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The Northwest Atlantic fisheries have a rich history, and a great deal of research has been sponsored and encouraged by NAFO and its predecessor ICNAF. NAFO has been a leader amongst international organizations in the application of science to fishery management and in the regulation of fisheries in areas beyond national jurisdiction. In accordance with its mandate to disseminate information on fisheries research to the scientific community, the Scientific Council of NAFO publishes the *Journal of Northwest Atlantic Fishery Science*, which contains peer-reviewed primary papers, and NAFO Scientific Council Studies, which contains unrefereed papers of topical interest and importance to the Scientific Council. Lists of these and other NAFO publications are given on the back of this issue.

Editorial Policy

The Journal provides an international forum for the primary publication of original research papers, with emphasis on environmental, biological, economic and social science aspects of fisheries and their interactions with marine habitats and ecosystems. While the Journal is intended to be regional in scope, papers of general applicability, and methodological and review papers, irrespective of region, are considered. Space is available for notes and letters to the editor to facilitate scientific discussion of published papers. Both practical and theoretical papers are eligible. All papers are peer-reviewed to determine their suitability for primary publication. Associate Editors arrange for the peer-reviews and ensure that the papers accepted for publication meet the high standards required for the Journal. Manuscripts approved for publication are accepted with the understanding that they are not copyrighted, published or submitted elsewhere except in abstract form. There are no page charges.

Editorial Board

NAFO CONVENTION AREA
(Showing Scientific and Statistical Subareas,
Divisions and Subdivisions)

Boundary of the Convention Area	
Boundary of Subareas	
Boundary of Divisions	
200-Mile Zone Boundary	
200-Meter Contour	
NAFO Regulatory Area (NRA)	

Mercator Projection Scale 1 : 8 500 000 at 60°

As shown in the chart below, 5Zc and 5Zu are sub-subdivisions of the Subdivision 5Ze established by the Scientific Council for the purpose of recording and reporting catches to NAFO from Canadian waters (5Zc) or USA waters (5Zu) (NAFO GC Doc. 86/2, 2nd revision, and GC Doc. 86/4, revised).

MASS.
CONN.
Boston
42° 20'N
66°00'W
42°20'N
65° 40'W
Cape Cod
5Zc
Georges S.H.
BK.
4X
Block I.
Nantucket I.
6A
5Zw
Georges
5Zu
5Ze
39° 00'N

This chart below represents the Exclusive Economic Zone (EEZ) of France (in respect of St. Pierre and Miquelon)

Newfoundland
St. Pierre and Miquelon
St. Pierre and Miquelon EEZ (France)
Canadian 200-mile Zone Boundary

Melville Bay

Baffin Bay

75° 00'N
73° 30'W

1A

BAFFIN
ISLAND

0

1

0A

68° 50'N

Christianshaab

Store Hellefiske Banke

1B

Davis Strait

66°15'N

Lille Hellefiske Banke

1C

0B

64°15'N

Fyllas Banke

Godthaab (Nuuk)

1D

Fiskenaes Banke

GREENLAND

62° 30'N

Danas Banke

Frederikshaab Glacier

Hudson Strait

61°55'N
66°20'W

61°00'N
59°00'W

1E

61°00'N

60°45'N

Cape Desolation

Ungava Bay

Cape Farewell

59° 00'N

2G

1F

57°40'N

Cape Mugford

2

2H

Hopedale

55°20'N

CANADA

LABRADOR

Hamilton Bank

2J

QUEBEC

52°15'N

52° 15'N
42° 00'W

Cape Bauld

3K

Pte. Des Monts

49°25'N
64°40'W

49°25'N
60°00'W

4S

4R

Cape Freels

49°15'N

Gulf of St. Lawrence

47°50'N
60°00'W

NEWFOUNDLAND

ATLANTIC OCEAN

4T

Magdalen I.

Cape Ray

St. John's

3L

3

Flemish Cap

NEW BRUNSWICK

P.E.I.

Miquelon (Fr.)

St. Pierre (Fr.)

Grand Bank

46°00'N

3M

4Vn

3Ps

St. Pierre Bk.

MAINE

45°40'N

44°10'N

3O

3N

USA

Halifax

44°20'N
Sable I.

43°30'N
55°00'W

Scotian Shelf

ONTARIO

VERMONT

NEW HAMPSHIRE

44°46' 35.56"N
66°54' 11.23"W

Portland

Gulf of Maine

NOVA SCOTIA

4

4Vs

NEW YORK

MASS.

5Y

42°20'N
66°00'W

New York

CONN.

R.I.

42°20'N
65°40'W

4W

PA.

Cape Cod

Georges Bk.

4X

N.J.

6A

5Zw

5

5Ze

39° 00'N

MD.

39°00'N

39°00'N

6B

DEL.

VA.

6C

Cape Hatteras

6D

6E

6

6F

6G

6H

BERMUDA

Contents

Contemporary analyses of comparative fishing data: a case study of Thorny skate on the Grand Banks (NAFO Divisions 3LNOP)

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Abstract

We re-analyze Thorny skate data from two comparative fishing experiments conducted by DFO in 1995 and 1996 using improved and more contemporary methods to estimate the relative efficiency of the Campelen 1800 demersal shrimp trawl survey protocol compared to the Engel 145 otter trawl. We correct possible bias in the method previously applied to these data. We investigate if there are size-based differences and if depth or spatial regions have important effects on results. We also investigate the influence and robustness of the estimation procedures, which was a concern in the original analyses of these data for other groundfish species. We did not find strong evidence that the relative efficiency of the Campelen trawl protocol compared to the Engel was different for smaller-sized Thorny skate compared to larger ones. However, we conclude that there is a potential that size-based differential catchability existed but there is insufficient information to reliably estimate these effects for Thorny skate. We also found evidence of significant differences in relative efficiency among NAFO Divisions and experiments, which is similar to other flatfish species. However, the mechanisms for these differences are unknown and it is not clear if spatial estimates should be used when converting Engel indices to Campelen equivalents. Hence, we do not recommend a different Engel-Campelen conversion factor than the one currently used in stock assessments for Thorny skates on the Grand Banks (NAFO Divisions 3LNOPs).

Keywords: Paired-tows; Binomial distribution; generalized linear mixed-effects model; influence; Robson estimator.

Introduction

Bottom-trawl surveys provide important inputs for the assessment of Grand Banks Thorny skate (*Amblyraja radiata* Donovan, 1808) in NAFO Divisions 3LNO and Subdivision 3Ps (Simpson and Miri, 2020). The main source of information comes from Fisheries and Oceans (DFO) research vessel (RV) surveys in the spring that cover the entire stock area. DFO RV surveys in autumn in Divisions 3LNO are also examined but these surveys do not cover the stock component in 3Ps. Stock status is based on spring survey indicators since 1971; however, different vessels and survey gears have been used throughout this time-period, and some of these changes had substantial impacts on survey catch rates. Survey indices during 1984–1995 when the Engel trawl was employed were adjusted to be comparable with recent survey protocols that used the Campelen trawl; however, there is substantial

uncertainty about values for the adjustments, which is the focus of this paper.

During 1971–1982 the DFO spring surveys were conducted using the research vessel *A.T. Cameron* which fished with a Yankee 41.5 otter trawl. Starting in 1983, surveys were conducted using the stern trawler *Wilfred Templeman* with the Engel 145 High Lift otter trawl. Although comparative fishing (see below) between the two vessels and gears was conducted (Gavaris and Brodie, 1984), no length data were collected for Thorny skate. Hence, survey catch rates from these vessels used during different periods may not be directly comparable to indicate stock trends.

Major changes in both the spring and fall surveys occurred in the mid-1990s. In 1995, DFO changed survey vessels, bottom trawls, and tow durations in their fall RV surveys

on the NL shelves. The vessel CCGS *Teleost* replaced the MV *Gadus Atlantica*, and the Engel 145 High Lift otter trawl was replaced by the Campelen 1800 shrimp trawl. The Campelen trawl was known to be much more efficient at catching small fish (Walsh, 1996). The Engel survey trawl was also changed to the Campelen trawl on another research vessel, the CCGS *Wilfred Templeman*, which was used for both spring and fall surveys. In both cases, tow times were reduced from 30 minutes to 15 minutes. Other changes in survey protocols were summarized in Warren (1996; 1997), McCallum and Walsh (1997), and more recently by Cadigan *et al.* (2022). Well-designed scientific surveys can produce annual indices, I_y, t size, N_y (*i.e.*, $I_y \approx QN_y$). If *catchability (Q)* is the same each year then trends in indices reflect trends in stock size. However, a large change in survey protocols can affect Q and that disrupts the survey index time-series as an indicator of stock size.

Comparative fishing experiments can provide information about the relative change in Q for the old survey protocol compared to the new one, $\rho = Q_{old}/Q_{new}$, which we refer to as the relative efficiency of the old protocol. This can be used to adjust for changes in survey index catchability. Comparative fishing experiments usually involve paired-trawling by two vessels that use the old and new survey protocols. Comparative or calibration fishing is the international standard in developed countries for calibrating catches and integrating pre-existing/current time-series with new time series (Bagley *et al.*, 2015; Thiess *et al.*, 2018). However, it is often difficult to conduct comparative fishing (*e.g.* when only a trawl gear is changed in a single vessel survey) or it may be prohibitively costly, especially in cases where multiple vessels are used each year to conduct surveys (*e.g.*, ICES, 2006; Bagley *et al.*, 2015; ICES, 2022). In these cases, survey index standardization is aided by using a phased-in approach for changes in survey protocols, where some vessels use the old protocols and some use the new protocols, during the same survey and so that both protocols are used in some nearby locations. Index standardization can be performed using statistical models (*e.g.* Berg *et al.*, 2014; Thorson and Ward, 2014; O'Leary *et al.*, 2021) that include vessel and/or gear effects. However, such model-based approaches may not be reliable if there is insufficient overlap in the vessels and gears used (*e.g.* Winker *et al.*, 2017). Dedicated comparative fishing ensures this overlap.

In 1995 and 1996, DFO conducted comparative fishing experiments to 1) investigate the relative efficiency of the *Gadus Atlantica* with the Engel trawl versus the *Teleost* with the Campelen, and 2) the *Alfred Needler* with the Engel trawl and the *Wilfred Templeman* and the Campelen trawl. The *Alfred Needler* and the *Wilfred Templeman* were

sister ships, and it was expected that their differences in catchabilities would provide a good approximation of the differences in catchabilities of the *Wilfred Templeman* using the Engel trawl versus the Campelen trawl. In effect, the assumption was that the *Alfred Needler* and the *Wilfred Templeman* would have the same catchability when each vessel used the same Campelen survey gear; that is, there was no vessel effect. This assumption was later validated in subsequent comparative fishing experiments between these two vessels, both fishing with the Campelen trawl (Cadigan *et al.*, 2006). Additional information on the comparative fishing results is provided in Warren (1996) and Warren *et al.* (1997).

Simpson and Kulka (2005) initially analyzed the comparative fishing results for Thorny skate to estimate the relative efficiency of the Campelen surveys compared to the Engel surveys. Their purpose was to convert *Gadus Atlantica* catches with the Engel trawl to values equivalent to what would have been obtained by the *Teleost* and the Campelen. Similarly, *Wilfred Templeman* catches using the Engel trawl were converted to Campelen equivalents. Simpson and Kulka (2005) did not find evidence of size-based differential catchability of the Campelen and Engel trawls for Thorny skate. However, the relative efficiency of the Campelen trawl survey protocol compared to the Engel was strongly length-dependent for the target groundfish stocks in these comparative fishing experiments (Warren, 1996; Warren *et al.*, 1997; Cadigan *et al.*, 2022). Hence, it is reasonable to expect that Thorny skate relative efficiency may also be length dependent, but there was insufficient length measurements to detect the effect.

There have been few other comparative fishing studies for thorny skate using the Campelen trawl. To our knowledge the most relevant one was conducted in the northern Gulf of St. Lawrence in 2004 and 2005. This involved paired-tow comparative fishing between the *Alfred Needler* with a with a URI 81'/114' shrimp trawl compared to the *Teleost* with the Campelen shrimp trawl (Bourdages *et al.*, 2007). They found that, when standardized for the same area swept, the Campelen trawl was about eight times more efficient than the URI for catching large thorny skate (~ 60 cm) but only 2.5–3.1 times more efficient for thorny skate between 10–20 cm. However, their results (Fig. 5 in Bourdages *et al.*, 2007) did not provide strong evidence of a change in relative efficiency for sizes greater than 20 cm, as evidence by the flat exponential curve at these sizes. We caution that the results in Bourdages *et al.* (2007) may have little relevance to the relative efficiency of the Campelen trawl compared to the Engel trawl because the URI shrimp trawl used in northern Gulf of St. Lawrence research surveys was substantially different than the Engel groundfish trawl used in the surveys we investigate.

The methods used to estimate conversion factors for a change in survey protocols have improved since Simpson and Kulka (2005). It is now common to analyze comparative fishing using Binomial or Beta-binomial logistic regression and to account for between-tow variability in relative efficiency using mixed-effect models (*e.g.* Benoît and Swain, 2003; Benoît, 2006; Fowler and Showell, 2009; Cadigan and Dowden, 2010; Cadigan and Power, 2011; Miller, 2013; Fabrizio *et al.*, 2017; Jones *et al.*, 2021; Cadigan *et al.*, 2022; Delargy *et al.*, 2022). In this paper we re-analyze the DFO 1995 and 1996 Engel-Campelen comparative fishing data for Thorny skate using these methods to estimate the relative efficiency of the Campelen trawl survey protocol compared to the Engel protocol. We correct possible bias caused by the methods used by Simpson and Kulka (2005). We also investigate for size-based differences in relative efficiency, which there is strong evidence for other species (*e.g.* Cadigan *et al.*, 2022). This latter issue is difficult for Thorny skate because sizes were measured infrequently, which we describe below. Also, the comparative fishing tows were not randomly distributed throughout the stock area. If there are significant covariate effects (*i.e.*, depth, location) for relative efficiency, then this may also be a source of bias

if the distribution of these covariates in the comparative fishing experiments is different than the distribution of the covariates that is typical in a survey. Hence, we also investigate if there were significant effects for depth or spatial region. We also investigate the robustness of the estimation procedures, which was a concern in the original analyses of these data for other groundfish species (Warren, 1996; Warren *et al.*, 1997).

Materials and Methods

We first describe the data collected for Thorny skate in the DFO 1995 and 1996 Engel-Campelen comparative fishing experiments. This is then followed by a description of the model we use to estimate relative efficiency, which is naturally influenced by the data available.

Data

The *Gadus Atlantica-Teleost* and *Alfred Needler-Wilfred Templeman* comparative fishing experiments were conducted in NAFO Divisions 3LNOP (Fig. 1) with some sets also in Subdivision 4Vn (west of 3Ps). Sets locations

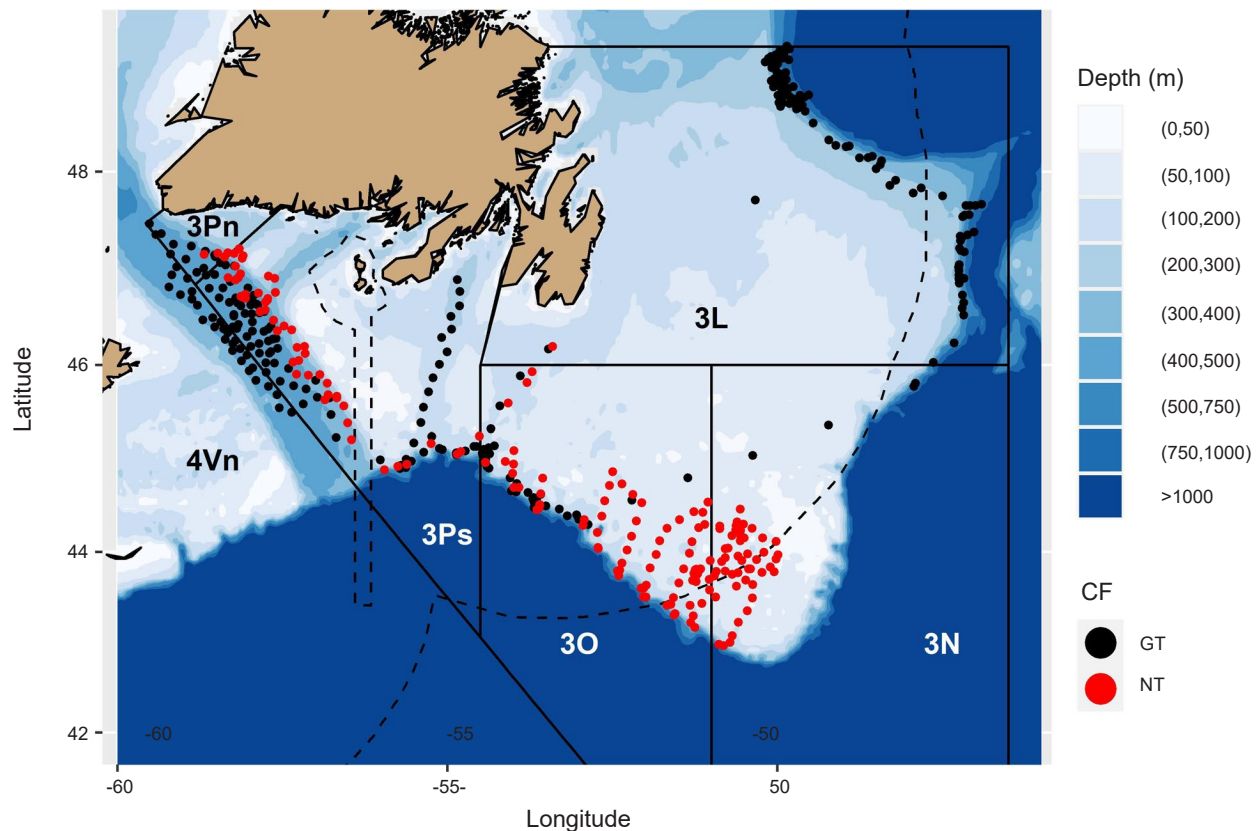Fig. 1.   The locations of comparative fishing tow sites (red and black points). GT indicates the *Gadus Atlantica* and the *Teleost* experiment, and NT indicates the *Wilfred Templeman* and the *Alfred Needler* experiment. Black lines indicate boundaries of NAFO Divisions 3L, 3N, 3O and 3P (*i.e.* 3Pn + 3Ps). Black dashed lines indicate Canada's EEZ. White-blue shaded regions indicate depth intervals shown in the legend.

were targeted in areas and depths where target species were thought to occur (Warren, 1996; Warren *et al.*, 1997). Although Thorny skate was not a target species, the catches of this species were recorded and some length information was collected (see below). The locations fished in the comparative fishing experiments are also somewhat different than the recent typical distribution of Thorny skate (*e.g.* see Figs. 11a,b in Sosebee *et al.*, 2022). The *Alfred Needler-Wilfred Templeman* CF sets in 3Ps were located along the northeast slope of Laurentian Channel (western part of Div. 3Ps, Fig. 1) and did not cover much of the Burgeo, Hermitage, and Halibut channels (in Div. 3Ps, see https://www.dfo-mpo.gc.ca/oceans/publications/ nfld-atlas-tnl/page02-eng.html#grandbanks) where there have been relatively high catches of Thorny skate in recent years. Similarly, there were no CF sets in the southeast part of 3N where thorny skate are also found. There was only one *Alfred Needler-Wilfred Templeman* CF set in 3L, although this Division has lower thorny skate abundance compared to 3NOPs. This has potential implications on how these data should be used, which is described below. Both experiments involved three trips to different areas (Fig. 2).

The methods used by Warren (1996), Warren *et al.* (1997) and Cadigan *et al.* (2022) to estimate length-based relative efficiency required lengths to be measured by both vessels in each paired-tow, and these methods are not applicable to Thorny skate because lengths were usually not measured by each vessel for the same paired-tows (see Results). Lengths were only measured for 10 *Wilfred Templeman* sets and 15 *Gadus Atlantica* sets, but for the latter there were no length measurements by the *Teleost* and for the same paired-tows. A coarse way to assess if there were size effects in relative efficiency is to stratify total catches (from both trawls and for all sizes) by average body weight. Basically, this involves estimating relative efficiency in sets with catches of mostly smaller fish compared to sets with mostly larger fish. Because of the much smaller Campelen trawl mesh size compared to the Engel, we expect to see relatively more catch from the Campelen trawl in tow-pairs that caught smaller fish in total (*i.e.* both trawls) than in tow-pairs that caught larger fish. Defining large and small sizes is subjective, and to achieve reasonable sample sizes of small and large sizes of fish we divided the catches based on the weight of a 45 cm fish (0.93 kg), which was closer to the median weight of 1.02 kg for the *Gadus Atlantica-Teleost* experiment and 1.65 kg for the *Alfred Needler-Wilfred Templeman* experiment.

Catchability and relative efficiency may also vary spatially because of habitat differences (*e.g.* slope, sediment type) that may affect escapement through the footgear (Kotwicki

et al., 2013; Thorson *et al.*, 2013), among other reasons. Cadigan *et al.* (2022) found that spatial region effects (*i.e.*, NAFO Divisions) were important for the flatfish species they studied. Relative efficiency may also vary with depth because of depth-dependent differences in trawl geometry (*e.g.*, Weinberg and Kotwicki, 2008; Dean *et al.*, 2021) and fish behavior (Winger, Eayrs, and Glass, 2010). This is important because the set locations in the comparative fishing experiments were not distributed randomly throughout 3LNOP and therefore the average relative efficiency at the locations sampled in these experiments may not apply to the whole survey area if relative efficiency varies with space and depth. Data were too limited to attempt to estimate spatial or depth effects at a fine scale. However, we investigate this using coarse post-stratification of the catches. For spatial effects we used NAFO Divisions, but we combined 3N and 3O because of the low number of sets in the *Gadus Atlantica-Teleost* experiment in this area, and the sets in the *Alfred Needler-Wilfred Templeman* experiment occurred mainly in a relatively small region in Divisions 3N and 3O (see Fig. 1). We also post-stratified by depth: < 200 m, 200–500 m, and > 500 m. These three depths bins were selected so that there was a balance of tows in each depth bin for the two experiments. The number of comparative fishing sets for each size, depth, and region bin are shown in Table 2 and Table 3. There was only one tow-pair in 3L which did not catch any Thorny skate in the *Alfred Needler-Wilfred Templeman* experiment, and these vessels also did not fish greater than 500 m.

