Development of a New Zealand Seafloor Community Classification (SCC)

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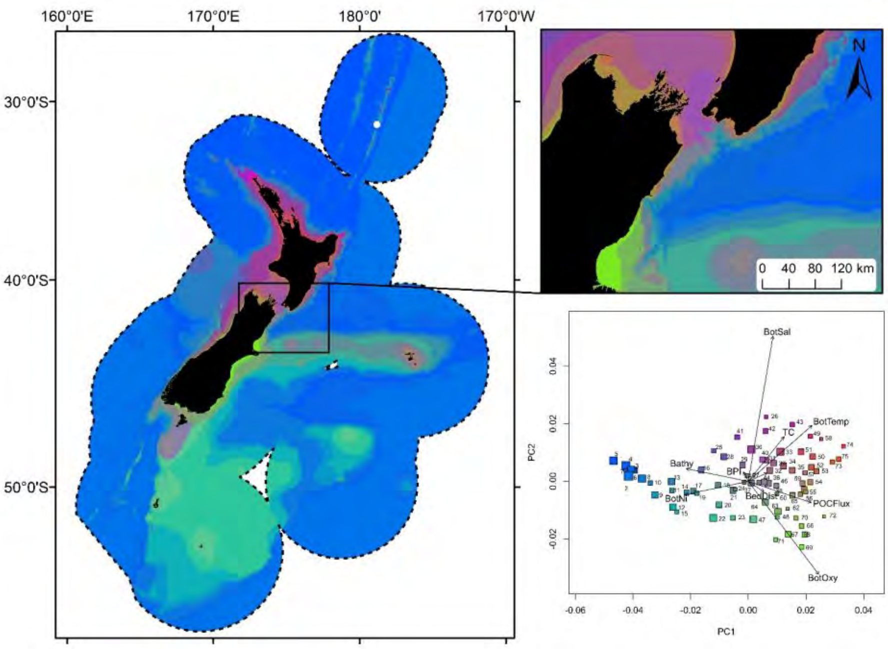

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Image caption: Geographic distribution of the Seafloor Community Classification (75 groups)

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Executive summary

Marine habitats and ecosystems are under increasing pressure from human activities including sedimentation, eutrophication, fishing, mineral extraction, waste disposal, and dredging. Well-designed networks of marine protected areas (MPAs) can be highly effective tools for conserving biodiversity and associated ecosystem functions and services. In New Zealand, ongoing work to improve scientific inputs to be considered in decision-making associated with the establishment of MPAs is supported by a MPA research programme funded via the Department of Conservation’s (DOC’s) Biodiversity 2018 Programme. DOC commissioned the development of a fit-for-purpose, numerical classification of the marine environment, to support ongoing MPA planning and reporting at a national scale and complement work to develop Key Ecological Areas mapping for New Zealand.

Working with experts and members of the Marine Protected Areas Science Advisory Group (MSAG) at a workshop held on the 9th August 2019 it was agreed that Gradient Forest (GF) models would be used to produce a numerical classification of the seafloor environment and communities within the New Zealand Territorial Sea and Exclusive Economic Zone (jointly referred to as the New Zealand marine environment). Occurrence records for four biotic groups, demersal fish (317 species at 28,599 unique sample locations), benthic invertebrates (958 genera at 33,187 unique locations), macroalgae (349 species at 3,320 unique locations) and reef fish (92 species at 339 unique locations), were used to inform the transformation of 33 gridded environmental variables to represent spatial patterns of taxa compositional turnover. Environmental variables were available at two resolutions: 250 m grid resolution from the coastline to the edge of the Territorial Sea (12 NM from shore) and a 1 km grid resolution from the edge of the Territorial Sea to the edge of the Exclusive Economic Zone.

Predicted spatial patterns of compositional turnover for taxa in each of the four biotic groups were then combined to represent overall compositional turnover in seafloor communities, with the combined predictors classified using a hierarchical procedure to define groups at different levels of classification detail, (i.e., 30, 50, 75 and 100 groups). Associated uncertainty estimates of compositional turnover for each of the seafloor communities were also produced, and an added measure of uncertainty – coverage of the environmental space – was developed to further highlight geographic areas where predictions may be less certain due to low sampling. A 75-group classification – termed the New Zealand ‘Seafloor Community Classification’ (SCC) – was described.

As would be expected, the geographic and environmental patterns of the SCC closely reflect the patterns of compositional turnover on which the SCC was based. At broad scales, SCC groups were differentiated primarily according to oceanographic conditions such as depth and bottom temperature. Environmental differences among groups in deep water were relatively muted, but greater environmental differences were evident among groups at intermediate depths, particularly with respect to bottom temperature, bottom oxygen concentration and bottom salinity. These more pronounced environmental differences among groups at intermediate depths were aligned with well-defined oceanographic patterns observed in New Zealand’s oceans, with a clear latitudinal separation along the boundaries of the Subtropical Front. Environmental differences became even more pronounced at shallow depths, where variation in more localised environmental conditions such as productivity, seafloor topography, seabed disturbance and tidal currents were important differentiating factors. Environmental similarities in SCC groups were mirrored by their biological compositions. A more detailed description of individual groups is provided in an associated publication.

The SCC is a significant advance on previous numerical classifications in New Zealand (the New Zealand Marine Environment Classification (MEC) and the Benthic Optimised Marine Environment Classification (BOMEC)), at least in part due to large amount of biological and environmental data used. The SCC is critically appraised and considerations for use in spatial management are discussed.

1 Introduction

1.1 Background

Marine habitats and ecosystems are under increasing pressure from human activities including sedimentation, eutrophication, fishing, mineral extraction, waste disposal, and dredging (Halpern et al. 2008). These anthropogenic impacts threaten biodiversity, which in turn can affect ecosystem functioning and services, resulting in a need for management and conservation of the marine environment (Ramirez-Llodra et al. 2011). Well-designed networks of marine protected areas (MPAs) can be highly effective tools for conserving biodiversity and associated ecosystem functions and services (Halpern et al. 2010; Edgar et al. 2014; Rowden et al. 2018).

In New Zealand, ongoing work to improve scientific inputs to decision-making associated with implementing marine protection is supported by a dedicated MPA research programme via DOC's Biodiversity 2018 Programme. This programme is guided by a Marine Protected Areas Science Advisory Group (MSAG). The MSAG includes representatives from the Department of Conservation (DOC), Ministry for the Environment (MfE) and Fisheries New Zealand (FNZ).

DOC recently commissioned a review of the marine habitat classification systems currently available in New Zealand, and relevant overseas examples (Rowden et al. 2018). The recommendation from Rowden et al. (2018) was that a numerical classification and / or a thematic classification should be developed for the coastal and marine habitats of New Zealand. Numerical classifications are generally bottom-up statistical grouping of multiple (usually) continuous variables (Rowden et al. 2018), whereas thematic classifications are generally top-down sub-divisions of individual information layers (Rowden et al. 2018). The MSAG agreed that a fit-for-purpose numerical classification would be advantageous for ongoing marine protection planning and reporting at a national scale, as well as providing essential support for delivering on goals to develop a representative network of marine protected areas and complement work to develop Key Ecological Areas mapping for New Zealand (Stephenson et al. 2018b; Lundquist et al. 2020b).

A workshop convened on August 9th, 2019, attended by members of the MSAG and NIWA researchers, discussed which numerical classification methods could be used, the availability of environmental and biological datasets, possible methods for including estimates of model uncertainty, and considered the number of classes suitable for MPA planning. Following this workshop, it was decided that Gradient Forest models would be used to produce the numerical classification that would be 'tuned' using biological records of demersal fish, benthic invertebrates, rocky reef fish and macroalgae.

1.2 Gradient Forest environmental classifications

In marine protected area planning, there is interest in how species and communities respond to environmental gradients, and in identifying the environmental variables that best predict patterns of biodiversity. Random forest models allow assessment of the importance of predictor variables for individual species and to indicate where along gradients abundance changes (RF; Breiman 2001). Gradient Forest models (GF; Pitcher et al. 2011) extend random forest models to whole assemblages, by aggregating Random Forest models. Information from GF models is used to inform the selection, weighting and transformation of environmental layers to maximise their correlation with species compositional turnover and establish where along the range of gradients important compositional changes occur (Ellis et al. 2012). These transformed environmental layers (representing species compositional turnover) can then be classified to define spatial groups that capture variation in species composition and turnover.

A GF-trained classification was recently used to describe spatial patterns of demersal fish species turnover in New Zealand using an extensive demersal fish dataset (>27,000 research trawls) and high-resolution environmental data layers (1 km^2 grid resolution) (Stephenson et al. 2018a). Using a large set of independent data for evaluation, this 30-group classification was found to be highly effective at summarising spatial variation in both the composition of demersal fish assemblages and species turnover (Stephenson et al. 2018a).

Such classifications have several key features that make them particularly useful for resource management and conservation planning. Firstly, they can be created at various hierarchical levels of group-detail (e.g., 30 groups as presented in Stephenson et al. (2018a), to 500+), a feature that makes them particularly useful when they need to be applied at differing spatial scales (national to regional to local) (Stephenson et al. 2020c). Secondly, because the classification is based on GF models of species turnover functions across environmental gradients, it can accurately reflect non-linear environmental differences in species composition, e.g., across depth gradients. Together, these two attributes mean that a single classification can reflect the dynamic environments in inshore areas with a greater number of classes compared to fewer classes in the more homogenous offshore areas. Thus, this approach to classification obviates the need for separate classifications of coastal and marine classifications. Finally, such classifications also contain information on (predicted) biological inter-group similarities, allowing greater priority to be given during conservation planning to classification groups that occupy unusual environments and are therefore likely to support unusual species assemblages.

