



FEATURE ARTICLE

Distributions of threatened skates and commercial fisheries inform conservation hotspots

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ABSTRACT: Bycatch in commercial fisheries is a pressing conservation concern and has spurred global interest in adopting ecosystem-based management practices. To address such concerns, a thorough understanding of spatiotemporal relationships among bycatch species, their environment and fisheries is required. Here we used a generalized linear mixed model framework incorporating spatiotemporal random effects to model abundance patterns for 3 skate species caught as bycatch in commercial fisheries (thorny skate *Amblyraja radiata*, winter skate *Leucoraja ocellata* and smooth skate *Malacoraja senta*), as well as 10 target species on the Scotian Shelf, NW Atlantic. Spatiotemporal estimates of relative abundance for at-risk skates within the years 2005–2015 were modelled from research trawl survey data and overlaid with those for target species to identify hotspots of bycatch risk. In addition, abundance estimates for at-risk skates within the years 1975–1985, a period of higher stock abundance, were used to identify areas of previously important habitat. Historically, skate species densely occupied areas near Sable Island and Banquereau Banks, Georges Bank and the Bay of Fundy. Bycatch hotspots between at-risk skates and commercial targets were identified in regions across the Scotian Shelf. These hotspots were independently validated by predicting species presence from at-sea observer data that monitor skate bycatch directly. We discuss spatial relationships between target and bycatch species, highlighting limitations of at-sea observer programmes that this method helps to address. This framework can be applied more broadly to inform ecosystem management and priority areas for conservation or fisheries regulation.



Smooth skate *Malacoraja senta* photographed in the Jordan Basin Conservation Area, Scotian Shelf.

Photo: Fisheries and Oceans Canada

KEY WORDS: Ecosystem-based management · Bycatch · Spatiotemporal models · Threatened species · Data-limited species

1. INTRODUCTION

Sustained exploitation of fisheries worldwide has left nearly half of scientifically assessed fish stocks currently in an overfished state (Hilborn et al. 2020) and has reduced many populations of incidentally caught species to low abundance (Lewison et al. 2004, 2014, Beddington et al. 2007, Sims & Queiroz 2016, Pacoureau et al. 2021). In response to these multi-species challenges, fisheries management authorities have aimed to move towards ecosystem-based approaches to ocean resource management

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(Smith et al. 2007, Hegland et al. 2015, Cucuzza et al. 2021). Ecosystem-based management aims to balance resource exploitation while avoiding ecosystem degradation and accounting for all ecosystem components, including non-commercial species and habitat. A primary objective of many ecosystem-based management strategies is to identify spatial areas of conservation priority (Pikitch et al. 2004). These can include core areas of habitat or high abundance for protected species (Williams et al. 2014), or areas where the risk of anthropogenic impacts are elevated, including the risk of bycatch, the incidental catch of non-target species in a fishery (Kirby & Ward 2014). Traditional methods to mitigate deleterious effects of fishing and protect habitat involve static area closures, establishment of marine protected areas and modifications to fishing gear and practices (Cox et al. 2007, Poisson et al. 2014, Senko et al. 2014). These often result in trade-offs between protecting a species or habitat, and maintaining economically viable fisheries (O'Keefe et al. 2014). Another limitation is that a static approach does not inherently account for shifting species distributions in response to climate variability and change (Kleisner et al. 2017). A more dynamic ecosystem-based management approach, where regulations shift in space and time in a fluid response to changes in biological and oceanographic parameters, is widely viewed as a possible solution (O'Keefe & DeCelles 2013, Maxwell et al. 2015, Hazen et al. 2018, Welch et al. 2020).

The basis of such dynamic ecosystem-based management is a comprehensive understanding of the spatial domains of habitats, species and human activities. In the past 2 decades, statistical modelling of species distributions has advanced considerably (Fink et al. 2010, Ward et al. 2012), with the spatial and temporal variation in abundance and correlations with climate and oceanographic parameters garnering particular interest (Lewison et al. 2009, Ward et al. 2015). Understanding the patterns and drivers of species distributions is critical to addressing broader fisheries management and conservation issues. For example, identification and protection of core areas for depleted species can increase population productivity (Rodwell et al. 2003, Shackell et al. 2005). Geostatistical tools have been applied to identify discrete regions of high species density (Morfin et al. 2012, O'Brien et al. 2012, Legare et al. 2015), and can enhance marine management and protected area effectiveness (Knip et al. 2012). Another key application is mitigation of bycatch in commercial fisheries. Bycatch is a pressing ecological threat

worldwide contributing up to 40% of total global catch (Davies et al. 2009). Statistical modelling is instrumental in elucidating the spatial patterns of species and drivers of bycatch (Cosandey-Godin et al. 2015, Breivik et al. 2016, 2017, Hazen et al. 2018, Hurley et al. 2019, Stock et al. 2020), and co-occurrence between species can inform where the probability of bycatch is elevated (Ward et al. 2015, Runnebaum et al. 2020). For mixed-species fisheries such as those for groundfish, many species co-occur, and a given species may be affected by the cumulative impacts of combined methods of fishing (Foster et al. 2015). Within multi-species fisheries complexes, a comprehensive approach incorporating information from multiple affected target and non-target stocks should be taken when evaluating the spatial distribution of bycatch for a depleted, threatened or protected species.

In Atlantic Canada, a complex groundfish community has been a major target of regional fisheries for over 500 yr (Lear 1998). Groundfish landings on the Scotian Shelf and Bay of Fundy totaled nearly 40 000 t in 2018, with the majority of landed weight comprised of cod, haddock and pollock (referred to as the 'CHP complex'), Atlantic halibut, Acadian redfish and silver hake. The fishery generally operates in Northwest Atlantic Fisheries Organization (NAFO) divisions 4VWX5, the management boundaries straddling the Scotian Shelf and Bay of Fundy within the NAFO Convention Area. The majority of catch landed by bottom-trawl is harvested on the western Scotian Shelf, and involves a variety of bycatch species (Peacock & Annand 2008). Among these are several species of skate (Family Rajidae), which have been designated as endangered or of special concern by the Committee on the Status of Endangered Wildlife in Canada (COSEWIC), following substantial declines in stock abundance (Table 1). As a whole, skates and other elasmobranchs exhibit primarily *K*-selected life-history traits, such as late age-at-maturity and low fecundity relative to many bony fishes. Because of this, they are intrinsically less resilient to overexploitation (Stevens et al. 2000, Dulvy et al. 2008, Hobday et al. 2011). On the Scotian Shelf, abundance of thorny skate *Amblyraja radiata* has declined by upwards of 90% in and remains low. Populations of smooth skate *Malacoraja senta* have declined well below 1970s levels (DFO 2017a). Both have been assessed by COSEWIC as endangered or special concern in some or all of their Atlantic Canadian range (Table 1). The winter skate *Leucoraja ocellata* population on the Eastern Scotian Shelf has declined by up to 98% in the past 40 yr (DFO 2017b).

Table 1. Skate bycatch and commercial target species and their assessment status from the Committee on the Status of Endangered Wildlife in Canada (by designatable unit, if applicable). CHP represents the cod-haddock-pollock fisheries complex. Number of records where each species was present within the research vessel (RV) survey dataset are shown for each decade of interest. Values in *italics* were not used in the analysis for that time period. Data collected annually in late summer by Fisheries and Oceans Canada in random-stratified bottom trawl survey of the Scotian Shelf (SS); NFLD: Newfoundland; GSL: Gulf of St. Lawrence

Species or complex	Latin name	COSEWIC status	RV survey records with species present	
			1975–1985	2005–2015
Skates				
Smooth skate	<i>Malacoraja senta</i>	Endangered (Funk Island Deep); special concern (Laurentian–Scotian)	389	335
Thorny skate	<i>Amblyraja radiata</i>	Special concern	1088	589
Winter skate	<i>Leucoraja ocellata</i>	Endangered (East SS/ NFLD, GSL); not at risk (West SS)	210	255
Targets				
Atlantic halibut	<i>Hippoglossoides hippoglossus</i>	Not at risk	281	563
Silver hake	<i>Merluccius bilinearis</i>	Not assessed	578	1375
Redfish	<i>Sebastes</i> spp.	Threatened (<i>S. fasciatus</i>)	520	1153
CHP				
Atlantic cod	<i>Gadus morhua</i>	Endangered	1154	1172
Haddock	<i>Melanogrammus aeglefinus</i>	Not assessed	994	1475
Pollock	<i>Pollachius virens</i>	Not assessed	404	618
Flatfishes				
American plaice	<i>Hippoglossoides platessoides</i>	Threatened	981	1421
Witch flounder	<i>Glyptocephalus cynoglossus</i>	Not assessed	604	1150
Yellowtail flounder	<i>Limanda ferruginea</i>	Not assessed	475	851
Winter flounder	<i>Pseudopleuronectes americanus</i>	Not assessed	181	511
Total sets			1595	2234

COSEWIC has assessed this population of winter skate as endangered (Table 1). Winter skate is currently under consideration for federal protection under the Canadian Species At Risk Act (SARA) following a review by COSEWIC (2015). Protection under SARA would compel the Canadian government to design and implement a recovery strategy for the winter skate on the Scotian Shelf.

