = Gulf of Maine; GB = Georges Banks; SNE = southern New England; MAB = Mid-Atlantic Bight).

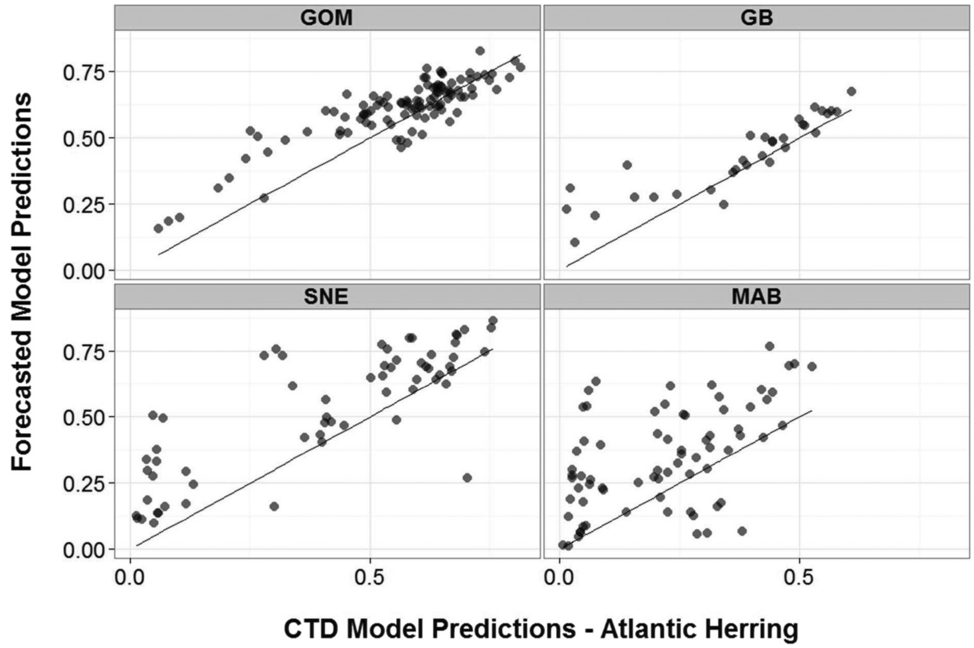

Fig. A6. Model-predicted probability of Atlantic mackerel presence using ocean forecasts models plotted against modeled probability using observed conditions; solid line indicates 1:1. Panels represent regions of the Northeast US Continental Shelf (GOM = Gulf of Maine; GB = Georges Banks; SNE = southern New England; MAB = Mid-Atlantic Bight).

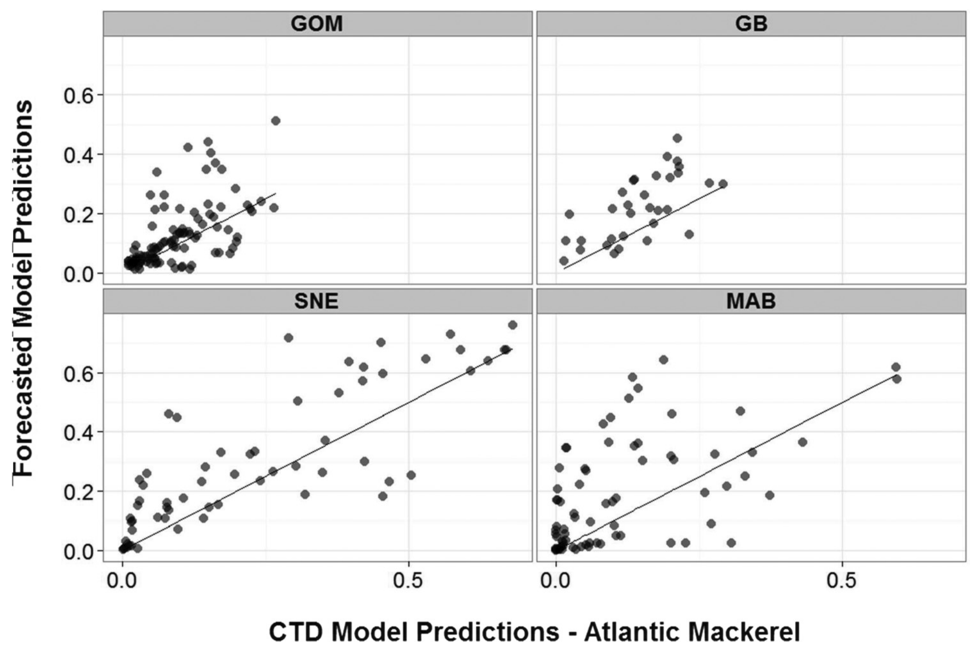

Fig. A7. Histograms of the distributions of model-predicted probability of alewife presence. Solid bars indicate probabilities where fish were not observed; hollow bars indicate where fish were observed. Vertical dashed lines represent thresholds used for confusion matrices.

