North Pacific Fisheries Commission

NPFC-2021-BFME02-WP05

Using Predictive Habitat Models and Visual Surveys to Identify Vulnerable Marine Ecosystems on Seamounts in the North Pacific Fisheries Commission Convention Area

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December 2021

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ABSTRACT

The United Nations General Assembly called upon States to manage fisheries sustainably and protect vulnerable marine ecosystems (VMEs) from destructive fishing practices when they adopted Resolution 61/105 in 2006. The Convention on the Conservation and Management of High Seas Fisheries Resources in the North Pacific Ocean requires North Pacific Fisheries Commission (NPFC) members to develop a process to identify VMEs using the best scientific information available. NPFC identified four taxonomic groups of corals as indicators of potential VMEs but has not yet developed objective and quantitative definitions of VMEs based on catches, visual surveys, predictive models, or other types of information. Moreover, to date no VMEs have been identified in the northeast (NE) part of the NPFC Convention Area (CA). In 2021, the NPFC's Small Working Group (SWG) on VMEs proposed the first step in a framework to use the best available data to identify VMEs, including visual data (i.e. video and/or photographic images) and predictive models. Canada has limited visual data and model predictions of the suitable habitat for VME indicator taxa in the NE part of NPFC's CA where it fishes for Sablefish (*Anoplopoma fimbria*). In this working paper, we propose one quantitative method of VME identification that integrates visual data and model predictions in a manner that aligns with the SWG VME's framework, the precautionary approach, the Convention, and the research plan of NPFC's Scientific Committee. We use data from Cobb Seamount to illustrate our proposed methodology. Exploratory application of our approach leads to the identification of 83 1-km^2 areas that are likely to be VMEs at depths ranging from the pinnacle of Cobb at 18 m to 1,573 m, including one VME on the northwest flank of Cobb Seamount. The primary goal for this working paper is to propose and receive feedback on our approach before applying it to identify VMEs and areas that are likely to be VMEs in the NE part of the NPFC's CA. Next steps include (1) revising our approach based on input from NPFC members, stakeholders, and observers,

(2), applying our revised method and identifying VMEs and areas that are likely to be VMEs in the NE part of the NPFC CA, and (3) engaging in periodic review of the analyses, especially when new data become available.

Table of Contents

INTRODUCTION

Reason for identifying Vulnerable Marine Ecosystems

Bottom-contact fishing gears are known to harm fragile seafloor habitats, including biogenic structures formed by corals and sponges (Ardron et al. 2014). In 2006, the United Nations General Assembly (UNGA) Resolution 61/105 called upon "*States to take action immediately, individually and through fisheries management organizations and arrangements, and consistent with the precautionary and ecosystem approaches, to sustainably manage fish stocks and protect vulnerable marine ecosystems (VMEs), including seamounts, hydrothermal vents and cold water corals, from destructive fishing practices, recognizing the immense importance and value of deep sea ecosystems and the biodiversity they contain*" (UNGA 2006). The Food and Agriculture Organization (FAO) subsequently published guidelines for the management of deep-sea fisheries in international waters. Those guidelines outlined five criteria of areas, habitats, or ecosystems that should be used individually or in combination to identify VMEs: (1) uniqueness or rarity, (2) functional significance of the habitat, (3) fragility, (4) life-history traits of component species that make recovery difficult, and (5) structural complexity (FAO 2009). The FAO also recommended the development of case-specific operational definitions of VMEs for their application (see examples in Kenchington et al. 2014, Morato et al. 2018, Miyamoto & Yonezaki 2019, Rowden et al. 2020).

In its research plan, the North Pacific Fisheries Commission's (NPFC) Scientific Committee recognizes the importance of developing a process for identifying VMEs so that they can be protected from significant adverse impacts (SAIs) caused by bottom fishing practices. Article 10(4) of the Convention on the Conservation and Management of High Seas Fisheries Resources in the North Pacific Ocean (henceforth the Convention) asserts that the NPFC shall "*develop a process to identify vulnerable marine ecosystems, including relevant criteria for doing so, and identify, based on the best scientific information available, areas or features where these ecosystems are known to occur, or are likely to occur...*" The NPFC Scientific Committee's 2020-24 Research Plan aims specifically to "*develop consensus on criteria used to identify VMEs and how this might be applied in the NPFC*." The NPFC's Conservation and Management Measures (CMMs) 2019-06 (NPFC 2019) and 2021-05 (NPFC 2021a) provide science-based standards and criteria for identification of VMEs and state: "*The purpose of the standards and criteria is to provide guidelines for each member of the Commission in identifying VMEs and assessing SAIs of individual bottom fishing activities on VMEs or marine species in the Convention Area* (CA)." Guidance on science-based standards and criteria for identification of VMEs in the CA are given in NPFC's CMMs 2019-06 and 2021-05 (see Annex 2 in NPFC 2019, 2021a). Although seamounts, hydrothermal vents and cold-water corals are referred to as examples of VMEs in paragraph 83 of UNGA Resolution 61/105 (UNGA 2006), there is no definitive list of specific taxa or areas that are to be regarded as VMEs. In the context of VMEs, vulnerability is related to the likelihood that a population, community, or habitat will be substantially altered by fishing activities, and the timing of recovery from fishing-related impacts (NPFC 2019, 2021a). As noted in CMMs 2019-05 (NPFC 2021a) and 2021-06 (NPFC 2019), "*in these ecosystems, ecological processes are usually highly dependent on these structured systems. Further, such ecosystems often have high diversity, which is dependent on the structuring organisms.*"

Balancing the objectives of protecting VMEs while minimizing impacts to commercial bottom fisheries

We recognize that there is a delicate balance between the NPFC's mandate to identify and protect VMEs and areas likely to be VMEs, and the desire of many stakeholders to minimize costs to commercial bottom fisheries. One approach to balancing these two objectives was outlined by Warawa et al. (2020) who applied a spatial optimization approach to identify VME areas for protection from SAIs that was modelled after the South Pacific Regional Fisheries Management Organization's (SPRFMO) application of Zonation software, a publicly available decision support tool used for spatial conservation planning. Warawa et al. (2020) recognized that catch, visual (video and/or photos), and other types of data, including outputs from predictive models, may also be used to identify VMEs. In that context, in the process of identifying VMEs and areas likely to be VMEs we recognize the role of uncertainties in balancing objectives. Therefore, we propose a methodology to identify VMEs and areas likely to be VMEs that addresses uncertainties associated with limited data in the NPFC's CA. We use the best available data for meeting our objectives of identifying VMEs, while minimizing impacts to the NPFC's bottom fisheries and propose a quantitative and repeatable method that can be easily updated when new information becomes available.

Seamounts in the North Pacific Ocean

As defined by the International Hydrographic Organization (IHO 2019), a seamount is "*A distinct, generally equidimensional [i.e., conical-shaped] elevation greater than 1000 m above the surrounding relief as measured from the deepest isobaths that surrounds most of the feature*". As a consequence of their global distribution and the concentration of sensitive benthic ecosystems and fishing pressure that occur at seamounts, several RMFOs have prioritized seamounts in efforts to protect VMEs (Clark et al. 2010). Identifying VMEs at seamounts requires quantifying the ecological functions and services characterized by their biological communities (Clark et al. 2010). Many seamounts can harbour dense assemblages of cold-water corals and sponges (CWCS).

What are VME indicator taxa?

The FAO Guidelines (FAO 2009) provide examples of potential vulnerable species groups, communities, and habitats as well as features that potentially support them (see Annex 2.1 of CMM 2019-05 and 2021-06 (NPFC 2019, 2021a). The NPFC currently recognizes four taxonomic groups of corals (Alcyonacea (excluding Gorgonians), Antipatharia, Gorgonacea (now within the Alcyonacea), and Scleractinia) as VME indicator taxa (NPFC 2019, 2021a). Other regional fisheries management organizations (RFMOs) recognize additional groups of CWCS as indicators of VMEs (FAO 2019), including sea pens (order Pennatulacea) and glass sponges (class Hexactinellida). In this working paper, we focus our analyses on the four groups of corals recognized by the NPFC as VME indicator taxa.

Structural complexity formed by VME indicator taxa

Structural complexity is one of the FAO's five criteria to identify VMEs (FAO 2009). Acting as biogenic habitat, CWCS increases structural complexity on the seafloor which in turn enhances biodiversity and the abundance of other animals in an area (Rowden et al. 2020). The capacity to form structural complexity (i.e., biogenic habitat) is a key biological trait associated with using CWCS as the umbrella taxa (i.e., "*species whose conservation confers a protective umbrella to numerous co-occurring species*", Fleishman et al. 2000) for delineating areas that are VMEs. Additional life history traits of CWCS, such as slow growth, long life spans, and rarity of occurrence, make them vulnerable to physical disturbance caused by bottom fishing activities. Thus, identifying areas of habitat-forming CWCS communities serves to meet the criteria used for identifying sites as VMEs (Chu et al. 2019; see also the five VME criteria identified in FAO 2009).

Approaches applied to identifying VMEs

While criteria are available for identifying VMEs (e.g. FAO 2009), there are few case-specific definitions of VMEs and areas likely to be VMEs. Ardron et al. (2014) drew on a review of existing approaches to develop a 10-step systematic approach for identifying and protecting VMEs. Specifically, these are:

"(1) Comparatively assess potential VME indicator taxa and habitats in a region

(2) determine VME thresholds

(3) consider areas already known for their ecological importance

(4) compile information on the distributions of likely VME taxa and habitats, as well as related environmental data

(5) develop predictive distribution models for VME indicator taxa and habitats

(6) compile known or likely fishing impacts

(7) produce a predicted VME naturalness distribution (areas of low cumulative impacts)

(8) identify areas of higher value to user groups

(9) conduct management strategy evaluations to produce trade-off scenarios, and

(10) review and re-iterate, until spatial management scenarios are developed that fulfil

international obligations and regional conservation and management objectives"

Many approaches to identifying VMEs rely on using qualitative information and expert judgement, which can be inconsistent and lack transparency (Morato et al. 2018). Morato et al. (2018) emphasize that it would be advantageous for analysts to develop robust and repeatable quantitative methods to identify VMEs. At least three quantitative and repeatable approaches have been applied since Ardron et al. (2014). Those approaches draw on catches from scientific surveys, existing data on the distribution of VME indicator taxa, and/or visual data from scientific surveys of benthic organisms.

Based on FAO's criteria for identifying VMEs (FAO 2009), Kenchington et al. (2014) used a kernel density estimation (KDE) approach to analyze research trawl survey data and identify areas of relatively high biomass of four VME indicator taxa (large-sized sponges, sea pens, and small and large gorgonians) in the Northwest Atlantic Fisheries Organization (NAFO) Regulatory Area. Using KDE they identified significant concentrations of VME indicator biomass, which they interpreted as VMEs. They also independently assessed the VMEs they identified with images, benthic sampling, and/or predictive models.

In the NW part of the NPFC CA, Japan recently used seafloor images, fisheries bycatch data, research surveys, and a KDE method to map concentrations of fishing effort and areas of overlap between the distribution of VME indicator taxa and fishing activities (Miyamoto & Yonezaki 2019). They then visually surveyed areas that were potential VMEs and qualitatively assessed those areas relative to the five FAO criteria for identification of VMEs (FAO 2009).

In the NE Atlantic Ocean, Morato et al. (2018) used a spatial and quantitative method to identify VMEs by applying a multi-criteria assessment to a database of VME records compiled by the International Council for the Exploration of the Sea (ICES).