Our understanding of important areas of habitat and bycatch hotspots for skates in the Scotian Shelf groundfish community is presently poor. All 3 species are heavily depleted and exist as remnants of their former populations whose current distributions may not reflect true core areas (Shackell et al. 2005, Carson et al. 2017). Bycatch is estimated to be high within the CHP complex, redfish and Atlantic halibut fisheries (DFO 2017b); however, these estimates are complicated by problems with taxonomic identification of skates in landings records and by at-sea observers (Benoît 2006). Furthermore, observer coverage on vessels targeting groundfish is consistently low at 5–10% of fishing trips (Clark et al. 2015), well below the recommended 50% coverage required for

reasonable estimates of rare or depleted species (Babcock et al. 2003).

For skate species, the most taxonomically and spatially complete data come from annual research vessel (RV) surveys undertaken by the Department of Fisheries and Oceans Canada (DFO) on the Scotian Shelf each summer. These surveys cover the Scotian Shelf and Bay of Fundy areas (Fig. 1) and directly sample the groundfish community by bottom trawling. The random stratified surveys account for all fish to the genus level at minimum and have been ongoing since 1970, prior to the expansion of Canadian domestic fisheries and harvest moratoria being implemented for Scotian Shelf groundfish stocks (Bundy 2005, Peacock & Annand 2008), and continues to the present. The RV survey dataset, containing decades of presence and abundance data for all groundfish, can be used to predict previous areas of high species abundance and to evaluate species co-occurrence. Species co-occurrence has previously been used to predict bycatch hotspots (Ward et al. 2015, Runnebaum et al. 2020), but these predictions have been limited to a single pair of species or single

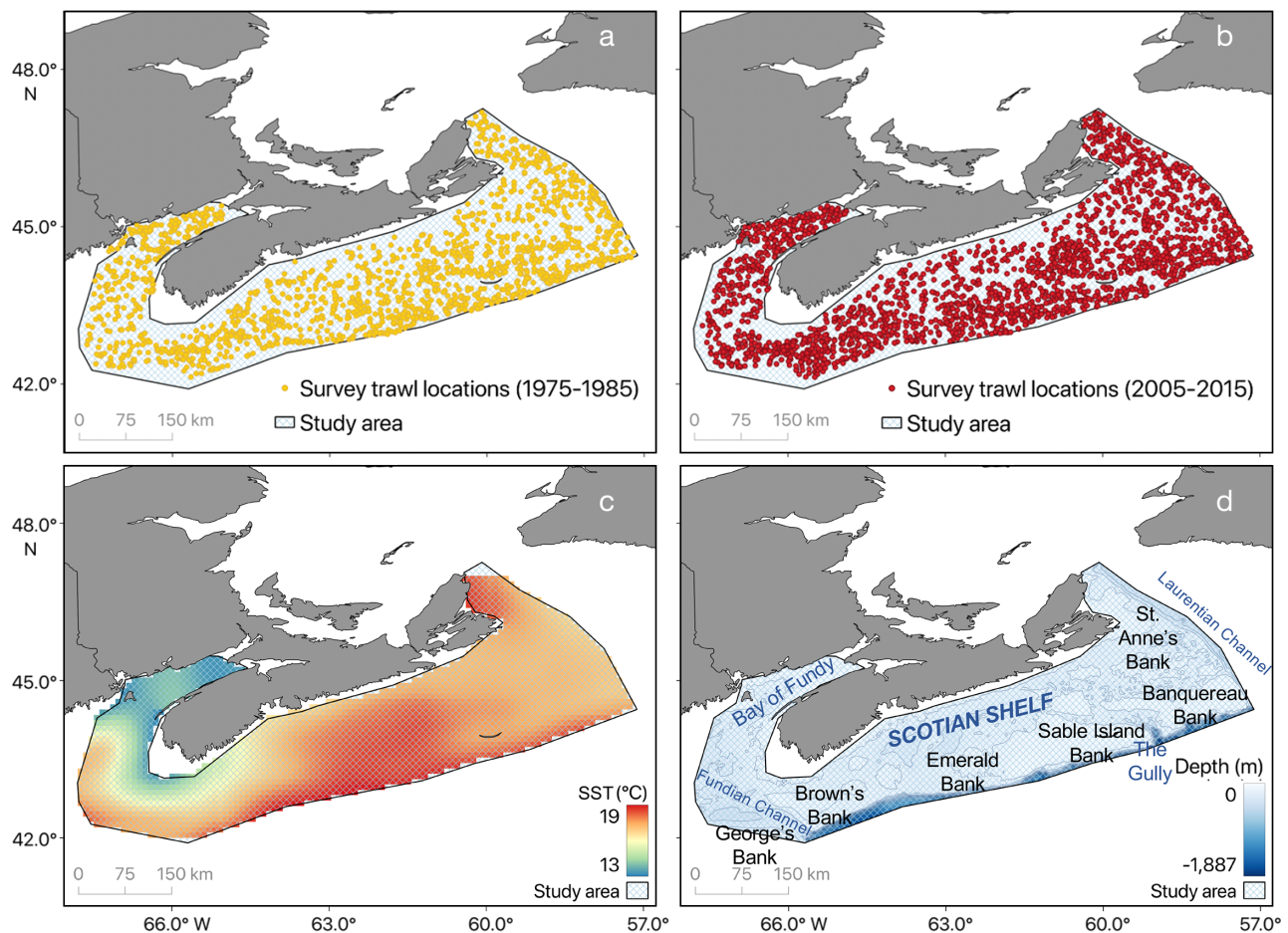


Fig. 1. Study area in Atlantic Canada, showing research vessel (RV) survey trawl locations for the years (a) 1975–1985 and (b) 2005–2015. (c) Mean August sea surface temperature (SST) within and around the study area for the years 2005–2015. Temperature is reported at a 0.1° resolution. (d) Depth reported at a resolution of 1 arc-minute. Contour lines represent 100 m intervals. Shelf features are noted for reference with results

fishery. In our study, we aimed to identify important areas of habitat for 3 threatened skates, and present an approach to use the relative abundance of individual species to predict bycatch hotspots on the Scotian Shelf.

Our goal is to present a modelling approach for identifying spatial regions of conservation concern for data-limited or rare species. Here we used a novel R package, 'staRve' (Lawler 2020), designed for fitting spatiotemporal models to research survey data (E. Lawler et al. unpubl., preprint: <https://arxiv.org/abs/2105.06902>), and employed a long-standing bottom-trawl survey of the groundfish community. We sought to identify historical regions of high species density for skates, indicative of important habitat regions. In addition, we aimed to predict areas where current bycatch risk to skates is elevated based on a co-occurrence framework between 3 threatened skates and 5 bottom-trawl fisheries represented by

10 target species. We then used data collected by at-sea fisheries observers to introduce a proof-of-concept method to validate predictions of bycatch risk.

2. METHODS

2.1. Data

In order to identify historically important habitat for at-risk skate species and potential regions of high bycatch in their present distributions, we used a fishery-independent survey dataset. DFO undertakes a bottom otter-trawl survey each summer on the eastern Scotian Shelf and Bay of Fundy. The survey area corresponds to NAFO divisions 4VWX and follows a random stratified design across depths between 50 and 500 m, where tows are conducted at a speed of approximately 3 knots for 30 min. Onboard, trained

DFO technicians equipped with species identification guides sample the catch and identify all fish to the genus level at minimum. For species of conservation concern, including skates in particular, morphological differences between species are specified using detailed photographic guides. Variables that were extracted from the RV dataset include the start and end latitude and longitude of the tow; the duration of the tow; and each species caught and their total catch weight. Catch per unit effort (CPUE, kg trawl h^{-1}) was calculated by dividing the total weight of the catch by the duration of the tow. Here, our study area covers the same region as the RV survey, extending approximately to the continental shelf boundary. The average latitude and longitude of each tow was used to represent the spatial locations of each set in the survey dataset. Fig. 1 shows the locations of all RV survey sets within each study period.

Two decades of survey data were considered separately in our study. To identify historically important habitat areas for at-risk skates, we used spatiotemporal models fit to RV data extracted for the years 1975–1985. These years correspond to the approximate time in Canadian fisheries governance when foreign fisheries were expelled from the 200 nautical mile exclusive economic zone in 1977 (UN General Assembly 1982) but prior to the proliferation of local fisheries, leading to an increase in the abundances of many groundfish species (Lear 1998, DFO 2017c). To predict current hotspots of bycatch, relative abundances of skates and other groundfish species that are targeted by bottom-trawl fleets were modelled using RV data extracted for the years 2005–2015. This was a period of relative stability in terms of fisheries legislation, but where some groundfish populations (including at-risk skates) remained at low abundance. A list of all species considered is shown in Table 1, with annual trends in mean CPUE across each decade for all species shown in Fig. 2. We overlaid the relative spatial abundances of at-risk skates with those of 9 high-value commercially fished groundfish species on the Scotian Shelf.

