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Broadband acoustic classification of Atlantic cod, polar cod, and northern shrimp in *in situ* mesocosm experiments

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ABSTRACT

The northern shrimp (*Pandalus borealis*) and the Atlantic cod (*Gadus morhua*) fisheries are prone to bycatch of polar cod (*Boreogadus saida*), a key Arctic forage fish species. Discrimination between the acoustic signals from these coinciding species could provide information on the risk of bycatch in addition to improving the accuracy of non-lethal scientific stock assessment surveys. As a step towards automatic *in situ* classification, we conducted a series of single-species mesocosm experiments for broadband target strength spectra measurements of Atlantic cod, polar cod and northern shrimp. Mesocosm experiments were completed with a Wideband Autonomous Transceiver (WBAT) and collected individual target strength spectra, TS(f), between 90–170 kHz and 185–255 kHz. Hundreds of TS(f) were extracted for each species and used to train machine-learning classification algorithms (i.e. classifiers). We found that two supervised learning classifiers, LightGBM and support vector machine, were able to achieve high classification performance (89%) on target spectra shape with a single 200 kHz transducer operating in broadband mode. This is promising for acoustic classification from autonomous platforms with limited payload. We explore the utilization of single transducer target spectra shape variability and provide recommendations to overcome challenges associated with scaling the method successfully for *in situ* marine species classification not only in the Arctic, but globally.

1. Introduction

The northern shrimp, *Pandalus borealis*, fishery is one of the most economically valuable fisheries in the Northwest Atlantic, the eastern Canadian Arctic, and the Barents Sea. It generates 90% of Greenland's export value (Garcia, 2007), and is the most valuable invertebrate fishery in the Barents Sea (Berenboim et al., 2000). However, shrimp fisheries are associated with bycatch issues (Howell and Langan, 1992; Grimaldo and Larsen, 2005) in particular from juvenile gadoids, such as Atlantic cod (*Gadus morhua*) (Isaksen et al., 1992), and polar cod (*Boreogadus saida*) (Walkusz et al., 2020). Moreover, polar cod has a circumpolar distribution, can account for >95% of the pelagic fish assemblage in the Arctic, and has a pivotal role in the Arctic food web as a key forage fish species (Geoffroy et al., 2023). The ecology and stock abundance of all three species is monitored through trawl or acoustic-trawl surveys (Zimmermann et al., 2024; Korsbrekke et al., 2001; McQuinn et al., 2005). However, sampling in ice-covered waters is generally impossible. There is a need to develop a method to validate and classify their acoustic signal using solely acoustics to improve assessment surveys, evaluation of bycatch risks, and ultimately forecasts in stock dynamics at high latitudes. The classification of coincident species could help assess the bycatch risk prior to setting the trawls or to inform policy and models on ecosystem distribution patterns and biomass attributions. Remote target classification with broadband acoustics could also benefit stock assessment surveys and estimates by increasing spatial resolution, access to remote areas, and sustainability

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Table 1
Overview of mesocosm experiments (left side) and trawling operations (right side) in 2023. The pelagic trawl was used unless otherwise noted.

Species (n)	Experiment date	Experiment duration (h)	Trawl date (UTC)	Location (°N, °E)	Sampling depth (m)
Polar cod (90)	19 Jan	6	17 Jan 22:26	Billefjorden (78.62, 16.54)	102
Polar cod (133)	24 Jan	6.5			
Northern shrimp (100)	26 Jan	5.25	19 Jan 00:10	Outer Krossfjorden (79.05, 11.35)	150
Atlantic cod (5)	20 Jan	8			
Atlantic cod (11)			19 Jan 19:54	Outer Kongsfjorden (79.04, 11.34)	352[a]

[a] Bottom depth – bottom trawl was used.

by reducing survey time and costs related to trawling and sorting of catch.

A protocol to process and classify broadband acoustics is not only required in the Arctic, but would improve hydroacoustic surveys globally. Hydroacoustic surveys are widely used to monitor pelagic fish stocks (Rudstam et al., 2009). They provide high spatio-temporal resolution of fish abundance and distribution, and are less invasive than traditional net monitoring (Trenkel et al., 2019). Because the acoustic scattering of a target, which depends on size, orientation, and material properties, is also dependent on frequency, broadband echosounders have been increasingly used to infer species composition and increase the taxonomic resolution (e.g., Ross et al., 2013; Loranger et al., 2022; Dunn et al., 2024). However, broadband acoustic scattering measurements of an individual target, conventionally recorded as target strength spectra, TS(f) in dB re 1 m^2, have high variability which cannot be explained by length or orientation (Briseño-Avena et al., 2015; Dunning et al., 2023). The increased variability, complexity and size of broadband datasets have required powerful data analysis methods, such as machine learning algorithms (Malde et al., 2020). There is therefore a pressing need to develop clear protocols to classify broadband acoustic data from fisheries surveys.