Rowden et al. (2020) noted that many quantitative approaches to identification of VMEs focused on predicting the distribution of VME indicator taxa, however, they also recognized that the presence of one or more VME indicator taxa does not necessarily mean that a VME is present. They proposed a quantitative approach to determine a density threshold of VME indicator taxa above which a VME was present in the SPRFMO area, drawing on FAO's VME criterion of structural complexity (FAO 2009). Specifically, Rowden et al. (2020) analyzed video and still images to identify areas where corals support a high diversity of associated taxa. They found significant relationships between coral density and the richness of associated benthic organisms and suggested that a density threshold could be used in combination with predictive models to map areas where the density of VME indicators was equal to or greater than that threshold and were therefore VMEs at risk of SAIs. Rowden et al. (2020) also emphasized the value of thresholds to make the identification of VMEs less subjective. They hypothesized that the thresholds used to identify VMEs would likely vary among regions. Indeed, the types of thresholds that can be used to identify VMEs depend on available data to map VMEs or areas that are likely to be VMEs.

Data limitations for identification of VMEs in the Northeast Pacific Ocean

Three of the quantitative approaches described above (Kenchington et al. 2014, Morato et al. 2018, Rowden et al. 2020) require data on the abundance or density of CWCS sampled over the general study area to identify VMEs and areas that are likely to be VMEs. There are many records of bycatch of CWCS in research trawls in the NAFO Regulatory Area, which has allowed individual VME indicator taxa to be used for identifying VMEs using a KDE approach in the NW Atlantic Ocean (Kenchington et al. 2014). The ICES database used by Morato et al. (2018) also contained thousands of records of CWCS from many sources that can be used to identify VME indicator taxa distributions and areas that are likely to be VMEs. Similarly, there has been a significant effort in the SPRFMO CA to identify and accumulate VME records from fisheries bycatch and conduct directed research surveys that can be used to determine VME thresholds and the distribution of VME indicator taxa (Rowden et al. 2020).

In the NPFC's CA there is limited CWCS abundance data available. Most of the existing CWCS abundance data in the NPFC CA are from fisheries bycatch and research surveys in the NW region of the North Pacific Ocean (Miyamoto & Yonezaki 2019, Dautova et al. 2020, Calder & Watling 2021).

Due to the limited availability of abundance data in the NE region of the NPFC's CA, we are unable to fully apply one or more of the approaches outlined above. The majority of CWCS data available in the NE Pacific Ocean are research trawl data and visual survey data that almost entirely fall within domestic waters of Canada and the United States of America. The only bottom fishery operating in the NE part of the NPFC CA is Canada's Sablefish fishery at seamounts (primarily on Brown Bear, Cobb, Corn, Eickelberg, and Warwick Seamounts). Canada has extensive data on the location and catches in the Sablefish fishery since 1996. Canada's Sablefish fishery is conducted with long-lined traps or hook and line gear, which typically do not retain VME indicator taxa, thus there are insufficient records of CWCS bycatch available for this region that might support an analysis such as KDE (as in Kenchington et al. 2014). In addition, relatively few seamounts have been visually surveyed in the NE part of the NPFC CA (but see Curtis et al. 2015), and even few visual surveys have been sufficiently annotated to document the distribution, richness, or density of VME indicator taxa or associated benthic species. Although habitat suitability of the NPFC's VME indicator taxa has been predicted (Chu et al. 2019), there are insufficient data to predict the density or abundance of those same VME indicator taxa. Therefore, the scarcity of visual survey data coupled with the inability to predict VME indicator density or abundance in the NE part of the NPFC's CA, limits application of the threshold method described by Rowden et al. (2020).

A quantitative method for identifying VMEs in the NE Pacific Ocean using predictive models and visual surveys

Our proposed approach uses the best scientific information following the decision tree recommended by the NPFC's SWG on VME to identify data for VME identification in the NW and NE parts of the NPFC CA (NPFC 2021b) (Figure 1). We propose a quantitative approach similar to Rowden et al. (2020) by first resolving the non-linear, threshold relationship between species richness (dependent variable) associated with the presence of the four NPFC VME indicator taxa (independent variable) in visual survey data. Due to differences in the type of available data, we quantified the threshold of the independent variable as the frequency of occurrence of VME indicator taxa rather than the density of VME indicator taxa used in Rowden et al. (2020). This threshold quantifies the minimum frequency of occurrence of VME indicator taxa where richness of associated epibenthic species is at a maximum in visual data. We then use predictive habitat models (PHMs) to generate maps of suitable habitat for each VME indicator taxon. We examine areas where the predictions are equal to or greater than our quantitative threshold to identify areas likely to be VMEs. Finally, we identify VMEs as areas where both the predictions and visual survey data are in confirmation. Our general application of PHMs can be used to assess all seamounts in the NPFC's CA to preliminarily identify areas that are likely to be VMEs. Targeted visual surveys can then be used to groundtruth high priority areas identified in the PHMs to confirm VME areas.

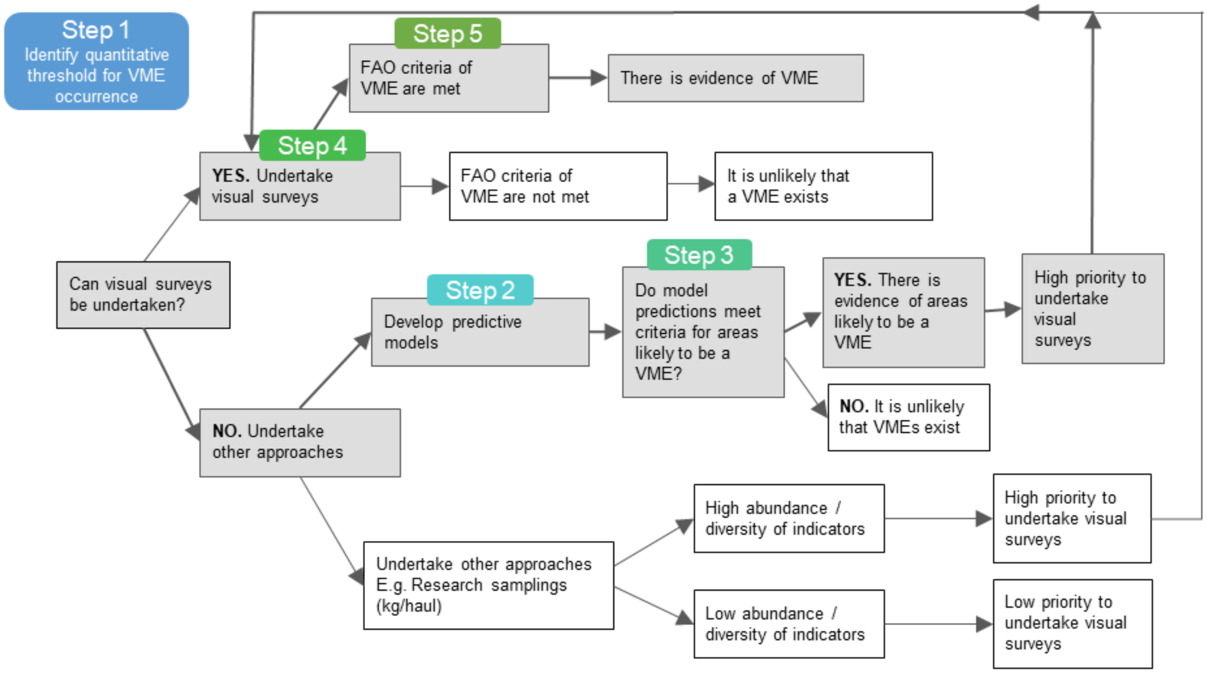

Figure 1. Decision tree used to identify data that can be used to identify VMEs in the NW and NE parts of the NPFC Convention Area (NPFC 2021b) and how it relates to our proposed approach in this working paper. The primary steps in our approach are highlighted (Steps 1-5) in this figure and are described in the methods section of this working paper.

A case study of our proposed approach on Cobb Seamount

We use data collected during a scientific visual survey of Cobb Seamount in 2012 to illustrate our quantitative method for identifying VMEs and areas likely to be VMEs on seamounts in the NE Pacific Ocean. At present, Cobb Seamount is the only seamount in the NPFC CA that has been visually surveyed by Canada. Fisheries and Oceans Canada (DFO) and the United States National Oceanographic and Atmospheric Agency (NOAA) led a joint survey of the seamount in 2012 (Curtis et al. 2015). The survey characterized the benthic community structure and quantified the distribution of observed VME indicator taxa. 17 of the coral taxa observed were on the NPFC's list of VME indicator taxa (Curtis et al. 2015).

METHODS

VME indicator taxa

We use the four groups of corals recognized by NPFC as VME indicator taxa for identifying areas that are VMEs and likely to be VMEs in the NE part of the NPFC CA; the orders Antipatharia (black corals), Scleractinia (stony corals), and Alcyonacea (soft corals and gorgonian corals). The NPFC recognizes gorgonian and soft corals as separate groups and they can be split into taxonomically valid groups using a family level of identification. For the North Pacific Ocean, Miyamoto et al. (2017) list gorgonian coral families as Anthothelidae, Paragorgiidae, Coralliidae, Keroeididae, Acanthogorgiidae, Plexauridae, Gorgoniidae, Chrysogorgiidae, Primnoidae, and Isididae and non-gorgonian soft-coral families as Clavulariidae, Alcyoniidae, Nephtheidae, Nidaliidae, and Paralcyoniidae.

Study area

We apply our proposed method as a case study to identify VMEs and areas likely to be VMEs on Cobb Seamount, which is in the NE part of the NPFC CA, close to Canada's domestic waters at 46° 44′ 24″ N, 130° 48′ 0″ W (Figure 2). Cobb Seamount is a 27 million year old symmetrical and terraced guyot with a centrally located pinnacle (Budinger 1967) that rises from a base of 2,743 m to within 24 m of the surface (Parker & Tunnicliffe 1994), with an area of approximately 824 km^2 (Budinger 1967). The seamount flanks average 12° in slope and are marked by four terraces (Budinger 1967). Cobb Seamount was discovered in 1950 and has been the site of biological, geological, and oceanographic research, as well as several commercial fisheries, including sablefish (*A. fimbria*). The history of Cobb Seamount and details of the methodology and data collected during a scientific visual survey led jointly by DFO and NOAA in 2012 are described in Curtis et al. (2015) and Du Preez et al. (2015).

The primary aim of the scientific survey in 2012 was to characterize the benthic community structure. In summary, DFO used a customized Deep Ocean Engineering Phantom remotely operated vehicle (ROV) capable of diving to approximately 220 m, and NOAA deployed a SeaBED-class autonomous underwater vehicle (AUV) capable of diving to 1,400 m. Curtis et al. (2015) describe the survey, including specifics of the submersible setups, cameras, deployments, and sampling design, and Du Preez et al. (2015) provide a photo-documented checklist of species observed at Cobb Seamount in 2012.

Overall, 144 benthic taxa were observed from 12 DFO ROV and 4 NOAA AUV transects carried out from 34 m to 1,154 m in depth. The taxa with the greatest densities on the Cobb Seamount plateau (<225 m depth) included the stony coral *Desmophyllum dianthus*, the brachiopod *Laqueus californianus*, colonies of *Stylaster* spp. hydrocorals, and annelids. At greater depths (>435 m) on the AUV transects, a bamboo coral *Lepidisis* sp., the black corals *Bathypathes* sp. and *Lillipathes* cf *lillei*, and an unidentified black coral species (Antipatharia sp. 1, as described in Du Preez et al. 2015), were among the more abundant taxa. Sand, boulders and creviced rock habitats were more prevalent on Cobb Seamount's plateau, with creviced bedrock being more common at depths >435 m.

Video from the DFO ROV's cameras was recorded continuously throughout 12 dives, from the time of deployment to retrieval. Cameras on the AUV were configured to produce orthogonal images of the seafloor. The AUV was programmed to maintain a height of approximately 3 m above the seafloor and was programmed to take a photograph every 10 seconds during survey transects. Overall, 8,321 photos were collected along the four AUV transects, most of which were of sufficient quality to quantitatively record species and habitat data. All photos from the AUV's port side camera were annotated to document the occurrences of discernable taxa, with the exception of brittle stars (Curtis et al. 2015).