In addition to the RV set locations, 2 spatially referenced environmental variables, sea surface temperature (SST) and depth, were included in the analysis of RV data from the period 2005–2015 to explore the degree to which these variables influence the relative abundance of a given species. These covariates were selected as common abiotic factors that predict distribution of demersal fishes (Mueter & Norcross 1999). Thorny skates are known to associate closely with cooler, deeper waters (Sguotti et al. 2016), and

both thorny and winter skates have been shown to occupy greater depths as their abundances have declined (Nye et al. 2009). For analyses examining the years 1975–1985, SST was extracted as a decadal summer mean temperature from the World Ocean Atlas (Boyer et al. 2018). For analyses of the years 2005–2015, high-resolution SST data were derived from NOAA High-Resolution Blended Analysis of Daily SST (NOAA/OAR/ESRL PSL, Boulder, Colorado, USA, <https://psl.noaa.gov/>). Mean August SST ($^{\circ}\text{C}$) was extracted within the study area at a resolution of $0.25^{\circ} \times 0.25^{\circ}$ for each year between 2005 and 2015. Although temperature at the seafloor is a variable in the RV survey, there were many missing values, making interpolation unreliable. As a proxy, depth (m) values were extracted from the NOAA ETOPO1 Global Relief Model raster (Amante & Eakins 2014), which is provided at a resolution of 1 arc-minute \times 1 arc-minute ($0.0167^{\circ} \times 0.0167^{\circ}$). Raw values for oceanographic data in their native resolutions are shown in Fig. 1. All oceanographic data were bilinearly resampled to a common grid with a resolution of $0.1^{\circ} \times 0.1^{\circ}$ within the extent of the study area. This spatial scale was used to maximize the resolution of the model output while avoiding over-interpolation of environmental variables and maintaining reasonable computation time in later analyses. All annual SST ($^{\circ}\text{C}$) raster layers were stacked, and the depth (m) raster layer was replicated for each year in the 2005–2015 analysis ($n = 11$) and stacked. SST and depth data were compiled to a common covariates file according to ‘staRve’ package documentation (Lawler 2020). Spatial operations were performed using the ‘raster’ package (Hijmans 2020) in R version 4.1.0 (R Core Team 2020).

While direct observations of bycatch are collected by DFO through various at-sea observer programmes, observer coverage in the Atlantic groundfish fisheries is consistently low (Clark et al. 2015), and at-sea observer programmes in general can introduce ‘observer effects’ in which fishing practices and behaviour change in the presence or absence of observers (Benoît & Allard 2009). For some bycatch species that may be difficult to identify, such as skates, species-level differentiation by observers may be lower priority during particularly large fishing sets. As an added complication, at-sea observer data in Canada are screened to protect the privacy of individual fishing vessels. This involves spatially aggregating the observed catch from 5 different vessels or licences into 1 centroid point (Butler & Coffin-Smout 2017) in what has been referred to as the ‘rule-of-5’. In areas where fishing activity is high, the

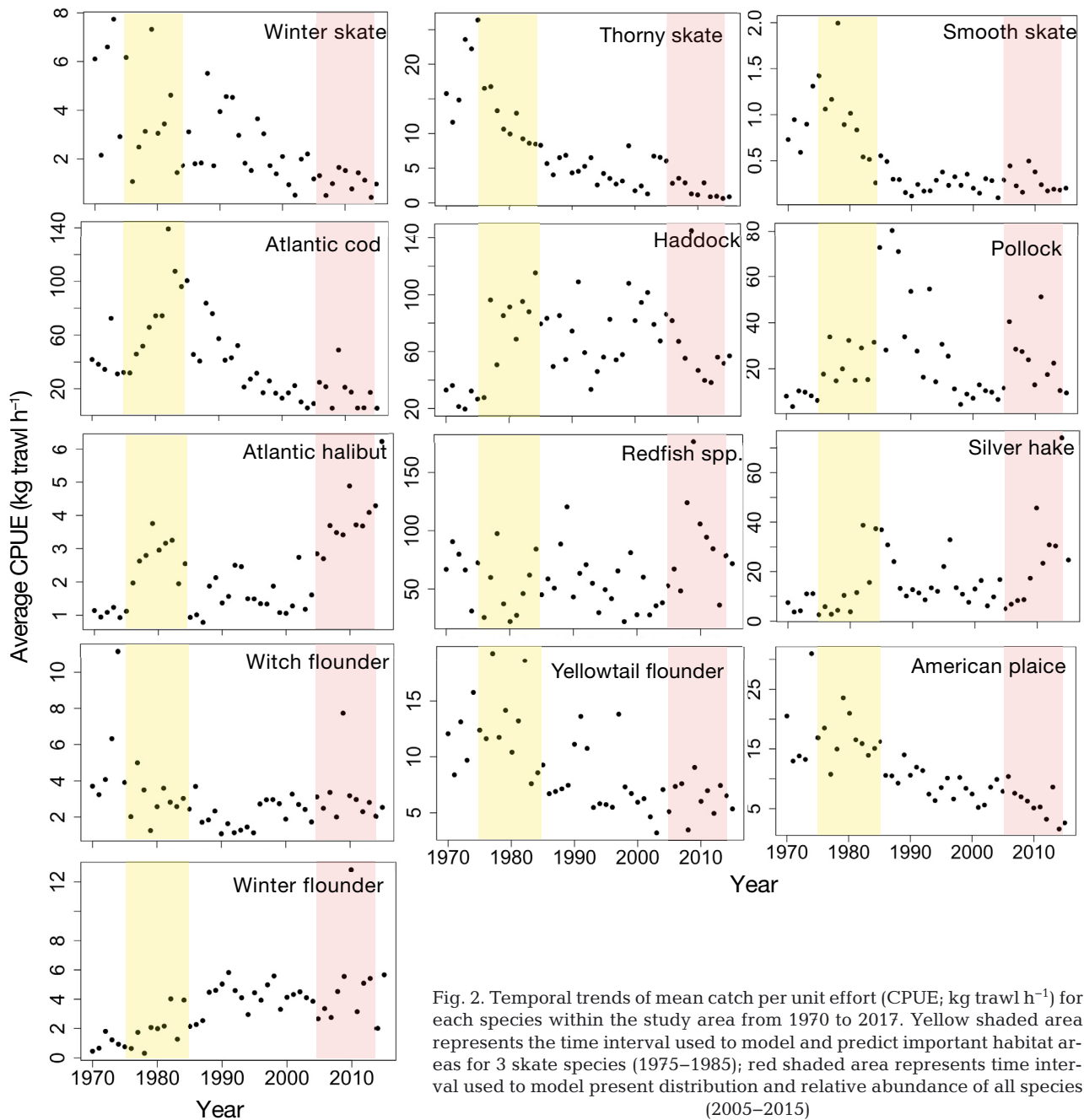


Fig. 2. Temporal trends of mean catch per unit effort (CPUE; kg trawl h^{-1}) for each species within the study area from 1970 to 2017. Yellow shaded area represents the time interval used to model and predict important habitat areas for 3 skate species (1975–1985); red shaded area represents time interval used to model present distribution and relative abundance of all species (2005–2015)

spatial resolution of observer data is relatively high, and this aggregation of catch data does not result in a significant loss of spatial accuracy. In regions where the rule-of-5 cannot be satisfied without losing significant spatial resolution, the areas are removed from the dataset by DFO prior to release to the researcher.

Because the RV survey employs a bottom trawl, we used data provided from at-sea observer programmes from 2 bottom trawl fisheries: 4X5Y

groundfish bottom trawl (CHP directed) and Unit 3 redfish bottom trawl (Fig. 3). Observed catch data for each species, including the total catch weight, mean catch weight and total count, were provided aggregated into 2 intervals of 5 yr (2005–2009, 2010–2014) and across a 2 arc minute hexagonal grid. The centroid of each grid cell was extracted to represent the spatial location of the catch (Fig. 3). For each hexagon, the number of fishing trips was approximated from the summed total weight of catch divided by the

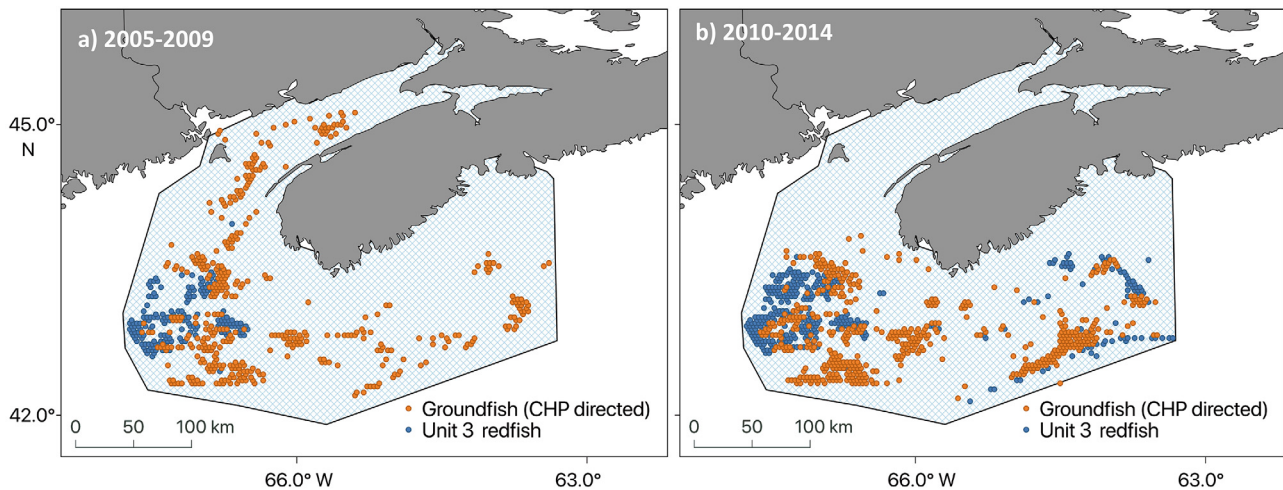


Fig. 3. Subset of the study area, with point locations for at-sea observations of catch from cod-haddock-pollock (CHP)-directed groundfish and Unit 3 redfish bottom-trawl fisheries for the years (a) 2005–2009 and (b) 2010–2014. Each point represents the spatially aggregated observed catch from 5 different vessels following Fisheries and Oceans Canada privacy screening requirements. Data were temporally aggregated into 5 yr intervals to reduce privacy screening effects and preserve spatial resolution