Supervised machine learning algorithms require training datasets containing measurements of known targets. To achieve this, the first step is to develop a library of TS(f) from known targets of interest in a controlled environment that reproduces real environmental conditions as much as possible, such as *in situ* mesocosms. A mesocosm-trained classification approach has proven to be a promising avenue to improve taxonomic resolution from broadband hydroacoustics (Dunn et al., 2024). The *in situ* mesocosm approach allows for the collection of a large amount of detections for a known population with semi-natural swimming behaviours and is possible for many different species. Mesocosm classification of target spectra has been successfully used to differentiate between two coincident swim-bladdered fish species: whitefish (*Coregonus wartmanni*) and stickle-back (*Gasterosteus aculeatus*) (Gugele et al., 2021). Furthermore, tethered individual Pacific herring (*Clupea pallasii*) and Pacific chub mackerel (*Scomber japonicus*) species displayed slopes in their target spectra that could be used to discriminate between species but require a method to measure target spectra from a wider range of individuals (Wang et al., 2025). By conducting series of single-species mesocosm experiments, a library of detections can be created for supervised model training for discrimination of species with distinct spectra shapes or different spectral complexities. In addition, the method can be used to validate sound scattering models and improve our understanding of broadband variability.

This study reports on a series of single-species mesocosm experiments with broadband hydroacoustics to classify the acoustic backscatter from three sympatric species: Atlantic cod, polar cod, and northern shrimp. It provides a protocol to measure target spectra of pelagic organisms, not only from the Arctic, but globally. We further discuss how to overcome challenges associated with scaling the method successfully for *in situ* marine species classification.

2. Methods

2.1. Species collection

Atlantic cod, polar cod, and northern shrimp were collected from R/V *Helmer Hanssen* using a Harstad pelagic trawl (8 mm mesh, 110 m^3 mouth opening area) and bottom trawl (Campelen 1800 shrimp trawl with rockhopper gear) at 3 knots for 15 to 20 min in three fjords in Svalbard (Billefjorden, Krossfjorden, and Konsgsfjorden) (Fig. 1) on 17 and 19 January 2023 (Table 1). The trawled depth was selected based on the depth of the strongest scattering layer seen on the vessel's echosounder (Kongsberg Discovery AS; Simrad EK60, 18 and 38 kHz, 1.024 ms pulse duration, 0.5 s ping interval). A FISH-LIFT, an aquarium attached to the trawl codend that reduces turbulence and minimizes the impact of trawling on the caught animals (Holst and McDonald, 2000), was used to maximize the fitness and health of the live fish and shrimp. The fish and shrimp were kept on board in large tanks (1 m^3) with running seawater and delivered to the wharf in Ny-Ålesund in Kongsfjorden (Fig. 1B). At the Kings Bay Marine Laboratory, the fish and shrimp were sorted by species and stored in 6 m^3 holding tanks with a flow-through system of filtered ambient seawater (~1 °C) for 2 to 7 days, depending on weather and experiment priority. The species were not fed in the holding tanks.

2.2. Mesocosm experiment

Broadband target strength data of single species were collected during four experiments conducted in January 2023 (Table 1) using a mesocosm deployed from a wharf in Ny-Ålesund, Svalbard (red square; Fig. 1B). The mesocosm, or AFKABAN (Arrested Fish Kept Alive for Broadband Acoustics Net experiment), was fitted with a large cuboid fish net (H7 × W2 × L2 m) with a 6 mm by 3 mm oval mesh or a small cuboid zooplankton net (H3 × W2 × L2 m) with a 500 μ m-mesh (Dunn et al., 2024)(Fig. 2A). The net was mounted on an 8 m high by 2 m wide and 2 m long aluminium frame oriented vertically (Fig. 2A). Ropes with hook and loop straps attached the eyelets on the net to the frame at each corner and along the edges. A zipper on the top panel was opened to introduce species into the submerged mesocosm.

The transducers (ES120-7CD and ES200-7CDK-split; Kongsberg Discovery AS, Horten, Norway) were mounted side by side on a plate centred inside the mesocosm through a hole on the top panel of the net with the acoustic axis pointing directly down. The smaller transducer (ES200-7CDK-split) was mounted on raisers to level the transducer faces. The transducer plate was fixed to the frame to ensure the transducer, the frame, and the net moved as a unit under the stress of currents. The AFKABAN frame was purpose-built by Havbruksstasjonen (Ringvassøya, Norway) and wide enough to have two side-by-side beams of 7° opening angle transducers inside the net. AFKABAN was suspended from a crane and lowered into the sea (Fig. 2B) until the depth of the transducer face was approximately 1 m below the surface. A Wideband Autonomous Transceiver (WBAT; Kongsberg Discovery

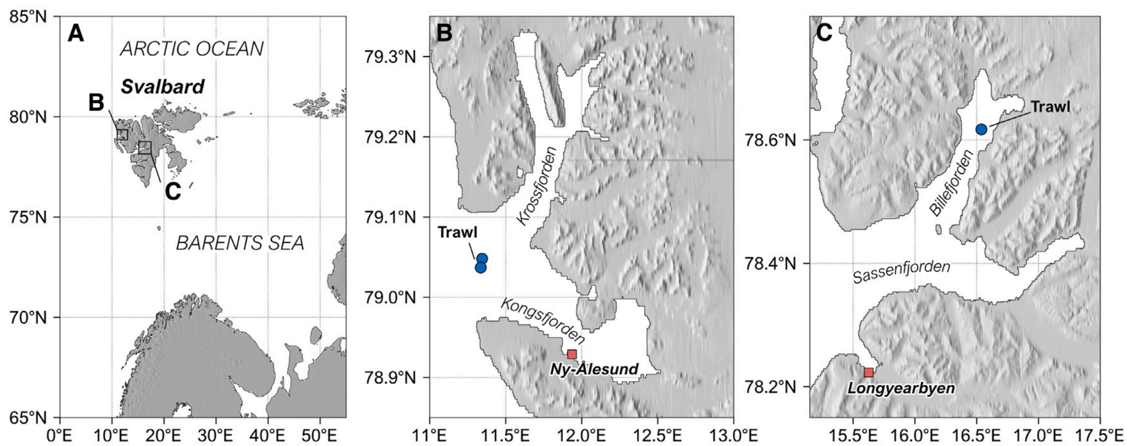

Fig. 1. (A) Svalbard archipelago. Trawling locations (blue circles) in (B) outer Krossfjorden and outer Kongsfjorden and in (C) Billefjorden. The experiment was conducted in Ny-Ålesund.

