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TECHNICAL COMMUNICATIONS

Multispectral Acoustic Backscatter: How Useful Is it for Marine Habitat Mapping and Management?

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ABSTRACT

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Marine managers routinely use benthic habitat maps to make decisions about the ocean, its resources, and associated human uses. Acoustic backscatter from multibeam echosounders (MBES) is often critical for developing these habitat maps. Recent advances now allow MBES to collect backscatter at multiple acoustic frequencies. This type of data may help researchers more accurately map benthic habitats and managers more confidently make decisions. However, new research is needed quantifying how much multispectral backscatter improves the habitat characterization process and identifying which management needs would benefit most from its collection. To begin answering these questions, a case study was conducted opportunistically in Bedford Basin, Canada, with MBES bathymetry and backscatter collected at 100, 200, and 400-kHz frequencies. Underwater photos and boosted regression trees were used to characterize seven dominant benthic habitats and calculate the relative importance of multispectral backscatter to the characterization process. Response curves were generated to identify key relative frequency thresholds for differentiating among habitat types. These results indicated that multispectral backscatter can enhance the discrimination of soft bottom by 17.4%, hard bottom by 5.7%, and all habitats by 9.1%. Topographic information (*e.g.*, depth) contributed the most to the hard-bottom maps (51.8% ± 4.0), whereas multispectral backscatter contributed the most to the soft-bottom map (46.9%). The 100-kHz frequency was the most important frequency for all habitat types. These findings suggest that multispectral backscatter maybe most useful to management applications focused on soft-bottom habitats. Single-frequency (*i.e*. 100 kHz) backscatter may be adequate for applications focused on hard bottom, because it only improved the models by a small amount. Researchers and marine managers can start to use this information to decide *a priori* which backscatter frequency (or frequencies) are best suited to support their research objectives, mapping needs, and management actions.

ADDITIONAL INDEX WORDS: *Multispectral backscatter, acoustic backscatter, multibeam echosounders, MBES, 100 kHz, 200 kHz, 400 kHz, benthic habitats, benthic characterization, marine management.*

INTRODUCTION

Marine managers routinely use benthic habitat maps to make decisions about the seascape (Cogan *et al*., 2009). These decisions can range from designating critical habitats that support fisheries (Smith and McConnaughey, 2016), to siting marine infrastructure (*e.g*., cables or wind turbines) (Multon, 2013), to shoreline protection and beach nourishment (Finkl, Khalil, and Andrews, 1997; Finkl and Walker, 2005). In the United States, marine managers at the National Oceanic and Atmospheric Administration (NOAA) rely on baseline information about the seafloor, including high-quality maps of benthic habitats, to make informed decisions in support of coastal economies and to address evolving marine uses of the U.S. exclusive economic zone (NOAA, 2017, 2018). For example, NOAA's National Marine Fisheries Service uses benthic habitat maps to manage productive and sustainable fisheries under the Magnuson-Stevens Fishery Conservation Act (NOAA, 2007). This act requires that managers protect essential fish habitat, which is defined as the waters and hard/soft substrates necessary for economically important fish to spawn, breed, feed, and mature (Smith and McConnaughey, 2016).

Acoustic backscatter, particularly from multibeam echosounders (MBESs), is often a critical piece of baseline information needed by marine managers. Backscatter is critical because it is needed to produce high-quality benthic habitat maps (Brown and Blondel, 2009; Holliday, 2007; Smith and McConnaughey, 2016). Most MBES systems in use today collect backscatter using only one acoustic frequency (Anderson *et al*., 2007; Brown *et al*., 2011). However, recent technological advances now allow MBES systems to collect backscatter at multiple acoustic frequencies (*i.e*., multispectral backscatter). This multispectral information can be collected by wide-band MBES

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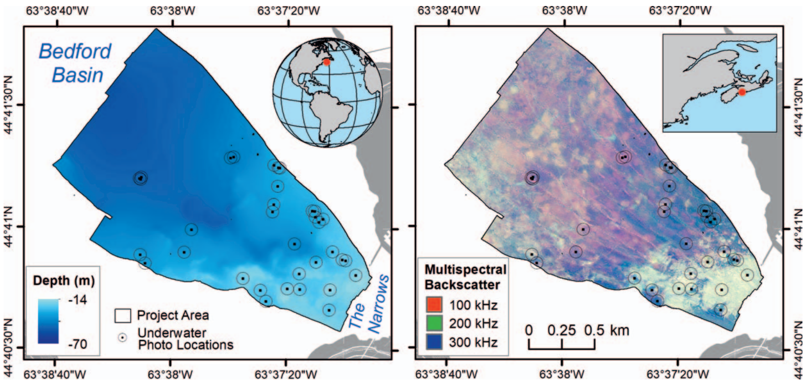

Figure 1. Map of Bedford Basin, Nova Scotia, Canada. (Left) Depth surface (m) and (right) false color multispectral backscatter surface for Bedford Basin. The false color surface depicts the 100, 200, and 400-kHz frequencies as the red, green, and blue channels, respectively. The circles denote the location of underwater photos. These datasets were provided by R2 Sonic (2017).

systems (like the R2 Sonic 2026) or by multiple MBES systems whose frequencies differ by one or more octaves (Hughes-Clarke, 2015). The potential for multispectral backscatter is exciting to the benthic habitat characterization community because backscatter strength depends on the size of the wavelength (*i.e.* frequency) in relation to the size of the particles on the seafloor (*i.e.* roughness) (Ogilvy and Merklinger, 1991). This relationship means that different frequencies provide distinct information about seafloor geology and benthic habitats. Specifically, lower acoustic frequencies (*e.g.*, 100 kHz) often penetrate deeper into softer sediments on the seafloor, potentially detecting habitats that higher frequencies cannot (Anderson *et al*., 2007; Cuff, Anderson, and Devillers, 2009, Gaida *et al*., 2018). Conversely, higher frequencies (*e.g*. 400 kHz) detect smaller features on the seafloor, potentially detecting habitat features that lower frequencies miss (Cuff, Anderson, and Devillers, 2009). Combined, this new way of mapping the seafloor has the potential to enhance the ability of the habitat characterization community to discriminate among different bottom types (Anderson *et al*., 2008; Hughes-Clarke, 2015) and develop more robust and accurate maps of the seafloor.

To date, most research on multispectral backscatter has focused on describing backscatter responses for different frequencies, substrates, and grazing angles (da Cruz Peçanha, 2016; Hughes-Clarke, 2015; Kist, 2017), trying to derive benthic habitats from multispectral backscatter (Cuff, Anderson, and Devillers, 2009; Kist, 2017; Gaida *et al*., 2018), or both. These studies have shown that for soft sediments (*e.g*., sand), backscatter strength often decreases as the frequency and grazing angles decrease (Gaida *et al*., 2018; Hughes-Clarke, 2015). This means that in softer, finer sediments, lower frequency backscatter (*e.g*., 100 kHz) may detect and map surficial substrates that are not visible in higher frequency backscatter (*e.g*., 400 kHz) (da Cruz Peçanha, 2016, Gaida *et al*., 2018; Hughes-Clarke, 2015). This physical relationship was the basis for testing different methods of creating benthic habitat maps from multispectral backscatter on the Scotian Shelf, Canada (Cuff, Anderson, and Devillers, 2009), in Charleston Harbor, South Carolina (Kist, 2017), and in the Bedford Basin, Canada (Gaida *et al*., 2018). Although these studies helped advance the understanding of multispectral backscatter, they did not investigate key questions that remain about this type of data, including: (1) How much (%) does multispectral backscatter improve the ability to characterize benthic habitats? (2) Do some habitat classifications benefit more than others? (3) How important is multispectral backscatter compared with other well-studied information about the seafloor (*e.g*., depth, slope, rugosity, *etc*.)? (4) What relative acoustic thresholds may be ecologically important and relevant to management actions? These questions were the focus of this study because they are critical for understanding not only the utility of multispectral backscatter for habitat characterization, but also in what situations its collection and processing is worth the additional effort required (Hughes-Clarke, 2015). Answers to the above questions will help researchers and marine managers make more informed decisions about whether to collect multispectral backscatter and, if so, where and when its collection would benefit their project the most. Understanding not only why but also when to use this mapping tool is critical for resource managers and other benthic habitat map users moving forward.