mean weight of catch of the primary target species. The total counts (kept and discarded) for each species of skate, number of fishing trips and corresponding latitude and longitude were extracted from the shapefile at each centroid point for each time interval and each fishery. Data extraction was completed in QGIS version 3.12.0 (<https://QGIS.org>), and subsequent operations were performed in R. The kept and discarded counts were summed and bycatch data were compiled into a data-frame, containing the latitude and longitude for each centroid point, the total number caught for each skate species and the respective time interval. Species presence (0 = absent, 1 = present) was defined as a count ≥ 1 for each skate species at each centroid point. Although bycatch risk hotspots were analysed for the Atlantic halibut and silver hake fisheries, we chose to validate our predictions using only data from comparable bottom-trawl fisheries to reduce uncertainty due to differences in catchability between gear types. Because the Atlantic halibut fishery employs long-lines and the 4VWX silver hake fishery mandates the use of 40 mm separator grates on trawls (Showell et al. 2010), observer data from these fisheries were not included in the analysis.

2.2. Statistical analyses

Generalized linear mixed models (GLMMs) with spatiotemporal random effects were used to individually predict the distributions of skates and ground-

fish species on the Scotian Shelf. Models were fit individually for each species considered using the ‘staRVE’ package (Lawler 2020) in R. ‘staRVE’ uses a GLMM framework, assuming univariate spatiotemporally referenced point data in continuous space \mathbf{s} and time t . A description of the model and discussion of the statistical considerations attendant with spatiotemporal GLMMs is provided in Text S1 in the Supplement at www.int-res.com/articles/suppl/m679p001_supp.pdf. Our analysis comprises 2 components, the first of which is the process model describing the of presence (or abundance) of a species in space. The second component is the observation model which captures the RV survey sampling data-generating process. The realized model is interpreted as a time-series of spatial processes, for which a nearest-neighbour Gaussian process gives spatial structure to the data while maintaining reasonable computation time.

We used a 2-stage hurdle model for relative species abundance. The first part models species presence (P) probability using a Bernoulli distribution and logit link function. Where oceanographic parameters are included in the analysis, they are denoted by the term $X_{i,t,p}(\mathbf{s})\beta$, where i is the i th observation at location \mathbf{s} at time t , and β is the vector of covariate effects.

The second part of the hurdle model involves a Gaussian distribution and identity link function for logCPUE, where only observations with a non-zero catch are included.

Fitted models were then used to generate predictions for presence probability and logCPUE indi-

vidually for each species. In each analysis and for each species of interest, presence probabilities were predicted across the study area on a $0.1^\circ \times 0.1^\circ$ raster grid for all given years as a function of observed values for SST and depth (Fig. 1c,d). logCPUE was predicted for each year on the same grid. Yearly predicted presence (Pr) and predicted logCPUE in each grid cell were multiplied to create annual predictions for total density ($D_{sp,t}$) for each species sp in year t :

$$D_{sp,t} = Pr_{sp,t} \times e^{\log CPUE_{sp,t}} \quad (1)$$

Annual estimations of standard error for species density (SE_D) were calculated using Eq. (2). This formula for standard errors follows from statistical first principles on the variance of products of independent random variables (for example, see Dekking et al. 2005). Pr represents presence probability as predicted from the presence part of the model, CPUE represents log CPUE as predicted from the positive catch part of the model, and SE_{Pr} and SE_{CPUE} represent the estimated standard errors of each:

$$SE_D = [(SE_{Pr} \times SE_{CPUE}) + (SE_{Pr} \times CPUE) + (SE_{CPUE} \times Pr)] \quad (2)$$

Mean species density ($\overline{D_{sp}}$) in each grid cell was calculated from annual predictions in each grid cell for all species examined in each analysis.

The predictive ability of the models was studied through K -fold cross-validation; however, due to computational burden the study is limited to winter skate with relatively few folds. Presence/absence models used a 3-fold cross-validation scheme, while the CPUE models used a 10-fold cross-validation scheme. We note that an ideal cross-validation scheme would have more than 3 (or 10) folds, preferably using leave-one-out cross-validation. Predictive ability of the presence/absence models was measured by the area under the receiver operator characteristics curve (AUC) and the average probability score of the observations in the testing set. Higher values of AUC correspond to better predictive ability, where predictive models that are perfectly able to classify new observations into their correct classes (presence vs. absence) have an AUC score of 1. The average probability score measures the ability of the predictive model to assign high probabilities of presence to new presence observations and low probabilities of presence to new absence observations, with values closer to 1 being better. Predictive ability of the CPUE models was measured through root mean square error (RMSE) and median absolute error (MAE). Both measure the average deviation of predictions from

the observed values. MAE is a measure of the typical deviation and is not greatly affected by a small number of large errors, while RMSE is a measure of the overall deviation and is more affected by a small number of large errors.

2.3. Identification of historical space use

We fit separate GLMMs for each species of skate to RV data from the years 1975–1985 using the ‘starVe’ package. Oceanographic covariates were not specified for this analysis. The models were used to generate annual predictions of presence probability and relative abundance for each species across a $0.1^\circ \times 0.1^\circ$ grid over the defined spatial extent. Predicted annual presence and relative abundance was multiplied (Eq. 1), and mean predicted density was calculated for each skate species for the years indicated. The top 10% of density values were extracted to show important habitat areas for each species. Standard errors for predictions were calculated using Eq. (2).

2.4. Identification of bycatch hotspots

Separate models were constructed for each species of skate and commercial target to predict their distributions for the years 2005–2015. Models were fit to RV data, and depth and SST were specified as oceanographic covariates in the presence stage of the model. Annual predictions of presence probability and CPUE were generated across a $0.1^\circ \times 0.1^\circ$ grid over the study area and annual predicted density was calculated using Eq. (1). Standard error for species densities were calculated using Eq. (2). To compare between species, we standardized predicted species density between 0 and 1. Annual bycatch risk ($BR_{sp,t}$) hotspots were then identified by the multiplicative overlap of estimated relative spatiotemporal abundance of at-risk skates with commercial targets. For species that are targeted as multi-species complexes (such as CHP or flatfishes; Table 1), annual density estimates for each species in the complex were summed together before being scaled and treated as a single target. Scaled annual density rasters were then summed for all at-risk skates (‘Skates’), as well as for all targets (‘Targets’). Hotspots were defined in 2 ways: first, a species-at-risk centric approach was taken in order to examine regions of high bycatch risk for one at-risk skate within multiple fisheries. The predicted scaled relative abundance raster of a single skate species was

multiplied by the summed scaled relative abundances rasters for all fisheries targets. For example, a species-at-risk approach to identify bycatch risk (BR) hotspots for winter skate is:

$$BR_{W.Skate,t} = D_{W.Skate,t} \times \sum D_{Targets,t} \quad (3)$$

A fisheries-centric approach was secondarily used to generate maps of bycatch risk areas particular to high-value fisheries targets. Here, the relative abundance of the target species was multiplied by the summed relative abundance of all at-risk skates. For example, a fisheries-centric approach to identify bycatch risk hotspots for all threatened skates that are particular to the Atlantic halibut fishery is as follows:

$$BR_{Halibut,t} = D_{Halibut,t} \times \sum D_{Skates,t} \quad (4)$$

Mean bycatch risk for each skate species (\overline{BR}_{sp}) was calculated from annual predictions of bycatch risk in Eqs. (3) and (4). High values in resulting maps indicate where co-occurrence is greater between one or more at-risk skate, and one or more commercial fishing target. All output maps for both approaches were then scaled between 0 (low bycatch risk) and 1 (high bycatch risk).

2.5. Proof of concept to validate bycatch hotspot predictions using at-sea observer data

To validate our predictions of relative bycatch risk, we constructed a spatiotemporal model fit to skate presence data from at-sea observers over a subset of the initial study area (Fig. 2). This model included spatial bycatch risk as a covariate in order to estimate its effect size on predicted skate presence in observed fishing sets. Annual bycatch risk predictions for each species of skate were averaged over 2 time intervals (2005–2009, 2010–2014), and the 5 yr mean value for bycatch risk at that location was extracted for each point in the observer dataset.

