Using acoustic backscatter from a sidescan sonar to explain fish and invertebrate distributions: a case study in Bristol Bay, Alaska

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Yeung, C., and McConnaughey, R. A. 2008. Using acoustic backscatter from a sidescan sonar to explain fish and invertebrate distributions: a case study in Bristol Bay, Alaska. – ICES Journal of Marine Science, 65: 242–254.

Environmental variables that are ecologically relevant and easily measured over large areas are useful for modelling species distributions and habitats. Continuous acoustic, sonar-backscatter data convey information about physical properties of the seabed, and hence could be a valuable addition to that suite of variables. We tested the potential utility of acoustic backscatter for improving habitat models of marine species using data from a pilot sidescan-sonar survey. Raw digital-backscatter data were processed with QTC SIDEVIEW and CLAMS software. Resultant acoustic variables—Q-values (Q1, Q2, and Q3), representing the first three principal components of the data derived from image analysis of backscatter echoes, and a complexity metric (compx) measuring the variance of Q-values in a geographic area—were used in multiple linear regression to model individual species abundance from bottom-trawl survey data. Habitat models for flathead sole (*Hippoglossoides elassodon*), Pacific cod (*Gadus macrocephalus*), walleye pollock (*Theragra chalcogramma*), red king crab (*Paralithodes camtschaticus*), basket star (*Gorgonocephalus eucnemis*), and sponges (Porifera) included acoustic variables as significant predictors. For these six taxa, full models explained 67–86% of variability in abundance, with 9–54% of that total contributed by the acoustic predictors, suggesting that acoustic data could advance habitat research for some bottom-associated marine species.

Keywords: acoustic backscatter, benthic invertebrates, Bering Sea, groundfish, habitat, trawl survey.

Received 5 June 2007; accepted 16 January 2008.

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Introduction

Effective management and conservation of marine species requires clear understanding of their habitat needs. In the USA, the Sustainable Fisheries Act mandates essential fish habitat (EFH) definitions in all federal fishery-management plans (Pautzke, 2005). In practice, systematic survey data are commonly used to identify suitable habitat as those areas supporting high relative abundance (e.g. Packer and Hoff, 1999; Anderson *et al.*, 2005; Shucksmith *et al.*, 2006). This approach presumes that density data reflect habitat utilization, and the degree to which a particular habitat is utilized is considered to be indicative of habitat quality. Initially, habitat requirements may be represented as simple ranges in common environmental variables that are known to support a population. Ultimately, more informative quantitative models can be developed that spatially link fish densities with a diverse set of environmental variables.

Environmental variables that are ecologically relevant and easily measured over large areas are of great value to habitat research. Overall, the value of an environmental variable in habitat-distribution models will be related to its capacity to explain variance in abundance or predict distributions. Temperature and depth are perhaps the most common environmental descriptors of aquatic habitat. They have generally been effective in explaining a substantial portion of variability in fish distribution (e.g. Rubec *et al.*, 1999; Reynolds, 2003; Rooper *et al.*, 2005), probably because of their well-known effects on the physiology and ecology of marine organisms (Vernberg and Vernberg, 1972). Their widespread use in habitat models may also be related to their ready availability; for example, standard instruments exist to measure these variables continuously while a research vessel is underway. Other variables (e.g. salinity, substratum, and prey availability) are also useful predictors in many habitat models (e.g. Rogers, 1992; Maravelias, 1999; Shucksmith *et al.*, 2006; Vinagre *et al.*, 2006), but such data are generally less available and their usage correspondingly limited.

Surficial sediments are known to affect the distribution and abundance of marine fish (McConnaughey and Smith, 2000; Nasby-Lucas *et al.*, 2002). However, direct sampling with grabs and cores is prohibitively inefficient for even moderately large areas, and bedforms that are important to certain species (Tupper and Boutilier, 1995; Norcross and Mueter, 1999; Stoner *et al.*, 2007) cannot be discerned. Conversely, trackline surveys with echo-sounders and sidescan sonars can provide information about the seabed efficiently over extensive areas with a resolution that is on the scale of tens of metres or better. It is also known that acoustic backscatter from multibeam and sidescan-sonar systems conveys information about physical properties of the seabed, including porosity, grain size, surface wave form, roughness, and density difference between water and seafloor material, in addition to certain biological and chemical properties, such as faunal and organic content (Anderson *et al*., 2002). As such, backscatter data collected by sonar systems could be a valuable addition to the suite of environmental predictors that are suitable for habitat modelling. However, acoustic data are generally unproven as a proxy for sediment data in habitat models and rigorous testing is needed.

Automated-processing methods exist to relate acoustically acquired seabed data to surficial sediments on the seabed. There is considerable variability in the methodology for specific tools but, in general, echo returns are analysed digitally and decomposed into quantitative parameters that represent physical properties of the seabed in unspecified ways. These parameters are then assembled into groups (sediment classes) with similar acoustic properties. These tools fall into two broad categories, based primarily on the expected level of knowledge about sediments in the survey area. In supervised classification, a reference catalogue of acoustic data representing all known seabed types is generated to which subsequently collected data are compared and classified. Unsupervised classification, on the other hand, characterizes sediments during post-processing, with no requirement for *a priori* knowledge of sediment diversity in the survey area. In both cases, ground-truth sampling is undertaken to characterize the identified classes of sediments.

Fish-habitat studies thus far have generally correlated species abundances with categorical seabed classifications, resulting in largely descriptive definitions of habitat (Gregory *et al*., 1997; Nasby-Lucas *et al*., 2002; Freitas *et al*., 2003; Hewitt *et al*., 2004). The question remains whether species distributions can be explained using acoustic backscatter as a continuous, quantitative measure of the environment, analogous to the use of temperature and depth data. If so, we would expect the information content of acoustic data to be greater than that for discrete bottom types produced by clustering these same data. Clearly, this would be advantageous for modelling the habitats of marine species. As such, we investigated the potential utility of continuous acoustic backscatter in marine-habitat modelling using data from a pilot sidescan-sonar survey in Bristol Bay, Alaska. We tested whether the addition of backscatter parameters as predictors can improve the modelling of species distribution, when compared with models composed solely of conventional habitat-predictor variables (e.g. temperature, depth, and geographic position).

Bristol Bay lies between the Alaska Peninsula and the mainland on the generally flat and featureless Bering Sea shelf (Figure 1). Whereas the deeper shelf sediments are generally muddy, the sediments of Bristol Bay and other partially enclosed bays on the shelf are primarily sands and gravels (National Research Council, 1996). The bathymetric gradient is very gentle, with depth varying from 40 m (northeast) to 80 m (southwest) over ~400 km, suggesting that local slope (i.e. angular) effects on backscatter would be minimal (von Szalay and McConnaughey, 2002). Differences in acoustic backscatter should therefore accurately represent characteristics of the sediments. If variables derived from acoustic-backscatter measurements contribute significantly in habitat-distribution models, then broad-scale remote sensing of seabed properties with acoustic systems would benefit habitat research and fisheries management.