Model and Estimation

The basic data obtained from the paired-tow calibration studies are the catch numbers Y_{ij} at the ith paired-tow station ($i=1, \ldots$) by the old and new survey protocols at sites $j=1$ (old) or $j=2$ (new). Site refers to the different locations fished at a trawl station. Let λ_{ij} denote the fish densities encountered at station i and site j. The distribution of Y_{i1} (*i.e.* catch-at-length from the old protocol) conditional on the total catch-at-length by both vessels ($N_i = Y_{i1} + Y_{i2}$) was assumed to be Binomial (*e.g.*, Cadigan and Dowden, 2010; Cadigan *et al.*, 2022) with probability p_i that a caught fish came from the old survey protocol. If $log\{\rho_1\} = \tau$ then the Binomial probability is defined via the logistic equation,

$$log\left\{\frac{p_i}{1-p_i}\right\} = \tau + \delta_i, \qquad (1)$$

where $\delta_i = log\left(\lambda_{i1}/\lambda_{i2}\right)$. If survey catches are subsampled or there are within-survey variations in tow distances and swept-areas then this should be accounted for (*e.g.*,

Cadigan *et al.*, 1996; Miller, 2013) in Eqn. (1); however, we ignore these issues for simplicity because they were not problems for the Thorny skate CF data. We assumed δ_i varied randomly and independently from station to station (*i.e. i*). Note that if $\lambda_{i_2} = \lambda_{i_1}$ then $\delta_i = 0$. Like Cadigan and Dowden (2010), we assumed that the δ_i's were independent Normal random variables with mean

zero and variance $\sigma_{\delta_.}^2$. We estimated the model using the glmer() function with the lme4 R package (Bates *et al.*, 2015). We also fit linear models with τ being a function of size, depth, and regions effects.

We examined model goodness of fit using Gaussian quantile residuals and the R package DHARMa (Hartig,
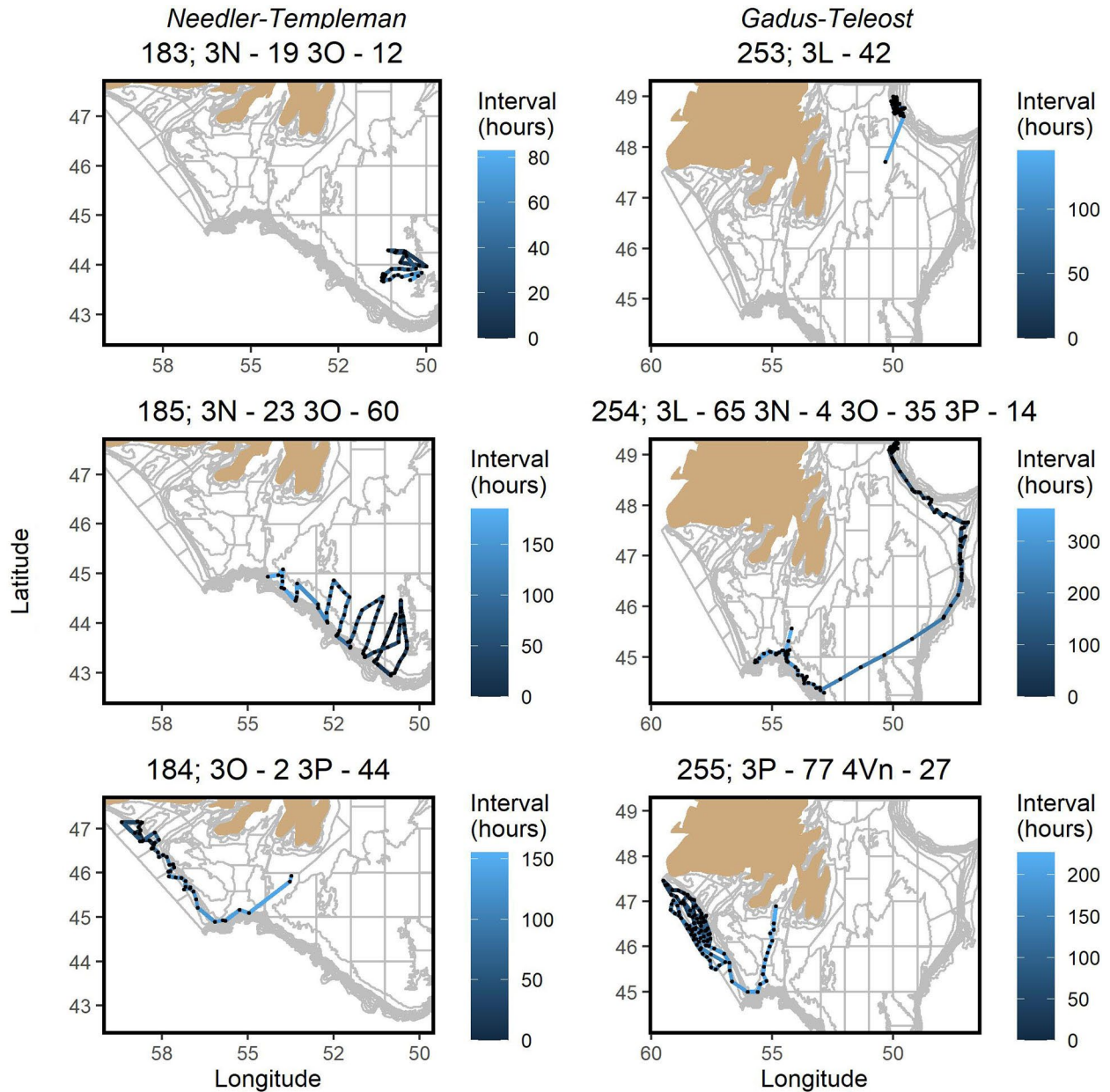
Fig. 2. Panels show the locations (points) where Thorny Skate were caught during trips (rows). Columns are for the two comparative fishing experiments. *Gadus Atlantica* and *Alfred Needler* trip numbers are indicated at the top of each panel, along with the number of paired-sets in each NAFO Division. The line segments connect the trip route and the color indicates the hours since the start of the trip.

Table 2. Number of sets (No. Sets), catch numbers (N) and percent of sets with non-zero catches for the *Gadus Atlantica*+Engel vs *Teleost*+Campelen comparative fishing experiment. Size bins were divided by an average weight (both trawls) of 0.93 kg.

Size Bin	Depth Bin (m)	Region	No. Sets	Average N per Set			Sets with N>0 (%)	
				Camp	Engel	Ratio	Camp	Engel
	<200	3L	0	-	-	-	-	-
		3NO	18	58.94	16.72	3.52	100	72
		3P	10	36.90	40.70	0.91	100	90
Large	200–500	3L	0	-	-	-	-	-
		3NO	14	10.57	6.00	1.76	100	79
		3P	87	5.39	2.14	2.52	75	75
	>500	3L	7	2.86	3.86	0.74	71	100
		3NO	0	-	-	-	-	-
		3P	0	-	-	-	-	-
	<200	3L	1	1.00	6.00	0.17	100	100
		3NO	5	4.40	8.00	0.55	80	40
		3P	8	21.38	6.38	3.35	88	100
Small	200–500	3L	30	16.63	13.17	1.26	100	80
		3NO	0	-	-	-	-	-
		3P	13	2.23	1.00	2.23	77	62
	>500	3L	69	5.32	4.70	1.13	94	86
		3NO	2	2.00	6.50	0.31	100	100
		3P	0	-	-	-	-	-

Table 3. Number of sets (No. Sets), catch numbers (N) and percent of sets with non-zero catches for the *Alfred Needler*+Engel vs *Wilfred Templeman*+Campelen comparative fishing experiment. Size bins were divided by an average weight (both trawls) of 0.93 kg.

Size Bin	Depth Bin (m)	Region	No. Sets	Average N per Set			Sets with N>0 (%)	
				Camp	Engel	Ratio	Camp	Engel
	<200	3NO	74	16.99	9.09	1.87	99	82
		3P	3	461.0	21.67	21.28	100	100
Large	200–500	3NO	20	10.45	1.75	5.97	95	70
		3P	31	30.06	11.48	2.62	97	58
	<200	3NO	21	12.48	8.52	1.46	90	76
		3P	1	75.00	60.00	1.25	100	100
Small	200–500	3NO	1	1.00	1.00	1.00	100	100
		3P	9	10.44	0.895	11.75	78	56

2022). Fig. 3 and Fig. 4 indicate that there were a few tow-pairs with relatively large catches that could potentially have large influence on the estimates of τ. We used the R package influence.ME (Nieuwenhuis *et al.*, 2012) to compute Cook's distance C_i for each tow-pair (i), which is a measure of the size of $\hat{\tau} - \hat{\tau}_{-i}$, where $\hat{\tau}$ is the estimate of τ using all tow-pairs and $\hat{\tau}_{-i}$ is the estimate with the i'th tow-pair removed. A relatively large value for C_i indicates that tow-pair has a relatively large effect on the estimate of τ.

Results

Data

The total catch-per-tow of Thorny skate (one trawl versus the other) for all comparative fishing tows are shown

in Fig. 3 for the *Gadus Atlantica-Teleost* experiment and Fig. 4 for the *Alfred Needler-Wilfred Templeman* experiment. These data are also summarized in Table 1.

Length data collected in the comparative fishing experiments are summarized in Fig. 5. These data are inconsistent with the length-aggregated results. For example, the proportion of total catch-at-length from the Engel trawl in the *Alfred Needler-Wilfred Templeman* experiment was usually around 0.9 whereas Table 1 indicated that the Campelen trawl caught about three times more Thorny skate than the Engel trawl. Thorny skate were usually measured for length in only one trawl for each tow-pair (bottom panel of Fig. 5) and this may be the reason for the difference in the length-specific and total catch results. The distribution of total catch-at-length

Table 1. Summaries of comparative fishing catches for Thorny Skate. Average weight is the average fish body weight.

		3L	3NO	3P	all
Gadus Atlantica+Engel vs *Teleost*+Campelen					
	Region	3L	3NO	3P	all
	No. Sets	107	39	118	264
Total catch Number	Camp	887	1235	1038	3160
	Engel	752	438	657	1847
	Ratio	**1.18**	**2.82**	**1.58**	**1.71**
Total catch weight (kg)	Camp	242.87	3 178.34	2 180.39	5 601.6
	Engel	341.83	1 079.11	1634.8	3 055.74
	Ratio	**0.71**	**2.95**	**1.33**	**1.83**
Average weight (kg)	Camp	0.27	2.57	2.10	1.77
	Engel	0.45	2.46	2.49	1.65
No. sets with catch > 0 (%)	Camp	94	97	78	88
	Engel	85	72	76	79
Alfred Needler+Engel vs *Wilfred Templeman*+Campelen					
	No. Sets	-	116	44	160
Total catch Number	Camp	-	1729	2484	4213
	Engel	-	888	489	1377
	Ratio	**-**	**1.95**	**5.08**	**3.06**
Total catch weight (kg)	Camp	-	2 954.8	5 642.27	8 597.07
	Engel	-	1 317.05	1 325.72	2 642.77
	Ratio	**-**	**2.24**	**4.26**	**3.25**
Average weight (kg)	Camp	-	1.71	2.27	2.04
	Engel	-	1.48	2.71	1.92
No. sets with catch > 0 (%)	Camp	-	97	93	95.6
	Engel	-	79	61	74.4
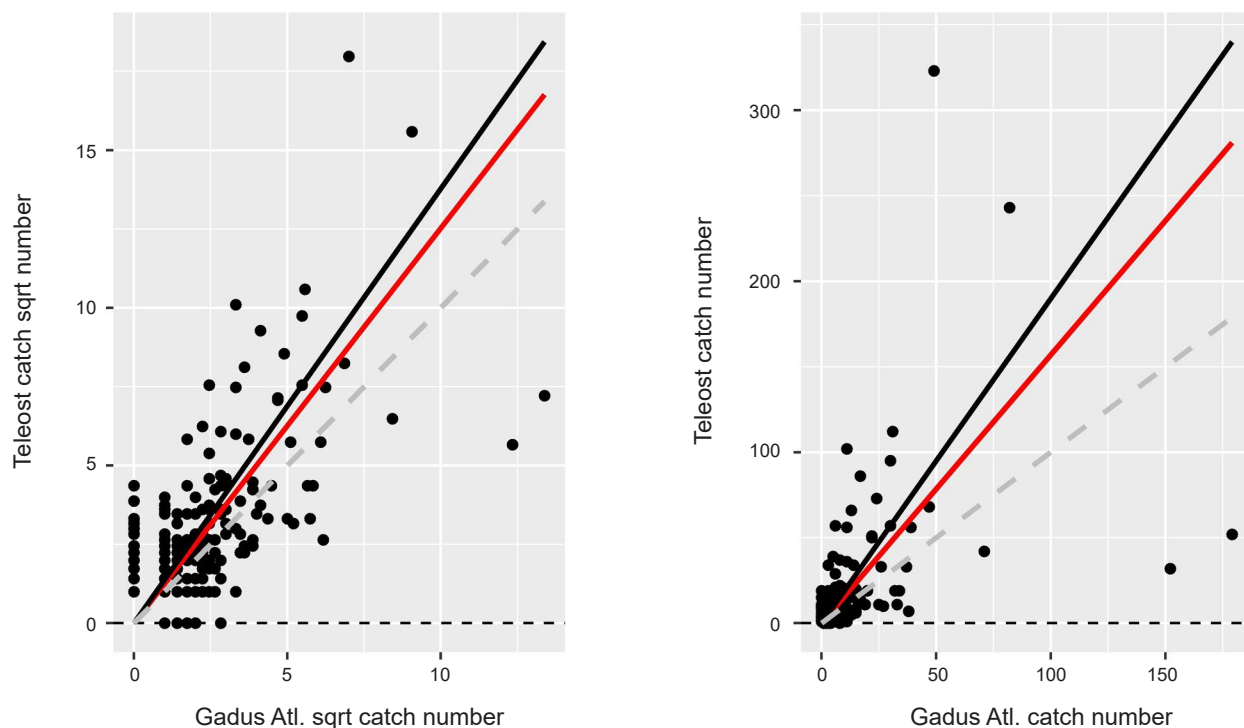
Fig. 3.   Total catch per set (right-hand panel) of the *Gadus Atlantica*+Engel vs *Teleost*+Campelen (points). The left-hand panel shows the square root of catch. The black line has slope equal to the Common τ model estimate of relative efficiency (ρ) and the red line has a slope equal to the Robson estimate in Simpson and Kulka (2005). The grey-dashed line has a slope equal to one.
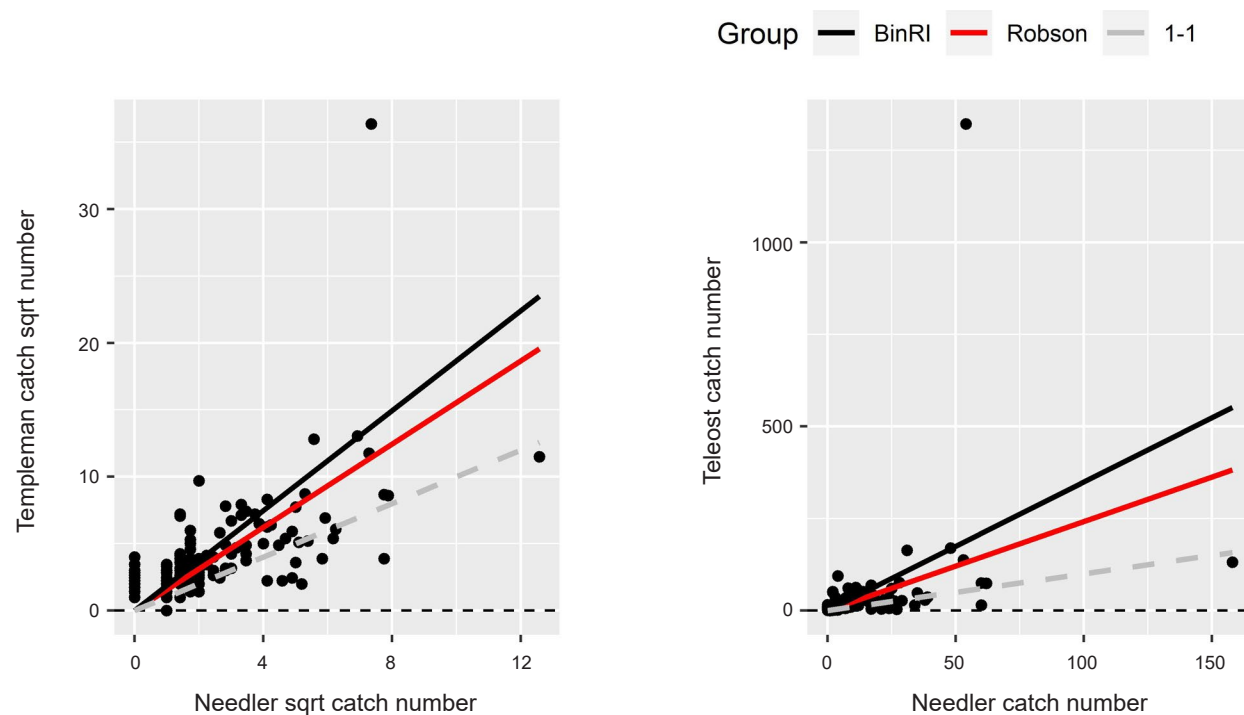
Fig. 4.   Total catch per set (right-hand panel) of the *Alfred Needler*+Engel and *Wilfred Templeman*+Campelen (points). The black line has slope equal to the Common τ model estimate of relative efficiency (ρ) and the red line has a slope equal to the Robson estimate in Simpson and Kulka (2005). See Fig. 3 for other details.

for the *Alfred Needler-Wilfred Templeman* experiment in Fig. 5 is very similar to Simpson and Kulka (2005; Fig. 3a). Hence, it seems that Thorny skate were not measured for length consistently for each tow-pair and the length data are not reliable for estimating length-effects in ρ. Samples sizes were too low to compare average catch-at-length across tows; for example, those averages were strongly influenced by two tows with relatively large catches by both vessels in the *Gadus Atlantica-Teleost* experiment.

Model

We investigated potential covariate effects by fitting a model with main effects for size class, depth, and region, and interaction between depth and region (Table 4). The data are insufficient to estimate interactions with size, and we can only assume that size effects are approximately the same at different depths and spatial regions. This model indicated that the relative efficiency of the Campelen trawl was significantly lower for smaller sizes than larger sizes

Fig. 5.   Top panel: Proportion of total catch-at-length (Engel+Campelen) from the Engel trawl for the *Gadus Atlantica*+Engel vs *Teleost*+Campelen (GT) and the *Alfred Needler*+Engel vs *Wilfred Templeman*+Campelen (NT) comparative fishing experiments. Middle panel: total catch-at-length. Bottom panel: total catch for each set for which length was sampled from at least one trawl.

compared to the Engel trawl for the *Alfred Needler-Wilfred Templeman* experiment (small size effect = -0.52). The total catch by the *Wilfred Templeman*+Campelen was 3.3 times larger than the *Alfred Needler*+Engel for tows with larger Thorny skate (Table 3), but only 1.7 times larger for tows with smaller fish. This is opposite to our expectations based on the much smaller mesh size of the Campelen trawl; however, this result may be strongly influenced by the very large catch in one tow by the *Wilfred Templeman*+Campelen (Fig. 4). The size effect was not statistically significan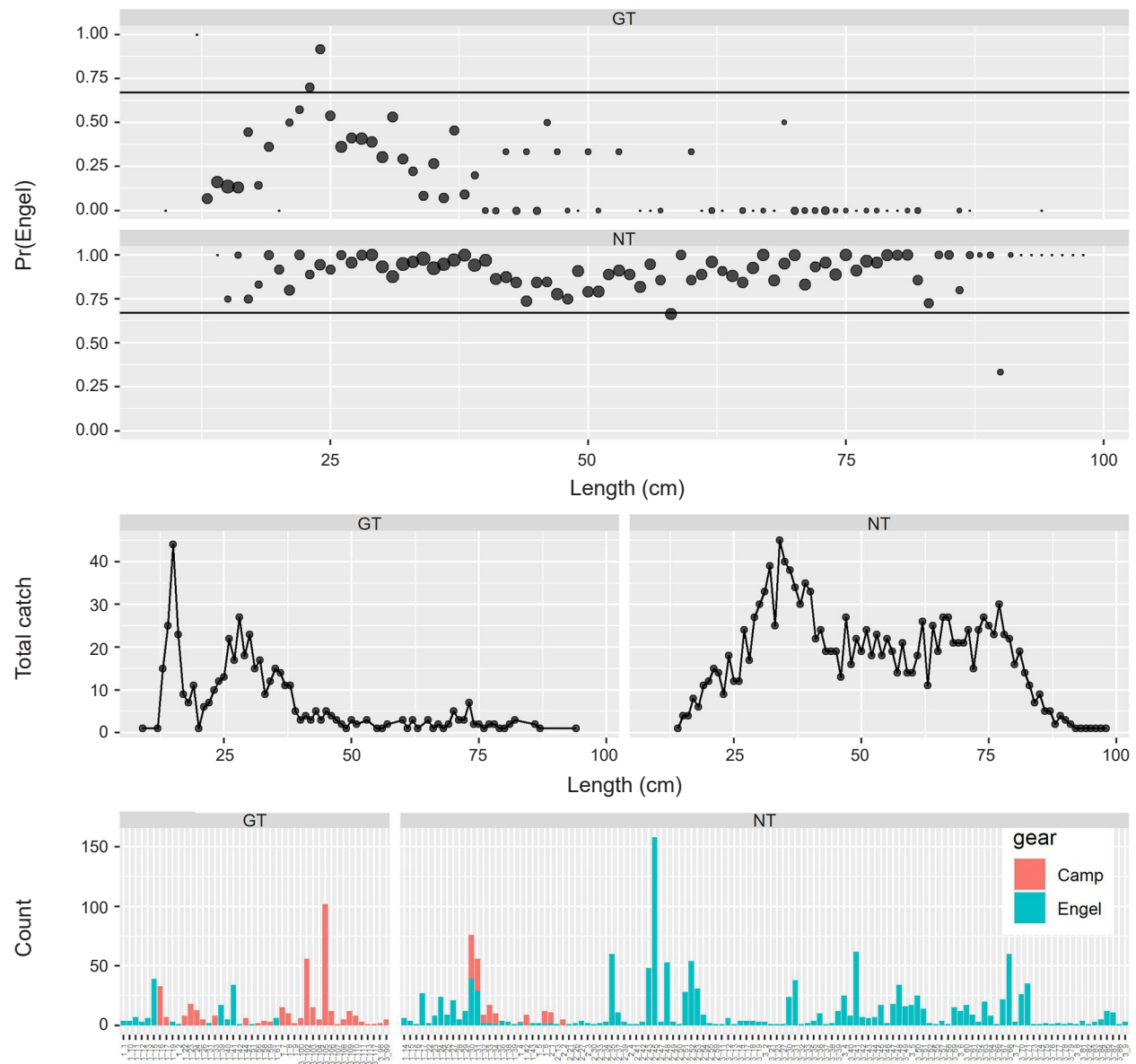t for the *Gadus Atlantica-Teleost* experiment. Some of the region and depth interaction terms were significant; however, some parameter correlations were large so we decided to fit models without interaction terms (Table 5). Size effects for both experiments still indicated lower relative efficiency for the Campelen trawl for small sized fish, whereas we expected the size effect to be substantially positive. Some parameter correlations were still large for these models, especially for the *Gadus Atlantica-Teleost* experiment. Hence, we also investigated models with only spatial region effects (Table 6), and no covariate effects at all, similar to Cadigan *et al.* (2022). These simple models indicated that relative efficiency was significantly lower in 3L compared to 3NO and 3P with the *Gadus Atlantica-Teleost* experiment, but there was no significant difference between 3NO and 3P. Also, relative

efficiency was significantly higher in 3P compared to 3NO with the *Alfred Needler-Wilfred Templeman* experiment. The estimate of ρ for 3P was about 2.4 times the estimate for 3NO.