A spatiotemporal model was fit to records of skate catch from observer data to model the presence probability of skates as a function of predicted bycatch risk. The time-series contained only 2 steps, i.e. 2005–2009 and 2010–2014, as data were provided by DFO aggregated over these intervals. Bycatch risk as predicted from RV data was included as a covariate for each respective skate species. Species presence was modelled using the ‘starVe’ package in R. Estimated presence probability was corrected

for the number of observed fishing trips and was modelled using the ‘atLeastOneBinomial’ distribution implemented in the ‘starVe’ package with a logit link function to estimate the probability of an encounter in one fishing trip. The parameter estimate for bycatch risk and its 95 % lower bound of confidence were estimated at increasing values of the spatial range parameter. Where the 95 % lower bound is >0 , bycatch risk is indicated to have a positive effect on predicting species presence in observed fishing sets.

In addition to computing the parameter estimate values for RV-predicted bycatch risk against observer-predicted species presence, centroid points of observed skate catch for the years 2005–2014 were overlaid with predicted multi-fishery bycatch hotspots for each skate species to qualitatively evaluate the similarities in overall patterns between predicted and observed areas of bycatch.

3. RESULTS

3.1. Identification of historical space use

A total of 1595 RV survey trawl sets were completed between 1975 and 1985. Within these sets, the number of sets with at least one individual of each skate species is recorded in Table 1. Models fit to these data were used to predict the distribution and density (kg trawl h^{-1}) of each skate species within the study area during this time period of high groundfish abundance. Polynomial parameter estimates for SST and depth within each model are shown in Fig. 4. Thorny and smooth skates show negative, concave relationships with depth, while winter skate presence probability shows a positive convex relationship with depth. Winter skate presence probability declines linearly with SST, while smooth skate exhibits a negative and concave relationship with SST (Fig. 4).

The top 10 % of density values are shown to indicate abundance hotspots and important areas of habitat (Fig. 5). Standard errors for annual predicted historical density are shown in Figs. S1–S3. All species exhibited spatiotemporal variation in abundance. Thorny skate was concentrated on Banquereau Bank, with a small additional hotspot in the Bay of Fundy. Winter skate hotspots were present along Sable Island and Banquereau Banks and in the Bay of Fundy. Smooth skate hotspots occurred in several areas along Sable Island and Emerald Banks, Georges Bank and in the Bay of Fundy (locations for reference in Fig. 1d).

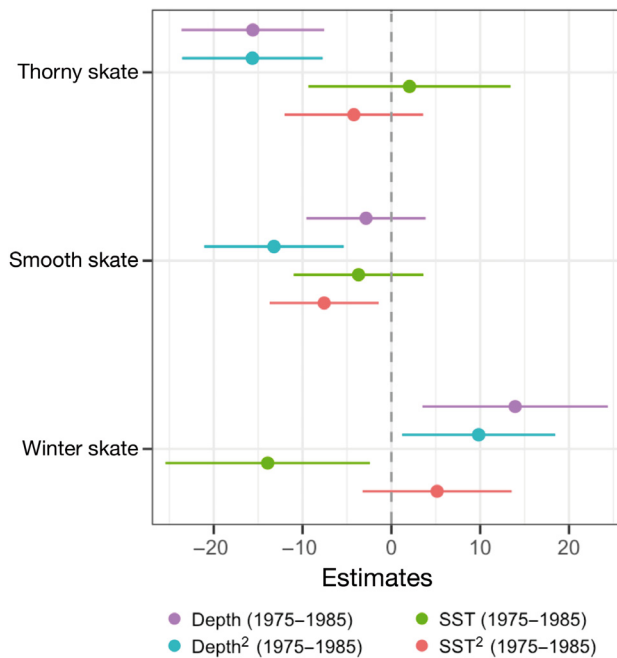


Fig. 4. Point estimates and 95% confidence intervals for parameter estimates of first- and second-order polynomial environmental covariates (sea surface temperature [SST] and depth). Covariates included in presence models were fit to research vessel survey data for the years 1975–1985

Cross-validation for winter skate gave promising results, particularly for the predictions of presence probability. The AUC was measured as equal to +1 for all 3 folds, meaning that all of the presence test cases were given higher probabilities than all of the absence cases, and the model exhibited perfect discriminatory ability between presences and absences. The average probability score in all 3 folds was approximately +0.82. Thus in addition to perfect discriminatory ability, the model predicts fairly high probabilities for new presence cases and fairly low probabilities for new absence cases. The RMSE and MAE measures for CPUE predictions were essentially equal to 0 for all 10 folds, which is highly suspect. We triple checked the code for the cross-validation but could not find any reason why the predictions were so accurate. Taken at face value, the cross-validation results suggest that the predictive ability of the fitted winter skate model is quite high.

3.2. Identification of bycatch hotspots

The number of records of each species within the RV survey dataset for the years 2005–2015 are shown in Table 1. Spatiotemporal models fit to RV data were

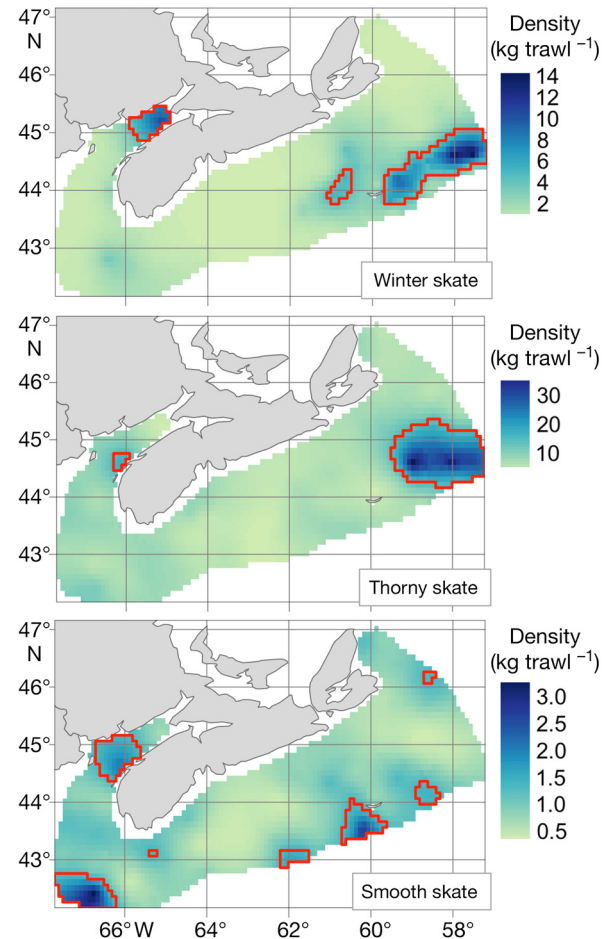


Fig. 5. Historical mean species distributions of 3 at-risk skates (thorny skate, winter skate and smooth skate) within the study area for the years 1975–1985. Important habitat areas are shown by the top 10% of density values (outlined in red)

used to generate predictions of CPUE for skates and target species across the study area (Fig. S4). First- and second-order polynomial effects of environmental covariates on species presence varied between species by magnitude and significance (Fig. 6). Time-effect parameter estimates (ar1) are shown in Table S1, and standard errors for annual predicted species density are shown in Figs. S5–S17.

The spatiotemporal distribution for each species was predicted (Fig. S4) and multi-species co-occurrence trends were mapped to show predicted potential bycatch hotspots. Yearly means of abundance for each species are shown in Fig. S18. A species-at-risk approach to evaluating bycatch risk for thorny skate, winter skate and smooth skate revealed spatially explicit bycatch risk hotspots for each species, where co-occurrence with one or more fisheries targets is

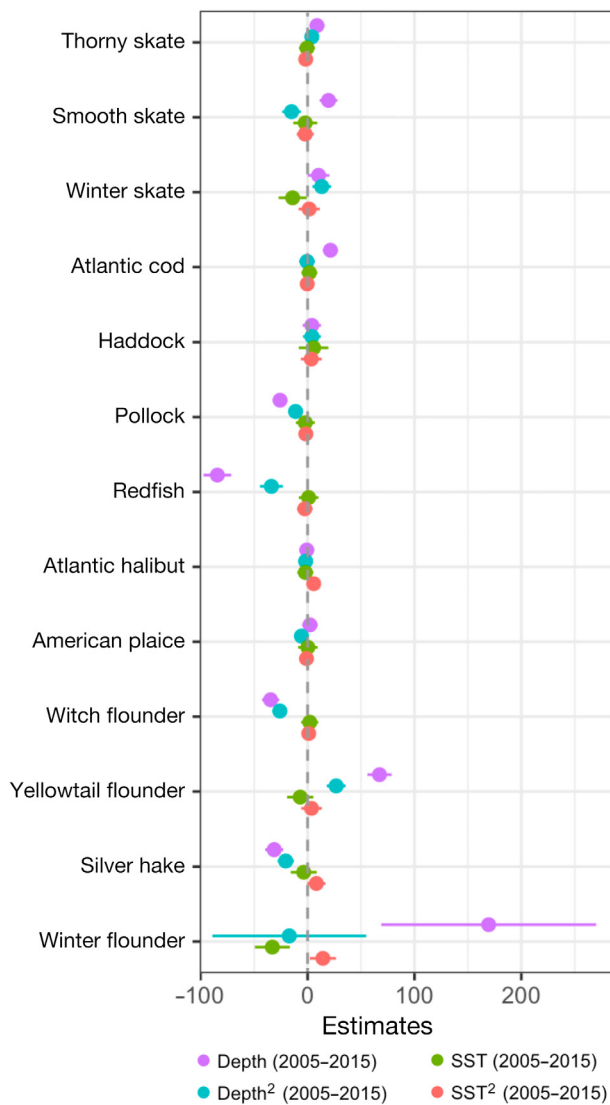


Fig. 6. As in Fig. 4, for the years 2005–2015

high (Fig. 7). Thorny skate bycatch hotspots were detected on Banquereau Bank and in the Bay of Fundy. Winter skate bycatch risk was concentrated in an area near the Fundian Channel and Brown's Bank. Smooth skate bycatch risk was high in the Bay of Fundy and on the western Scotian Shelf, with a small additional hotspot near The Gully, an extensive submarine canyon east of Sable Island (location references in Fig. 1d).

