A novel technological and collaborative approach to mapping deep-sea benthic habitats and assessing risks from bottom contact fishing

by

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Abstract

Bottom longline fishing gear can damage sensitive benthic areas (SBAs) in the ocean; however, the risks to these habitats are poorly understood. In this study we describe a collaborative academic-industry-government approach to mapping SBAs and measuring gear interactions with seafloor habitats via novel deepwater trap camera and motion-sensing systems on commercial longline traps for Sablefish (*Anoplopoma fimbria*) within the SGaan Kinghlas - Bowie Seamount Marine Protected Area. We obtained direct presence-absence observations of cold-water corals and sponges that were used to develop species distribution models of gorgonian corals (Alcyonacea) in fished areas. Video, accelerometer and depth sensor data were used to classify gear movement, estimating a mean bottom footprint of 3 200 m² (95% CI = 2 400 - 3 900 m²) for a 60-trap Sablefish longline set approximately 3 km in length. Our successful collaboration demonstrates how research partnerships with the fishing industry offer new opportunities for conducting SBA risk assessments over large spatial and temporal scales.

**Keywords:** bottom-contact fishing impacts; species distribution modelling; benthic habitat, cold-water corals; ecosystem-based management, risk assessment
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1. Introduction

Sensitive benthic areas (SBAs), such as cold-water coral and sponge communities, occur throughout the world’s oceans often providing three-dimensional habitat for fish and invertebrate populations (Krieger and Wing 2002; Buhl-Mortensen et al. 2010; Stone et al. 2014). SBAs and associated communities are prone to damage when contacted by fishing gear and recovery from such damage can take decades (Sainsbury et al. 1997; Williams et al. 2010; Rooper et al. 2011). Spatial management strategies such as marine protected areas that permanently close large areas to bottom-contact fisheries are increasingly used to limit or avoid damage to SBAs in many parts of the world (Hourigan 2009; Wright et al. 2015). However, for most remote parts of the deep ocean, there is little information about the locations, diversity, abundance, and composition of SBAs, as well as the potential risks to these habitats from bottom-contact fishing methods other than trawling. Without better information, misplaced marine protected areas (i.e., both location and size) could have a dual effect of (1) shifting fishing effort to more valuable, yet unprotected, SBA locations and (2) creating unnecessary fishery economic losses or increases in fishing cost (Lagasse et al. 2015a). These potential consequences create incentives for the fishing industry to engage in new scientific research aimed at mapping SBA distributions (e.g., Woodby et al. 2009; Rooper et al. 2014, Lagasse et al. 2015), as well as forecasting potential fishery impacts to these habitats (e.g., Welsford et al. 2014b, Eigaard et al. 2015). Such research could better inform ecosystem-based fisheries management that minimizes risks to bottom habitats, while allowing fisheries to maintain access to fishing grounds where risks of damage are acceptable.

It is reasonably well established that bottom trawling and dredging can cause extensive damage to benthic communities by removing large amounts of sessile epifauna and dramatically altering certain bottom communities (Collie et al. 2000; Kaiser et al. 2006; Clark et al. 2015). However, we know much less about the potential impacts
of bottom longline fisheries, even though these fisheries are more common and occur over a wider range of depths and bottom habitats (Heifetz et al. 2009). In general, bottom longline gear (e.g., hook-and-line) is thought to be less damaging owing to a much smaller bottom contact area, lighter weight, and relative stationarity on the seafloor (Hourigan et al. 2007, Pham et al. 2014). However, there is little scientific research available to support this assertion (Shester and Micheli 2011). Bottom longline gear using baited hooks or traps have potential to damage corals and sponges by landing on them when deployed or by dragging over them during retrieval (Eno et al. 2001; Stone 2006; Stone et al. 2014). Lateral movement of the groundline during hauling operations can create shearing forces that may break corals off at their base, while hooks, lines, and traps can entangle freestanding corals during retrieval (Troffe et al. 2006; Bo et al. 2014; Ewing and Kilpatrick 2014). On the other hand, the extent of dragging that occurs is likely influenced by particular circumstances of, for example, bottom bathymetry, hauling direction, wind, and currents (Eno et al. 2001; Stone 2006). Groundline for some types of trap gear are also positively buoyant as a measure to avoid entanglement with bottom structure and may not even contact the bottom, (e.g., the BC Sablefish trap fishery, High 1998). Therefore, unlike trawls and dredges, the footprint from bottom longline gear involves more than a computation of length times width of a tow.

In this project, I demonstrate a novel deepwater trap camera and motion-sensing system. The system was developed via a collaborative academic-industry-government commitment for improving the information for assessing bottom-contact with cold-water corals and sponges by bottom longline trap fisheries. Understanding the risks that result from interaction of bottom longline fisheries with seafloor habitats requires four general types of information: (1) presence or presence-absence data for mapping suitable habitat for corals and sponges; (2) the effective bottom contact area or footprint of gear deployed within the fishing area; and (3) the damage or mortality rate arising from gear contact with sensitive habitats or individual organisms, and (4) the recovery rates from damage. Mapping habitats for deepwater corals and sponges is challenging because data are very expensive and difficult to collect over large spatial scales and in remote areas of the deep ocean. By designing our cameras to work on commercial fishing gear, we are able to (1) vastly improve the input data to species distribution models for corals and sponges by using direct presence-absence data rather than the typical presence-
only data (Hastie and Fithian 2013; Lagasse et al. 2015) and (2) provide a cost-efficient means of covering the large-scale spatial areas needed to produce species distribution models that accurately predict the distribution of benthic habitats. Additionally, depth and accelerometer sensors on our camera systems allowed us to quantitatively estimate the contact area of fishing sets based on gear behaviour during set, soak, and hauling periods.

Role of industry-academic-government collaboration in deep-sea research

Between 2012 and 2015, bottom contact fisheries off British Columbia, Canada generated an average total landed value of CAD $122 million with longline hook and longline trap fisheries for Pacific Halibut (*Hippoglossus stenolepis*) and Sablefish accounting for CAD $66 million. Longline fisheries operate along most of the continental slope and shelf (Fig. 1), including within complex terrain (e.g., canyons, boulder outcrops, rocky reefs) that is inaccessible by bottom trawl (Sinclair et al. 2005; Wallace et al. 2015). This ability to fish a variety of terrain over a broad area increases the likelihood of bottom contact in areas where cold-water corals and/or sponges probably occur (Mortensen and Buhl-Mortensen 2004; Woodby et al. 2009).

In 2010, conservation groups in British Columbia questioned the Marine Stewardship Council's (MSC) certification of British Columbia's Sablefish fishery on grounds that there was no information about impacts of bottom longline fishing effort on vulnerable habitats (Furness et al. 2010). In response, Wild Canadian Sablefish, Ltd (WCS) joined with Simon Fraser University (S.P. Cox) and Fisheries and Oceans Canada (DFO Pacific Region) to design, build, and deploy an autonomous video camera and motion-sensing system capable of operating at extreme depths of 200 m - 1500 m where Sablefish occur (Beamish and McFarlane 1988; Wyeth et al. 2007). As part of a collaborative research partnership, the camera system, along with accelerometers and depth sensors, have been deployed annually on selected commercial fishing trips to SGaan Kinglas Bowie (SK-B) Seamount and on the annual stratified-random, fishery-independent Sablefish survey that is jointly funded by WCS and DFO (Wyeth et al. 2007).
Deep-water observations of bottom habitats are typically collected using submersibles or remotely operated vehicles (ROVs) that require dedicated research cruises and highly trained personnel, which can be prohibitively expensive and limited by available ship time. The collaborative approach described here offers an alternative model that pools resources and allows for an efficient distribution of research responsibilities between industry, government and academia, without which this study would not have been possible. WCS provided financial and in-kind support for all stages of this project from the initial design of the camera system to field deployments and analysis. This research would have taken many more years and financial resources to complete, if attempted by government or academia alone, and is unlikely to have occurred without the fishing industry’s contribution of vessel time and the vessel master’s fishing expertise for conducting sampling in remote areas at SK-B Seamount. This project was also made possible by numerous Fisheries and Oceans Canada Science staff who assisted with camera design, data collection, data processing, equipment preparation, training of at-sea observers and coordinating field sampling. Finally, SFU provided guidance in research planning, sampling design, additional financial support through research grants and lead the data analysis.