One challenge with these classifications is the communication of a statistically complex product in a way that facilitates their use by management agencies and others involved in marine protection planning (Rowden et al. 2018; Stephenson et al. 2020c). This challenge can be overcome, at least in part, through the provision of maps and descriptions of the habitats and biotic assemblages associated with each classification group. A detailed description for a 30-group classification was produced by Stephenson et al. (2020c), which aimed to bridge the gap between the typical output from numerical classifications and the readily understandable habitat and assemblage descriptions that result from thematic classifications (see Rowden et al. 2018 for discussion on the stregnths and weaknesses of different classifications globally and in New Zealand). The descriptions of Stephenson et al. (2020c) included geographic locations, environmental characteristics, and species' assemblages in a hierarchy based on the dominant environmental variables identified in the analysis (e.g., depth, tidal current, productivity). Class descriptions may facilitate the use of environmental classifications by both managers and stakeholders because they summarize complex multi-species data to a more manageable number of groups which are more user friendly for participatory process and ecosystem-based management.

Stephenson et al. (2020c) recommended extending the 30-group demersal fish classification to include other taxonomic and ecological groups (e.g., macroalgae and benthic invertebrates), and thus more broadly represent benthic communities associated with coastal and marine habitats.

1.3 Aims and objectives

The aim of this project was to develop a numerical environmental classification and associated spatially explicit estimates of uncertainty, using a broad suite of taxonomic and ecological groups (demersal fish, benthic invertebrates, macroalgae and reef fish), extending from the coastal marine area (inclusive of estuaries where data existed) to the full extent of the EEZ. This involved:

- Working with experts and members of the MSAG to detail the planned approach (Objective 1). This workshop, which took place on 9th August 2019, reached broad agreement on: a list of all relevant environmental and biological datasets; the use of Gradient Forest modelling; the need to develop estimates of spatial uncertainty; and several options for the number of classes and spatial resolution of outputs which would be suitable for MPA planning.
- Collating all relevant biological and environmental datasets (Objective 2).
- Developing a Gradient Forest environmental classification and spatially explicit estimates of uncertainty extending from the coastal marine area (inclusive of estuaries) to the full extent of the EEZ (Objective 3).
- Providing a concise and comprehensive report (Objective 4) detailing all environmental and biological datasets, methodology used and overview of the final environmental classification.
- Providing a detailed environmental and biological (community) description of the classification for dissemination both within and outside marine management agencies (Objective 5), e.g., as in Stephenson et al. (2020c). This final objective is provided as a separate report (Petersen et al. 2020).

2 Biological and environmental datasets (objective 2)

2.1 Study area

The study area extended over 4.2 million km^2 of the South Pacific Ocean within the New Zealand Territorial Sea (TS) and Exclusive Economic Zone (EEZ) herein referred to as the New Zealand marine environment (≈25 – 57°S; 162°E – 172°W; Figure 2-1).

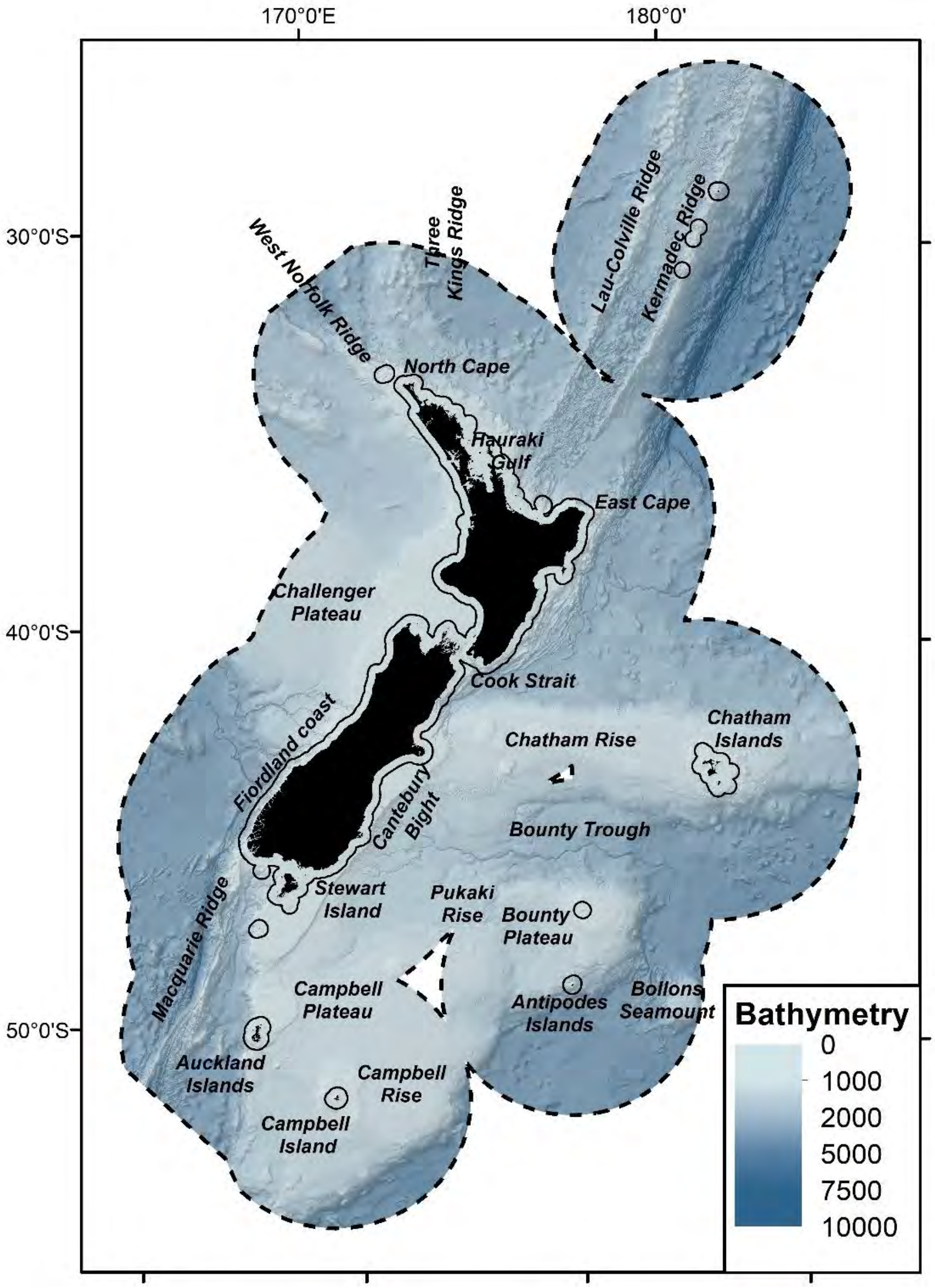

Figure 2-1: Map of the study region. New Zealand Exclusive Economic Zone (EEZ, black dashed line), Territorial Sea (TS, solid black line), water depth and feature names used throughout the text are displayed.

2.2 Biological samples

Occurrence records for demersal fish, benthic invertebrates (from coastal/offshore waters and separately from estuaries and harbours), macroalgae and reef fish were collated from various sources (Table 2-1). All records were groomed: records located on land, outside the New Zealand EEZ and/or duplicated within and between databases were removed. Taxonomy was standardised across datasets and years to the most recent nomenclature (metadata for biological data are provided in Supplementary materials 1).

Records for each of the groups were separately aggregated to unique locations of different spatial resolutions (see further information in sections 2.2.1 – 2.2.5). Taxa with ≥ 10 unique sample locations were retained for the analysis (e.g., as in Stephenson et al. 2018a) because this ensured that there were sufficient samples to run GF models. All available records were used, regardless of the year and/or season in which they were collected, to maximise the number of species and samples available for GF modelling. Following quality control and spatial aggregation, a total of 630,997 records across biotic groups occurring at 39,766 unique locations were retained for final analysis. However these were unequally distributed among taxa (Table 2-1) and across the study region (distribution of samples in Supplementary materials 2: Figure 7-1; Figure 7-2; Figure 7-3; Figure 7-4).

Table 2-1: Summary of information for collated taxa records (after grooming).

Biotic group	Source	Sampling years	Spatial aggregation	Number of taxa (>10 occurrences)	Number of unique locations
Demersal fish	*trawl* database (FNZ-NIWA)	1979 – 2016	1 km	317	28,599
Benthic invertebrates (coastal and offshore)	*NIWA invert* database	1896 – 2019	1 km	954	27,274
	Te Papa	1966 - 2015	1 km	66	
	Auckland Museum	1905 - 2018	1 km	218	
	trawl database (FNZ-NIWA)	1979 - 2016	1 km	132	
Macroalgae	NIWA (2019); Te Papa (2012); Auckland Museum (2019); Duffy (1979 – 2007) and Shears & Babcock (1999 – 2002)	1850 - 2018	250 m	349	3320
Reef fish	DOC dataset	1986 - 2004	250 m	92	339
Benthic invertebrates (Estuarine, intertidal)	OTOT: National Estuary Dataset	2001 – 2017	NA (see section 2.2.5)	188	NA (see section 2.2.5)

2.2.1 Demersal fish

Demersal fish species occurrence and abundance records (n = 391,198) (including information on research cruise identifier, gear type, date, min and max depth of trawl, and lat/lon) from 1979 – 2016 were extracted from the research trawl database '*trawl*' (NIWA 2014, 2018). These data were groomed to only keep those records identified to species level. Species records were spatially aggregated (based on presence/absence information) to a 1 km grid resolution (e.g., as in Stephenson et al. 2018a). Species with ≥ 10 unique sample locations at this resolution were retained for the analysis (e.g., as in Stephenson et al. 2018a). The final demersal fish dataset included observations for 317 species at 28,599 unique sample locations (Supplementary materials 2: Figure 7-1).