Bycatch risk hotspots in particular target fisheries were identified (Fig. 8). Skate bycatch hotspots within the distribution of Atlantic halibut were identified in the Bay of Fundy, Fundian Channel and The Gully. Within the distribution of CHP, hotspots for skate bycatch were identified on Brown's Bank and

Georges Bank and in the Bay of Fundy. For redfish, 1 skate bycatch hotspot was identified north of Brown's Bank. Within the distribution of the flatfish complex, skate bycatch risk was concentrated on Banquereau Bank. A cumulative map of co-occurrence between all skates and all fisheries targets shows overall hotspots on Browns Bank near the Fundian Channel, in the Bay of Fundy and along Banquereau Bank (location references in Fig. 1d).

The cross-validation for winter skate again gave promising results, and the cross-validation for the CPUE predictions are more believable. The AUC measure averaged +0.96 across the 3 folds, which is still very good if not perfect. The average probability score in all 3 folds was approximately +0.86, which agrees with the results seen from the historical analysis. The RMSE for CPUE predictions average 8.45 across the 10 folds, with a minimum value of 4.09 and a maximum value of 16.63. The MAE measure averaged 1.02, with a minimum value of 0.4 and a maximum value of 1.7. The mean \pm SD of the CPUE data was 10.03 ± 15.07 . The low MAE values compared to the CPUE SD suggests that on the whole, the fitted model produces accurate predictions, although the large RMSE values suggest that the predictions cannot predict some outlier values.

3.3. Proof of concept to validate bycatch hotspot predictions using at-sea observer data

A total of 1578 spatially- and temporally aggregated records of skate species presence or absence were represented in the at-sea observer dataset (Table 2). Spatiotemporal models fit to at-sea observer records of skate bycatch were used to validate predicted bycatch risk values on the Scotian Shelf. To account for spatial confounding, we estimated the bycatch risk effect with a different assumed value of the spatial range parameter. Smooth, winter and combined skates each exhibited a significant effect when the assumed spatial range was relatively small, but with large spatial range values, the effect diminished. Thorny skate exhibited the opposite behaviour where the estimated effect increased with increasing spatial range; however, the effect never becomes significant. Parameter estimates and corresponding 95% one-sided confidence intervals are plotted as a function of the spatial range in Fig. 9.

Point-referenced data indicating total count of each skate species from at-sea observer data for the years 2005–2014 were overlaid onto predicted bycatch risk hotspots. In general, point data generally

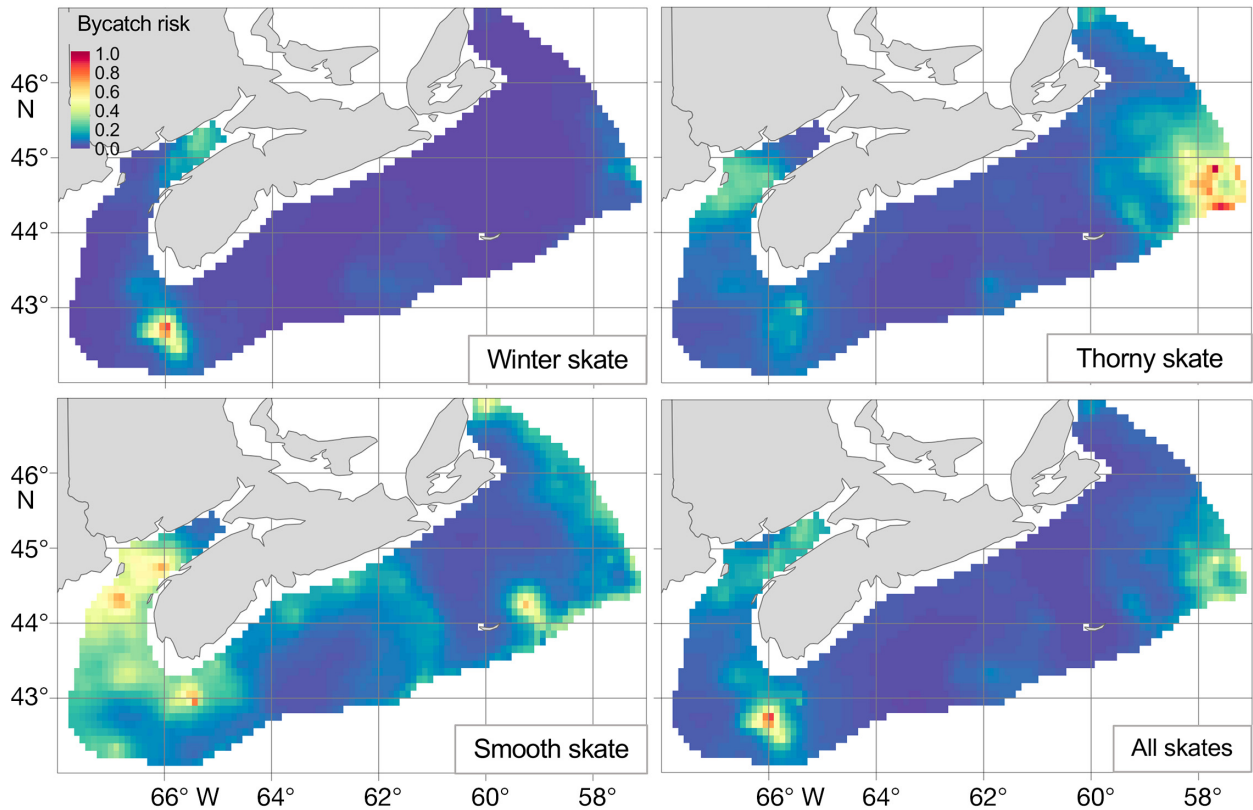


Fig. 7. Mean relative bycatch risk (2005–2015) for 3 at-risk skate species (thorny skate, winter skate and smooth skate) within the distributions of all target fisheries. High bycatch-risk areas, or ‘hotspots’ (red) indicate a high degree of co-occurrence between the at-risk skate and one or more target fisheries. Cumulative bycatch risk for all threatened skates within all target fisheries’ distributions is also shown. Low-risk areas (blue) indicate low co-occurrence between at-risk skates and fisheries targets

aligned well with mean predicted bycatch hotspots for each species over the 10 yr period, particularly given the spatial aggregation of observations (Fig. 10).

4. DISCUSSION

Our study aimed to present a modelling framework to identify spatial areas of conservation priority for depleted species affected as bycatch by multiple fisheries. We used a longstanding scientific RV survey dataset and GLMMs to evaluate the distribution of skates prior to heavy exploitation in order to map important habitat areas for each species. Bycatch risk hotspots were identified by overlaying spatial distribution patterns between skates and fisheries targets (Table 1). We then independently validated predicted bycatch risk using similar spatiotemporal models fit to records of skate bycatch from at-sea observer data. The framework we present builds on efforts to incorporate data-driven and ecosystem-based fisheries

management practices in response to the global overexploitation of fish stocks (Hilborn et al. 2020). Our results demonstrate a widely applicable framework to identify areas of conservation priority for depleted or rare species and support growing interest in employing data-driven, ecosystem-based tools in fisheries management.

4.1. Identification of historical space use

For all 3 species of at-risk skate, historical patterns of high abundance (Fig. 5) differed from current high-density areas (Fig. S4), suggesting that skates may have been fished out of those areas during the height of the fishery, or that environmental conditions have changed. Our results show that the relationships of skate species with SST and depth have changed between the periods 1975–1985 and (Figs. 4 & 6), which may support hypotheses that conditions in their preferred habitats have become unfavourable.