Model selection results (Table 7) indicated that the models with spatial region effects were the most parsimonious. This model had the lowest BIC statistic for both experiments, and reasonably low AIC values. However, the model with main effects was also a good choice for the *Alfred Needler-Wilfred Templeman* experiment.

The estimates of ρ from the "Common τ" model (ρ equal for all trips, see Table 6) were significantly greater than one and greater than the Robson estimates in Simpson and Kulka (2005). The estimate for the *Gadus Atlantica-Teleost* experiment was $\hat{\rho}$ =1.90 compared to the Robson estimate of 1.57 (Fig. 3). The estimate for the *Alfred Needler-Wilfred Templeman* experiment was $\hat{\rho}$ = 3.48 compared to the Robson estimate of 2.42 (Fig. 4). The "Common τ" model 95% confidence intervals did not contain the Robson estimates for either experiment.

There was no evidence of lack-of-fit in residual diagnostics for both experiments; the "Common τ" model p-values for KS test of normality were 0.95 and 0.86 for the *Gadus*

Table 4.   Size, spatial region, and depth effects (with region-depth interactions) for relative efficiency. SE is standard error. Significant effects (at the 95% level) are in bold.

Effect	Estimate	SE	Z	P-value
Gadus Atlantica+Engel vs *Teleost*+Campelen				
τ intercept	-1.95	1.51	-1.29	0.20
Size:Small	-0.03	0.28	-0.11	0.91
Region:3NO	**3.26**	**1.53**	**2.14**	**0.03**
Region:3P	2.72	1.52	1.79	0.07
Depth:200–500	2.60	1.50	1.73	0.08
Depth:>500	2.12	1.49	1.42	0.16
Region:3NO & Depth:200–500	**-3.18**	**1.56**	**-2.04**	**0.04**
Region:3P & Depth 200–500	-2.43	1.54	-1.58	0.11
Region:3NO & Depth >500	**-4.75**	**1.80**	**-2.64**	**0.01**
Alfred Needler+Engel vs *Wilfred Templeman*+Campelen				
τ intercept	**1.02**	**0.14**	**7.41**	**0.00**
Size:Small	**-0.52**	**0.26**	**-2.02**	**0.04**
Region:3P	0.81	0.53	1.53	0.13
Depth:200-500	0.55	0.34	1.61	0.11
Region:3P & Depth:200-500	-0.39	0.65	-0.59	0.55

Table 5.   Size, spatial region, and depth effects (no interactions) for relative efficiency, without interactions. SE is standard error. Significant effects (at 95% level) are in bold.

Gadus Atlantica+Engel vs *Teleost*+Campelen				
Effect	Estimate	SE	Z	P-value
τ intercept	**0.97**	**0.44**	**2.23**	**0.03**
Size:Small	-0.20	0.27	-0.76	0.45
Region:3NO	0.12	0.40	0.31	0.76
Region:3P	0.04	0.34	0.13	0.90
Depth:200–500	-0.13	0.25	-0.51	0.61
Depth:>500	-0.69	0.35	-1.98	0.05
Alfred Needler+Engel vs *Wilfred Templeman*+Campelen				
τ intercept	**1.03**	**0.14**	**7.64**	**0.00**
Size:Small	**-0.53**	**0.26**	**-2.03**	**0.04**
Region:3P	0.55	0.31	1.78	0.08
Depth:200–500	0.44	0.29	1.52	0.13

Table 6.   Estimates of log relative efficiency (τ) and relative efficiency (ρ). SE indicates standard error. L and U are 95% confidence interval limits for ρ. Model 1 has the same ρ for each Division, and Model 2 has Division-specific ρ's.

	Region	τ	SE	ρ	L	U	σ_δ^2
Gadus Atlantica+Engel vs *Teleost*+Campelen							
1: Common τ	all	0.64	0.09	1.90	1.60	2.26	1.21
2: Region τ	3L	0.28	0.13	1.33	1.04	1.70	
	3NO	0.99	0.20	2.7	1.81	4.03	1.07
	3P	0.88	0.14	2.42	1.85	3.18	
Alfred Needler+Engel vs *Wilfred Templeman*+Campelen							
1: Common τ	all	1.25	0.11	3.49	2.81	4.32	1.12
2: Region τ	3NO	1.01	0.12	2.74	2.16	3.47	0.98
	3P	1.88	0.21	6.58	4.36	9.94	

Atlantica-Teleost and *Alfred Needler-Wilfred Templeman* experiments, respectively.

Robustness and sensitivity of estimates to a small number of tows is a concern. There were some tows with Cook's distance values (Fig. 6 and Fig. 7) greater than the rule-of-thumb threshold indicated in Nieuwenhuis *et al.* (2012). To further investigate this issue, we deleted the data for the tow in 3P of the *Alfred Needler-Wilfred Templeman* experiment (Fig. 7) with the largest Cook's distance. However, this had only minor impacts on results. The estimate of ρ decreased from 3.49 to 3.39. The Model 2

(see Table 6) estimate of ρ for 3P decreased from 6.58 to 6.17 and estimates for 3NO hardly changed at all. Also, Model 2 still fit significantly better (Chi-square p-value = 0.0007). This suggests that our results are not sensitive to a small number of anomalous tow-pairs.

Discussion

We re-analyzed comparative fishing data collected by DFO in 1995 and 1996 dealing with changes in surveys vessels, gears, and other protocols that occurred then. The data collected for Thorny skate were originally analyzed

Table 7.   Model fit statistics, and a Chi-square test that ρ was the same for each trip. Minimum values of
          AIC and BIC are in bold. p is the number of model parameters.

			Gadus Atlantica+Engel vs *Teleost*+Campelen			
Effect	p	AIC	BIC	Dev	ChiSq	df	p-value
Common τ	2	1126.20	1133.30	1122.20			
Region τ	4	1116.80	**1131.10**	1108.80	13.39	2	<0.00
Main effects	7	1117.20	1142.20	1103.20	5.62	3	0.13
Full model	10	**1114.10**	1149.80	1094.10	9.06	3	0.03
			Alfred Needler+Engel vs *Wilfred Templeman*+Campelen			
Common τ	2	738.29	744.44	734.29			
Region τ	3	727.06	**736.29**	721.06	13.23	1	<0.00
Main effects	5	**723.65**	739.03	713.65	7.41	2	0.02
Full model	6	725.30	743.75	713.30	0.35	1	0.55

by Simpson and Kulka (2005); however, the Robson conversion factors they estimated were based on a linear model of log-transformed catches and this estimator could only be applied to paired-tows in which both vessels caught Thorny skate. When one vessel had a different proportion of sets with no catch, which is the case for Thorny skate in the 1995 and 1996 DFO comparative fishing experiments (see Table 1), then this will be a source of bias. We think this is the reason why the Robson estimates in Simpson and Kulka (2005) were significantly lower than our estimates (*i.e.*, less than our lower confidence interval limits). The estimation procedures we used are consistent with current practice (Cadigan and Dowden, 2010; Miller, 2013; Cadigan *et al.*, 2022) based on the distribution of the catch from one vessel/gear, conditional on the total catch from both vessels/gears, with random effects to accommodate between-tow variation in relative efficiency or variations in the fish densities encountered by each vessel at a paired-tow site. These two sources of variation are confounded. We also demonstrated
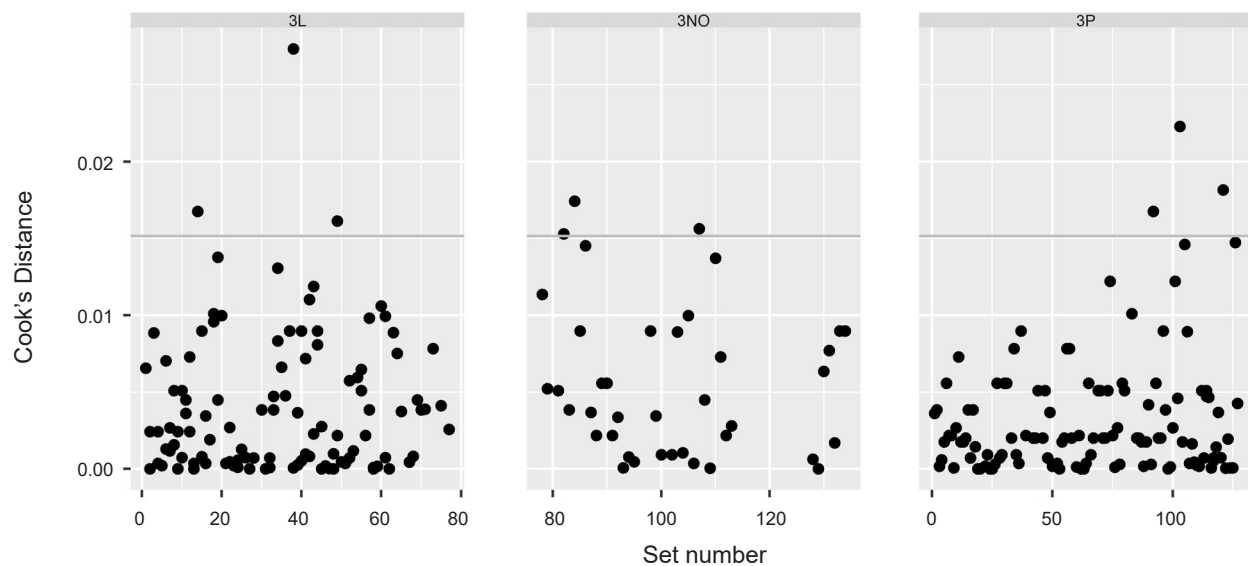

Fig. 6.   Cook's distance influence versus set number for Common τ model estimates of relative efficiency (ρ) based on the *Gadus Atlantica*+Engel vs *Teleost*+Campelen comparative fishing catches. Each panel is for a region. The grey vertical line is a rule of thumb threshold for "too influential" (Nieuwenhuis *et al*., 2012).
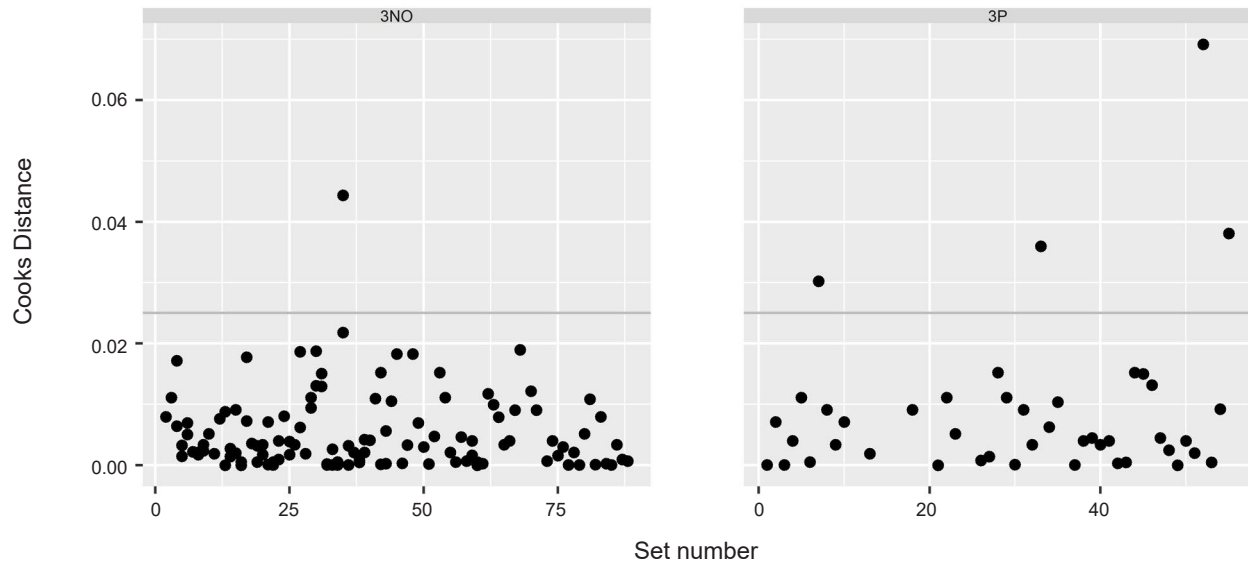
Fig. 7.   Cook's distance influence versus set number for Common τ model estimates of relative efficiency (ρ) based on the *Alfred Needler*+Engel and *Wilfred Templeman*+Campelen comparative fishing catches. Each panel is for a region. See Fig. 6 for other details.

that our estimates of relative efficiency were robust to anomalous catches which was a concern with these data (Warren, 1996; Warren *et al.*, 1997). Hence, we conclude that our estimation methodology is an improvement over Simpson and Kulka (2005). Nonetheless, our estimates of relative efficiency of the Campelen trawl survey protocol compared to the Engel were similar to Simpson and Kulka (2005) in that both approaches estimated much greater catchability by the Campelen trawl, although our approach estimated a substantially higher increase in catchability compared to Simpson and Kulka (2005). Based on a model with a single relative efficiency parameter (ρ), we estimated ρ = 1.90 for the *Gadus Atlantica*+Engel vs *Teleost*+Campelen experiment, which was 21% higher than the value ρ = 1.57 in Simpson and Kulka (2005). Similarly, we estimated ρ = 3.49 for the *Alfred Needler*+Engel vs *Wilfred Templeman*+Campelen experiment, which was 44% higher than the value ρ = 2.42 in Simpson and Kulka (2005).

We also investigated if there were differences in relative efficiency among NAFO Divisions, depth categories, or size categories. This is important because tow-pairs were not randomly allocated in the 1995 and 1996 comparative experiments and conversions factors may not be generally applicable to surveys if there were spatial/depth variation in relative efficiency or differences among sizes of Thorny skates. The data available did not support detailed modelling of these effects, especially for length-effects. Our results indicated that the relative efficiency of the Campelen trawl protocol compared to the Engel for smaller-sized Thorny skate was lower than for larger-sized fish. We found this result for both comparative fishing experiments, although the difference in relative efficiency for small and large sizes was only significant for the *Alfred Needler*+Engel vs *Wilfred Templeman*+Campelen experiment. This result was opposite to our expectation that relative efficiency for smaller sizes should be greater than for larger sizes because of the smaller mesh size in the Campelen trawl. Our size-based results were based on a post-stratification of surveys catches by average body weights caught by both vessel/gears, which we admit is a crude approach. Unfortunately, length information was not consistently collected for Thorny skate by both vessels at each paired-tow site so we were unable to implement more detailed estimators like Cadigan and Dowden (2010), Miller (2013), and Cadigan *et al.* (2022). However, overall, our model selection results indicated the most parsimonious model did not include size effects which is consistent with Simpson and Kulka (2005) who concluded that there was no evidence of size-based differential catchability of the Campelen and Engel trawls for Thorny skate. However, we conclude that there is a potential that size-based differential catchability existed but we have insufficient information from the 1995 and 1996 comparative fishing experiments to reliably estimate these effects.

Our best-fitting models included spatial regions effects (*i.e.*, NAFO Divisions). We found that relative efficiency was significantly lower in 3L compared to 3NO and 3P with the *Gadus Atlantica-Teleost* experiment, but there was no significant difference between 3NO and 3P. Also, relative efficiency was significantly higher in 3P compared to 3NO with the *Alfred Needler-Wilfred Templeman* experiment. The estimate of ρ for 3P was 2.4 times greater than the estimate for 3NO. The latter result is consistent with Cadigan *et al.* (2022) who estimated lower relative efficiency of the *Alfred Needler*-Engel trawl survey protocols compared to the *Wilfred Templeman*-Campelen in 3P for larger sizes of yellowtail flounder (*Limanda ferruginea*), witch flounder (*Glypocephalus cynoglossus*), and American plaice (*Hippoglossoides platessoides*) but little difference for Greenland halibut (*Reinhardtius hippoglossoides*). We do not know why the Campelen relative efficiency was higher in this experiment and region compared to other regions. Also, the estimates of Campelen relative efficiency for larger-sized flatfish in Cadigan *et al.* (2022), which were broadly consistent with original estimates in Warren (1996) and Warren *et al.* (1997), were in the range of 0.8–1.7 at 40 cm, which is much lower than the value we estimated for Thorny skate (*i.e.* ρ = 3.49).

Since the swept area of the Engel trawl was almost 3-times as large as the Campelen (McCallum and Walsh, 1997; Cadigan *et al.*, 2022), our results, and Simpson and Kulka (2005), indicate that the catch numbers per unit area of the Campelen trawl for Thorny skate was about nine times greater than the Engel trawl. A partial explanation is high escapement of Thorny skate through the larger bobbin footgear used with the Engel trawl compared to the smaller rockhopper footgear of the Campelen trawl, which results in more seabed contact. Walsh (1992) found that 69% of Thorny skate encountered by the Engel trawl escaped through the footgear, but the mean size of fish that escaped was only slightly less than those retained in the trawl. Similar experiments were not conducted with the Campelen trawl (*e.g.* Kulka and Miri, 2007). Hence, about 30% of the Thorny skate encountered by the Engel trawl were captured according to the results in Walsh (1992). However, if we assume that 1) there was no escapement through the Campelen rockhopper footgear, 2) Thorny skate that entered the Engel and Campelen trawls were retained equally, and 3) if the Engel trawl survey protocol encountered about three times more Thorny skate than the Campelen protocol because of the 3-times larger swept-area, then we would expect the relative efficiency of the Campelen and Engel survey protocols to be about one. Our CF estimates are much greater than one. Hence, we conclude that other factors affected catches of Thorny

skates by the two survey protocols than only swept area and escapement through the footgear, or that escapement through the Engel rockhopper gear was much greater than indicated by Walsh (1992). Evidence of higher escapement for cod and yellowtail flounder was provided by Walsh (1996). It is possible that increased retention of small fish by the Campelen trawl could account for its much higher catch numbers per unit area compared to the Engel trawl. In this case a common conversion factor for all sizes, as is currently applied in assessments of this stock, would not be appropriate. The appropriate conversion factor for large and mature sizes of Thorny skate may be lower than the one that has been used to convert Engel catches to Campelen equivalents.

The *Alfred Needler*-Engel versus *Wilfred Templeman*-Campelen comparative fishing sets in Division 3P occurred mostly along the southwest slope of the Laurentian Channel. The Campelen survey protocol seemed to be more efficient than the Engel there compared to 3NO, for Thorny skate and some flatfish species. We are unsure why this was. However, if we did not use the 3P results and only used comparative fishing sets in 3NO then the estimate of relative efficiency we obtained (ρ = 2.74) was more similar to the value ρ = 2.42 in Simpson and Kulka (2005), and their value is well within our 95% confidence interval for ρ in 3NO. Hence, we do not recommend a different Engel-Campelen conversion factor than the one currently used in stock assessments for Thorny skates in NAFO Divisions 3LNOPs (*e.g.* Simpson and Miri, 2020).

Acknowledgements

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What the Hakes? Correlating Environmental Factors with Hake Abundance in the Gulf of Maine

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Abstract

According to the latest estimates, the Gulf of Maine is currently warming faster than 99% of the world's oceans. As a result, this region has become an ideal location for research into the effects that warming has on the historical fisheries that make up this ocean basin. Both white hake (*Urophycis tenuis*) and red hake (*Urophycis chuss*) are common Gulf of Maine groundfish species, distributed both inshore and offshore. While these two species are closely related phycid hakes, white hake stocks are recognized in the Gulf of Maine as rebuilding, while red hake are above target biomass levels. As a species commonly found throughout the Gulf of Maine that prefers cooler waters (4–12°C), we hypothesize the effects of climate change might influence stock behavior, such as changes in species distribution. We used generalized additive models (GAMs) to describe the relationship between hake abundance and environmental conditions using bottom temperature, bottom salinity, depth, and catch data contributed by the Maine Department of Marine Resources during their Maine – New Hampshire Inshore Trawl Surveys of the last 22 years (2000 – 2021). Our results reveal species-specific preferences for bottom temperature (white hake ~9 to ~13°C, red hake < 12°C) and depth (white hake ~55 to ~100m, red hake > ~65m), with no significant correlation to bottom salinity. Spatially over time, white hake abundance displayed a gradual center of gravity northward, while red hake rapidly increased inshore. Overall, these results highlight species-specific density changes in inshore distribution, consistent with previous studies, with considerable implications on future management strategies in this region.

