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Progress on predicting the distribution of Vulnerable Marine Ecosystems and options for designing spatial management areas for bottom fisheries within the SPRFMO Convention Area

Martin Cryer,
Ministry for Primary Industries

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1. Introduction

Vulnerable marine ecosystems (VMEs) are ecosystems that are considered susceptible to damage or degradation through the impacts of human activities in the sea. Potential VMEs are identified by the vulnerability of their species, communities, or habitats to damage or disturbance. Significant adverse impacts to VMEs can potentially be caused by fishing on the High Seas (FAO 2009). The United Nations General Assembly (resolutions 61/105, 64/72), the Fisheries and Agricultural Organization (FAO), international conservation organisations (e.g., IUCN), and fisheries management agencies all aim to implement management strategies to safeguard VMEs from significant adverse impacts, and thereby conserve biodiversity and ecosystem function in the deep sea.

Progress in designing and implementing such strategies within the SPRFMO Convention Area (and elsewhere) has been limited by the sparsity of information on the characteristics and distribution of VMEs outside areas of national jurisdiction. The sparsity of biological information necessitates the use of models to predict the distribution of key VME indicator taxa from information that is more readily available, especially physical and chemical variables that can be remote-sensed or predicted more easily than biological features. The modelling technology to make these predictions and remote-sensing tools are both developing rapidly, but the amount of biological information on the location and characteristics of VME indicator taxa is developing less rapidly and will probably always be limiting.

A variety of decision-support tools are available to use predictions of the distribution of habitat and VME indicator taxa to design spatial management measures to avoid significant adverse impacts of fishing or other disturbance. These tools are based on different precepts and have different analytical approaches, but all depend on knowledge of the spatial distribution of the habitats or indicator species of concern. Additional constraints can be included in scenarios generated using some of these tools, including cost layers (value for existing uses), stratification (e.g., geographical, bioregional, or by depth), connectivity, and design characteristics like protected area fragmentation or boundary length:area ratio.

This paper summarises progress made by New Zealand in predicting and mapping the distribution of VME indicator taxa and in using those predictions together with decision-support software tools to show how spatial management measures for bottom fisheries can be designed to protection VMEs from significant adverse effects. This paper does not propose particular spatial management areas; it is a summary of progress and an indication of what can be done.

2. Predicting the distribution of VMEs and VME indicator taxa

2.1. Compiling biological data and developing modelling approaches

The SPRFMO Convention Area comprises about 59 million km^2 of the South Pacific Ocean beyond areas of national jurisdiction. Very little information exists on the spatial distribution of VMEs within the area and it is too large for cost-effective surveying to determine the distribution of VMEs directly (Rowden et al. 2013). Many studies have used habitat suitability models to predict the potential distribution of benthic fauna that may be indicators of VMEs in other areas (e.g., Davies & Guinotte 2011, Yesson et al. 2012, Rengstorf et al. 2013, 2014). The use of such models has been recommended as one aspect of designing effective management approaches to protect VMEs from significant adverse effects of fishing on the High Seas (Ardron et al. 2014, Vierod et al. 2014). Several recent studies have suggested that habitat suitability models can be used to predict the occurrence of seabed animals in the region that could indicate the presence of VMEs (e.g., Davies & Guinotte 2011, see Figure 1, Tracey et al. 2011).

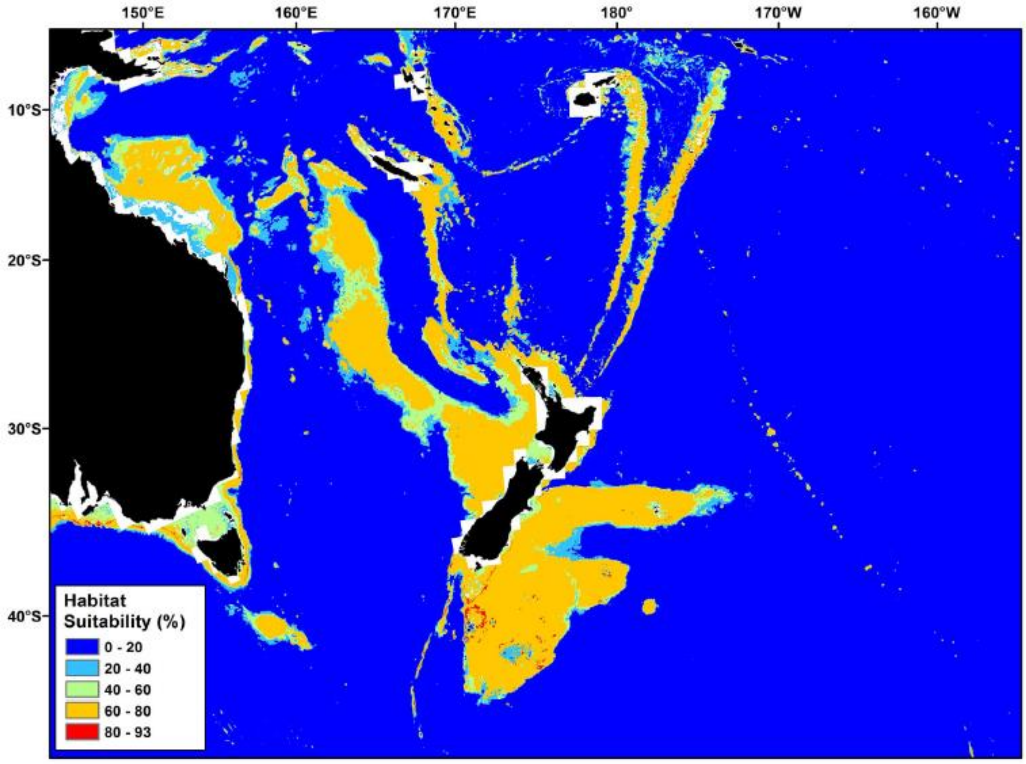

Figure 1 (from Penney & Guinotte 2011): Predicted scleractinian coral habitat suitability (*Goniocorella dumosa*, *Solenosmilia variabilis*, *Madrepora oculata*, *Enallopsammia rostrata* and *Oculina varicose*) in the New Zealand region.

New Zealand funded research to investigate the development and utility of such models for estimating the distribution of a range of VME indicator taxa (*sensu* Parker et al. 2009) in New Zealand's EEZ and High Seas. Rowden et al. (2013) collated over 31 000 records for 10 VME indicator taxa (Actinaria, Alyconacea, Antipatharia, Brisingida, Crinoidea, Gorgonacea, Pennatulacea, Porifera, Scleractinia, and Stylasteridae) and 11 environmental data layers. The available biological data ranged from 505 to 9187 records for different VME indicator taxa and the distribution of data across both geographic and environmental space shows systematic bias; most data come from the New Zealand EEZ and there has been very little sampling in SPRFMO Area.

Environmental variables were grouped into a "regional" set of 11 environmental data layers largely developed or tuned specifically for the New Zealand region and a "global" set of 9 layers collated and processed from global data sources (Figure 2). Habitat suitability models were developed for each VME indicator taxon using two commonly used machine-learning approaches: maximum entropy (MaxEnt, Phillips et al. 2006) (using global and regional environmental data) and Boosted Regression Trees (BRT, De'ath 2007, Elith et al. 2008) (using regional environmental data). Results were used to assess the potential utility of such models for use in spatial management planning.

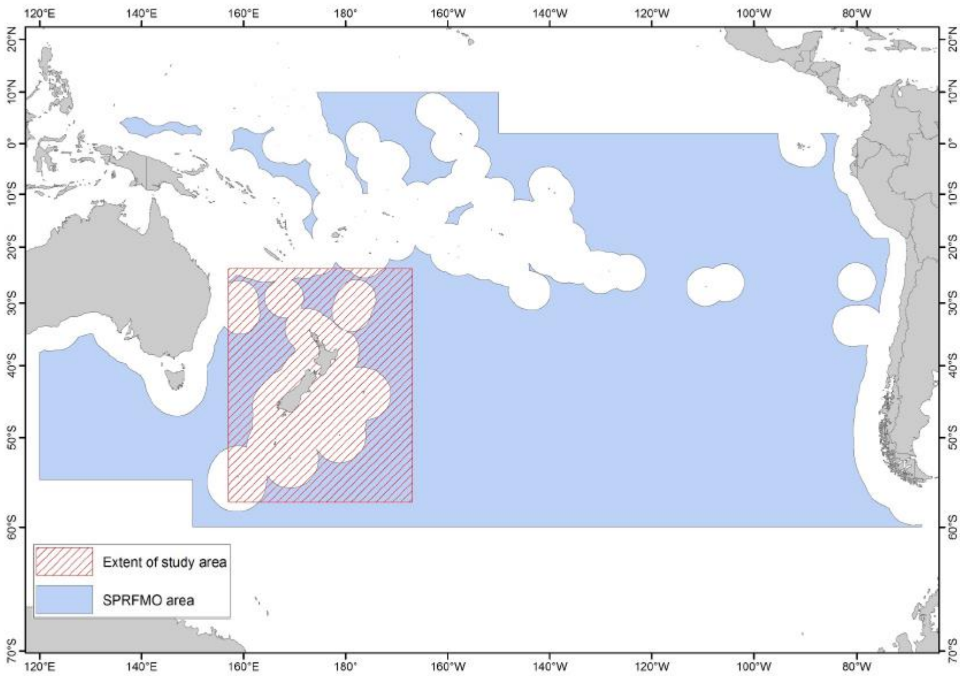

Figure 2 (after Figure 2 of Rowden et al. 2013): Map showing the SPRFMO Area (blue) and the study area (red hatch) for the habitat suitability modelling.

Rowden et al.'s (2013) preliminary habitat suitability maps from MaxEnt and BRT models for the ten VME indicator taxa were almost all qualitatively dissimilar to one another. In general, MaxEnt models predicted suitable habitat mostly in areas where data records exist, whereas BRT models had a greater tendency to predict suitable habitat in un-sampled (but apparently suitable) areas (e.g., Figure 3). BRT models also produced greater variability than MaxEnt models in their predictions of habitat suitability at the smallest spatial scales. MaxEnt models using regional and global environmental data layers generated qualitatively similar predicted distributions for particular VME indicator taxa (e.g., Figure 4). All preliminary models developed predicted that substantial parts of the New Zealand region should contain suitable habitat for VME indicator taxa but models generally had poor ability to finely discriminate highly suitable habitat.