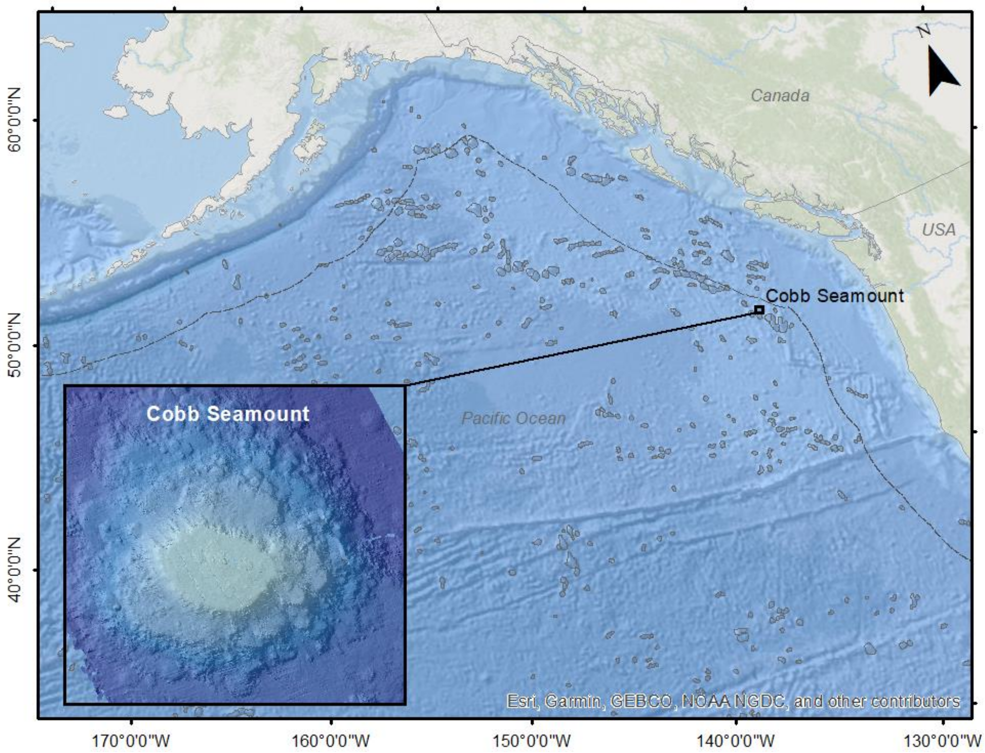

Figure 2. Study area showing the NE part of the NPFC Convention Area (dashed line boundary) and location of Cobb Seamount (inset map).

General approach to identifying VMEs

The main steps in our quantitative approach (Figure 3) are: 1) identify a quantitative threshold that indicates where VMEs are likely to occur; 2) develop predictive models and generate probability maps of suitable habitat for VME indicator taxa; 3) apply the threshold to the probability maps to identify areas likely to be VMEs, 4) prioritize those areas for gathering visual data; and 5) combine the predictive models, visual data, and other available scientific information to determine if the VME criteria (FAO 2009) are met.

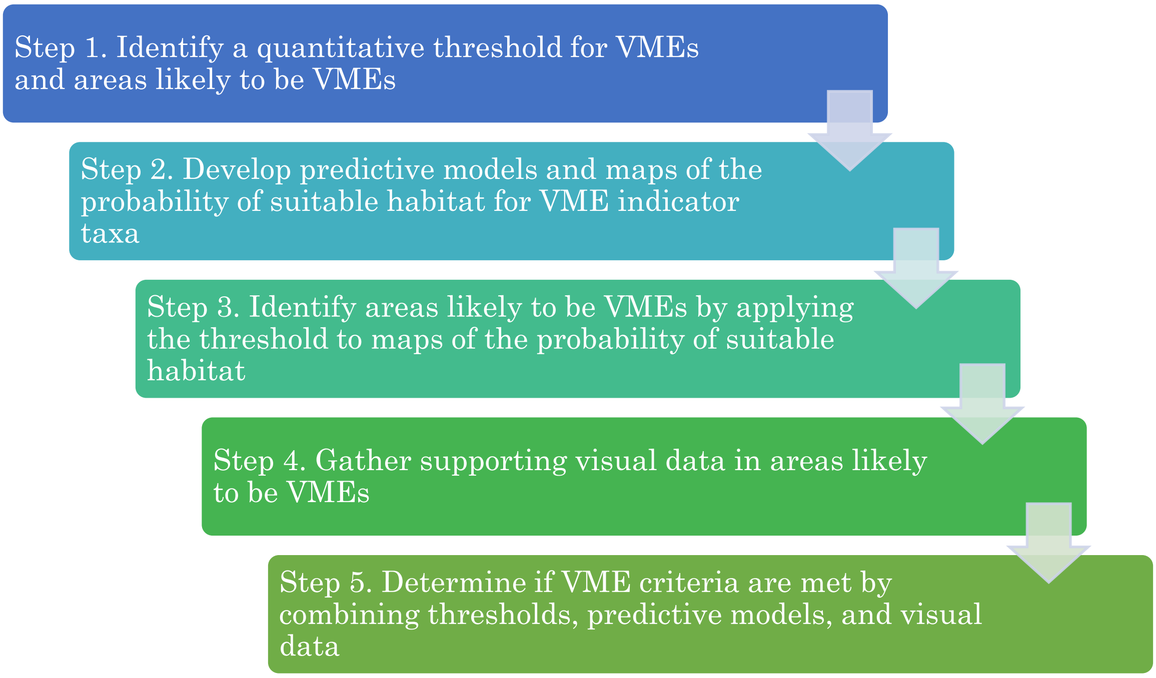

Figure 3. General steps in our proposed method to identifying VMEs and areas likely to be VMEs.

Step 1. Identify a quantitative threshold for VME occurrence

The objective of our threshold analysis is to identify the proportion of transect where VME indicator taxa occur (independent or explanatory variable on the x-axis) that corresponds to the greatest richness of associated benthic taxa (dependent or response variable on the y-axis). We assume that areas with greater species richness are also areas with a greater diversity of micro-habitat types and thus structural complexity provided by VME indicator taxa presence, one of FAO's five criteria for identifying VMEs (FAO 2009). We used the proportion of transect where NPFC VME indicator taxa occur as our threshold variable so it can be applied to the output of our predictive habitat models (PHMs) that predict the probability of suitable habitat of the four VME indicator taxa, as well as observations of those VME indicator taxa in our visual data (Curtis et al. 2015). Hereafter, we refer to the threshold calculated from the visual survey data as the "visual occurrence threshold", which is defined at the proportion of transect where one or more VME indicator taxa occur.

Data requirements for visual occurrence threshold

The visual occurrence threshold is based on the relationship between the proportion of transect where VME indicator taxa occur (independent variable) and the species richness of associated benthic taxa (dependent variable). This generally requires data to be collected at a site where

NPFC VME indicator taxa are present in varying abundances, and where the presence of associated taxa has been annotated. When different sources of visual data are available the collection methods should be compared to ensure there are no detection biases and that biodiversity data can be pooled.

Visual occurrence threshold analysis

For our case study, we used the fully annotated dataset generated from the analysis of AUV photos collected at Cobb Seamount in 2012 (Curtis et al. 2015). Although ROV photos and video records were also collected during that survey, the ROV survey was designed to capture close-up imagery at the seafloor (a 0.16 m^2 area compared to the 1.8 m^2 – 21.2 m^2 area of the AUV images) and did not reliably capture VME indicator taxa for annotation (Cobb et al. 2015). Due to detection biases among different survey methods, biodiversity annotations generated from the resulting imagery should not be pooled for analyses (Chu & Leys 2010). Thus, we did not use visual data from the ROV in our analyses.

We subdivided the four AUV transects (average length = 1,806 m) into 50 m sub-transect segments for the threshold analysis and followed general methods outlined in Rowden et al. (2020). Sub-transect segments were included in our analyses if they contained 3 or more images.

For each sub-transect segment (n=136), we calculated the proportion of that segment where any VME indicator taxon was observed by dividing the number of images with a VME indicator taxon present by the total number of images in that segment. The proportion of transect where VME indicator taxa occur (the visual occurrence threshold) was calculated as:

$$\text{proportion of transect where VME indicator taxa occur} = \frac{\text{\# of images with VME indicator taxa per sub-transect}}{\text{\# of images per sub-transect}}$$

We used a piecewise regression to identify the breakpoint, or threshold, in the proportion of transect where one or more VME indicator taxa occurred (independent variable) as a predictor of the richness of associated taxa (dependent variable). A piecewise regression, also known as segmented or broken-stick regression, fits two linear regressions through a dataset and identifies a breakpoint at the intersection between the two regressions. We use this breakpoint as the threshold at which the richness of associated taxa reaches a plateau beyond which increasing the proportion of transects where at least one VME indicator taxa occurred no longer corresponds to higher biodiversity (see discussion in Rowden et al. 2020). To account for uncertainty due to our limited data we used the upper 99 % CI as our final threshold to identify

VMEs and areas likely to be VMEs. To determine if our data follow a threshold response and not a simple linear response, we used an ANOVA to compare the piecewise regression and linear regression.

Step 2. Develop predictive models for VME indicator taxa

Predictive habitat models (PHMs), also referred to as species distribution models, can be used to predict areas of high habitat suitability for marine species of interest. In general, PHMs are statistical methods that relate known presences of a species to a set of environmental variables. Models can then be used to extrapolate where species are likely to occur within the extent of the environmental variables, including in areas where biological survey data are lacking (Franklin 2010). Model outputs can also be used to generate hypotheses about the factors that influence species distributions, such as key environmental drivers, which can help identify priority areas for future data collection. Prediction maps generated from a standard PHM are usually presented as a logistic index with values ranging from 0 to 1. Depending on the model and data used, the logistic index is commonly interpreted as a probability of presence or as an index of habitat suitability, with predictions corresponding to low (0) and high (1) probability of presence or habitat suitability. We interpret the output of our four models as the probability that there is suitable habitat for the corresponding VME indicator taxon and we assume that the taxa can exist where there is suitable habitat.

Data requirements for PHMs

PHM development requires a dataset of georeferenced species presences as well as gridded environmental data layers representing variables that influence the distribution of the modeled species. In addition, data on species absences – areas where a species has been observed to not exist – can also be valuable. The environmental data should cover the entire extent of the area of interest, and the species presence/absence data should ideally be broadly distributed across the spatial and environmental gradients in the same area.

For our study, we use the Maximum Entropy model (MaxEnt) to develop PHMs for each of our four VME indicator taxa. MaxEnt is a machine learning, statistical method that originated in the fields of statistical mechanics and information theory (Phillips et al. 2006). MaxEnt has also been the most commonly applied PHM for examining distributions of CWCS when only presence data are available which is most often the case for deep-sea taxa (Winship et al. 2020). By default, MaxEnt uses ‘pseudo-absences’ sampled from the surrounding background area to generalize the habitat conditions of an area; presence is unknown at the location of these background sampled locations. Although MaxEnt is known as a ‘presence-only’ model by default, absence data, instead of 'pseudo-absences', can be used with the MaxEnt algorithm. For our PHMs both presence and absence observations were sampled mostly within the adjacent exclusive economic zones of Canada and the United States of America. The availability of presence and absence observations of VME indicator taxa allows for the exploration of alternative models (e.g. GAM, Boosted Regression Trees, Random Forest models) in future iterations of PHM development.

Species records

Presence records – We compiled a large dataset of georeferenced species records of NPFC's VME indicator taxa in the NE Pacific Ocean (Figure 4a). Records were queried as of September 2021 and come from scientific surveys data and museum records deposited in (1) the NOAA deep-sea coral data portal (https://deepseacoraldata.noaa.gov/), (2) standardized bottom trawl catch data from research surveys in the Gulf of Alaska, Aleutian Islands and eastern Bering Sea, (3) standardized bottom trawl catch data from DFO research surveys in British Columbia, Canada, and (4) standardized bottom trawl catch data from research surveys on the U.S. West Coast of Washington Oregon and California (Stauffer 2004, Nottingham et al. 2018).