To answer these questions, a machine learning technique was applied to a multispectral MBES dataset (*i.e*. at 100, 200, and 400-kHz frequencies) collected in Bedford Basin, Nova Scotia, Canada (Figure 1). This multispectral MBES dataset was collected by researchers at Nova Scotia Community College, QPS Canada, and R2 Sonic as a technology demonstration (Brown *et al*., 2017). It was used opportunistically as a case study to better understand and quantify the mathematical relationship among acoustic frequencies and benthic habitats in the basin, including Rock, Cobble, Mud, Clams, Limpets, Urchins, and uncolonized substrates. This information was the focus of this study, and the influence of other environmental conditions (*e.g*., tides), ecological mechanisms (*e.g*., predation), and human activities (*e.g*., dredging) on the distribution of benthic habitats in the basin were outside the scope of this research.

METHODS

Bedford Basin is a bowl-shaped area approximately 5 km long by 3 km wide (Figure 1). It is open to the Atlantic Ocean with tidal ranges around 1.5 m. Tidal waters flow in and out of "The Narrows," located at its mouth to the southeast. Depths in this area are approximately 14 m and drop off rapidly to approximately 70 m. The area around the basin is largely developed because it is the largest port in Atlantic Canada (Natural Resources Canada, 2007). It is home to a variety of industrial, military, and urban areas, with the cities of Halifax to the SE, Burnside to the east, the Canadian Forces Ammunition Depot to the north, and Bedford to the NW. The basin's importance as a hub of maritime activity also means it has been well studied. Acoustic mapping, geological cores, sediment grabs and remotely operated vehicle surveys have been conducted in the basin to characterize the geology, biology, and oceanography of the Basin (Courtney 1993; Fader, Miller, and Pecore, 1991; Lawrence, 1989). Geochemistry analyses were conducted on the sediment cores and grabs to understand the sediment history and presence of contaminants (Fader, Miller, and Pecore, 1991). This information was combined to produce maps depicting the surficial geology and geochemistry of Bedford Basin (Fader and Buckley 1995). These maps show that gravel and rock are present in large abundances closer to "The Narrows" but that sediments inside Bedford Basin are primarily mud (LaHave Clay) (Fader, Miller, and Pecore, 1991).

Description of Data Collection and Processing Methods

The multispectral data and underwater photographs analyzed here were collected by researchers at the Nova Scotia Community College, QPS Canada, and R2 Sonic, and were provided courtesy of R2 Sonic (R2 Sonic, 2017). Underwater photographs were collected at 34 sites with a SubC camera on 8–10 March 2016 and 7, 9, and 24 March 2017 (Brown *et al*., 2017; R2 Sonic, 2017). A benthic expert visually interpreted underwater photos at these sites according to the Coastal and Marine Ecological Classification Standard (FGDC, 2012) to annotate the presence and percent cover of four substrate types (Rock, Cobble, Shell, and Mud) and eight biological cover types (Algae, Anemones, Bare, Clams, Limpets, polychaete Worms, Sponges, and Urchins).

The multispectral dataset was collected by the MV *Eastcom* (12-m fiberglass survey vessel) with a pole-mounted R2Sonic 2026 on 20 April 2016 and 2 May 2017 (Brown *et al*., 2017, 2019). In total, 15 and 13 survey lines (respectively) were collected mapping approximately 2 km^2 of seafloor in depths from 14 to approximately 70 m in the basin. The position and attitude of the R2 2026 were recorded by a POS MV Wave Master and dual Trimble GPS antennas. Sound velocity (SV) was measured at the transducer head by a Valeport SVP probe, and conductivity, temperature, and pressure (CTD) casts were conducted periodically with an AML Base•X_2. Outputs from these sensors were integrated with the data from the R2 Sonic 2026 by QPS QINSy (QPS, 2018). Depths were corrected for motion, sound velocity, and tides (with a tidal gauge at the Bedford Institute of Oceanography) in QPS Qimera (QPS, 2018) and exported as 1 × 1 m GeoTIFF surface. Please see Brown *et al*. (2017, 2019) for a full description of the data acquisition parameters and processing specifications.

Backscatter snippets were collected simultaneously at 100, 200, and 400-kHz frequencies and were continuously monitored for saturation (Brown *et al*., 2017). Backscatter snippets were processed in QPS FMGT software (QPS, 2018) and corrected for acoustic source levels, pulse lengths, receiver sensitivity, beam patterns, spherical spreading and absorption, time varying gains, and angular dependence from local seafloor slopes (Hughes-Clarke *et al*., 2008). Absorption coefficients for backscatter processing were calculated with the CTD data. The exported backscatter snippet values were in decibels and exported at the same spatial resolution as the bathymetry (*i.e*. 1 × 1 m). These backscatter values were calibrated across survey years using the guidelines published by the GeoHab Backscatter Working Group (Lurton and Lamarche, 2015). This process created normalized, relative backscatter surfaces for each frequency. Although these surfaces were calibrated with each other, the MBES systems were not calibrated absolutely in the field. *In situ* absolute calibration requires accounting for biases in several components of the MBES system with targets of known acoustic responses (Brown *et al*., 2015). This type of MBES backscatter calibration is rare because it is time consuming, complex and subject to in-water heterogeneities (Lurton and Lamarche, 2015). As a result, the habitat mapping community widely uses and accepts relative backscatter (calibrated across years or vessels) for seafloor characterization (Lurton and Lamarche, 2015).

Description of Habitat Modeling Approach

Boosted regression trees were used to develop benthic habitat predictions and maps in Bedford Basin and to investigate the relative importance of multispectral backscatter and key acoustic thresholds for characterizing different habitat types. This modeling technique was chosen because it has been shown to perform well compared with other techniques (Elith *et al*., 2006), including generalized linear models, generalized additive models, and multivariate adaptive regression splines, among others (De'ath, 2007; De'ath and Fabricius, 2000; Elith, Leathwick, and Hastie, 2008). This modeling technique also has diagnostic tools, which can be used to quantify which environmental predictors (*e.g*., 100, 200, or 400-kHz backscatter) are relatively more important, and identify environmental thresholds (*e.g*., –5, –10, –15 dB) that are useful for distinguishing among habitat types. These tools were critical for answering the four research questions above. Although this approach was tested on multispectral data here, it has also been used to map benthic habitat successfully by satellite imagery and single-frequency MBES data (Costa *et al*., 2017; Kendall *et al*., 2017).