Keywords: hakes, environmental factors, Gulf of Maine, abundance, climate change

Introduction

The Gulf of Maine (GoM) is known historically for its commercial fisheries, including demersal Atlantic cod (*Gadus morhua*) and American lobster (*Homarus americanus*), and pelagic migratory Atlantic bluefin tuna (*Thunnus thynnus*) (Jones and Borque, 1998; Lotze and Milewski, 2004). These fisheries have been, and continue to be, a staple of New England's economy and culture (Lotze and Milewski, 2004). However, in recent decades the GoM has been subject to record trends in warming, faster than reported 99% of the global ocean (Pershing *et al.,* 2015), with signs of continued warming (Saba *et al.,* 2016). These unprecedented temperature increases are alarming to fishery managers, as Pershing *et al.* (2015) directly correlated the decline of the Atlantic cod fishery to such warming. Despite speculation into the drivers of

declining fish stocks, it is clear that increased warming in the GoM region will have major effects on New England communities, and native fishery species (Perry *et al.,* 2005; Cheung *et al.,* 2013; Mills *et al.,* 2013, Pershing *et al.,* 2021).

With this increasing awareness of the correlation between climate pressures and population dynamics, research into how climate change will affect the fish assemblages in the GoM have increased (Overholtz and Link, 2009; Gaichas *et al.*; 2014; Hare *et al.*, 2016). While such investigations have proven useful to track this ecosystem, finer scale, species-specific investigations are still necessary. Species-specific investigations have been conducted on a range of species including American lobster, (Goode *et al.*, 2019), Atlantic herring (*Clupea harengus*) (Moyano *et al.*, 2020), Atlantic mackerel (*Scomber scombrus*) (Overholtz *et al.*,

2011), Atlantic cod (Pershing *et al.*, 2015; Fogarty *et al.*, 2008), and northern shrimp (*Pandalus borealis*) (Richards *et al.*, 2012). However, there is still a wide range of species yet to be investigated, including GoM hakes.

White hake are a historically important groundfish species in the GoM (Ames, 2012). Found primarily in muddy substrates along the continental shelf and slope (Musick 1974; Ames, 2012), this once prominent commercial species dominated the GoM in the 1960s (Fritz, 1965). Although primarily caught as bycatch, historical reports state white hake landings were at a time higher than both Atlantic cod and haddock (*Melanogrammus aeglefinus*) in the fall months (Fritz, 1965). This dominance however was short lived, with white hake showing a decrease in landings by 62% between 1992 and 1996 (Sosebee *et al.*, 1998). In the last decade, white hake have been variously assessed as overfished and not subject to overfishing (Northeast Fisheries Science Center 2019, 2021), and not overfished and not subject to overfishing (Northeast Fisheries Science Center 2013, 2017, 2022). While white hake are common in New England commercial fisheries, they are not the only hake species found in the GoM.

Red hake (*Urophycis chuss*) are a sibling species to white hake. Unlike white hake, the red hake fishery is historically very small in the GoM (O'Brien *et al.*, 1993), occasionally targeted as a bait species but primarily landed as bycatch (New England Fishery Management Council, 2022). Currently, the GoM red hake stock status is unknown (Northeast Fisheries Science Center, 2020a) with overexploitation unlikely (Northeast Fisheries Science Center, 2020b) and catch limits well above recent landings since a productive year class in 2014 (National Marine Fisheries Service and New England Fishery Management Council, 2021).

A comparison of these two species by Markle *et al.* (1982) theorized that both ontogenetic and interspecific environmental partitioning between species was found for a range of fundamental life history characteristics. For reproduction, both species show variation with white hake employing the "get big quick" strategy, while red hake employ the "get mature quick" strategy (Markle *et al.,* 1982). These distinct strategies distinguish internal physiology of these species, focusing energy to contrasting life stages and at different rates to fulfill their respective reproductive strategies (Markle *et al.,* 1982).

While both species begin life as plankton, red hake migrate from the pelagic environment as post-larvae much earlier than white hake (~30 mm compared to 80 mm respectively) (Musick 1974; Sosebee *et al.,* 1998), settling at the bottom. At the bottom, red hake display a

symbiotic relationship with sea scallops (*Placopecten magellanicus*), residing in the scallop's mantle until they outgrow their host (~110–140 mm) (Musick, 1974; Markle *et al.,* 1982). No accounts of a sea scallop and white hake symbiotic relationship have been recorded, making this relationship unique to red hake (Musick, 1974; Markle *et al.,* 1982; Sosebee *et al.,* 1998). Early juvenile habitat selection is distinct for both species, with white hake preferring nearshore eelgrass beds and estuaries (Sosebee *et al.,* 1998), while red hake prefer sea scallop beds (Markle *et al.,* 1982; Steiner *et al.,* 1982; Haedrich, 2003). While they show early habitat separation, both later stage juveniles and adults have been shown to coexist in both inshore and offshore soft bottom habitats, with both species showing preference to moderate temperatures (4–12°C) (Musick, 1974; Markle *et al.,* 1982). While white hake are widely dispersed from Florida to Newfoundland, red hake are more geographically concentrated in the mid-Atlantic bight and GoM (Musick, 1974).

The current lack of extensive ecological knowledge in later life stages, paired with the impending pressures of climate change in the GoM, results in uncertain future viability of a GoM hake fishery. Hare *et al.* (2012) included both species in their risk assessment analysis, finding both species to be experiencing high climate exposure (temperature increase), with the biological sensitivity of red hake being low, while white hake was moderate. Hare *et al.* (2012) included a combination of factors ranging from stock status, prey specificity, and mortality. This correlates with the findings of Adams *et al.* (2018), which suggests that fishing pressure, like climate change, can also drive density changes in species distributions. Recent stock volatility of white hake in the GoM (rapid increase and decrease in population size), coupled with continued warming introduces potential drivers of increased risk, ultimately causing distribution fluctuations. Both studies highlight the need for continued investigations over a long-term data series, in aims to highlight the changing sensitivity of vulnerable species.

For this study, we aimed to correlate white and red hake abundance to environmental variables (bottom temperature, bottom salinity, and depth) over the past 22 years. While we do expect both hake species to have different environmental preferences, we hypothesize observable overlap in preference due to their close biological relationship. Based on documented habitat density changes in other species, as well as prior understanding of hake habitat preferences, we expect to observe northern, offshore movement through time for both species (Kleisner *et al.,* 2017; Adams *et al.,* 2018). Ultimately, we expect hakes to be affected in both abundance and distribution due to climate change, with

white hake being affected adversely due to their recent volatile stock trends, similar to the findings of Hare *et al.* (2012), supported by the claims of Adams *et al.* (2018).

Methods

Data Collection

White and red hake abundance and environmental data from the Maine Department of Marine Resources (ME DMR) Maine New Hampshire Inshore Trawl Survey (MENH survey) were used in these analyses. This survey has been conducted since the fall of 2000, sampling out to the 12 nm line, from Seabrook, NH to the Canada-United States border. The survey consistently has sampled depth strata from 6.9–100 m, including depths >100 m (maximum = 223.1 m) starting in 2004 (Fig. 1). This fisheries independent, multispecies trawl survey specifically targets inshore waters of both Maine and New Hampshire to enhance knowledge of exploited and

other fish populations. Furthermore, this survey is unique in that it samples areas where federal trawl surveys run by National Oceanic and Atmospheric Administration (NOAA) fisheries (Northeast Fisheries Science Center (NEFSC) offshore trawl survey) are unable to reach, providing data for inshore species distributions.

The gear for this survey consists of a modified shrimp net, which has 5.1 cm mesh wings and a 2.5 cm mesh liner in the cod end. The foot rope is 17.4 m long, and the head rope is 21.3 m long, with 15.2 cm rubber cookies. This gear was chosen due to its light weight, aiming to minimize habitat disruption during sampling, as well as its ability to sample multiple species of different sizes. Fishers in this region collaborated with ME DMR on the trawl survey design and gear type. The target trawl is aimed to be 20 minutes, with an average of 18.8 ± 2.2 minutes covering 0.78 ± 0.12 nautical miles. In addition to physical characteristics of the catch being recorded (species, length frequencies, weight), environmental
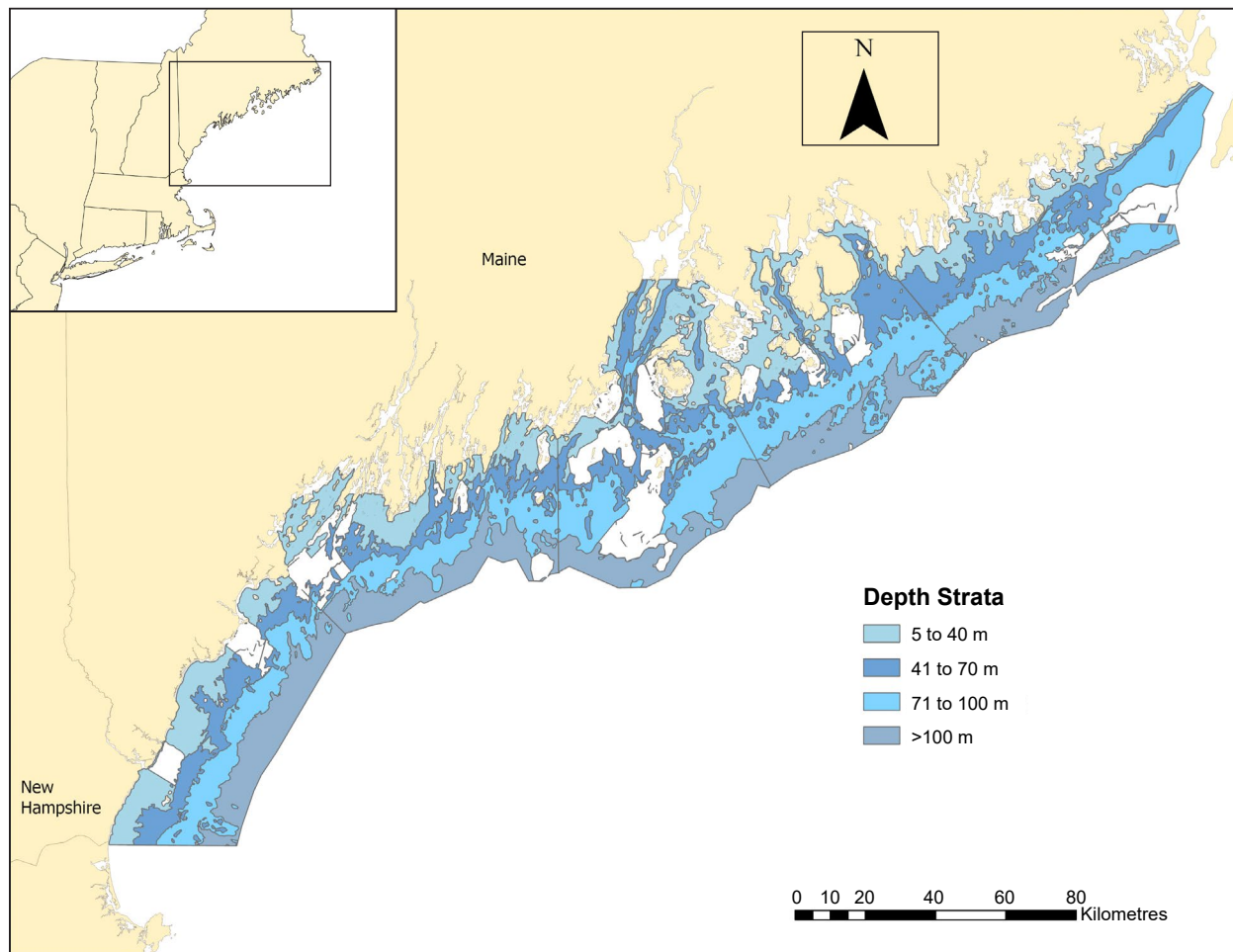
Fig. 1.   Survey depth map from the Maine-New Hampshire fall Inshore Trawl Survey from 2000–2021.

variables (bottom temperature, bottom salinity, and depth) were recorded using a SeaBird CTD (19plus) after the trawl net is recovered on deck. This analysis only includes trawls where all three environmental conditions (temperature, salinity, and depth) as well as catch were recorded, excluding those where data was missing (83 trawls). Length frequencies were conducted for both white and red hake, for all tows, up to ~125 individuals. In cases where total catch for a species was > ~125 individuals, a random subsample was taken later extrapolated to calculate the total catch. While these trawl surveys have been conducted both in the spring and fall, ~87% of white

hake and ~82% of red hake sampled (by both weight and number caught) came from the fall survey and therefore only fall survey data was used in our analysis. This was to be expected based on the known seasonal distributions of hake in this region (Fahay and Able, 1989; Ames 2012) .

Generalized Additive Models

We compared environmental conditions collected during sampling to the overall biomass of both white and red hake sampled. Abundance is calculated by the following formula, where X represents either white or red hake:

$$X \text{ Abundance} = \frac{\text{Number of X caught}}{\text{Length of Tow} * \text{Average Wing Spread of Trawl Net}}$$

The length of each tow (m) was recorded for each survey set, and the average wing spread (m^2) of the net was previously calculated by ME DMR.

From the abundance calculation for each individual tow over the 22 years of sampling, generalized additive models (GAMs) using RStudio (version 4.1.2 using the mgcv package) were developed to relate hake abundance to each continuous environmental variable (bottom temperature, bottom salinity, depth). GAMs are extensions of generalized linear models (GLMs), where data does not fit a linear trend, but is rather more complex and nonlinear (Hastie and Tibshirani, 1987). The GAMs were fitted with the following equation:

$$E[y] = g^{-1}\left(\beta_0 + \sum_k S_k(X_k)\right)$$

In the GAM equation, E[y] is the expected value of the response variable (in this case species abundance), g is the link function, β_0 is the y-intercept, X is an explanatory variable (in this case a set of environmental conditions), k is the number of knots, and S_k is the smoothing function for the explanatory variables.

Due to identical number of sampling attempts and conditions for both species (multispecies sampling), we chose to run identical model conditions for both species, with only the dependent variables (species abundance) changing. We deemed that the high overlap in model conditions will allow us to compare these species over the last 22 years with increased confidence.

Before models were constructed, multicollinearity between environmental conditions were checked using the corrplot package in RStudio (Wei *et al.,* 2017). No two environmental variables exceeded a correlation coefficient of 0.5, suggesting multicollinearity was

not significant. Abundance estimates were scaled by a factor of eight (smallest factor possible) and rounded to whole integers for modeling purposes. For each GAM, logarithmic links with cubic regression splines were fitted, in order to increase the smoothness of the curve. Both models employed four degrees of freedom, to reduce the likelihood of overfitting the model, as well as creating unrealistic ecological predictions based on the limited explanatory variables (Lehmann *et al.,* 2002; Mohan *et al.,* 2017). A negative binomial distribution was used, due to a high abundance of zeros in the data set (Drexler and Ainsworth, 2013). GAM response plots were generated for significant environmental variables (bottom temperature and depth), whereas nonsignificant variables (salinity) were not investigated further (Table 1). In order to examine the overall fit of both generated models, percent deviance explained (DE) was calculated using the following equation and reported (Table 1):

$$DE = \frac{null\ deviance - residual\ deviance}{null\ deviance} * 100$$

Temporal Variations

In addition to the generated GAMs for both white and red hake, a mapped time series of trawl data over the entire survey region was conducted. Trends in white hake abundance, red hake abundance, and bottom temperature were visualized over the past 22 years to examine spatial and temporal variability in this survey. Maps were created using ODV (version 5.5.2) using weighted average gridding. In aims to reduce outliers and display data trends, the 22-year sampling period was split into three sampling intervals of seven to eight years: (2000–2006, 2007–2014, and 2015–2021). Depth data was pooled across the 22-year sampling period (Fig. 1) and mapped using the same procedure.

Table 1: Number of white hake and red hake landed per fall survey season. Number sampled per tow is an average of all of tows conducted for that year. Average and Standard Deviation of all three values are reported as well.

| | | Number Sampled Tow | |
Year	Number of Tows	White hake	Red hake
2000	77	12.21	26.03
2001	51	22.65	21.69
2002	55	26.07	14.86
2003	48	25.69	11.59
2004	57	17.11	34.73
2005	43	48.14	24.20
2006	73	30.44	18.40
2007	73	30.32	52.46
2008	64	89.23	87.02
2009	78	34.40	75.92
2010	74	21.78	101.48
2011	73	34.58	26.03
2012	86	11.43	21.69
2013	85	10.58	14.86
2014	93	29.34	11.59
2015	79	84.97	34.73
2016	83	21.83	24.20
2017	101	30.39	18.40
2018	95	73.78	52.46
2019	99	41.00	87.02
2020	91	28.09	75.92
2021	72	17.94	101.48
$\bar{x} \pm \sigma$	82.63 ± 24.35	19.24 ± 21.76	40.36 ± 38.89

Results

Overall, 1590 ($\bar{x}_{Year} \pm SD = 82.63 \pm 24.35$) individual trawls spanning from the fall of 2000 through the fall of 2021 were analyzed (Table 1). In total, 57 555 white hake were caught ($\tilde{x} \pm SD = 19.24 \pm 21.76$ per tow), and 77 029 red hake were caught ($\tilde{x} \pm SD = 40.36 \pm 38.89$ per tow) over the 22-year sampling period (Table 2). Length frequency data collected suggests the majority of the catch were small individuals ($\leq$30 cm, white hake = 86%, red hake = 78%. Fig. 2). Distribution of length frequencies were consistent over the three sampling

intervals. Environmental conditions were measured for all analyzed trawls, covering a wide range of temperature (3.6–16.6°C), salinity (26.0–34.8 ppt), and depth (6.9–223.1 m).

Abundance Trends

Results indicate similar trends between white and red hake catch over the past 22 years (Fig. 3), with relatively low catch in the first few years of sampling (2000 – 2005). This trend changes after 2005, with both species displaying an increase in catch, with white hake hitting a maximum in

Table 2:   Variable range and deviance explained for significant environmental variables (bolded, p<0.05) for generated generalized additive models (GAMs) collected during trawling for both white hake and red hake.

Species Abundance	Temperature (°C) (3.6–16.6)	Salinity (ppt) (26.0–34.8)	Depth (m) (6.9–223.1)	DE (%)
White hake	**< 0.001**	0.383	**< 0.001**	11.7
Red hake	**< 0.05**	0.357	**< 0.001**	31.5

2008, and red hake hitting a maximum in 2010, with both species returning to lower abundance until around 2013. Around this time, both species begin to diverge in trends, with white hake displaying volatile abundance (sharp increase and decrease in abundance), while red hake have displayed an almost uninterrupted growth. Since 2017, white hake have shown a continuous decline in catch for this survey, the longest decline observed in the survey's 22-year history.

Generalized Additive Models

GAMs were generated for both white and red hake, each with a deviance explained of 11.7% and 31.5%

respectively. For both models, salinity was found to be an insignificant variable in abundance calculation, therefore was excluded from each model and not plotted. Both bottom temperature and depth were both found to be significant and these variables were included in each model. From the generated GAM response plots, we observe that white and red hake display distinct variations in abundance based on the environmental variables (bottom temperature and depth).

Bottom Temperature

For white hake, bottom temperatures ranging from ~9 to ~13°C displayed a positive influence on abundance.
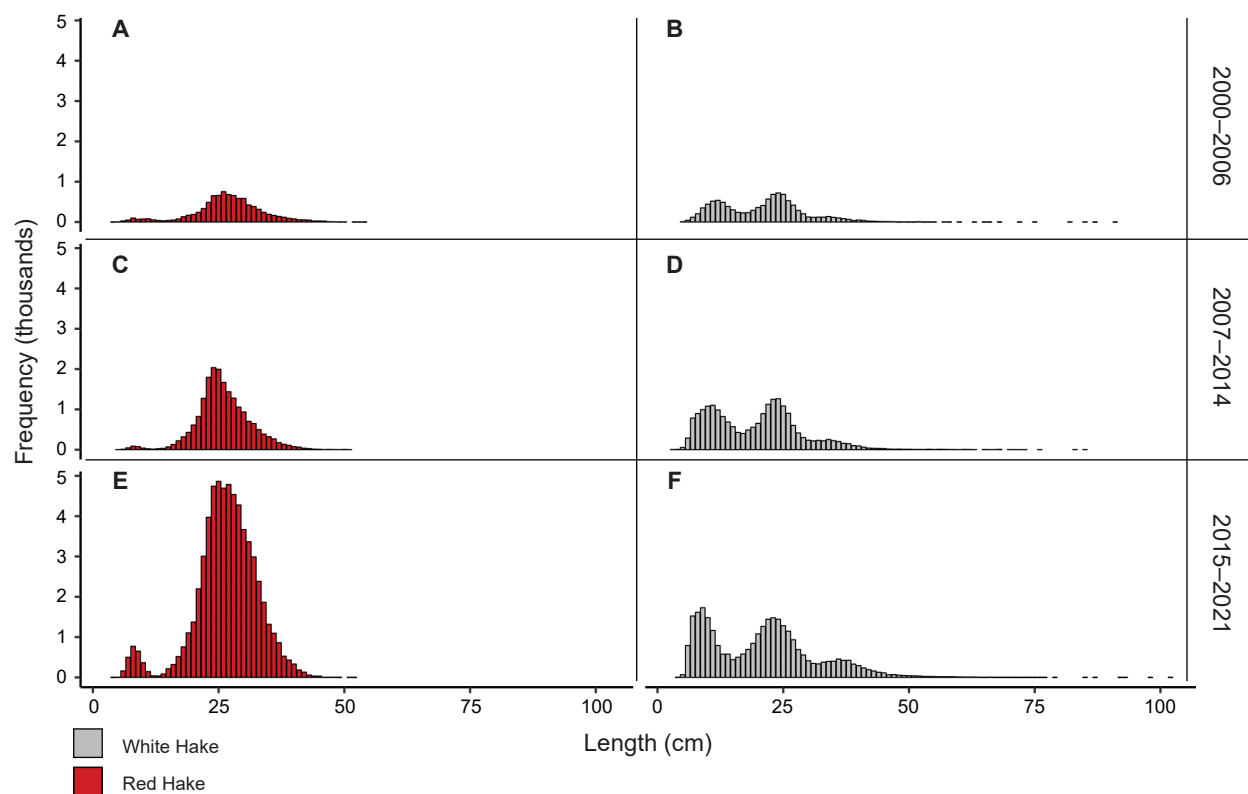
Fig. 2.   Length distribution of red hake (**A, C, E**) and white hake (**B, D, F**) sampled by the Maine-New Hampshire fall Inshore Trawl Survey from 2000–2006 (**A** and **B**), 2007–2014 (**C** and **D**), and 2015–2021 (**E** and **F**). Column widths are 1 cm increments. Length data was collected up for each species, per trawl up to ~125 individuals per species.
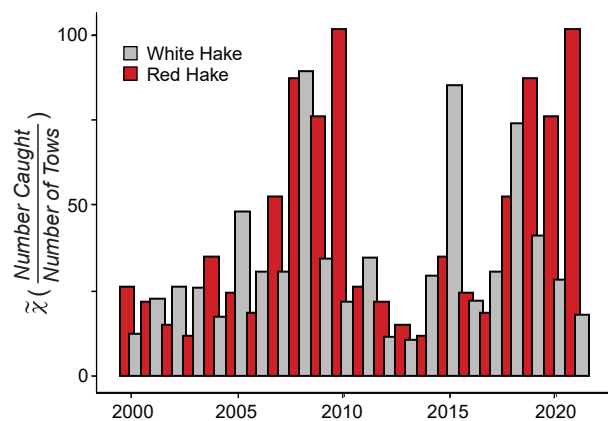
Fig. 3.   Trends in average number caught per trawl for both white hake and red hake in the Maine-New Hampshire fall Inshore Trawl Survey from 2000–2021.