2.2.2 Benthic invertebrates (coastal and offshore)

Benthic invertebrate species occurrence records (*n* = 127,330) (including lat/lon, species name, collection date, and sampling gear used) from 1896 – 2019 were extracted from *trawl* (*n* = 56,841), NIWA's Invertebrate Collection database '*NIWA invert*' (*n* = 59,144), and databases at Te Papa (*n* = 2943), and Auckland Museum (*n* = 8402). These databases also included records for demersal cephalopod species but for simplicity we refer to them as 'benthic invertebrates'. In contrast to the trawl data, which reliably record both species presence and absence of demersal fish, trawl records do not provide a reliable indication of where benthic invertebrate species do not occur. One way to overcome this lack of true absence data for the modelling is to use a random selection of points from the analysis area, treating these as 'pseudo-absences'. Alternatively, as was undertaken here, the individual RF species models (generated for GF models) can be constructed using the locations at which other species not being modelled were present to provide an indication of the 'relative absence', also sometimes referred to as 'target-group background data' (Phillips et al. 2009). Better results can generally be achieved using relative absences compared to randomly selected pseudo-absences, particularly when the relative absences are drawn from other species records forming part of the same broad biological group and have been collected using similar methods with the same sampling biases (Phillips et al. 2009).

Given that the benthic samples were collected using a variety of sampling methods (208 different gear types), the benthic invertebrate records were grouped into gear categories to reflect 'catchability'. Many of these gear types were name variants of commonly used sampling gear types, but for most records, the specific sampling parameters (e.g., mesh size, tow length, etc) were not recorded. In order to account for both the large number of gear types recorded and the differences in sampling parameters, gear types were grouped into catchability categories. Catchability was assumed to be influenced by gear size, deployment area and selectivity (Table 2-2) (Stephenson et al. 2018b).

Table 2-2: Categories used to reflect catchability of sampling gear types. Table modified from (Stephenson et al. 2018b).

Type	Category	Description	Example
Gear size	Small	< 1m	Devonport dredge, box corer
	Medium	1-3m	Benthic sled
	Large	> 3m	Otter trawls
Deployment area	Small	< 1m	Box corer
	Medium	1m – 1km	Beam trawls
	Large	> 1 km	Otter trawls
Selectivity	HS	Highly selective	Collected by hand
	G	General	Benthic sled

Sampling gear types were assigned codes for each of the three catchability types and combined to yield 'catchability' groups (Table 2-3). Out of 18 possible 'catchability' groups, six 'catchability' groups occurred in the available invertebrate samples (Table 2-3):

- LLG: Large gear types, deployed over large areas, which were not selective (e.g., otter trawls);
- LMG: Large gear types, deployed over medium-sized areas, which were not selective (e.g., beam trawls);
- MMG: Medium sized gear types, sampling medium sized areas, which were not selective (e.g., benthic sled);
- SMG: Small gear types, sampling medium sized areas, which were not selective (e.g., Devonport dredge);
- SMHS: Small gear types, sampling medium sized areas, which were highly selective (e.g., collected by hand, bottom longline);
- SSG: Small gear types, sampling small areas, which were not selective (e.g., box corer).

Records of LLG and LMG were combined as these catchability groups represent commercial fishing practices with similar catches of invertebrates likely to be more demersal in nature (i.e., squids). All records collected from highly selective gear types (e.g., SMHS) were excluded from the analysis, because methods classified within this group were considered too variable to provide reliable records of absence (20,010 records were excluded across 412 genera and 2,097 unique locations, including 190 genera unique to selective methods). Varying degrees of overlap occurred between genera captured by the different gear type classes in the records retained for analysis - LLG.LMG = 34 % unique genera not shared with other gear types 66% overlap, MMG = 37% unique genera, SMG = 47% unique genera, SSG = 21% unique genera (see Table 2-3 for number of unique genera per gear type).

Benthic invertebrate records were groomed to keep only those records identified to genus and species level and within the New Zealand EEZ. These records were aggregated to genus level, resulting in 127,330 records across 958 genera. Genus records were then spatially aggregated (to presence - relative absence) at 1 km grid resolution (Supplementary materials 2: Figure 7-2). Records were aggregated to genus level because this provided a greater number of unique locations than when records based on species level were aggregated (33,187 vs 28,263 respectively). In addition, at genus level, benthic invertebrate records were more inclusive across all benthic invertebrate taxa than records at species level.

Table 2-3: Gear type codes used to reflect catchability, number of benthic invertebrate genera > 10 occurrence, number of unique genera > 10 occurrence and number of unique sample locations (see text and Table 2-2 for Gear type code explanations).

Gear type	Number of genera > 10 occurrence	Number of unique genera > 10 occurrence	Number of unique locations
LLG.LMG	453	152	23,793
MMG	566	210	1375
SMG	444	208	1883
SSG	43	9	364
All gear types combined	958	958	27,274
SMHS (excluded)	412	190	20,010

2.2.3 Macroalgae

Macroalgae occurrence records were sourced from herbarium records, opportunistic data and observational datasets. Herbarium records were extracted from databases held at Te Papa Tongarewa - Museum of New Zealand, Auckland Museum, and NIWA. Opportunistic data were sourced from citizen science observations of large brown algae collected using iNaturalist (iNaturalist 2019) and verified by photographs as part of an FNZ funded project (ZBD201406). Observational data were extracted from dive logs collected by Clinton Duffy (DOC) that recorded large brown seaweed around New Zealand between 1979 and 2007. A second observational dataset was collected by Shears and Babcock (2007) as part of a research programme on subtidal communities around New Zealand.

For all datasets, only records that had been identified to species level were used. Occurrence data were initially restricted to those between 70 m depth and 10 m elevation (including some records on land) using a New Zealand bathymetry (and elevation) data layer. Records apparently occurring on land were associated with the closest available marine environmental data. The small number of records that were obtained from depths between 70 and 200 m depth were checked by macroalgal experts (W. Nelson and K. Neill) and included in the dataset only if they were considered valid. Macroalgal presence/absence records were aggregated to 250 m grid resolution. Species with ≥ 10 unique sample locations at this resolution were retained for the analysis. Similarly to the benthic invertebrate records, 'target-group background data' were used as absences. The final macroalgae dataset consisted of 349 species at 3,320 unique locations (Supplementary materials 2: Figure 7-3).

2.2.4 Reef fish

The relative abundance of reef fishes were obtained from 467 SCUBA dives made around the coast of New Zealand over an 18-year period from November 1986 to December 2004 (for detailed methodology see Smith et al. (2013)). These data had previously been groomed and all records were identified to species level. Records were aggregated (to presence/absence) spatially to a 250 m grid resolution. Species with ≥ 10 occurrences were retained for the analysis. The final rocky reef fish dataset included observations of 92 species at 339 unique locations (Supplementary materials 2: Figure 7-4).

2.2.5 Benthic invertebrates (Estuarine, Intertidal)

The abundance of benthic invertebrates collected from estuaries was retrieved from the National Estuary Dataset (Berthelsen et al. 2020) which was compiled as part of the MBIE-funded Oranga Taiao, Oranga Tangata (OTOT) programme. The dataset is comprised of primarily regional council and unitary authority monitoring data collected from throughout New Zealand. The raw dataset includes data from 70 estuaries, 421 sites and 8305 sampling events collected and analysed by a range of organisations. On average, there were 5.8 sample sites per estuary across 14 councils. All datapoints were collected from the intertidal. Between 3 and 15 replicates were collected at each sampling location, with the maximum sampled area at each location ranging between 1,800 m^2 and 10,800 m^2. Samples were collected over the period from 2001 to 2017, with variation in the months over which sampling was conducted.

This dataset represents some of the best estuarine data available in New Zealand, comprising consistently collected, paired biological and environmental samples. However, sample data were generally collected to investigate change through time rather than to facilitate spatial mapping of environmental and biological patterns. Environmental predictor information for areas outside of sampled locations was very limited and for most estuaries, lacked the resolution required for description of within-estuary variation in environmental and biological character. Therefore, it was not possible to include the estuarine benthic invertebrate data with data from other biotic groups. We provide a separate analysis using this dataset to investigate broad patterns in estuarine bioregionalization. Further details on the methods and results are presented in Supplementary Materials 3 – Estuarine benthic invertebrates.

2.3 Environmental variables

New Zealand's marine environments were described using 33 gridded environmental variables, collated at two resolutions (Table 2-4): a 250 m resolution grid from the coastline to the edge of the Territorial Sea (12 NM from shore), and a 1 km resolution grid from the edge of the Territorial Sea to the edge of the Exclusive Economic Zone (Figure 2-1). Some environmental variable layers were produced at a native resolution of 250 m, e.g., Bathymetry, whereas others required interpolation, e.g., Bottom nitrate (interpolation methods and further information on the environmental layers are available as metadata: Env_pred_metadata – for further information see Supplementary materials 1). Spatial layers were projected using an Albers Equal Area projection centred at 175°E and 40°S (EPSG:9191) now accepted by DOC and Fisheries New Zealand (FNZ) as the standard projection for use with spatial data covering New Zealand's EEZ (Wood et al. in prep).