Developing Habitat Models and Predictions from Multispectral Data

Three main steps were used to develop the benthic habitat models and predictions for Bedford Basin (Figure 2). These steps were conducted primarily in R software (R Core Team, 2015) with the dismo (Hijmans *et al*., 2014) and raster (Hijmans, 2014) packages. The first step was to generate 17 habitat predictors (Table 1) for the study area on a 1 × 1-m grid (Du Preez, 2015; Esri, 2017; Jenness, 2015; Roberts *et al*.,

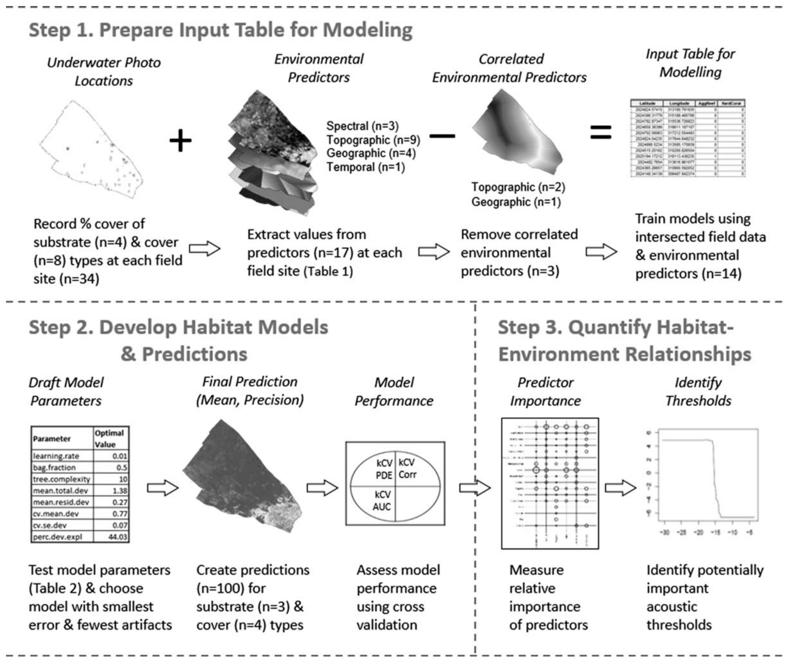

Figure 2. Diagram depicting steps in modeling process to predict seven habitat types in Bedford Basin.

2010). These 17 predictors and the tools used to generate them are listed in Table 1. Twelve of these predictors were derived from the multispectral MBES dataset, including nine from the depth data describing the topography of the seafloor and three from the backscatter data at the 100, 200, and 400-kHz frequencies. Four predictors described the geography (*e.g.*, latitude, longitude, and distance and direction to shoreline) were generated as proxies to account for the spatial variation in benthic habitats that was not explained by the MBES predictors (*e.g.*, by local oceanography, ecology, or human activities). One temporal predictor was used to determine whether there were systematic biases between the two years the input datasets were collected and whether these differences affected the ability to characterize benthic habitats in the basin. Three predictors (*i.e.* depth uncertainty, rugosity, and distance to shore) were removed from the modeling process because they were found to be highly correlated (Spearman Rank $r \geq 0.9$ or $r \leq -0.9$) with other predictors.

The second step in the process was to create a table combining benthic habitat information (from underwater photos) with predictor datasets, and use this input table to develop habitat models and spatial predictions (Figure 2, Step 2). A total of 3600 models were created by testing 15 parameter combinations ($n = 15$) (Table 2) for each habitat type ($n = 12$) and each response variable ($n = 2$) by k-fold cross validation (kCV, $k = 10$). Response variables described the percent cover (in a 1×1-m area) and probability of occurrence (*i.e.* the likelihood that a habitat is present) for each habitat type. Model performance was measured with percent deviance explained (PDE), Pearson correlation coefficients, and area under the curve (AUC) averaged across the 10 folds. Models failed to converge for five habitat types, including Shell, Algae, Sponges, Worms because these habitats were rare (prevalence <10%) (Liu *et al.*, 2005; Manel, Williams, and Ormerod, 2002). The model for Anemone abundance converged, but it contained artifacts from the distance to shoreline predictor, reducing its utility for the research questions posed here. These five habitat types were consequently excluded from further analysis. The seven best performing models (*i.e.* models with the highest kCV PDE) were selected for the remaining three substrate and four cover types. These selected models were used to predict the probability of occurrence for three habitats (*i.e.* Rock, Clams, Limpets) and predict the percent cover for four habitats (*i.e.* Cobble, Mud, Bare, Urchins). They were rerun for each habitat 100 times (by bootstrapping) to create 100 separate predictions. These predictions were used to compute the mean and precision (coefficient of variation) for each habitat type. Coefficient of variation (CoV) is a measure of model precision representing the standard deviation as a proportion of the mean (Leathwick *et al.*, 2006). Larger CoVs indicate lower precision and higher uncertainty associated with the spatial prediction.

Describing Habitat-Environmental Relationships with Multispectral Data

After the habitat models and predictions were developed, the third and last step in the process (Figure 2, Step 3) was to quantify the relationships between these benthic habitats and their environment, including multispectral backscatter. This analysis included ranking the predictors by their importance to the modeling process and describing important thresholds for habitats along relative acoustic gradients. It is important to point out that the intent here was not to explain the direct environmental condition(s) or underlying ecological mecha-

Table 1. *The environmental predictors, including multispectral backscatter, used to develop habitat predictions and maps in Bedford Basin. Year was included to determine whether decibels were systematically biased or offset between the two years the input datasets were collected and whether these differences affected the ability to map benthic habitats in the Basin reliably. Other variables (e.g., oceanographic, ecological, anthropogenic, etc.) were excluded from the models because they were beyond the scope of this research.*

No.	Group	Predictor	Units	Description	Software Tool
1	Multispectral	Backscatter (100 kHz)	dB	Backscatter at 100-kHz frequency. Values are relative because the MBES system was not calibrated.	Fledermaus FMGT (QPS, 2018)
2		Backscatter (200 kHz)	dB	Backscatter at 200-kHz frequency. Values are relative because the MBES system was not calibrated.	Fledermaus FMGT (QPS, 2018)
3		Backscatter (400 kHz)	dB	Backscatter at 400-kHz frequency. Values are relative because the MBES system was not calibrated.	Fledermaus FMGT (QPS, 2018)
4	Topographic	Arc-chord	Unitless ratio	Contoured area of the surface divided by the area of the surface orthogonally projected onto a plane of best fit.	ArcGIS ACR Rugosity Toolbox (Du Preez, 2015)
5		Plan curvature	Radians/m	Curvature of surface perpendicular to the direction of the maximum slope. Surface can be convex (−), concave (+), or flat (0).	ArcGIS DEM Surface Tools (Jenness, 2015) Curvature Tool
6		Profile curvature	Radians/m	Curvature of surface parallel to the direction of the maximum slope. Surface can be convex (−), concave (+), or flat (0).	ArcGIS DEM Surface Tools (Jenness, 2015) Curvature Tool
7		Total curvature	Radians/m^2	Curvature of the seafloor. Seafloor can be convex (−), concave (+), or flat (0).	ArcGIS DEM Surface Tools (Jenness, 2015) Curvature Tool
8		Depth	m	Water depth.	Fledermaus D-Magic (QPS, 2018)
9		Depth uncertainty†	m	Uncertainty (International Hydrographic Organization Order 1) associated with water depth.	Fledermaus D-Magic (QPS, 2018)
10		Rugosity†	Unitless ratio	Ratio of surface area to planar area. The higher the number, the bumpier the seafloor.	ArcGIS DEM Surface Tools (Jenness, 2015) Calculate Surface Ratio Raster Tool
11		Slope	Degrees	Maximum rate of change in depth.	ArcGIS Slope Tool (Esri, 2017)
12		Slope rate of change	Degrees	Maximum rate of change in slope.	ArcGIS Slope Tool (Esri, 2017)
13	Geographic	Longitude (x)	m	Easting in Bedford Basin.	ArcGIS MGET Toolbox (Roberts *et al.*, 2010) Create X Coordinate Raster Tool
14		Latitude (y)	m	Northing in Bedford Basin.	ArcGIS MGET Toolbox (Roberts *et al.*, 2010) Create Y Coordinate Raster Tool
15		Distance to shoreline†	m	Euclidean distance to the shoreline.	ArcGIS Euclidean Distance Tool (Esri, 2017)
16		Direction to shoreline	Degrees	Direction to the closest shoreline.	ArcGIS Euclidean Direction Tool (Esri, 2017)
17	Time	Year	—	Year the MBES data were collected.	ArcGIS Reclassify Tool (Esri, 2017)

†*Predictor removed from modeling process because it was highly correlated (Spearman Rank $r \geq 0.9$ or $r \leq -0.9$) with other predictors.*

nism(s) driving benthic habitat distributions. Rather, it was to help answer the four primary research questions including: (1) How much (%) does multispectral backscatter improve the ability to characterize benthic habitats? (2) Do some habitat classifications benefit more than others? (3) How important is multispectral backscatter compared with other well-studied information about the seafloor (*e.g.*, depth, slope, rugosity, *etc.*)? (4) What relative acoustic thresholds may be ecologically important and relevant to management actions and outcomes?