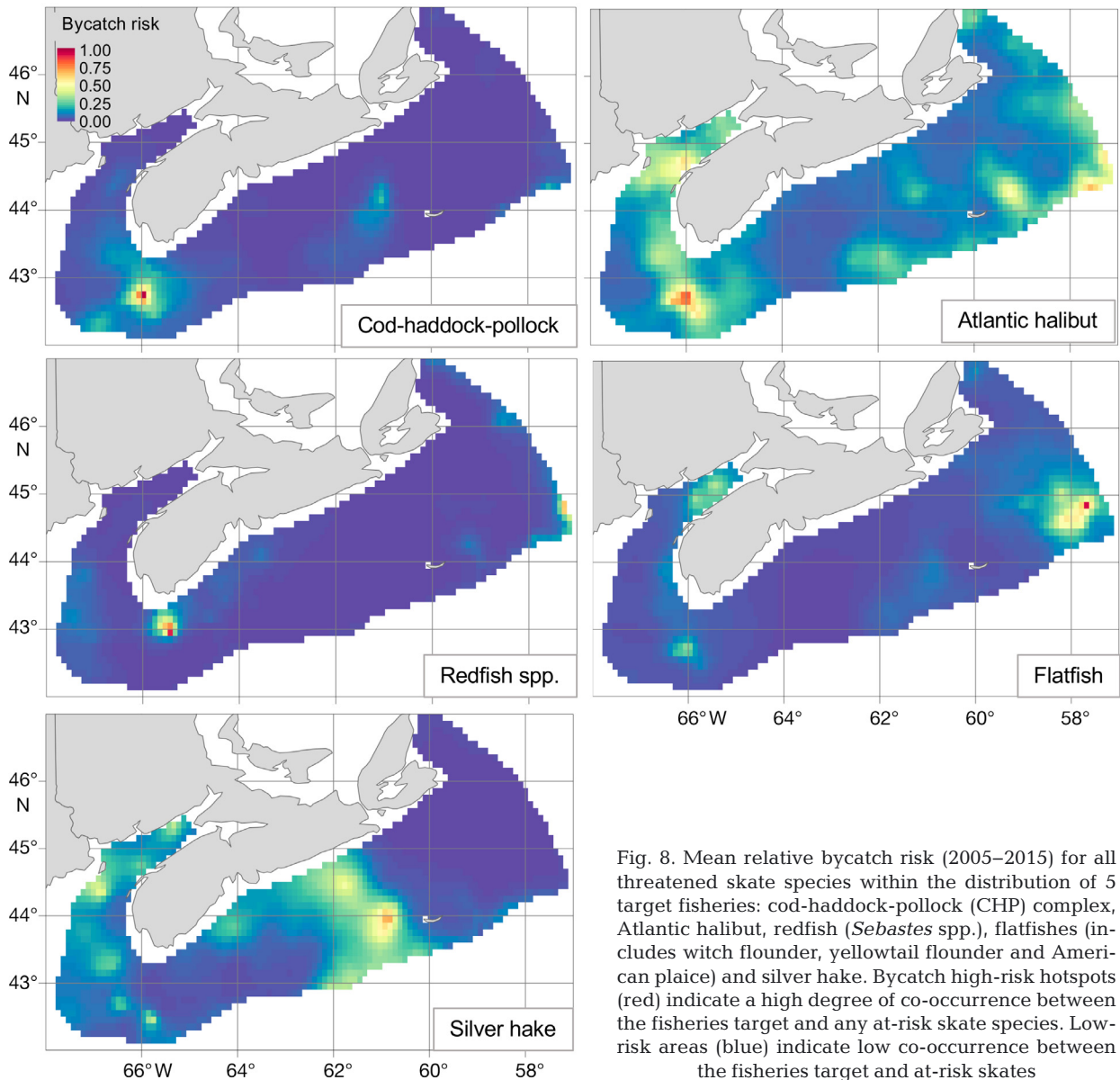


Fig. 8. Mean relative bycatch risk (2005–2015) for all threatened skate species within the distribution of 5 target fisheries: cod-haddock-pollock (CHP) complex, Atlantic halibut, redfish (*Sebastes* spp.), flatfishes (includes witch flounder, yellowtail flounder and American plaice) and silver hake. Bycatch high-risk hotspots (red) indicate a high degree of co-occurrence between the fisheries target and any at-risk skate species. Low-risk areas (blue) indicate low co-occurrence between the fisheries target and at-risk skates

For both thorny skate and winter skate, however, historically dense habitat was identified on Banquereau Bank, a region which has been heavily impacted by a surf-clam dredge fishery since 1986 (Roddick et al. 2007). Both species were also affected heavily as

Table 2. Number of aggregated records (i.e. centroid points) from at-sea observers in each directed fishery aggregated June–October for each year in 2005–2009 and 2010–2014

Target fishery	2005–2009	2010–2014
4VWX Groundfish	424	528
Unit 3 Redfish	198	428

bycatch on the eastern Scotian Shelf following the expansion of Canadian inshore fisheries. Thorny skates were highly co-occurrent with cod around Banquereau Bank from the late 1970s to the early 1990s, and areas occupied by thorny skates on Banquereau Bank were eroded due to directed fishing effort (Shackell et al. 2005). Although harvest moratoria for groundfish on the eastern Scotian Shelf were introduced in 1993 (Bundy 2005), thorny skate and winter skate abundance remains low on Banquereau Bank. Several causes for a lack of recovery of skates on the eastern Scotian Shelf have been investigated, including increased predation by a recovering population of grey seals (Swain et al. 2019). However, the

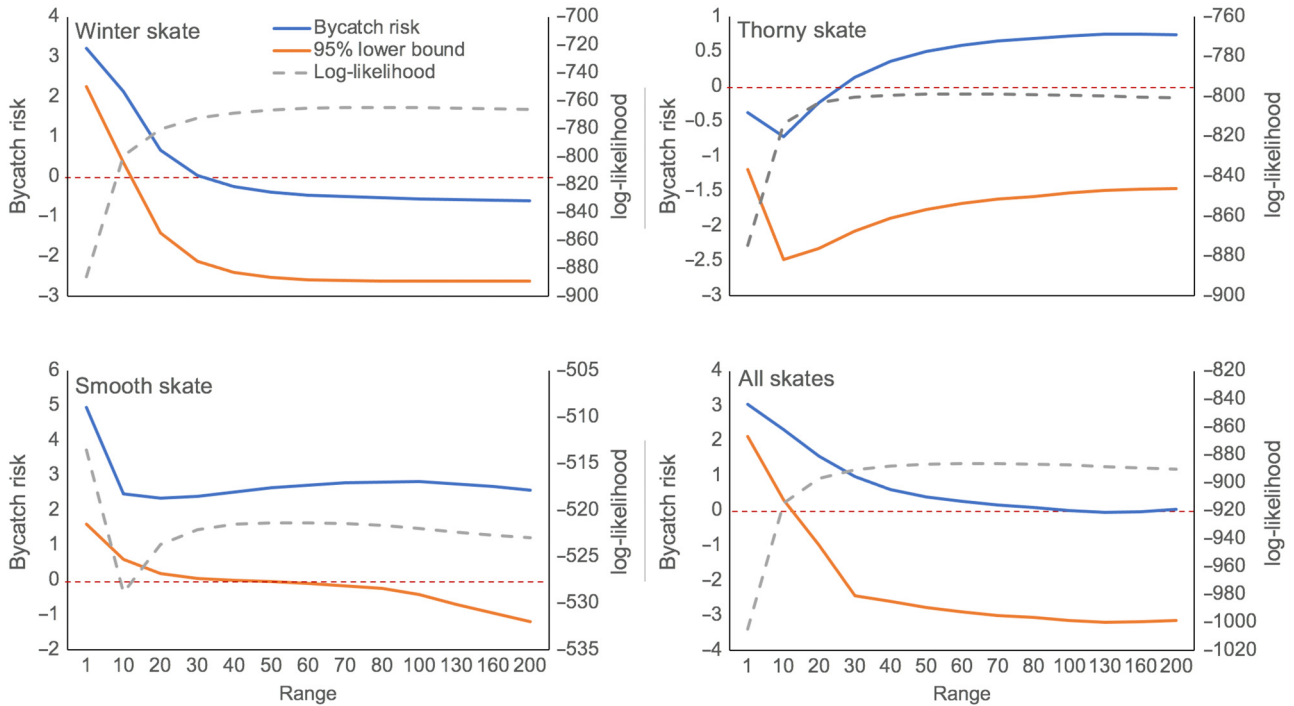


Fig. 9. Bycatch risk validation results, showing parameter estimates for bycatch risk with 95 % lower bound as a function of increasing values for spatial range parameters. Estimates and 95 % lower bounds >0 indicate that estimated relative bycatch risk has a positive effect on the response variable at that range parameter value