In this project, I report the first results from this collaborative academic-industry-government approach to improving the scientific information for protecting cold-water corals and sponges from bottom contact fishing at SGaan’Knighlas - Bowie (SK-B) Seamount, which is part of the Bowie Seamount Marine Protected Area created in 2008 under Canada's Oceans Act (laws-lois.justice.gc.ca/eng/regulations/SOR-2008-124/). The scientific challenges of finding and protecting sensitive benthic areas at SK-B Seamount are indicative of those that are occurring, or are likely to occur, in other areas as Canada aims to implement a large-scale marine protected area strategy (DFO 2005; Government of Canada 2014).
2. Materials and Methods

In this section I first describe (1) the study area, and (2) the camera system developed for Sablefish trap gear, along with the sampling protocols and steps leading to spatially explicit presence-absence data for deepwater corals and sponges. I then describe (3) the methods used to fit presence-absence observations to environmental data for developing species distribution models of gorgonian corals, and, finally, (4) an algorithm for estimating the bottom-contact area of bottom longline trap gear.

Study area

SGaan Kinglas - Bowie (SK-B) Seamount is the southernmost seamount in the Kodiak-Bowie Seamount Chain (also called the Pratt-Welker Chain) that runs 1000 km northwest from SK-B Seamount up to the Kodiak Seamount and encompasses 14 major and several smaller seamounts (Turner et al. 1980, Chaytor et al. 2007). SK-B Seamount has an oblong shape oriented in the southwest - northeast direction with a linear ridge extending approximately 20 km northeast from its northern end (Fig.1, Chaytor et al. 2007). The slopes of SK-B Seamount extend from a base depth of approximately 2800 m up to a flat summit area of 26 km², with depths ranging from 200-250m (Chaytor et al. 2007). Several pinnacles extend from an elevated area near the centre of the summit with the tallest pinnacle extending to a 24 m depth (Halcro 2000). The average slopes on the seamount are between 10-20 degrees, however slopes on the southwest and northeast flanks are more variable, ranging from 0-50 degrees with both flat and steep slopes; likely created by solidified lava flows (Chaytor et al. 2007).

In 2008, Marine Protected Area status was granted to SK-B Seamount and the surrounding area encompassing two seamounts to the North (Hodgkins and Davidson), dividing the area into 3 zones with different regulations. Zone 3 comprises Hodgkins and Davidson Seamounts and Zone 1 comprises depths shallower than the approximate
457 m contour of SK-B Seamount, both of which restrict all fishing activity. The Sablefish fishery by longline trap is the only fishing permitted within the SK-B Seamount Marine Protected Area and is restricted to fishing in Zone 2 of SK-B Seamount at depths below the approximate 457 m contour (DFO 2015; Fig. 1). Although Zone 2 is greater than 2 500 km², the Sablefish fishery primarily operates at depths between 457 m and 1 500 m, resulting in a potential fished area of approximately 200 km². The SK-B Seamount has documented areas with diverse deepwater coral and sponge communities (Canessa et al. 2003; Buchanan et al. 2015) and has been isolated from other bottom-contact fisheries since 2000.

**Autonomous video camera system and sampling protocol**

The trap camera housing contains a GoPro HD Hero® that produces 1080p video and 4 LED lights (Cree XLamp XM-L) that can generate up to 500 total lumens. The camera, lights, lithium-ion battery pack (Ultra Life UBBL24-FL), depth sensor, and triaxial accelerometer are contained within a 3.6 kg stainless steel housing rated to 1 500 m depth. A custom circuit board and controller contained inside the housing allows programming the cameras to record video at both regularly timed intervals and/or using motion-activation thresholds via link to an accelerometer, by moderating power delivery to the GoPro camera. The battery life allows camera deployments for up to 48-hours with 1-minute video recordings every hour.

Over the 2013-2015 period, we deployed the camera systems on Sablefish traps (Fig. 2) along with external accelerometers (Actilife wGT3x-BT monitors) and depth-temperature sensors (Sea-Bird SBE 39). Cameras were programmed to record 1-minute video clips at 2-hour intervals while the trap was stationary on the bottom. Accelerometers within the camera housing system were used to trigger additional video recordings of trap movement during gear retrieval at impact forces greater than 0.6 g units. Depth-temperature sensors recorded at 10-second intervals. A total of six trap camera systems were deployed individually, alongside depth-temperature sensors and accelerometers, in single traps as part of commercial bottom longline sets that contained between 41 and 60 traps (Fig. 2). Traps are a conical design with a circular steel base of 137 cm diameter that extends to a smaller circular top of 84 cm diameter. During fishing
the traps are connected to stainless steel rings on a polypropylene groundline, which includes chain anchors of approximately 60 kg at each of the set ends to reduce groundline movement (Wyeth et al. 2007). Vessel position was recorded at the terminal ends of the set, \((x^{(i)}_{\text{START}}, y^{(i)}_{\text{START}})\) and \((x^{(i)}_{\text{END}}, y^{(i)}_{\text{END}})\), with a linear distance between set endpoints ranging from 1.8 km to 4.0 km (median of 3.0 km). For each set \(i\) we recorded the total number of traps deployed, \(N^{(i)}\), and the relative position \(n^{(i)}\) of the camera trap (and depth sensor) along the deployment track. We estimated the surface deployment coordinates \(\bar{u}^{(i)} = (\bar{x}^{(i)}, \bar{y}^{(i)})\) of the camera trap by taking a weighted average of the deployment track start and end locations, where:

\[
\bar{x}^{(i)} = x^{(i)}_{\text{START}} + \frac{n^{(i)}}{N^{(i)}}(x^{(i)}_{\text{END}} - x^{(i)}_{\text{START}})
\]

\[
\bar{y}^{(i)} = y^{(i)}_{\text{START}} + \frac{n^{(i)}}{N^{(i)}}(y^{(i)}_{\text{END}} - y^{(i)}_{\text{START}})
\]

An annotated Microsoft Access database of trap camera videos was created using the VideoMiner software version 3.0.8.0 developed by DFO (available at: downloads.crmltd.ca/f/Crm1335/). Video clips were reviewed to record observations of all species, benthic habitat, physical substrate, and gear substrate-interactions. All epifauna were identified to the lowest taxonomic rank possible, which was often the order or family level because positive identification of deepwater corals and sponges to genus or species was limited by: (1) a lack of close-up images required to identify distinguishing morphology; (2) views of specimens obstructed by traps, netting, boulders or other animals; (3) an absence of physical samples that are often needed to confirm identification to species level; and (4) the potential for observations of previously undescribed species (Cairns 2007, Austin et al. 2013, Reiswig 2015). Video still frames of coral and sponge observations and a list of the resources used for taxa identification are available in Doherty and Cox (In press).
Species distribution modelling

The following two sections describe the predictor variable data sources and steps for fitting species distribution models to presence-absence data (n=92) for gorgonian corals. I fit linear logistic regression models with a logit link function for predicting the probability of coral presence in i specific 100 m x 100 m grid cells:

$$\log\left(\frac{\pi_i}{1 - \pi_i}\right) = \logit(\pi_i) = \alpha + \sum_{j=1}^{9} \theta_j x_{ij} + \varepsilon_i$$

where \(j = \{1, 2, ..., 9\}\) different combinations of linear terms for 7 predictor variables (Table 1) and 2-way interactions between depth x aspect and slope x rugosity, \(\alpha\) is the intercept term, and \(\theta\) is a vector of coefficients for \(j\). I identified multiple candidate models and used model-averaged coefficients to generate predicted probabilities of gorgonian coral presence in each \(i\) 100 m x 100 m grid cells in fishing areas at SK-B Seamount.

Predictor variables

I considered 7 predictor variables based on data derived from multibeam bathymetry, oceanographic models, and historical fishing information (Table 1). All predictor variables were converted into 100 m x 100 m grid cell raster maps that encompassed the fishable area at SK-B Seamount. I used a Universal Transversal Mercator projection (zone 8) for all raster layers and prediction maps with a grid of 41 km x 24 km (longitudinal range: -135.9° to -135.3°, latitudinal range: 53.2° to 53.4°).