The relative importance of each predictor was quantified by calculating the number of times it was used in a model and weighted by how much it improved the model (Elith, Leath-

Table 2. *Model parameters tested to develop habitat predictions and maps in Bedford Basin.*

Model Parameter	Values Tested	Description	Impact
Learning rate (lr)	0.01, 0.001, 0.005	Determines contribution of each tree to the growing model	Decreasing (slowing) lr increases the no. of trees required for optimal prediction.
Tree complexity (tc)	2, 3, 4, 5, 10	Controls how many predictor interactions are fitted in a tree	Decreasing tc will shrink the size (no. of nodes) in a tree.
Bag fraction (bf)	0.75	Controls proportion of data randomly selected to build each tree	Decreasing bf will reduce the no. of points randomly used to build a tree.

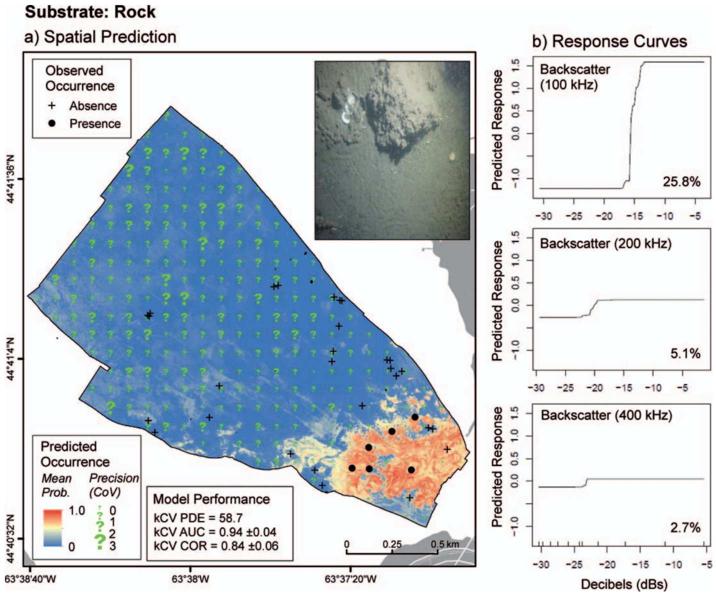

Figure 3. Predicted probability of occurrence for the Rock habitat. (a) Rock habitat (inset) and a map denoting its observed presence and absence and predicted probability of occurrence. (b) Multispectral backscatter response curves associated with this prediction.

wick, and Hastie, 2008; Friedman, 2001; Friedman and Meulman, 2003). The relative score for each predictor was scaled so the sum added up to 100. Higher numbers indicated that the predictor was more important and more useful for explaining the spatial distribution of habitats. In addition to rankings, important predictor thresholds were identified by response curves (also known as partial dependence plots). They were created for each habitat model and for the 100, 200, and 400-kHz backscatter predictors. Response curves show the effect of a predictor on the habitat prediction after accounting for the average effects of all other predictors in the model (Elith, Leathwick, and Hastie, 2008). They describe the distribution of habitats along an environmental and acoustic gradient and can provide a useful basis for interpretation (Friedman and Meulman, 2003; Hosmer and Lemeshow, 2000).

RESULTS

Seven habitats were successfully modeled and mapped with multispectral MBES data in Bedford Basin. Agreement between the field data and habitat predictions suggest that models were able to describe the relationships among the benthic habitats and predictors well. Specifically, the performance of the seven habitat models (Figures 3–9, panel a) was considered good to excellent on the basis of three evaluation metrics calculated by kCV) For all the models, kCV PDE ranged from 18.1% to 65.7% ($\bar{x} = 47.7\% \pm 6.3$). The Bare model had the highest kCV PDE, and the Cobble model had the lowest kCV PDE (18.1%). The kCV correlation coefficient values were also moderate to high for all models, ranging from 0.55 to 0.89 ($\bar{x} = 0.80 \pm 0.05$). The Limpets model had the highest kCV correlation coefficient (0.89), and the Clams model had the lowest kCV correlation coefficient (0.55). AUC was also calculated for the probability of occurrence models, describing their ability to distinguish correctly between the presence and absence of habitats. AUC values for these models ranged from good (0.89) to excellent (0.94) ($\bar{x} = 0.93 \pm 0.02$) (Hosmer and Lemeshow, 2000). The Rock and the Limpets models had the highest kCV AUC (0.94), and the Clams model had the lowest kCV AUC (0.89). The average precision (CoV) of these models ranged from 0.06 to 1.44 ($\bar{x} = 0.68 \pm 0.18$). The Bare model had the highest precision (0.06 ± 0.002), followed by the Mud model (0.15 ± 0.01), the Cobble model (0.45 ± 0.03), the Urchins model (0.67 ± 0.03), the Clams model (0.75 ± 0.02), the Limpets model (1.24 ± 0.04), and the Rock model (1.44 ± 0.06). These findings align with previous research (Cuff, Anderson, and Devillers, 2009; Hughes-Clarke, 2015; Kist, 2017), suggesting that multispectral data can be used successfully to predict and accurately map the distribution of benthic habitats.

Key Thresholds for Multispectral Backscatter

The multispectral backscatter response curves (Figures 3–9, panel b) identified several important relative thresholds for distinguishing among benthic habitats. The multispectral backscatter thresholds were consistent across the substrate models. Specifically, for the Rock and Mud models, the –16, –20, and –23-dB thresholds were important at the 100, 200, and 400-kHz frequencies, respectively. The same thresholds were important for the Cobble model at the 100-kHz frequency. However, no threshold was identified at the 200 and 400-kHz frequencies because they did not contribute notably (<0.4%) to the Cobble model. Although these threshold values were consistent, they marked a change in the directionality of the predicted response for hard *vs.* soft substrates. Specifically, the predicted response for the Rock and Cobble models increased when backscatter values were greater than –16, –20, and –23 dB at the 100, 200, and 400-kHz frequencies, respectively. For

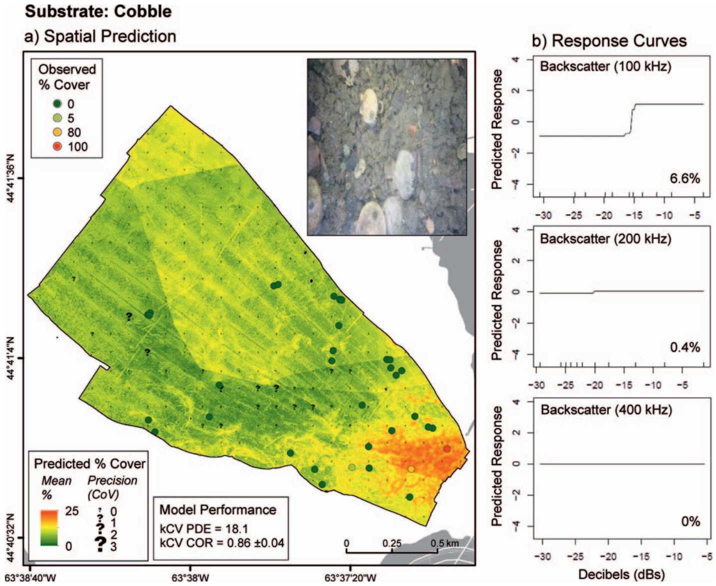

Figure 4. Predicted percent cover of the Cobble substrate. (a) Cobble habitat (inset) and a map denoting its observed and predicted percent cover. (b) Multispectral backscatter response curves associated with this prediction.

the Mud model, this trend was reversed, and the predicted response increased when backscatter values were below these thresholds (*i.e.* <–16, –20, –23 dB). These results suggest that there are discrete, frequency-dependent backscatter thresholds for distinguishing among different substrate types. However, the exact decibel values for these thresholds may differ for other MBES systems, geographic areas, or both, because these backscatter values are relative.