Methods

Acoustic data

A pilot acoustic survey was conducted in the Bristol Bay region of the eastern Bering Sea (EBS) from 28 June to 3 July 2002 (Figure 1). A Klein model 5410, multibeam, interferometric sidescan sonar was deployed over approximately 1375 km of trackline using the 75 m range-scale setting (i.e. 150 m cross-track swathe). (Note that reference to trade names does not imply endorsement by the National Marine Fisheries Service, National Oceanographic and Atmospheric Administration.) This trackline intentionally crossed 26 grid cells containing fixed bottom-trawl stations (Figure 2) that are sampled annually by the Alaska Fisheries Science Center (AFSC), Resource Assessment and Conservation Engineering (RACE) Division of the US National Marine Fisheries Service (NMFS) (Acuna and Kotwicki, 2004).

The Quester Tangent Corporation (Sidney, BC, Canada) was contracted by the AFSC to process raw digitized-sidescan imagery with their commercially available acoustic seabed-classification software QTC SIDEVIEW (Preston *et al*., 2004; Quester Tangent Corporation, 2004). A technical report to the AFSC (Quester Tangent Corporation, 2005) detailed the manual and automated steps undertaken to classify objectively the Bristol Bay seabed (unsupervised classification). In the report, unsupervised classification results were compared with expert interpretations by a marine geologist familiar with the Bristol Bay region, and ground-truth data were summarized. In brief, during processing, raw imagery was digitized and subjected to quality-control procedures, segmented, compensated, and ultimately classified using QTC SIDEVIEW. Rectangular patches measuring 513 pixels cross-track (24 m) × 129 pixels along-track (17 m) were placed over areas of high-quality data that had unusable portions of imagery masked and that complied with a set of quality-control rules (Figure 3). A series of algorithms was then used to compensate imagery for angular and range effects before extracting a vector of 132 parameters, called a full-feature vector (FFV), from each patch. The parameters describe the backscatter amplitude and sediment texture within each image patch. A FFV record was generated for each of 214 449 patches in this dataset. The resultant vector was georeferenced to the centre of the patch.

Subjecting the entire dataset to numerical analysis was beyond the practical limit of computer resources at the time of analysis (2003). A subset of the data (43 segments of trackline, with a total of 13 259 records, or 6% of the complete dataset) was selected that included segments that were evenly distributed over the survey area, in addition to segments over ground-truth sites, trawl stations, and areas of distinctive acoustic characteristics. Principal components analysis (PCA) was conducted on this subset. The FFVs were reduced by PCA to the first three principal components, called Q-values (Q1, Q2, and Q3), which together explained 96.8% of the variance in the data (77.4%, 15.9%, and 3.5%, respectively). These three Q-values were used as predictor variables representing the acoustic-backscatter characteristics of the benthic habitat. We also included the "complexity" (compx) metric generated by the QTC CLAMS software as another acoustic predictor variable in our analyses. The compx metric measures the spread of Q-values within a specified geographic area. The spread is defined as the square root of the sum of the Q-value variances (root-mean-square). For each query record (patch), the Q-values of its 20 nearest neighbours (including itself) were used to calculate the compx value (Quester Tangent Corporation, 2005).

Abundance data

The AFSC conducts annual bottom-trawl surveys of the EBS continental shelf (Acuna and Kotwicki, 2004). These surveys

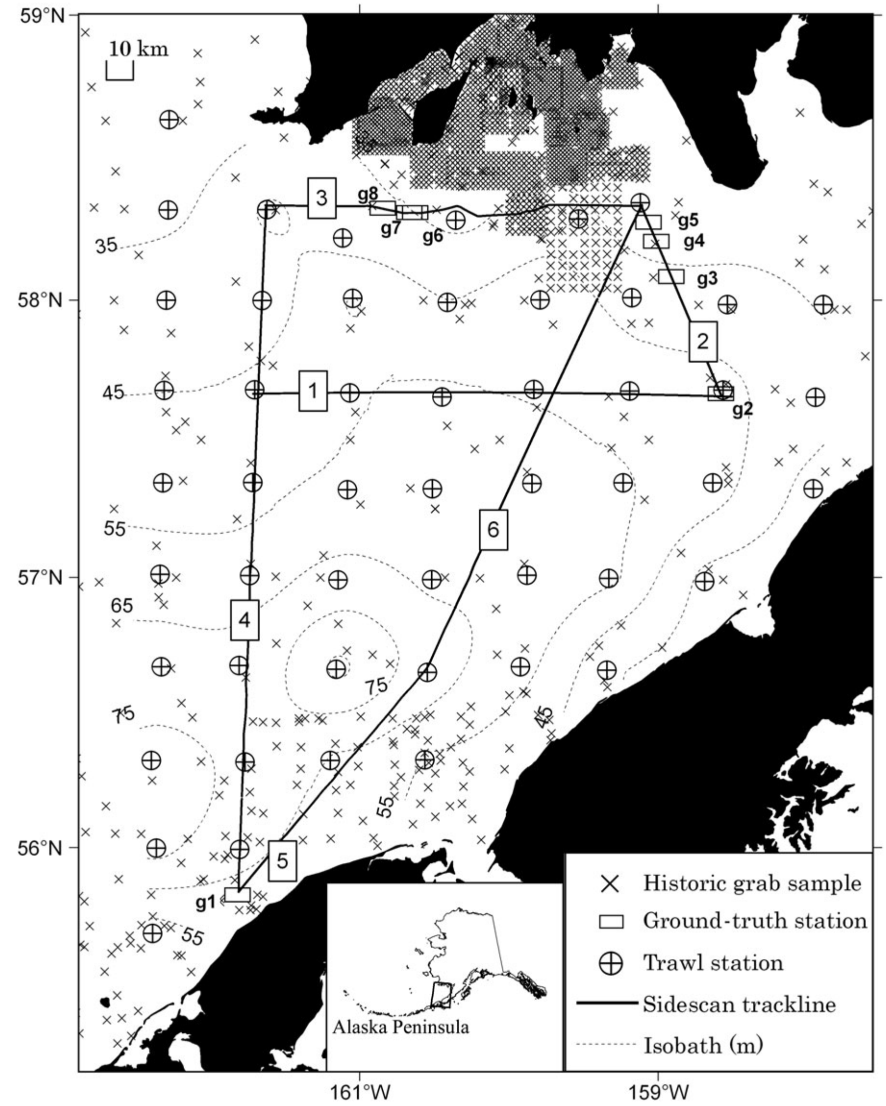


Figure 1. Bristol Bay site map showing 2002 sidescan-survey tracklines (1–6) and associated video/grab ground-truth locations (g1–g8), locations of historical grab samples from the EBSSED database (Smith and McConnaughey, 1999), and 2002 AFSC groundfish trawl-survey stations.

provide an index of biomass for stock assessments of groundfish resources. Between June and August each year, the EBS shelf ($\sim$463 400 km^2) is systematically surveyed at depths ranging from 20 to 200 m. An 83–112 eastern otter trawl is deployed from chartered vessels at 356 standard stations in a sampling grid with 37 × 37 km (20 × 20 nautical mile) cells. Each sample consists of a 30-min tow at 3 knots. The catch is processed to determine total weight and numbers by species and sex, and a variety of biological measurements and samples are collected from individual specimens. Acoustic net-mensuration data and a global-positioning system are used to standardize catches according to area swept (i.e. $kg\ ha^{-1}$). These standardized catches (abundance) are considered to be representative of the entire survey grid cells. We worked with a subset of 35 benthic invertebrate and groundfish taxa commonly found in Bristol Bay, based on bottom-trawl survey data (1982–2004; Table 1). We examined catches of these taxa in the years 2002–2004 so as to correspond with the timing and location of the Bristol Bay acoustic data presented here.