SK-B Seamount seafloor bathymetry data from the Canadian Hydrographic Services (Halcro 2000) were obtained for a 10 m x 10 m grid and were aggregated to a 100 m x 100 m raster using the arithmetic mean of cell values with the raster package in R (R Core Team 2015). In addition to depth, I used four derivatives of bathymetry (BPI, rugosity, slope, and aspect) as predictor variables that may be indicative of areas with hard substrate or suitable coral habitat (Masuda and Stone 2015). Bathymetry derivatives were calculated as rasters using 10 m x 10 m grid cells and then aggregated...
to 100 m x 100 m raster layers using the arithmetic mean of cell values. The bathymetrical position index (BPI) is a second order derivative of bathymetry that can be useful to identify areas of different elevations such as depressions, slopes, ridges, or mounds. A positive BPI indicates an area of higher elevation relative to the neighbouring landscape (e.g., mounds, seamounts, knolls, ridges), and a negative BPI indicates an area of lower elevation relative to neighbouring landscape (e.g., depressions, valleys, troughs). The benthic terrain modeller extension (Wright et al. 2012) in ArcGIS was used to calculate a broad-scale BPI (inner radius of 15 m and an outer radius of 30 m) raster layer. Rugosity was calculated as the contoured surface area divided by the planar area (e.g., arc-chord ratio rugosity index) in each cell using the DEM surface tools extension (Version 2.1, Jenness 2013) to ArcGIS, following the methodology in Du Preez (2015). Slope and bathymetry aspect (e.g., slope direction relative to north) were calculated using the 4-cell method in the DEM surface tools extension (Version 2.1, Jenness 2013) in ArcGIS. The bathymetry aspect predictor was considered in an attempt to capture local environmental variations on different sides of the seamount that may not be represented by the other variables. I also considered 2-way interaction terms for slope x rugosity and depth x aspect.

Tidal speeds were obtained from tidal inversion software (TPXO8-atlas solution, volkov.oce.orst.edu/tides) using a 100 m resolution forward solution (Egbert and Erofeeva 2002) that was parameterized using 100 m x 100 m bathymetry for SK-B Seamount and the surrounding area that includes Hodgkins and Davidson seamounts to the north (175 km x 219 km area, longitudinal range: -137.5 ° to -134.1° and latitudinal range: 52.6° to 54.1°). Tidal speeds were generated for 1-hour intervals over 368 consecutive days from January 1, 2009 to January 3, 2010. The maximum tidal speeds observed in each cell \( i \) during the time series were used to generate the maximum tidal speed raster.

The final predictor variable used was the historical fishing locations of the Sablefish longline trap fishery at SK-B. The start and end deployments of fishing sets and the number of traps deployed from 1991-2014 were obtained from the DFO groundfish database archived at the Pacific Biological Station in Nanaimo, BC. I assumed that traps were equally spaced in a straight line between the terminal
deployment locations of sets and calculated the total number of traps deployed in each 100 m x 100 m grid cell from 1991-2014.

The estimated surface deployment coordinates for trap camera deployments (n=92) were used to extract environmental predictor data from rasters. All predictor variable rasters were used for both model parameterization and model prediction with the exception of depth. When available I used the median Sea-Bird depth sensor measurements from the period that the trap was stationary on the seafloor as the observation depth for parameterizing model coefficients for depth. When Sea-Bird depth data were not available, I used depth data from the internal trap camera depth sensors and when no depth sensor data were available (2 deployments), depths were obtained from the corresponding bathymetry values at the estimated camera position.

**Model selection and performance**

I fit logistic regression models with presence-absence observations of gorgonian corals using an all subsets selection procedure to fit all possible combinations of the $j$ predictor variables. I used the Corrected Akaike Information criteria (AICc) (Burnham and Anderson 2002) to identify the top model with the lowest AICc (model 1) containing $p_1$ predictor variables as well as a candidate set of additional models. According to Burnham and Anderson 2002, models that include additional predictor variables and are within 2 AICc units of the top model are not supported if the maximized log likelihood is essentially the same as that of the top model. Thus I only considered additional candidate models that were within 2 + $2(p_1 - p_m)$ AICc units of the top model where $p_m$ is the number of predictor variables selected for a set of $m = \{1, 2, ..., R\}$ candidate models. For example, if the top model selected included 5 predictor variables, I considered additional candidate models that were within 2 AICc units and also contained 5 predictor variables, candidate models that were within 4 AICc units and contained 4 predictor variables, candidate models that were within 6 AICc units and contained 3 predictor variables, and so on. This procedure selects for the models with the fewest parameters, which is particularly useful for predictive models with small sample size and when trying to select for variables that have the largest effects. The $j = \{1, 2, ..., 10\}$
parameter estimates \( \hat{\theta}_{m,j} \) for the predictor variables and intercept term of the top \( m = \{1, 2, \ldots, R\} \) models were averaged using Akaike weights \( w_i \) to generate model-averaged parameters \( \tilde{\theta}_j \) and prediction estimates using the full-model averaging approach described in Burnham and Anderson (2002) and Lukacs et al. (2010) by the equation:

\[
\tilde{\theta}_j = \sum_{m=1}^{R} w_m \hat{\theta}_{m,j}
\]

This full-model averaging approach includes all top models when estimating parameters for each predictor variable. Models that exclude a predictor variable \( j \) have \( \hat{\theta}_{m,j} = 0 \), and thus contribute a zero to the model-averaged calculations of the parameter estimate \( \tilde{\theta}_j \) for that predictor variable. I used the revised unconditional variance estimator from Burnham and Anderson (2004) to generate standard errors of model-averaged parameters. The model-averaged parameter estimates and environmental predictor rasters were then used to generate predictive maps for the probability of gorgonian coral presence at each \( i \) 100 m x 100 m grid at SK-B Seamount.

Following the AICc model selection procedure, I used three metrics to evaluate the performance of top candidate models and model-averaging:

1. the area under the receiver operating characteristic curve (AUC),

2. the maximum kappa (\( \kappa \)) statistic, and

3. adjusted D squared (\( D_{adj}^2 \)).

The \( D_{adj}^2 \) is a measure of the proportion of deviance explained in GLM model fits that takes into account the number of observations and predictors in different models (Guissan and Zimmerman 2000). This test is analogous to the adjusted \( R^2 \) in normal linear regression.
Both AUC and kappa are derived from confusion matrices that can be generated by comparing model predictions for binary classification with the observed data. Since logistic regression does not generate discrete values of 1 (e.g., presence) and 0 (e.g., absence) but rather predicted probabilities on a continuous scale from 0 to 1, confusion matrices require that a probability threshold is selected to convert model predicted probabilities into presence-absence. For example, if a threshold of 0.5 is selected, then any model predicted probability $\geq 0.5$ would be considered a predicted presence location and any probability $< 0.5$ would be considered an absence location. Confusion matrices summarize the number of true positives (e.g., model predicted presence for observed presence location), false positives (e.g., model predicted presence for observed absence location), true negatives (e.g., model predicted absence for observed absence location) and false negatives (e.g., model predicted absence for observed presence location).

The receiver operating characteristic curve (ROC) is generated by computing confusion matrices for all probability thresholds between 0 and 1 and plotting the true positive rate (sensitivity) vs. the false positive rate (1-specificity) for each of the probability thresholds. The AUC measures the total area under the ROC curve and is a threshold independent measure of model accuracy since it is does not depend on a single probability threshold. AUC estimates the probability that the model's predicted probability for a randomly selected presence observation will be greater than that for a randomly selected absence observation (DeLong et al. 1988). Hosmer and Lemeshow (2005) provide general guidelines for interpreting AUC values as poor or only marginally better than chance (0.50-0.69), acceptable (0.70-0.79), excellent (0.80-0.89) and outstanding ($\geq 0.90$) discrimination.

Confusion matrices are also used to develop a variety of threshold-dependent measures (e.g., percent correctly classified (PCC), specificity, sensitivity, kappa) that assess binary model classification accuracy. These metrics differ from AUC in that they are calculated from only one confusion matrix and thus are dependent on the specified probability threshold (Fielding and Bell 1997, Freeman and Moisen 2008a). Sensitivity is the true positive rate, equivalent to the proportion of presence observations correctly classified by the model predictions, while specificity is the true negative rate, equivalent to the proportion of absence observations correctly classified by model predictions.
Freeman and Moisen (2008a) compared 11 different criteria for selecting probability thresholds that optimize map accuracy and found that the best two thresholds for producing unbiased maps of species presence and absence were (1) the probability threshold where predicted prevalence is equal to the observed prevalence and (2) the threshold that maximizes the kappa statistic. The Cohen (1961) kappa statistic is one of the only measures that uses all information in the confusion matrix and is considered one of the more robust diagnostic statistics for evaluating model classification accuracy for categorical data (Forbes 1995, Fielding and Bell 1997, Manel et al. 2001, Freeman and Moisen 2008a). Kappa varies from -1 to 1 and measures the improvement in the proportion of correctly predicted presence-absence locations over chance expectations, with values of 0 indicating performance no better than random. Landis and Koch (1977) suggest benchmarks for values of Kappa that indicate slight (0.00-0.20), fair (0.21-0.40), moderate (0.41-0.60), substantial (0.61-0.80) or near perfect (0.81-1.00) agreement between model predictions and observations. I used the maximum kappa statistic obtainable by varying probability thresholds between 0 and 1 as another measure for comparing candidate model and model-averaging performance. I evaluated different probability thresholds for the model-averaged predictions that optimize for kappa, sensitivity, specificity PCC, and the threshold where model predicted prevalence equals the observed prevalence of coral presence observations using the methods developed by Freeman and Moisen 2008b, as implemented in the PresenceAbsence package for the R language (R Core Team 2015).