Temperatures outside that range showed a negative correlation to abundance, with warmer temperatures (>~13°C) showing a considerable decrease in abundance. Of the total 57 555 white hake caught, 89% (51 402 white hake) were caught within this positive temperature window. Red hake showed a variation of this trend, where warmer temperatures (>~12°C) showed a negative effect on abundance, with all temperatures colder (<~12°C) displaying an increased positive trend (Fig. 4). Of the total 77 029 red hake caught, 96% (73 975 red hake) were caught within this positive temperature window.

Depth

For white hake, abundance showed positive correlation to a distinct range in depth (~55 to ~110 m). Depths outside this range display a negative trend in abundance, however, deeper waters (>~200 m) also display a positive trend in abundance. Of the total 57 555 white hake caught, 60% (34 567 white hake) were caught within this positive depth window. Red hake displayed a wide range depth where abundance was positively influenced in deeper waters (>~65 m, Fig. 4). Of the total 77 029 red hake caught, 93% (71 451 red hake) were caught within this positive depth window. We observe that 74% of the white hake caught were in waters <100 m, while 64% of red hake were caught in waters >100 m.

Temporal Variations

A time series of spatial distribution of fish density for both white hake and red hake as well as bottom temperature for three sampling intervals (2000–2006, 2007–2014 and 2015–2021) over the 22-year sampling period was conducted (Fig. 5). As previously stated, the sampling of waters >100 m started in 2004, which is observed in our sample distribution, where tows >100 m made up 18% in the first interval (2000–2006), compared to 28% (2007–2014) and 27% (2015–2021) in the following intervals respectively. These time series showed changes in both bottom temperatures observed, as well as in hake abundance over the sampling intervals.
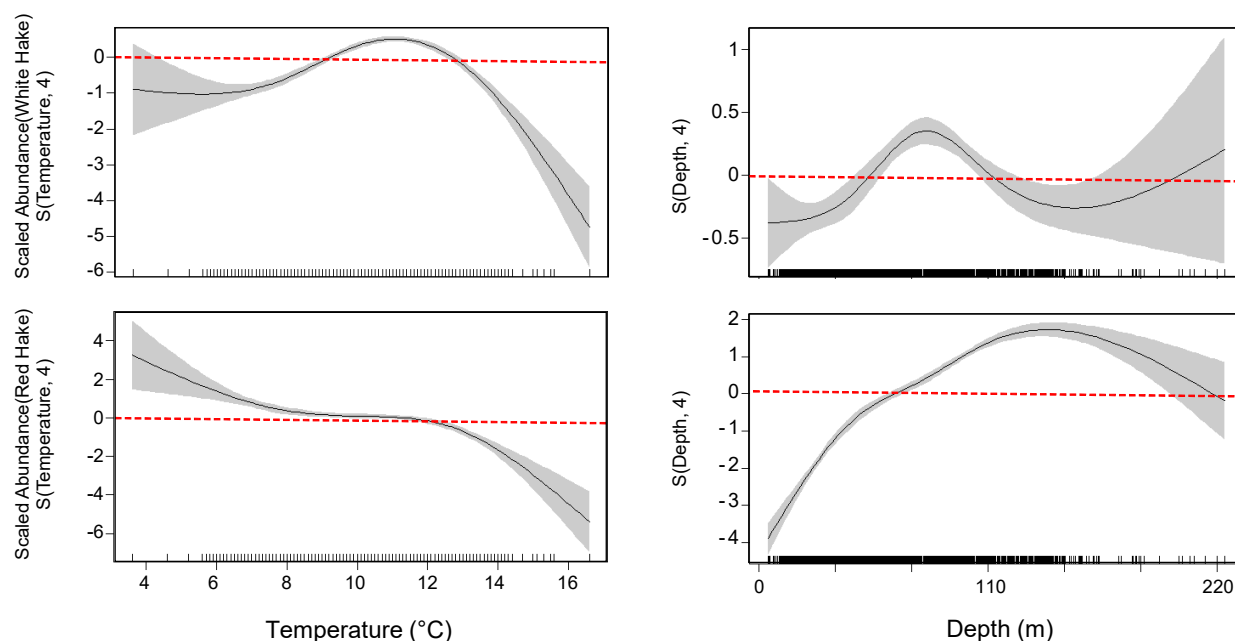
Fig. 4.   Generalized Additive Model (GAM) response plots in which display the additive effect of environmental conditions on the scaled abundance of white and red hake caught in the Maine-New Hampshire fall Inshore Trawl Survey from 2000–2021. The dotted red line indicates threshold where the additive effect is 0.

White Hake

White hake catch show northern trends in abundance, in this spatially limited survey. Between the first (2000–2006, Fig. 5A) and second (2007–2014, Fig. 5B) sampling intervals, there are no considerable differences observed. A major hotspot in the mid sampling regions slightly intensifies and expands between periods, as well as a slight uptick in catch in the northern regions. A major change occurs between the second (2007–2014, Fig. 5B) and third (2015–2021, Fig. 5C) sampling intervals, where there is a rapid density change in northern waters. Major aggregation sites, once located in the mid sampling region, became more prominent in northern areas, and spread across the region, opposed to the once highly concentrated areas. It also appears that there is a wide depth gradient preference in this last sampling interval, with white hake being caught in all depth strata (Fig. 5C).

Red Hake

Inshore red hake abundance showed a clear increase, in a spatially limited survey. Between the first (2000–2006, Fig. 5D) and second (2007–2014, Fig. 5E) sampling intervals, there is a clear trend of aggregation sites emerging in the mid to southern deeper inshore regions, with areas surrounding also showing increased abundance. The northern most aggregation site in the second sampling interval (Fig. 5E) was also prevalent during the first sampling interval (Fig. 5F), but of less significance. A continued change occurs between the second (2007–2014, Fig. 5E) and third (2015–2021, Fig. 5F) sampling intervals, with extended aggregation sites in the deep inshore regions of the survey. Red hake abundance appears to spread along this deep inshore area, with aggregations extending both north and south.
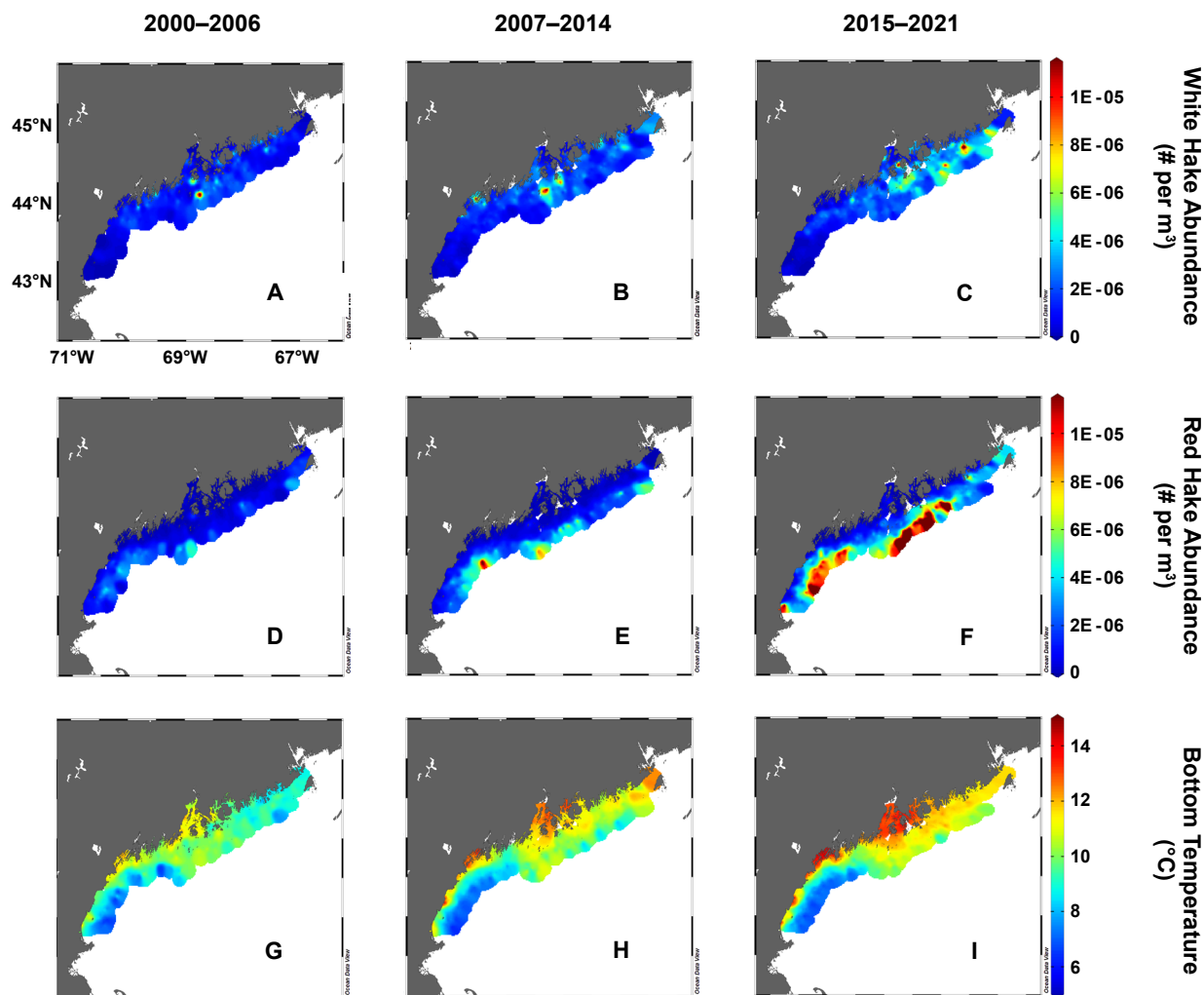
Fig. 5. Spatial and temporal trends in white hake Abundance (**A, B, C**), red hake Abundance (**D, E, F**), and Bottom Temperature (**G, H, I**) from the Maine-New Hampshire fall Inshore Trawl Survey from 2000–2021. Maps summarize a range of years combined for clearer analysis (2000–2006 (**A, D, G**), 2007–2014 (**B, E, H**), and 2015–2021 (**C, F, I**).)

Bottom Temperature

Over the 22-year sampling period, there is a distinct bottom temperature warming trend displayed in the inshore sampling region. Between the first (2000–2006, Fig. 5G) , second (2007–2014, Fig. 5H), and third (2015–2021, Fig. 5I) sampling intervals, bottom temperatures display an increase, with warming of northern deep water regions as well. Only the southern deep water sampling region displayed a consistent cool bottom temperature of the entire sampling period. Over the three sampling intervals, we observe a clear increase in stratification of bottom temperature between areas, with less uniformity throughout the inshore environment.

Discussion

Based on our analysis, white and red hake display distinct environmental preferences for bottom temperature and depth, with no significant response to bottom salinity. Spatial and temporal trends in hake abundance and bottom temperature show correlations between northern, inshore deep water density increases in abundance, paired with inshore shallow water warming. Both species display different responses to a warming inshore environment, with white hake displaying a narrow range in preferred bottom temperature and depth, while red hake displaying a single threshold value for both environmental conditions. This highlights distinct behavioral responses to change can occur between two closely related species in the same region.

Environmental Preferences

Both white and red hake show a strong preference towards cold waters (<~12°C), with both species abundances displaying a negative relationship with warmer waters (>~13°C). White hake display a temperature corridor, (~9 to ~13°C) a characteristic not displayed by red hake. Both species displayed a distinct preference for deeper waters (> 65 m), with red hake having an extended depth range into deeper areas. Due to the nature of this survey, adults and juveniles of both sexes were all sampled for both species, with the assumption that their habitat selection is consistent in this survey region, regardless of sex or age. Due to the lack of extensive sampling of all age classes for both species, a pooled approach was deemed appropriate for this analysis. The majority of the hake sampled were small individuals (≤30 cm, white hake = 86%, red hake = 78%, Fig. 2), which may overshadow environmental preferences of the larger fish sampled. Also as previously mentioned, the sampling of waters >100 m did not begin until the fall of 2004, potentially influencing these results, especially for depth.

White Hake

In a species overview by Chang *et al.* (1999), juvenile white hake showed a preference of 7–16°C in the fall survey months, at depths <75 m. These results are similar to previous studies, which report a preference for cooler waters (4–12°C) (Musick, 1974; Markle *et al.,* 1982). Our model demonstrates a species more tolerant of warmer waters (~9–12°C), similar to that of Han and Kulka (2009) (4–7°C), who described white hake aggregations in the warmer southwest waters of the Grand Banks. These results indicate that white hake have both a distinct and narrow temperature preference, which may cause concern in a warming ecosystem.

Chang *et al.* (1999) reports age class separation across a depth gradient, with older fish found in deeper waters offshore. Since our study was conducted in inshore waters, and primarily sampled smaller fish (≤30 cm, 86%, Fig. 2) the observed behaviors/preferences described here are limited to specific size classes. This explains the preferred depth range in the generated GAM model, displaying the depth preferences of the juveniles/developing adults. The preferences of larger, adult white hake were likely overshadowed in this study, with future research focusing on their offshore habits needed.

Red Hake

As reported in Fahay (1999), juvenile and adult red hake are most prominently found in temperatures ranging from 3–16°C. The results of this study show red hake prefer colder waters (<~12°C), with a strong negative correlation to warmer waters. This is similar to the findings of Fahay (1999), however our results suggest a lack of tolerance for warmer waters which has not been previously described. Similarly, Fahay (1999) found juvenile red hake most prevalent in shallower waters (<120 m) and adults even deeper (<300 m), which overlaps with our findings (~65 m–220 m). We found that 64% of the red hake landed were in waters >100 m, with a majority of these individuals being smaller fish (≤30 cm, 78%, Fig. 2). This is similar to the white hake results, where the preferences of juveniles were shallower waters (<120 m) and deeper waters for adults (120 m–220 m), with red hake showing a wider range offshore during their juvenile life stage compared to white hake. This extended range may allow these developing red hake to escape the pressures of a warming inshore environment, a behavior white hake are not displaying.

Habitat Selectivity

In addition to the habitat preferences of white and red hake being displayed in our analysis, we must also

consider the reasoning behind their choice of residency. A major component of a species habitat selectivity is prey availability, competition, and predator avoidance (Kotler and Holt, 1989; Hugie and Dill ,1994). The diet of juveniles of both species mostly consists of polychaetes, copepods, shrimps, and other crustaceans, with adult diets consisting mainly of a variety of fish species and squids (Langton and Bowman, 1980; Steiner *et al.,* 1982; Garman, 1983; Bowman and Michaels, 1984). Both species as juveniles have many predators as well, including larger hake, other gadoid fishes, elasmobranchs, sea birds, and pinnipeds. The habitat selectivity of these individuals is hypothesized to be a combination of factors (prey availability, predators, environmental conditions), with this study focusing on portion of that specific habitat niche (environmental conditions: bottom temperature and depth). Identifying these other factors is key, as they have the potential to better describe the habitat preferences of these species compared to environmental conditions.

Developing juvenile white hake prefer inshore eelgrass beds (Sosebee *et al.,* 1998) but have shown the ability to settle in deeper waters (70–80 m) on the Grand Bank (Han and Kulka, 2009). Juvenile red hake prefer sea scallop beds (Markle *et al.,* 1982; Steiner *et al.,* 1982; Haedrich, 2003), with both species moving away from eelgrass beds but still occupying shallower waters as they mature. While we do not observe our samples to be of developing hakes, it is still noteworthy that developing individuals can tolerate shallow, warm waters during development. Han and Kulka (2009) suggests that white hake recruitment on the Grand Bank is highly impacted by environmental conditions, specifically near surface currents impacting settlement rate. These factors were not investigated in this study but may explain density changes in species distribution over the study period.

Additionally, both species have been shown to have strong preferences to fine grain, muddy substrates (Chang, *et al.,* 1999; Fahay, 1999), all of which are details that were not investigated in this study. Similar to conclusions made by Kleisner *et al.* (2017), accurately predicting a species future habitat requires complex knowledge that is currently unknown for our study species. Extended research incorporating additional environmental and biological factors would provide stronger habitat predictions.

Temporal Variations

Over the 22-year sampling period, the data collected displays distinct variations in white and red hake abundance and habitat selectivity, as well as warming trends in bottom temperature. Based on the GAM model

results, we conclude that there is overlap between the habitat selectivity trends of these species over time with the warming of the inshore waters, with the caveat that other unmeasured factors are also in play.

White Hake

The temporal trends in white hake abundance over the 22-year sampling period supports our hypothesis regarding the species-specific response to a warming inshore region. White hake display a northern movement in abundance, as well as an uptick in aggregations in later years, despite a decrease in abundance. These results align with findings of Hare *et al.* (2012) and Adams *et al.* (2018), which suggest that a combination of fishing pressures and a warming environment contribute to white hake distribution variations. As described in Pershing (2015), northern migrations of cool-water dependent Atlantic cod as a result of a warming GoM directly corresponded to the collapse of the once prominent fishery. This northern movement of multiple GoM species has been described as a result of a shifting Gulf Stream and weakening Atlantic meridional overturning circulation (AMOC), with risks of permanent changes in local species distributions (Mountain and Kane, 2009; Nye *et al.,* 2011).

Red Hake

Unlike white hake, red hake did not exhibit a distinct northern movement as bottom temperatures increase, but rather a movement towards deeper inshore areas. Similar to white hake, red hake have displayed a preference for deeper waters (up to 220 m) and cooler temperatures (up to 16.6°C), making their lack of distinct northern movement highly species specific. While it is theorized that species that fall within similar taxonomic groups respond to climate pressures similarly, species specific habitat preferences may affect the way a species behaves to a changing climate (Pinsky *et al.,* 2013). A study by Kleisner *et al.* (2016) described white hake as higher trophic level species compared to red hake, with a broader offshore range. This distinction was theorized to drive distribution shifts in both latitude and depth (Kleisner *et al.,* 2016). While white hake may have the ability to thrive in northern regions due to a combination of desirable environmental variables, red hake may be able to thrive in more offshore regions instead, without the necessity of moving poleward.

Bottom Temperature

As previously suggested by Pershing (2015), a poleward shifting Gulf Stream and weakening AMOC is theorized to be the main contributor to warming in the GoM, impacting the behavior of species within the region. The results of

this study are consistent with previous research, which expects bottom temperatures in the region to increase through time, especially in fall months (Pershing *et al.,* 2015, 2021; Thomas *et al.,* 2017), thus reducing suitable habitat for many species (Kleisner *et al.,* 2017). Only the deep water southern region displayed a continued cool temperature, most likely a cause of depth stratification and other external forcings (currents, bathymetry). While our time series covers an extended period of time, sampling only occurred during the fall months, thus do not provide the level of fine scale detail of a year that other studies have reported. Therefore, we can only attribute the change in bottom temperature recorded for this specific season, in the inshore survey area.

Preferences of smaller hake

Although we observe correlations in our spatial data to bottom temperature, we do acknowledge that other factors not measured in this study may also affect hake habitat preferences. Our trawl data suggest that the majority of the hake samples were smaller individuals (≤30 cm, white hake = 86%, red hake = 78%, Fig. 2), therefore we feel confident that our observed temporal variations may be aligned with recruitment success and the settling preferences of juveniles/developing adults. We observe white hake preferring northern regions, while red hake preferring deeper areas of the inshore GoM. Investigations into the historical preferences of the juveniles during times of low and high abundance would allow us to conclude if juvenile hake habitat preferences are changing or constant based on recruitment success. As the GoM continues to change, understanding the preferences of juvenile groundfish like hake is essential for future management.

Limitations and Future Study

While our findings are informative for two understudied hake species in the GoM, we do acknowledge the limitations of this study. Primarily, our data comes only from fisheries independent data, targeting only inshore waters during the fall months. While this survey has strength in determining inshore presence or absence in the fall months, it does not consider seasonal shifts in abundance across the entire GoM. We propose further study combining inshore surveys and offshore surveys (*i.e.* NEFSC offshore trawl survey), as well as combining fisheries independent data sources with fisheries dependent data. Furthermore, habitat preference is very complex to determine, and involves a range of variables that were not recorded for this study (substrate type, prey, predators, currents, reproduction, etc.). While we are confident in our findings that these two hake species have specific bottom temperature and depth preferences,

understanding their entire scope of habitat selectivity is still widely unknown. With the lack of sampling of deeper waters (> 220 m), the trend in both white and red hake abundance in deeper waters is unclear based on these models. While depth in the GoM is mostly constant, the impending threat of temperature shifts due to climate change causes greatest concern to both of these cold-water hake species. Future research using data from the NEFSC offshore trawl survey should be conducted to investigate deeper habitats in the GoM.

Conclusion

While our study is the first investigation into the direct effects of climate change on inshore white and red hake populations, there is still much unknown. The scope of sampling gives us a limited understanding regarding the pressures both species are experiencing as a result of a warming environment. While these two species share many physical and morphological characteristics, their habitat preferences and tolerance are very dissimilar. These preferences go as far as each species displaying a unique response to their changing environment. While this study does not consider all drivers of habitat preferences, the observed patterns of both species through time is hypothesized to help better inform management practices as well as highlight the gap in published data regarding these species, specifically in inshore areas. Specifically in Canadian waters, environmental aspects are considered for stock assessments (Kulka *et al.*, 2022), a practice we suggest implementing in the GoM for hake. Ultimately, unlike the findings of Pershing *et al.* (2015), we do not feel that there is currently enough data analyzed to strongly support a proper mitigation plan with both white and red hake, although we feel confident that increased investigations into their life history will allow managers the ability to impose future management decisions with confidence.