Environmental variables were selected based on their known influence on growth, survival and distribution of benthic and demersal taxa, and therefore their likely influence on species composition, richness and turnover (e.g., see Leathwick et al. 2006; Compton et al. 2013; Smith et al. 2013; Anderson et al. 2016; Rowden et al. 2017; Stephenson et al. 2018a; Georgian et al. 2019). Several environmental variables showed some co-linearity within records for biotic groups but all levels of co-linearity were considered acceptable (Pearson correlation < 0.9) for tree-based machine learning methods (Elith et al. 2010; Dormann et al. 2013) and more specifically GF modelling (Ellis et al. 2012).

The final environmental variables used for GF modelling were selected through a model tuning process which aimed to maximise model fit (see section 3.1). Twenty environmental variables were selected for GF modelling for all biotic groups (grey rows, Table 2-4). In most cases, the inclusion of many variables is avoided because they generally only provide minimal improvement in predictive accuracy and complicate interpretation of model outcomes (Leathwick et al. 2006). However, here, the interpretation of model outcomes (i.e., the drivers of distribution) was of secondary interest, the primary focus being on maximising the predictive accuracy of the model. Values for environmental variables were derived for each taxon record location by overlay onto the environmental predictor layers using the “raster” package in R (Hijmans & van Etten 2012). For demersal fish and benthic invertebrate records this was undertaken using 1 km grid resolution environmental variables (including in areas where information was available at a 250 m grid resolution in order to match the spatial scale at which these were sampled), whereas environmental values for reef fish and macroalgae records were extracted from the 250 m grid resolution environmental variables.

Table 2-4: Spatial environmental predictor variables used for the Gradient Forest analyses. Environmental variables are ordered alphabetically. Environmental variables used in the final GF models are highlighted in grey.

Abbreviation	Full name	Temporal range	Description	Native Resolution	Units	Source
Bathy	Bathymetry	Static	Depth at the seafloor was interpolated from contours generated from various sources, including multi-beam and single-beam echo sounders, satellite gravimetric inversion, and others (Mitchell et al., 2012).	250 m	m	Mitchell et al. (2012)
Beddist	Benthic sediment disturbance	1/7/2017-30/6/2018	One-year mean value of friction velocity derived from (1) hourly estimates of surface wave statistics (significant wave height, peak wave period) from outputs of the NZWAVE_NZLAM wave forecast, at 8-km resolution, (2) median grain size (d50), at 250 m resolution, (3) water depth, at 25-m resolution. Benthic sediment disturbance from wave action was assumed to be zero where depth ≥ 200m.	250 m	ms^{-1}	Swart (1974); updated in 2019
BotNi	Bottom nitrate	Static	Annual average water nitrate concentration at the seafloor (using NZ bathymetry layer) based on methods from Dunn et al. 2002. The oceanographic data used to generate these climatological maps were computed by objective analysis of all scientifically quality-controlled historical data from the Commonwealth Scientific and Industrial Research Organisation (CSIRO) Atlas of Regional Seas database (CARS2009, 2009).	approx. 41 km (1/2 degree)	umol l^{-1}	NIWA, unpublished
BotOxy	Dissolved oxygen at depth	Static	Annual average water oxygen concentration at the seafloor (using NZ bathymetry layer) based on methods from Dunn et al. 2002. Oceanographic data from CARS2009 (2009).	Approx. 41 km (1/2 degree)	ml l^{-1}	NIWA, unpublished
BotOxySat	Oxygen saturation at depth	Static	Annual average oxygen saturation at the depths.	Approx. 41 km (1/2 degree)	umol l^{-1}	NIWA, unpublished
BotPhos	Bottom phosphate	Static	Annual average water phosphate concentration at the seafloor (using NZ bathymetry layer) based on methods from Dunn et al. 2002. Oceanographic data from CARS2009 (2009).	Approx. 41 km (1/2 degree)	umol l^{-1}	NIWA, unpublished
BotSal	Salinity at depth	Static	Annual average water salinity concentration at the seafloor (using NZ bathymetry layer) based on methods from Dunn et al. 2002. Oceanographic data from CARS2009 (2009).	Approx. 41 km (1/2 degree)	psu	NIWA, unpublished

Abbreviation	Full name	Temporal range	Description	Native Resolution	Units	Source
BotSil	Bottom silicate	Static	Annual average water silicate concentration at the seafloor (using NZ bathymetry layer) based on methods from Dunn et al. 2002. Oceanographic data from CARS2009 (2009).	Approx. 41 km (1/2 degree)	umol l^{-1}	NIWA, unpublished
BotTemp	Temperature at depth	Static	Annual average water temperature at the seafloor (using NZ bathymetry layer) based on methods from (Ridgway et al. 2002). Oceanographic data from (CARS2009 2009).	Approx. 41 km (1/2 degree)	°C km^{-1}	NIWA, unpublished
BPI_broad	BPI_broad	Static	Terrain metrics were calculated using an inner annulus of 12 km and a radius of 62 km using the NIWA bathymetry layer in the Benthic Terrain Modeler in ArcGIS 10.3.1.1 (Wright et al. 2012). Bathymetric Position Index (BPI) is a measure of where a referenced location is relative to the locations surrounding it.	250 m	m	NIWA, unpublished
BPI_fine	BPI_fine	Static	Terrain metrics were calculated using an inner annulus of 2 km and a radius of 12 km using the NIWA bathymetry layer in the Benthic Terrain Modeler in ArcGIS 10.3.1.1 (Wright et al. 2012). Bathymetric Position Index (BPI) is a measure of where a referenced location is relative to the locations surrounding it.	250 m	m	NIWA, unpublished
carbonate	Percent carbonate	Static	The percent carbonate layers for the region were developed from >30,000 raw sediment sample data compiled in dbseabed, which were then imported into ArcGIS and interpolated using Inverse Distance Weighting (Bostock et al. 2019).	1 km	%	Bostock et al. (2019)
Chl-a	Chlorophyll-a concentration	July 2002 – March 2019	A proxy for the biomass of phytoplankton present in the surface ocean (to ~30 m depth). Blended from a coastal Chl-a estimate (quasi-analytic algorithm (QAA), local a_{ph}*(555)) and the default open-ocean chl-a value from MODIS-Aqua (v2018.0).	4 km (ocean) 500 m (coastal)	mg m^{-3}	NIWA unpublished, updated in 2020; Based on processing described in Pinkerton et al. (2016) and updated in Pinkerton et al. (2019). QAA algorithm detailed in (Lee et al. 2002; Lee et al. 2009)
Chl-a.Grad	Chlorophyll-a concentration spatial gradient	July 2002 – March 2019	Smoothed magnitude of the spatial gradient of annual mean Chl-a. Derived from Chl-a described above.	500 m	Mg m^{-3} km^{-1}	NIWA unpublished, updated in 2020; Based on processing described in (Pinkerton et al. 2018)

Abbreviation	Full name	Temporal range	Description	Native Resolution	Units	Source
DET	Detrital absorption	July 2002 – March 2019	Total detrital absorption coefficient at 443 nm, including due to coloured dissolved organic matter (CDOM) and particulate detrital absorption. Estimated using quasi-analytic algorithm (QAA) applied to MODIS-Aqua data, blended with *adg_443_giop* ocean product (Werdell, 2019).	4 km (ocean) 500 m (coastal)	m^{-1}	NIWA unpublished, updated in 2020; Based on processing described in (Pinkerton et al. 2018). Processing for *adg_443_giop* ocean product described in (Werdell 2019).
DynOc	Dynamic oceanography	1993-1999	Mean of the 1993-1999 period sea surface above geoid, corrected from geophysical effects taken for the NZ region. This broadly corresponds to mean surface velocity recorded from drifters in the NZ region (Hadfield pers comm).	250 m	m	NIWA, unpublished
Ebed	Seabed incident irradiance	July 2002 – March 2019	Broadband (400–700 nm) incident irradiance (E m^{-2} d^{-1}) at the seabed, averaged over a whole year. Estimated by combining incident irradiance at the sea surface ((Frouin et al. 2012); this table), diffuse downwelling irradiance attenuation (K_{PAR}; this table) and bathymetric depth at monthly resolution. Derived from blended coastal (QAA) and open-ocean attenuation products.	4 km (ocean); 500 m (coastal)	E m^{-2} d^{-1}	NIWA unpublished, updated in 2020, based on processing described in Pinkerton et al. (2018)
POCFlux	Downward vertical flux of particulate organic matter at the seabed	July 2002 – March 2019	Net primary production in the surface mixed layer estimated as the VGPM model ((Behrenfeld & Falkowski 1997); this table). Export fraction and flux attenuation factor with depth estimated by refitting sediment trap and thorium-based measurements to environmental data (VGPM, SST) as Lutz et al. (2002), Pinkerton et al. (2016) and using data from Cael et al. (2017).	9 km	mgC m^{-2} d^{-1}	NIWA unpublished, updated in 2020. Based on processing described in Pinkerton et al. (2016) with new data from Cael et al. (2018).
Gravel	Percent gravel	Static	The percent gravel layers for the region were developed from >30,000 raw sediment sample data compiled in dbseabed, which were then imported into ArcGIS and interpolated using Inverse Distance Weighting (Bostock et al., 2019).	1 km	%	Bostock et al., 2019
K_{par}	Diffuse downwelling attenuation	July 2002 – March 2019	vertical attenuation of diffuse, downwelling broadband irradiance (Photosynthetically Available Radiation, PAR, 400–700 nm). Merged coastal and open-ocean product based on MODIS-Aqua data. Coastal: estimated from inherent optical properties (QAA). Ocean: estimated from K_{490} using (Morel et al. 2007).	4 km (ocean) 500 m (coastal)	m^{-1}	NIWA unpublished, updated in 2020; Based on processing described in Pinkerton et al. (2018)