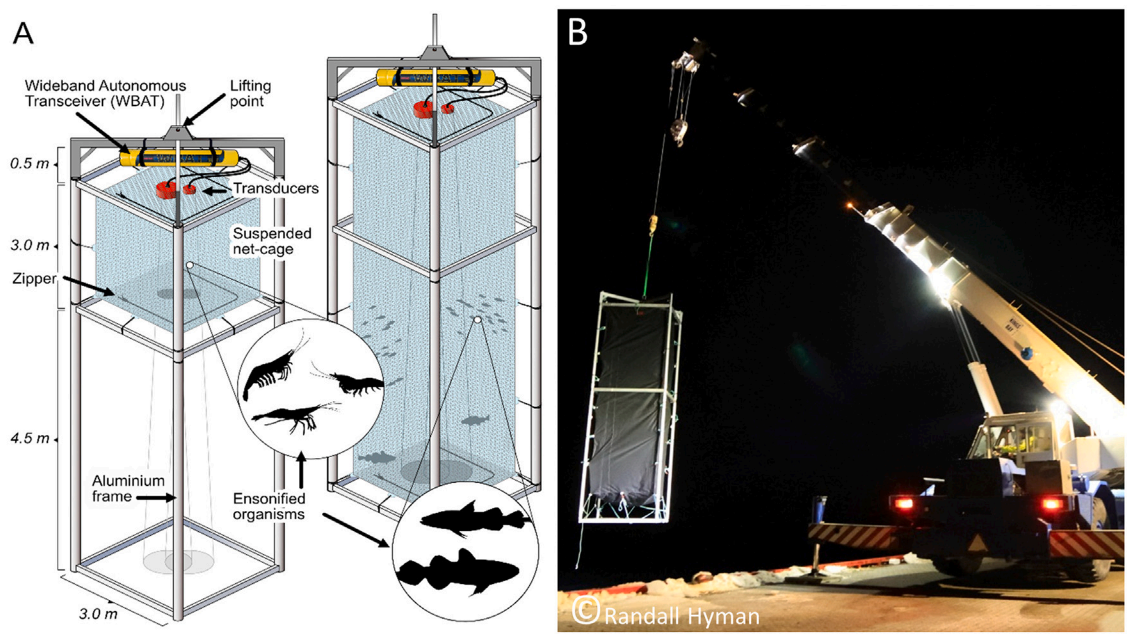

Fig. 2. (A) Schematic of the frame with the small zooplankton net (left; northern shrimp experiment) and large fish net (right; Atlantic cod and polar cod experiments). The acoustic transceiver (yellow cylinder) is attached to the frame and the transducers (orange cylinder, two in this experiment). There is a hole at the top of the net for the transducer faces to be unobstructed inside the net. (B) The AFKABAN mesocosm with the large fish net lifted with the crane at the end of the experiment. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

AS) was fastened horizontally to the frame to operate the transducers (Fig. 2A).

The acoustic data were collected using a WBAT programmed to emit frequency-modulated chirps alternating between two bandwidths; 90–170 kHz and 185–255 kHz. The emitted pulses had a fast taper, a pulse duration of 0.512 ms with 200 W and 113 W emitted power for the 120 kHz and 200 kHz transducers, respectively. The ping interval was set to the minimum allowable value, between 2 and 2.5 s, to maximize the number of single target detections and improve target tracking; it was limited by factors such as the internal processing time and range. We selected a fast taper to have the maximal bandwidth available at full power for the classifier. A short pulse length was selected to resolve targets near the net boundary, reduce reverberation volume (Soule et al., 1997), and increase the chances of sampling clean echoes from single targets in the mesocosm (Gugele et al., 2021). Data collection for analysis started at least 25 min after the mesocosm was fully submerged with the species inside the net to leave enough time for the organisms to acclimate and bubbles to disperse.

Sound speed was calculated by continuous conductivity, temperature, and pressure measurements during all experiments with a Sea-Bird SBE19plus for the fish experiments and SeaBird 37SI MicroCAT CTD for the northern shrimp experiment.

Immediately after the experiment, the frame was lifted to the wharf and the species were removed from the net via a zipper on the bottom panel. The shrimp and fish were euthanized in an overdose of Finquel MS-222 (tricaine methane sulfonate) compound solution (500–600 mg l^{-1}). Length and weight measurements were taken on the euthanized individuals after the experiment. The treatment and use of species in these experiments were approved by the Norwegian Food Safety Authority (FOT 29801, 22/231325).