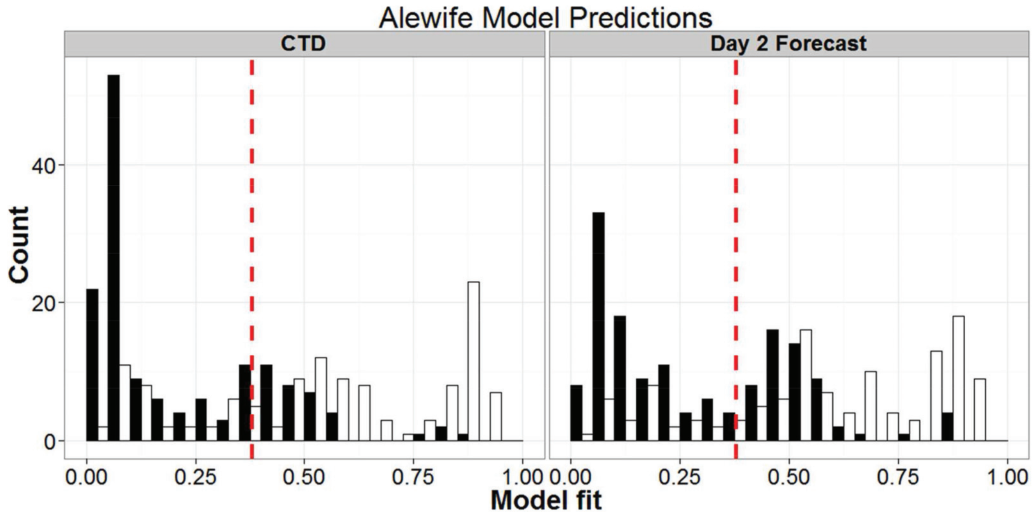

Fig. A8. Histograms of the distributions of model-predicted probability of blueback herring presence. Solid bars indicate probabilities where fish were not observed; hollow bars indicate where fish were observed. Vertical dashed lines represent thresholds used for confusion matrices.

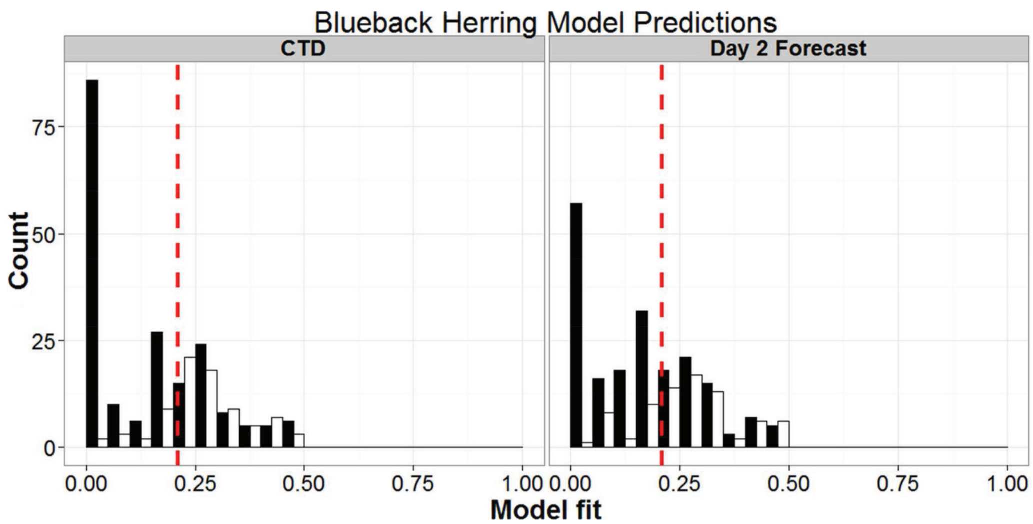

Fig. A9. Histograms of the distributions of model-predicted probability of Atlantic herring presence. Solid bars indicate probabilities where fish were not observed; hollow bars indicate where fish were observed. Vertical dashed lines represent thresholds used for confusion matrices.