These same two patterns were visible in the response curves for the biological cover models. Specifically, the thresholds for the biological cover models were also consistent across the modeling group and were almost the same (±2 dB) as the substrate model thresholds. For the Bare, Limpets, and Urchins models, the –15, –20, and –23-dB thresholds were important at the 100, 200, and 400-kHz frequencies, respectively. For the Clams model, the –15-dB threshold was

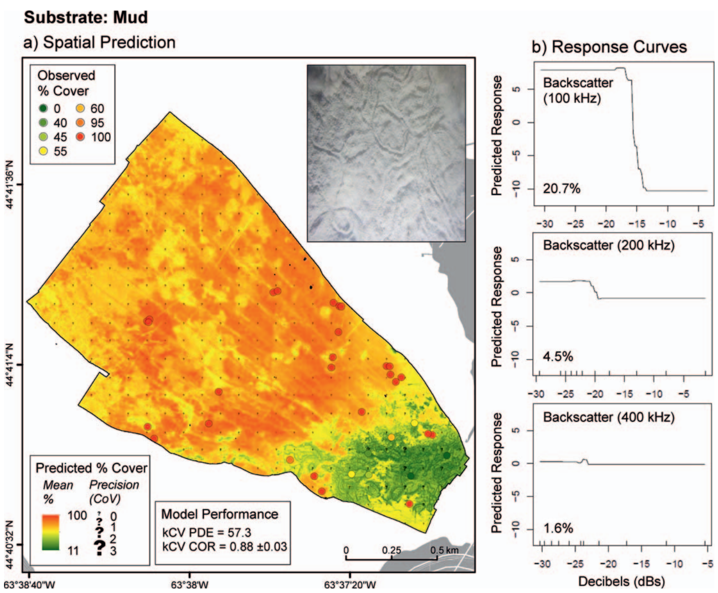

Figure 5. Predicted percent cover of the Mud substrate. (a) Mud habitat and a map denoting its observed and predicted percent cover. (b) Multispectral backscatter response curves associated with this prediction.

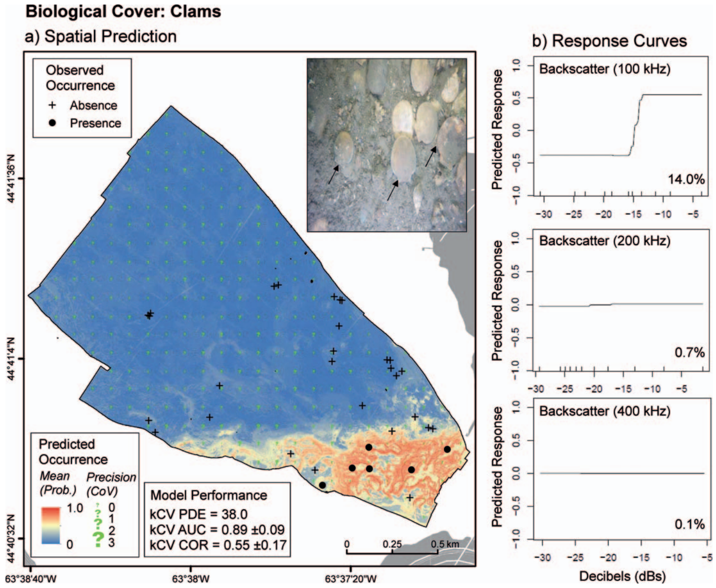

Figure 6. Predicted probability of occurrence for Clams. (a) Clam habitat (inset, black arrows) and a map denoting its observed presence and absence and predicted probability of occurrence. (b) Multispectral backscatter response curves associated with this prediction.

important at the 100-kHz frequency. No thresholds were identified at the 200 and 400-kHz frequencies because they did not contribute notably (0.8%) to the Clams model. Also, as for the substrate models, these acoustic thresholds denoted a change in the directionality of the predicted response for the biological communities most commonly associated with hard and soft substrates. Specifically, the predicted response for the Limpets, Clams, and Urchins models increased for backscatter values >–15, –20, and –23 dB at the 100, 200, and 400-kHz frequencies, respectively. These biological communities were most commonly associated with hard substrates (Rock and Cobble) in Bedford Basin (Figure 10; Spearman rank $\rho = 0.58$–0.99, $p \leq 0.00$). For the Bare model, this trend was reversed, and the predicted response increased when backscatter values were below these thresholds (*i.e.* <–15, –20, and –23 dB). Bare substrates were most

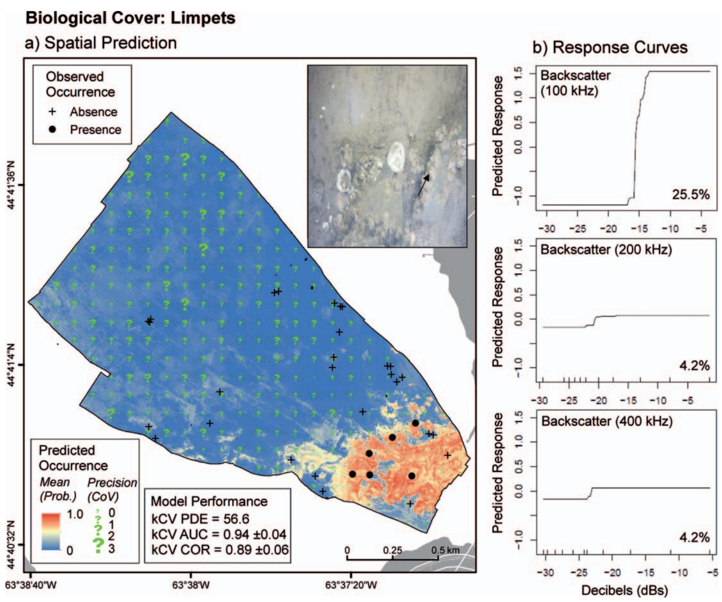

Figure 7. Predicted probability of occurrence for Limpets. (a) Limpets habitat (inset, black arrow) and a map denoting its observed presence and absence and predicted probability of occurrence. (b) Multispectral backscatter response curves associated with this prediction.

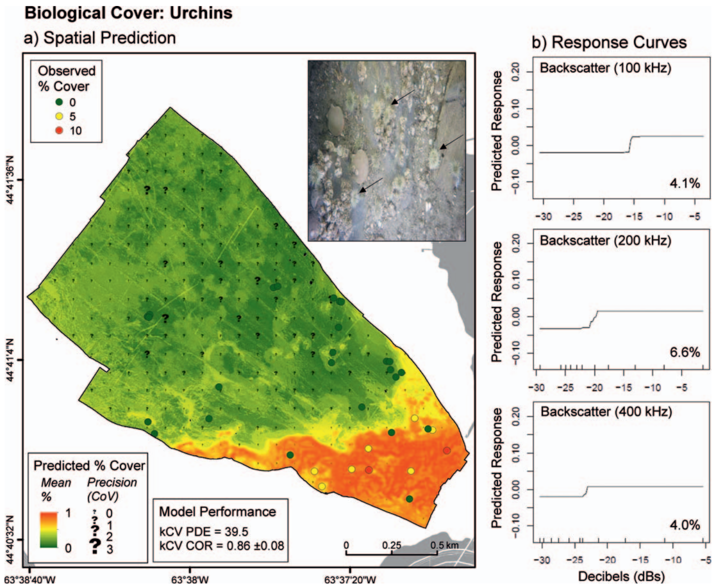

Figure 8. Predicted percent cover of Urchins. (a) Urchin habitat (inset, black arrows) and a map denoting its observed and predicted percent cover. (b) Multispectral backscatter response curves associated with this prediction.

commonly associated with mud in Bedford Basin (Figure 10; Spearman rank $\rho = 0.71, p \leq 0.00$). These results suggest that there are discrete, frequency-dependent backscatter thresholds that can help distinguish among biological communities commonly associated with hard and soft substrates. However, the exact decibel values for these thresholds may differ for other MBES systems, geographic areas, or both, because these backscatter values are relative.