2.3. Acoustic data analysis

The WBAT and transducers were calibrated using the standard sphere method adapted to broadband echosounders (Demer et al., 2015; Andersen et al., 2024). The calibrations required two tungsten

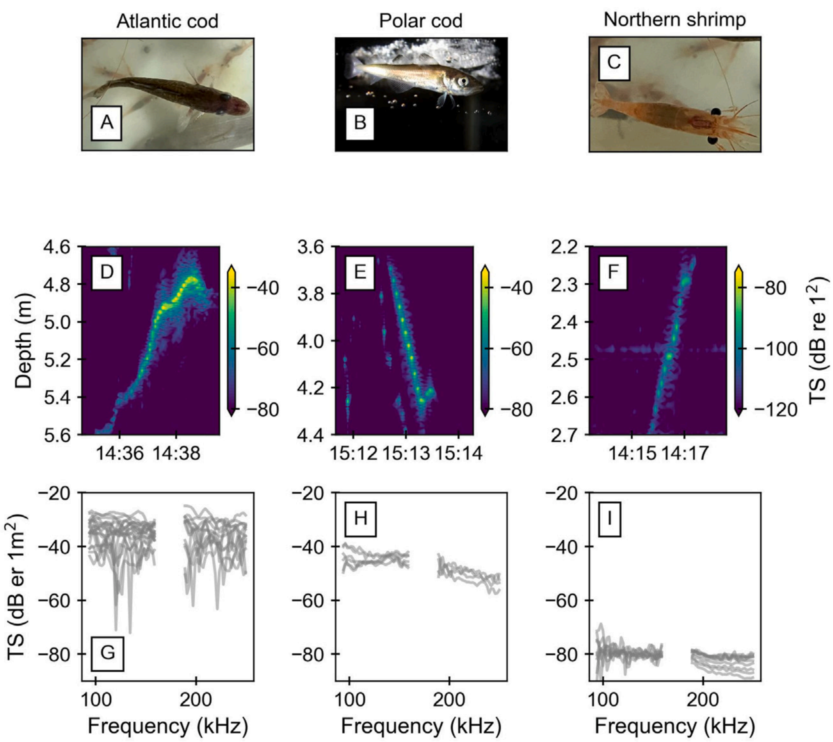

Fig. 3. Examples of the target spectra of each selected detection from an individual track of each species using multiplexing broadband echosounders. An image of the species from the experiment: (A) Atlantic cod (*Gadus morhua*), (B) polar cod (*Boreogardus saida*) (C) northern shrimp (*Pandalus borealis*). (D–F) Echogram from 120 kHz transducer of a selected isolated track from each species labelled above. Measured target spectra of the selected tracks; (G) Atlantic cod with 19 detections in the 94–158 kHz bandwidth and 13 detections in the 189–249 kHz bandwidth (grey lines), (H) polar cod track with 6 in the 94–158 kHz bandwidth and 4 target spectra in the 189–249 kHz bandwidth, (I) northern shrimp track with 9 target spectra in the 94–158 kHz bandwidth and 10 target spectra in the 189–249 kHz bandwidth.

Table 2
Single echo detection — wideband 1 detector settings, where TS is target strength.

Parameter	Value
TS threshold (dB re 1 m^2)	fish: −75 shrimp: −120
Pulse length determination level (dB re 1 W^2)	8
Normalized pulse length (min, max)	(0.5, 1.5)
Minimum target separation (m)	0
Off-axis angle filter (degrees)	4

carbide spheres for each transducer (38.1 mm and 22 mm) to collect calibration parameters for the available frequency bandwidths (Supplementary Material Figure S1, S2, S3). Calibrations were performed on 26 January 2023 in Ny-Ålesund, Svalbard.

All acoustic data were processed in Echoview 13.1 (Echoview Software Pty Ltd, Hobart, Tasmania). The data analysis range was bounded by the near-field region (Simmonds and MacLennan, 2008), and by the echo from the bottom of the net (i.e., 1.0 m–6.8 m for the fish experiments and 1.0 m–2.4 m for the shrimp experiments). The "single target detection — wideband 1" operator was applied to the pulse-compressed target strength to select qualifying targets for each transducer (Table 2). The target strength, TS, threshold was adjusted for the different experimental species. All other parameters were consistent between experiments.

The detected single targets from both transducers were merged based on ping time stamp for manual target selection. The selected single echo detections (SEDs) were manually organized into tracks by visual assessment to ensure each track came from a single organism (Khodabandeloo et al., 2021). We selected isolated SEDs that did not contain adjacent targets from other individuals in the Fourier transform window (0.25 m above and below) (Fig. 3D–F). Adjacent targets from other individuals can distort the frequency response because of interference between the backscattered signals. Target spectra graphs (Fig. 3G–I) were used to assess the presence of adjacent targets; these can be identified by regularly spaced nulls (Stanton et al., 1996; Reeder et al., 2004; Khodabandeloo et al., 2021). The single target tracks were formed by following SEDs traces from ping to ping and verifying the location sequence of the single target tracks across the acoustic beam. The ping-to-ping target strength variability was due to the small beam width at the sample range and the relative slow ping rate for each transducer (Fig. 3G-I). We ensured each selected track had a minimum of 4 SEDs to have enough information for the target trajectory across the acoustic beam. Only one SED per ping could be selected for each track, in the case of multiple SED candidates in a single ping, the centre, strongest SED was selected for the track. We are confident that a single organism formed each track because we used both frequency response patterns and target tracking location in the acoustic beam to select and create tracks. The analysis used SED rather than track averaged target spectra to ensure the spectral variability of each detection was represented.