**Trap movement and bottom contact estimates**

I used depth measurements, accelerometer data, and video recordings to classify different periods of trap movement and to estimate the bottom contact area of traps during gear retrieval for 2015 commercial fishing sets. Observations from 2013-2014 sets, as well as 3 sets from 2015, were excluded from analyses because time stamps from video recordings and motion-sensing equipment could not be reliably synchronized. I analysed 21 independent fishing sets from 2015 and focussed our analysis on the last hour of fishing when gear retrieval occurs, because video observations showed traps were stationary prior to the last hour. The last hour of the set
was determined as the final 60 minutes for which depth sensor readings were below 5 m.

I developed an algorithm for classifying 1-second intervals of bottom longline trap movement during the last hour (i.e., 3 600 seconds) using:

- fishing time series of depth \( d_t \),
- the depth change over 10-second intervals \( d_t - d_{t-10} \),
- acceleration in g units \( a_t \),
- acceleration variance over 10-second intervals in \( g^2 \) units \( \sigma^2_{t(t+10)} \),
- and observed trap movement from 1-minute video.

Trap movement was classified as either "stationary", "dragging", or "suspended" (Figs. 3,4), using the following procedure:

**Step 1.** Define start and end times for drag window:

a) Choose the start of the drag window as the first time step subject to (s.t.) 1 of 3 conditions being true, i.e.,

\[
 t_{\text{start}} = \min \left\{ t \mid \begin{array}{l}
 |d_t - d_{t-10}| > 5 \text{cm}; \quad \text{or} \\
 \log \sigma^2_{t(t+10)} < -10 \text{g}^2; \quad \text{or} \\
 a_t > a_{\text{video}}
\end{array} \right\}.
\]

where \( a_{\text{video}} \) = the camera’s acceleration trigger threshold for recording videos during gear movement.
b) Choose the end of the drag window as the first time step subject to two conditions being true:

\[ t^{end} = \min \{ t \text{ s.t. } t > t^{start} \text{ and } (d_t - d_{t-10}) > 6\text{cm} \}. \]

**Step 2.** Determine the class \( C_{(t-10)_{tr}} \) of trap behaviour over 10-second intervals for each \( t \) within the drag window:

\[
C_{(t-10)_{tr}} = \begin{cases} 
"stationary" & d_t = d_{tr-10}, \\
"dragging" & d_t \neq d_{tr-10}.
\end{cases}
\]

**Step 3.** Set the classes of trap behaviour to \( C_{t_{start-1}} = "stationary" \) for each \( t \) prior to the drag window and \( C_{t_{end+1}} = "suspended" \) for each \( t \) after the drag window.

Video clips of dragging and suspended traps provided lower and upper bounds for the drag window. The difference between the start and end times of the drag window was considered the maximum potential dragging time; however, traps do not always drag continuously during this period (Fig. 4). Videos, accelerometer data, and depth readings indicated that traps sometime drag and stop several times within the drag window. To account for these starts and stops, I classified traps as stationary for any 10-second interval where there was 0 cm of depth change for consecutive depth measurements (Step 2).

I estimated the distance that a trap is dragged along the bottom by multiplying the estimated drag time by the estimated hauling speed \( (H) \) for each set, where haul speed was calculated using depth and time measurements during gear retrieval between 600 m and 200 m, i.e.,
\[ H = \frac{\max(d_t < 600) - \min(d_t < 200)}{t_{600} - t_{200}} \]

Where \( \max(d_t < 600) \) and \( t_{600} \) are the first depth measurement and time during the trap retrieval above 600 m and \( \min(d_t < 200) \) and \( t_{200} \) are the last depth measurement and time during the trap retrieval below 200 m.

I estimated the possible furrow width created by a dragging trap by individually dragging 54-inch (1.37 m) bottom diameter Sablefish traps along a sandy beach in 5 replicates of 5 m distance each (Fig. 5). Traps were pulled by the trap bridle that is connected to the upper hoop cross bars (Fig. 2) with the bottom hoop in contact with sand, to best replicate the orientation of the trap typically observed during dragging in videos. Measurements of furrow width were taken at 0, 1, 2, 3, 4 and 5 m intervals along the tracks and averaged for each trial. The total bottom contact area of traps during fishing was estimated by multiplying the mean drag furrow width by the estimated trap drag lengths for each set. An estimate of the bottom contact area for a typical 60-trap set was then obtained by multiplying the trap bottom contact area by 60 for each set.
3. Results

**Direct observations of coral and sponge presence-absence**

Deepwater corals or sponges were present at 26 locations and absent at 66 locations out of the 92 successful camera deployments at SK-B seamount (Table 2, Fig. 6). Gorgonian corals (Order Alcyonacea) were the most commonly observed and diverse group with at least 6 different species or taxonomic groups, including *Heteropolypus ritteri*, Isididae spp., *Paragorgia* spp., *Parastenella* sp., Primnoidae sp., and *Swiftia simplex*. The most common coral taxonomic group was *Parastenella* sp. colonies (Table 3). Two locations in the northeast had particularly high densities with counts of 24 and 42 gorgonian coral colonies observed during single camera deployments. We also observed sponges (Classes Demospongiae and Hexactinellida), seapens (Order Pennatulacea), hydrocorals (Family Stylasteridae) and black coral (Order Antipatharia) during camera deployments (Table 2).

**Species distribution modelling**

There were 4 models selected that were used to generate model-averaged predictions (Table 4). Slope and rugosity were included in all 4 models and had the largest effect size (Table 5). Maximum tidal speed, aspect, depth, and the aspect x depth interaction term were also selected in some of the candidate models. The BPI and historical fishing predictor variables were not selected in any of the top models. The candidate model set and averaged-model explained between 25 - 34 % of deviance, had AUC values ranging from 0.84 (SD = 0.05) - 0.90 (SD=0.04) and maximum kappa values ranging from 0.55 (SD=0.11) - 0.61 (SD=0.11) (Table 4). Results from bootstraps used for comparing candidate model performance are available in Appendix A.
The observed prevalence of locations with coral presence in the data was 20% (e.g., 18 presence and 74 absence observations, Table 2) and the 0.38 probability threshold is where the prevalence of model-averaged predicted coral presence is also 20% (Fig. 7). Probability classification thresholds that optimize for maximum kappa were highly variable between the candidate and averaged-models, ranging between 0.22 - 0.54 (Table 4). For model-averaged predictions kappa is maximized at 0.56 using the 0.22 probability threshold, however plots of the kappa measure over varying thresholds show that kappa is above 0.45 for all thresholds between 0.13 - 0.55, with three other local maximums of 0.55 for thresholds of 0.18, 0.49 and 0.50 (Figure 7b). The probability threshold where sensitivity (true positive rate) and specificity (true negative rate) are equal is 0.22. The maximized percent of correctly classified (PCC) observations is 88%, obtained by setting the probability threshold at 0.5, however PCC remains above 80% for all thresholds > 0.17 due to the low prevalence of coral in the observations.

Model-averaged predictions include a large proportion of the area in the 400 m - 800 m depth range with high probabilities (> 0.5) of gorgonian coral presence (Fig. 8). There are several patches of high probability areas located on the northeast and southwest flanks of the seamount, and more high probability areas on the south slopes than the north slopes.

Bottom-contact area

The results from the classification of trap movement and estimates of bottom contact area are shown in Fig. 9 and Table 6. These statistics exclude one set where the trap was wedged in a rock crevice that prevented any trap movement during retrieval, as this behaviour was not observed in any of the other 92 sets with video observations. The estimated drag window and drag time for the excluded set were 5.9 minutes and 0.4 minutes, respectively. The mean estimated bottom contact area for a 54-inch trap was 53 m² (95% CI= 40-65 m²), which is 36 times the static trap footprint of 1.47 m² (i.e., the bottom area of the trap). The estimated drag times, drag lengths and bottom footprint were highly variable between the 20 sets, while there was considerably less variability in the haul speeds and the measured drag widths.
The start of the drag window is indicated by an increase in the acceleration variance and increased magnitude of depth change (Figs. 3,4). As gear retrieval continues, there is a noticeable decrease in depth until eventually the trap moves vertically off the bottom and becomes suspended in the water column (e.g., the end of the drag window). When this occurs, there is usually a decrease in acceleration variance and a positive increase in the rate of depth change (Figs. 3,4).