Records were identified to various levels of taxonomy and required up-to-date taxonomy verification with the World Register of Marine Species (WoRMS, Horton et al. 2021). After updated taxonomy was appended to the records, records with at least an order (black corals, stony corals) or family (gorgonian corals, non-gorgonian soft corals) level of identification were pooled for use as the presence data for each of their respective PHMs. Final sets of presence records used for PHM model development were also spatially restricted to those occurring within the four marine ecoregions of the world (MEOW) that characterize the oceanographic conditions from the Gulf of Alaska to the West Coast of North America (Spalding et al. 2007). No commercial bycatch records were included in the data used for PHMs.

Absence records – Multiple depth-stratified research trawl surveys record the occurrence of all species captured over the latitudinal extent of our study area. We generated absence records (Figure 4b) from the fishing events that did not yield a species corresponding to our VME indicator taxa (e.g. Beazley et al. 2018, Chu et al. 2019). Because the trawl surveys occurred only on the continental shelf and slope, there is a sampling bias in location of the absence records relative to the presence records which include observations of VME indicator taxa at several offshore seamounts. With the exception of visual data from Cobb Seamount (Curtis et al. 2015), we prioritized keeping as many of these rare seamount observations in our models as possible and addressed this sampling bias by restricting the inclusion of offshore presence records to those occurring within the sampling depth range of the absence records which sampled a maximum depth of 1,600 m.

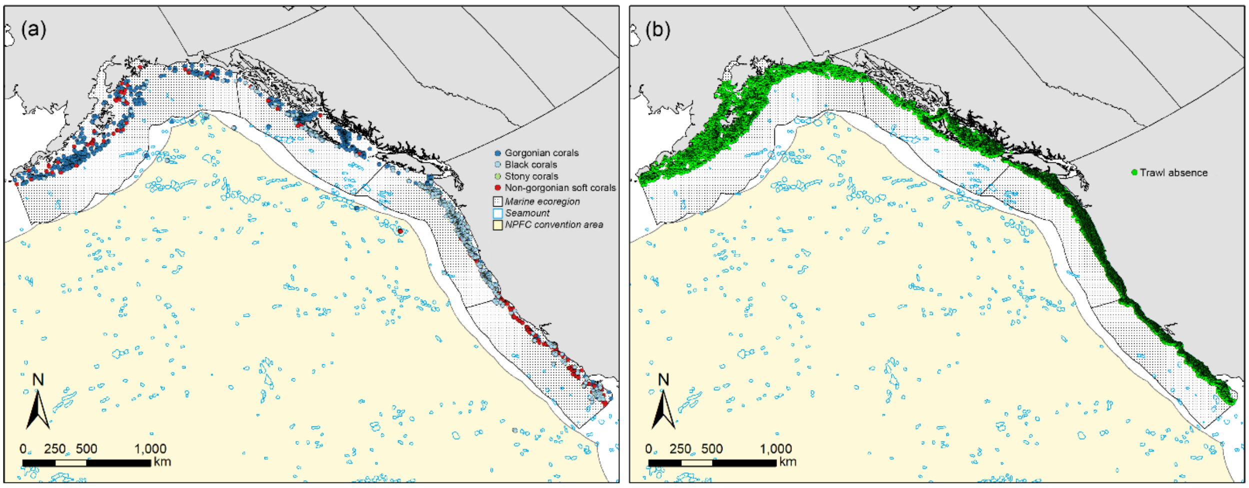

Figure 4. Species occurrence data used in PHM models. (a) Distribution of VME indicator taxa presence records and (b) Distribution of trawl absence data. Records were geographically limited to those occurring within four marine ecoregions and the adjacent international waters (Spalding et al., 2007). Seamount areas are from Harris et al. (2014). Note that the four groups of VME indicator taxa are plotted in panel (a) but are not visible because of the overlapping points.

Environmental data layers

We used the gridded environmental data from Chu et al. (2019) developed by the North Pacific Marine Science Organization (PICES) Working Group 32 on Biodiversity of Biogenic Habitats, which were created for the development of PHMs for the North Pacific Ocean (Chu et al. 2019, 2020). This set of 30 environmental layers are gridded at a 1 km^2 resolution and include bathymetry-derived variables, physiochemical variables, and oceanographic properties that can be strong predictors of benthic species distributions. Please refer to Table 1 in Annex 1 for a summary of details, resolutions, and units associated with the environmental data layers. Davies and Guinotte (2011), Chu et al. (2019), and Georgian et al. (2021) provide general background on the data layers, original data sources, processing steps involved in their creation, and examples of their general use in PHM development for VME indicator taxa and identifying VMEs in the Pacific Ocean.

MaxEnt modeling settings

We followed the general MaxEnt model workflow described by Chu et al. (2019) and developed a PHM for each of the four VME indicator taxa. Species data were spatially thinned to include only one record per 1 km^2 grid cell. We applied several best practices to test initial models and to prevent general overfitting (e.g. Merow et al. 2013, ICES 2021). Collinearity among predictors was addressed by examining variance inflation factors (VIF) and iteratively reducing the set of environmental data layers used for each model until the final subset of variables all had VIF < 10 (Table 1). Model performance was assessed using the area under the receiver operating characteristic curve (ROC) (AUC, Phillips et al. 2006). AUC values of 1.0 indicate a model that can perfectly predict presence and absences and 0.5 indicates a model that performs no better than random. We tested a range of MaxEnt regularization coefficient values (to balance model overfitting, see Merow et al. 2013) and set the value to 1.0 which yielded models with the highest AUC. We used five-fold cross validation to assess how well each model performed. Occurrence (presence and absence) data was randomly sampled and split into five equal data partitions and models were trained on four partitions and tested with the remaining fold; this procedure was repeated five times with a unique partition used for testing in each iteration. Final models used the entire set of species presences and absences from each taxon to generate maps of presence probability.

Table 1. Input data used in MaxEnt models: Number of 1 km^2 gridded presence and absence records, and the subset of environmental data layers used as predictors. BPI is the Bathymetric Position Index at the corresponding scale in metres, PAR is the Photosynthetically Active Radiation, and SST is Sea Surface Temperature. Table 1 in Annex 1 provides details on the full set of environmental variables considered for use in PHM development.

VME taxa	**Presence records**	**Absence records**	**Environmental variables included in final model**
Black corals	497	22,145	Chlorophyl-a, cross-sectional curvature, current angle, current aspect, current direction, east-facing aspect, north-facing aspect, oxygen, PAR, particulate organic carbon, regional current velocity, slope, SST, BPI20000, vertical flow velocity, roughness
Stony corals	291	22,145	Omega Aragonite, Chlorophyl-a, cross-sectional curvature, current aspect, current direction, east-facing aspect, north-facing aspect, oxygen, PAR, particulate organic carbon, regional current velocity, slope, SST, BPI20000, roughness
Gorgonian corals	1,378	22,145	Omega Aragonite, Chlorophyl-a, current direction, east-facing aspect, north-facing aspect, oxygen, PAR, particulate organic carbon, regional current velocity, slope, SST, BPI5000, BPI20000, roughness
Non-gorgonian soft corals	611	22,145	Omega Aragonite, Chlorophyl-a, cross-sectional curvature, current direction, current angle, east-facing aspect, north-facing aspect, oxygen, PAR, regional current velocity, slope, SST, BPI20000, roughness

Spatial uncertainty in the model predictions

To examine spatially-explicit measures of uncertainty in the model predictions, we applied a non-parametric, bootstrap resampling procedure before running the final models for each of the four VME indicator taxa (e.g. Anderson et al. 2017, Rowden et al. 2017, Chu et al. 2019). For a model's occurrence dataset, observations were randomly sampled with replacement to match the ratio of presence and absence records respective to their model (Table 1); each bootstrapped random sample was used to generate a model prediction. This process was done n=100 times which allowed a mean and standard deviation (SD) to be calculated among model runs where areas with high SD indicated higher uncertainty associated with model predictions. For each grid cell, we calculated a confidence interval (CI) using the mean and SD generated from the 100 model runs. We use 99% CI values for our steps where we applied the visual occurrence threshold to the mapped prediction.

Validating the model predictions with the visual survey data

We use the independent visual survey data from Curtis et al. (2015) to test how well the models perform when compared to an independent dataset. We use AUC as a metric of general performance but calculate additional metrics. Percent correctly classified (PCC) is the proportion of the visual data correctly classified into presence and absence categories. Sensitivity calculates the proportion of the visual data presence records that were correctly classified. Specificity calculates the proportion of the visual absence records that were correctly classified. For PCC, sensitivity, and specificity to be calculated, the logistic predictions need to be converted into binary presence-absence values. Therefore, we examined ROC plots (ANNEX 1, Figure 1) and used a value that maximizes sensitivity and specificity for the binary conversion.

Step 3. Determine areas likely to be VMEs

We use model predictions to determine areas likely to be VMEs, following the decision tree in Figure 1 (NPFC 2021b). We apply the visual occurrence threshold to the mean of the four NPFC VME indicator taxa PHMs to quantitatively determine which areas meet the criterion of being likely to be a VME. Areas where the PHM value is equal to or greater than the visual occurrence threshold are identified as areas likely to be VMEs.

The aerial extent of areas likely to be VMEs in our analyses is 1 km^2 because the environmental variables used to produce the PHM predictions were gridded at a resolution of 1 km^2 (Chu et al. 2019). Based on these methods areas likely to be VMEs will be defined as areas where the mean of the four VME indicator taxa predicted model values is equal to or greater than the visual occurrence threshold.

Step 4. Use supporting visual data in areas likely to be VMEs

Following the NPFC decision tree on identifying data for VMEs (Figure 1), areas that are likely to be VMEs become high priority areas to undertake visual surveys. If visual data do not exist or cannot be collected, then an area cannot be confirmed to be a VME. To illustrate our proposed methodology, we use the visual data collected at Cobb Seamount in 2012 by Curtis et al. (2015).

Step 5. Determine if VME criteria are met

The criterion used to identify VMEs in our approach is when the proportion of a transect where one or more VME indicator taxa occur in the visual data is equal to or greater than the visual occurrence threshold, and thus meets the FAO criterion of structural complexity (FAO 2009).

We first segmented the visual data into 50 m sub-transects. Then we calculated the proportion of those segments where VME indicator taxa were present using the equation in step 1. In the absence of comprehensive visual data to delineate the areal extent of the VME, this step in our methodology uses the same resolution (1 km^2) as that used to identify areas that are likely to be VMEs in Step 3. If one or more segments of the transect within a 1 km^2 area was equal to or greater than the visual occurrence threshold, then a VME was identified for that 1 km^2 area. Applying the visual occurrence threshold in this manner is similar to our method of identifying areas likely to be VMEs but uses visual data instead of the PHMs' predicted values.

RESULTS & DISCUSSION

The primary goal of this working paper is to propose and receive feedback on our approach before applying it to identify VMEs and areas that are likely to be VMEs in the NE part of the NPFC's CA. We propose one quantitative method of VME identification that integrates model predictions and visual data in a manner that aligns with the SWG VME's framework, the precautionary approach, the Convention, and the research plan of NPFC's Scientific Committee. We recognize that other methods have (e.g. Miyamoto & Yonezaki 2019) and will be applied to identify VMEs in the NPFC's CA. Our approach factors in the data limitations in this region which dictates how available visual data can be analyzed for identifying and modelling VME areas in the NE part of NPFC's CA where Canada fishes for sablefish (*A. fimbria*).

We use data from Cobb Seamount to illustrate an initial application of our methodology which identifies 1 km^2 areas that are likely to be VMEs at depths ranging from 18 m to 1,573 m, and one VME on the northwest part of Cobb Seamount. With future iteration of our approach through peer review and feedback, we aim to identify VMEs and areas that are likely to be VMEs in the NE part of the NPFC's CA during the coming years.