Acknowledgments

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Analysis of bycatch patterns in four northeastern USA trawl fisheries

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Abstract

Discards from commercial fisheries have been linked to detrimental effects on ecosystems and stocks of living marine resources. Understanding spatial and temporal patterns of discards may assist in devising regulatory practices and mitigation strategies and promote sustainable management policies. This study investigates data from bycatch monitoring programs using a machine learning approach. We used a gradient boosting classifier for describing catch and bycatch patterns in the U.S. Mid-Atlantic Black Seabass (*Centropristis striata*), Summer Flounder (*Paralichthys dentatus*), Scup (*Stenotomus chrysops*), and Longfin Squid (*Doryteuthis pealeii*) fisheries. We used oceanographic, biological, spatial, and fisheries data as explanatory model features. We found positive associations between target species volume and bycatch. Although we found that sea surface temperature and year were important model features, the direction of impact of those predictors was variable. From our findings, we conclude that machine learning approaches are promising in supplementing traditional methodologies, especially with the increase in data availability trends.

Keywords: bycatch, machine learning, finfish, fisheries management, demersal fishery

Introduction

The discard of unwanted catch is a long-reported problem in many fisheries worldwide (Alverson *et al.,* 1994; Davies *et al.,* 2009; O'Keefe *et al.,* 2014; Savoca *et al.,* 2020). Kelleher (2005) estimated that the annual magnitude of worldwide discarded biomass averaged 7.3 million tons or around 8% of the total global catch. In that analysis, Kelleher (2005) reported that demersal finfish trawling had a relatively low discard rate but contributed substantially to the total amount of discards worldwide because of its ubiquity. The impacts of discards are both economic and ecological.

Direct economic losses of bycatch occur to fishers in two ways. The first is the cost to fishers when they must handle and discard unwanted taxa in terms of fuel and manpower (Alverson *et al.*, 1994). Indirect economic impacts on the fishers include the costs of onboard observers and efforts for quota monitoring for bycatch. The cost of global monitoring, assessment, and management is estimated at $4.5 billion a year, though it is unclear what proportion of this cost is attributable to bycatch monitoring (Alverson

et al., 1994). In many fisheries, such as those managed under catch quota, bycatch magnitude is monitored, and the discarded, unmarketable living marine resources can be counted against the allowable quota (Dunn *et al.*, 2014). Discard of unwanted bycatch is a primary issue in the trawl fisheries of the mid-Atlantic that target Summer Flounder (*Paralichthys dentatus*), Scup (*Stenotomus chrysops*), and Black Seabass (*Centropristis striata*). These fisheries are managed under a joint management plan that employs annual and seasonal quotas and trip possession limits for the commercial fishery (https://www.mafmc.org). Fishers are penalized when unwanted bycatch reduces the quota of marketable fish.

In addition to financial costs, incidental bycatch has ecological impacts. Ecological and ecosystem effects of bycatch can include diminished biodiversity and altered community structure (Gilman *et al.,* 2020). Alteration of the biological components of ecosystems can result in trophic cascades that deleteriously impact managed stocks (Scheffer *et al.,* 2005; Baum and Worm, 2009). Alternatively, discards may be a source of food subsidy for seabirds, pelagic fishes, and benthic organisms (Heath

et al., 2014). Thus, bycatch may have short-term benefits. Short-term benefits, however, may not translate into permanent ecological gains.

Incidental catches and discards can occur from a variety of causes. These include mandated or elective actions taken by fishers or because of the nature of the non-selective gear used to target the stock. Discard activity from regulatory conditions results from fish being below the minimum landing size or the fisher holding insufficient quota for the species (Bellido *et al.*, 2011). In mixed fisheries, such as the mid-Atlantic trawl fisheries that are regulated through allocation, fishers may continue to fish when the quota for some stocks is met (Poos *et al.*, 2010), resulting in discards. Differences in market conditions may lead to high-grading or the process of prioritizing (and keeping) living marine resources of greater value (Batsleer *et al.*, 2015). Because of the nature of non-selective gear, discards can occur (Poos *et al.*, 2010).

Monitoring programs have been implemented in many fisheries to account for discards' taxonomic richness and weight. Of these programs, at-sea observer programs are thought to produce the most accurate data (Suuronen and Gilman, 2020). Black Seabass, Summer Flounder, Scup, and Longfin Squid (*Doryteuthis pealeii*) fisheries are conducted using various configurations of trawl gear (Shepherd and Terceiro, 1994; Link *et al.,* 2011)*.* Onboard observers record the discards in these fisheries for a subset of fishing trips targeting these stocks, and the incidentally caught individuals are either kept or discarded overboard. One of the factors impacting management is the incidence of unwanted bycatch in these fisheries. Data from at-sea monitoring are used to produce independent information about bycatch temporal and spatial patterns by sector, harvesting gear, and stock area. Fisheries bycatch information, in turn, is used to support in-season monitoring, assessment of ecosystem impacts, and single-species stock assessment.

As the volume of observer bycatch data increases alternative analytical approaches may be called for to supplement traditional methodologies. The process we offer in this paper is one approach, commonly referred to as machine learning (ML). ML algorithms learn patterns in data to arrive at predictions (Jordan and Mitchell, 2015). In this work, using data from the federal observer program, we investigate the ability of ML to analyze temporal and spatial patterns in the catch of incidentally caught living marine resources in a suite of mid-Atlantic fisheries. We evaluate the observer data collected by NOAA Fisheries in the federal waters of the northeastern and mid-Atlantic regions. We describe fishery-specific bycatch patterns for the Summer Flounder, Scup, Black Seabass, and Longfin Squid fisheries. We then use these data to understand the spatial and temporal characteristics that influence bycatch weight and species richness using machine learning. Our specific objectives are to (1) describe temporal and spatial patterns of bycatch in the Scup, Black Sea Bass, Longfin Squid, and Summer Flounder fisheries, and (2) to use ML techniques to understand how gear, temporal, spatial, and environmental characteristics can be used to describe contrasts in bycatch magnitude and taxonomic richness.

Methods

We used data collected between 1994 and 2020 by the Northeast Fisheries Science Center Observer-at-Sea Monitoring Program (OSMP; Northeast Fisheries Science Center, 2010). The OSMP collects information from commercial fishing vessel trips of incidental finfish and invertebrate taxa. These data allow federal stock and ecosystem assessment personnel to understand the magnitude of the impacts of a given fishery. Data from OSMP were anonymized by NOAA Fisheries' personnel for confidentiality before distribution to the authors. Confidentiality was maintained to avoid tracing discarded data to individual vessels and fishers.

The data collected by OSMP are comprehensive. The OSMP data relevant to this work include the NOAA statistical areas designation, the quarter degree square of the trip, year, quarter of year (January to March, April to June, July to September, and October to December), latitude (°N) and longitude (°E) where the first haul began, bycatch disposition (kept or discarded), cod mesh size (mm), gear type (one of four types of trawl gear), the declared (primary, secondary, and tertiary) target stock of the trip, a code for indicating whether the haul was observed by the monitoring personnel, an indicator of whether the species was dressed (processed on board) or round, and the weight (kg) of each incidentally caught taxa (Table 1). We worked with NOAA personnel to anonymize the data to maximize the records available for analysis. Thus, the data that we analyzed represented a trade-off between the number of public records and their spatial and temporal resolution. The resulting temporal resolution of the data was a quarter of the year, and the spatial resolution was 0.25° × 0.25° grid squares. The spatial domain of the data was between latitudes 33.87° and 43.05° N to longitude 61.04° W (Fig. 1).

We performed data processing on variables, which we term "features" following ML terminology, and observations (records) of the OSMP data (Fig. 2). Our initial quality

control effort was made to remove unidentified, ambiguous (*e.g.*, seaweed), and inanimate (*e.g.*, wood and rocks) bycatch records. We then removed observations from 1994 to 2002, due to suspected inconsistent data collection protocols for those years, following our initial data evaluation. We also removed candidate features "gear type" and "cod mesh size". We found that the representation of these features in the data was predominately composed of a single gear type and cod mesh size (Table 1). Records with impossibly large weights and those with latitude and longitude values outside of our spatial domain (*e.g.*, those located on land) were also removed. We only used records of taxa that were discarded and observed. Finally, we extracted uninformative data columns, including row identifiers, columns with little contrast, and features with significant correlations to other features. We used linear and rank correlations to identify features that exhibited correlations of 0.90 or greater, keeping only one of the features in the model.

Following the selection of informative features, we performed feature engineering to produce additional predictors (Table 1). All categorical features were one-hot encoded for conversion into numerical features to enable model runs (Yang *et al.*, 2019). We defined six zones corresponding to regions of interest to commercial fishers in the region. Each zone comprised all OSMP records from grid squares bounded by latitudinal bands within the spatial domain of the study area. Latitudinal zones were "South of the Delamar Peninsula," "Between the Delamar Peninsula and Cape May," "Between Cape May and Hudson Canyon," "Between Hudson Canyon and the southern tip of Long Island," "Between the southern tip of Long Island and Martha's Vineyard," and "North of Martha's Vineyard" (Fig. 1). We engineered a categorical feature such that the quarter-degree grid squares were designated as inshore if the square intersected with any land and offshore otherwise. We developed quarterly estimates of sea surface temperature (SST) at the spatial resolution (0.25° × 0.25° grid squares) of the OSMP data. Sea surface temperature estimates were obtained from the ocean-color images available from Moderate Resolution Imaging Spectroradiometer (MODIS) sensor (https://modis.gsfc.nasa.gov/data/). Data from this sensor

Table 1. Description of the processed NOAA Northeast Fisheries Science Center Observer and At-Sea Monitoring Program data analyzed in this work.

	Predictor	Feature Type	Model Usage	Description
Spatial	Habitat zones	One-hot encoded	Model predictor	Six bands bound by latitude
	Inshore	True/False	Model predictor	The grid square of the record is adjacent to land
	NOAA Statistical Area	One-hot encoded	Model predictor	Five values
	Quarter Degree Square	Integer	Not used; correlated with statistical area	120 values
	Latitude	Decimal	Model predictor	
	Longitude	Decimal	Model predictor	
Temporal	Year	Integer	Model predictor	2003 to 2020
	Quarter	Integer	Model predictor	Winter, Fall, Summer, and Spring
	Biological			
	Bycatch disposition	Categorical	Not used; only disposition 'discarded' considered	Kept or discarded
Fisheries-Related	Declared target species	One-hot encoded	Model predictor	Up to three targets specified; eight combinations
	Cod mesh size	Decimal	Not used; low contrast	56, 120, 133, or 151 mm
	Gear type	One-hot encoded	Not used, majority of records belonged to one gear type	Fish, Ruhle, Scallop, or Twin
Oceanographic	Sea Surface Temperature	Decimal	Model predictor	NASA MODIS sensor
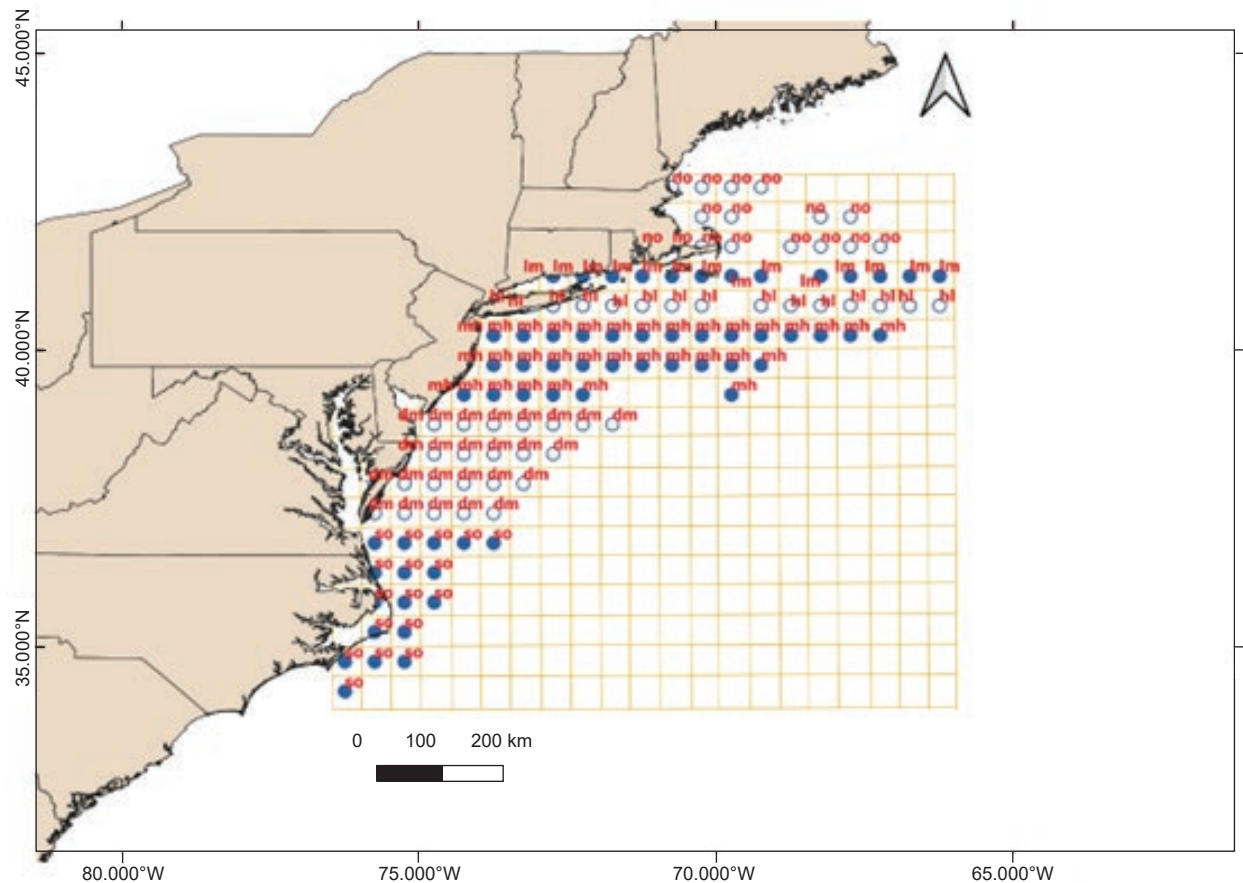
Fig. 1. Spatial domain of study region with quarter degree squares and latitudinal zones ($n = 6$). The six latitudinal zones are marked and are "so" (south of the Delamar Peninsula), "dm" (between the Delamar Peninsula and Cape May, New Jersey), "mh" (Between Cape May and Hudson Canyon), "hl" (between Hudson Canyon and the southern tip of Long Island), "lm" (between the southern tip of Long Island and Martha's Vineyard), and "no" (north of Martha's Vineyard).

provided an uninterrupted time series of ocean color images for the duration of the OSMP data. We used level-3 processed data at 9 km and monthly spatial and temporal resolutions. These data were used to develop monthly grid-square ($0.25° \times 0.25°$ grid squares) values of mean SST. Finally, we engineered a feature to represent the trip's declared target(s). The record included primary, secondary, and tertiary target species in other trips. The reported target for the trip was the combination of the stated target species. In some cases, only a single species was the declared target.

We developed two features as the responses for analysis. The first was a binary categorical feature that indicated if the weight of the bycatch taxa for that trip was greater than or less than the median of the weight of that bycaught taxa for all trips. We removed taxa found in a percentage of records less than 0.5% to develop this feature. We then log-transformed the weight of each record. The taxonomic group-specific median of the log-transformed weight was

determined to produce the binary categorical feature. A one was assigned if the value of the group was greater or equal to the value of the taxa-specific median, and a zero otherwise. The full data set was then partitioned by the declared primary target of the fishing trip: Summer Flounder, Scup, Black Seabass, or Longfin Squid (Table 2). The partitioning resulted in four groups of data for analysis of bycatch weight. The second analysis was a binary categorical feature that indicated if the richness (number of taxa) of bycatch for that trip was greater than or less than the median of the richness for all trips. The taxonomic group-specific median number of species was determined, and a one was assigned if the value of the group was greater or equal to the value of the taxa-specific median value and a zero otherwise.

We used a gradient-boosting ensemble machine learning algorithm to classify the categorical outcome features for bycatch weight and taxonomic richness. Gradient boosting was used because it captures complex non-linear

dependencies at a low computational cost, especially for data with a low signal-to-noise ratio (Friedman, 2001). Gradient boosting was also used for transparency and ease of the interpretability of results (Arrieta *et al.,* 2020). For model training, a random subset of 70% of data records was used as a training set, and the remainder was used for model testing. The best number of boosting trees and their depths were determined using cross-validation. The Adaboost loss function was used for the model optimizer, decision tree stumps were the base learner, and subsampling was the regularization method. Model performance evaluation metrics were classification accuracy, recall, precision, and F1 scores (Natekin and Knoll, 2013). We evaluated accuracy using a confusion matrix and provided information to understand how the frequency of the predicted classification compares to the frequencies observed in the data. The recall is the ratio of the frequency of the true positive to the sum of the true positive's frequency and the false negative's frequency. Recall indicates the proportion of the actual positives the model correctly identified. Similarly, precision is the ratio of the frequency of the true positive to the sum of the true positive's frequency and the false positive's frequency.

The precision measurement's value indicates the model's correctness level for those predicted to be positive. The F1 value is a function combining precision and recall:

$$F1 = 2\left(\frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}\right).$$

The F1 score balances the precision and recall estimates, correcting for the uneven distribution of observed classes.

Because an ensemble of trees was used as the underlying algorithm for each model, result transparency can be a challenge (Du *et al.,* 2019). Two techniques were used to interpret and understand the classification outcome as a function of spatial, temporal, and biological features. We first calculated the feature importance metric. Measures of feature importance allow an understanding of how much of the variability in a model is ascribed to a specific candidate feature. Only features contributing to predictions in at least 2% of cases were considered. We used gain to estimate feature importance metric. This estimates how effective each feature is at improving accuracy in the prediction. The second approach used in
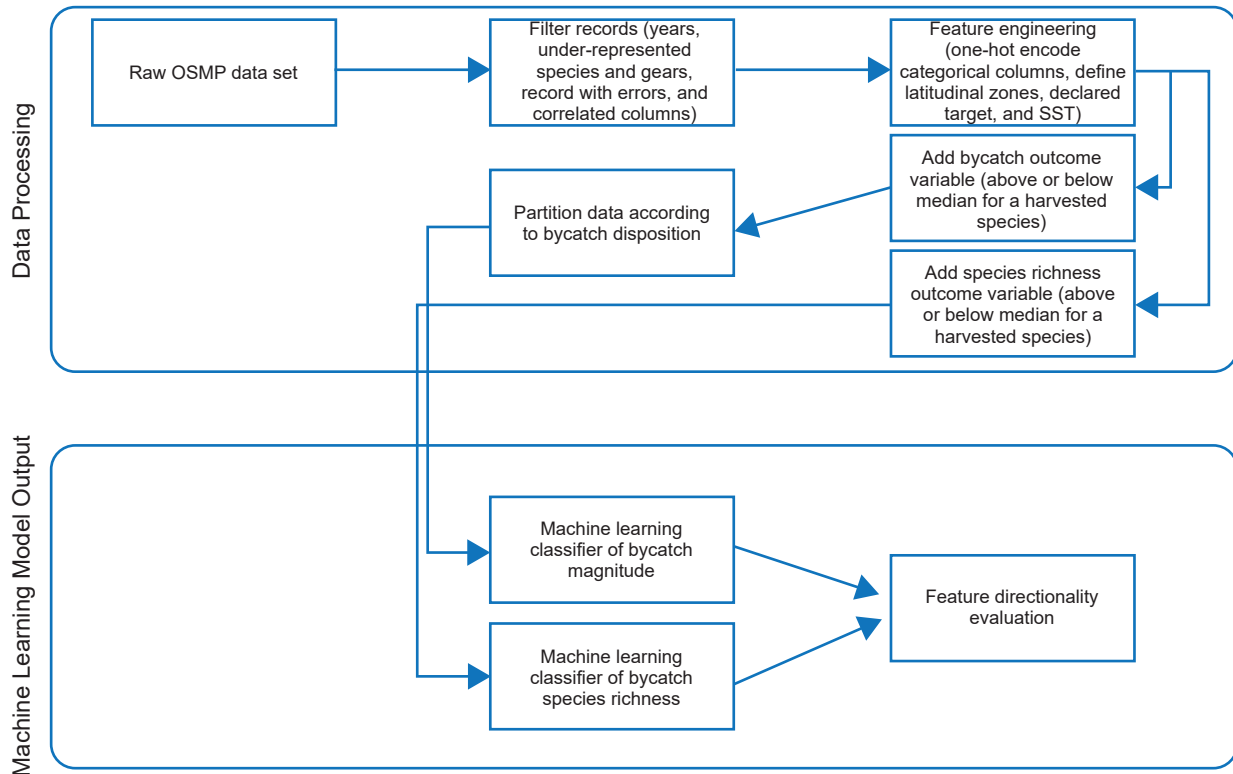
Fig. 2.   Model development pipeline from raw OSMP (NOAA Observer and At Sea Monitoring Program) to model final outcome.

Table 2.   Incidentally caught species (the percent of total records and the number of records) from the NOAA Northeast Fisheries Science Center Observer and At Sea Monitoring Program for 2003 to 2020. Only incidentally caught species that comprise frequencies greater than 5% are shown.

Incidentally Caught Species	Vernacular	Percent of records	Number
Paralichthys dentatus	Summer Flounder	9.58	61 435
Doeyteuthis pealeii	Longfin Squid	8.00	51 348
Stenotomus chrysops	Scup	6.65	42 637
Peprilus triacanthus	Butterfish	5.68	36 456
Centropristis striata	Black Sea Bass	5.37	34 440
Lophius piscatorius	Common Monkfish	5.26	33 715
Merluccius bilinearis	Silver Hake	4.96	31,836
Hippoglossina oblonga	American Fourspot Flounder	3.74	23 967
Squalus acanthias	Spiny Dogfish	3.71	23 773
Prionotus carolinus	Northern Searobin	3.45	22 119
Beringraja binoculata	Big Skate	3.31	21 225
Urophycis regia	Spotted Hake	3.28	21 042
Scophthalmus aquosus	Windowpane Flounder	2.89	18 551
Prionotus evolans	Striped Searobin	2.67	17 143
Mustelus canis	Dusky Smooth-hound	2.55	16 337
Illex Illecerosa	Northern Shortfin Squid	1.96	12 571
Raja eglanteria	Clearnose Skate	1.95	12 481
Pseudopleuronectes americanus	Winter Flounder	1.89	12 144
Pomatonus saltatrix	Bluefish	1.80	11 560
Homarus americanus	American Lobster	1.67	10 684
Urophycis chuss	Red Hake	1.59	10 193
Dipturus laevis	Barndoor Skate	1.52	9 758
Scomber scombrus	Atlantic Mackerel	1.16	7 421
Libinia emarginata	Portly Spider Crab	1.10	7 055
Limulus polyphemus	Atlantic Horseshoe Crab	1.02	6 531

this study to understand classification outcomes was the shapley additive explanation method (termed SHAP). This metric is a theoretic approach to model explainability (Lundberg and Lee, 2017). We calculated SHAP values to understand the directionality of feature importance. A visualization for SHAP values was used as a qualitative tool to assess feature importance and associated data influence on model performance. The approach allowed visualiztion of whether an observation of a feature on model prediction was high or low (horizontal position on graph) and the magnitude of that same observation (a grayscale value for the observation point).