Video observations, depth and accelerometer data indicate that traps do not always drag continuously (Fig. 4) and that traps can start and stop dragging frequently during gear retrieval. The stationary intervals during the drag window were classified as such when the rate of depth change for a 10-second interval was zero. This step of the classifying algorithm is important since deviations between the drag window and the estimated drag time can be substantial (Fig. 10). The estimated mean drag window (i.e., the period in which there is potential for the gear to drag along the seafloor) was 1.25 times longer than the estimated mean drag time (Table 6). The maximum difference between the drag window and drag time estimates was 9 minutes, where the drag window was nearly 2.9 times longer than the estimated drag time. If the drag window was used in the bottom footprint calculation, the mean footprint would be 4 000 m$^2$ instead of the 3 200 m$^2$ calculated using the estimated drag time, which would overestimate the contact area.
4. Discussion

Contemporary fisheries are increasingly challenged to improve conservation of both fish stocks and essential habitats as part of government and eco-certification requirements. (DFO 2010; Furness et al. 2010; Heupel and Auster 2013). Fisheries in Canada will also need to adapt to a growing number of marine protected area (MPA) closures. The Government of Canada recently re-affirmed commitments to protect 10% of coastal and marine waters by 2020 as part of the Aichi Biodiversity Targets, with plans to implement half this area by 2017. For habitat conservation, we lack the detailed knowledge about species distribution, composition, vulnerability, and habitat productivity necessary to effectively protect important deepwater habitats. In this study, we demonstrate how a collaborative academic-industry-government approach to studying deepwater ocean habitats and the risks posed by longline fishing gear could provide an improvement in our ability to design and implement protections for essential ocean habitats. In particular, (1) we obtained high-quality presence-absence observations for corals and sponges and developed species distribution models for the entire fished area within the SK-B Seamount MPA, and (2) we obtained direct video observations of gear interactions with the seafloor, which we used, in combination with accelerometer and depth sensors data, to develop an algorithm for estimating the total bottom contact area of longline trap gear.

Mapping coral and sponge habitats

The trap camera deployments during commercial fishing trips from 2013-2015 provided presence-absence observations of deepwater corals and sponges from 92 different locations in Zone 2 of the SK-B Seamount Marine Protected Area. The highest observed concentration of gorgonian corals is along the southwest and northeast flanks of Zone 2 in the SK-B Seamount. Other sensitive benthic taxa such as black corals,
hydrocorals, sea whips and sponges were less commonly observed on camera deployments without any obvious consistency in their locations.

The model-averaged predictions for gorgonian corals at SK-B Seamount suggest a large portion of suitable habitat in the 400-800 m depth range with high probabilities (> 0.5) of gorgonian coral presence. The candidate models considered suggest that slope, rugosity, maximum tidal speed, and depth can be important predictors for coral habitat at SK-B, which is consistent with findings from other studies (Woodby et al. 2009; Rooper et al. 2014; Masuda et al. 2015). Slope and rugosity had the largest effect in all models considered and may be indicative of high relief areas with hard substrate (Dunn and Halpin 2007) that is required for most corals for settlement. Maximum tidal speed, as well as rugosity and slope, can be related to areas experiencing high flow rates that may influence favorable conditions for coral growth by (1) providing more food through higher rates of plankton availability and (2) limiting the settlement of suspended particles that may smother corals (Genin et al. 1986; Mortensen et al. 2004; White et al. 2005). Depth is often considered to act as a proxy for other important environmental variables for corals such as temperature, oxygen and aragonite concentration (Woodby et al. 2009). The aspect term was used as a proxy to represent environmental variability, such as current direction and flow rate, and was included in the top 3 candidate models. This result potentially indicates that there are local environmental conditions on different sides of the seamount that are more favourable for coral. The model-averaged predictions indicate there is likely higher coral presence at the northeast and southeast flanks of the seamount.

Metrics derived from confusion matrices, such as AUC, kappa, sensitivity (i.e., true positive rate), specificity (i.e., true negative rate), and the percent of observations correctly classified (PCC), were used to evaluate model performance and the ability of model-averaged predictions to correctly classify presence or absence under different probability thresholds. The threshold dependent criteria suggest acceptable model classification performance over a wide range of probability thresholds between approximately 0.20 - 0.50, and thus there is no 'best' threshold that can be identified for generating maps with presence-absence. The optimal threshold will depend on specific objectives and tolerance for false positives, false negatives and overall prediction
accuracy. Thresholds can be adjusted to place more emphasis on reducing false positives (e.g., model predictions of coral presence where corals do not actually occur) or false negatives (e.g., model predictions of coral absence where corals do actually occur). The wide-range of probability thresholds with near optimal kappa values are likely due to trade-offs between decreasing false positives and false negatives when moving between thresholds. It also seems reasonable that there may be some transitional areas with sub-optimal habitats, where habitats at SK-B transition from suitable or optimal environmental conditions for corals to non-suitable environmental conditions. It is possible that some areas with model predictions of coral presence in the 0.20 - 0.50 probability range are indicative of such transitional areas, and this may explain why confusion matrix-based metrics identify a wide range of classification thresholds. Since our observations are non-randomly collected during regular fishing operations, the observed prevalence of 20% corals in the data is not necessarily representative of the actual prevalence of coral found throughout the 400 m - 1400 m depth range at SK-B Seamount. Trap cameras were deployed in the middle of sets and observations are concentrated in the intermediate depth range, with 75% of observations occurring between 800 m - 1150 m. In 2016 a new stratified sampling design was implemented to improve sampling coverage for shallow and deep areas, as well as sampling for the full range of rugosity, slope and maximum tidal speed predictor variables. The model-averaged predicted probabilities of gorgonian coral presence are better suited for use in a risk assessment framework, since the probabilities provide more information than assigning discrete values of presence or absence to each cell.

It is important to note that the model-averaged predictions for coral habitats are reflective of presence and absence only and do not take into account observations where higher densities of corals were observed. Enhanced information for assessing the probability of contact and the subsequent risks to SBAs due to fishing could be provided in the future by developing model predictions for coral abundance or density, for example, using the number of colonies observed per camera deployment as an index of density. As new observations are collected during fishing trips, models can be regularly updated to improve model performance and reduce uncertainty in the predicting SBAs. Thus each fishing trip has the potential to provide both landings value to the vessel and value to science and management in the form of new information. The value to the fleet
is demonstrating whether fishing activities are operating within acceptable risk tolerance levels for bottom-contact impacts on corals and sponges, as defined by measurable objectives for protecting SBAs. An advantage of deploying cameras on commercial fishing trips is that more observations are collected in areas that are most heavily fished, leading to less uncertainty in species mapping for areas that experience the greatest amount of bottom contact. Since the distribution of corals and sponges does not vary seasonally, the fleet can deploy cameras at sites opportunistically when they are in the area, according to predefined sampling plans that optimize sampling effort for species distribution modelling and model validation (@Hirzel_2002a). For example, in 2016 a new sampling design was implemented for fishing trips to SK-B Seamount deploying cameras at sampling locations stratified by 4 predictor variables (depth, maximum tidal current, rugosity, and slope) and at completely random sampling sites; the data collected will be used to provide training and testing data to improve and evaluate the performance of species distribution models, respectively.

There is massive potential within the fishing industry to deploy cameras on commercial fishing gear to map deepwater benthic habitats that offers an alternative to submersibles and ROVs, or coral and sponge bycatch data. Submersible and ROV surveys can collect high-resolution spatial data and high-quality video imagery of deep-sea bottom habitats in small areas but are too costly to conduct regularly for large areas of the coast. Submersible and ROV surveys have been occasionally conducted in British Columbia but are often limited by available ship time, equipment breakdowns and weather conditions (Yamanaka 2005; Du Preez 2011; Galand et al. 2012; Curtis 2015). Most of the existing coral and sponge occurrence records for British Columbia are from bycatch data collected during bottom trawling (Finney and Boutillier 2010). The current DFO database for coral and sponge occurrences has presence records from approximately 11,300 unique locations collected between 1875-2010 (Boutillier and Gillepsie G In prep). the majority of which are from bycatch records in the BC groundfish commercial trawl fishery and fishery-independent trawl surveys for groundfish and invertebrates (Finney and Boutillier 2010). Coral and sponge bycatch trawl data offer lower quality data input for species distribution modeling in comparison with in-situ video observations because (1) bycatch provides presence-only information, (2) has high spatial uncertainty since the location of the coral/sponge encounter during a trawl tow
path is unknown, and (3) may fail to detect presence if specimens fall through the trawl mesh or are crushed during the tow. In contrast, bycatch data does have some advantages in that it provides catch rates that can be used as an index of abundance (Rooper et al. 2011; Rooper et al. 2014) and physical specimens that can assist with species identification. The trap camera systems used in this study are also regularly deployed on the annual stratified-random coastwide survey for Sablefish. In addition to the observations at SK-B Seamount, the cameras have collected presence-absence records for corals and sponges in over 200 locations between 2013 and 2015 that encompass the full range of the BC Sablefish fishery. There is also potential to expand this approach and deploy cameras in other bottom longline surveys or commercial fisheries on the coast. If cameras are deployed on a fraction of commercial longline fishing or survey sets, presence-absence datasets for SBAs can quickly be collected in many fishing areas (Fig. 1). Collaborative research partnerships with members of the groundfish fishing industry provide an alternative path forward for mapping bottom habitats on large spatial scales.