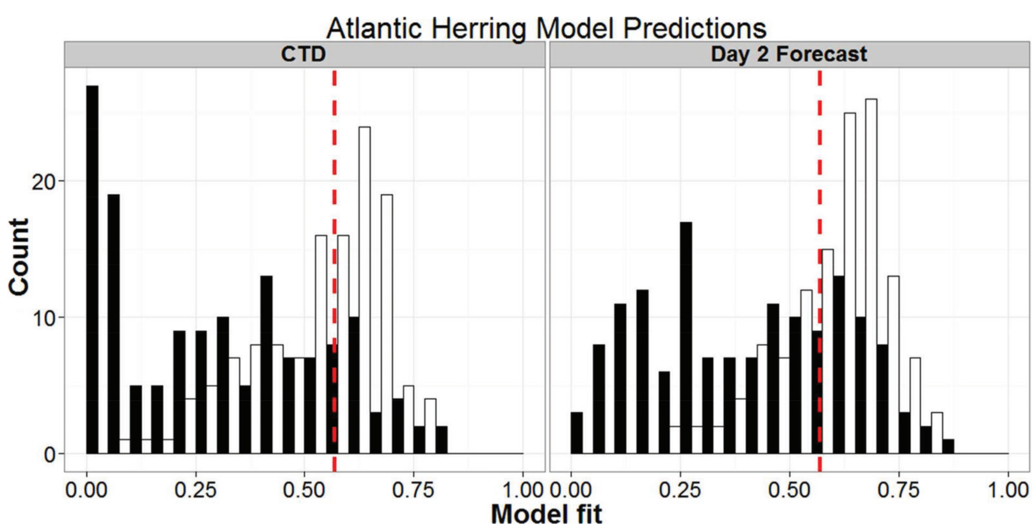

Fig. A10. Histograms of the distributions of model-predicted probability of Atlantic mackerel presence. Solid bars indicate probabilities where fish were not observed; hollow bars indicate where fish were observed. Vertical dashed lines represent thresholds used for confusion matrices.

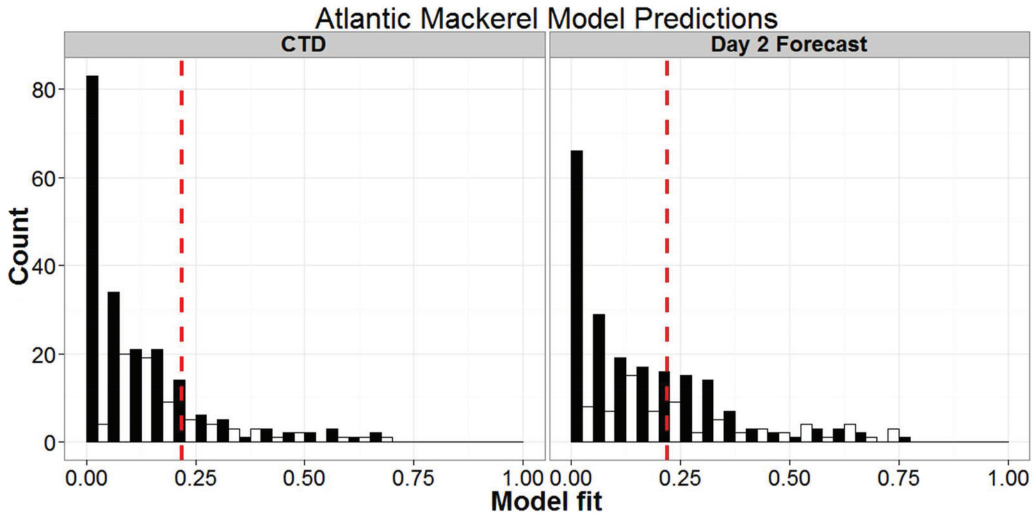

Fig. A11. Histograms of the distributions of model-predicted probability of alewife–Atlantic herring overlap. Solid bars indicate probabilities where overlap was not observed; hollow bars indicate where it was. Vertical dashed lines represent thresholds used for confusion matrices.

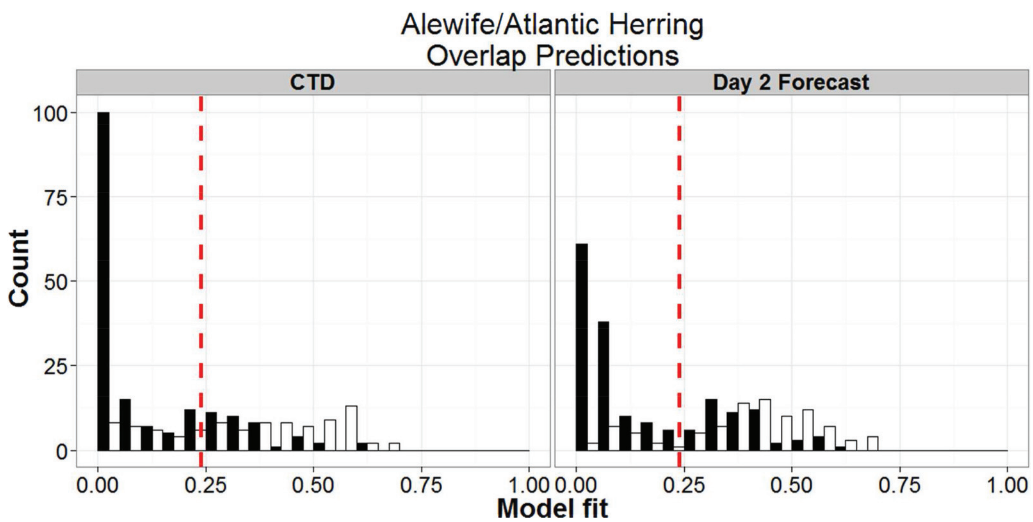

Fig. A12. Histograms of the distributions of model-predicted probability of blueback herring–Atlantic herring overlap. Solid bars indicate probabilities where overlap was not observed; hollow bars indicate where it was. Vertical dashed lines represent thresholds used for confusion matrices.