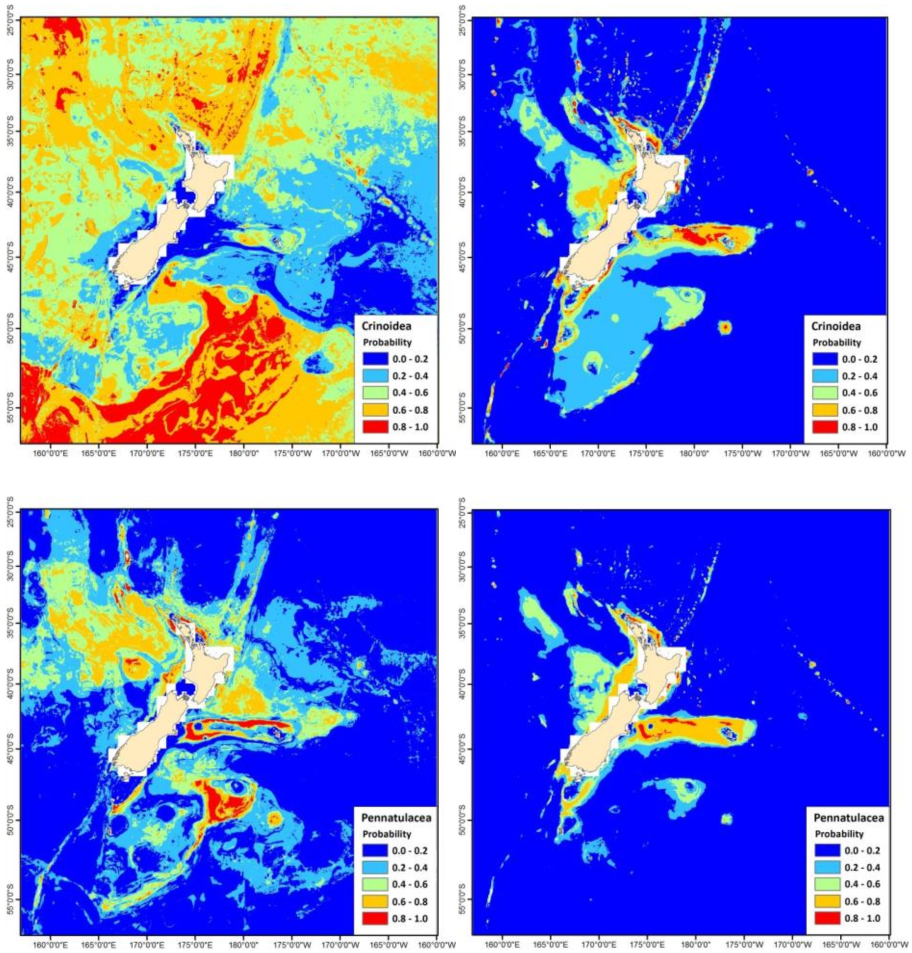

Figure 3 (after Rowden et al. 2013): BRT (left) and MaxEnt (right) habitat suitability predictions for example VME indicator taxa showing contrasting prediction (crinoids, top) and similar predictions (sea pens, bottom).

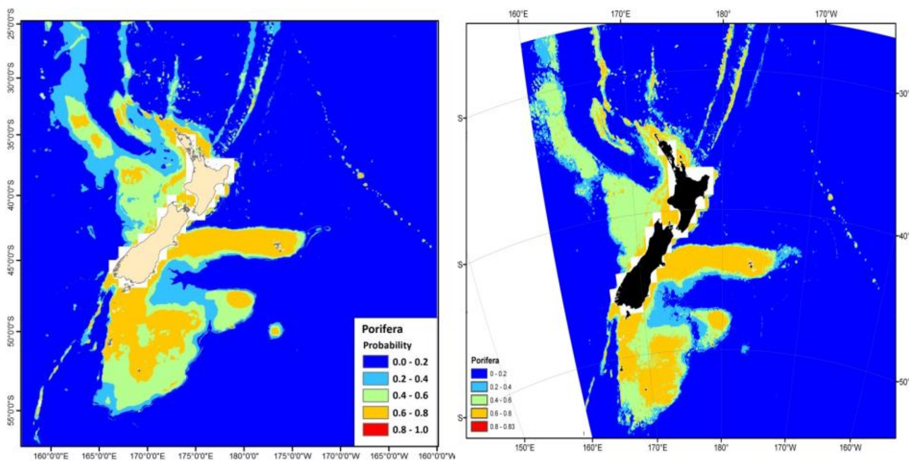

Figure 4 (after Rowden et al. 2013): MaxEnt model predictions based on regional (left) and global (right) environmental data layers for an example taxon (Porifera) showing large area of seafloor shallower than750 m deep as being suitable habitat (more than 0.6 probability).

Rowden et al. (2013) recommended that:

- BRT and MaxEnt, as well as other modelling approaches, should continue to be developed;
- the criteria for identifying VME indicator taxa should be revised;
- in order to refine the identification of VMEs, predictive models should be generated that combine the presence of particular taxa;
- a survey should be undertaken of the Louisville Seamount Chain (and/or West Norfolk Ridge, Lord Howe Rise) to obtain data for VME indicator taxa and habitat, ground truth the preliminary models, and develop new models;
- new models for the SPRFMO region should include those that model VME habitat (e.g. deepwater coral reef) directly, and if possible incorporate estimates of genetic connectivity, as well as spatially explicit measures of uncertainty;
- where multibeam surveys have been undertaken in the SPRFMO Area, bathymetric and backscatter data should be used to make high resolution habitat suitability maps.

2.2. Developing and testing SPRFMO-scale models

Following one of the recommendations above, new preliminary BRT and MaxEnt models were constructed for the entire SPRFMO Area (and New Zealand region) using global environmental data (Anderson et al. submitted). Because of the scarcity of data and the great expense of collecting additional data, testing and validation of most model predictions of habitat suitability is performed using non-independent data. For instance, the performance of New Zealand's preliminary habitat suitability models for the SPRFMO Area was evaluated by internal cross-validation whereby most of the data are used to develop the model but a proportion is set aside to test the results. This approach gives a reasonable measure of internal consistency, but field-based tests of predictions give model users a firmer understanding of their reliability for developing management options. Few studies have attempted to verify modelled predictions of VME indicator taxa by direct comparison with independent field data, despite many authors advocating the need (e.g. Tittensor et al. 2009, Davies and Guinotte, 2011; Guinotte and Davies 2014). This leads to uncertainty surrounding the accuracy of the modelled results, and this becomes particularly important for data-poor areas that are of high interest to commercial fisheries. A good example of this issue can be found on the Louisville Seamount Chain where New Zealand vessels trawl for orange roughy (*Hoplostethus atlanticus*). The seafloor habitats in this area have rarely been sampled and data on key VME indicator taxa like reef-forming scleractinian corals come mainly from government observers on board fishing boats.

Anderson et al. (submitted) collated presence records for the wider Pacific region from the Ocean Biogeographic Information System (OBIS) databases (http://www.iobis.org/) and various organisations in Chile, New Zealand, and Australia. These records were in addition to the ones compiled by Rowden et al (2013). The final dataset (Table 1) contained 202 579 records of VME indicator taxa, including 120 792 of scleractinian corals. Duplicates and records from outside the SPRFMO area, shallower than 200 m, or deeper than 3000 m were removed prior to the habitat suitability modelling analysis. Preliminary models for the SPRFMO Area were made using the 1 643 records of the four reef-forming species (*Solenosmilia variabilis*, *Goniocorella dumosa*, *Enallopsammia rostrata*, *Madrepora oculata*). Records for these species were not widely distributed across the SPRFMO area, with nearly 75% coming from the New Zealand EEZ and environs, and most of the remainder from the north-western corner of the SPRFMO Area (Australia, Indonesia, Philippines, and Melanesia) (Figure 5).

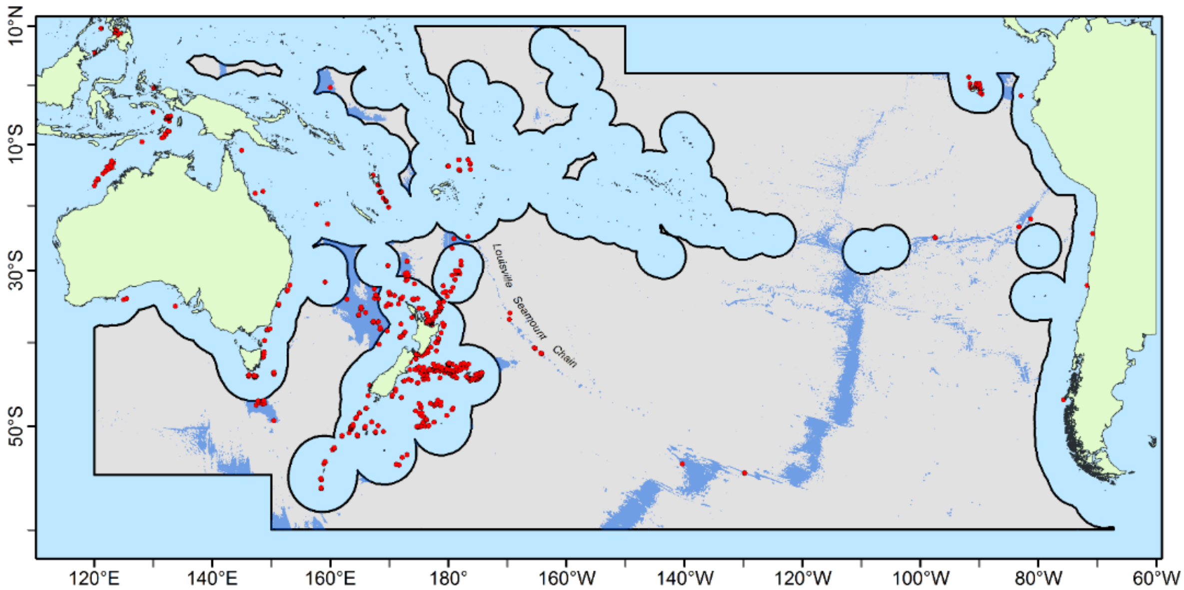

Figure 5: The SPRFMO Convention Area (grey) and regions within it where water depth is between 200 and 3000 m (dark blue). Red dots indicate the location of the 1643 presence records of reef-forming scleractinian corals used in the habitat suitability models (note the paucity of information outside EEZs).

Table 1: Number of unique presence records available for modelling of VME indicator taxa within the SPRFMO Area and adjacent EEZs.

Taxon / group	N records
Phylum Porifera – Sponges	31 405
Phylum Cnidaria, Class Anthozoa,	
Order Actiniaria – Anemones Order Alcyonacea – Soft corals and the gorgonian sea	14 315
fans (previously Gorgonacea)	25 005
Order Pennatulacea – Sea pens	1 432
Order Scleractinia – Stony corals	120 792
Order Antipatharia – Black corals	2 837
Class Hydrozoa, Order Anthoathecatae, Family Stylasteridae – Hydro corals	4 034
Phylum Echinodermata, Class Crinoidea – Sea lilies	2 006
Class Asteroidea, Order Brisingida – Armless stars	754

Anderson et al. (submitted) describe the predictions of “presence-only” MaxEnt and BRT habitat suitability models developed for these four deep-sea reef-forming coral species, with a focus on the Louisville Seamount Chain east of New Zealand. The likelihood of habitat suitable for reef-forming corals on these seamounts was predicted to be variable, but very high in some regions, particularly where levels of aragonite saturation, dissolved oxygen, and particulate organic carbon were suitable (Figure 6). Eleven environmental variables were included in the models, based on global seafloor estimates from Davies & Guinotte (2011) who re-scaled 3-dimensional gridded datasets of existing information on using the highest resolution (~1km^2) predictions of global bathymetry available (SRTM30, Becker et al. 2009). This approach was necessary to provide seafloor estimates for environmental variables where actual bathymetry and local environmental data have not yet been collected.

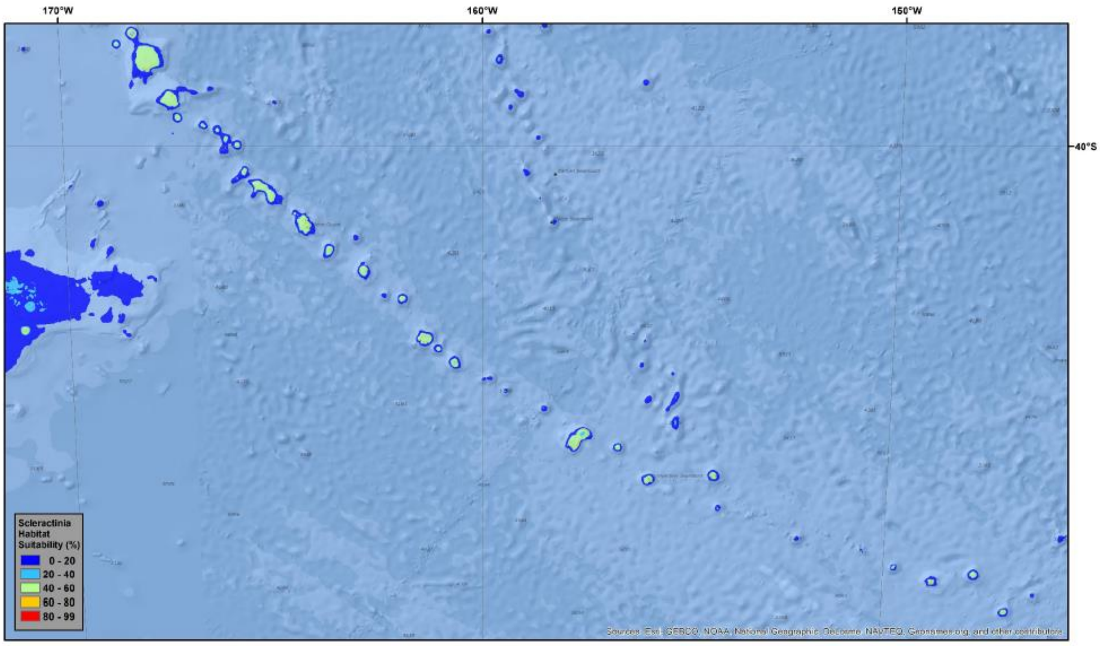

Figure 6 (after Figure 5 of Rowden et al. 2015): Map showing the predicted habitat suitability for the key indicator taxon, Scleractinia (stony corals) on the southern part of the Louisville Seamount Chain.