Here I only show trap camera observations in 2 km by 2 km grid cells due to privacy restrictions associated with commercial fishing data, however the GPS coordinates from surface deployment locations allow for greater spatial resolution for camera observations of benthic habitat. In this study I used a weighted average of the deployment track start and end locations, however future sampling could improve estimates by recording GPS locations at the actual surface deployment and retrieval locations. As an alternative to using a single grid-cell as a point-estimate of the observation locations, estimators that produce a probability distribution for observation locations could be used in future modelling to weight multiple grid cells when extracting predictor data from environmental raster layers. For example, the probability of different landing locations can be estimated by identifying grid cells with depths that match the depth sensor data at the bottom position with a Bayesian approach using surface deployment locations as priors.
Understanding bottom contact area of longline gear

Video observations and accelerometer measurements confirm that Sablefish traps are typically stationary once the gear has settled on the bottom and that the main interaction with the seafloor occurs over a short window of time during the gear retrieval when traps drag along the bottom. Fishing sets at SK-B Seamount are normally deployed along the slopes of the seamount (i.e., perpendicular to contour lines) with one end of the set in shallow water and the other in deeper water. Gear retrieval typically begins at the deep end of the set and attempts are made to minimize dragging by pulling the string of connected traps straight up off the bottom. Thus, the short period of increasing depth sensor measurements during the drag window that is observed suggest that traps initially drag in the downslope direction during hauling. Video and accelerometer data also indicate that traps start and stop dragging frequently during gear retrieval, presumably because of breaks in hauling to remove catch as traps reach the surface.

In this study I provide the first estimate of bottom-contact area for longline trap fishing gear. Our gear movement classifier allows for estimates of bottom-footprints in longline trap fisheries that can be used to map the fishing effort distribution on the seafloor that is within or near sensitive benthic habitats. Such information could be used to quantitatively determine longline trap gear footprints at the relatively fine-scale resolution needed to develop management strategies that mitigate contact with corals and sponges at SK-B Seamount. Note that estimates in this study are from a small sample size of fishing trips at SK-B Seamount; trap footprints may differ for other fishing vessels, fishing conditions, substrate types, and fishing areas on the coast. Further experiments under different fishing conditions will likely improve our ability to estimate how different environmental conditions and fishing characteristics influence gear movement and bottom contact area.

Our approach to estimating gear movement can be adapted to other types of longline fisheries. This will allow a quantitative assessment of the cumulative impacts and comparison of footprints from different bottom-contact fisheries (e.g., longline hook, longline trap and bottom trawl) in overlapping areas (Welsford et al. 2014a). For
example, our mean estimate of the footprint for a 60-trap longline Sablefish set (3 200 m$^2$) is 6% of the mean footprint estimates for bottom longline hook sets (55 000 m$^2$) in the Heard Island and McDonald Islands, based on a footprint width of 6.2 m and mean set length of 8.9 km (Ewing and Kilpatrick 2014; Welsford et al. 2014a). Estimates of footprint widths do not exist for the different BC longline hook fisheries, and set lengths are shorter than those in Welsford 2014a, with median lengths of 3.0 km, 2.6 km, 2.4 km and 1.8 km for sets during 2006-2011 in the Sablefish trap, and Halibut, Schedule II and ZN longline hook fisheries, respectively (data from DFO groundfish database archived at Pacific Biological Station, Nanaimo, BC). Bottom trawl footprint estimates vary based on the width of the trawl net and the length of the tow, and are much larger than longline hook and trap footprints. The mean trawl footprints per fishing event estimated by Welsford et al. (2014a) ranged from 295 000 m$^2$ - 1 134 000 m$^2$ for 4 different vessels, based on footprint widths ranging from 100 - 160 m and mean tow lengths ranging from 2.9 km - 7.6 km. Other metrics can also be used to compare the bottom impacts of different fishing gear, such as the footprint per hour of fishing (Eigaard et al. 2015) or catch per m$^2$ of bottom contact.

Longline trap gear used in the BC Sablefish fishery appears to have properties that result in smaller footprints in comparison with other longline hook and trap gears. For example, as we confirmed by video observations, extruded polypropylene groundline on Sablefish longline trap gear is buoyant (see also High 1998) even at extreme depths and rarely contacts the seafloor, except potentially in instances where the groundline is suspended over high relief. Lack of bottom contact means that lateral movement of the groundline during retrieval is not likely to cause damaging shearing effects along the bottom as observed for groundlines used in longline hook fisheries (Ewing and Kilpatrick 2014). In addition, conical traps with a circular base create narrower furrow widths during dragging compared to a square trap base of the same total area. The trap bridle connection at the top of a Sablefish trap causes traps to be pulled sideways on retrieval with only a portion of the bottom hoop in contact with substrate, leading to a furrow width that is much less than the trap bottom diameter. In contrast, observed drag furrows created by box-shaped King crab pots on longlines in Alaska ranged from 2 m to 9 m (Stone 2006) for 2.4 m x 2.4 m pots.
Next Steps - Understanding risks to seafloor habitats

The first two steps in evaluating specific fishery risks to deep-sea bottom habitats are (1) mapping the locations of sensitive benthic areas and (2) calculating the seafloor area that is contacted by fishing gear. In this study I've described the methods and on-going data-collection that provides this information by generating high-resolution species distribution models and for estimating the historical fishing footprint at SK-B Seamount. Additional information needed for better understanding risks to seafloor habitats involves estimates of fishing mortality and recovery rates, as well as methods to mitigate bottom-contact.

Our bottom footprint estimates can be used to estimate the historical fishing footprint of the Sablefish trap fishery in Zone 2 of the SK-B Seamount MPA and identify areas where high fishing intensity overlap with areas of high probability of coral presence. Using historical set deployment locations it is possible to estimate the contact area for each trap that has been deployed in the SK-B Seamount area and measure the number of times specific patches of the seafloor have been contacted by fishing gear. This provides essential information for assessing the risks posed by Sablefish longline trap fishing to SBAs at SK-B Seamount. Bottom footprint estimates can also be used as part of a management strategy evaluation that predicts the total bottom-contact area within SBAs under different levels of fishing effort. However, the risks to habitat are not only influenced by the amount of gear that is deployed per year and the frequency that specific areas with coral habitats are contacted, but also by the total damage cause from each gear contact-event and the recovery rates from damage during the time between contact-events (Constable 2009).

The next step in understanding fishing bottom impacts is to estimate the mortality rate or damage to coral or sponge populations that occurs when fishing gear is deployed in a specific area, as well as recovery rates from fishing damage. For example, what is the probability that a trap landing in a 100 m² area will cause damage to individual coral colonies or sponges within the bottom contact-area? Ewing et al. (2014) estimated the probability that individuals or colonies within the bottom contact-area of different fishing gears would experience no damage, sub-lethal damage or lethal damage, based on a
variety of data sources such as life history, morphology and in-situ observations. Both High (1998) and Eno et al. (2001) observed cases where flexible corals bent during contact with traps and longlines with no visible damage. Non-lethal damage such as lesions to gorgonian coenenchyme can allow for full recovery, however in some cases it may also increase the probability of lethal damage from future fishing events (Bavestrello et al. 1997; Ewing et al. 2014). Different species or groups of species will also have different recovery rates from fishing damage. Rooper et al. (2011) estimated intrinsic growth rates for corals and sponges in the Aleutian Islands were slow and that recovery from a large mortality of biomass could take several decades. More detailed studies on the life history of specific coral and sponge species that occur in SK-B could reduce parameter uncertainty and improve our ability to assess fishing risks to these habitats.