General approach to identifying VMEs

Step 1. Identify a quantitative threshold for VME occurrence

Visual occurrence of VME indicator taxa was calculated for 50 m divisions of the AUV transects on Cobb Seamount (n=136). Associated species richness ranged from 1 to 19 and the proportion of transect where VME taxa occurred ranged from 0 to 1, where 1 indicated at least one of the four VME indicator taxa was present in all images for that transect segment (Figure 5). All four VME indicator taxa were represented in the AUV data (see Table 4 in Annex 3 for a list of observed VME taxa).

A general comparison of model fit showed the piecewise regression (R^2=0.19, AUC=678.35) fit our data better than a linear regression (R^2=0.13, AUC=686.54) which indicates a threshold relationship occurring in our data. A break point was resolved for associated species richness where the proportion of transect where one or more VME indicator taxa occurred was 0.7 (99% CI range of 0.54-0.86) from the piecewise regression (Figure 5).

We use the upper 99% CI value of the visual occurrence threshold, which is 0.86, in the following methods to account for uncertainty in the threshold analysis. See Annex 2 for alternative results using a visual occurrence threshold of 0.7.

We expect that the relationship between the amount of structurally complex habitat, which we estimate using the proportion of transect where the NPFC's VME indicator taxa occur, and the associated species richness increases steeply until the number of species that can be supported by the complex habitat begins to reach a threshold and then plateaus (as discussed in Rowden et al. 2020).

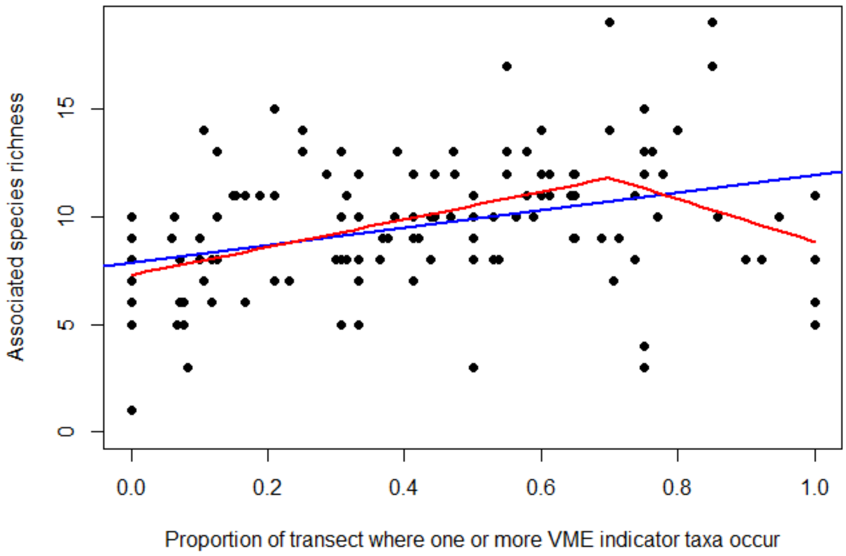

Figure 5. Proportion of transect where the NPFC's VME indicator taxa occur vs associated species richness from Cobb Seamount AUV transects divided into 50 m segments. A comparison of anova tables between piecewise (red, R^2 = 0.193) and a linear regression (blue, R^2=0.131) models fitted to the data indicates a significant breakpoint occurs at 0.7 (p <0.05).

Step 2. Develop predictive models for VME indicator taxa

All MaxEnt models developed using presence-absence data performed well with AUC scores ranging from 0.86-0.91 among modelled taxa (Table 2). The most important predictors varied slightly among models but all shared dissolved oxygen among their top two ranked predictors. Additional importance predictors included water column properties associated with surface water conditions (photosynthetically active radiation, particulate organic carbon, sea surface temperature, chlorophyll-A), seafloor characteristics (roughness), and broad scale currents (regional current velocity). The slight differences among the most important predictors also resulted in differences in the general footprint of areas predicted to have a high habitat suitability varied among models (Figure 6, Figure 1 in Annex 1). However, shared areas of high habitat suitability among models were generally concentrated along the continental shelf in domestic waters and mostly at seamount areas within the international waters of the NPFC CA (Figure 6). These results mirror those of Chu et al. (2019) who used a similar PHM approach but focused within a smaller study area inside Canadian domestic waters. The complimentary findings reinforce the importance of the expansive oxygen minimum zone in the Northeast Pacific ocean and its influence on the distribution of VME indicator taxa in this region.

Table 2. Summary of final MaxEnt model parameters. Training AUC and the top three most important predictor variables based on their relative importance in each model are presented. Values are the mean among the 100 bootstrap resampling model runs that used the entire occurrence dataset. Variable acronyms: PAR – photosynthetically active radiation, POC – particulate organic carbon, BPI20000 – bathymetric position index at a 20,000 m scale, Regfl – Regional current velocity. Chl-a – Chlorophyl-A. SST – Sea Surface Temperature. The full ranked list of variable importance is provided in Table 2 of Annex 1.

VME group	**Training AUC**	**1st ranked**	**2nd ranked**	**3rd ranked**
Black corals	0.90	Oxygen (48%)	PAR (19%)	Regfl (7%)
Stony corals	0.90	Oxygen (14%)	Chl-A (13%)	SST (13%)
Gorgonian corals	0.85	PAR (37%)	Oxygen (16%)	BPI20000 (11%)
Non-gorgonian soft corals	0.92	Roughness (36%)	Oxygen (16%)	POC (8%)

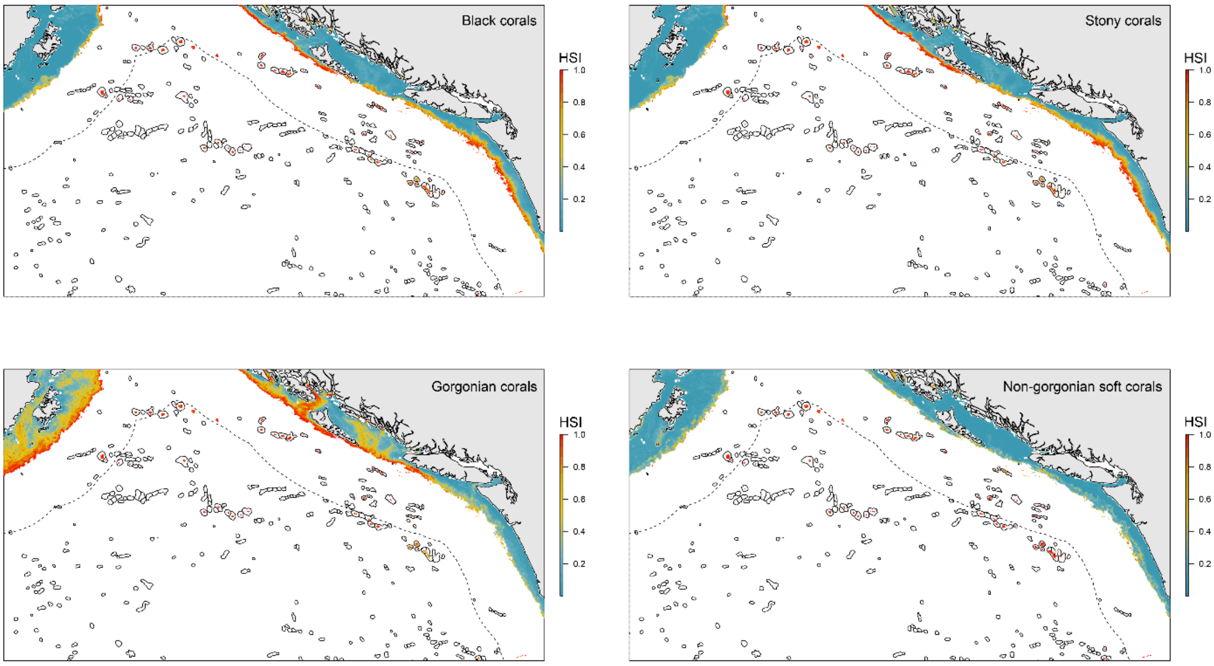

Figure 6. MaxEnt predictions of habitat suitability index (HSI) for the four NPFC VME indicator taxa in the NE Pacific Ocean. The majority of high habitat suitability areas in the NPFC CA (boundary indicated by dash line) occur at seamounts. Model predictions have been restricted to the maximum depth of 1,600 m reflected in the species data.

Transect lines from the visual surveys intersected with only 13 grid cells in the PHM predictions which limits the extent at which PHM performance can be tested with the available independent data. Results are still informative and illustrate the process of validation with independent visual survey data. Performance varied among models with stony corals and gorgonian corals performing better than those for black corals and non-gorgonian soft corals (Table 3). However, single classification errors currently have a relatively large influence on validation testing because of their relative proportion to the sample size (n=13). Additional factors such as differences in detectability and catchability between the data used to train the PHMs (acquired mostly from trawl surveys) and the visual survey data could influence model validation. Ideally, additional data could be acquired from visual surveys designed using the model predictions that would allow a more comprehensive validation of model performance.

Identifying areas that are likely to be VMEs using PHMs will be strongly influenced by the taxa being modelled. Although our PHM models performed well, the NPFC's VME indicator taxa groups (black corals, stony corals, gorgonians and non-gorgonian soft corals) are taxonomically broad and capture a wider range of habitat conditions than what species-specific PHMs would resolve. Ideally, we would develop PHMs for taxa at lower taxonomic levels (e.g. species or family) which could reduce the amount of species-specific habitat requirements being pooled into a single model. This could improve how well our PHMs predict the occurrence of VME indicator taxa, which were identified to lower taxonomic levels in the visual data collected by Curtis et al. (2015) (see Annex 3).

Table 3. Model performance statistics when tested with the visual survey data. AUC is the area under the receiver operating characteristic curve. Test AUC is the average AUC among the five folds of data used for internal model cross validation. Training AUC is the average of the 100 bootstrapped model runs used to generate the final model predictions. Validation AUC is calculated using the independent visual survey data to test the average prediction from the 100 bootstrap model runs. Additional validation metrics presented are: PCC which is the percentage of the observations that were correctly classified (n=13), sensitivity is the proportion of true positives correctly classified by a model, and specificity is the proportion of true absences correctly classified.

Model	**Test AUC**	**Training AUC**	**Validation AUC**	**PCC**	**Sensitivity**	**Specificity**
Black corals	0.88	0.90	0.53	0.54	0.5	0.67
Stony corals	0.87	0.92	0.92	0.92	1	0.92
Gorgonian corals	0.86	0.85	0.82	0.62	0.64	0.5
Non-gorgonian soft corals	0.91	0.92	0.67	0.77	0.89	0.5

Step 3. Determine areas likely to be VMEs

Areas that are likely to be VMEs in the NE Pacific region of the NPFC CA occur almost exclusively at seamounts covering a total area of 3,137 km^2 (Figure 7).

On Cobb Seamount, a total of 83 1-km^2 grid cells were identified as areas likely to be VMEs (Figure 8), resulting in a total area of 83 km^2. The depth range for this area is from the pinnacle of Cobb at 18 m to 1,573 m.