Anderson et al. (submitted) described tests of these model predictions using a photographic survey (voyage TAN1402, Clark et al., 2015, see Figure 7) of six large seamounts in the Louisville Seamount Chain, selected to provide as wide a geographic range as possible given the voyage duration. Bottom trawling has occurred on all of these seamounts and most (excluding Forde and Censeam) are currently open to bottom trawling by New Zealand vessels. All six seamounts examined have a vertical elevation of more than 1 km from the surrounding seafloor. Bathymetric surveying, photographic transects, CTD casts, and collection of specimens using epibenthic sleds were nested in a stratified random design (Figure 8, see also Table 3).

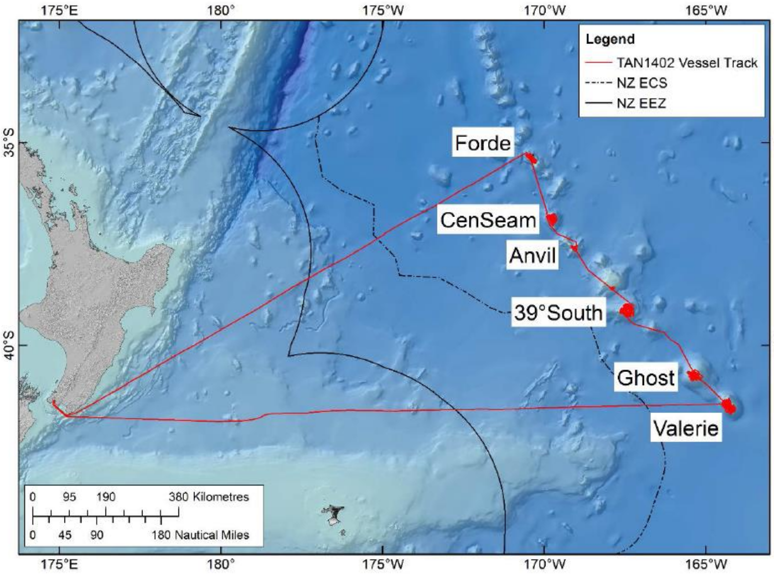

Figure 7: Track of RV Tangaroa during voyage TAN1402 (showing the route from Wellington to Forde Guyot, southeast along the Louisville Seamount Chain to Valerie Guyot, and return to Wellington), 31 January to 6 March 2014. New Zealand's Exclusive Economic Zone and Extended Continental Shelf are shown as solid and dashed black lines, respectively.

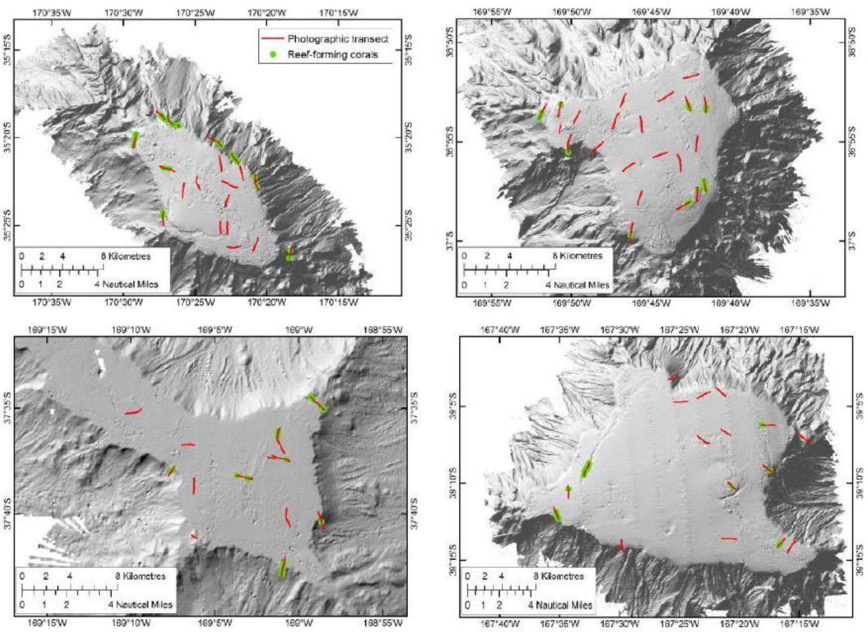

Figure 8 (after Clark et al. 2015): Example distributions of VME indicator taxa: reef-forming scleractinian (stony) corals on Forde (top left) Censeam (top right), Anvil (bottom left), and 39 South (bottom right) seamounts (data from Ocean Floor Observation Protocol software (OFOP)).

A key finding of the field validation was that the global SRTM30 bathymetry dataset of predicted depths was not accurate for most of the area sampled during the voyage. For some seamounts, there was reasonable correlation between predicted and observed depths (Table 2), but there was a strong and systematic bias such that many locations predicted to be very deep were found to be many hundreds of metres shallower (Figure 9). This is important because the environmental predictor variables used in models of VME indicator taxa are highly dependent on depth, and large errors in predicted depth will be propagated through the predictor variables and into the habitat suitability predictions. This is particularly relevant in locations where there is very little ship sounding data or multi-beam acoustic mapping to tune global bathymetry models.

Table 2: Correlation between depths predicted from the global SRTM30 dataset and observed during voyage TAN1402 and the number of cells sampled in each area.

Seamount	Estimated correlation coefficient	Number of cells sampled
Forde	0.26	46
CenSeam	0.35	57
Anvil	0.17	28
39 South	0.70	49
Ghost	0.78	95
Valerie	0.73	47
All combined	0.58	326

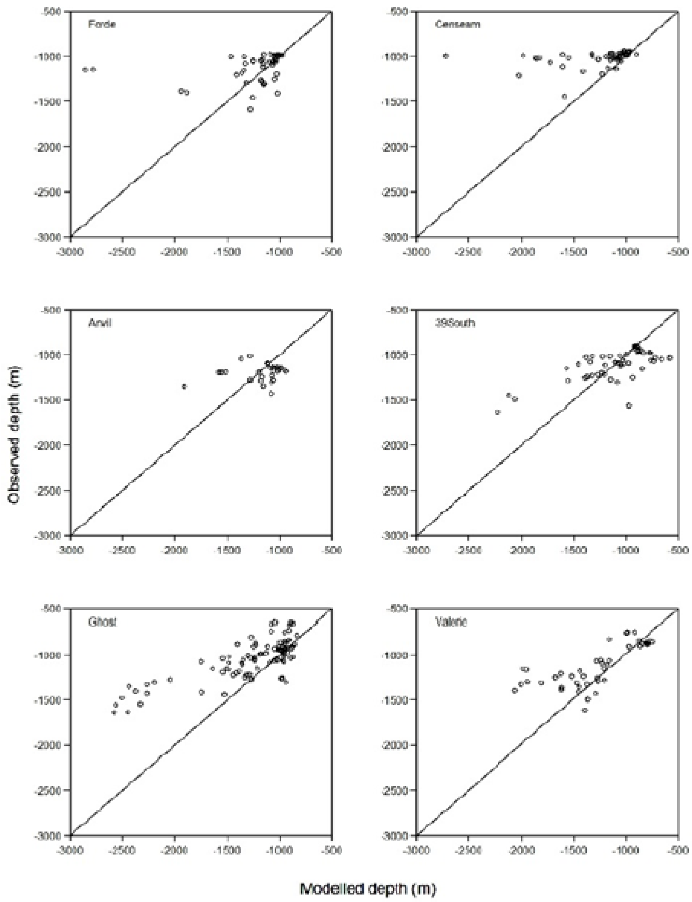

Figure 9: Relationship between depths predicted from the global SRTM30 bathymetry dataset and observed depth by cell for the six seamounts sampled during TAN1402.

The observed frequency of coral occurrence in photographs (descriptive data in Figure 10) was much lower than expected during the field validation survey, and patterns of observed versus predicted coral distribution were not well correlated. The authors considered this was largely because many of the environmental predicator variables used were scaled to 1 km resolution using a global bathymetry data set that was found to be very imprecise in the validation area (sometimes biased by many 100s of metres depth). In addition, models are difficult to fit because of the great scarcity of recorded species absences and the lack of data on the geomorphology and substrate of the seamounts at scales appropriate to the modelled taxa. Despite these challenges, Anderson et al. (submitted) consider that the models predict the likelihood of suitable habitat for coral VME indicator taxa at a coarse-scale (i.e., at the scale of a large topographic feature such as a seamount or ridge, but not at within-feature scale.

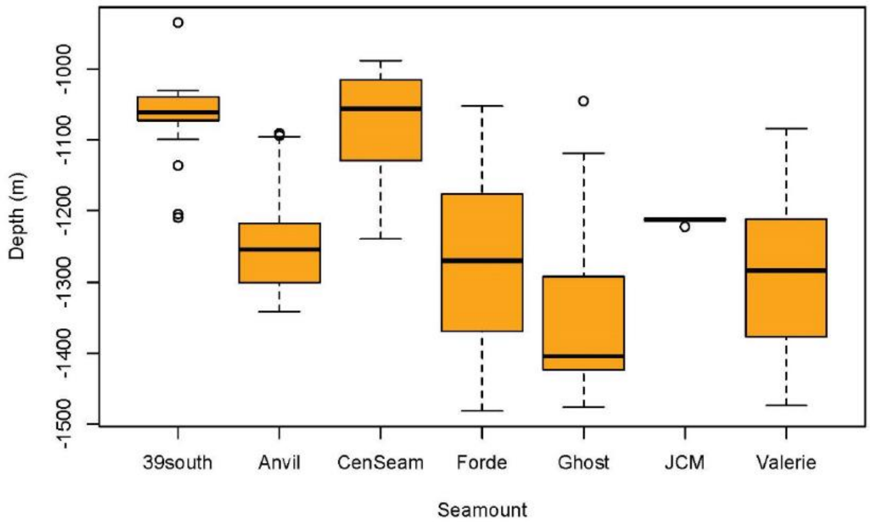

Figure 10: Depth distribution of live scleractinian (stony) corals on the surveyed seamounts. The plot shows the median (bar), upper and lower quartiles (box), and total range (circles) (from Clark et al. 2015).

Anderson et al.'s (submitted) field-based test demonstrates the need to use caution when interpreting and applying broad-scale, presence-only model results for fisheries management and conservation planning in data poor areas of the deep sea. Future improvements in the predictive performance of broad-scale models (i.e. SPRFMO Area-scale models) will rely on the continued advancement in modelling of environmental predictor variables, refinements in modelling approaches to deal with missing or biased inputs, and incorporation of true absence data. Additional biological data on the distribution of VME indicator taxa will undoubtedly help, but such data will probably always be limiting. Meanwhile, regional-scale models that use regional-tuned environmental data offer potentially more reliable information on the likely distribution of VME indicator taxa in the part of the SPRFMO Area of most interest to the New Zealand High Seas fishery.