There is also potential to mitigate risk by behaviour alteration that reduces damage from bottom longline fishing gear. The bottom footprint estimator developed in this study provides a method to estimate and compare the bottom-contact area of different fishing events and evaluate strategies that minimize fishing footprints. For example, do certain fishing characteristics (e.g., hauling speed, haul direction, catch weight, crew experience) or environmental conditions (e.g., depth, slope, rugosity, current, wind) have an effect on the size of the trap footprint? The ability to estimate fishing footprints can also provide a means to test the effectiveness of different gear modifications (e.g., trap numbers, trap size, trap shape, bridle connections, groundline material) for reducing bottom impacts. In this study I looked only at traps deployed in the middle of the set, and assume the same footprint for each trap when estimating footprints for the full set; however, it may be that traps at either end of the string may drag more or less than traps located in the middle.

Future analysis could deploy cameras, accelerometers and depth sensors on multiple traps in different areas along the set to improve footprint estimates. With more analysis and data collection it is possible to develop a model that classifies gear movement using only the accelerometer data as a predictor. Accelerometers are small and a relatively inexpensive piece of equipment (e.g., 100 - 250 USD); it would be feasible to place multiple accelerometers on a larger proportion of commercial fishing
sets. I found that the accelerometer data works well for classifying the start of the drag window (i.e., the transition from a stationary trap to a dragging trap) but the changes in acceleration for different types of movement are more difficult to detect (i.e., the transition from a dragging trap to a suspended trap).

**Conclusion**

The deployment of cameras and motion-sensing equipment on commercial fishing gear, such as Sablefish traps, can provide regular observations of the seabed and bottom footprints, providing essential information for forecasting fishing impacts on bottom habitats. Estimates of the effective bottom contact area of fishing sets and maps of sensitive benthic habitats in fishing areas can provide valuable information needed to investigate strategies for reducing risks to sensitive bottom habitats, while still allowing fisheries access to valuable fishing grounds. There is massive potential to expand this approach to other bottom-contact fisheries to collect bottom observations on large spatial scales, and by which fisheries will participate in mapping sensitive benthic areas and informing ecosystem-based management.
## Tables

### Table 1. Predictor variables used for species distribution modelling at SGaan Kinglas - Bowie Seamount

<table>
<thead>
<tr>
<th>Predictor Variable</th>
<th>Description</th>
<th>Source/Method</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Bathymetry and derivatives:</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Depth (m)</td>
<td>10 m resolution seafloor bathymetry collected using multibeam sonar.</td>
<td>Halcro 2000</td>
</tr>
<tr>
<td>Bathymetric Positional Index (BPI)</td>
<td>Second order derivative of bathymetry that indicates depressions, flats, ridges, and mounds.</td>
<td>Wright et al. 2012</td>
</tr>
<tr>
<td>Rugosity</td>
<td>Ratio of surface over planar area (e.g. arc-chord ratio rugosity index).</td>
<td>Du Preez 2015</td>
</tr>
<tr>
<td>Slope (%)</td>
<td>Absolute value of vector sum of east-west and north-south gradient computed using 4 neighbouring cell method.</td>
<td>Fleming and Hoffer 1979; Zevenbergen and Thorne 1987</td>
</tr>
<tr>
<td>Aspect</td>
<td>Mathematical direction of the slope</td>
<td></td>
</tr>
<tr>
<td><strong>Other Variables:</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Maximum tidal speed (cm/s)</td>
<td>Maximum predicted tidal speeds from OTIS model outputs over 368 days</td>
<td>Egbert and Erofeeva 2002</td>
</tr>
<tr>
<td>Historical fishing locations (traps per 100 m²)</td>
<td>Cumulative number of fishing traps deployed in 100 m x 100 m grid cells between 1991 and 2014</td>
<td>Derived from DFO Pacific Region groundfish catch database</td>
</tr>
</tbody>
</table>
Table 2. Presence(P)-absence(A) frequencies by sampling year, and total frequencies and percentages over all years from 92 video sample sites during May 2013-2015 Sablefish fishing trips at SK-B Seamount.

<table>
<thead>
<tr>
<th>Observations</th>
<th>2013</th>
<th>2014</th>
<th>2015</th>
<th>2013-2015</th>
<th>% P</th>
<th>%A</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gorgonian corals (Order Alcyonacea)</td>
<td>3-9</td>
<td>9-45</td>
<td>6-20</td>
<td>18-74</td>
<td>20</td>
<td>80</td>
</tr>
<tr>
<td>Sponges (Phylum Porifera)</td>
<td>4-8</td>
<td>3-51</td>
<td>0-26</td>
<td>7-85</td>
<td>8</td>
<td>92</td>
</tr>
<tr>
<td>Sea whips (Order Pennatulacea)</td>
<td>1-11</td>
<td>2-52</td>
<td>2-24</td>
<td>5-87</td>
<td>5</td>
<td>95</td>
</tr>
<tr>
<td>Hydrocorals (Family Stylosteridae)</td>
<td>1-11</td>
<td>2-52</td>
<td>0-26</td>
<td>3-89</td>
<td>3</td>
<td>97</td>
</tr>
<tr>
<td>Black corals (Order Antipatharia)</td>
<td>1-11</td>
<td>0-54</td>
<td>0-26</td>
<td>1-91</td>
<td>1</td>
<td>99</td>
</tr>
<tr>
<td>Corals or sponge</td>
<td>6-6</td>
<td>12-42</td>
<td>8-18</td>
<td>26-66</td>
<td>28</td>
<td>72</td>
</tr>
</tbody>
</table>

Table 3. Summary of gorgonian corals observed from drop camera deployments at SK-B Seamount during May fishing trips from 2013-2015.

<table>
<thead>
<tr>
<th>Taxonomic Group</th>
<th>Lowest Taxa Identified</th>
<th>Distinct Colonies</th>
<th>Locations Observed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alcyonacea (Order)</td>
<td>Unidentified Alcyonacea</td>
<td>33</td>
<td>13</td>
</tr>
<tr>
<td>Alcyoniidae (Family)</td>
<td>Heteropolypus ritteri</td>
<td>7</td>
<td>5</td>
</tr>
<tr>
<td>Isididae (Family)</td>
<td>Unidentified Isididae</td>
<td>9</td>
<td>2</td>
</tr>
<tr>
<td>Paragorgiidae (Family)</td>
<td>Paragorgia sp.</td>
<td>4</td>
<td>2</td>
</tr>
<tr>
<td>Plexauridae (Family)</td>
<td>Swiftia simplex</td>
<td>8</td>
<td>6</td>
</tr>
<tr>
<td>Primnoidae (Family)</td>
<td>Parastenella sp.</td>
<td>42</td>
<td>3</td>
</tr>
<tr>
<td>Primnoidae (Family)</td>
<td>Unidentified Primnoidae</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td><strong>106</strong></td>
<td><strong>18</strong></td>
</tr>
</tbody>
</table>
Table 4. Model selection criteria and performance diagnostics for top candidate models and model-averaging.

<table>
<thead>
<tr>
<th>Diagnostic</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model Average</th>
</tr>
</thead>
<tbody>
<tr>
<td># predictors</td>
<td>5</td>
<td>4</td>
<td>4</td>
<td>3</td>
<td>6</td>
</tr>
<tr>
<td>ΔAICc</td>
<td>0</td>
<td>2.6</td>
<td>3.6</td>
<td>5.1</td>
<td></td>
</tr>
<tr>
<td>wi</td>
<td>0.66</td>
<td>0.18</td>
<td>0.11</td>
<td>0.05</td>
<td></td>
</tr>
<tr>
<td>AUC (SD)</td>
<td>0.89 (0.04)</td>
<td>0.89 (0.04)</td>
<td>0.87 (0.05)</td>
<td>0.84 (0.05)</td>
<td>0.90 (0.04)</td>
</tr>
<tr>
<td>max kappa (SD)</td>
<td>0.58 (0.11)</td>
<td>0.61 (0.11)</td>
<td>0.59 (0.10)</td>
<td>0.55 (0.11)</td>
<td>0.56 (0.10)</td>
</tr>
<tr>
<td>max kappa threshold</td>
<td>0.54</td>
<td>0.36</td>
<td>0.22</td>
<td>0.34</td>
<td>0.22</td>
</tr>
<tr>
<td>$D_{adj}^2$</td>
<td>0.34</td>
<td>0.30</td>
<td>0.28</td>
<td>0.25</td>
<td>0.34</td>
</tr>
</tbody>
</table>

Table 5. Scaled predictor variable parameter estimates for top candidate models and model-averaging. Variables not shown were not selected in top candidate models.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rugosity</td>
<td>-2.4 (0.7)</td>
<td>-2.1 (0.6)</td>
<td>-1.8 (0.6)</td>
<td>-1.5 (0.5)</td>
<td>-2.2 (0.7)</td>
</tr>
<tr>
<td>Slope</td>
<td>2.7 (0.7)</td>
<td>2.3 (0.6)</td>
<td>1.9 (0.6)</td>
<td>1.7 (0.5)</td>
<td>2.5 (0.8)</td>
</tr>
<tr>
<td>Aspect</td>
<td>-1.0 (0.4)</td>
<td>-0.8 (0.4)</td>
<td>-0.6 (0.3)</td>
<td></td>
<td>-0.9 (0.5)</td>
</tr>
<tr>
<td>Depth</td>
<td>-1.7 (0.6)</td>
<td>-0.9 (0.3)</td>
<td></td>
<td></td>
<td>-1.3 (0.8)</td>
</tr>
<tr>
<td>Aspect x Depth</td>
<td>0.8 (0.4)</td>
<td></td>
<td></td>
<td></td>
<td>0.5 (0.5)</td>
</tr>
<tr>
<td>Max. Tidal Speed</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.1 (0.3)</td>
</tr>
</tbody>
</table>
Table 6. Summary statistics for trap movement and bottom contact area estimates from longline trap fishing sets at SK-B seamount in 2015. N=5 for path width estimates and 20 for all other statistics.