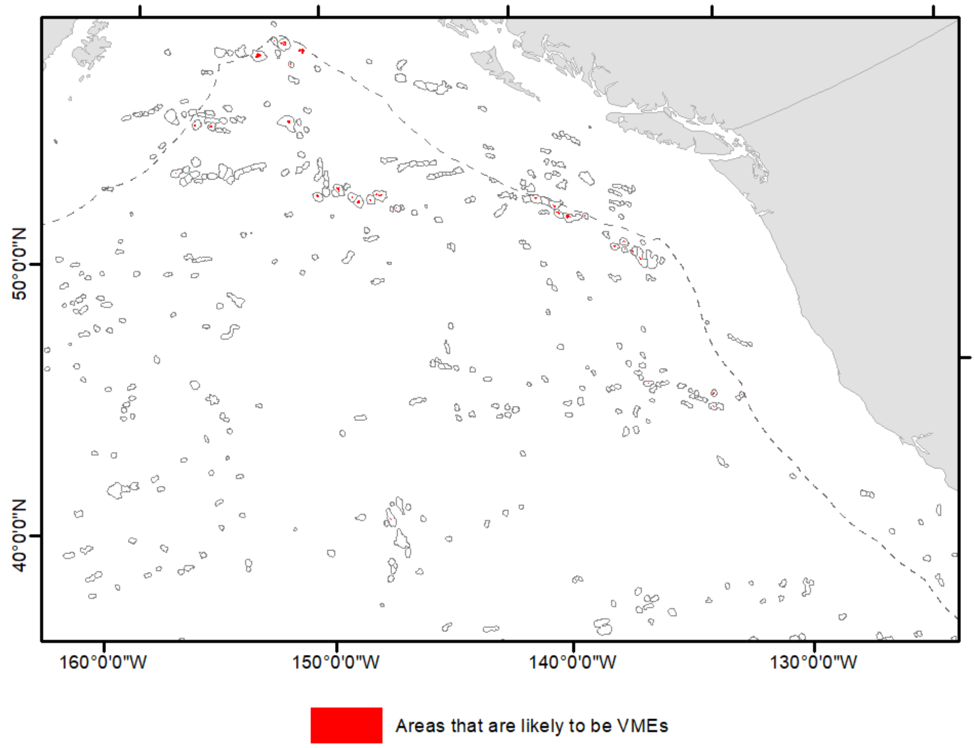

Figure 7. Areas likely to be VMEs in the Eastern North Pacific based on the mean VME indicator taxa predicted model value meeting or exceeding the visual occurrence threshold of 0.86. Seamount areas are from Harris et al. (2014). Note – only PHM predictions that meet or exceed the threshold in the NPFC CA (international waters) are shown.

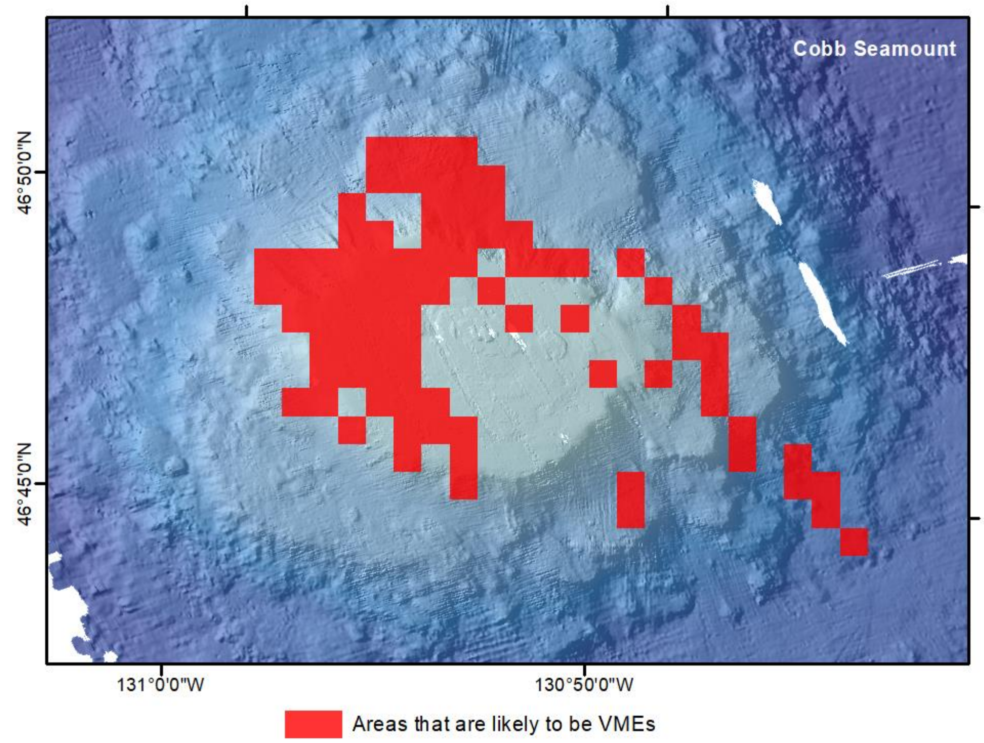

Figure 8. Areas likely to be VMEs on Cobb Seamount based on the mean VME indicator taxa predicted model value meeting or exceeding the visual occurrence threshold of 0.86.

Step 4. Gather supporting visual data in areas likely to be VMEs

Visual data are available for two of the 83 grid cells identified as areas likely to be VMEs on Cobb Seamount. This includes data from AUV transects 2 and 4 from the 2012 Cobb Seamount visual survey (Figure 9).

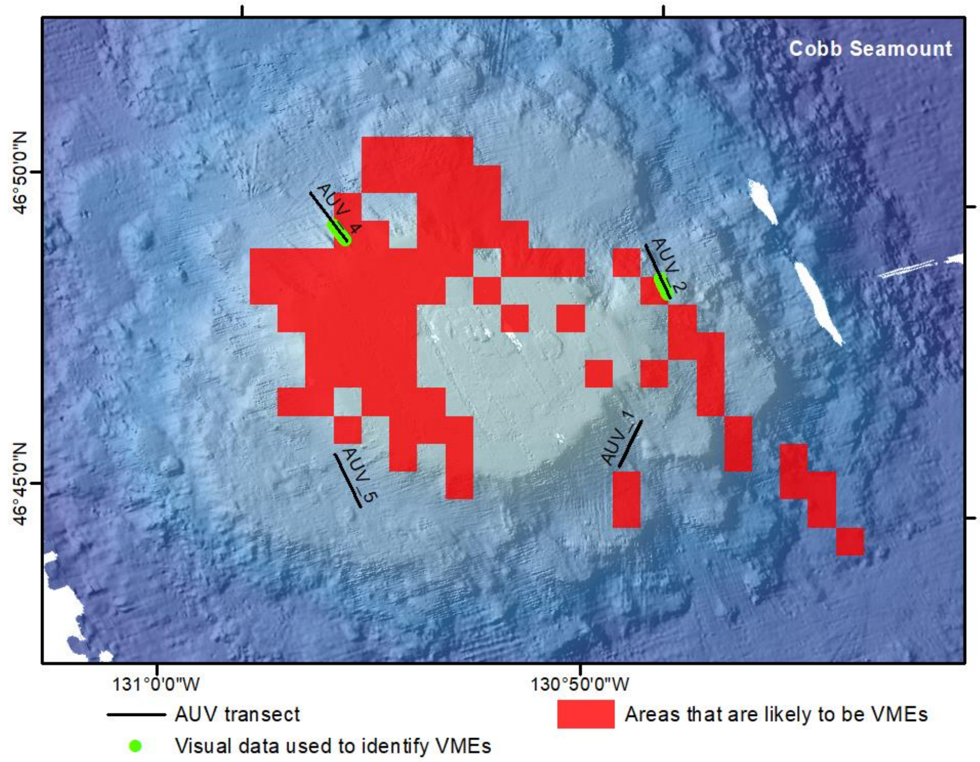

Figure 9. Supporting visual data used to identify VMEs on Cobb Seamount (green). AUV transects are from the 2012 Cobb visual survey (see Curtis et al. 2015). Areas likely to be VMEs (red) were identified by using predictive models of VME indicator taxa and applying a visual occurrence threshold of 0.86.

Step 5. Determine if VME criteria are met

The overlapping portion of transects AUV 2 and AUV 4 with the areas likely to be VMEs was divided into 12 and 13 sub transect segments of 50 m, respectively. The proportion of transect where one or more VME indicator taxa occur ranged from 0.06 to 1 (Figure 10). AUV transect 2 does not contain segments that meet the visual occurrence threshold and is therefore not identified as a VME (Figure 10a).

AUV 4 does contain two segments that meet the visual occurrence threshold. Sub-transect segments number 2 and 3 have a proportion of transect where one or more VME indicator taxa occur of 1 and 0.86, respectively (Figure 10b). Therefore, this portion of AUV 4 meets the criterion of being a VME. The 1-km^2 grid cell that this transect overlaps is therefore used to delineate the boundary of this VME.

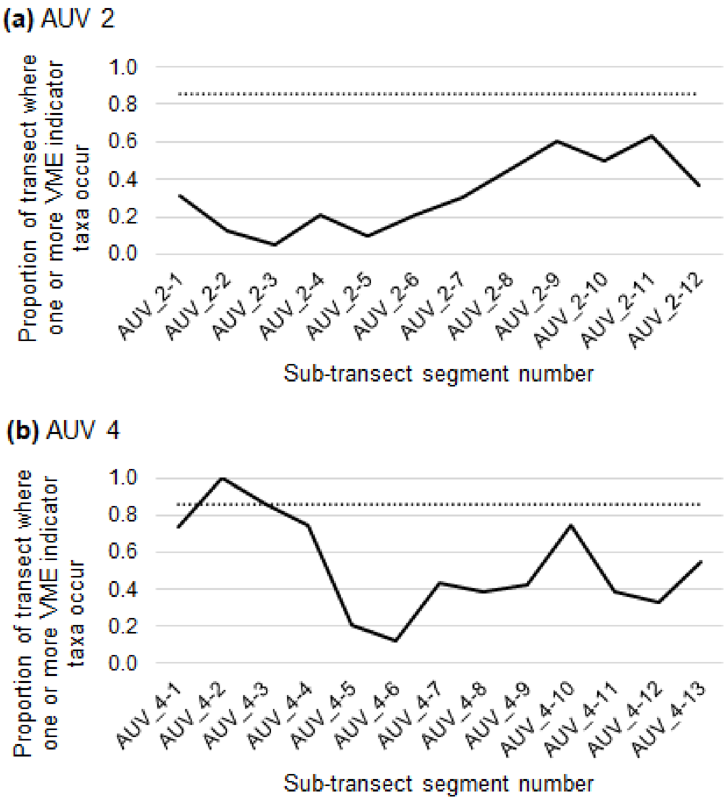

Figure 10. Proportion of visual transect where one or more VME indicator taxa occur calculated per 50 m segment that overlaps with areas likely to be VMEs from (a) AUV transect 2 and (b) AUV transect 4 from the 2012 Cobb Seamount visual survey. The visual occurrence threshold is equal to 0.86 (dashed line) and transects with at least one segment that is equal to or greater than this threshold meets the criteria for a VME. There are two sub-transect segments where the proportion of transect with one or more VME indicator taxa occur meets or exceeds our visual occurrence threshold (AUV 4 sub-transect segments 2 and 3).

Our preliminary results for this Cobb Seamount example suggest one preliminary VME identified on the northwest part of Cobb Seamount at a depth of approximately 600 m with an area of 1km^2 (Figure 11). The two 50-m sections of transect AUV 4 that fall at or above our visual occurrence threshold had at least 16 colonies of 3 species of corals. Associated benthic epifauna included at least two species of fish, 5 species of sea stars, 2 species of sponges, and 1 species of decapod. Brittle stars were also common.