Assigning acoustic data to trawl stations

Mismatched spatial scales and dissimilar data densities are pervasive issues when correlating physical and biological data. The raw acoustic data acquired by the sidescan sonar initially have extremely high resolution (3 cm cross-track × 20 cm along-track), which is reduced substantially during segmentation processing to 17 × 24 m. The resolution of the trawl-survey data, by comparison, is quite coarse, and data density is very low owing to the large area sampled by the net. As it is unknown when individual organisms enter the trawl, the catch is treated in the aggregate for the area defined by the horizontal opening of the net ($\sim$16 m) and the distance towed (averaged 2.7 km in 2002). The effective resolution of the fish and invertebrate densities from the bottom trawl is therefore $\sim$43 200 m^2. In our analysis, we consider the trawl

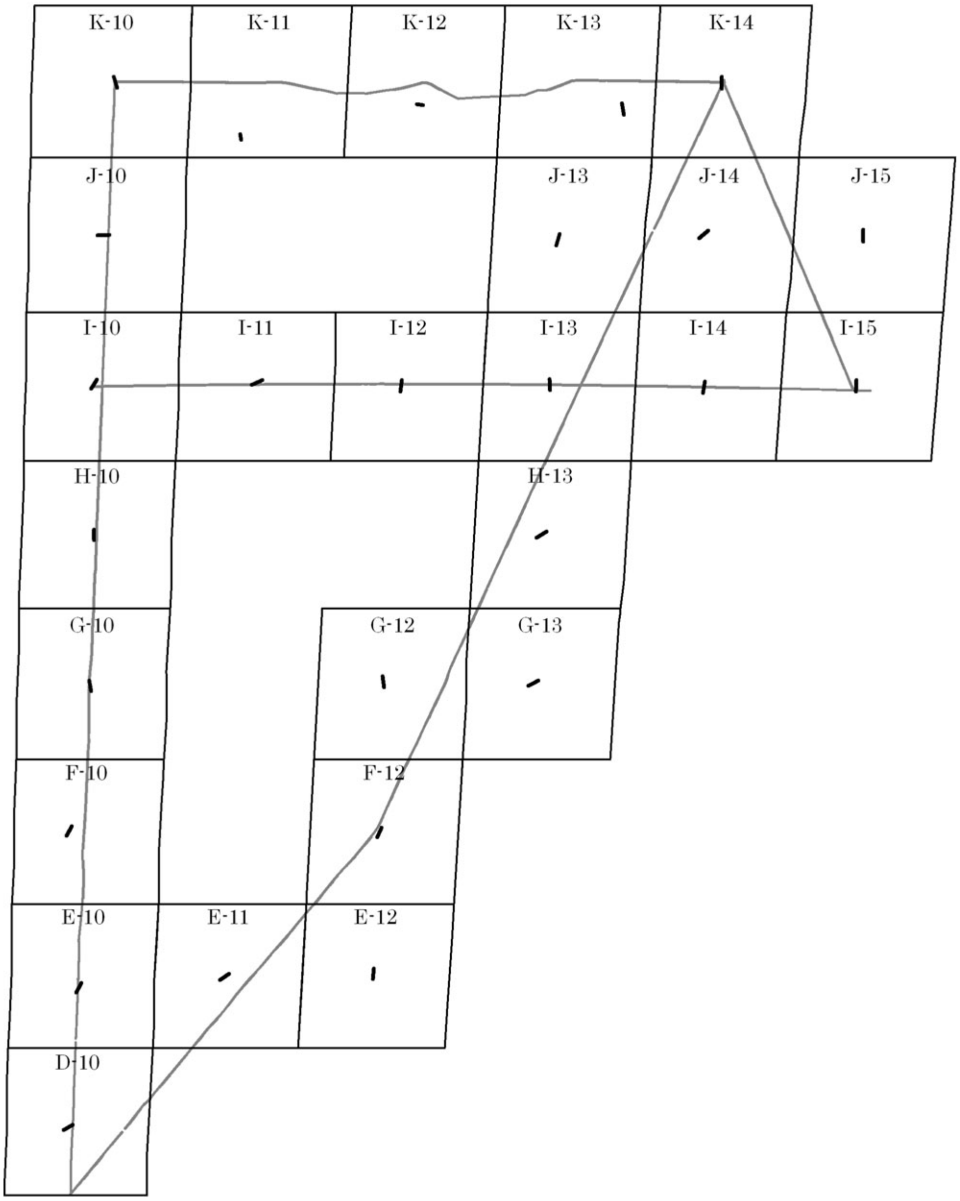


Figure 2. Standard station grid cells (labelled) crossed by the 2002 Bristol Bay sidescan-sonar-survey trackline. The 2002 trawl-survey tow track is drawn for each station within each cell.

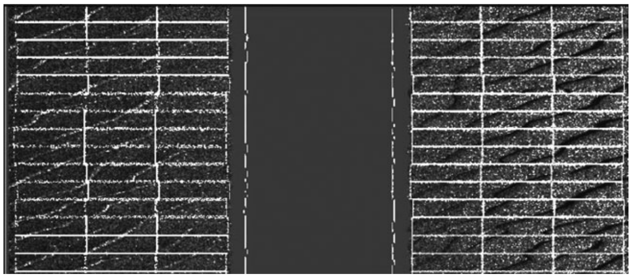


Figure 3. Sidescan-sonar image of seabed in QTC SIDEVIEW image viewer with rectangular patches placed over high quality data areas to either side of the data mask at the centre. The mask removes noise artefacts from the water column.

track to be a straight line, using the start and end positions of the tow (Figure 2). The midpoint of this track was used to approximate the geographic point location of the station. Two methods for assigning the value of an acoustic variable (Q1, Q2, Q3, and compx) to a trawl station were compared: first, use the mean value of the variable within a single trawl cell (1392 km^2); and second, use the inverse, distance-squared, weighted (IDW) interpolation of the 15 nearest neighbours to a trawl station in any direction. These spatial-join procedures were implemented in ArcGIS and its Geostatistical Analyst extension.

Ground-truthing of sediment properties

Ground-truth data from several sources were used to compare acoustic variables with sediment properties. In this study, sampling with a 0.1-m^2 van Veen grab and a drop video camera

Table 1. Taxa from 2002 trawl survey selected for analysis. Some taxa may contain more than one species.

Taxon	Common name
Hippoglossus stenolepis	Pacific halibut
Hippoglossoides elassodon	Flathead sole
Limanda aspera	Yellowfin sole
Limanda proboscidea	Longhead dab
Platichthys stellatus	Starry flounder
Lepidopsetta polyxystra	Northern rock sole
Pleuronectes quadrituberculatus	Alaska plaice
Podothecus acipenserinus	Sturgeon poacher
Myoxocephalus jaok	Plain sculpin
Gadus macrocephalus	Pacific cod
Theragra chalcogramma	Walleye pollock
Mallotus villosus	Capelin
Gersemia rubiformis	Sea raspberry
Actiniaria	Sea anemone
Chionoecetes bairdi	Tanner crab
Hyas coarctatus	Arctic lyre crab
Hyas lyratus	Pacific lyre crab
Chionoecetes opilio	Snow crab
Telmessus cheiragonus	Helmet crab
Paguridae	Hermit crab
Pagurus ochotensis	Alaskan hermit
Paralithodes camtschaticus	Red king crab
Erimacrus isenbeckii	Horsehair crab
Neptunea ventricosa	Fat whelk
Neptunea heros	Northern whelk
Mactromeris polynyma	Arctic surfclam
Evasterias echinosoma	Giant sea star
Asterias amurensis	Purple-orange sea star
Gorgonocephalus eucnemis	Basket star
Cucumaria fallax	Sea football
Porifera	Sponge
Boltenia ovifera	Sea onion
Aplidium sp.	Sea glob
Empty bivalve shells	Clam shells
Empty gastropod shells	Snail shells

was conducted at eight locations along the survey trackline (Figure 1; Bornhold *et al.*, 2005). Sampling locations were selected *ad hoc* so as to be representative of the different substrata encountered. Most of these samples were collected in the northern part of the study area where seabed variability was greatest. For these samples, textural analysis and the calculation of grain size were conducted according to the scheme of Folk (1980). The mean percentage weights of gravel (>2 mm diameter), sand (0.0624–2 mm), and mud (<0.0625 mm) for all samples falling in a trawl cell were attributed to that station.