<table>
<thead>
<tr>
<th>Metric</th>
<th>Mean</th>
<th>95% CI</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drag window (min)</td>
<td>8.72</td>
<td>6.65 - 10.79</td>
<td>1.42 - 15.52</td>
</tr>
<tr>
<td>Drag time (min)</td>
<td>6.97</td>
<td>5.23 - 8.71</td>
<td>1.08 - 14.00</td>
</tr>
<tr>
<td>Haul speed (m·s⁻¹)</td>
<td>0.75</td>
<td>0.72 - 0.78</td>
<td>0.64 - 0.89</td>
</tr>
<tr>
<td>Drag length (m)</td>
<td>310</td>
<td>238 - 383</td>
<td>44 - 610</td>
</tr>
<tr>
<td>Drag path width (m)</td>
<td>0.17</td>
<td>0.15 - 0.19</td>
<td>0.15 - 0.20</td>
</tr>
<tr>
<td>Single trap footprint (m²)</td>
<td>53</td>
<td>40 - 65</td>
<td>7.4 - 104</td>
</tr>
<tr>
<td>Footprint for 60-trap set (m²)</td>
<td>3200</td>
<td>2400 - 3900</td>
<td>400 - 6200</td>
</tr>
</tbody>
</table>
Figure 1. Average annual effort density of bottom longline hook and trap sets (2006-2011) for BC coastal groundfish fisheries and the SGaan Kinghlas-Bowie (SK-B) Seamount Marine Protected Area. The Zone 1 area (top 457 m contour) in the SK-B Seamount MPA is closed to all fishing.
Figure 2  Close-up configuration of the camera housing, external accelerometer, and Sea-Bird SBE 39 temperature and depth sensor in a commercial Sablefish trap (top). The trap's front mesh panel has been cut out to provide unobstructed field of view (bottom photo).
Figure 3: Example of observations used to classify trap movement during the last hour of bottom longline trap fishing for a case where the trap is estimated to have dragged during the entire drag window (e.g. drag window = drag time). Raw accelerometer and depth data are shown in (a) and (b) and algorithm output for classifying trap movement in (c).
Example of observations used to classify trap movement during the last hour of bottom longline trap fishing for a case where the trap is estimated to have been stationary for multiple intervals during drag window (e.g. drag window ≠ drag time). Raw accelerometer and depth data are shown in (a) and (b) and algorithm output for classifying trap movement in (c).
Figure 5 Drag paths (top) created by dragging Sablefish commercial traps along a sandy beach, and example furrow width measurement (bottom).
Figure 6  Presence-absence (pres-abs) video sample sites in 2 km x 2 km grid cells for (a) Alcyonacea, (b) Porifera, (c) Pennatulacea and (d) Other (Antipatharia or Stylasteridae) from trap camera deployments during May 2013-2015 fishing trips at SK-B. The coloured cells are grid cells with presence observations during at least 1 camera deployment in that cell, while white cells indicate that the specified taxa was absent (i.e., 0 presence observations) for all video samples within that cell. Numbers indicate video sampling sites in the grid cell with presence and absence observations (presence-absence). For example, a value of 1-2 in (a) indicates 1 video sample site where Alcyonacea was present and two video sample sites where Alcyonacea was absent.
Figure 7  Diagnostic plots for assessing optimal probability thresholds for predicting presence-absence locations of gorgonian corals. (a) Histogram showing the distribution of presence-absence observations for corresponding model-averaged predicted probabilities and classification thresholds where sensitivity = specificity, kappa is maximized, the percent correctly classified (PCC) observations are maximized, and predicted prevalence = observed prevalence (PredPrev = ObsPrev). (b) Performance of different criteria under varying probability thresholds for presence classification. (c) ROC plot for model-averaged predictions (AUC = 0.90) and what would be expected from chance (AUC = 0.50).
Figure 8  Model-averaged a) predictions for probability of gorgonian coral presence at SK-B Seamount for depths between 400-1400 m, and b) predicted presence locations under different probability thresholds where sensitivity = specificity (0.22), kappa is maximized (0.22), predicted prevalence = observed prevalence (0.38), and the percent of correctly classified (PCC) observations are maximized (0.50). Contour lines are shown for 400 m, 800 m and 1200 m depths.
Figure 9  Distributions (n = 20 sets) of (a) estimated drag times of camera traps, (b) mean haul speed between 200 m and 600 m depths for camera traps, (c) estimated drag lengths for camera traps, and (d) estimated bottom contact areas for a 60-trap bottom longline set using an average drag width of 17.0 cm (SE 0.8).
Figure 10  Classified drag window (i.e., period where there is potential for dragging), and estimated drag times for 20 sets. Sets rank number is ordered by increasing drag time estimates. Set Numbers 19 and 15 correspond with sets shown in Figs. 3 and 4, respectively.
References


DFO. 2010. Pacific region cold-water coral and sponge conservation strategy 2010-2015. Oceans Program, Fisheries and Oceans Canada, Vancouver, BC.


Fleming, M. D. and Hoffer, R. M. 1979. Machine processing of landsat MSS data and DMA topographic data for forest cover type mapping. LARS Technical Report 062879, Department of Forestry and Natural Resources, Purdue University, West Lafayette, IN.


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Appendix A.

Bootstrap model validation

Methods

We completed 1000 bootstrap samples to split our data into training and test data sets to evaluate model performance. We randomly resampled the full set of observations with replacement, to generate a training data set that was the same size as the full data set (n=92). The training data was used to refit logistic regressions for the 4 candidate models. Data points that were not included in the training data set were used in a separate test data set to evaluate model performance using AUC, maximum kappa and the ‘.632+ bootstrap’ corrected mean squared prediction error (Efron and Tibshirani 1997). The results from the 1000 bootstraps were used to calculate 95% confidence intervals.

Results

Bootstrap results produced similar scores for model diagnostics to those for models fit with the full set of data (Table 4). As expected, there is a decline in AUC when comparing the test data and training data scores, however mean AUC scores for the test data are still in the range indicating acceptable or excellent model performance according to the Hosmer and Lemeshow (2005) scale. There is overlap in the 95% confidence intervals between all models for all metrics, and thus the bootstrap results do not provide evidence for selecting one candidate model over another.

Table A1  Performance metrics for candidate models from 1000 bootstrap samples with replacement from 92 presence-absence observations. 95% bootstrap confidence intervals are shown in ().

<table>
<thead>
<tr>
<th>Model</th>
<th>Training data AUC</th>
<th>Test data AUC</th>
<th>Test data maximum kappa</th>
<th>Test data .632+ bootstrap MSPE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.91 (0.82 - 0.98)</td>
<td>0.80 (0.60 - 0.97)</td>
<td>0.54 (0.25 - 0.84)</td>
<td>0.11 (0.08 - 0.16)</td>
</tr>
<tr>
<td>2</td>
<td>0.90 (0.80 - 0.98)</td>
<td>0.81 (0.60 - 0.96)</td>
<td>0.56 (0.25 - 0.84)</td>
<td>0.12 (0.08 - 0.17)</td>
</tr>
<tr>
<td>3</td>
<td>0.88 (0.78 - 0.96)</td>
<td>0.81 (0.62 - 0.96)</td>
<td>0.54 (0.26 - 0.84)</td>
<td>0.12 (0.09 - 0.17)</td>
</tr>
<tr>
<td>4</td>
<td>0.86 (0.75 - 0.95)</td>
<td>0.80 (0.62 - 0.95)</td>
<td>0.53 (0.24 - 0.79)</td>
<td>0.13 (0.09 - 0.17)</td>
</tr>
</tbody>
</table>

References