Relative Importance of Multispectral Backscatter

Certain predictor groups were more important for characterizing hard *vs*. soft substrates (Figure 11). Specifically, the topographic predictors were the most important group for characterizing hard-bottom habitats and the most important group overall. These predictors contributed an average of 49.0% ± 1.6 to all habitat models and 51.8% ± 4.0 to the hard-bottom habitat models alone. The multispectral backscatter

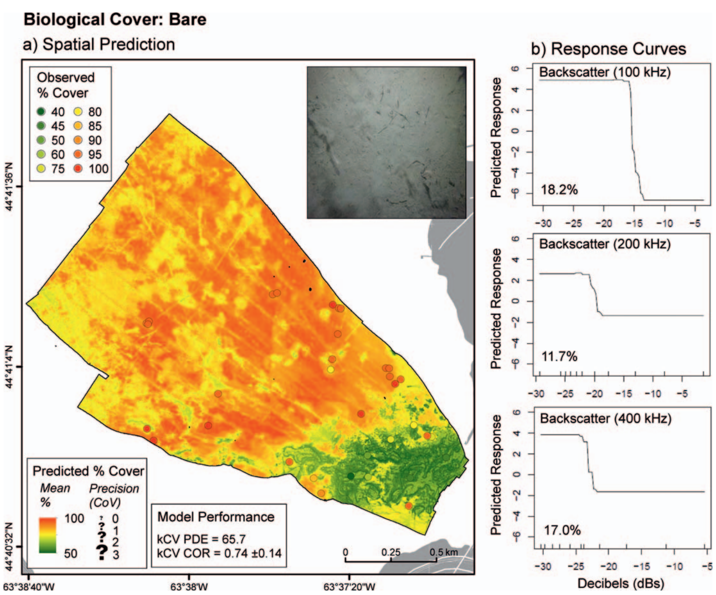

Figure 9. Predicted percent cover of the Bare substrate. (a) Bare habitat (inset) and a map denoting its observed and predicted percent cover. (b) Multispectral backscatter response curves associated with this prediction.

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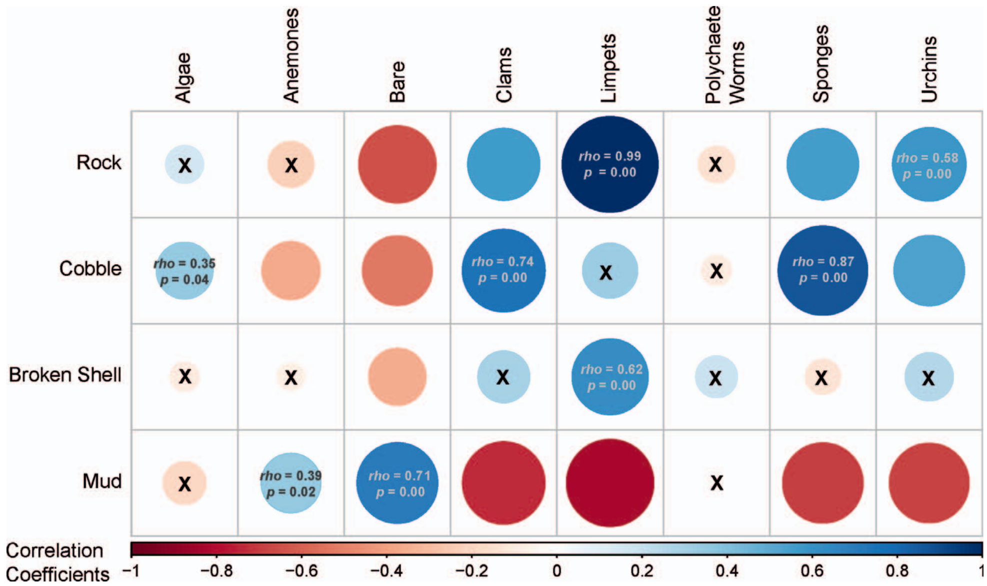

Figure 10. Spearman rank correlations among substrate and biological cover types. Blue circles denote habitat types that were positively correlated, and red circles denote habitat types that were negatively correlated. Stronger correlations are denoted by larger circles and darker colors. Correlation coefficients and *p* values are reported for the highest, positive correlation for each substrate-biological cover pair. Circles with an "x" denote habitat types that were not significantly correlated.

predictors were tied for second with the geographic predictors, contributing an average of 25.4% ± 5.4 and 25.6% ± 3.9 to the habitat models and 20.8% ± 4.9 and 27.5% ± 4.5 to the hard-bottom models, respectively. However, multispectral backscatter was the most important predictor group (46.9%) for the Bare habitat model. This habitat model was highly correlated with the Mud prediction and was the only prediction for which all the backscatter frequencies (*i.e.* 100, 200, and 400 kHz) had similar relative rankings (11.7%, 17.0%, 18.2%). The Bare and Mud predictions also had the highest precision (*i.e.* the lowest amount of uncertainty) associated with them (Figures 5a and 9a). These results suggest that multispectral backscatter is less important than the topographic predictors for mapping hard-bottom habitats, but it is highly important for characterizing soft-bottom habitats with high precision.

Although multispectral backscatter was not the top predictor group for hard-bottom habitats, certain acoustic frequencies were consistently ranked highest at an individual level. Specifically, 100-kHz backscatter was the most important backscatter predictor overall, explaining an average of 15.1% ± 4.0 for hard-bottom habitats and 19.4% ± 0.9 for soft-bottom habitats. It was also ranked highest for four habitat models, including Rock, Mud, Bare, and Limpets. This frequency was more consistently important than any other individual topographic, geographic, or temporal predictor, except depth. This pattern is in contrast to the relative importance of backscatter at the 200 and 400-kHz frequencies. These backscatter frequencies were relatively unimportant to most habitat models, contributing an average of 4.8% ± 1.3 and 4.3% ± 2.1, respectively. As mentioned above, the one exception was the Bare model, wherein all three frequencies (*i.e.* 100, 200, and 400 kHz) had similar relative rankings (11.7%, 17.0%, and 18.2%). This trend suggests that these additional frequencies (*e.g.*, 200 and 400 kHz) have utility for mapping Bare Mud habitats, but they may have limited utility for mapping the other habitat types examined here. The 100-kHz frequency might be a better choice (than 200 or 400 kHz) for characterizing the full mosaic of hard- and soft-bottom habitats across the seascape.

DISCUSSION

The research presented here was designed to answer four primary research questions: (1) How much (%) does multispectral backscatter improve the ability to characterize benthic habitats? (2) Do some habitat classifications benefit more than others? (3) How important is multispectral backscatter compared with other well-studied information about the seafloor (*e.g.*, depth, slope, rugosity, *etc.*)? (4) What acoustic thresholds may be ecologically important and relevant to management actions? These questions were explored with seven high-performing habitat models generated from multispectral data in Bedford Basin, Canada (Figures 3–9, panel a). This technical communication was designed to help marine researchers and managers begin to make more informed decisions *a priori* about the backscatter frequency (or frequencies) that are potentially best suited to support their research objectives, mapping needs, and management actions.