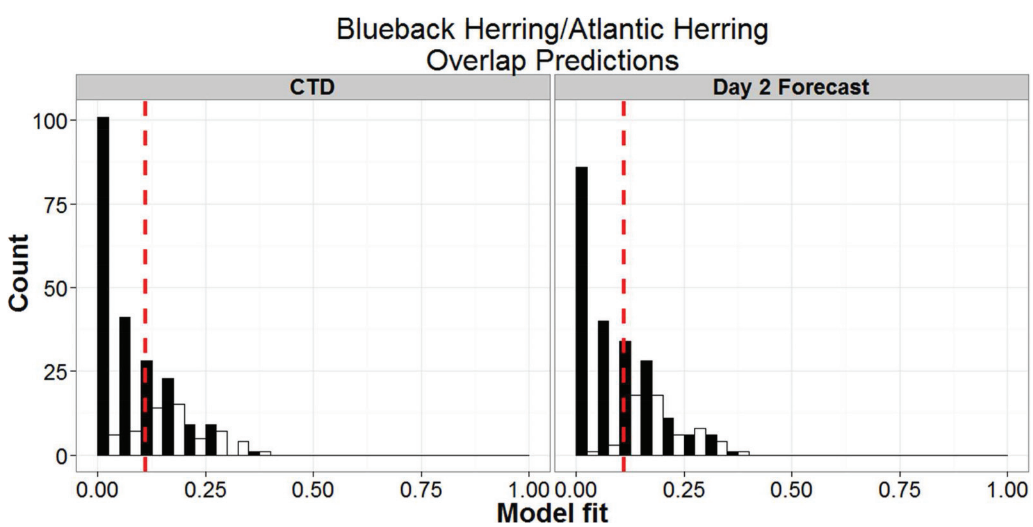

Fig. A13. Histograms of the distributions of model-predicted probability of alewife–Atlantic mackerel overlap. Solid bars indicate probabilities where overlap was not observed; hollow bars indicate where it was. Vertical dashed lines represent thresholds used for confusion matrices.

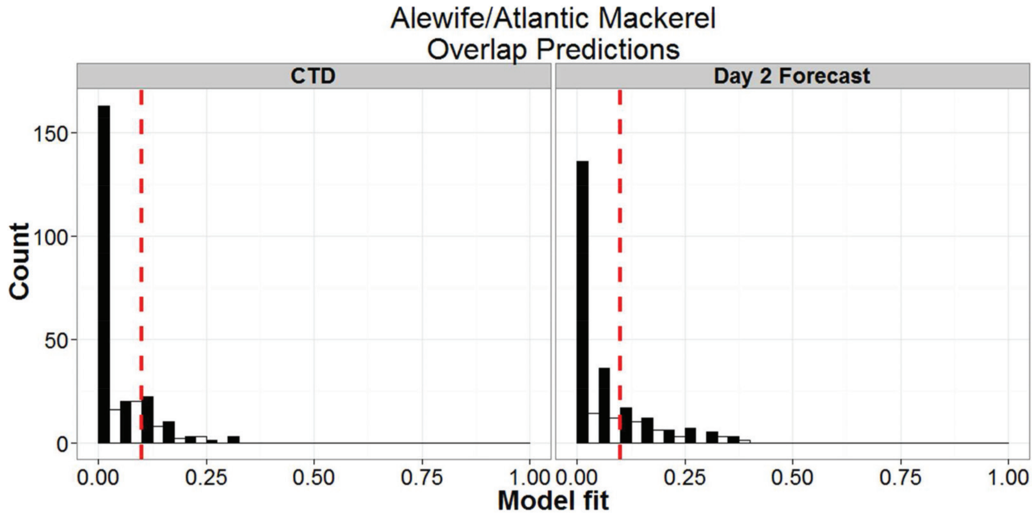

Fig. A14. Histograms of the distributions of model-predicted probability of blueback herring–Atlantic mackerel overlap. Solid bars indicate probabilities where overlap was not observed; hollow bars indicate where it was. Vertical dashed lines represent thresholds used for confusion matrices.