Results

The analysis of bycatch patterns in the Summer Flounder, Scup, Black Seabass, and Longfin Squid fisheries indicated that six species of living marine resources were incidentally caught in more than 5% of the records (see Table 2). These species were Summer Flounder, Longfin Squid, Scup, Butterfish (*Peprilus triacanthus*), Black Sea Bass, and Common Monkfish (*Lophius piscatorius*). An additional 25 species were found in at least 1% of the records. These were a diverse group of taxa, including cartilaginous fishes (*e.g.*, Spiny Dogfish, Big Skate, Dusky Smooth-hound, and Clearnose Skate), crustaceans (American Lobster and Portly Spider Crab), chelicerate

arthropods (Atlantic Horseshoe Crab), and bony fishes. Less than 1% of the taxa accounted for 22.0% of the total number of records, including crabs, rays, flounders, and scallops.

The most commonly occurring bycatch in terms of frequency of records was the same as the declared primary target of the trip each fishery. The exception was for the Longfin Squid fishery, in this fishery Butterfish, Spotted Hake, Windowpane Flounder, and Silver Hake were the primary bycatch. For all years evaluated, the fisheries targeting Summer Flounder had the largest discards (1 539.1 MT), followed by fisheries for Longfin Squid (1 189.7 MT), Scup (498.9 MT), and Black Sea Bass (312.0 MT; Table 3). For all four fisheries, discards followed a species-specific pattern. For the Summer Flounder, Sea Bass, and Scup fisheries, spiny dogfish (*Squalus acanthias*) comprised the majority of discards and were present in each. Spotted Hake (*Urophycis regia*) is a dominant bycatch species for the Longfin Squid fishery. The greatest number of incidentally caught taxa in greater than 5% of records were found in the Summer Flounder fishery, with seven, and the smallest in the Longfin Squid fishery, with four. The directed fisheries for the Black Seabass and Scup fisheries exhibited six taxa each in greater than 5% of the records. Species of non-commercial interest commonly occurred in each fishery examined included skates, sea robins, and flatfishes (Table 3).

Model accuracies were generally consistent for each fishery, and there were no discrepancies between accuracy and the other performance metrics. Model classification accuracy was greatest for the Summer Flounder fishery (0.73), and recall was largest for the Longfin Squid fishery (0.75) for the above median classification of bycatch weight. The model performance metrics were consistently greater for taxonomic richness classification than for bycatch weight classification in each of the four fisheries (Table 4). The number of model features was greatest for Longfin Squid ($n = 269$), followed by Summer Flounder ($n = 263$) for the bycatch classification model. The data set for the classification model of taxonomic richness had the fewest number of records (10 084) and the fewest number of features ($n = 82$).

Different spatial, temporal, biological, and fishery features were identified as important in classifying the magnitude of taxa-specific bycatch in the four fisheries examined. Across all models, the oceanographic feature sea surface temperature and the temporal feature year were the most important factors in classifying the median weight of bycatch (Figs. 3 to 6). Among the

spatial features, longitude was ranked among the top four important features in all models, while latitude was present but ranked lower in importance. The spatial features "inshore" and "Area Southern Massachusetts" were only significant in predicting the median weight of bycatch for the Longfin Squid fishery model (Fig. 6). The biological features important in classifying bycatch magnitude in the Summer Flounder fishery included the presence or absence of cartilaginous fishes such as Clearnose Skate, Barndoor Skate, and Winter Skate as well as Spiny Dogfish (Fig. 3 to 6). The presence or absence of Spiny Dogfish was also important in classifying bycatch in the Black Seabass and Scup models (Figs. 4 and 5). In the Black Seabass classification model, three fishery features reflecting the absence of a secondary declared target species (ranked sixth), a declared secondary target of Southern Flounder (ranked eighth), and a declared secondary target of Scup (ranked ninth) were found to be important (Fig. 4A).

The SHAP analysis was informative for some features but less informative for others. Although we observed that the feature sea surface temperature consistently ranked as the most important feature in all classification models, our SHAP analysis did not indicate a clear pattern in its direction of influence on the model outcome. High and low sea surface temperature values had positive and negative impacts on the predicted outcome. Conversely, the biological features representing specific bycatch species negatively influenced the model outcome, implying a tendency for the model to predict below median bycatch weight if these taxa were also present on the trip. We observed that only a few high observations exerted a highly positive influence. For each fishery's bycatch classification model, the SHAP values for the temporal feature year indicated that more recent years positively impacted the model outcome (Figs. 3 to 6 and 8). For Black Seabass and Scup bycatch classification models, records with more recent years were classified as having greater than median bycatch. We found that the feature quarter of the year negatively influenced the predicted outcome, where greater than median bycatch weights were observed early in the year. Among the spatial features, the SHAP values for the feature longitude indicated a negative impact on the model outcome for feature values, with greater bycatch magnitudes occurring in the eastern parts of the geographic domain. For the feature longitude, SHAP values indicated that more easterly values tended to have positive impacts (greater than median bycatch weight) on the model outcome for Black Seabass and Scup. Scup and Longfin Squid's feature longitude indicated that the geographic domain's eastern regions had reduced bycatch. Features reflecting inshore fishing locations and fishing

in Southern Massachusetts negatively impacted bycatch in the Longfin Squid classification model. Scup was the only model in which the presence of its species (Scup) was an important biological feature representing bycatch (Figs. 4 to 6).

The relationship between the number of records from a square grid location and taxonomic richness showed a positive, non-linear trend (Fig. 7A). The maximum taxonomic richness observed was 192 taxa, with a median of 75 and a minimum of 5 taxa. The highest richness was found in quarter-degree grid squares located offshore in the southern part of the study area, ranging from 37 to 41° N and -76 to 70° W (Fig. 7B). Conversely, the lowest richness was observed north and south of this region. For the model predicting taxonomic richness, sea surface

Table 3.   Fishery-specific patterns of bycatch in the northeastern and mid-Atlantic finfish fisheries from the NOAA Northeast Fisheries Science Center Observer and At Sea Monitoring Program for 2003 to 2020. Percent of records is the number of trips five percent or greater of positive occurences of the species. Discards are the sum of biomass in metric tons of incidentally caught species.

Primary target of the trip	Incidentally Caught Species	Common Name	Percent of Records	Discarded
Black Seabass	Centropristis striata	Black Sea Bass	10.98	56.8
	Prionotus evolans	Striped Sea Robin	9.17	41.5
	Squalus acanthias	Spiny Dogfish	9.12	95.8
	Prionotus carolinus	Northern Sea Robin	8.4	41.8
	Stenotomus chrysops	Scup	8.37	35.5
	Paralichthys dentatus	Summer Flounder	6.81	26.6
	Lophius piscatorius	Common Monkfish	5.19	14
Total			58.04	312.0
Summer Flounder	Paralichthys dentatus	Summer Flounder	8.08	159.9
	Prionotus carolinus	Northern Sea Robin	6.61	212.9
	Beringraja binoculata	Fourspot Flounder	6.13	99.6
	Raja eglanteria	Windowpane Flounder	5.89	130.7
	Prionotus evolans	Striped Sea Robin	5.65	123.3
	Squalus acanthias	Spiny Dogfish	5.5	327.7
	Lophius piscatorius	Common Monkfish	5.43	166.9
	Dipturus laevis	Clearnose Skate	5.36	318.1
Total			48.65	1 539.1
Scup	Stenotomus chrysops	Scup	10.48	135.5
	Centropristis striata	Black Sea Bass	8.17	69.8
	Paralichthys dentatus	Summer Flounder	7.26	58.0
	Squalus acanthias	Spiny Dogfish	7.03	137.3
	Prionotus carolinus	Northern Sea Robin	6.02	48.6
	Prionotus evolans	Striped Sea Robin	5.5	29.4
	Hippoglossina oblonga	Fourspot Flounder	5.03	20.3
Total			49.49	498.9
Longfin Squid	Peprilus triacanthus	Butterfish	8.01	335.3
	Urophycis regia	Spotted Hake	5.91	404.8
	Hippoglossina oblonga	Windowpane Flounder	5.71	155.8
	Merluccius bilinearis	Silver Hake	5.54	293.8
Total			25.17	1 189.7

Table 4. Model performance metrics showing precision, recall, and F1-ratio for the label above/below the median bycatch weight classification models (the primary targets of the trip) in the northeast and mid-Atlantic tr last row in the table presents the performance metrics of the machine learning model to classify taxonc

The primary target of the trip	Number of records	Number of features	Accuracy	Precision	Recall
Black Sea Bass	18 643	123	0.70	0.69/0.70	0.65/0.74
Summer Flounder	141 300	263	0.73	0.72/0.74	0.72/0.74
Scup	35 871	200	0.68	0.66/0.71	0.66/0.70
Longfin Squid	203 809	269	0.71	0.71/0.71	0.75/0.67
Taxonomic richness	10 084	82	0.78	0.78/0.78	0.77/0.79

temperature and year were consistently the most important features, indicating a trend of increasing richness in recent years (Fig. 8A). Longitude and latitude also played a role in the model, with richness increasing to the east and north (Fig. 8B). Additionally, the Longfin Squid bycatch feature had a positive influence on the model outcome, with increasing values of this feature leading to higher median richness.

Discussion

In this study, we examined the bycatch composition in four commercial fisheries in the northeastern U.S. We employed machine learning classification models to gain insights into the spatial, temporal, biological, and fishery characteristics that describe contrasts in fishery-specific bycatch magnitude and the richness of bycatch. Our primary findings indicate that six species each accounted for at least 5% of the records, including each targeted species. The observed bycatch magnitude for the four fisheries ranged from 312 to 1 539 mt over the 17-year data duration. We found that the binary classification accuracies of the models were only moderate, never exceeding 80% classification accuracy. All classification models consistently showed that the oceanographic feature sea surface temperature and the temporal feature year are important in determining model performance. Feature importance, however, does not provide an indication of the direction of the response. The SHAP analysis indicated little consistent pattern in the value of the response. The findings of this study show the promise and challenges of using ML approaches for describing contrasts in bycatch abundance and taxonomic richness for mobile gear fisheries in the mid-Atlantic. The benefits of using an ML approach in this case is that we do not need to rely on *a priori* models to describe the phenomena to be studied. ML approaches are "model agnostic".

The contrast in the features that detect the importance of bycatch magnitude reflects differences in the nature of each of the fish stocks. The feature importance analysis for the Scup model indicated that the presence of Scup was an important biological feature that predicts bycatch. This finding implies that Scup catch has a very large component of discarded Scup. This is a well-documented concern in the mid-Atlantic and has necessitated management intervention. Indeed, gear restrictions and time-area closures have been implemented in the mid-Atlantic to reduce discarding Scup below the minimum legal size limit (Powell *et al.*, 2004). In addition, for the classification of bycatch in the Scup fishery, the SHAP values of the category shark (a multi-taxa feature that includes all elasmobranchs) showed a positive impact, and Longfin Squid, a negative association with the above-median bycatch weight class. A co-occurrence of sharks and Scup, together with distinct habitat segregation with Longfin Squid, might be expected for Scup. The classification model of discard bycatch for the Black Seabass fishery was positively associated with the shark and sea robin species categories and negatively with the Longfin Squid category. Records of Black Seabass discard weight greater than the median were associated with bycatch of species from the shark, sea robin, and Longfin Squid categories, potentially reflecting Black Seabass co-occurrence with the latter two fish species. The co-occurrence of Black Sea Bass and sharks may be trophically related. The Northeast Fisheries Science Center (NEFSC) food habits database lists spiny dogfish *(Squalus acanthias),* Atlantic angel shark *(Squatina dumeril)*, and a variety of skates as predators of Black Sea Bass (Steimle *et al.*, 1999). Greater biomass of discarded Summer Flounder as bycatch was accompanied by lower catches of Longfin Squid, hakes, and Scup. A possible explanation for the negative association is interactions between gear selectivity and seasonal changes in species distribution leading to

separation in the distribution of demersal fish (Shepherd and Terceiro, 1994; Gabriel, 1996; Link *et al.,* 2002). Small-scale changes in habitat use within an area and season have been reported for Scup and Summer Flounder, where one species inhabits sandy bottoms and the other occupies complex hard bottom habitats (Shepherd and Terceiro, 1994). Such patterns of occurrence and habitat preferences may account for the observed associations in the Summer Flounder observations. In the analysis of bycatch in the Longfin Squid fishery, only the category Longfin Squid was negatively associated with the above-

median bycatch class. Discards of Longfin Squid in that fishery indicate that the harvest of small or unmarketable Longfin Squid is responsible for this pattern. We note that of the fishery-related predictors, only the declared target species (or combination of species) if a secondary and or tertiary species were reported. Due to the constraints of the data available to the authors, it was not possible to analyze the impacts of cod mesh size and gear type.

We found some patterns in species richness observed from the bycatch analysis. Primarily, we saw an increase
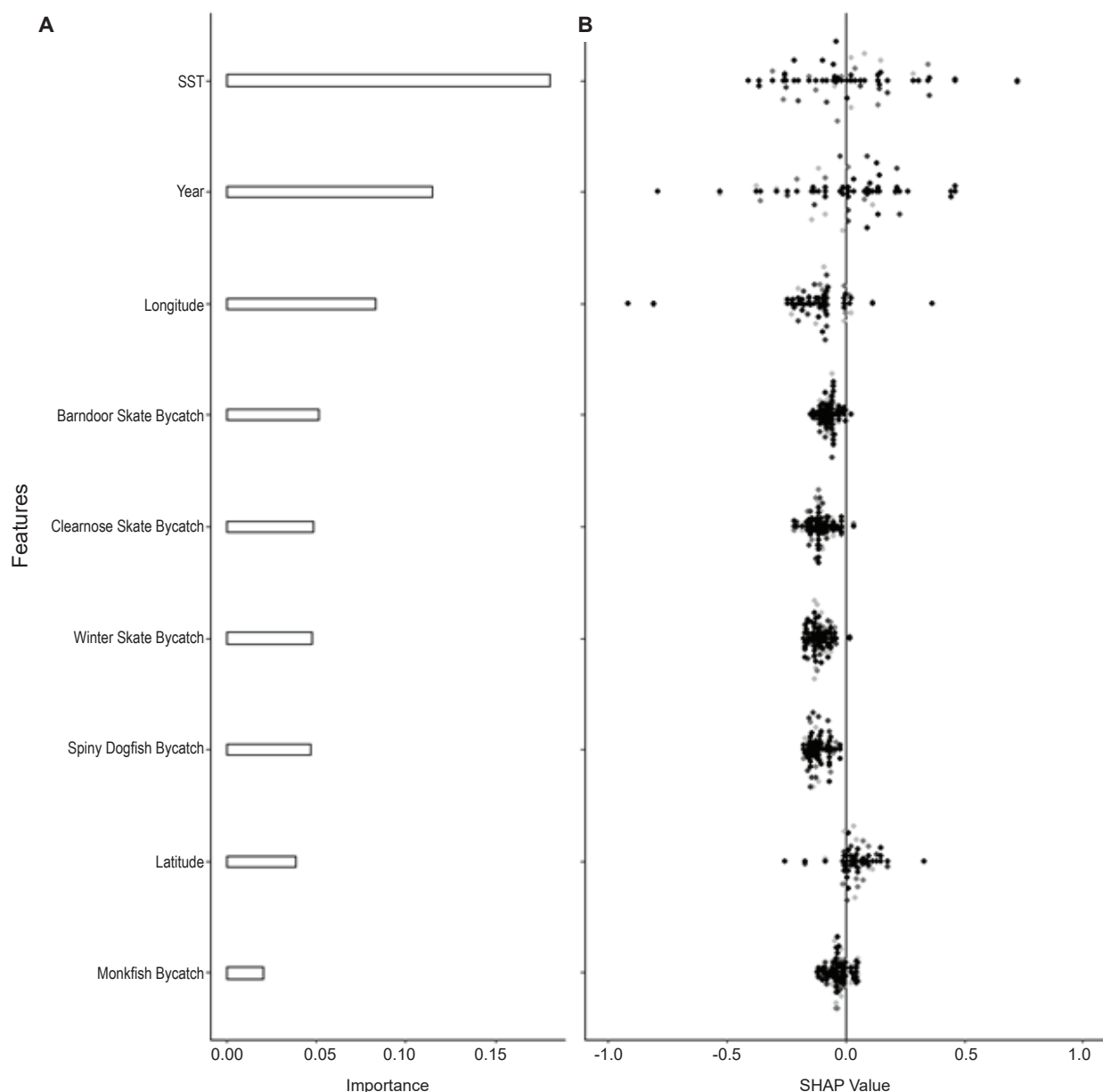
Fig. 3.   Feature importance (**A**) and SHAP values (**B**) for the classification of taxa-specific weight categories for primary target Summer Flounder.

in richness from 2018 onwards. Alternatively, low species richness was associated with longitude toward the western areas and offshore habitats in the spatial domain of the study. This latter was expected, as offshore habitats may offer less habitat complexity and species richness than habitats closest to shore. Features reflecting spatial distribution were not always intuitive. For the species richness classification model, an increase in richness is predicted easterly, and north in the study domain was counter-intuitive. One explanation for this result might

be that interactions between gear selectivity and seasonal changes in species distribution lead to the segregation of species-specific populations of demersal fish (Shepherd and Terceiro, 1994; Gabriel, 1996; Link *et al.,* 2002).

SHAP values for each feature are presented to elucidate the relationship between feature magnitude and directionality on the outcome of regression tree models (Lundberg and Lee, 2017). Although important features in most models, sea surface temperature and year were suggestive
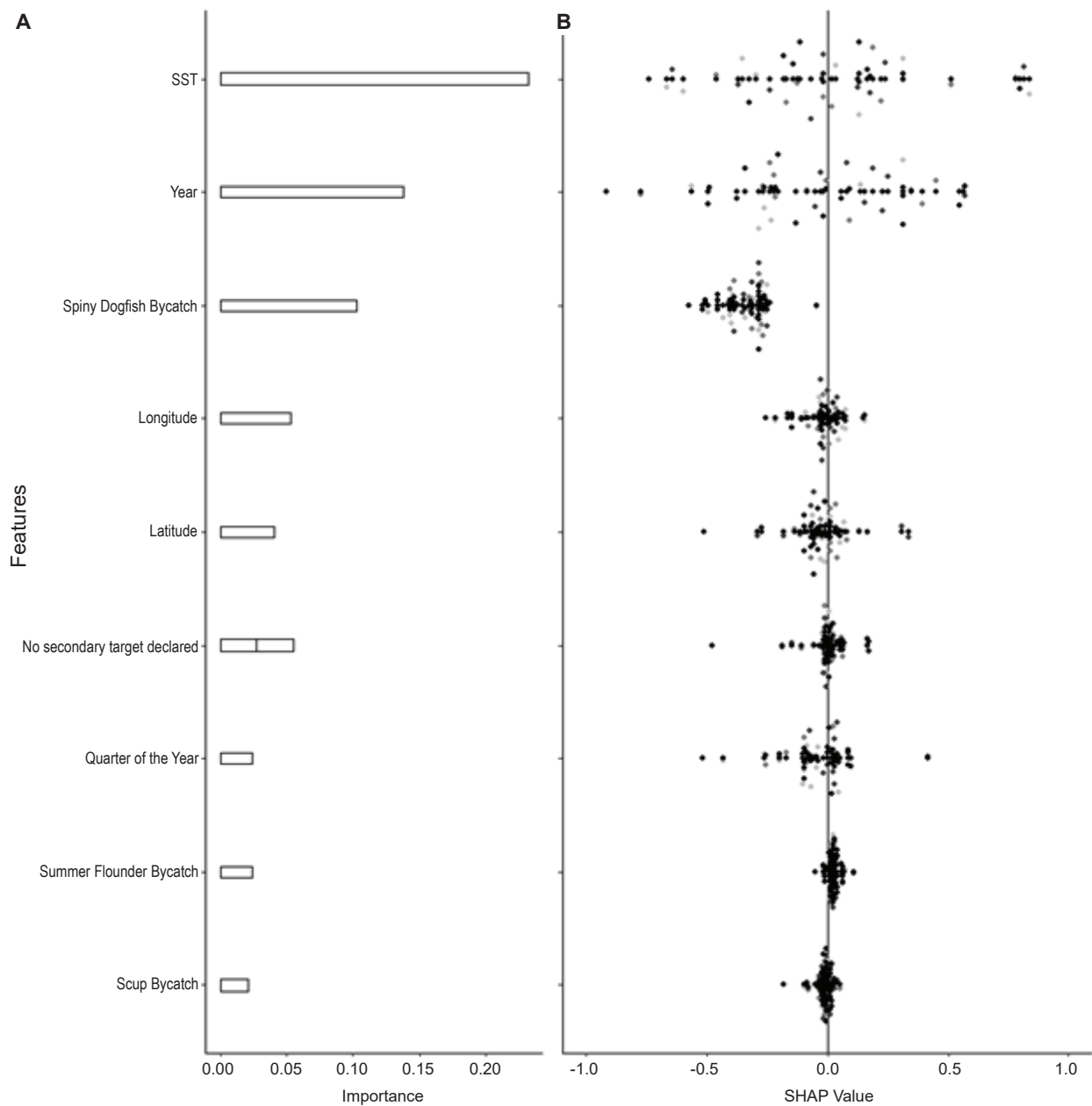
Fig. 4.   Feature importance (**A**) and SHAP values (**B**) for the classification of taxa-specific weight categories for primary target Black Seabass.
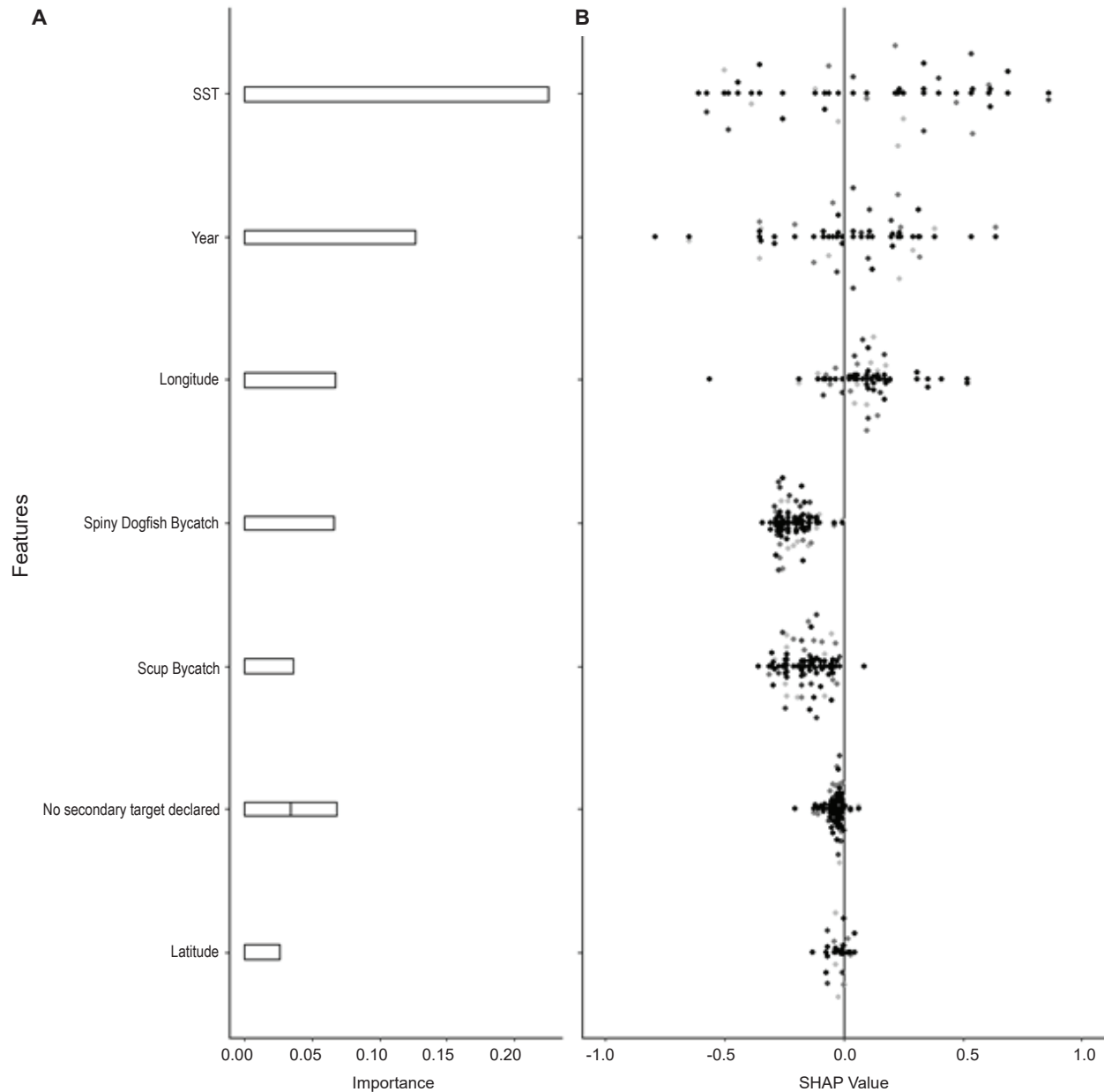
Fig. 5.   Feature importance (**A**) and SHAP values (**B**) for the classification of taxa-specific weight categories for primary target Scup.