Table 3: Stratification of sampling on voyage TAN1402 to the Louisville Ridge to test the predictive power of models of the distribution of VME indicator taxa (summarised from Tables 2 and 11 of Clark et al. 2015). BRT, boosted regression tree; MaxEnt, maximum entropy; DTIS, deep-towed imaging system.

Stratum	Conditions	Stony coral predicted?	N DTIS tows	N stony coral observed
1	High probability (>0.8) of suitable habitat for stony corals, both BRT and MaxEnt models, unfished	Yes	40	19
2	Low probability (<0.2) of suitable habitat for stony corals, both BRT and MaxEnt models, unfished	No	13	11
3	Models predict different probabilities (one high, one low), unfished	Yes/No	23	2
4	Intermediate probability of suitable habitat for stony corals (neither high nor low), BRT model, unfished	Yes/No	29	12
5	High probability of suitable habitat for stony corals, both BRT and MaxEnt models, fished.	Yes/No	12	4

2.3. Recent New Zealand regional-sale models

Anderson et al. (in prep) have made improved regional-scale habitat suitability models for VME indicator taxa. They used additional biological data (see Table 4), including records of absence from historical survey data, and new bathymetry data combined with existing environmental, chemical and physical data to produce a set of 52 predictor variables for the seafloor (Appendix 1). Nine of these variables were selected for use in new regional-sale models based on low covariance with other variables and high explanatory power (Table 5) and two other variables were included in some models based on their expected importance for eco-physiological requirements (bottom of Table 5).

As in previous habitat modelling work for the SPRFMO Area, BRT and MaxEnt modelling approaches were used to make new predicted distribution maps for these 11 VME indicator taxa in the New Zealand region (Figure 11). Historical biological survey data was used to provide models with absence data (BRT) or target-group background data (MaxEnt). Model agreement was high, with each model predicting areas of suitable habitat both in the vicinity of known VME indicator taxa presence locations as well as across broad regions of un-sampled seafloor where environmental conditions were suitable. Comparison with outputs for the earlier models (see Section 2.1) shows a much greater agreement between BRT and MaxEnt model predictions for the new regional models. Model performance measures, including cross-validation testing of models against sets of spatially independent data, did not clearly indicate a preferred model type across all taxa modelled (Tables 6 and 7).

Table 4: VME "vulnerable" taxa and habitat indicator taxa modelled, and number of presence and absence records used. The codes used in Tables 5 and 7 are also given.

Modelled taxa	**Number of records**		**Code**
	Presence	**Absence**	
Vulnerable taxa			
Phylum Cnidaria			
Order Scleractinia			
Solenosmilia variabilis	475	26 025	SVA
Madrepora oculata	246	26 072	MOC
Enallopsammia rostrata	242	26 061	ERO
Goniocorella dumosa	536	25 968	GDU
Order Anthoathecatae			
Family Stylasteridae	1 585	26 311	COR
Order Antipatharia	1 278	26 481	COB
Order Pennatulacea	917	26 497	PTU
Phylum Porifera			
Class Demospongiae	3 459	25 969	DEM
Class Hexactinellidae	1 562	26 208	HEX
Habitat indicators			
Phylum Echinodermata			
Order Brisingida	653	26 574	BRG
Class Crinoidea	479	26 446	CRI

Table 5: Selected variables for regional habitat predictive models for each of 11 taxa based on analysis of correlations and expected eco-physiological importance. Variables are listed here in approximate order of importance from initial model runs for reef-forming scleractinian corals.

Variable	**SVA**	**MOC**	**ERO**	**GDU**	**DEM**	**HEX**	**COB**	**COR**	**PTU**	**BRG**	**CRI**
oa_w, omega aragonite	√	√	√	√	–	–	–	–	–	–	–
poc, particulate organic carbon export	√	√	√	√	√	√	√	√	√	√	√
sal_w, salinity	√	√	√	√	√	√	√	√	√	√	√
sigma_w, sigma theta	√	√	√	√	√	√	√	√	√	√	√
temp_w, temperature	√	√	√	√	√	√	√	√	√	√	√
stdev_slop, SD of slope	√	√	√	√	√	√	√	√	√	√	√
bpi_broad, bathymetric position index	√	√	√	√	√	√	√	√	√	√	√
slope_per, slope (%)	√	√	√	√	√	√	√	√	√	√	√
oxy_w, oxygen	√	√	√	√	√	√	√	√	√	√	√
oc_w, omega calcite	–	–	–	–	–	–	–	–	–	√	√
sil, silicate	–	–	–	–	√	√	–	–	–	–	–

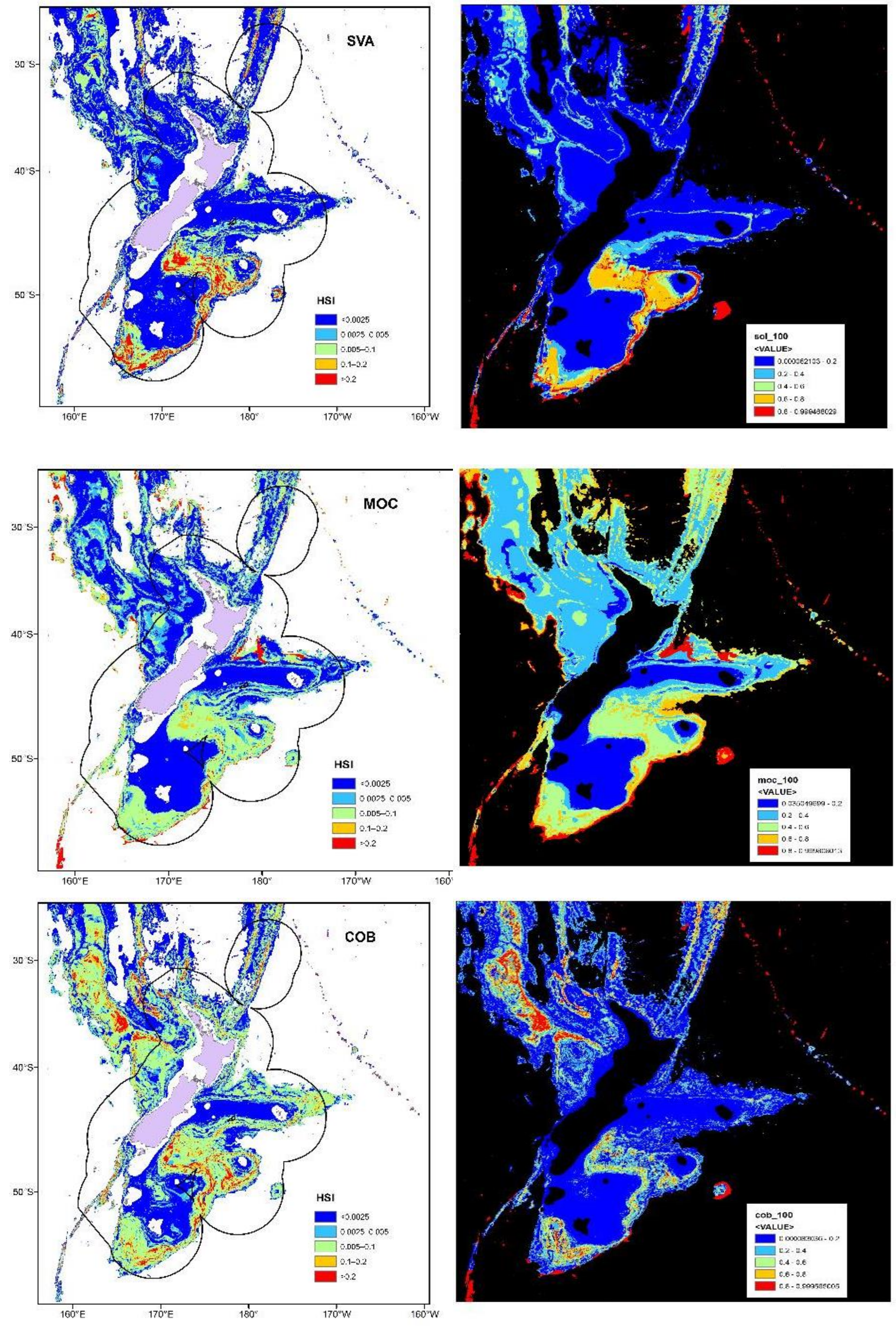

Figure 11: Results of New Zealand regional-scale predictive modelling of the distribution of the reef-forming stony corals *Solenosmilia variabilis* (top) and *Madrepora oculata* (centre) and black corals, Antipatharia (bottom). In each case, BRT maps on the left and MaxEnt maps on the right.

Table 6. Model performance. Percent deviance explained, AUC from external 10-fold cross-validation, AUC from train/test data (25%/75%).

BRT models	%deviance	Internal CV	External CV	AUC 25% test data
Enallopsammia rostrata	69.1	0.956	0.741	0.853
Solenosmilia variabilis	55.0	0.980	0.752	0.939
Madrepora oculata	77.8	0.936	0.716	0.842
Goniocorella dumosa	75.6	0.963	0.659	0.853
Stylasteridae	71.5	0.950	0.733	0.875
Antipatharia	57.7	0.965	0.803	0.914
Pennatulacea	81.6	0.901	0.674	0.832
Demospongiae	77.8	0.965	0.622	0.884
Hexactinellidae	84.1	0.887	0.696	0.821
Brisingida	85.4	0.860	0.680	0.835
Crinoidea	75.0	0.941	0.772	0.875
MaxEnt models				
Enallopsammia rostrata	–	–	0.796	0.889
Solenosmilia variabilis	–	–	0.832	0.896
Madrepora oculata	–	–	0.632	0.883
Goniocorella dumosa	–	–	0.726	0.890
Stylasteridae	–	–	0.756	0.837
Antipatharia	–	–	0.772	0.905
Pennatulacea	–	–	0.637	0.799
Demospongiae	–	–	0.571	0.785
Hexactinellidae	–	–	0.665	0.789
Brisingida	–	–	0.615	0.775
Crinoidea	–	–	0.734	0.881

Table 7. Estimated performance of NZ regional-scale models: results of external 10-fold taxon-by-site cross-validation.

	site1	**site2**	**site3**	**site4**	**site5**	**site6**	**site7**	**site8**	**site9**	**site10**	**Av AUC**
MaxEnt models:											
PTU	0.59	0.58	0.74	0.58	0.62	0.56	0.71	0.76	0.72	0.51	0.64
HEX	0.75	0.81	0.65	0.72	0.55	0.69	0.79	0.53	0.62	0.57	0.67
SVA	0.93	0.84	0.75	0.77	0.86	0.88	0.85	0.69	0.91	0.84	0.83
GDU	0.58	0.52	0.82	0.72	0.76	0.80	0.85	0.73	0.77	0.72	0.73
MOC	0.53	0.24	0.68	0.75	0.79	0.82	0.75	0.42	0.76	0.58	0.63
ERO	0.74	0.86	0.92	0.78	0.60	0.80	0.83	0.83	0.85	0.74	0.80
COB	0.76	0.93	0.83	0.89	0.74	0.79	0.76	0.69	0.60	0.72	0.77
DEM	0.67	0.76	0.59	0.73	0.54	0.58	0.54	0.29	0.51	0.52	0.57
BRG	0.51	0.54	0.47	0.60	0.74	0.58	0.68	0.77	0.66	0.61	0.62
COR	0.83	0.87	0.86	0.82	0.54	0.76	0.85	0.55	0.69	0.78	0.76
CRI	0.87	0.72	0.61	0.60	0.71	0.80	0.93	0.59	0.79	0.73	0.73
BRT models:											
PTU	0.65	0.62	0.74	0.78	0.64	0.62	0.77	0.67	0.71	0.54	0.67
HEX	0.64	0.77	0.75	0.80	0.72	0.71	0.65	0.61	0.57	0.74	0.70
SVA	0.84	0.67	0.93	0.75	0.82	0.71	0.69	0.70	0.72	0.69	0.75
GDU	0.51	0.59	0.64	0.73	0.59	0.68	0.71	0.72	0.76	0.66	0.66
MOC	0.68	0.73	0.83	0.80	0.69	0.69	0.70	0.65	0.79	0.60	0.72
ERO	0.75	0.93	0.95	0.64	0.85	0.63	0.56	0.84	0.36	0.90	0.74
COB	0.79	0.95	0.85	0.96	0.85	0.79	0.68	0.82	0.62	0.72	0.80
DEM	0.69	0.75	0.60	0.78	0.58	0.52	0.60	0.39	0.66	0.65	0.62
BRG	0.57	0.70	0.61	0.76	0.75	0.72	0.77	0.76	0.59	0.57	0.68
COR	0.75	0.79	0.77	0.84	0.71	0.66	0.76	0.60	0.76	0.69	0.73
CRI	0.75	0.79	0.79	0.66	0.83	0.80	0.80	0.68	0.91	0.71	0.77

Despite their importance to spatial management planning, previous habitat suitability analyses and distribution maps have rarely accounted for model precision. Anderson et al. (in prep) used a bootstrap re-sampling technique to produce precision maps to accompany each habitat suitability map (Figure 12). These maps show wide differences in the uncertainty of predictions for different taxa, in different areas, and, sometimes, using different modelling approaches.