Additional information about surficial sediments near the survey trackline was obtained from a database of historical samples for the EBS continental shelf (EBSSED database; Smith and McConnaughey, 1999). These samples were classified into seven "low-resolution" descriptive textural classes according to their gravel–sand–mud composition: gravel, mixed gravel–sand, mixed gravel–sand–mud, mixed gravel–mud, sand, mixed sand–mud, and mud, based on a simplified form of Folk's (1954) standard gravel–sand–mud ternary diagram (Smith and McConnaughey, 1999). The low-resolution scheme was developed to utilize the maximum number of historical samples from different sources and sampling methods, with diverse descriptions of grain size ranging from qualitative to granulometric. This scheme also permits an approximate comparison between historical sediment data and sediment data from this study. The class-frequency distribution of the historical samples, i.e. the number of samples classified to each of the seven low-resolution classes, was used to characterize the main sediment type and the variability in a trawl-survey cell.

Distribution models

Least-squares, multiple linear regression (MLR) was used to assess whether acoustic data could improve species-distribution models built using only standard environmental data collected on AFSC trawl surveys. All analyses were carried out in the R computing environment, using associated statistics packages. The $\log(x+1)$-transformed abundance estimates of the 35 chosen taxa at the 26 Bristol Bay trawl stations whose cells contained acoustic data were derived from 2002 trawl-survey data. The habitat predictors used in the models were the acoustic variables Q1, Q2, Q3, and compx, and the trawl-survey variables bottom depth (Z), surface (ST) and bottom (BT) temperatures, latitude (lat), and longitude (lon).

In exploratory analysis, first-order MLR models without interaction terms, i.e. main-effects only, were compared with non-linear models and MLR models with interaction terms. More complex models generally did not produce significantly better fits. Therefore, simpler main-effects models were deemed appropriate here. We examined all possible MLR models involving the trawl survey and acoustic-habitat predictors to select the "best" MLR model for a taxon, defined as the subset of predictors with the minimum Bayes information criterion (BIC; Schwarz 1978) value. Best MLR models that included significant acoustic terms (partial regression coefficients) and had an $r^2 \geq 0.5$ were selected for further analyses. These analyses included: (i) a *post-hoc* power analysis (Cohen, 1988; Green, 1991) to estimate the power of finding an acoustic predictor significant when added to a model already populated with the significant trawl-survey predictors ($n = 26$, $r^2 = 0.5$, and $\alpha = 0.05$); (ii) comparing the r^2 for the best MLR model including acoustic predictors with a model containing only trawl-survey predictors (lat, lon, BT, ST, and Z); and (iii) validating the best MLR models based on 2002 acoustic data using corresponding abundance and environmental observations from 2003 and 2004 trawl surveys, respectively, making the assumption that textural characteristics of surficial sediments on the EBS shelf and trawl-cell means for the acoustic variables were reasonably constant over the period 2002–2004 (Smith and McConnaughey, 1999).

Multicollinearity was not of major concern when comparing the MLR models, because our objective the prediction (maximizing r^2) and assessment of the marginal contribution of acoustic predictors, rather than explaining the underlying relationships between variables (Legendre and Legendre, 1998; Graham, 2003). The use of "all possible subsets" of habitat predictors instead of "stepwise" procedures to select the model mitigates some of the negative effect of multicollinearity on the power to detect a significant effect (Graham, 2003). Evaluating the significant acoustic predictor in the best model as "last one in" further isolates its unique variance contribution over trawl predictors already in the model, in keeping with the objective of our analysis.

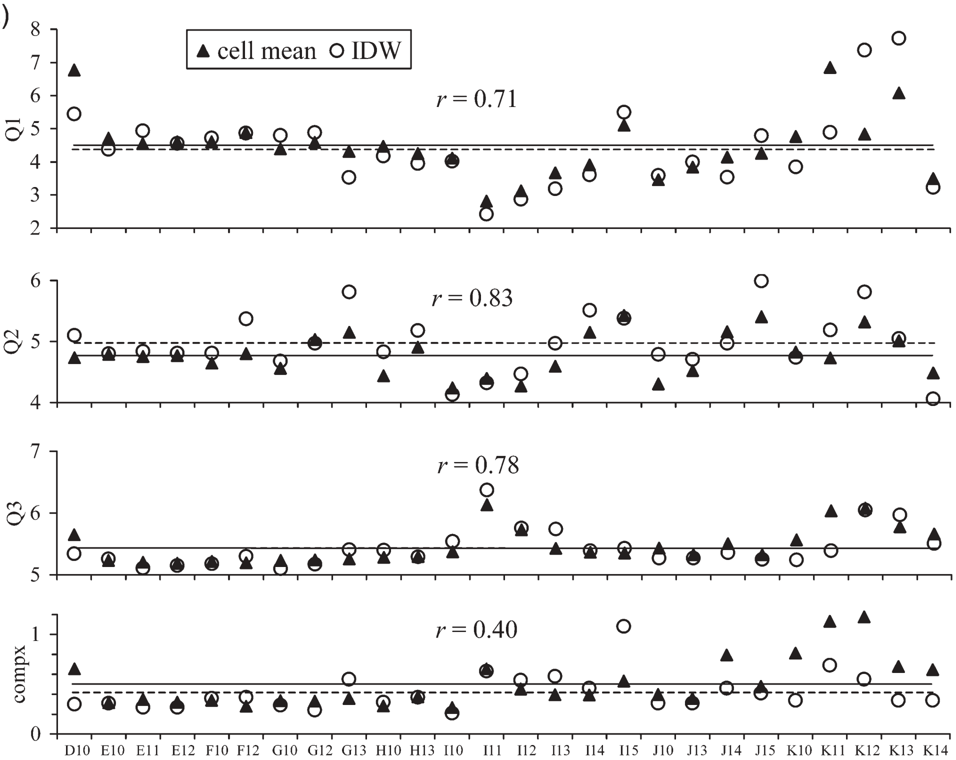
Results

Model inputs

There was a high density of acoustic data in each of the 26 trawl survey cells analysed, and a representative value was assigned to each by a robust method. On average, a trawl cell used in the analysis contained 8112 (s.d. = 3450, range = 660–17 028) of the 17 × 24 m acoustic-image patches and the associated data vectors (Q1, Q2, Q3, and compx). For all acoustic variables except compx, the IDW-interpolated value at the trawl station and the mean value in the corresponding trawl cell were highly correlated ($r_{\mathrm{Q1}} = 0.71$; $r_{\mathrm{Q2}} = 0.83$; $r_{\mathrm{Q3}} = 0.78$; $r_{\mathrm{compx}} = 0.40$; Figure 4). Discrepancies were mainly in the northern (tracklines 2, 3; stations J, K) and southernmost parts of the survey area (Figures 1 and 2), where compx and variability in Q-values were highest (Figure 4). For simplicity, trawl-cell means of acoustic variables were used in modelling species distribution.