Abbreviation	Full name	Temporal range	Description	Native Resolution	Units	Source
MLD	Mixed layer depth	July 2002 – March 2019	The depth that separates the homogenized mixed water above from the denser stratified water below. Based on GLBu0.08 hindcast results using a potential density difference of 0.030 kg m^{-3} from the surface. Models used are: (1) hycom: from day 265 (2008) to present; (2) fnmoc: from day 169 (2005) to present; (3) soda: from day 249 (1997) to end of 2004; (4) tops: from day 001 (2005) to 225 (2010).	9 km	m	NIWA unpublished, updated in 2020; (Chassignet et al. 2007; Wallcraft et al. 2009; Metzger et al. 2010); Data: orca.science.oregonstate.edu
Mud	Percent mud	Static	The percent mud layers for the region were developed from >30,000 raw sediment sample data compiled in dbseabed, which were then imported into ArcGIS and interpolated using Inverse Distance Weighting (Bostock et al., 2019).	1 km	%	Bostock et al., 2019
OxyUt	Apparent oxygen utilization		The difference between the measured dissolved oxygen concentration and its equilibrium saturation concentration in water with the same physical and chemical properties.	Approx. 41 km (1/2 degree)	umol l^{-1}	NIWA, unpublished
PAR	Photo-synthetically active radiation	July 2002 – March 2019	Daily-integrated, broadband, incident irradiance at the sea-surface based on day length, solar elevation and measurements of cloud cover from ocean colour satellites (Frouin et al. 2012).	4 km	E m^{-2} d^{-1}	NIWA unpublished, updated in 2020; Frouin et al. (2012)
PB555nm	Particulate backscatter at 555 nm (previously used to generate 'turbidity')	July 2002 – March 2019	Optical particulate backscatter at 555 nm estimated using blended coastal and ocean products. Coastal: QAA v5 product bbp555 from MODIS-Aqua data. Ocean: *bbp_555_giop* ocean product (Werdell 2019). Result calculated as long-term (2002–2017) average.	4 km (ocean) 500 m (coastal)	m^{-1}	NIWA unpublished, updated in 2020; Based on processing described in Pinkerton et al. (2018). Processing for *bbp_555_giop* ocean product described in Werdell (2019).
Reef	Rocky reefs	Static	Locations of subtidal rocky reefs inferred from navigational charts (Smith et al., 2013). Polygon data converted to raster grids based on > 50% of polygon in cell.	polygon data	Presence / absence of reef	DOC
Rough	Roughness	Static	Roughness of the seafloor calculated as the as the variation in three-dimensional orientation of grid cells within a neighborhood. Vector analysis is used to calculate the dispersion of vectors normal (orthogonal) to grid cells within the specified neighbourhood.	250 m	m	NIWA, unpublished data, updated in 2019

Abbreviation	Full name	Temporal range	Description	Native Resolution	Units	Source
sand	sand	Static	The percent sand layers for the region were developed from >30,000 raw sediment sample data compiled in dbseabed, which were then imported into ArcGIS and interpolated using Inverse Distance Weighting (Bostock et al., 2019).	1 km	%	Bostock et al., 2019
SeasTDiff	Annual amplitude of sea floor temperature	Static	Smoothed difference in seafloor temperature between the three warmest and coldest months. Providing a measure of temperature amplitude through the year.	250 m	°C km^{-1}	NIWA, unpublished data, updated in 2018
Sed.class	Sediment classification	Static	Classification of Mud, Sand and Gravel layers (this table) using the well-established (Folk et al. 1970) classification. Subtidal rocky reefs (this table) were incorporated. This classification provides a broad measure of hardness Mud – Rock.	1 km	NA; Mud; Muddy gravel; Muddy sandy gravel; sand; Gravely mud; Gravelly sandy mud; Gravelly sand; Gravel; Rock	NIWA unpublished, updated in 2020
Slope	Slope	Static	Bathymetric slope was calculated from water depth and is the degree change from one depth value to the next.	250m	°	NIWA, unpublished, updated in 2019
SST	Sea surface temperature	1981-2018 (ocean) 2002-2018 (coastal)	Blended from OI-SST (Reynolds et al., 2002) ocean product and MODIS-Aqua SST coastal product. Long-term (2002–2017) average values at 250 m resolution.	0.25° (ocean) 1 km (coastal)	°C	NIWA unpublished, updated in 2020; Coastal based on processing described in Pinkerton et al. (2018). Ocean: (Reynolds et al. 2002)

Abbreviation	Full name	Temporal range	Description	Native Resolution	Units	Source
SSTGrad	Sea surface temperature gradient	1981-2018 (ocean) 2002-2018 (coastal)	Smoothed magnitude of the spatial gradient of annual mean SST. This indicates locations in which frontal mixing of different water bodies is occurring (Leathwick et al. 2006).Derived from SST described above at two resolutions and merged.	0.25° (ocean) 1 km (coastal)	°C km^{-1}	NIWA unpublished, updated in 2020
SuspPM	Suspended particulate matter		Indicative of total suspended particulate matter concentration. Based on SeaWiFS ocean colour remote sensing data (Pinkerton & Richardson 2005); modified Case 2 atmospheric correction (Lavender et al. 2005); modified Case 2 inherent optical property algorithm (Pinkerton et al. 2006).	4 km	Indicative of total suspended particulate matter concentration (g m-3)	NIWA unpublished, updated in 2020; Pinkerton (2016)
TC	Tidal Current speed	2009 -	Maximum depth-averaged (NZ bathymetry) flows from tidal currents calculated from a tidal model for New Zealand waters (Walters et al. 2001). Tidal constituents (magnitude A and phase phi, represented as real and imaginary parts X + iY = A*exp(i*phi)) for sea surface height and currents (8 components) were taken from the EEZ tidal model, on an unstructured mesh at variable spatial resolution. The complex components were bilinearly interpolated to the output grid.	250 m	ms^{-1}	Walters et al., 2001; NIWA unpublished, updated in 2020
TempRes	Temperature residuals	1/7/2017-30/6/2018	Residuals from a GLM relating temperature to depth using natural splines – this highlights areas where average temperature is higher or lower than would be expected for any given depth.	250 m	°C	Leathwick et al. (2006)
VGPM	Net primary production by the vertically-generalised production model	July 2002 – March 2019	Daily production of organic matter by the growth of phytoplankton in the surface mixed layer, net of phytoplankton respiration. Estimated at monthly resolution based on satellite observations of chl-a, PAR and SST, and model-derived estimates of mixed-layer depth, using the vertically-generalised production model (Behrenfeld & Falkowski, 1997).	9 km	mgC m^{-2} d^{-1}	Behrenfeld & Falkowski (1997); NIWA unpublished, updated in 2020

3 Development of a Gradient Forest environmental classification (Objective 3)

GF models were used to analyse and predict spatial patterns of compositional turnover for species in each of four biotic groups: demersal fish, reef fish, benthic invertebrates, and macroalgae, following analytical methods described in Ellis et al. (2012); Pitcher et al. (2012). These four turnover models were then combined to derive estimates of compositional turnover along each of the environmental gradients. Associated uncertainty estimates were also produced. Finally, the combined compositional turnover was hierarchically classified to a 30-, 50-, 75-, and 100-group level (i.e., inferred community groups) across the New Zealand TS and EEZ (Figure 3-1). Here we describe in detail the 75-group classification, which we refer to as the 'New Zealand Seafloor Community Classification' (SCC). All modelling was undertaken in R (R Core Team 2020). Metadata for all data used in the models, R code, and output files are provided in Supplementary Materials 1.

3.1 Methods

3.1.1 Estimating compositional turnover

For each biotic group (demersal fish, macroalgae and reef fish) and for the different benthic invertebrate sampling gear types (LLG.LMG, MMG, SMG and SSG) GF models were fitted using the 'extendedForest', (Liaw & Wiener 2002) and 'gradientForest' (Ellis et al. 2012) R packages (Figure 3-1). GF models were fitted with 500 trees and default settings for the correlation threshold used in the conditional importance calculation of environmental variables. For each of the 7 GF models, we extracted information on the predictive power of the individual RF models (R^2_f for each taxon measured as the proportion of out-of-bag variance explained) (Ellis et al. 2012) and the importance of each environmental variable (R^2 assessed by quantifying the degradation in performance when each environmental variable was randomly permuted[1] (Pitcher et al. 2012). The environmental variables used in each GF model were selected to maximise the number of taxa effectively modelled (i.e., taxa with $R^2_f > 0$) and increase model fits for the most poorly modelled taxa (i.e., taxa with low R^2_f).