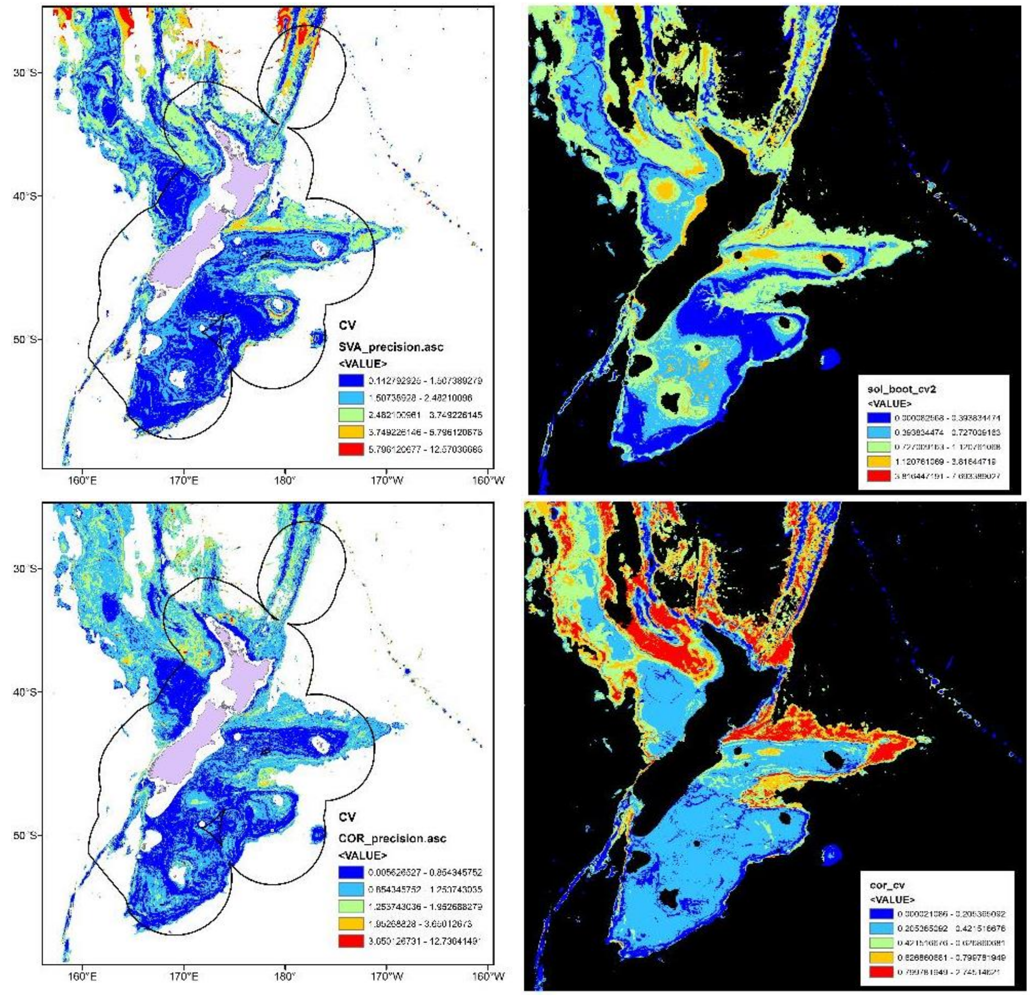

Figure 12: Estimated (bootstrap) model uncertainty of habitat suitability indices for *Solenosmilia variabilis* (top) and Stylasteridae (bottom) (left, BRT; right, MaxEnt)

Because of the similar performance and predictions of BRT and MaxEnt habitat suitability models in their most recent study, Anderson et al (in prep) suggest that the best approach to incorporating model results into spatial management planning, for example using decision-support tools, may be to use both models, or to average predictions from the two techniques or select the model with the best performance for each taxon.

3. Options for designing spatial management measures

3.1. Available approaches

The practical challenges of objectively selecting an optimum or near-optimum set of areas to conserve biodiversity (e.g., to protect VMEs) over large geographic areas that support numerous species has led to the development of a number of decision-support software tools (Leslie et al., 2003). Such tools have the ability to integrate the diverse natural (e.g., biological and oceanographic) and social (e.g., economic) data sets needed to implement effective spatial management. Marxan and Zonation are the two most commonly used such tools mentioned in studies published in the scientific literature, but many other approaches and tools have been used (including methods applied by CCAMLR for the design of potential Ross Sea protected area(s) (Sharp & Watters 2011).

Marxan is primarily designed to achieve some minimum representation of specified conservation targets for the least possible cost (Ball & Possingham 2000, McDonnell et al., 2002, Game & Grantham 2008). Marxan executes a user-specified number of runs and identifies alternative sets of priority areas for achieving the conservation targets for each iteration. The software finds multiple alternative putative solutions starting from a completely random reserve system. Trial solutions are iteratively explored and evaluated through sequential random changes to the reserve system. This process allows the software to explore sub-optimal solutions, increasing the number of routes by which the global optimum might be reached (Possingham et al., 2000), thereby minimising the risk of choosing local optimums. The best run is the one that meets the largest number of the user-defined biodiversity targets with the minimum cost, but solutions are not required to achieve all biodiversity targets and cost can be defined in multiple ways. Marxan can identify locations that are “irreplaceable” in the reserve system in the sense that these locations are present in a very high proportion of solutions and few options exist for their replacement in the system (Ferrier et al., 2000). Conversely, locations that occur in a lower proportion of solutions can be replaced in the reserve system by other locations with similar biodiversity characteristics (Nel et al., 2009).

Zonation does not require the specification of target representation levels, minimum site sizes or minimum number of areas or replicates (Moilanen et al., 2005, Moilanen & Kujala 2006). Zonation starts by assuming that the full landscape is protected and progressively identifies and removes locations that cause the smallest marginal losses in conservation value. The estimate of marginal loss can include considerations such as species weighting or species-specific connectivity. Generating options for spatial measures to protect a wide variety of species is best done using the Core Area Zonation (CAZ) cell removal rule (Moilanen 2007, Leathwick et al., 2008). This approach gives the highest values to the most important locations within each species distribution, regardless of whether these sites are also important to other species (Moilanen et al., 2009), and thus aims to protect at least some high-quality area for all species, including those that occur in otherwise species-poor areas (Leathwick et al., 2008). Zonation produces a nested hierarchical prioritisation of the landscape based on the conservation value of locations such that, for example, the best 1% of the landscape occurs within the best 2%, which is within the best 5% and so on. The priority values can be used to identify cells that have high value for protection at any level of geographic representation. Zonation does not specifically identify optimal set(s) of locations or irreplaceability measures.

Sharp & Watters (2011, but see also Sharp et al. 2010 for extensive source data) describe New Zealand's approach to the design of a potential Ross Sea protected area using the following steps:

1. Define specific protection objectives for protected areas that will contribute to achievement of the overall management aims.
2. For each protection objective, identify target areas, the protection of which will contribute to achievement of the objective. Typically these come from spatially explicit data layers.
3. For each target area, assign a numerical protection target reflecting the desired level of protection for that area.
4. Define spatially explicit representations of the cost of protected area designation to competing objectives such as fishing.
5. Define additional constraints (if any) on protected area scenario design.
6. Develop and evaluate scenarios that meet protection targets for each identified target area to the extent possible while minimising cost, and mindful of other constraints.
7. Optimisation may be possible by iterative adjustment and evaluation against agreed performance metrics related to protection targets and cost, or by the use of a decision-support tool such as MARXAN or Zonation.

It can be seen that this procedure mirrors or duplicates the algorithms within software tools when suitable data layers are available and, indeed, there was remarkable concordance between the New Zealand protected area scenario for the Ross Sea and output from a parallel analysis using Marxan informed by the same data layers, conservation targets, and cost assumptions (Figure 13, Sharp & Watters 2011).

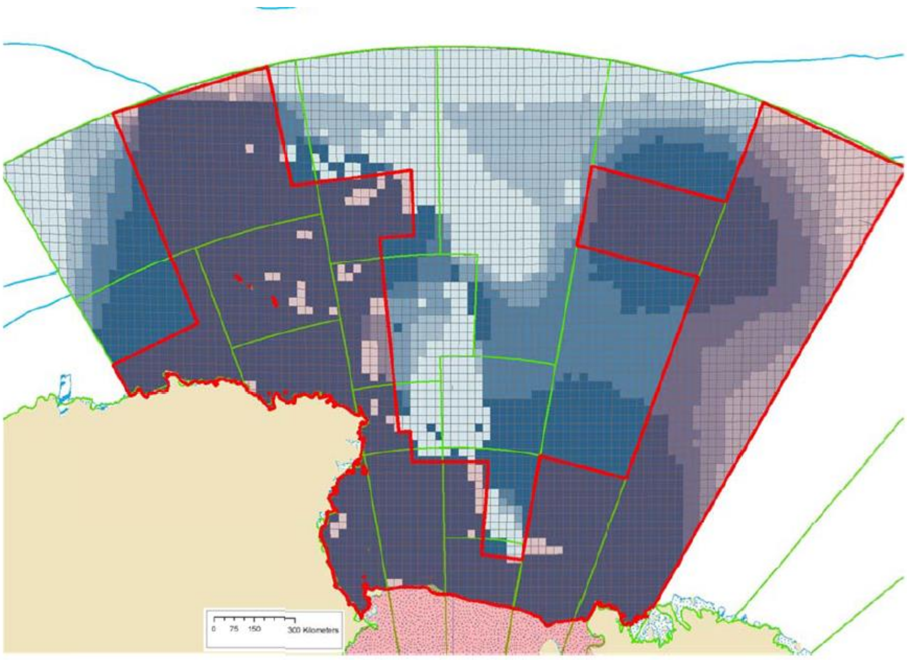

Figure 13 (after Figure 4 of Sharp & Watters 2011): Comparison of New Zealand's protected area scenario for the Ross Sea (outlined in red) and Marxan output (shades of blue, darker colours show higher frequency of inclusion in Marxan solutions) using the same targets and cost layers. CCAMLR management areas are outlined in green.