Key Relative Thresholds for Multispectral Backscatter

Hard- and soft-bottom maps are often critical baseline products for many resource managers making decisions about ocean and coastal resources (Cogan *et al.*, 2009). This analysis showed that in Bedford Basin, multispectral backscatter was useful for distinguishing between hard and soft substrates and

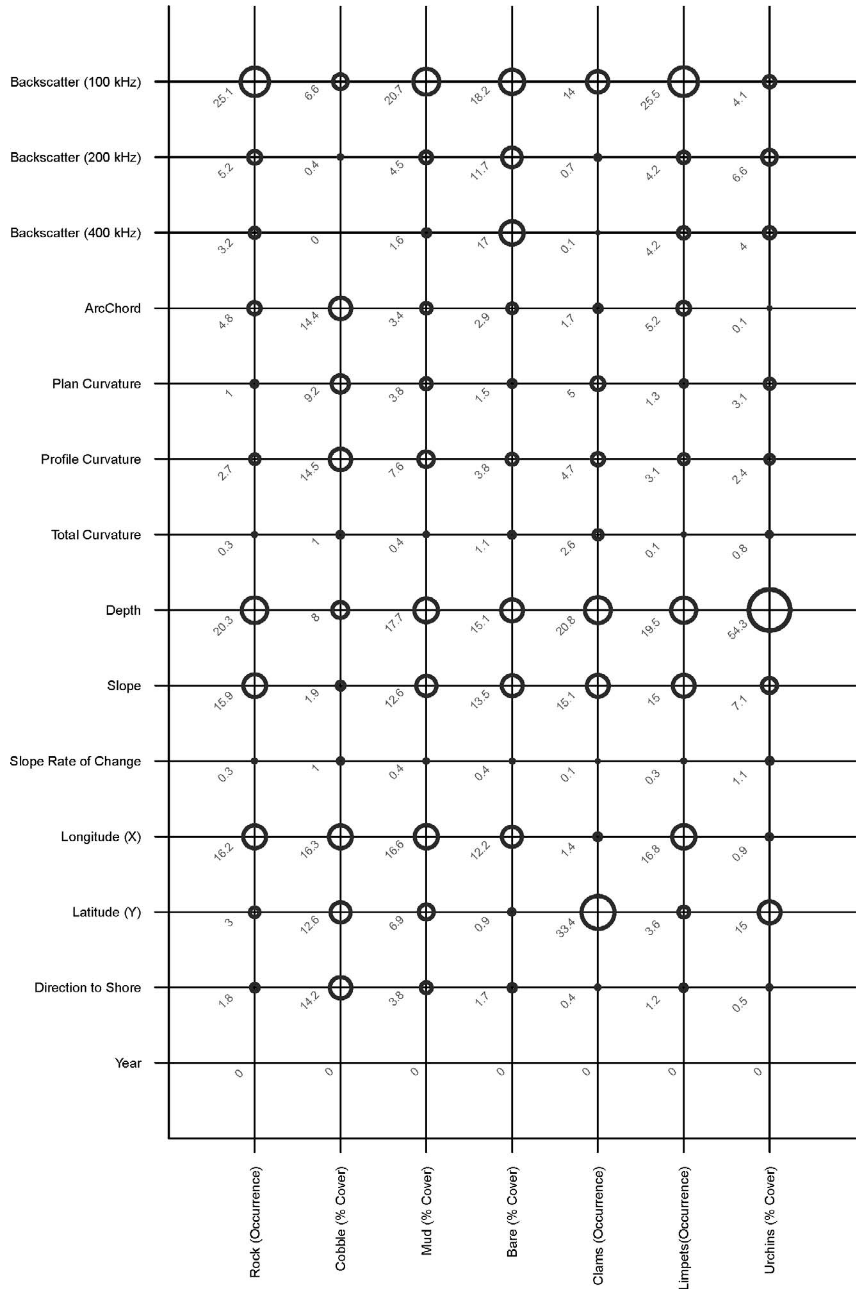

Figure 11. Relative importance of the environmental predictors used to develop the habitat models and predictions. Circle size is proportional to a predictor's relative importance averaged across 100 model iterations. The larger the circle, the more important the predictor. The gray numbers next to each circle denote their specific relative importance value.

associated biological communities. Specifically, three acoustic thresholds were consistently identified for the 100, 200, and 400-kHz frequencies for all habitat models. These relative thresholds were –15, –20, and –23 $\pm$ 2 dB, respectively. These frequency-dependent thresholds were useful to the habitat characterization process here because they provided clear, acoustic dividing lines between hard and soft substrates and associated biological communities. Above ($<$) these thresholds, the seafloor was reliably mapped as hard substrates (Rock, Cobble) with hard-bottom–associated biological communities (Limpets, Clams, and Urchins). Below ($>$) these thresholds, the seafloor was consistently characterized as soft substrates (Mud) with little biological cover (Bare).

These acoustic thresholds align with other multispectral backscatter research in similar temperate environments. Specifically, this research has shown that for the same habitat

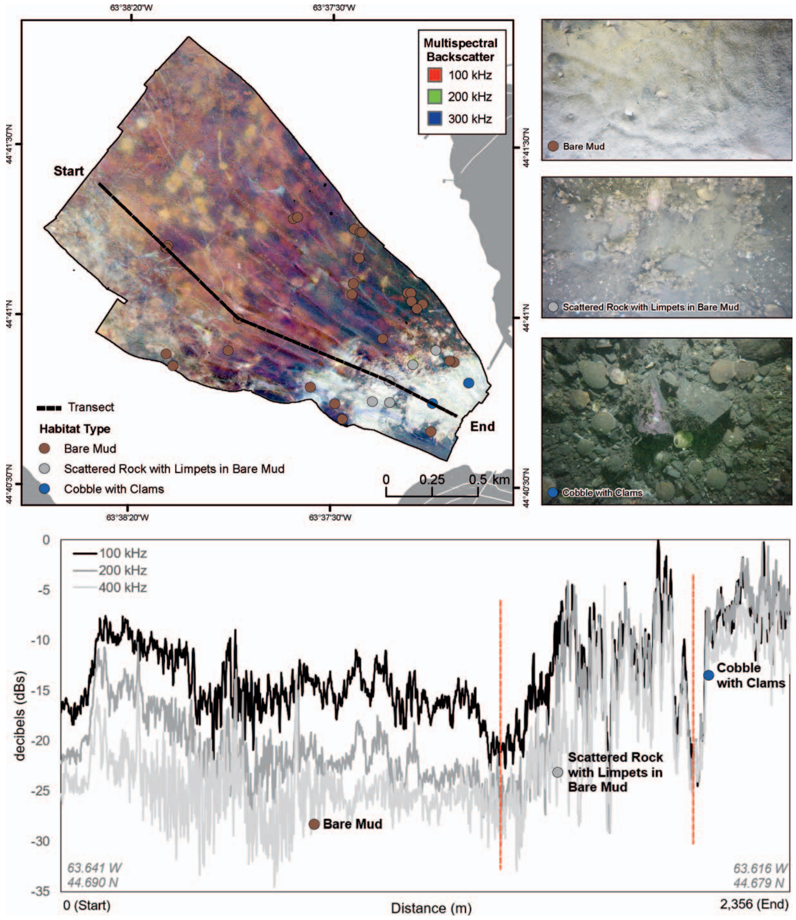

Figure 12. Comparison of backscatter from 100, 200, and 400-kHz frequencies along a transect (black dotted line). The 100, 200, and 400-kHz backscatter values along this transect are depicted below. The backscatter values for these three frequencies differ the most on Bare Mud habitats and deviate the least on Cobble with Clams.

type, backscatter responses are frequency dependent and differ by ±3–5 dB between octaves (*i.e.* 100 *vs.* 200 kHz or 200 *vs.* 400 kHz) (Hughes-Clarke, 2015). In addition to identifying thresholds, backscatter values were found to be generally higher (+) for lower frequencies (*e.g.*, 100 kHz) and lower (−) for higher frequencies (*e.g.*, 400 kHz) (Brown *et al.*, 2019; Gaida *et al.*, 2018; Hughes-Clarke, 2015). These same acoustic patterns were seen in Bedford Basin, where frequency-dependent backscatter values differed by 3–5 dB over Bare Mud habitats (Figure 12). Backscatter values for the three frequencies converged and became similar over the rocky and cobbly habitats. These similarities explain why the 200 and 400-kHz frequencies did not contribute notably to the Cobble or Clams model. They also aligned with findings from Gaida *et al.* (2018), which noted that the 100, 200, and 400-kHz responses diverged noticeably when sediments transitioned from or to Mud (grain size = 4.5 ϕ) (Gaida *et al.*, 2018). This divergence was a function of how deep the acoustic signal penetrated the seafloor.