Based on comparisons with ground-truth data from this study and historical sediment samples, the acoustic variables showed some qualitative correlation with sediment grain size and

(a)



(b)

	D10	E10	E11	E12	F10	F12	G10	G12	G13	H10	H13	I10	I11	I12	I13	I14	I15	J10	J13	J14	J15	K10	K11	K12	K13	K14
Gravel																								33	7	
Gravel–sand				2		1													4			1	2	51	83	3
Gravel–sand–mud																									1	
Gravel–mud																										
Sand	3	1	2	9	1	1	2	2	2	2	1	2	2	1	2	3	2	2	14	6	2	1	3	27	96	31
Sand–mud					1														3	6					11	13
Mud																								3		

(c)

Grab station	g1		g2		g3		g8		g7		g6		g4	g5	
Replicates	3		3		3		3		3		3		1	3	
Trawl cell	D10		I15		J14		K11		K11/K12		K12		K14	K14	
%	Mean	s.d.	Mean	s.d.	Mean	s.d.	Mean	s.d.	Mean	s.d.	Mean	s.d.		Mean	s.d.
Gravel	0.0	0.0	0.3	0.2	7.8	8.8	38.1	11.8	0.0	0.1	0.1	0.1	4.1	0.4	0.5
Sand	97.0	1.7	97.4	0.1	87.9	12.6	58.6	13.1	97.7	0.7	96.7	2.0	85.2	96.7	1.0
Mud	3.0	1.7	2.4	0.2	4.2	3.8	3.3	1.4	2.3	0.8	3.2	1.9	10.7	3.0	0.7

Figure 4. (a) Comparison of two methods (IDW and cell mean) for assigning a summary value of an acoustic variable (*y*-axis) to a trawl-survey cell (*x*-axis). For each acoustic variable, the cell values are plotted by method, with the mean of all cell values indicated (cell mean, solid line; IDW, dotted line; means generated by the two methods for Q3-values are so close that the lines overlap). The correlation (*r*) between the means calculated by each method is given. (b) The number of historical samples in each of seven "low-resolution" sediment classes in each trawl-survey cell. (c) Percentages (mean and standard deviation) of three sediment types in trawl-survey cells determined from grab samples in this survey (Figures 1 and 2); station g4 has only one sample (replicates = 1) and therefore no statistics; station g7 straddled trawl cells K11 and K12.

texture. Trackline 3, which crossed the K trawl cells (Figures 1 and 2), had higher-than-average Q1, Q3, and compx values (Figure 4a). The higher structural complexity or heterogeneity in the sediments of this area is consistent with existing evidence from sediment analyses (Figure 4b). Cells K12 and K13 have the largest numbers of historical samples, and according to the data, these two cells not only have a wide range of sediment classes but also are unique in containing the class "gravel" (Figure 4b). K12 has the widest range of sediment classes, because it is the only cell that also contains the class "mud". Besides K12 and K13, all other cells have relatively few samples, and all were classified as sand except for a few which were classified as mixed gravel–sand, or mixed sand–mud. Overall, sand is the predominant sediment class except in K12 and K13.

Grab samples collected during the survey (Figure 4c) supported the general sediment classifications derived from historical data, particularly with respect to sand being the predominant substratum. Regarding the gravel fraction, some discrepancy exists between historical sediment data and sediment data from this study: K12 had almost no gravel according to the few (6) sediment samples from this study, but many historical samples in this cell (84), as well as historical samples and samples from this study in neighbouring K cells, were classified as containing gravel (Figure 4b and c). K12 is probably more gravelly than grab samples from this study suggest, and high Q1- and perhaps also high Q3-values (e.g. in the K cells) are likely correlated with the hardness and thus higher backscatter of gravelly surficial sediment. There is no obvious explanation for the fluctuation of Q2-values in relation to sediment texture. The discrepancy in sediment class depicted by different sources is likely caused by the spatial heterogeneity of the substratum within a trawl cell. Different scales of sampling would then offer different perspectives of the substratum type in the cell—more samples with wider spatial coverage, such as achieved by acoustic survey, would be expected to provide a more representative picture. For example, in the southernmost trawl cell of D10 (Figure 1), the three grab samples from this study and the three historical sediment samples available to us indicate a sandy substratum (Figure 4b and c), whereas the relatively high Q1- and compx-values (Figure 4a) suggest the presence of gravel and spatial heterogeneity in the substratum. In this case, the acoustic information is more consistent with the generalization that nearshore sediments in Bristol Bay proper consist of extremely poorly sorted gravel and coarse sand (Sharma, 1979).

MLR models

The best MLR models for six taxa included significant acoustic-predictor terms and had an $r^2 \geq 0.5$: flathead sole (*Hippoglossoides elassodon*), Pacific cod (*Gadus macrocephalus*), walleye pollock (*Theragra chalcogramma*), red king crab (*Paralithodes camtschaticus*), basket star (*Gorgonocephalus eucnemis*), and sponges (Porifera) (Table 2). Overall, these six best models include 1–2 acoustic predictors out of a total of 3–4 predictors, excluding the regression constant. These models explained 67–86% of the variability in taxon abundance, with the contribution of a single acoustic predictor being 6–31% of that total, or a combined 9–54% by all acoustic predictors in the model (Table 3). Based on the algorithms and tables in Cohen (1988), for a cumulative model r^2 of 0.5 (50% of variability explained), the statistical power of detecting a significant r^2 increment of 0.06 when a new (acoustic) predictor is added, given 1–3 significant (trawl) predictors already present in the MLR model, is ~0.3, and 0.9 for an r^2 increment of 0.31.

Table 2. Best MLR models of species-habitat relationships that contain significant ($\alpha = 0.05$) acoustic predictors, and that have model $r^2 \geq 0.5$.

Parameter	Estimate	s.e.	*t*-value	$p(>\|t\|)$
Flathead sole ($r^2 = 0.8593$)				
Intercept	−45.8682	9.5793	−4.788	9.90e−05
Q3	1.1064	0.3809	2.905	0.0085
compx	−2.1257	0.4492	−4.733	0.0001
lon	−0.2540	0.0618	−4.112	0.0005
Z	0.0228	0.0065	3.523	0.0020
Pollock ($r^2 = 0.7529$)				
Intercept	−9.9578	2.2909	−4.347	0.0003
Q3	1.1768	0.3593	3.276	0.0035
BT	0.3171	0.1544	2.054	0.0520
Z	0.0772	0.0102	7.538	1.56e−07
Red king crab ($r^2 = 0.6804$)				
Intercept	20.9345	8.0730	2.593	0.017
Q1	−0.3445	0.0965	−3.569	0.0018
lat	−0.2963	0.1423	−2.083	0.0497
ST	0.1423	0.0781	1.822	0.0827
BT	−0.4808	0.1425	−3.374	0.0029
Cod ($r^2 = 0.6678$)				
Intercept	−45.1446	11.3583	−3.975	0.0007
compx	−0.7737	0.3246	−2.384	0.0266
lat	0.7386	0.1857	3.978	0.0007
BT	0.2917	0.1211	2.41	0.0252
Z	0.0645	0.0128	5.038	5.49e−05
Basket star ($r^2 = 0.6677$)				
Intercept	8.0919	4.1744	1.938	0.0661
Q1	−0.2009	0.0532	−3.777	0.0011
Q3	1.0599	0.2133	4.97	6.43e−05
lat	−0.2126	0.0818	−2.6	0.0167
ST	−0.1106	0.04	−2.767	0.0116
Sponges ($r^2 = 0.6676$)				
Intercept	−3.6835	1.2752	−2.889	0.0088
compx	−1.6047	0.5126	−3.13	0.0051
Q2	0.5169	0.2625	1.969	0.0623
Z	0.0196	0.0087	2.241	0.036
ST	0.2651	0.0796	3.331	0.0032

The predictors are listed in the order they entered the model.