All target spectra were calculated using a Fourier transform window length of 0.33 times the pulse length (i.e., 0.25 m) and exported from Echoview with a 2 kHz frequency resolution, determined by the pulse duration (Medwin and Clay, 1998; Khodabandeloo et al., 2021). The Fourier transform window size was selected to maximize the information from the echo while reducing the risk of contamination from nearby targets.

The first and last 5% of each target spectra were removed to eliminate the effects of the pulse taper. The frequency band from 158–170 kHz was removed because of inconsistent calibration results at this frequency range (Supplementary Material Figure S2). The resulting trimmed target spectra corresponding to the 94–158 kHz and 189–249 kHz bandwidth were used to train the classifiers. The target spectra from SED were classified for each transducer separately due

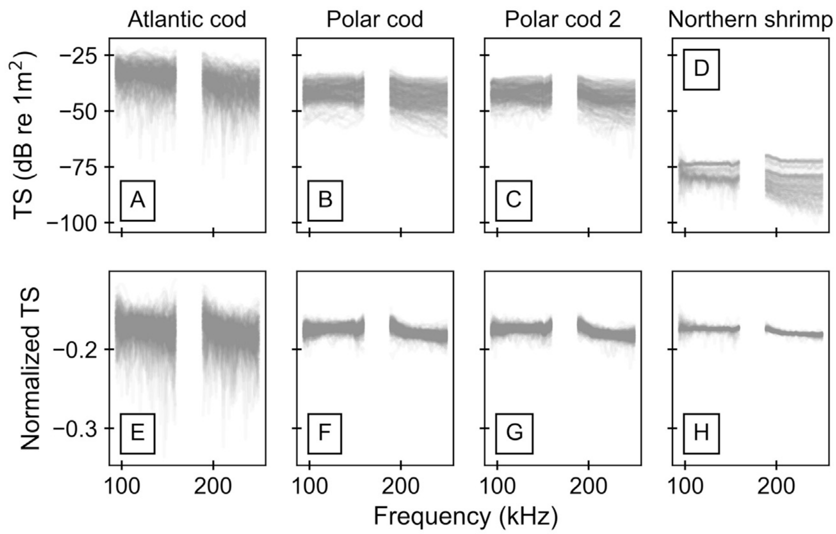

Fig. 4. Target spectra of all single target detections from all single species experiments. Each target spectra was recorded as target strength (TS) over the 94–158 kHz or the 189–249 kHz bandwidth. *Panel A-D:* target spectra of single echo detections organized by species from the 200 kHz transducer. *Panel E–H*: L^2-normalized target spectra.

to the alternate pinging. Therefore, the SED between the transducers could not be coupled into one combined target spectra from two separate SEDs. However, by separating the target spectra between each transducer, we aim to find: (1) if one transducer is enough to discriminate targets, and (2) which single transducer performs best at SED classification.

An L^2-normalization was applied to each target spectra so that if the values were to be squared and summed, the sum would equal 1 (Komer et al., 2014). Normalizing by observation was done to make the method scalable to other species and ecosystems and to ensure the classification was dependence on target spectra shape and not only dependent on dB differencing.

The total variation of each normalized target spectra was calculated by summing the absolute difference between each consecutive point. The total variation quantifies the overall oscillation in the spectra in the form of a statistical distance metric, therefore it is used here as a metric for spectral complexity. The higher the total variation, the greater the spectral complexity.

2.4. Classifier training

Classifier training was performed in Python (version 3.9.15) using the Scikit-Learn library (version 1.1.3, Pedregosa et al., 2011) and Hyperopt-Sklearn library (version 1.0.3; Komer et al., 2014). The number of target spectra per class was balanced by applying an over-sampling technique. Over-sampling was used to avoid removing samples and because the classes were not severely unbalanced (6:1). The samples in the minority classes (Atlantic cod and northern shrimp) were resampled randomly until they were balanced with the majority class (polar cod) to reduce the risk of bias in the model predictions (Goodfellow et al., 2016), reaching a total of 695 and 699 samples per species for the 94–158 kHz and 189–249 kHz bandwidths, respectively.

Three classifiers, K-Nearest Neighbours (kNN; Goldberger et al., 2004), LightGBM (Ke et al., 2017), and support vector machine (SVM; Cortes and Vapnik, 1995), were trained and Bayesian hyperparameter optimization was used for parameter selection. The classifiers were trained using a 10-fold cross-validation method (Stone, 1974) to split the data iteratively into a training subset (90%) and a testing subset (10%) of the single species target spectra from the mesocosm experiments. Target detections within a track were kept together throughout the cross-validation training to avoid bias from autocorrelation. Classifier performance was evaluated using a mean class-weighted F1 score because it is an evaluation metric that penalizes false positives and false negatives equally. The class-weighted F1 score was averaged by class and weighted by the number of true instances for each class (Pedregosa et al., 2011).

3. Results

3.1. Species composition

The 16 Atlantic cod in AFKABAN had a mean length of 52 ± 8 cm (L ± standard deviation (SD)), and their mean weight was 978 ± 346 g (W ± SD). The individuals for both polar cod experiments were smaller. The first polar cod experiment had fewer (n = 90; L = 19 ± 2 cm; W = 50 ± 10 g), whereas the second experiment had more individuals that were, on average, smaller (n = 133; L = 18 ± 2 cm; W = 30 g; weighed as a group and divided by the number of individuals). For the shrimp experiment, inside the small mesocosm configuration (Fig. 2A left), the 100 shrimps had an average length of 8 ± 1 cm (measured from eye to telson) inside the small mesocosm configuration. The shrimps were weighed as a group and divided by the number of individuals, which resulted in an average individual weight of 6 g.