of uncertain influence on directionality. This was an unexpected result. The feature engineering that we performed, to include sea surface temperature was done because we hypothesized that contrasts in bycatch magnitude could be described by this feature. That the SHAP analsyis indicated no consistency in the direction of this feature means that the feature was represented many times in the classification tree but that the predicted effect was contingent not on high and low values of sea surface temperatures. Instead, small increments in sea surface temperature lead to predictions of higher and lower than the median of bycatch weight. Similarly, the feature year may be considered a proxy for various interactive biological and abiotic processes. Like sea surface temperature, individual year values lead to processes that both increase or decrease taxa-specific bycatch magnitude. Conversely, although not as important for classification, biological features did indicate some direction of response. For example, features reflecting bycatch species were largely positive in their directionality, implying an

expectation of a positive relationship between the targeted species' weight and the weight of associated bycatch. The challenge is to make these associations actionable in a management context. Evaluation of bycatch composition of observer data in a multivariate framework could lead to insights into patterns of community composition of bycatch. That the spatial features "inshore" and "Area Southern Massachusetts" were a significant feature in predicting the median weight of bycatch for the Longfin Squid fishery model is more actionable.

The findings of this study point to the promise of using ML approaches for describing contrasts in bycatch data for fisheries in the mid-Atlantic using abundance and taxonomic richness metrics. The results of this study indicate that ML alternatives may successfully supplement traditional analytical approaches to fisheries research. Results from ML model runs captured generally expected patterns in the harvest according to target species. Given the inherent uncertainty associated with fisheries data, these results encourage adopting ML techniques to the
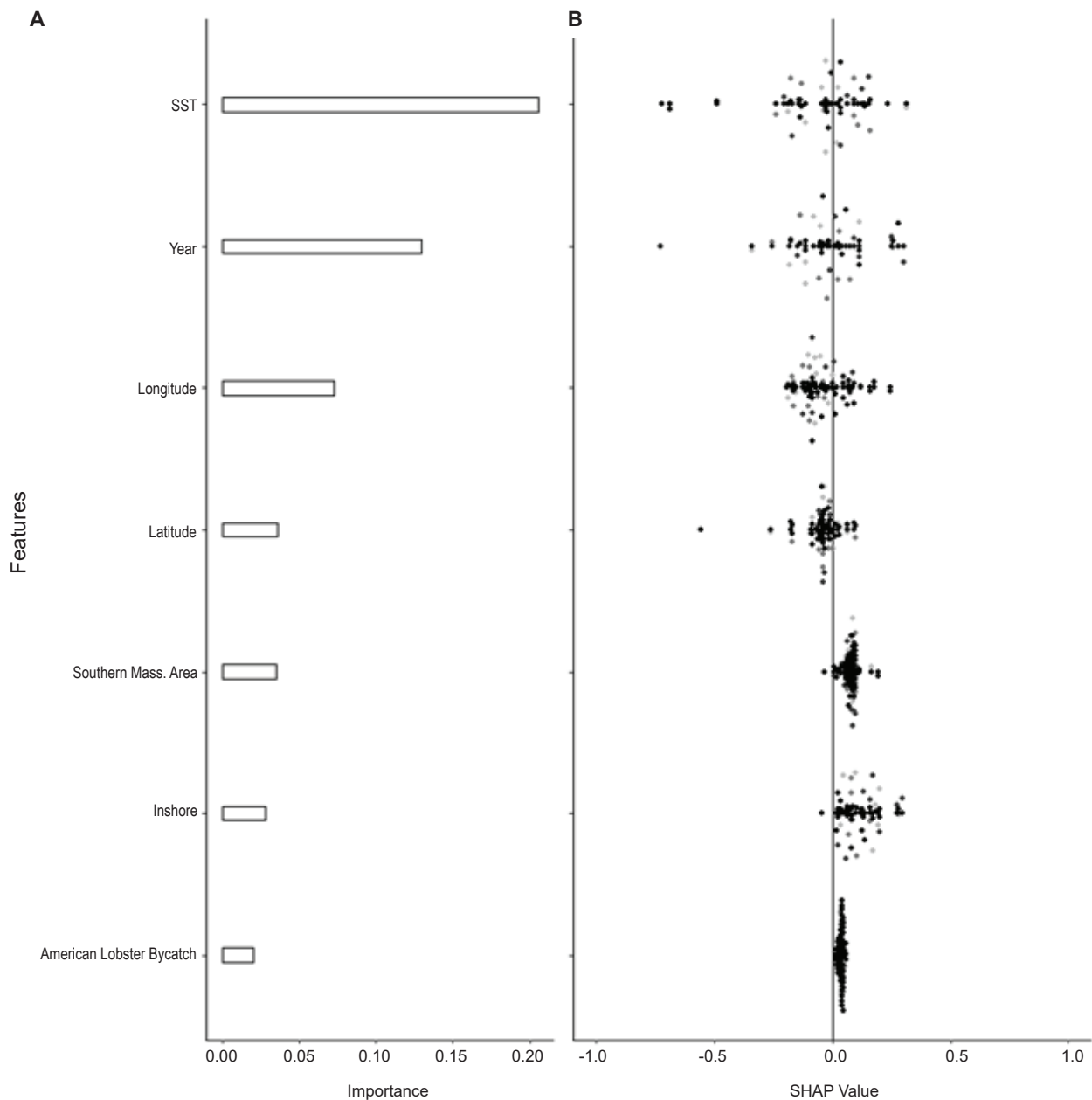
Fig. 6.   Feature importance (**A**) and SHAP values (**B**) for the classification of taxa-specific weight categories for primary target Longfin Squid.

A

B
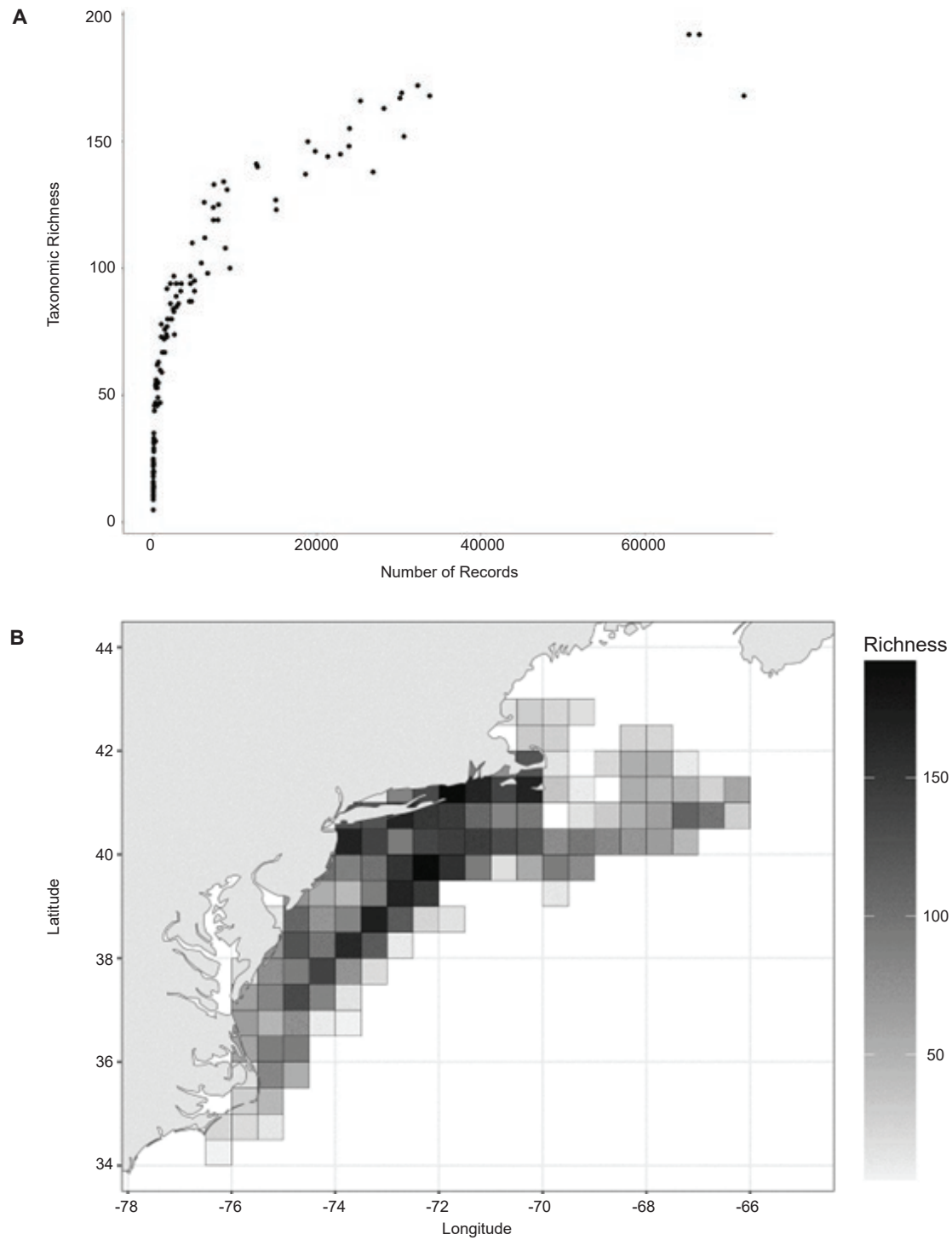
Fig. 7.   **A**: Rarefaction curve of the number taxonomic richness in relationship aggregated for quarter degree square, quarter of the year, and year; **B**: NOAA Northeast Fisheries Science Center Observer and At Sea Monitoring Program are of coverage.

field. However, adopting ML into the fisheries field must be done carefully, always with the analytical objective in mind. Adopting ML techniques blindly, without consideration of method explainability, may be a fruitful approach if classification is the only goal. ML techniques are best used in conjunction with traditional statistical analyses. These hypothesis-driven approaches allow model explanations.

Even with the encouraging results from the gradient-boosting ML approach used in this study, suggestions

for further improvements may be offered. Fine-grained vessel positioning may aid fisheries management decisions by better classifying movement patterns into activities associated with fishing and non-fishing practices. A limitation of this study rests on the high level of data aggregation provided by the onboard observation program. With less aggregation, data at trip levels, for example, more fine-grained, robust results would be possible, and better estimates of the effects of biological features could have been provided. Another limitation of complex resolution is observer coverage. Due to the high
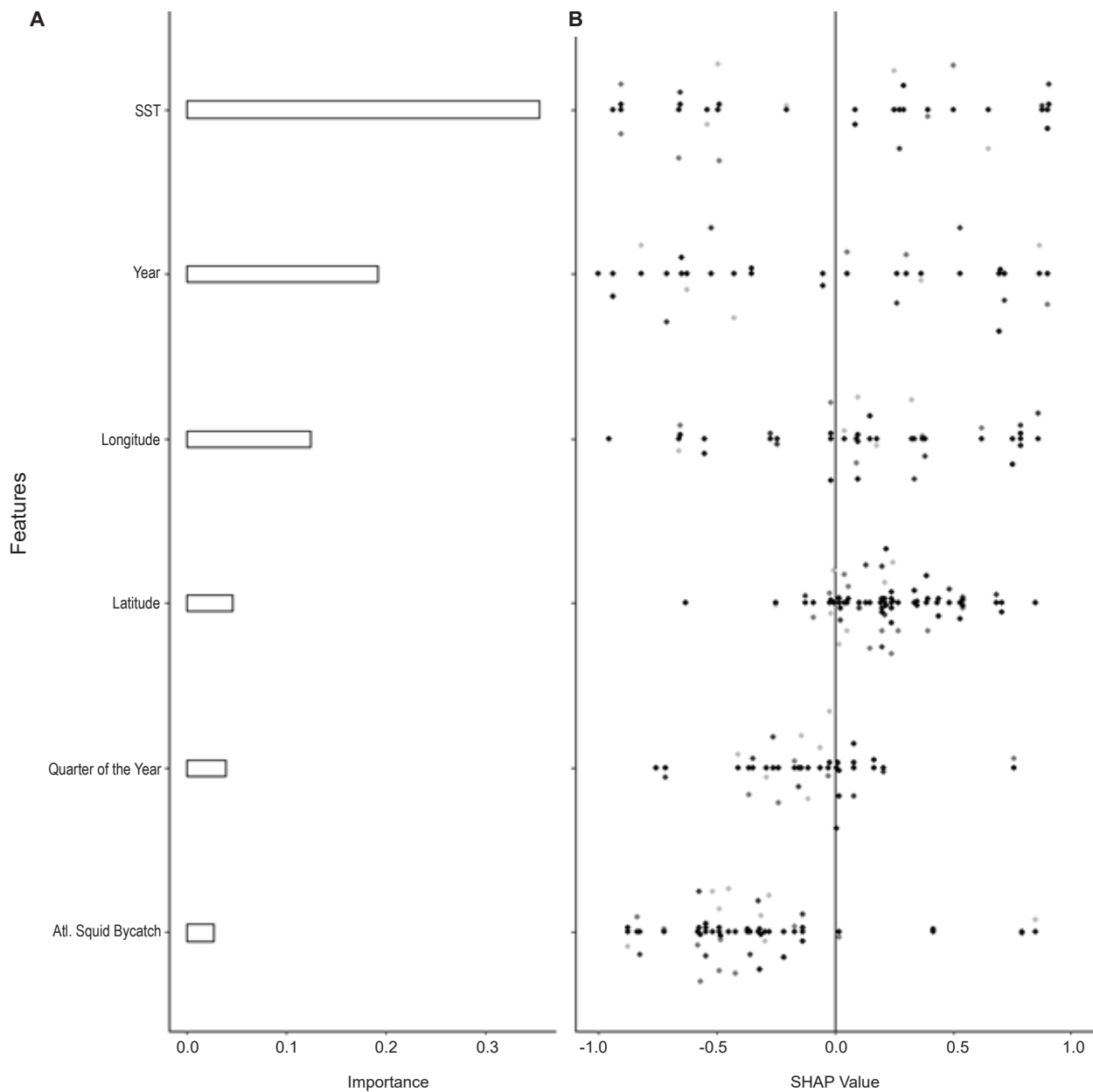
Fig. 8.   Feature importance (**A**) and SHAP values (**B**) for the classification of taxa-specific weight categories for bycatch species richness.

costs associated with observer programs, the spatial and temporal range may be insufficient to detect fine-grained results necessary for optimal fisheries management. Model quality of machine learning is contingent on data availability.

Additional benefits from this study may be achieved from an undertaking aimed at the automation of bycatch estimates, especially concerning the limitations above of observer coverage. With the advent of affordable, off-the-shelf global positioning devices, detailed information on the spatial dynamics of fishing efforts may be accurately estimated with classifiers as used in this study for small- and large-scale fisheries worldwide. Moreover, equipping vessels with cameras may also assist in assessing bycatch amounts. Camera images may be readily analyzed with computer vision approaches, such as deep learning algorithms (LeCun *et al.,* 2015), to automate data collection, allowing for widespread coverage of bycatch data (Khokher *et al.,* 2021). Computer vision has been successfully used in fish identification (Ditria *et al.,* 2020), estimation of fish abundance (Tseng and Kuo, 2020), and length distributions (White *et al.,* 2006), often surpassing the accuracy of human experts.

Machine learning approaches to analyzing fisheries data will likely not replace traditional modeling methods. In combination, formal modeling and ML may capture enough of the complexities and dynamics of ecological processes determining catch abundances to provide robust advice for sustainable harvest. A trend in augmenting the performance of traditional fisheries stock assessment and estimation models using ML has been observed recently (Pérez-Ortiz *et al.,* 2013; Syed and Weber, 2018; Kaemingk *et al.,* 2020; Yang *et al.,* 2020; Chan and Pan, 2021), attesting to the applicability of ML algorithms to fisheries data. With the increasing prospect of automation in fisheries data collection, ML techniques may be the only feasible approach for data processing and analysis as datasets become more complex. Automation, however, comes with the cost of transparency, primarily when deep learning techniques are used for classification. Because decisions based on such analysis most likely will have significant ecological, economic, and social impacts, explaining the results of ML techniques clearly and understandably is a must. Many ML techniques are defined as opaque, whereby how results are obtained is not clearly understood. Using mechanisms for explaining the results of an analysis, as done in this study, must accompany any opaque ML technique if the benefits of this new and ever-growing analytical alternative are to be fully realized.

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The paper should be in English. The sequence should be: Title, Abstract, Text, References, Tables and Figures.

Title

The paper should start with the title, followed by the name(s), address(es) and emails of the author(s) including professional affiliation, and any related footnotes.

Abstract

An informative concise abstract should be provided along with key words listed alphabetically.

Text

In general, the text should be organized into Introduction, Materials and Methods, Results, Discussion, and Acknowledgements. Authors should be guided by the organization of papers that have been published in the NAFO Journal or Studies.

Introduction should be limited to the purpose and rationale of the study.

Materials and Methods should describe in sufficient detail the materials and methods used, so as to enable other scientists to evaluate or replicate the work.

Results should answer the questions evolving from the purpose of the study in a comprehensive manner and in an orderly and coherent sequence, with supporting tables and figures.

Discussion should explain the main contributions from the study, with appropriate interpretation of the results focusing on the problem or hypothesis. Comparisons with other studies should be included here.

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The references cited in the text should be listed alphabetically. References should be mainly restricted to significant published literature. Unpublished documents and data, papers in preparation, and papers awaiting acceptance to other journals, may be cited with full contact addresses as unpublished or personal communications.

Examples:

King, M. 1995. Fisheries biology, assessment and management. Fishing News Books, UK, 341 p.

Crowder, L.B., and Murawski, S.A. 1998. Fisheries by-catch: implications for management. *Fisheries*, **23**: 8–16. doi:10.1577/1548-8446(1998)023<0008:FBIFM>2.0. CO;2

Ávila de Melo, A. M., Power, D. , and Alpoim, R. MS 2005. An assessment of the status of the redfish in NAFO Division 3LN, *NAFO SCR Doc.*, No. 52, Serial No. N5138, 19 p.

Text citations of the above would be (King, 1995; Crowder and Murawski, 1998; Ávila de Melo *et al.*, MS 2005). The surnames of two authors may be used in a citation, but *et al.* should be used for more than two authors. The citation of mimeographed reports and meeting documents should contain the abbreviation "MS". Abbreviations of periodicals can be found ftp://ftp.fao.org/fi/asfa/Monitoring_List/MASTER.txt . The Digital Object Identifier (doi) should be included if available. http://www.crossref.org/freeTextQuery/ can be used to checked this.

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