3.2. Initial assessment of the use of decision-support tools for the SPRFMO Area

Rowden et al. (2015) report on a study where the decision-support tool Zonation was applied to predictions from habitat suitability models and historical fishing data to develop options for the spatial management of the SPRFMO area. They used preliminary habitat suitability maps (not field-validated) for VME indicator taxa at bathyal depths across the entire SPRFMO area (see Figure 3), but noted the uncertainities inherent in the modelling approach, especially given the sparse data. They recommended that these issues be progressively addressed to make more reliable predictive maps for areas like the SPRFMO Convention Area (see also conclusions of section 2.2).

Rowden et al. (2015) incorporated a bioregional component in the prioritisation of areas for protection using an existing global biogeography. However, they noted that this physico-chemical based scheme was largely untested for the SPRFMO Area, and future spatial management design trials could use alternative biogeographic schemes or stratifications to achieve a geographic spread of protection prioritisation.

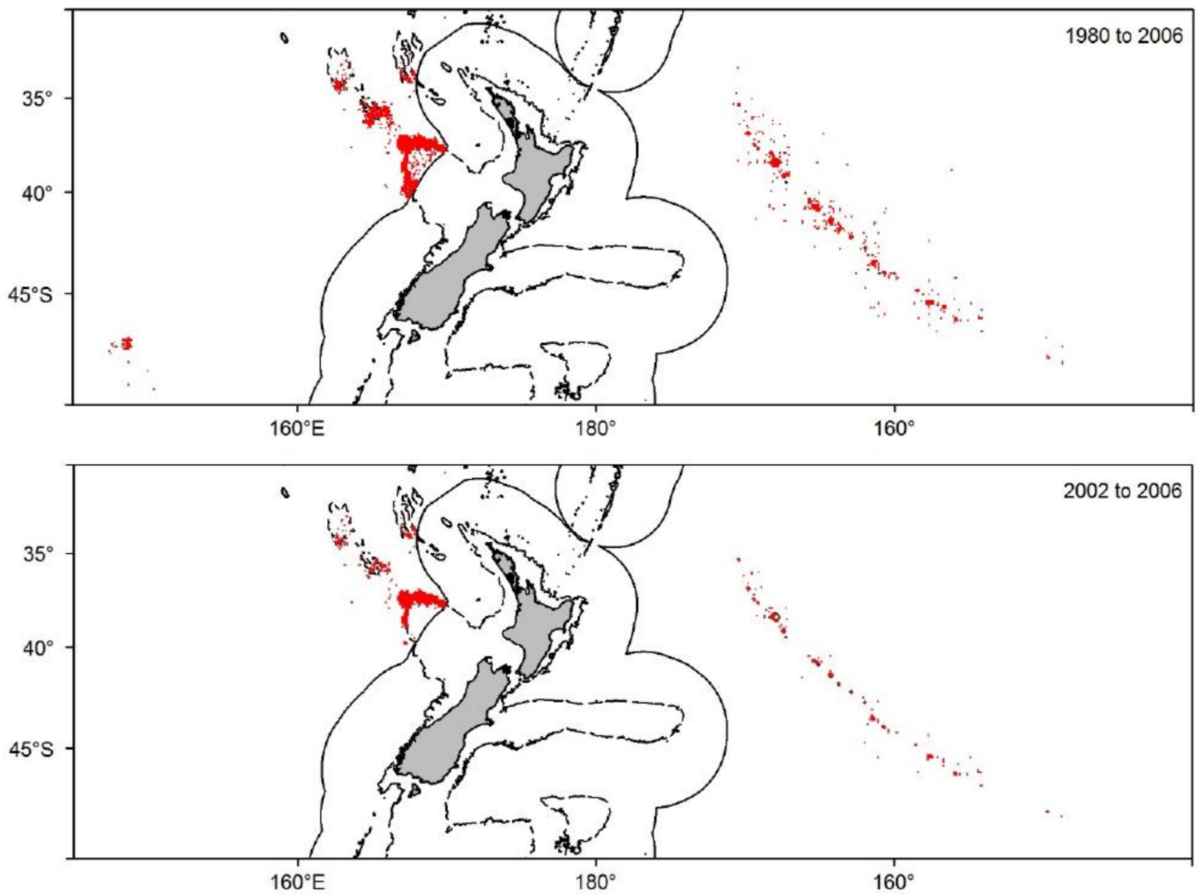

Figure 14 (after Figure 7 of Rowden et al. 2015): The bottom trawl footprint of the New Zealand orange roughy fishery between 1980 and 2006 (top) and for the reference years 2002 to 2006 (bottom), based on 0.1° latitude/longitude cells occupied.

Rowden et al. (2015) used data from the New Zealand orange roughy fishery as the cost layer (Figure 14) because reliable tow-by-tow information is available and, since New Zealand has taken a relatively large proportion of the total orange roughy catch, this data set is thought to be a reasonable proxy for the trawl footprint of all nations combined. The trawl footprint of the entire history of the fishery (1980–2012) is notably larger than the reference trawl footprint (2002–2006) that was used by New Zealand to design closed and open areas under the SPRFMO interim measures. Rowden et al.'s spatial management modelling results were sensitive to the choice of trawl footprint years, and this would be an important consideration for any future analyses. In particular, if the footprint over a short period is used, some locations may be identified as high priority for protection when they may no longer support VME indicator taxa. Penney & Guinotte (2013) pointed out that the observed age of the dominant habitat forming scleractinian coral in the New Zealand region, *Solenosmilia variabilis* (Neil et al. 2011), suggests that re-establishment of small colonies could take hundreds of years, and re-establishment of large colonies (2–3 m across) could take thousands of years. The degree to which seabed biodiversity is likely to have been reduced in fished areas is therefore an important factor to consider in risk assessments and when evaluating the cost-benefit of alternative spatial management measures (Penney & Guinotte, 2013, Rowden et al. 2015).

The cost to fishing (in terms of space or catch likely to be displaced or lost to the fishery) if high priority areas for VME indicator taxa were to be protected was estimated for a wide variety of scenarios. In general, the cost to fishing was relatively low, given the relatively high proportion of suitable habitat for VME indicator taxa protected (Table 8). Although some areas were frequently identified as high priorities for protection by Zonation, the location and patchiness of high priority areas varied, as expected, with modelling assumptions (especially aggregation rules), the choice of biogeographical treatment, the choice of footprint years, and the metric of "cost" (catch, space, or effort) (e.g., Figure 15).

Table 8 (after Table 13 of Rowden et al 2015): Estimates using Zonation software of the percentage of orange roughy catch within New Zealand's trawl footprint lost to fishing in the SPRFMO area, if high priority areas (top 5–20%) for VME indicator taxa are closed under different cost model scenarios.

	Top high priority areas for VME indicator taxa			
	5%	10%	15%	20%
Model Scenario				
Catch (1980–2012) with aggregation rule	1.30	1.54	18.23	18.37
Catch (1980–2012) without aggregation rule	0.01	0.03	0.04	0.05
Un-weighted bioregions, 1980–2012 catch, aggregation	0.09	0.15	0.56	1.38
Un-weighted, 1980–2012 catch, no aggregation	0.01	0.03	0.04	0.05
Catch (2002–2006) with aggregation rule	1.66	7.56	10.77	10.80
Catch (2002–2006) without aggregation rule	0.03	0.06	0.10	0.13

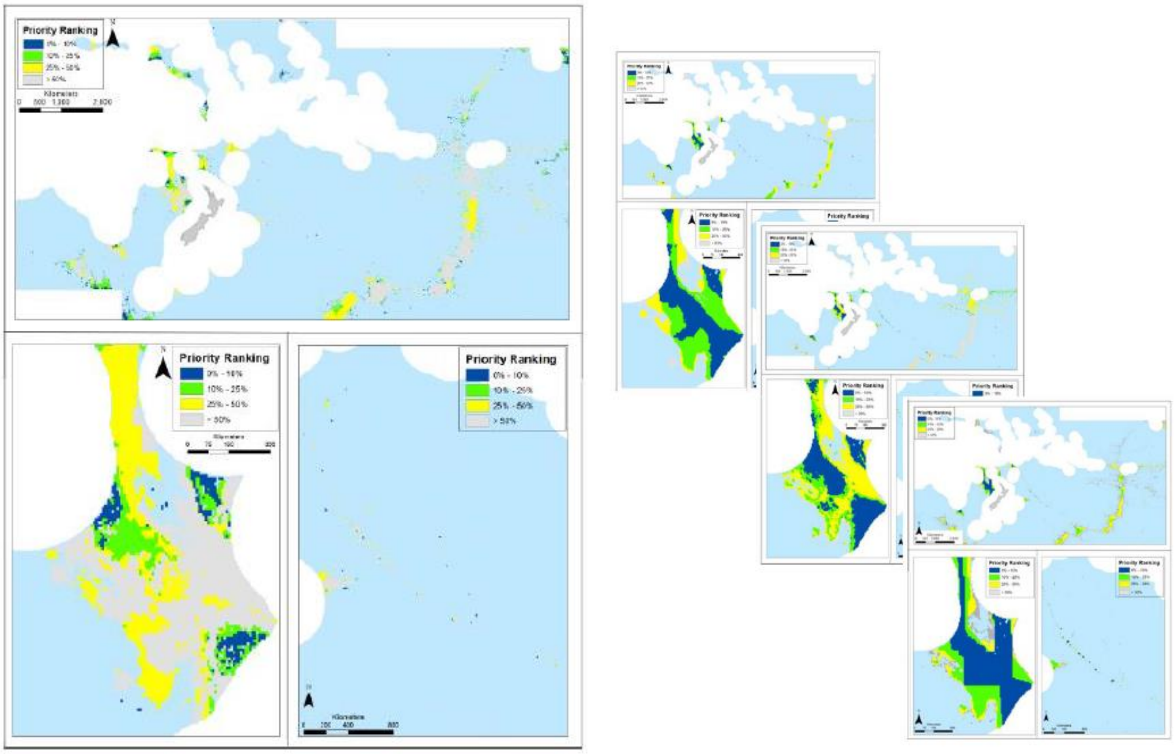

Figure 15: Example outputs from Zonation analyses conducted by Rowden et al. (2015). The left panel shows a run where the full range of suitability values for all VME indicator taxa were used, no aggregation rules were applied, the longest fishing footprint was applied as a cost layer (1980-2012), and un-weighted biogeographic provinces were applied. Under this scenario, closing the top 10% of priority areas for VMEs to fishing would displace or lose 0.03% of the catch from within the fishing footprint. The right panels show other clearly-different scenarios.

Rowden et al. (2015) concluded that, despite the need to improve the future application of Zonation and other similar software tools to develop spatial management options for VMEs in the SPRFMO Area, outputs from their study, or future similar studies, could be considered a starting point for discussions about where and what size closed areas could be put in place to protect VMEs and how such spatial management measures could be designed.

3.3. Recent progress using decision-support tools

3.3.1. General considerations

The exploration of the use of decision-support tools reported by Rowden et al. (2015) (section 3.2 above) is currently being updated using the recently improved regional-scale habitat suitability models for VME indicator taxa (see section 2.3). Both BRT and MaxEnt habitat suitability models for 11 VME indicator taxa are being used, along with the latest fishing catch and effort data for bottom and mid-water trawls for two time periods supplied by MPI. The scenarios explored using the

Zonation decision-support tool will not include the New Zealand EEZ. The output maps produced by the Zonation analysis are colour coded to indicate the sites (grid cells) that are of the highest to lowest priority for protection, based on the assumptions of each scenario.

The following sensitivity analyses have already been conducted to evaluate the usefulness and sensitivity of this particular decision-support tool to assist in the design of spatial management measures for VME indicator taxa in a part of the SPRFMO Area (Rowden et al. in prep)

- Changing the method of estimating the habitat suitability model
- Including uncertainty from the habitat suitability model
- Including different cost layers (potential lost fishing opportunities)
- Using different time periods for the index of fishing

Preliminary results for these four sensitivities are shown in the following section. Work continues on incorporating a revised bioregionalisation appropriate to the scale of this analysis and an index of "naturalness" of VMEs by cell.