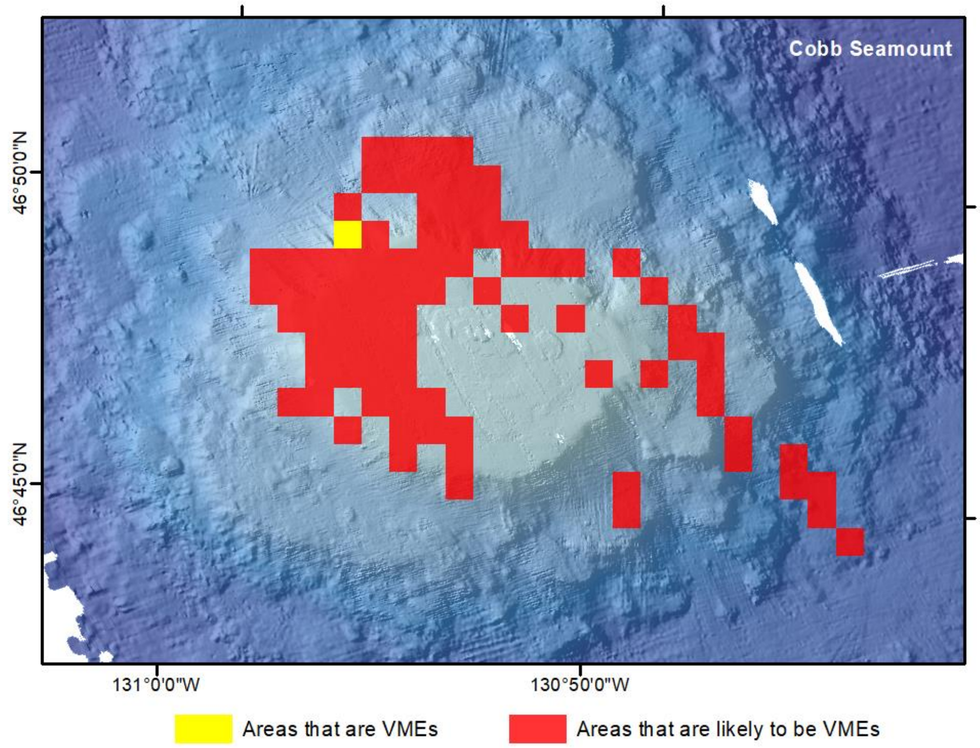

Figure 11. Preliminary areas that are likely to be VMEs (red) and one area that is a VME (yellow) using our proposed methodology applied to Cobb Seamount.

Fisheries interaction

In the NE part of the NPFC's CA, fishing activities are currently limited to a Canadian commercial Sablefish fishery. The fishery uses longline hook and trap gear, and trawl gear is not permitted in the seamount fishery (DFO 2013). Sablefish landings concentrate over several seamounts in the CA including Eickelberg, Warwick, Corn, Cobb, and Brown Bear Seamounts.

Canadian commercial Sablefish fishery landings data was obtained from the Fishery Operations System of DFO. Commercial fisheries data is protected as per Canada's Access to Information Act and Privacy Act. Therefore, landing locations in this working paper (Figure 12) were filtered to only display points where three or more vessels were reporting for a time and area of interest, also known as the "three boat rule."

By overlaying the Sablefish landing locations over the VMEs and areas likely to be VMEs on Cobb Seamount we see how the fishery is distributed compared to those areas and how they overlap (Figure 12). While the location of fishery landings in Figure 12 are approximate only, the true estimate of the fishery's landings that overlap with VMEs and areas likely to be VMEs are summarized in Table 3. Based on data from 2006-2019, 38 % of the total Sablefish fishery landings on Cobb Seamount overlapped with the VME and areas likely to be VMEs (Table 3).

Fishing has occurred in 51% of the areas likely to be VMEs and in the one 1-km^2 location identified as a VME.

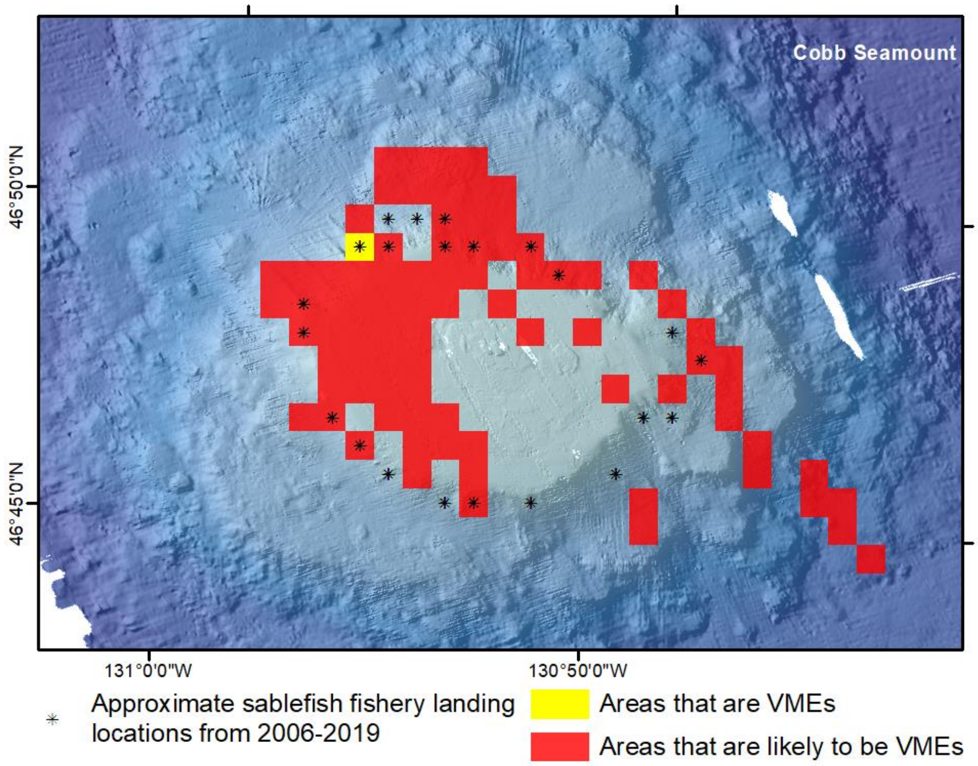

Figure 12. Preliminary VME area (yellow) and areas likely to be VMEs (red) overlayed with approximate sablefish fishery landings locations from 2006-2019 on Cobb Seamount, presented according to Canada's "three boat rule." Fishing locations in this map are limited to points where three or more vessels reported landings for a time or area of interest to preserve confidentiality.

Table 3. Summary of Sablefish fishery landings overlapping with the preliminary areas identified as VMEs and areas likely to be VMEs. Fishery values are based on fishing records from the years 2006-2019 and include all species landed by the sablefish fishery, including incidental catch.

Summary of Sablefish fishery interaction with preliminary areas	**Areas likely to be a VME**	**VMEs**
Total sablefish fishery landings overlapping with the proposed area (sum in kg)	18,919	1,399
Percent of sablefish fishery landings overlapping with the proposed area	38 %	2 %
Percent of area that fishing occurs in	51 %	100 %

CONCLUSIONS

In this paper, we propose one potential quantitative method to identify VMEs and areas likely to be VMEs in the NPFC CA. It is based on the current best available scientific data in the NE part of the NPFC CA and follows the SWG VME's decision tree to identify data that can be used to identify VMEs (NPFC 2021b). The NPFC has identified a total of four VMEs in its CA, including areas on Koko and Colahan Seamounts (Miyamoto & Yonezaki 2019), but the approaches used to identify them are semi-quantitative in nature and not easily repeatable by other members. Also, because of differences in the availability of data, Miyamoto and Yonezaki's (2019) approach is not readily applicable to the entire NPFC CA. We use PHM predictions and visual data from Cobb Seamount to demonstrate how our proposed methodology can be applied in the NPFC CA.

We describe our proposed quantitative method and aim to revise it and then apply it to the NE part of the NPFC's CA. The results of our case study on Cobb Seamount are preliminary and have no management implications; we are not recommending that these areas be identified as VMEs or areas that are likely to be VMEs. We also note that our proposed method may not identify all VMEs or areas likely to be VMEs; there may be areas in the NPFC's CA that meet criteria for being identified as such using other methods and/or that draw on a different set of the FAO (2009) criteria.

The application of quantitative methods (e.g. Kenchington et al. 2014, Morato et al. 2018, Rowden et al. 2020) for identifying VMEs in the NE part of the NPFC CA is currently constrained by general data availability. Additional visual surveys designed to collect community-level presence-absence data would strengthen the development of our PHMs and provide opportunities to validate our predictions. As more data are collected that can be incorporated into our approach, results can be iteratively updated through periodic review of our analyses.

Next steps

We welcome any comments or suggestion from NPFC members, observers, or stakeholders on the methodology we have outlined in this working paper to identify VMEs or areas likely to be VMEs in the NPFC's CA. We will use these comments and suggestions to revise our approach and apply it in the NE part of NPFC CA. When we have revised and applied our method to parts of the NE Pacific Ocean, areas that are identified as likely to be VMEs will become priorities for visual surveys to assess the abundance and richness of benthic species. We are also committed to undertaking periodic reviews of our analyses as new data or information become available.

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ANNEXES

ANNEX 1 – Additional details on Predictive Habitat Models (PHMs)

Table 1. PICES WG32 environmental data layers used in PHM development (from Chu et al. 2019 and Chu et al. 2020).

Variable name	Units	Native Resolution	Reference
Bathymetry-derived variables			
Bottom depth	metres	0.0083°	Becker et al. 2009; Sandwell et al. 2014
Aspect – east-facing [*eastness*]		0.0083°	Jenness 2013a
Aspect – north-facing [*northness*]		0.0083°	Jenness 2013a
Curvature – General [*gencurve*]		0.0083°	Jenness 2013a

Curvature – Cross-Sectional [*crosscurve*]		0.0083°	Jenness 2013a
Curvature – Longitudinal [*longcurve*]		0.0083°	Jenness 2013a
Slope	degrees	0.0083°	Jenness 2013a
Roughness [*VRM*]		0.0083°	Sappington et al. (2007)
Bathymetric position index [*bpi*] (1000m, 5000m, 10000m 20000m)		0.0083°	Jenness 2013b
Chemical variables			
Alkalinity	µmol l^{-1}	3.6 x 0.8–1.8°	Steinacher et al. (2009)
Dissolved inorganic carbon [*DIC*]	µmol l^{-1}	3.6 x 0.8–1.8°	Steinacher et al. (2009)
Omega - aragonite (Ω_{ARAG}) [*arag*]		3.6 x 0.8–1.8°	Steinacher et al. (2009)
Omega - calcite (Ω_{CALC}) [*calc*]		3.6 x 0.8–1.8°	Steinacher et al. (2009)
Dissolved oxygen [*oxygen*]	ml l^{-1}	1°	Garcia et al. 2014a
Phosphate	µmol l^{-1}	1°	Garcia et al. 2014b
Silicic acid [*dSi*]	µmol l^{-1}	1°	Garcia et al. 2014b
Nitrate	µmol l^{-1}	1°	Garcia et al. 2014b
Particulate organic carbon [POC]	G C m^{-2} yr^{-1}	0.5°	Lutz et al. (2007)
Physical variables			
Temperature	°C	0.25°	Locarnini et al. 2013
Salinity	pss	0.25°	Zweng et al. 2013
Current velocity — regional [*regfl*]	m s^{-1}	0.5°	Carton et al. (2005)
Current velocity — vertical [*vertfl*]	m s^{-1}	0.5°	Carton et al. (2005)
Current direction [*curdir*]	degrees	0.5°	Carton et al. (2005)
Current direction — relative to aspect [*curapsect*]	degrees	0.5°	Rooper et al. (2014)
3D current-surface angle [*curang*]	degrees	0.5°	Chu et al. (2019)
Surface-layer properties			
Chlorophyll-a [*chl-a*]	mg m^{-3}	4 km	Aqua Modis (NOAA)
Photosynthetically active radiation [*PAR*]	W m^{-2}	4 km	Aqua Modis (NOAA)
Sea Surface Temperature [*SST*]	°C	4 km	Aqua Modis (NOAA)

Table 2. The ranked, individual contributions of environmental predictors used in MaxEnt models of each VME indicator taxon. The ranked importance was calculated using a jackknife test that calculates model performance using AUC as variables are iteratively removed. Percent importance is presented as the mean of the n=100 bootstrapped model runs. Full variable names are described in Table 2 of Annex 3.