GF aggregates the values of the tree-splits from the RF models for all taxon models with positive fits ($R^2_f > 0$) to develop empirical distributions that represent taxa compositional turnover along each environmental gradient (Ellis et al. 2012; Pitcher et al. 2012). The turnover function is measured in dimensionless R^2 units, where taxa with highly predictive random forest models (high R^2_f values) have greater influence on the turnover functions than those with low predictive power (lower R^2_f). The shapes of these monotonic turnover curves describe the rate of compositional change along each environmental predictor; steep parts of the curve indicate fast assemblage turnover, and flatter parts of the curve indicate more homogenous regions (Ellis et al. 2012; Pitcher et al. 2012; Compton et al. 2013).

The use of the dimensionless R^2 to quantify compositional turnover enables information from multiple taxa to be combined, even if that information comes from different sampling devices, surveys or regions (Ellis et al. 2012). In the first instance, the compositional turnover functions from each of the benthic invertebrate gear type GF models were combined using the 'combinedGradientForest()' function to provide a combined benthic invertebrate GF model (herein

[1] Note that R^2 described by Pitcher et al., 2012 and Ellis et al., 2011 refers to a unitless measure of cumulative importance and should not be confused with the more commonly used R-squared (R^2) denoting coefficient of determination.

referred to simply as Benthic invertebrate GF model). In the second instance, a final 'combined' GF model was created using the 'combinedGradientForest()' function across all biotic groups (demersal fish, reef fish, benthic invertebrates, and macroalgae) (Figure 3-1). Broadly, this method of combining GF models accounts for the number of taxa, the number of samples, and the taxa R^2_f along the gradient of each environmental variable from individual GF models to provide a cumulative estimate of compositional turnover (for further details see, Ellis et al. (2012); Pitcher et al. (2012)).

The compositional turnover functions from each biotic group and the combined GF models (shapes of the turnover curves) were used to transform the gridded environmental layers (both 250m and 1 km grid resolutions), creating a 'transformed environmental space' representing compositional turnover. Variation within this transformed environmental space was summarised using principle components analysis (PCA) (Pitcher et al. 2011). The colours used in the PCA of each biotic group were based on the first three axes of their respective PCA analysis so that similarities/differences in colour corresponded broadly to pairwise similarities/differences in the transformed environmental space and thus, by inference, describe differences in taxa composition (Stephenson et al. 2018a). Predicted taxa compositional turnover for each biotic group was plotted geographically using the colour scheme derived from their respective PCA analyses.

GF models for each taxon and sampling gear type, as well as the cumulative GF models, were bootstrapped 100 times (Figure 3-1). That is, 100 combined GF models were fitted (as for the main model described above) to separate randomly selected subsets of the full input dataset. For biotic groups with ≥ 5000 samples (Table 2-1), a random selection of 5000 samples was selected from the full dataset. This number of samples was selected both to ensure reasonable computational time for the analysis, and because previous analysis using demersal fish data indicated that this number of samples was the lowest number of samples which provided stable (consistent) model outputs (Stephenson et al. 2018a). A GF using a larger number of samples of the demersal fish and invertebrate samples (20,000 samples each) were qualitatively consistent (respectively) to the mean bootstrap results. For biotic groups with < 5000 samples (Table 2-1), 75% of the dataset was randomly selected for each bootstrap iteration. The bootstrapping process was repeated 100 times, and at each iteration, species compositional turnover functions were used to transform the gridded environmental layers (both 250m and 1 km grid resolutions). Mean (± 1 standard deviation of the mean) estimates of taxa R^2_f and environmental variable importance (R^2) were calculated for each GF model from the 100 bootstrapped iterations.

3.1.2 Spatial predictions and estimating model uncertainty

Spatial estimates of compositional turnover from each GF model (i.e., for each biotic group, sampling gear type, and cumulative model), were averaged (mean) and a spatially explicit measure of uncertainty (measured as the standard deviation of the mean (SD) compositional turnover averaged across each environmental variable) was calculated for each grid cell using the 100 bootstrapped transformed environmental layers (Figure 3-1).

As an added measure of model uncertainty, for each GF model, we estimated 'coverage of the environmental space' (Smith et al. 2013; Stephenson et al. 2020b) (Figure 3-1). The 'environmental space' is the multidimensional space produced by considering each of the environmental variables as a dimension. Some parts of this environmental space will contain many samples - meaning we can be more confident of the relationships and the predictions (Smith et al. 2013) - while other parts will contain few samples. Predictions for the less sampled parts of the environmental space are considered less reliable, and should be interpreted with greater caution (Smith et al. 2013).

We modelled variation in sampling density within the environmental space by combining our samples (assigned as 'present') with an equal number of randomly sampled values from the environmental space (i.e., where we did not have any taxonomic samples – assigned as 'absences'). A Boosted Regression Tree (BRT, (Elith et al. 2006)) model was then used to model the relationship between these 'present' (true) samples and 'absent' (random) samples for the 20 environmental variables used in the GF analyses. The 'Dismo' package (Hijmans et al. 2017) was used with BRT models fitted using a Bernoulli error distribution, a learning rate that yielded 2,000 trees and an interaction depth of 2 (so that only pair-wise combinations of the environmental variables were considered). Predictions using this model yielded estimates of the probability of a sample occurring in each part of the environmental space, these estimates ranging between 0 and 1, where 0 indicated very low sampling of the environmental space and 1 a very high level of sampling (Stephenson et al. 2020b).

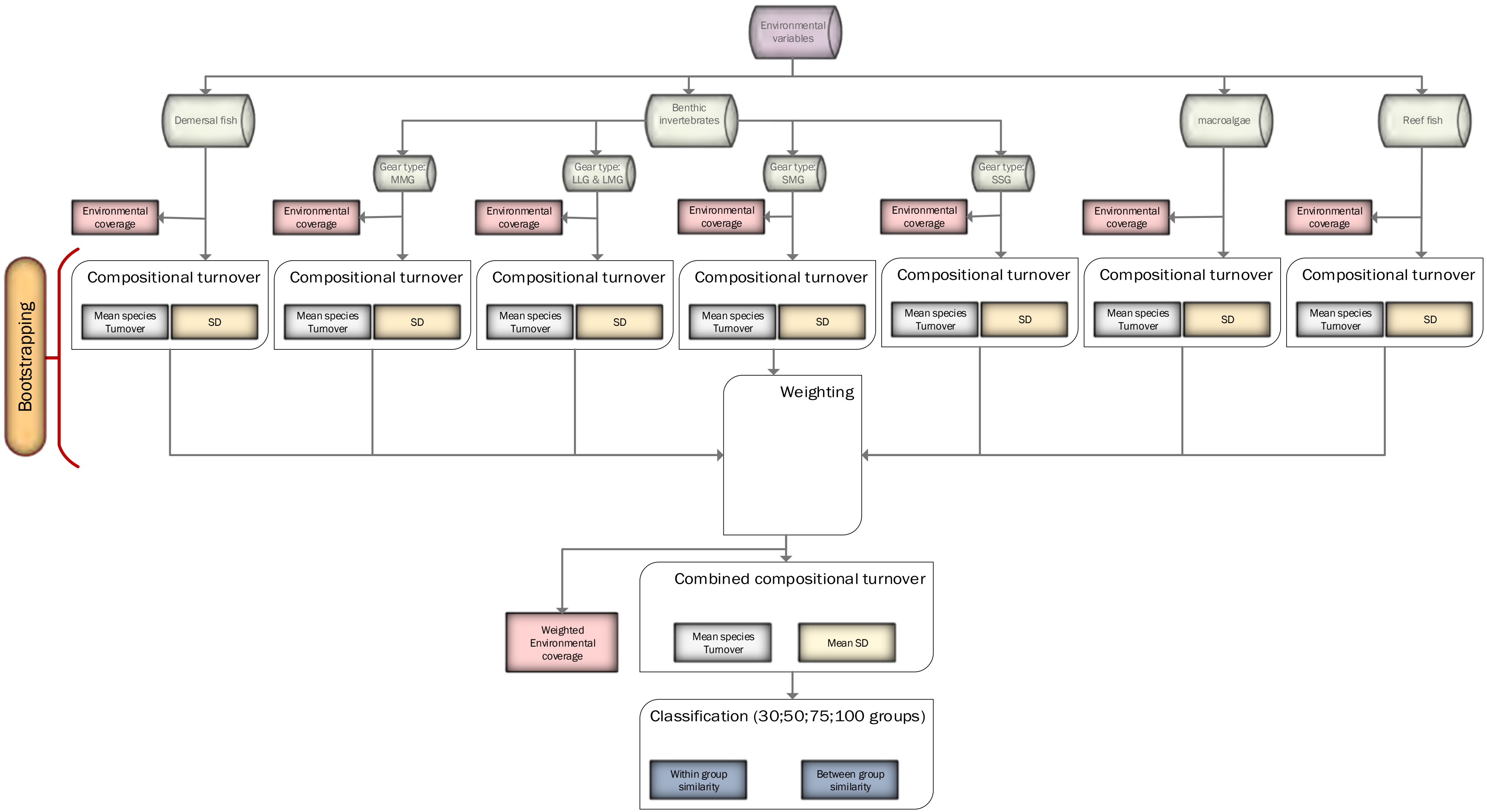

Figure 3-1: Summary of data inputs, analyses undertaken and key outputs and terminology used.