There are a number of options within the Zonation software that create more aggregated solutions, such that larger numbers of cells are grouped together in solutions more practical for management than a suite of smaller, more fragmented groups of cells. As this work progresses, two of these methods will be assessed: 'edge removal' and Boundary Length Modifier (BLM). Scenarios will be compared with and without the default 'edge removal' rule (where cells with fewer neighbours, i.e. on the edge, are given lesser priority for biodiversity). The second aggregation, BLM, is not taxa-specific, and uses algorithms that reduce the length of the perimeter of the combined cells, thus reducing fragmentation and increasing aggregation. All preliminary simulations were prepared using the edge removal rule.

3.3.2. Sensitivity to choice of habitat suitability model

Habitat suitability maps derived using both BRT and MaxEnt models for all 11 VME indicator taxa were used in Zonation to generate a protection prioritisation maps. Both model types were used because no single model type consistently outperforms the other (see section 2.3). Because the models produce different ranges of habitat suitability values, they were not simply averaged to generate a single habitat suitability input nor was the best model for each VME indicator taxa used selectively (as suggested by Anderson et al. in prep). Generally there was good concordance between the prioritisation maps produced using the two models, with notable exceptions for some hotspots of high priority protection areas (e.g. New Caledonia Trough, see Figure 16). These differences are considered significant for it to be sensible to proceed through all steps of the analysis using outputs from both habitat suitability models.

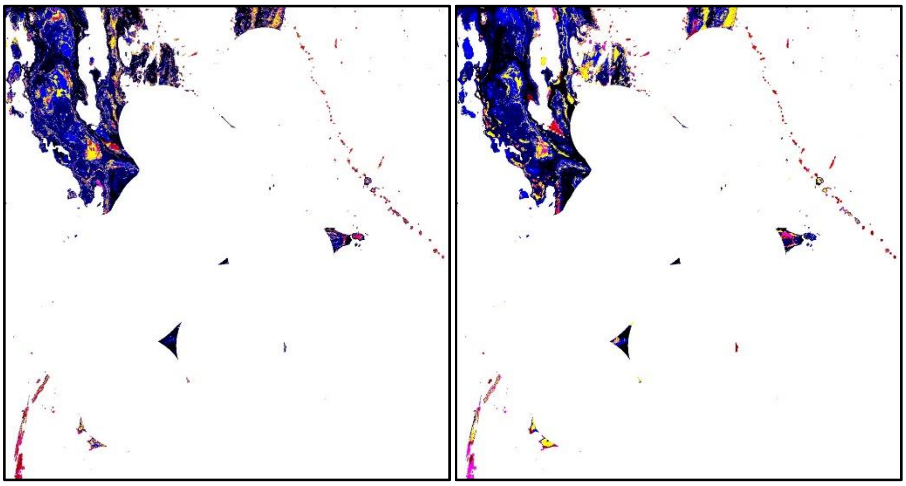

Figure 16: Preliminary Zonation output for the prioritisation protection scenario with full range of habitat suitability values for all VME indicator taxa but excluding uncertainty. [top 2% priority = red, 2-5% = brownish, 5-10% = pink, 10-25% = yellow, 25-50% = blue, 50-100% = black). Left, BRT habitat suitability model, right, MaxEnt habitat suitability model.

3.3.3. Sensitivity to including uncertainty

Data layers for the spatial distribution of uncertainty associated the habitat suitability maps for each of the 11 VME indicator taxa (see Figure 12 in section 2.3) were included in the next scenario. To incorporate uncertainty in Zonation, habitat suitability models are adjusted using 'distribution discounting', i.e., values in each cell for each species' model are reduced by the degree of uncertainty in that habitat suitability model; uncertainty layers can be weighted to determine the relative impact of uncertainty of the distribution. Initial assessments with different weightings for the uncertainty layers were completed to determine an appropriate weighting that incorporated the uncertainty data but did not bias the results such that uncertainty prevented the inclusion of the highest priority areas in the scenario solution. A weighting of 0.2 (from 0.0, 0.2, 0.5, 1.0, and 5.0 times the CV for each suitability model) was selected as the most appropriate weighting to apply to the uncertainty data layers for each habitat suitability data layer, for both models and a comparison between runs without uncertainty and an uncertainty weighting of 0.2 is shown in Figure 17.

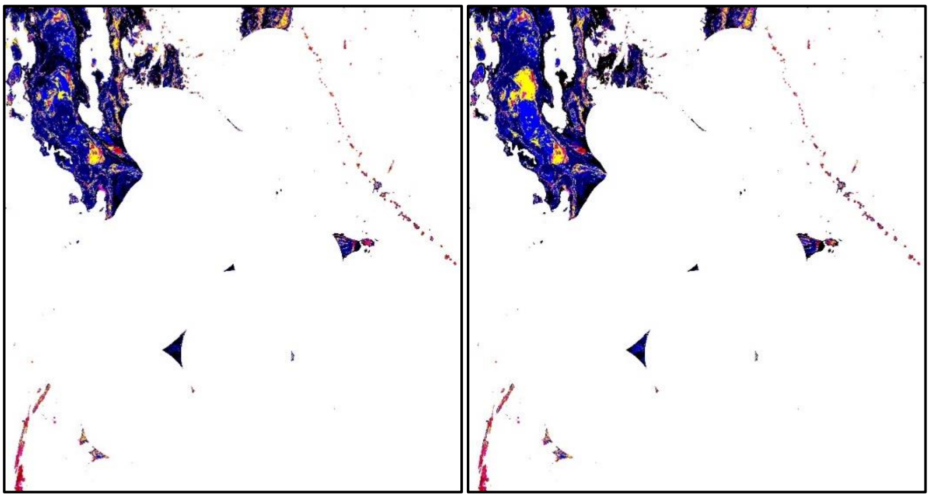

Figure 17: Preliminary Zonation output for the prioritisation model scenario with full range of habitat suitability values for all VME indicator taxa (based on BRT models) without uncertainty (left) and with weighted uncertainty at x0.2 (right) [top 2% priority = red, 2-5% = brownish, 5-10% = pink, 10-25% = yellow, 25-50% = blue, 50-100% = black]

3.3.4. Sensitivity to inclusion and choice of cost layer

Tow-by-tow trawl data were obtained from MPI for all bottom and midwater trawl fishing events by New Zealand vessels outside the EEZ from 1989/90 to 2013/14 (as at June 2015). Full effort details and catch by species information were provided, totalling ~50,000 records. A number of automated and manual checks and grooming procedures were carried out before these data were included in the Zonation analysis. The final dataset totalled 48,500 tows, of which 48,000 were bottom trawl. There were 500 midwater trawls or tows that targeted bentho-pelagic species such as alfonsino and bluenose. These data were then assigned to the 1 km^2 grid over the New Zealand region, and total catch (and number of tows for the naturalness scenario, see above) computed for input to the Zonation analysis as cost layers. Cost layers were generated for bottom trawl, midwater trawl, and another cost layer can be made by combining the data for both trawl types. Zonation analysis were run to compare the resulting prioritisation protection maps produced by these different cost scenarios using habitat suitability maps made by both BRT and MaxEnt models (Figure 18). These preliminary cost scenarios did not include the steps described above that would account for uncertainty in the model predictions for habitat suitability for VME indicator taxa, nor naturalness or bio-regionalisation. The output maps from this analysis show that the distribution of priority areas for protection in some areas of the region is subtly different for each trawl type, and that a combined trawl type cost layer may, subject to discussions with industry, be the most useful layer for future Zonation analyses.

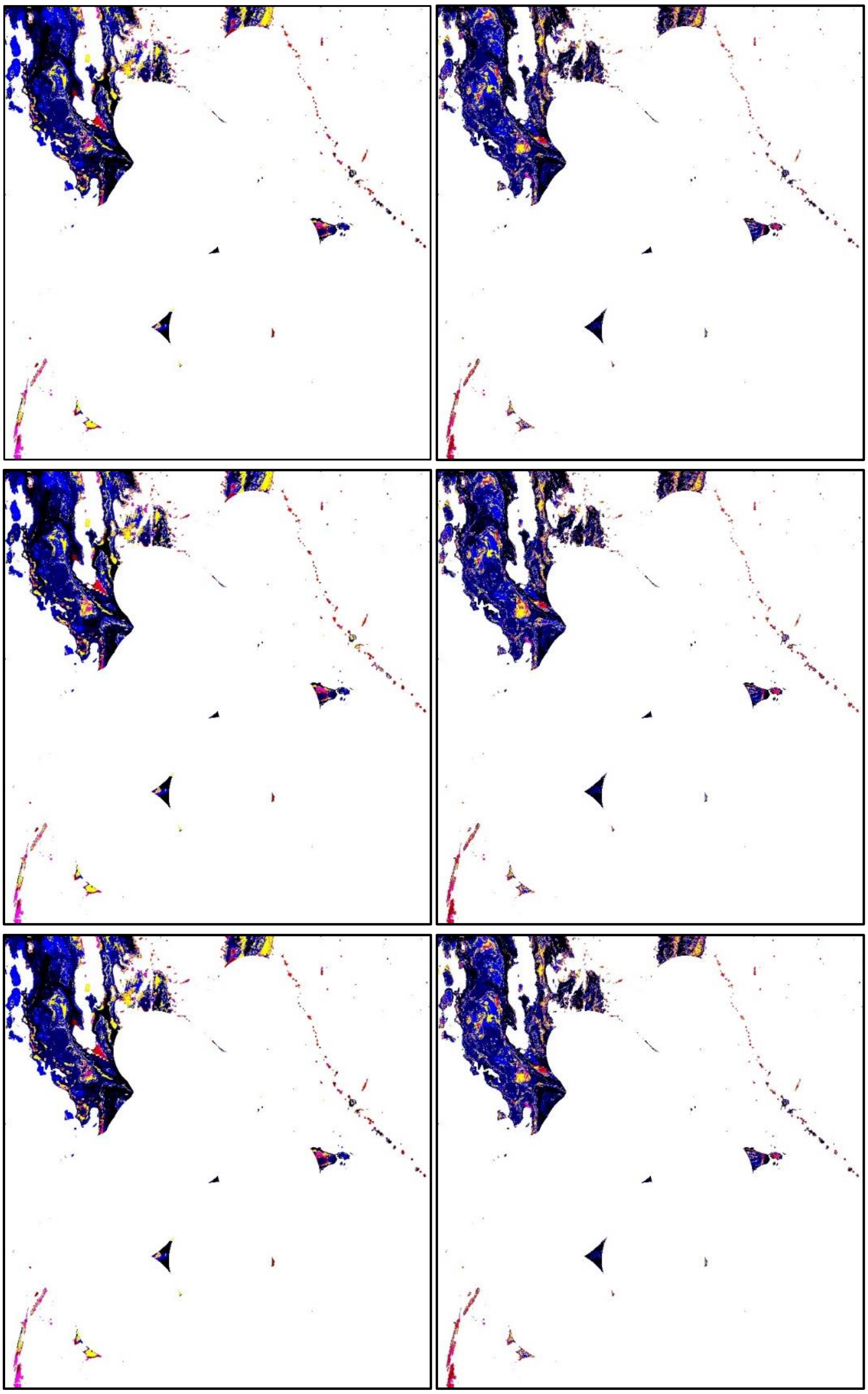

Figure 18: Preliminary Zonation output for the prioritisation protection scenario with full range of habitat suitability values for all VME indicator taxa from MaxEnt models (left) and BRT models (right), no uncertainty, no naturalness condition, no bio-regionalisation, and fishing cost layers for bottom trawl (top), midwater trawl (middle), and both trawl types (bottom) for all fishing years. [top 2% priority = red, 2-5% = brownish, 5-10% = pink, 10-25% = yellow, 25-50% = blue, 50-100% = black)

3.3.5. Sensitivity to choice of time period

The current SPRFMO reference period of bottom fishing footprints and catch limits is 2002-2006. The final scenario run in this preliminary analyses (under the same conditions described for the above scenario) was used to assess the difference between the Zonation prioritisation output for this reference period and using a cost layer for all fishing years (for a combination of both trawl types). It is difficult to see the difference in the map outputs that show the whole New Zealand region (Figure X), but close up maps for the northwestern part of the region indicate that the distribution of priority areas for protection is subtly different in some areas (Figure 19).