3.2. Single species target spectra

There were 60 selected tracks in the Atlantic cod dataset, comprised of 345 target spectra in the 94–158 kHz bandwidth and 273 target spectra in the 189–249 kHz bandwidth (Fig. 4A). All target spectra are from SED. The first polar cod experiment resulted in 62 selected tracks with 345 target spectra in the 94–158 kHz bandwidth frequency bandwidth and 362 target spectra in the 189–249 kHz frequency bandwidth (Fig. 4B). The second polar cod experiment was slightly shorter in length (Table 1) and had a total of 66 tracks with 350 target spectra in the 94–158 kHz bandwidth and 337 target spectra in the 189–249 kHz bandwidth (Fig. 4C). The northern shrimp experiment had the fewest tracks because of the shorter duration of the experiment and the small size of the individuals (Table 1). There were 25 selected tracks composed of 108 target spectra in the 94–158 kHz bandwidth and 180 target spectra in the 189–249 kHz bandwidth (Fig. 4D).

The classification analysis used all the selected target spectra and, in the case of Atlantic cod and northern shrimps, the replicates added to achieve balanced classes by having the same number of target spectra in each group (Fig. 4). Atlantic cod had the strongest average echo intensity with a mean target strength (standard deviation, SD) of −33 (SD +5, −4) dB re 1 m^2 for the 94–158 kHz bandwidth and −38 (SD +6, −5)

Table 3
Classifier F1 scores estimated by classifier training (mean ±SD) of the normalized target spectra collected with the 120 kHz and 200 kHz transducer.

	120 kHz			200 kHz		
	kNN	LightGBM	SVM	kNN	LightGBM	SVM
Mean class-weighted	0.75 ± 0.08	0.81 ± 0.08	0.85 ± 0.07	0.83 ± 0.07	0.89 ± 0.06	0.89 ± 0.06
Atlantic cod	0.73 ± 0.12	0.85 ± 0.11	0.82 ± 0.14	0.78 ± 0.07	0.92 ± 0.05	0.87 ± 0.06
Polar cod	0.71 ± 0.08	0.78 ± 0.06	0.84 ± 0.07	0.77 ± 0.11	0.85 ± 0.09	0.85 ± 0.10
Northern shrimp	0.74 ± 0.19	0.71 ± 0.19	0.84 ± 0.12	0.92 ± 0.07	0.88 ± 0.08	0.92 ± 0.09

dB re 1 m^2 for the 189–249 kHz bandwidth. Both polar cod experiments resulted in similar target strength values with a mean target strength of −41 (SD ± 4) dB re 1 m^2 for the 94–158 kHz bandwidth for the first polar cod experiment with the slightly larger individuals and −42 (SD +4, −3) dB re 1 m^2 for the 94–158 kHz bandwidth for the smaller polar cod experiment. In the 189–249 kHz bandwidth, both polar cod experiments resulted in an average target strength of −44 (SD +5, −4) dB re 1 m^2. The northern shrimp had the weakest echo with a mean target strength of −77 (SD +4, −3) dB re 1 m^2 and −82 (SD ± 6) re 1 m^2 in the 94–158 kHz and 189–249 kHz bandwidth, respectively. The mean target strength of all species decreased in the higher frequency range.

Atlantic cod had the largest variability in target strength intensity per individual (i.e., among pings forming a track) with a maximum range of 43 dB re 1 m^2 at the nominal frequency, 120 kHz, and 33 dB re 1 m^2 at the nominal frequency, 200 kHz. The variability in target strength intensity per track at the nominal frequency for the polar cod and northern shrimps were largest at 200 kHz than at 120 kHz, but smaller than the Atlantic cod target strength intensity variability. During the second polar cod experiment, the polar cod had a maximum target strength intensity range within a track of 21 dB re 1 m^2 at 200 kHz, and for northern shrimp it was 8 dB re 1 m^2 at 200 kHz.

The average total variation was greatest for the Atlantic cod target spectra at both frequencies (64 and 61 in normalized TS units in the 94–158 kHz and 189–249 kHz bandwidth, respectively), indicating that the Atlantic cod target spectra has the highest spectral complexity, highest amplitude of oscillations. The polar cod experiments both had a total variation of 20 for the 94–158 kHz bandwidth and had 16 for the first experiment and 15 for the second experiment for the 189–249 kHz bandwidth. The northern shrimp had the smallest total variation with 8 for the 94–158 kHz and 5 for the 189–249 kHz bandwidth.

3.3. *Classifier training*

The three classifiers trained on the normalized target spectra (Fig. 4E–H) showed a high performance in classifying the frequency response of polar cod, Atlantic cod, and northern shrimp across both the 94–158 kHz and 189–249 kHz bandwidths (mean class-weighted F1 scores: >70%; Tables 3). The 189–249 kHz bandwidth had the highest mean per-class classification performance for all three species (>75%; Table 3). Performance of the three classifier varied between species. For example, SVM performed best on northern shrimp target spectra (0.92 for the higher bandwidth) and LightGBM performed best on Atlantic cod (0.85 and 0.92 for the lower and higher bandwidth, respectively). Both complex and computationally expensive classifiers, LightGBM and SVM, had notably higher performance than kNN.