3.1.3 Classification

The mean spatial estimate of compositional turnover from the combined GF model (i.e., the bootstrapped GF model which included samples from all biotic groups and gear types) was classified to 30-, 50-, 75- and 100-group levels to represent seafloor communities at various spatial scales (Figure 3-1). Classification was undertake in two stages (Leathwick et al. 2011; Stephenson et al. 2018a) using the R package 'cluster' (Maechler et al. 2017). For the first stage, mean spatial estimates of compositional turnover were clustered to form 500 initial groups using non-hierarchical, k-medoids clustering. Average values for the transformed environmental predictors were then computed for each of these initial groups For the second stage, a hierarchical clustering approach – flexible UPGMA – using the Manhattan metric, and a value for beta of -0.1 (Belbin et al. 1992) was used to define each group from the initial 500.

Given the hierarchical nature of the GF classification, consideration will be required as to what constitutes the most appropriate level of classification detail for conservation planning purposes which may vary depending on spatial scale of the application and the required level of information needed for management. Using the biological data used in the GF models the discrimination across classification levels was assessed for each group (5 – 150 groups in increments of 5, as in (Snelder et al. 2007)) using an ANOSIM analysis (Clarke & Warwick 2001). The global R statistic was calculated as the difference in ranked biologic similarities arising from all pairs of replicate sites between different groups, and the average of all rank similarities within groups, adjusted by the total number of sites. Global R is equal to 1 if all replicates within groups are more like each other than any replicates from different groups and is approximately 0 if there is no group structure. The significance of the ANOSIM statistics were tested with a randomisation procedure based on the null hypothesis of no group structure. All ANOSIM analyses were undertaken in R using the 'Vegan' package (Oksanen et al. 2013). A large proportion of groups at any particular classification level had either few biologic sites or lacked them altogether. We therefore only undertook analysis on groups with adequate biological data (≥ 5 unique occurrences).

Finally, we describe the 75-group level classification in greater detail. We refer to this classification as the New Zealand 'Seafloor Community Classification' (NZ SCC). This classification level represented the highest number of groups that captured the majority of the variation across the New Zealand marine environment, based on examining the ANOSIM global R statistic for each taxa, and which contained adequate number of biological records. In section 3.2.2 we describe the 75-group level classification in greater detail. Group means for each of the transformed environmental variables were calculated and plotted in a PCA and their hierarchical similarities were displayed using a dendrogram. Groups were also plotted geographically.

Following methods developed by Stephenson et al. (2020c), individual group descriptions for the SCC are provided in Petersen et al. (2020). Descriptions included:

- The location of the SCC group within the New Zealand marine environment.
- Descriptions of a subset of each groups' environmental characteristics, termed "characterising environmental conditions". In addition, for each SCC group, the mean and range (25 – 75 quantile) of each environmental variable is available in: Summary_info_SCC (for further information see Table 6-3 in Supplementary materials 1).
- Descriptions of each groups' biological characteristics were provided by calculating mean frequency occurrence of each taxa within groups and investigating the contribution of individual

taxa to intra-group similarity (SIMPER analysis using Bray-Curtis similarity, in PRIMER v7.0.13) (Stephenson et al. 2020c). Characterising species were defined as those species contributing more than 4% to the SIMPER intra-group similarity. In addition, for each SCC group, the mean frequency occurrence of all taxa is available in: Mean_Taxa_Occ_SCC (for further information see Table 6-3 in Supplementary materials 1).

- Finally, as a measure of model confidence, for each classification group, the mean, 25% and 75% quantile for the uncertainty estimate of compositional turnover (SD of the combined bootstrapped GF) and the overall predicted environmental coverage were extracted. In addition, for each SCC group, the mean and range (25 – 75 quantile) for both measures of uncertainty by biotic group is available in: Summary_info_SCC (for further information see Table 6-3 in Supplementary materials 1).

For further details on methods and qualitative descriptions see Petersen et al. (2020). For reference, an example of a group description (Group 30) is provided in Supplementary material 1 – section 6.4.

3.2 Results

3.2.1 Compositional turnover and uncertainty

Models were able to be fitted for most taxa across all biotic groups (i.e., $R^2_f > 0$, Table 3-1). However, individual taxon R^2_f values varied widely, ranging from 0.19 (macroalgae, Table 3-1) to 0.94 (reef fish, Table 3-1). The GF models explained 47-53% of variation in occurrence on average across biotic groups (mean taxa R^2_f: 0.47 – 0.53, Table 3-1). Mean R^2_f (± SD) for individual taxa are presented by biotic group in: Sp_R2 ; for further information see Table 6-3 in Supplementary materials 1).

Table 3-1: Mean (±SD) model fit metrics of individual taxa (R^2_f) from bootstrapped GF models. The number of taxa retained in biotic group datasets is provided in brackets in the group headings.

Model fit metric	Demersal fish (317 taxa)	Benthic invertebrates (958 taxa)	Macroalgae (349 taxa)	Reef fish (92 taxa)
Mean taxa effectively modelled (± SD)	313.76 (±1.57)	955.20 (±3.36)	335.99 (±0.11)	91.99 (±0.11)
Min Taxa R^2_f (± SD)	0.36 (±0.04)	0.26 (±0.05)	0.19 (±0.08)	0.25 (±0.04)
Mean Taxa R^2_f (± SD)	0.52 (< 0.01)	0.48 (< 0.01)	0.47 (< 0.01)	0.53 (±0.01)
Max Taxa R^2_f (± SD)	0.91 (±0.01)	0.84 (±0.05)	0.61 (±0.04)	0.94 (±0.04)

Although all environmental variables contributed to predicting compositional turnover for all models (positive R^2, Table 3-2), their relative importance (in terms of mean cumulative importance) varied across biotic groups (Table 3-2). The most consistently important variables in the biotic group GF models were dissolved oxygen at depth (BotOxy) and bottom salinity (BotSal) (Table 3-2). Tidal current speed (TC) was important in GF models of demersal fish, benthic invertebrates and the combined GF model. Many of the environmental variables had moderate cumulative importance across all biotic groups and in the combined GF model, e.g., dissolved oxygen at depth (BotOxy), seabed incident irradiance (Ebed), downward vertical flux of POC at the seabed (POCFlux) (R^2: 0.0015 – 0.004, Table 3-2).

Table 3-2: Mean (±SD) cumulative importance (R^2) of environmental variables for bootstrapped GF models of each biotic group and for the 'combined' bootstrapped GF model. The four environmental predictors with the highest cumulative importance for each biotic group and for the combined GF models are highlighted in black.

Environmental variable	Demersal fish	Macroalgae	Reef fish	Benthic invertebrates	Combined
Bathy	0.0037 (±0.0001)	0.0009 (±0)	0.0019 (±0.0002)	0.0227 (±0.001)	0.0289 (±0.0012)
Beddist	0.0012 (±0.0001)	0.0013 (±0.0001)	0.0031 (±0.0003)	0.0267 (±0.0013)	0.0174 (±0.001)
BotOxy	0.0039 (±0.0001)	0.0024 (±0.0001)	0.0068 (±0.0004)	0.0408 (±0.0013)	0.0478 (±0.0011)
BotNi	0.0027 (±0.0001)	0.0018 (±0.0001)	0.0033 (±0.0002)	0.0176 (±0.0006)	0.0253 (±0.0006)
BotPhos	0.0026 (±0)	0.0013 (±0)	0.0036 (±0.0003)	0.0171 (±0.0008)	0.0257 (±0.0009)
BotSal	0.0038 (±0.0001)	0.0022 (±0.0001)	0.0073 (±0.0004)	0.0378 (±0.0023)	0.0437 (±0.0024)
BotSil	0.0023 (±0)	0.0034 (±0.0001)	0.0044 (±0.0004)	0.0197 (±0.0008)	0.045 (±0.0013)
BotTemp	0.0036 (±0.0001)	0.0013 (±0)	0.0062 (±0.0004)	0.022 (±0.0006)	0.0314 (±0.0013)
BPI_broad	0.0018 (±0.0002)	0.0021 (±0.0001)	0.005 (±0.0003)	0.0421 (±0.0025)	0.0443 (±0.0025)
BPI_fine	0.0009 (±0.0001)	0.0019 (±0.0001)	0.0038 (±0.0007)	0.0323 (±0.0017)	0.0345 (±0.0016)
Chl-a.Grad	0.0013 (±0.0005)	0.0013 (±0.0002)	0.0027 (±0.0002)	0.0237 (±0.003)	0.0212 (±0.003)
DET	0.0031 (±0.0001)	0.0021 (±0.0001)	0.0043 (±0.0004)	0.0308 (±0.0022)	0.0368 (±0.0017)
PB555nm	0.0022 (±0.0001)	0.0017 (±0)	0.0048 (±0.0004)	0.0284 (±0.0025)	0.0289 (±0.0017)
SeasTDiff	0.0013 (±0)	0.002 (±0.0001)	0.0042 (±0.0003)	0.0226 (±0.0008)	0.023 (±0.0006)
Slope	0.0022 (±0.0001)	0.0007 (±0)	0.0014 (±0.0002)	0.0233 (±0.0029)	0.0221 (±0.0025)
SSTGrad	0.0031 (±0.0003)	0.0024 (±0.0001)	0.0046 (±0.0006)	0.0311 (±0.0051)	0.034 (±0.0032)
Sed.class	0.0007 (±0)	0.0003 (±0)	0.0003 (±0.0001)	0.0084 (±0.0004)	0.008 (±0.0004)
TC	0.004 (±0.0001)	0.0015 (±0.0001)	0.0041 (±0.0004)	0.0476 (±0.0027)	0.0468 (±0.0025)
POCFlux	0.0023 (±0)	0.0019 (±0.0001)	0.0053 (±0.0004)	0.0299 (±0.0016)	0.0304 (±0.0012)
Ebed	0.0011 (±0.0004)	0.0018 (±0.0001)	0.0027 (±0.0003)	0.0306 (±0.0025)	0.0239 (±0.0013)