Analysis of variance (ANOVA) shows that all taxa have best models that significantly improve (reduce variance of) abundance prediction compared with versions with the acoustic variable(s) removed (Table 3). For all six taxa, the best model also had a higher r^2 than a model with only the five trawl-survey predictors, despite fewer parameters (Table 4). The difference between the r^2 of the best model (0.67) and that of the trawl-predictors-only model (0.18) was largest for the basket star.

Based on diagnostic procedures, it is appropriate to use MLR models with these data. Residuals plotted against fitted values showed no obvious trends, standardized residuals mostly conformed to a normal distribution, and fitted values modelled observed data reasonably well. The exceptions were basket star

Table 3. ANOVA tables that show marginal contribution of acoustic predictors to reducing variance (sum of square error) in the model, given the trawl predictors already in the model.

Parameter	d.f.	Sum of squares	Mean square	*F*-value	*p*(>*F*)	% sum of squares
Flathead sole						
lon	1	4.9919	4.9919	58.9944	1.57e−07	0.40
Z	1	3.8772	3.8772	45.821	1.07e−06	0.31
compx	1	1.2736	1.2736	15.0516	0.0009	0.10
Q3	1	0.7141	0.7141	8.4387	0.0085	0.06
Residuals	21	1.7769	0.0846	–	–	0.14
Pollock						
BT	1	1.7568	1.7568	9.513	5.42e−03	0.11
Z	1	8.6414	8.6414	46.794	7.16e−07	0.53
Q3	1	1.9817	1.9817	10.731	3.45e−03	0.12
Residuals	22	4.0627	0.1847	–	–	0.25
Red king crab						
ST	1	0.3083	0.3083	1.8155	0.1920	0.03
BT	1	4.811	4.811	28.3315	2.81e−05	0.43
lat	1	0.3098	0.3098	1.8245	0.1910	0.03
Q1	1	2.1627	2.1627	12.7361	0.0018	0.19
Residuals	21	3.566	0.1698	–	–	0.32
Cod						
lat	1	0.6254	0.6254	6.2929	0.0204	0.10
BT	1	0.2965	0.2965	2.9837	0.0988	0.05
Z	1	2.7087	2.7087	27.2575	3.57e−05	0.43
compx	1	0.5647	0.5647	5.6828	0.0267	0.09
Residuals	21	2.0869	0.0994	–	–	0.33
Basket star						
ST	1	0.3364	0.3364	6.6253	0.0177	0.10
lat	1	0.0744	0.0744	1.466	0.0239	0.02
Q3	1	1.0077	1.0077	19.8476	2.19e−04	0.31
Q1	1	0.7241	0.7241	14.262	0.0011	0.23
Residuals	21	1.0662	0.0508	–	–	0.33
Sponges						
Z	1	4.2038	4.2038	23.5554	8.48e−05	0.37
ST	1	1.187	1.187	6.6509	0.0175	0.11
compx	1	1.4439	1.4439	8.0905	9.71e−03	0.13
Q2	1	0.6919	0.6919	3.8767	0.0623	0.06
Residuals	21	3.7478	0.1785	–	–	0.33

The predictors are listed in the order they entered the model.

and sponges, where a large proportion of zero catches (73% and 50%) impaired model fit. In each of the four other species, three outliers were identified in the normal quantile plot. With the outliers removed from the data and the best model re-run, the r^2 increased substantially. In that case, the full models would explain 79–94% of the variability in abundance (Table 4).

The best model for flathead sole included two significant trawl-survey predictors (lon and Z) and two significant acoustic-predictors (compx and Q3); this model explained 86% of the total variation in flathead sole abundance ($r^2 = 0.86$; Table 2). The trawl-survey variables accounted for 71% of the data variance (total sum of squares; Table 3), with marginal contributions of 40% (lon) and 31% (Z). The acoustic predictors added another 16%, with marginal contributions of 10% (compx) and 6% (Q3). We report marginal contributions by acoustic variables as the last variables to enter the best model, in the order listed in Table 3. The best model for walleye pollock included two significant trawl-survey predictors (Z and BT) and one significant acoustic predictor (Q3); this model explained 75% of the total variation in pollock abundance ($r^2 = 0.75$; Table 2). The trawl-survey variables accounted for 64% of the data variance, with marginal contributions of 53% (Z) and 11% (BT). The acoustic predictor Q3 added another 12%. The best model for red king crab included two significant trawl-survey predictors (BT and lat), one marginally significant trawl-survey predictor (ST), and one significant acoustic predictor (Q1); this model explained 68% of the total variation in crab abundance ($r^2 = 0.68$; Table 2). The trawl-survey variables accounted for 50% of the data variance, with marginal contributions of 43% (BT), 3% (lat), and 3% (ST). The acoustic predictor Q1 added another 19%. The best model for Pacific cod included three significant trawl-survey predictors (Z, lat, and BT) and one significant acoustic predictor (compx); this model explained 67% of the total variation in cod abundance ($r^2 = 0.67$; Table 2). The trawl-survey variables accounted for 58% of the data variance, with marginal contributions of 43% (Z), 10% (lat), and 5% (BT). The acoustic-predictor compx added another 9%. For basket star, the best model included two significant trawl-survey predictors (ST and lat) and two significant acoustic predictors (Q3 and Q1); this model explained 67% of the total variation in starfish abundance ($r^2 = 0.67$; Table 2). The trawl-survey variables accounted for 12% of the data variance, with marginal contributions of 10% (ST) and 2% (lat). The acoustic predictors added another 54%, with marginal contributions of 31% (Q3) and 23% (Q1). For sponges, the best model included two significant trawl-survey predictors (Z and ST), one significant acoustic predictor (compx), and one marginally significant acoustic predictor (Q2); the model explained 67% of the variability in sponge abundance ($r^2 = 0.67$; Table 2). The trawl-survey variables accounted for 48% of the data variance, with marginal contributions of 37% (Z) and 11% (ST). The acoustic predictors added another 19%, with marginal contributions of 13% (compx) and 6% (Q2). This was the only "best model" of the six considered in which Q2 appeared as a (marginally) significant acoustic predictor.