4. Discussion

4.1. *Species-specific patterns*

The high classification performance (mean class-weighted F1 score of 89%) for three sympatric marine species is a promising result for spectral-based classification of targets from broadband echosounders. The results show that Atlantic cod, polar cod, and northern shrimp can be differentiated using their target spectra with a single 200 kHz transducer. Presumably, the range of target spectra complexity and morphological differences of the three species ensured the high performance of the classifiers.

Atlantic cod's target spectra were found to be the most complex, with the greatest total variation in the target spectra. The spectral complexity observed in the Atlantic cod target spectra could have suggested that the SEDs contained interferences from other targets (Fig. 3G; Khodabandeloo et al., 2021; Stanton et al., 1996). However, the rigorous manual target selection process ensured that only one individual was included per SED and no adjacent targets were included in the Fourier transform window (~0.25 m above and below the target). Therefore, the multiple scattering features (constructive and destructive interference) within the individual Atlantic cod targets must have originated from the backscatter of different organs interfering with each other (Demer et al., 2017; Reeder et al., 2004). We thus expect that discriminating and classifying between several morphologically complex species, such as Atlantic cod, will be more challenging (Au and Benoit-Bird, 2003; Clay, 1991, 1992), especially in aggregations.

In contrast, polar cod target spectra had an intermediate spectral complexity with some ripples and a relatively consistent slope across the spectra. During the target selection of polar cod, there was only one central dominant SED per ping, which suggested each individual had a single dominant scattering feature (i.e., the swimbladder) and explained the absence of large nulls and peaks (Fig. 3H). The northern shrimp had the lowest total variation in the target spectra with some ripples in the 94–158 kHz bandwidth but predominantly flat normalized target spectra, especially in the 189–249 kHz bandwidth (Fig. 4D). The emitted chirp from the 120 kHz transducer had a 10 kHz wider bandwidth than the 200 kHz transducer, which increased the spatial resolution to 9 mm (compared to 11 mm for the 200 kHz). The finer temporal resolution from the wider bandwidth may have revealed finer-scale scattering features, which are typically only discernible with higher frequencies (Reeder et al., 2004).

Target spectra amplitude and slope were used by Cotter et al. (2021) to classify target spectra into four classes based on selected scattering models (i.e., above, at, or below resonance for gas-bearing organisms or fluid-like organisms). These categories were used to classify mesopelagic fish into size classes with a mean F1 score of 0.90. Similarly, Roa et al. (2022) had a high performance (the best mean class-weighted F1 score was 0.96) with classifiers trained on scattering models for six different reef fish. They found that the nodes or "ripples", typically found at higher frequencies, were the prominent source of discriminating information. Discriminating nodes and ripples were not found in three of the four modelled zooplankton groups in Dunn et al. (2024), which resulted in moderate performance for the classifiers (best mean class-weighted F1 score was 0.71). Based on previous studies and the results from this study, we conclude that selecting classification groups that have different levels of spectral complexity, or average total variation, can positively impact classification performance.

4.2. Intensity variability of broadband target spectra

Broadband acoustic backscattering signals exhibit large unexplained variability between detections of a single target (Reeder et al., 2004; Gugele et al., 2021; Dunning et al., 2023). Our results show that this variability can be used to discriminate between different pelagic organisms. For example, an Atlantic cod target spectra study recorded a maximum target strength variation of 30 dB re 1 m^2 within a track of a single fish at 38 kHz (Dunning et al., 2023). Here, we observed a comparable maximum variation in target strength of 33 dB re 1 m^2 at 200 kHz within an Atlantic cod track. However, polar cod and northern shrimp exhibited a smaller variation of target strength per track. The target strength variability in broadband acoustics for a single target was found to be greater than could be explained with tilt angle or fish length (Dunning et al., 2023), which are traditionally used to explain the variability in narrowband target strength measurements (Khodabandeloo et al., 2021; Zhang et al., 2021). Presumably, the stochasticity found in the Atlantic cod target spectra tracks could be due to variations in the section of the fish being ensonified from ping to ping. In particular, the Atlantic cod had a similar length to the beam width; therefore, different parts of the fish body were likely impinged separately, adding variability to the measurements in this study. Different target spectra could be obtained at a farther detection range in the wild. A mesocosm experiment, similar to this study but with fewer individuals with a larger measurement range and optical verification, could develop a better understanding of broadband acoustic target strength variability.

In the classification process, the normalizing preprocessing algorithm removes the intensity component of the target spectra (Fig. 4I–L). Normalizing the target spectra had the largest effect on the within-spectra variability of northern shrimp. Though northern shrimp had the smallest maximum variability per track, 7 dB re 1 m^2 at 120 kHz and 8 dB re 1 m^2 at 200 kHz, the intensity between individuals varied greatly, especially over the 189–249 kHz bandwidth (Fig. 4D). The normalized shrimp target spectra reduced variance, which showed that the northern shrimp had the most consistent target spectra pattern despite the large variability in target strength intensity.