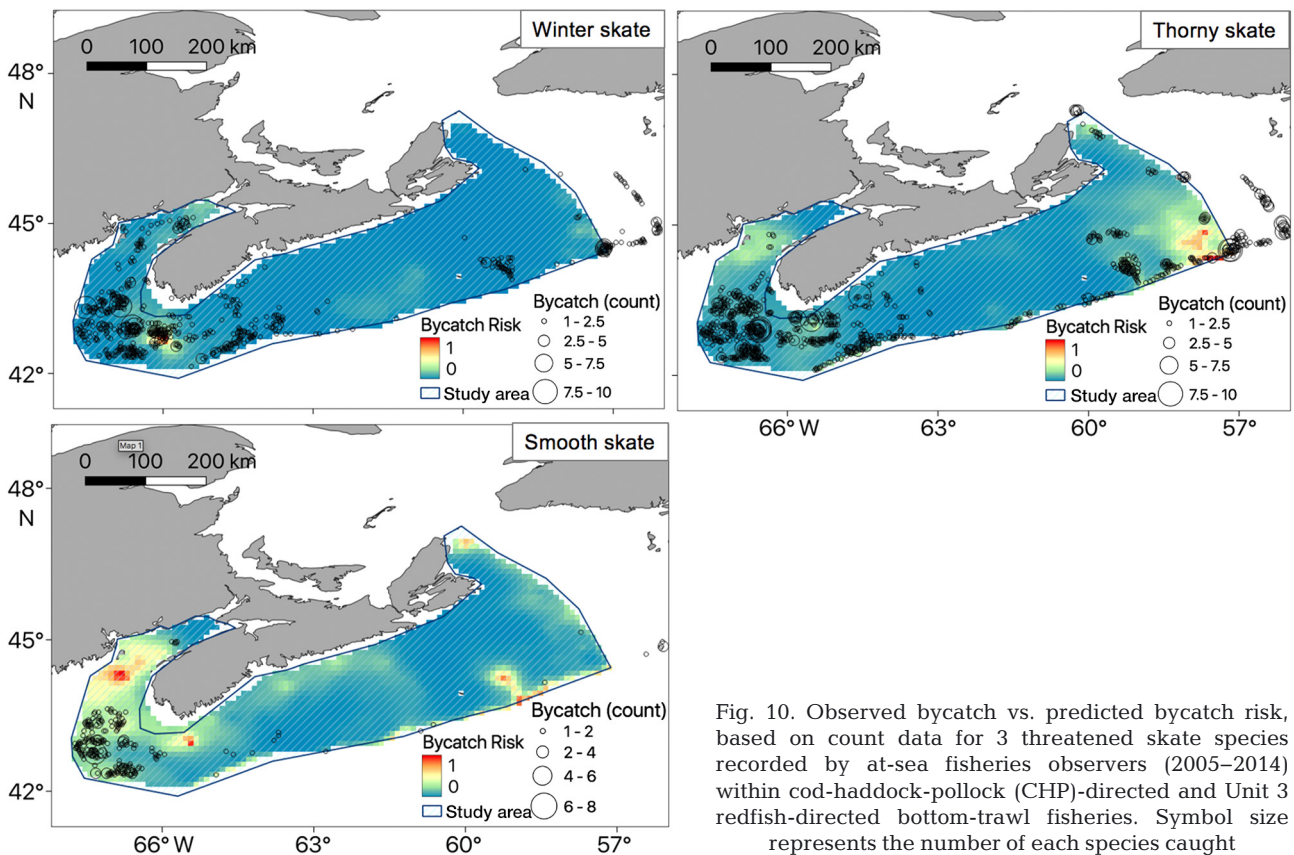


Fig. 10. Observed bycatch vs. predicted bycatch risk, based on count data for 3 threatened skate species recorded by at-sea fisheries observers (2005–2014) within cod-haddock-pollock (CHP)-directed and Unit 3 redfish-directed bottom-trawl fisheries. Symbol size represents the number of each species caught

ongoing surf clam dredge fishery reduces the forage base and greatly alters the affected seabed (Gilkinson et al. 2003). As such, core habitat for thorny and winter skates may have been altered in a significant way irrespective of temperature, particularly for 2 species that prey largely on benthic invertebrates.

4.2. Bycatch hotspot identification

There are increasing efforts to identify the spatial patterns and drivers of bycatch using spatiotemporal distributions of co-occurring species (Ward et al. 2015, Hazen et al. 2018) This was recently highlighted by Runnebaum et al. (2020) who used fishery-independent data to generate predictions of habitat suitability, and bycatch hotspots were inferred from overlapping suitable habitat between American lobster *Homarus americanus* and cusk *Brosme brosme*. In multi-species groundfish complexes, species at risk may be exploited in multiple target fisheries; therefore, a more comprehensive approach to identification of bycatch hotspots is necessary. It was our goal in this study to present a framework to evaluate spatial patterns of bycatch risk for a data-limited species exploited by multiple fisheries in a given region. Our results demonstrate a framework that can be applied on a dynamic temporal basis to identify and address changes in bycatch risk between fishing seasons and evaluate the efficacy of spatial fisheries closures or protected areas. This framework can provide an additional tool to fisheries managers and conservation authorities to examine relative bycatch pressure and protect vulnerable species within multiple fisheries.

Both a species-at-risk approach and a fisheries-centric approach were taken to identify bycatch risk hotspots for threatened skates. Alongside spatial predictions, realized bycatch risk for a species and fishery should be interpreted within the full context of the fishery. For example, smooth skate shares a bycatch hotspot with silver hake in the outer Bay of Fundy (Figs. 6 & 7). In reality, harvesters in the 4VWX silver hake bottom trawl fishery are required to affix separator grates with 40 mm spacing bars to their gear intended to reduce bycatch, and skates represented less than 0.05% of observed bycatch from 2000 to 2009 (Showell et al. 2010). Similarly, although bycatch hotspots were identified in areas of the eastern Scotian Shelf for some skates and fisheries, commercial fishing effort in these areas is greatly limited since the introduction of harvest moratoria in the 1990s and realized bycatch risk is likely small.

The information that fisheries managers can extract from these methods has broad applications, from near-real time direction of fishing effort away from high-risk areas (O'Keefe & DeCelles 2013) to informing and evaluating the efficacy of static or dynamic fisheries closures (Hazen et al. 2018). Employing a method such as this could provide complementary information to other planning and/or monitoring efforts to assess the species-specific benefits of the spatial placement of this protected area, such as the reduction of harvesters' access to bycatch hotspots.

4.3. Proof of concept to validate bycatch hotspot predictions using at-sea observer data

Many fisheries management jurisdictions employ at-sea observer programmes to directly record kept and discarded species; however, these data can be limited in coverage and taxonomic resolution (Benoît 2006, Clark et al. 2015). Nonetheless, it is important to examine the relationship between predicted regions of high bycatch and points where bycatch was empirically recorded, and we present here a proof-of-concept analysis to validate predictions of bycatch risk against observed records of skate bycatch using the 'starVe' package.

Bycatch risk as predicted from fishery-independent data was included as a spatiotemporal covariate in order to determine the size of its effect on predicting species presence in an at-sea observer dataset. Due to spatial confounding concerns, as well as uncertainties inherent to at-sea observer data, it is difficult to interpret the parameter estimates. The positive estimates, when they exist, indicate that the probability of catching a skate increases in areas where bycatch risk is predicted to be higher from RV survey data. However, spatial confounding concerns prevent us from claiming whether or not the true effects are significant.

Predicted bycatch hotspots and point-referenced observer records of skate bycatch for each species of interest generally matched well with each other (Fig. 10), particularly when considering the coarser scale introduced by aggregation of catch records per 5 vessels or licences (Butler & Coffen-Smout 2017). Despite the limitations and uncertainties associated with observer data, qualitative validation of predicted bycatch hotspots with observed bycatch provides further support for our results. For these reasons, we currently present this analysis as a proof-of-concept to validate bycatch risk predictions from at-sea observer data.

4.4. Limitations and conclusions

In our study, we made use of data from a long-standing RV survey occurring annually in the summer; therefore, our results do not reflect seasonality of species distributions and therefore seasonal changes in bycatch risk patterns. Several groundfish species on the Scotian Shelf undergo seasonal migrations to deeper waters (Swain et al. 1998, Methratta & Link 2006). While the majority of observed fishing trips occur in May through July (Themelis & den Heyer 2015), the groundfish season is open year-round. Predictions of bycatch hotspots along with observations based on a single season may not fully reflect the annual patterns of bycatch. This caveat may be addressed in regions or jurisdictions in which seasonal surveys are conducted. The availability of comprehensive data for a given fishery or region may improve over time, but likely not until bycatch mitigation becomes a priority for fisheries regulatory agencies.

An additional limitation of this study is the degree to which bycatch risk predictions can be confidently validated given the state of the at-sea observer dataset. Because of consistently low observer coverage in bottom-trawl fisheries in combination with DFO harvester privacy policies, the spatial resolution of observed fishing sets available for analysis is quite coarse. Bycatch risk predictions on the eastern portion of the Scotian Shelf were not validated, as at-sea observations in this area were limited and did not satisfy the DFO 'rule-of-5' vessel aggregation policy (Butler & Coffen-Smout 2017). Therefore, observations in this region were removed from the dataset prior to release to researchers. The temporal aggregation of 10 years of observer data (2005–2009 and 2010–2014) was done to reduce the spatial area affected by the 'rule-of-5'. Points in the dataset are representative of the midpoint between 5 individual vessels, but the distance of each vessel to the centroid point is unknown. The spatial and temporal aggregation of the data introduces unknown uncertainty; thus we present this analysis as a proof-of-concept only.

Furthering our understanding of the spatiotemporal distribution of bycatch can support conservation efforts for many species at risk and help support economically viable fisheries. In addition to exploring the cumulative impacts of fisheries that exploit multi-species complexes, managers can incorporate fluid environmental parameters to support dynamic ocean management strategies. Oceanographic processes and their associations with species are non-station-

ary (Myers 1998), and the waters of the northwest Atlantic around the Scotian Shelf in particular are warming rapidly (Saba et al. 2016). Making use of dynamic tools that incorporate near-real time environmental data will be critical in engaging in ecosystem-based fisheries management in the face of climate change. While no model is perfect, these frameworks are adaptable to the advancement of statistical techniques and the availability of new data. The methods presented in this study can be used to support ongoing efforts to include more dynamic approaches to ecosystem management and may thereby help to ensure the long-term sustainability of fisheries in a changing climate.

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