Rank	Black corals		Stony corals		Gorgonian corals		Non-gorgonian soft corals	
	Variable	%	Variable	%	Variable	%	Variable	%
1	Oxygen	47.8	Oxygen	14.0	PAR	36.9	Roughness	36.0
2	PAR	19.2	Chl-a	13.4	Oxygen	16.3	Oxygen	16.3
3	Regfl	7.4	SST	13.3	BPI20000	11	POC	8.2
4	SST	6.4	Roughness	10.8	Chl-a	7.4	PAR	7.3
5	Curdir	3.2	BPI20000	9.4	POC	5.2	Chl-a	7.1
6	Arag	2.4	POC	8.6	Eastness	4.0	Regfl	5.7
7	POC	2.3	Northness	5.2	Arag	3.9	Eastness	3.3
8	Chl-a	1.8	Curdir	5.2	SST	3.8	Arag	2.8
9	Eastness	1.8	Slope	4.9	Curdir	2.5	BPI20000	2.6
10	Slope	1.7	Regfl	4.2	Regfl	2.2	SST	2.5
11	Northness	1.6	Eastness	3.5	Roughness	1.9	Slope	2.4
12	BPI20000	1.5	Arag	3.4	Slope	1.6	Curdir	2.2
13	Curaspect	1.0	PAR	2.8	Northness	1.2	Northness	1.8
14	Roughness	0.9	Curaspect	0.9	Curapsect	1.0	Curaspect	1.4
15	Vertfl	0.6	Crosscurve	0.4	BPI5000	0.6	Vertfl	0.2
16	Crosscurve	0.3			vertfl	0.2	Crosscurve	0.1
17	curang	0.1					curang	0.04
18								

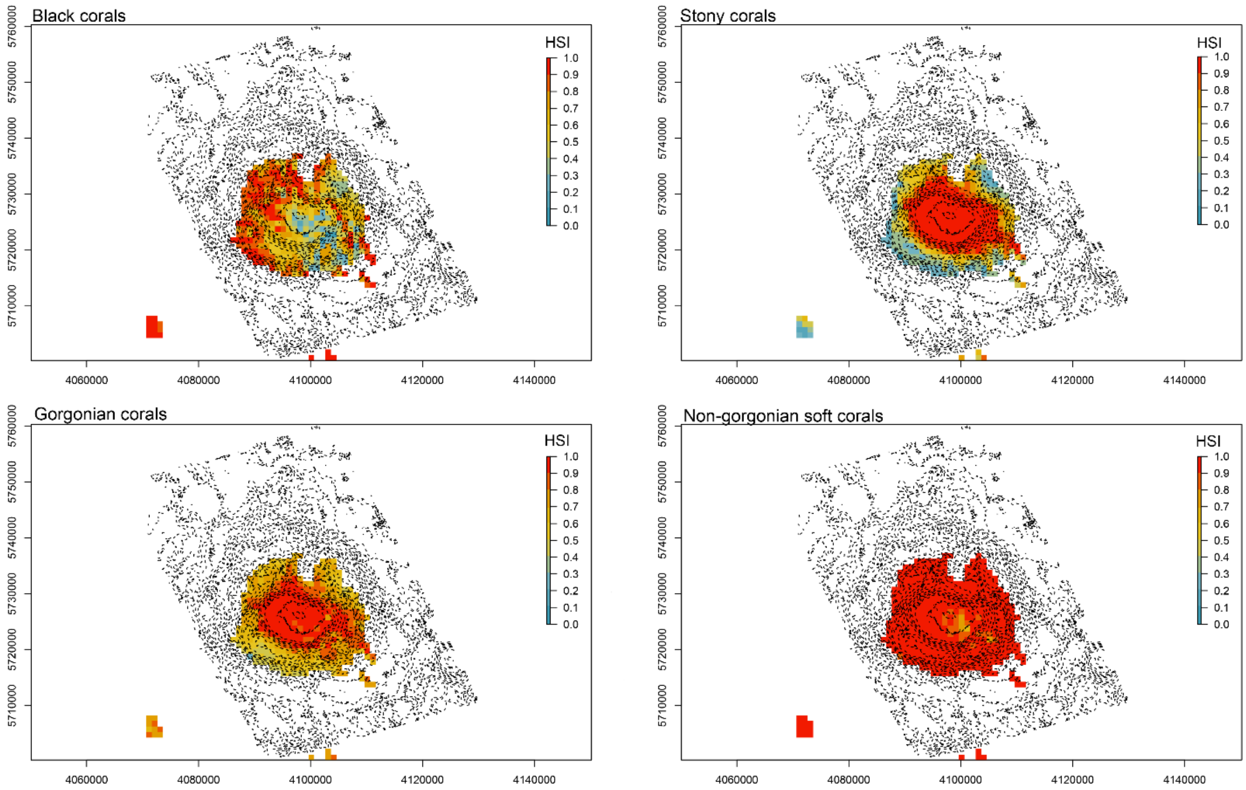

Figure 1. MaxEnt predictions of habitat suitability index (HSI) for the four NPFC VME indicator taxa at Cobb Seamount. Bathymetric contour intervals are in 100 m increments. Model predictions have been restricted to a maximum depth of 1,600 m.

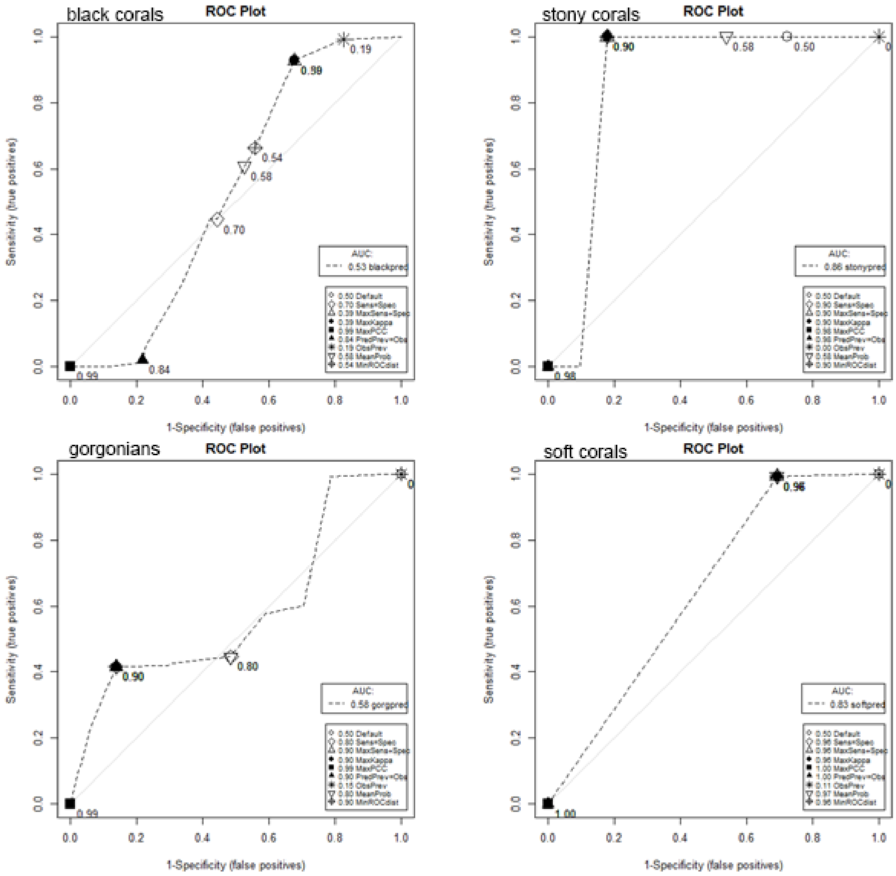

Figure 2. Receiver operating characteristic (ROC) curves used to assess performance with each of the PHMs. Independent presence and absence records of each of the VME indicator taxa observed in the visual survey data are used to validate the predictions from their respective PHM. We used the logistic prediction value that maximizes sensitivity and specificity to convert the logistic predictions into presence-absence binary values to calculate additional metrics presented in Table 3 of the main text.

ANNEX 2 – Alternative results for VMEs and areas likely to be VMEs

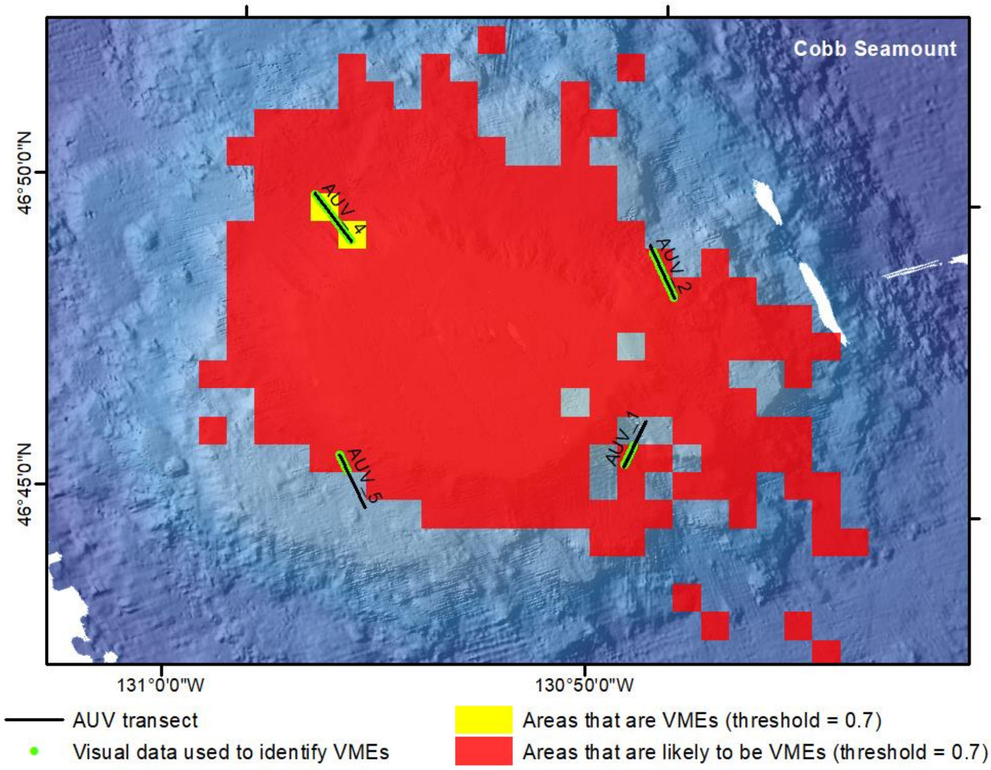

Figure 3. Alternative preliminary areas using a visual occurrence threshold of 0.7 to identify areas that are likely to be VMEs (red) and two areas that are VMEs (yellow) using our proposed methodology applied to Cobb Seamount.

Table 3. Summary of sablefish fishery landings overlapping with the alternative preliminary areas identified as VMEs and areas likely to be VMEs using a threshold of 0.7. Fishery values are based on fishing records from the years 2006-2019 and include all species landed by the sablefish fishery, including incidental catch.

Summary of Sablefish fishery interaction with preliminary areas (threshold = 0.7)	**Areas likely to be a VME**	**VMEs**
Total sablefish fishery landings overlapping with the area (sum in kg)	51,168	1,399
Percent of sablefish fishery landings overlapping with the area	65 %	2 %
Percent of proposed area that fishing occurs in	30 %	50 %

ANNEX 3 – Visual data taxa

Table 4. NPFC VME indicator taxa observed in the AUV photos from Cobb Seamount.

VME group	**Species**
Gorgonian	*Swiftia simplex*
Gorgonian	Isididae
Gorgonian	Primnoidae
Non-gorgonian soft Coral	*Heteropolypus ritteri*
Non-gorgonian soft Coral	*Gersemia* sp
Black Coral	*Bathypathes* sp
Black Coral	*Lillipathes* sp
Black Coral	*Stichopathes* sp
Stony Coral	*Desmophyllum dianthus*

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