4.3. Recommendations for the acoustic classification of *in situ* targets

The high performance of the classifiers in a controlled experiment is an important step towards *in situ* target classification. However, fundamental challenges should be addressed before *in situ* target classification can be achieved with mesocosm-trained classifiers. A significant limitation of supervised classification is the dependence on collecting training datasets for all classes (Handegard et al., 2021). Collecting target spectra from mesocosm experiments for all species and size groups in complex and dynamic environments such as the ocean, even in Arctic regions with relatively low species diversity, is unrealistic. A series of ship-based downward-looking lowered acoustic probe experiments were completed as part of this study, attempting to classify *in situ* targets using the trained classifiers. However, the trawls showed the community was dominated by herring and capelin among the Atlantic cod, polar cod and northern shrimps, which prevented validation of *in situ* classification. One method to validate the classifiers would be to repeat the lowered acoustic probe experiments in an enclosed region, such as a lake or smaller fjord, dominated by a single species to assess the error for that species. Single species-dominated regions are commonly used in fisheries acoustics to associate the backscatter to a single species (e.g., Geoffroy et al., 2016; De Robertis et al., 2019). A more widespread method to use mesocosm-trained classifiers would be to have broader classes and to group species based on morphological features and expected backscattering (Gugele et al., 2021). Alternatively, mesocosm measurements could be used to validate and improve broadband sound scattering models to improve on model-informed classification (Dunn et al., 2024) However, better knowledge of the impact of multiple scattering features and their contribution to target spectra complexity will also be necessary to successfully classify *in situ* broadband acoustic signals.

Another practical limitation to *in situ* broadband acoustic target classification is the manual track selection requirements. Better tracking algorithms for broadband data with reduced risk of interference from contaminating targets within the Fourier transform window will need to be developed. Currently, tracking algorithms (based on Blackman (1986) require manual validation for broadband measurements using frequency response and target location algorithms (Khodabandeloo et al., 2021), which is time-consuming and subjective. Manual selection of single echoes and tracks halts the potential of automation and reproducibility. With automatic and reproducible track selections, classifiers could be quickly applied to new datasets for large-scale analysis of hydroacoustic survey datasets.

Another challenge with applying mesocosm results to *in situ* measurements is the limited possible replicates of target spectra available from the enclosed species. There is a much wider range of shapes and swimming behaviour found in naturally occurring individuals. For the Atlantic cod experiment, only 16 individuals were enclosed in the mesocosm. Therefore, there were limited detection replicates possible from the experiment and their swimming behaviour is a limited representation of that from fish in the wild. The repeatability of the results from the two polar cod experiments showed consistency in the target spectra results between two groups of the same species; however, they were from the same fjord and trawl haul. Further mesocosm experiments with populations from different fjords could improve our understanding of the interspecies variability of target spectra and limit pseudoreplication (Hurlbert, 1984). The individual detections were used for the study because target spectra were variable within a track, and the spectral complexity factors from the target spectra would be flattened by averaging multiple detections from a track. Yet, even though challenges remain before applying classification algorithms to *in situ* targets, this study demonstrates: (1) that pelagic organisms can be discriminated based on the complexity of their target spectra shape using a single transducer, and (2) that machine learning algorithms can efficiently identify these target spectra.

5. Conclusion

Three sympatric species, Atlantic cod, polar cod, and northern shrimp, were found to have distinct enough target spectra relative to each other in monospecific mesocosm experiments. Machine learning classifiers achieved high performance, especially the LightGBM and SVM classifiers. We speculate the variability in the level of complexity from the target spectra shape of the different species lead to the high performance of the classifiers on the normalized target spectra. The within channel target spectra variability was distinct enough demonstrating that a classification can be conducted with a single-channel transducer centred at 200 kHz. Further studies should consider including target strength intensity in classification by not normalizing the target spectra to account for important target strength information. Based on a case study from Arctic species, this study advances the knowledge towards automating spectral classification for *in situ* classification from a lowered acoustic probes or autonomous underwater vehicles with payloads limited to a broadband echosounder and a single transducer. Further mesocosm studies could help determine the taxonomic resolution to which mesocosm-trained classifiers can be used for *in situ* classification, either by adding new classes of additional spatially coinciding species, such as herring and capelin, or by joining new classes in the existing ones based on their target spectra complexity. An important application of spectral classification is real-time warnings of bycatch risks to reduce cost and trawling impact. In Arctic regions, forecasting bycatch risks could greatly impact the shrimp fishery because excessive retention of non-regulated bycatch can increase fuel costs, loss of revenue, and practical problems of onboard with sorting the catch (Jacques et al., 2022). Finally, automated acoustic classification methods could increase our ability to monitor pelagic fish stocks using acoustic surveys (Fossheim et al., 2015; Morley et al., 2018; Morato et al., 2020).

CRediT authorship contribution statement

Muriel Dunn: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Geir Pedersen:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Malin Daase:** Writing – review & editing, Methodology, Investigation, Funding acquisition. **Jørgen Berge:** Writing – review & editing, Resources, Investigation, Funding acquisition. **Emily Venables:** Methodology, Investigation. **Sünnje L. Basedow:** Writing – review & editing, Resources. **Stig Falk-Petersen:** Methodology, Investigation. **Tom J. Langbehn:** Writing – review & editing, Visualization, Investigation. **Jenny Jensen:** Writing – review & editing, Methodology. **Lionel Camus:** Writing – review & editing, Resources, Funding acquisition. **Maxime Geoffroy:** Writing – review & editing, Supervision, Resources, Methodology, Investigation, Conceptualization.

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Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.fishres.2025.107388.

Data availability

The data underlying this article are available in Zenodo for Atlantic cod (https://doi.org/10.5281/zenodo.8289718), polar cod (https://doi.org/10.5281/zenodo.8289738), northern shrimp (https://doi.org/10.5281/zenodo.8289764), and calibrations (https://doi.org/10.5281/zenodo.8289670).

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