Relative Importance of Multispectral Backscatter

Although multispectral backscatter might be useful for dividing hard and soft habitats, these results suggest that it is less important for characterizing hard-bottom habitats compared with soft-bottom habitats. For hard habitats, other commonly collected and derived information about the seafloor (*e.g.*, depth, slope, *etc.*) was more important to the characterization process than multispectral backscatter. Specifically, the topographic predictors were the most influential group for hard-bottom habitats, contributing an average of 51.8% ± 4.0. Depth contributed the most overall (*i.e.* 24.6% ± 7.0) to the hard-bottom models. Conversely, the three backscatter frequencies contributed a combined average of 20.8% ± 2.0 to the hard-bottom models, which is approximately the same amount as depth alone. When looking at only two frequencies, the 100/200-kHz (18.5% ± 2.6) and 100/400-kHz (17.4% ± 4.9) pairings explained similar amounts of variation, but more variation in habitat distributions than the 200/400-kHz (5.7% ± 1.9) pairing.

Overall, the 100-kHz frequency emerged as the most important of the three frequencies, explaining an average of 15.1% ± 4.0 for hard-bottom habitat models. The 200 and 400-kHz frequencies contributed the least to the hard-bottom models, averaging 3.4% ± 1.1 and 2.3% ± 0.8, respectively.

These 200 and 400-kHz contributions are less than the average contribution of other easily derived information, like slope (11.0% ± 2.5) or longitude (10.3% ± 3.4). These results suggest that multispectral backscatter may not be needed for projects focused on characterizing hard bottom, because the addition of the 200 and 400-kHz frequencies improved the models by 5.7%. Researchers and managers should consider whether this additional explanatory power is important enough to make multispectral backscatter a priority. If it is not a priority, MBES systems operating at or near 100 kHz may be a suitable choice for projects focused on broadly characterizing hard-bottom habitats in temperate environments.

Although multispectral backscatter may not be needed for every project, its inclusion here enhanced the ability to characterize soft-bottom habitats, particularly Bare Mud habitats. The combination of the three acoustic frequencies explained 73.7% of the variation in these two soft-bottom models. The addition of the 200 and 400-kHz frequencies improved the ability to characterize soft-bottom habitats by 17.4%. The 100/400-kHz pairing explained the most about variation (28.7%) in habitat distributions, followed by the 100/200 and 200/400-kHz pairings. These findings are similar to those of Hughes-Clarke (2015) and Gaida *et al*. (2018) for Bedford Basin, which found that the 100/400-kHz pair contained more information about seafloor habitats than other frequency pairings. These additional frequencies also helped decrease the uncertainty associated with the Mud and Bare predictions, making these models three times more precise (CoV <0.15 *vs*. >0.45) than the other habitat predictions. In places like Bedford Basin, this additional information and reduction in uncertainty can be critical, because >90% of the survey area was classified as Bare Mud. This finding aligns with *in situ* grain size sampling and analysis by Brown *et al*. (2019) in the same survey area. Outside of Bedford Basin, this result suggests that multispectral backscatter might be more useful and effective for projects focused on mapping and characterizing soft-bottom habitats and associated biological communities. For example, finding bare sand or mud is of critical importance to a number of marine management applications, from siting marine infrastructure (like wind turbines) (Multon, 2013) to shoreline protection and beach nourishment (Finkl, Khalil, and Andrews, 1997; Finkl and Walker, 2005).

Potential Effect of Relative Backscatter Values

Although the above findings align with previous research, it is important to discuss the potential effect of relative backscatter values on their interpretation and applicability more broadly. As described earlier, the backscatter values for this study were calibrated across survey years. This created relative backscatter surfaces for each frequency in the study site. A temporal predictor was included in the modeling process to validate this relative calibration, identify areas on the seafloor that may have changed over time, and better understand whether these coupled issues affected the ability to characterize benthic habitats. These results showed that this temporal predictor had zero importance for model development, suggesting that the two collections were properly intercalibrated and that habitat changes were minimal between 2016 and 2017. These results were in agreement with Gaida *et al*. (2018), who created two separate benthic habitat maps with the same 2016 and 2017 multispectral data for the same geographic area inside Bedford Basin. When Gaida *et al*. (2018) compared the two maps, they found them to be nearly identical, suggesting that backscatter values for the two surveys were similar and that soft- and hard-bottom habitats remained relatively unchanged between years. The one exception was an area to the NW in the study area, where low backscatter returns were visible in the 400-kHz surface in 2016 and high backscatter returns in the 400-kHz surface in 2017 (Gaida *et al*., 2018). This seafloor change was captured by the modeling process used here and was predicted to have a lower percent cover of Bare Mud compared with the surrounding seafloor.

Although relative backscatter may have had little effect on the habitat predictions themselves, it is important to acknowledge that the acoustic thresholds identified above are specific to this study. They are unique to this study because the ~~absolute~~ decibel values (*i.e*. –15, –20, and –23 dB) would most likely shift if this approach were applied to other multispectral backscatter datasets collected in different geographic areas, using different MBES systems, or both. This change prevents these specific decibel values from being interpreted and applied more broadly. However, these thresholds (relative to each other) still have some utility beyond this study site because they are grounded in the physics of acoustics and capture changes in backscatter strength as a function of incident angles and sediment types (Gaida *et al*., 2018). They also align with previous research showing that backscatter responses depend on frequency and that backscatter returns are generally higher (+) for lower frequencies (*e.g*., 100 kHz) and lower (–) for higher frequencies (*e.g*., 400 kHz) (Brown *et al*., 2019; Gaida *et al*., 2018; Hughes-Clarke, 2015). They also confirm findings from other studies that show backscatter responses differ by ±3–5 dB between octaves (*i.e*. 100 *vs*. 200 kHz or 200 *vs*. 400 kHz) (Hughes-Clarke, 2015). Combined, this information is a step toward better understanding acoustic dividing lines between hard and soft substrates and associated biological communities and toward better understanding the utility of multispectral backscatter overall.

CONCLUSIONS

Acoustic backscatter, particularly from MBES, is often a key piece of information for producing accurate, high-quality benthic habitat maps for marine managers (Holliday, 2007; Smith and McConnaughey, 2016). Recent advances in MBES systems now allow the collection of spatially and temporally coincident multispectral backscatter. The work presented here used a case study to better understand the utility of this new type of data for benthic habitat mapping and potential marine management applications. These results from Bedford Basin indicate that multispectral backscatter data (particularly the 100/400-kHz paring) can enhance discrimination among soft-bottom habitats by 17.4% but is less important for mapping and characterizing hard-bottom habitats (5.7%). Consequently, multispectral backscatter might be most effective for supporting management applications that need soft-bottom maps, such as beach nourishment and coastline protection projects. Single-frequency (*i.e*. 100-kHz) backscatter might be adequate for other management applications that require comprehensive maps of hard- and soft-bottom habitats on the seafloor (*e.g*., protecting essential fish habitats). Although these results are interesting, the work presented here is a small first step toward quantifying the utility of multispectral backscatter. Future research should focus on understanding whether these patterns and acoustic thresholds change when multispectral MBES backscatter is calibrated absolutely *in situ* and whether these patterns hold true in other geographic locations and types of marine ecosystems. Continuing to better understanding the utility of multispectral data would help researchers and marine managers make more informed decisions *a priori* about the backscatter frequency (or frequencies) best suited to their mapping needs, research objectives, and desired management outcomes.

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