Overall, best MLR models based on 2002 data were validated except for taxa with substantial zero catches. Best-model predictions of flathead sole abundance in 2003 and 2004 correlated well with observed abundance ($r = 0.9$; Figure 5). For Pacific cod and red king crab, the correlations were also consistently high ($0.6 < r < 0.7$). Model predictions were, however, unreliable for basket stars and sponges because of the large proportions of zero catches. Zeros may also have affected the pollock model: the correlation between predicted and observed abundance was lower in 2003 ($r = 0.5$, 15% zeros) than in 2004 ($r = 0.8$, no zeros).

Discussion

Processed backscatter from a sidescan sonar explained a significant but variable portion of fish and invertebrate abundance in the Bristol Bay region of the EBS. The derived acoustic variables accounted for 9–16% of the variance in fish abundance (flathead sole, Pacific cod, and walleye pollock) and 19–54% of the variance

Table 4. Comparison of variance in species distribution explained by best MLR model with significant acoustic term(s), and MLR model containing only trawl predictors (lat, lon, Z, BT, and ST): predictors in best model, r^2 of best model, outliers (stations) in data as identified in normal quantile plot of standardized residuals from best model, r^2 if outliers were removed (basket star and sponges are not analysed for outliers because of the large number of zeros and consequent poor model fit), and r^2 of MLR model with only trawl predictors.

Taxon	Best	r^2 best	Outliers	r^2 best, outliers removed	r^2 trawl only
Flathead sole	Q3 + compx + lon + Z	0.8593	E12, F12, I14	0.9384	0.7542
Pacific cod	compx + Z + lat + BT	0.6678	I15, K11, K12	0.7686	0.6485
Pollock	Q3 + Z + BT	0.7529	E11, I12, K12	0.8116	0.6831
Red king crab	Q1 + lat + BT + ST	0.6804	D10, I15, K11	0.7944	0.4871
Basket star	Q1 + Q3 + lat + ST	0.6677	–	–	0.1811
Sponges	Q2 + compx + Z + ST	0.6676	–	–	0.5458

in invertebrate abundance (red king crab, basket stars, and sponges). The simple MLR models we used provided clear answers to our question about the utility of acoustic data, which, when other environmental data were included, explained 67–86% of the total variability for these six taxa. Given the relatively low power of the analysis, in part due to the small sample size, it is reasonable to expect that an underlying influence of acoustic habitat predictors on the distributions of additional taxa in the group of 35 may not have been detected.

The QTC statistical algorithms that we used for processing sonar-backscatter data have also provided useful information in a number of other studies (Gregory *et al.*, 1997; Hamilton *et al.*, 1999; Morrison *et al.*, 2001; Anderson *et al.*, 2002; Ellingsen *et al.*, 2002; Freitas *et al.*, 2003; Hewitt *et al.*, 2004; Brown *et al.*, 2005). These studies used habitat classes resulting from clustering acoustic-backscatter parameters or principal components derived from those parameters (e.g. Q-values), not the parameters or the principal components themselves, to seek qualitative habitat descriptions or correlations with species distribution or faunal communities. Our use of continuous acoustic data (the principal components), as opposed to the more common use of categorical results, has the advantage of avoiding the complexities of heuristic clustering methods (Anderson and Clements, 2000; Legendre *et al.*, 2002; Preston and Kirlin, 2003).

Various theoretical models and empirical field studies have shown that seabed backscatter is related to sediment properties, and that backscatter may therefore serve as a proxy for more direct measurements with grabs and coring devices. Although this is an active field of research in both military and academic sectors, the details of the relationships between sediment properties and seabed backscatter have not been established. With this study, we have demonstrated the utility of backscatter data for habitat characterization, and the relative efficiency with which these data can be collected and processed. It therefore seems reasonable, for the time being at least, to consider the acoustic data as suitable for incorporation into continental-shelf-scale habitat models as a “blind” variable related to marine-sediment characteristics. The statistical processing methods applied here can reasonably be extended to modelling marine-species habitats in other geographic areas. We would still need to find the appropriate method(s) of ground-truthing to establish the relationships between acoustic variables (e.g. Q-values, this study) and seabed properties for the ecological definition of habitat.

Limited ground-truthing in this study and the results of similar field studies suggest that sediment characteristics are an important component of the backscatter signal. Generally, high faunal abundances in Bristol Bay were negatively correlated with the acoustic variables Q1 (red king crab and basket star) and compx (flathead sole, Pacific cod, and sponges), and positively correlated with Q3 (walleye Pollock and basket star). Lower Q1-values corresponded with softer sediment texture (i.e. higher mud content, porosity, and bulk density) at the Great Barrier Reef of Australia (Hamilton *et al.*, 1999). Other work suggests that Q1 is related to the magnitude of backscatter, higher values indicating coarser, denser sediments (Goff *et al.*, 2004). In using sonar-backscatter values with multibeam-bathymetric data and submersible observations to characterize seafloor habitat, Nasby-Lucas *et al.* (2002) also found high backscatter values to be associated with mixed substrata of pebble, cobble, and boulder—essentially large particles with high reflectivity; low values were associated with mud bottoms with low reflectivity. Similarly, our analyses suggest a correlation between high Q1 (and perhaps Q3) and the higher backscatter associated with harder, gravelly sediment. Although myriad factors can affect the qualities of acoustic backscatter in a particular survey area (e.g. sonar frequency and extant geological processes), the consistencies found in these studies nevertheless support the theoretical underpinnings that link acoustic data to marine-sediment properties.

The importance of sediments as a habitat-defining characteristic is well known for a diverse group of groundfish and benthic invertebrates, notably crabs. It therefore is not surprising that acoustic variables are significant predictors of their distributions. Juvenile snow crabs preferentially occupy mud in the laboratory, which presumably is adaptive for burrowing to avoid predation (Dionne *et al.*, 2003). Adult red king crabs are found in sand–mud habitat and debris (Jewett and Onuf, 1988; Zhou and Shirley, 1998). Assuming that high Q1-values mean higher backscatter or harder substratum would mean that red king crab and basket stars in this study were in greater abundance on softer substrata, which is generally consistent with what is known about their distributions (Jewett and Onuf, 1988; Yeung and McConnaughey, 2006). The distribution and abundance of rockfish is statistically related to variability in sediment properties (Nasby-Lucas *et al.*, 2002). Atlantic cod at different ontogenetic stages and seasons prefer specific habitat types that are a combination of sediment grain size, bathymetric relief, water depth, and algae presence (Gregory *et al.*, 1997). Strong associations between pleuronectid flatfish and sediment type have been demonstrated using grab and core-sample data (McConnaughey and Smith, 2000; Rooper *et al.*, 2005). Rooper *et al.* (2005) found increased abundance of flathead sole at higher mud–sand ratios. Flathead sole preference for this sediment type may be attributed to the high density of ophiuroid prey (McConnaughey and Smith, 2000). Stoner and Titgen (2003) found in laboratory experiments that juvenile