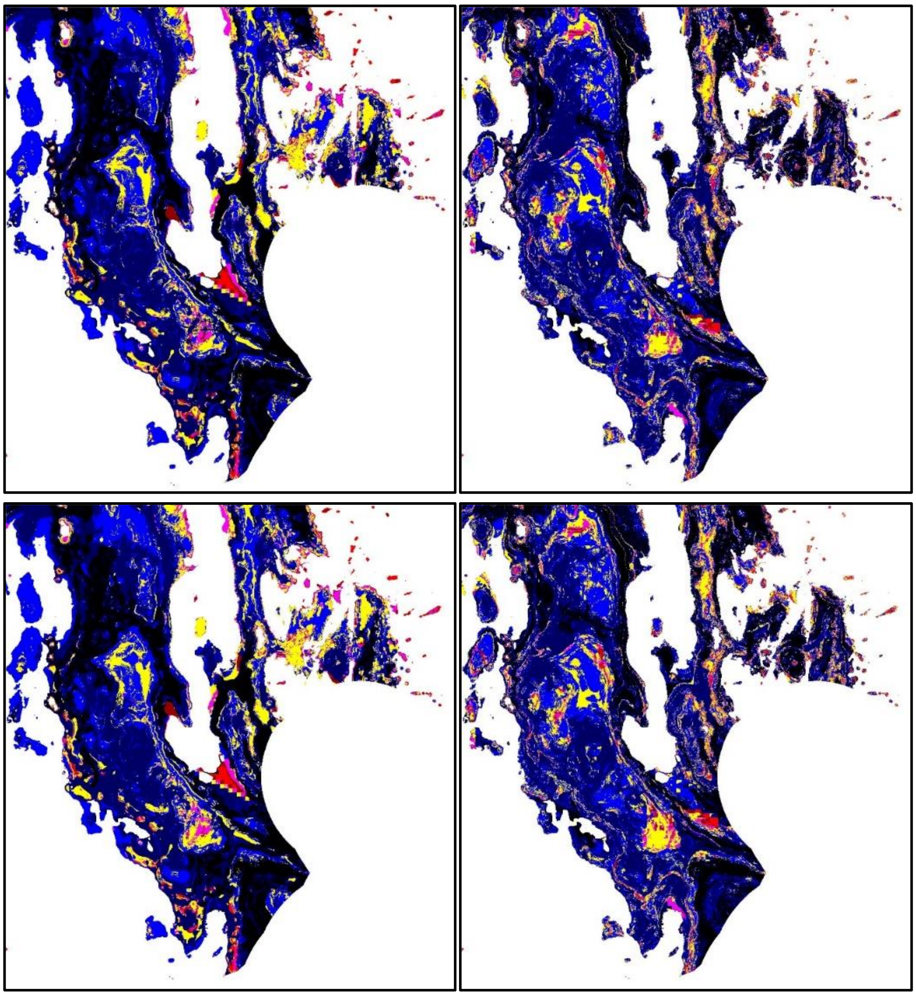

Figure 19: Preliminary Zonation output for the prioritisation protection scenario for the northwestern part of the New Zealand region with full range of habitat suitability values for all VME indicator taxa from MaxEnt models (left) and BRT models (right), no uncertainty, no naturalness condition, no bio-regionalisation, and fishing cost layers for both trawl types for all fishing years (top) and 2002-2006 (bottom). [top 2% priority = red, 2-5% = brownish, 5-10% = pink, 10-25% = yellow, 25-50% = blue, 50-100% = black]

3.3.6. Summary of preliminary scenario results

In general, Zonation software identified broadly similar maps of prioritisation throughout the preliminary sensitivity analyses, and this suggests the results are substantially more robust that previous work with the SPRFMO-scale models. This probably comes about largely from the greater concordance of the two habitat modelling approaches and the substantially better information on depth in the more restricted area examined. However, there were sufficient fine-scale differences in the prioritisation maps to make it worthwhile running multiple scenarios with different options in future design trials for spatial management measures. These scenarios should include, at the least, different habitat modelling approaches, exploration of the impact of uncertainty, and different cost layers and time periods for the trawl footprint (in discussion with industry).

4. Future directions

The current work on developing and testing NZ regional-scale habitat suitability models for VME indicator taxa will continue as resources permit. The preliminary sensitivity analyses at the NZ regional scale presented here will shortly be augmented by tests of different stratifications or bio-regionalisation of the area, and by including an index of naturalness (effectively "discounting" the conservation value of areas that have been more heavily fished). Such results can be expected within a few weeks of the date of the scientific committee meeting. Future runs of Zonation at this scale will also include information on connectivity among areas as revealed by genetic studies that the New Zealand government has funded.

Work is about to start on much smaller-scale models (i.e., at the scale of individual seamounts or features) for the Louisville Ridge. This work will apply the learnings and data from the SPRFMO-scale model test/validation survey and include predictive modelling of VME habitat such as coral 'reefs' or 'thickets' rather than individual VME indicator taxa. These models may eventually allow for the "within-feature" spatial management approaches that cannot be supported by models of NZ region or SPRFMO-wide scales.

It is clear from what is presented here and the work of other authors that predicting the distribution of VME indicator taxa on the High Seas is difficult and depends on both the available data (generally scarce) and modelling methods and assumptions (in a rapidly developing field). Further, designing spatial management measures to avoid significant adverse impacts of fishing on those VMEs depends on a range of other choices and assumptions. One way to deal with this accumulating uncertainty is through scenario analysis where the results of multiple runs can be compared and designs for spatial management measures assessed against a variety of different scenarios.

5. Recommendations

It is recommended that the Scientific Committee:

- **notes** New Zealand's work on the development and testing of methods and models to predict the distribution of VME indicator taxa
- **notes** New Zealand's work on assessing methods of designing spatial management measures to avoid significant adverse effects on VMEs while minimizing costs to the fishery
- **notes** that New Zealand may have preliminary results of its latest iteration of exploratory spatial management measure assessment using the Zonation decision-support tool before the committee meets in 2015
- **agrees** that this work should contribute to the development of a revised CMM for bottom fisheries in the SPRFMO Area and, in particular:
    - **agrees** that a range of data sources and modelling approaches should be explored to predict the distribution of VME indicator taxa in the SPRFMO Area and,
    - **agrees** that a range of methods and assumptions should be explored when designing spatial management measures to avoid significant adverse impacts of fishing on VMEs while minimizing costs to the fishery

6. Acknowledgments

Thanks are due to Owen Anderson, Ashley Rowden and Carolyn Lundquist for the provision of preliminary findings and unpublished data and to inform this paper, especially in relation to the most recent iterations of the VME indicator species modelling using New Zealand regional-scale data. That work was funded by New Zealand's Ministry for Business, Innovation, and Employment through their South Pacific VME project. The work was continuing as the Scientific Committee convened in September 2015.

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8. Appendices

Appendix 1: Initial set of geophysical and environmental variables used in New Zealand's recent regional-scale predictive habitat models; each variable is set within a higher level group of similar variables. The final set of variables used in the models was chosen from this set by examining correlations between all variables.

Variable name		Units	Name	Reference/Notes
Bathymetry variables	1			
Bathymetry		m	depth	
Bathymetry smoothed		m	depth3x3_fm	Derived
Standard Deviation of Elevation**			stdev_elev	Grohmann et al (2011), 3x3 window
Terrain variables - orientation				
Aspect**		Degree	aspect	Jenness (2012)
Aspect – Eastness**	1		eastness	Wilson et al. (2007)
Aspect – Northness**			northness	Wilson et al. (2007)
Terrain variables - curvature				
Curvature – Profile**	1		prof_curv	Jenness (2012)
Curvature – Plan**			plan_curv	Jenness (2012)
Curvature – Tangential**			tang_curv	Jenness (2012)
Terrain variable - slope				
Slope**		Degrees	slope	Jenness (2012)
Slope in percent**		Percent	slope_per	Jenness (2012)
Slope variability**			slopevar	Ruszkiczay-Rüdiger et al (2009), 10 circular window
Standard Deviation of Slope**			stdev_slop	Grohmann et al (2011), 3x3 window
Terrain variables – topographic position				
Bathymetric Position Index – Broad**			bpi_broad	Wright et al. (2005), 1+25
Bathymetric Position Index – Fine**			bpi_fine	Wright et al. (2005), 1+5
Topographic Position Index**			tpi	Wilson et al. (2007)
Terrain variables – variability				
Roughness**			roughness	Wilson et al. (2007)
Rugosity**			rugosity	Jenness (2012)
Terrain Ruggedness Index**			tri	Wilson et al. (2007)
Terrain Ruggedness Index – Riley**			tri_riley	Riley et al. (1999)
Vector Ruggedness Measure**			vrm3x3, vrm21x21	Sappington et al. (2007)
Carbonate chemistry variables				
Omega aragonite		Ω_{ARAG}	arag_stein	Steinacher et al. (2009)
Omega aragonite		Ω_{ARAG}	arag_orr	Orr et al. (2005)
Omega calcite		Ω_{CALC}	calc_stein	Steinacher et al. (2009)
Omega calcite		Ω_{CALC}	calc_orr	Orr et al. (2005)
Source data: Global data products				
Nitrate		$\mu mol\ l^{-1}$	nit	Garcia et al. (2006b)
Phosphate		$\mu mol\ l^{-1}$	phos	Garcia et al. (2006b)
Salinity		pss	sal	Boyer et al. (2005)
Silicate		$\mu mol\ l^{-1}$	sil	Garcia et al. (2006b)
Apparent oxygen utilisation		$mol\ O_2\ m^{-3}$	aoxu	Garcia et al. (2006b)
Dissolved oxygen		$ml\ l^{-1}$	diso2	Garcia et al.(2006a)

Percent oxygen saturation	% O_2^S	pos	Garcia et al. (2006b)
Temperature	°C	temp	Boyer et al. (2005)
Productivity variables***			
VGPM	mg C m^{-2} d^{-1}	vgpm_me, ma, mi, st	http://orca.science.oregonstate.edu/
VGPM – Eppley variant	mg C m^{-2} d^{-1}	epp_me, ma, mi, st	http://orca.science.oregonstate.edu/
CbPM	mg C m^{-2} d^{-1}	cb_me, ma, mi, st	http://orca.science.oregonstate.edu/
Particulate organic carbon export	mg C m^{-2} d^{-1}	poc	Lutz et al. (2007)
*Source data Williams 1km model**			
Omega Aragonite	Ω_{ARAG}	oa_w	Mike Williams
Omega Calcite	Ω_{CALC}	oc_w	Mike Williams
Oxygen	ml l^{-1}	oxy_w	Mike Williams
Salinity	pss	sal_w	Mike Williams
Sigma Theta	kg m^{-3}	sigma_w	Mike Williams
Temperature	°C	temp_w	Mike Williams

* used an updated version of Davies and Guinotte (2011) process to use Kriging interpolation instead of IDW for initial variables.
** Calculated using focal mean on bathymetry
*** these are all surface layers derived from MODIS data (annual mean, min, max for years 2002-2014). Resolution has been upscaled slightly using kriging and then resampled to match spatial scale of other layers. Initial resolution: 2160 x 4320.