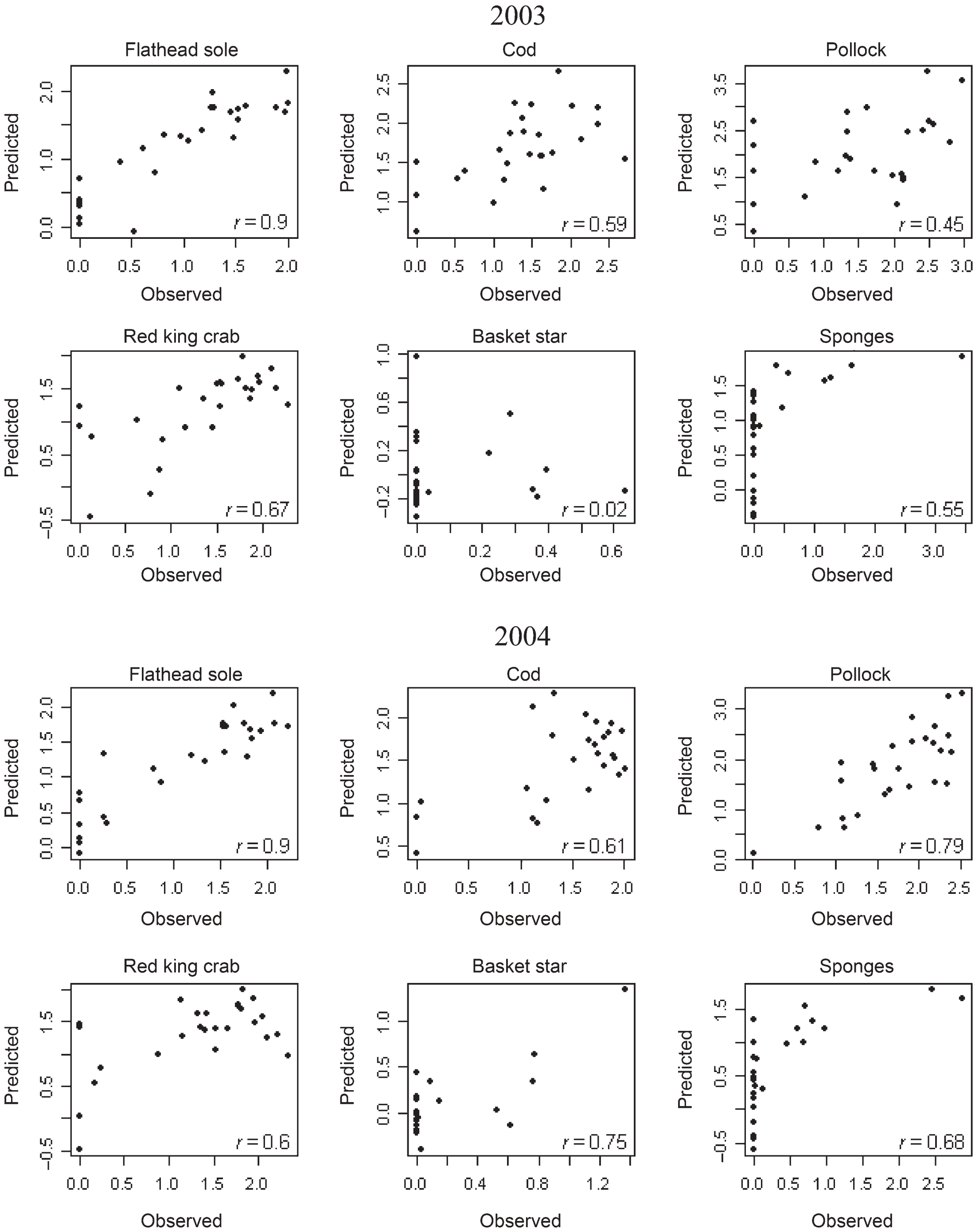


Figure 5. Predicted abundance (log-transformed kg ha^{-1}) for 2003 and 2004 using best MLR models built with 2002 data (Table 2) vs. observed abundance for those years.

halibut and northern rock sole preferred highly structured habitat, and concluded that habitat models would benefit from the inclusion of some measure of habitat complexity.

Interestingly, our MLR model for Pacific cod (all ages) included acoustic complexity as a significant predictor of distribution. In our study, acoustic complexity had a negative relationship with abundance (Table 2), whereas young-of-the-year Pacific cod apparently prefer substratum of high complexity (Abookire *et al.*, 2007). This discrepancy may reflect age/stage specificity in habitat preference (Shucksmith *et al.*, 2006), because mostly adult rather than young cod were caught in the AFSC trawl survey used for this study. Acoustic "complexity" as an index of backscatter variability in this study may also be distinct from complexity as a qualitative descriptor of habitat types (e.g. Stoner and Titgen, 2003; Stoner *et al.*, 2007). Results of these past studies and our present one in Bristol Bay show that habitat preferences and the relative importance of sediments vary directly and indirectly according to a number of factors, including species, life-history stage, geography, population density, and competition (McConnaughey, 1995; McConnaughey and Smith, 2000), and environmental factors such as hydrodynamics and temperature (Abookire and Norcross, 1998). Ultimately, habitat definitions and the importance of any specific component must be evaluated in the context of life history and in light of relevant ecological information (Fielding and Bell, 1997).

This study suggests that a broad-scale, acoustic-mapping programme that is coordinated with systematic abundance sampling, such as the AFSC annual bottom-trawl survey on the EBS continental shelf, would advance our understanding of EFH. We have demonstrated the potential value of this work using simple models applied to acoustic data collected in a limited geographic area. Admittedly, our findings are confined to Bristol Bay and we recognize that the relative importance of habitat predictors could change when considered over a considerably larger area. It is nevertheless encouraging that we were able to build distribution models that explained such a large proportion of the fish and invertebrate biomass, despite relatively homogeneous environmental conditions and correspondingly limited variability in the populations.

There are important issues to consider before fully endorsing a shelf-scale, acoustic-habitat-mapping survey. The first one is the matching of spatial and temporal scales between environmental and abundance data. Here, the acoustic and abundance data were not acquired concurrently, nor were they co-located. Acoustic data (metre-scale or less) were continuously collected over tracklines, and needed to be aggregated to correlate with lower resolution, point-abundance data (kilometre-scale). The scale and the method of data aggregation will likely influence model results (Levin, 1992; Irvine *et al*., 2004; Thrush *et al*., 2005; Brind'Amour and Boisclair, 2006). The spatial extent over which the independent variable is aggregated can change its relative contribution to a fish-habitat model (Brind'Amour and Boisclair, 2006), because heterogeneity in the variable may be smoothed over or accentuated. Although the two simple methods of aggregating acoustic data (mean and IDW) tested here gave comparable results, more sophisticated spatial methods such as variogram analysis to determine the maximum distance for the aggregation of variables (Brown *et al*., 2005) may be appropriate for larger-scale studies. A second issue is that the MLR models we used here are relatively simple, and although generally effective with Bristol Bay data were quite sensitive to zero values of abundance. As zero catch is a common feature of trawl-survey data (McConnaughey and Conquest, 1992), alternative model types may be required. Finally, although sonar is more efficient than traditional grab-sampling for determining surficial-sediment properties, there are substantial costs associated with acoustic-data acquisition, processing, and the requisite ground-truthing. The universal applicability of acoustic backscatter needs to be validated with more extensive experimentation. Ultimately, the balance between costs and benefits will be a determining factor in the use of acoustic data in marine-habitat models.

Acknowledgements

We thank L. Huff (Center for Coastal and Ocean Mapping, University of New Hampshire) for expert sidescan-sonar support; M. Farnam, B. Bunge, and T. Jamison (Naval Undersea Warfare Center—Division Keyport) for technical and field support; and fleet manager J. Downing, Capt. Shawn O'Brien, and the capable crew of the FV "Ocean Explorer". The study was partly funded by the NOAA Office of Exploration (to RAM; 2001–2002).

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doi:10.1093/icesjms/fsn011