The predicted cumulative changes in compositional turnover along each environmental variable from biotic group GF models (blue, yellow, orange and green lines, Figure 3-2) and the combined GF model (black line, Figure 3-2) indicate both the overall influence of each environmental variable (final height of the curve) and the rate of change. Steep parts of the curve indicate fast compositional turnover, and flatter parts of the curve indicate more homogenous regions (Ellis et al., 2012; Pitcher et al., 2012). There were differences both in overall influence of environment variables and rate of change between biotic groups, most likely reflecting differences in environmental preferences (or proxies thereof) and sampling of the different taxa (Figure 3-2). For example, compositional turnover of reef fish and macroalgal taxa increased rapidly along the gradient of bottom silicate concentrations (BotSil) from 0 – 5 umol l^{-1} with no turnover past these values (Figure 3-2), whereas compositional turnover of benthic invertebrates and demersal fish taxa was slower but occurred across a larger gradient (0 – 110 umol l^{-1}, plateauing past this point, Figure 3-2). Compositional turnover of the combined GF model incorporates both of these trends along the gradient of bottom silicate concentrations (Figure 3-2 and Figure 3-3). Cumulative changes and associated uncertainty in composition turnover along each environmental variable from individual biotic group GF models are available in Supplementary Materials 4 – Compositional turnover for individual biotic groups (Figure 9-1, Figure 9-4, Figure 9-7, Figure 9-10).

Overall, the variability in mean predicted cumulative changes in compositional turnover (measured as the SD of the mean) from the combined GF model was relatively low (Figure 3-3). However, there were some more pronounced differences both along individual environmental gradients and between different environmental variables (Figure 3-3). For example, the SD of mean compositional turnover between slope values of 0 - 15° was low but increased with increasing slope values (Figure 3-3), most likely reflecting the lower numbers of samples from sites with steep slopes. Among two of the most influential predictors, the SD of mean compositional turnover along the gradient of dissolved oxygen at depth (BotOxy) was much lower than the SD of mean compositional turnover in relation to sea surface temperature gradient (SSTGrad) (Figure 3-3).

There were strong similarities in spatial patterns in compositional turnover between biotic groups (Supplementary Materials 4 – Compositional turnover for individual biotic groups: Figure 9-2, Figure 9-5, Figure 9-8, Figure 9-11) and the combined GF models (Figure 3-4); reflecting broadscale patterns in environmental variables linked to well-defined oceanographic patterns observed in New Zealand's waters. Briefly, compositional turnover was minimal in deeper water (< 2000 m), although with progression to shallower waters (1000 – 2000m) there appeared to be differences in taxa occurring in in the northwest of the study area compared to all other deep water areas (Figure 3-4). With progression to intermediate depths (70 – 1000 m), there was a clear latitudinal separation along the boundaries of the Subtropical Front (STF), a highly productive zone of mixing between high salinity, nutrient poor, warm, northern waters, and low salinity, nutrient rich, cold, southern waters (Bradford-Grieve et al. 2006; Leathwick et al. 2006; Leathwick et al. 2012; Stephenson et al. 2018a) (Figure 3-4). In shallower water (0 – 70 m), patterns in compositional turnover were more closely associated both with latitude and with more localised environmental conditions which varied between biotic groups (Supplementary Materials 4 – Compositional turnover for individual biotic groups: Figure 9-2, Figure 9-5, Figure 9-8, Figure 9-11). For the combined GF model, these more localised environmental variables were particulate backscatter at 555 nm (PB555nm, a measure of water clarity), tidal currents (TC) and seafloor topography at different scales (BPI_broad and BPI_fine) (Figure 3-4, Table 3-2).

There were clear spatial differences in the uncertainty estimate (SD) of compositional turnover between biotic groups (Supplementary Materials 4 – Compositional turnover for individual biotic groups: Figure 9-3, Figure 9-6, Figure 9-9, Figure 9-12). However, the SD for all GF models was low compared to the mean compositional turnover, i.e., the uncertainty in the compositional turnover was low even for the most variable areas. The SD of mean compositional turnover for the combined GF model was highest close to shore in areas of high compositional turnover, for example, in Cook Strait and the Marlborough Sounds (Figure 3-5, A). Much of the continental shelf (areas shallower than 200 m) and the Chatham Rise displayed moderate to high variability in mean compositional turnover (Figure 3-5, A). Deep water areas displayed the lowest variability in mean compositional turnover, in part reflecting compositional homogeneity associated with these abyssal waters, but also likely reflecting, at least in part, the relative lack of sampling in these areas as environmental coverage was low for most areas deeper than 2000 m (Figure 3-5, A and B). Environmental coverage was high in areas close to shore and along the Chatham Rise (Figure 3-5, B) and moderate for parts of the Challenger and Campbell Plateaus (Figure 3-5, B).

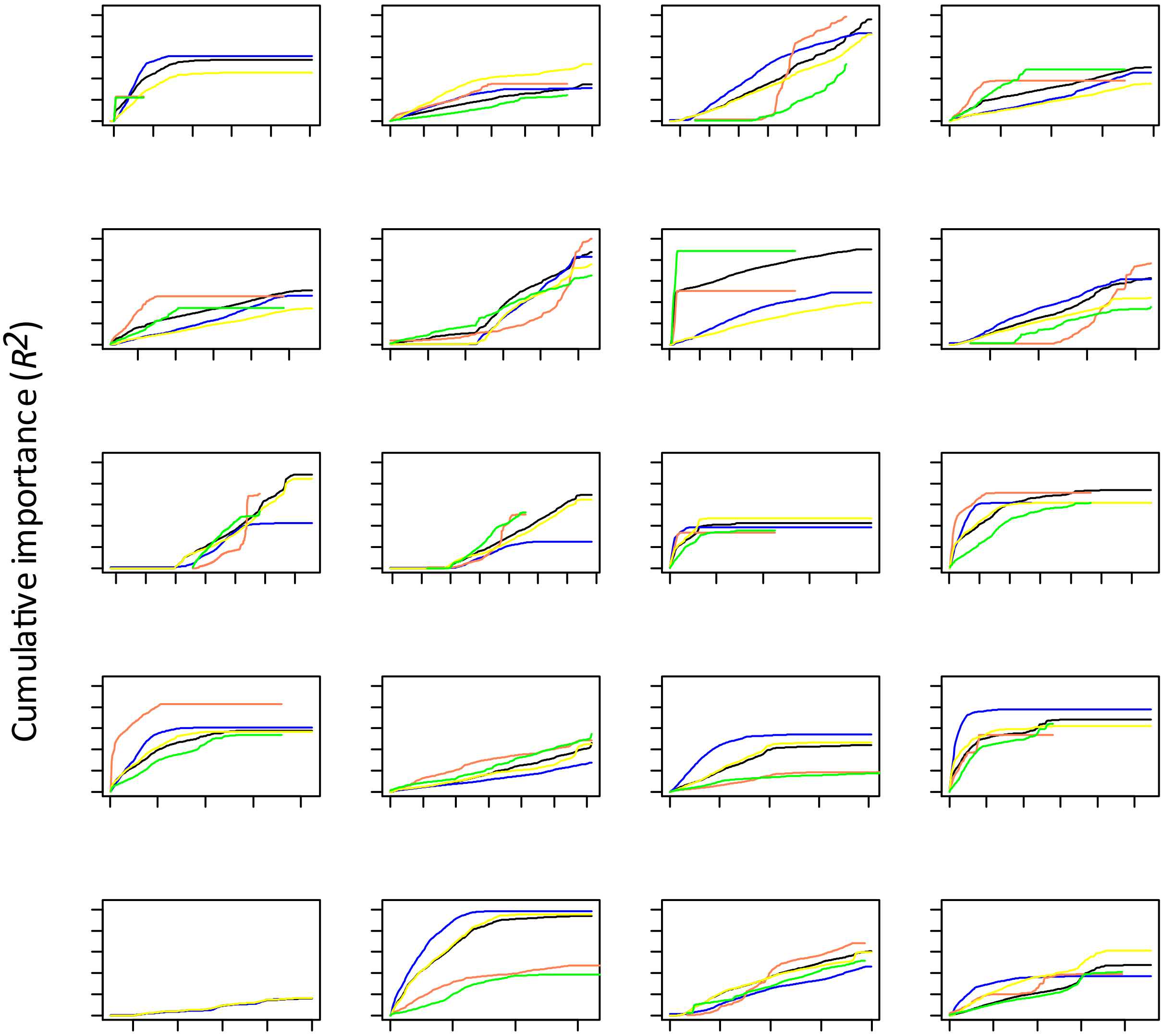

Figure 3-2: Mean functions fitted by bootstrapped GF models of demersal fish (blue), benthic invertebrates combined across gear types (yellow), reef fish (orange), macroalgae (green) samples and combined estimates (black) (R^2). Fitted functions indicate relative compositional turnover along the range of each predictor.

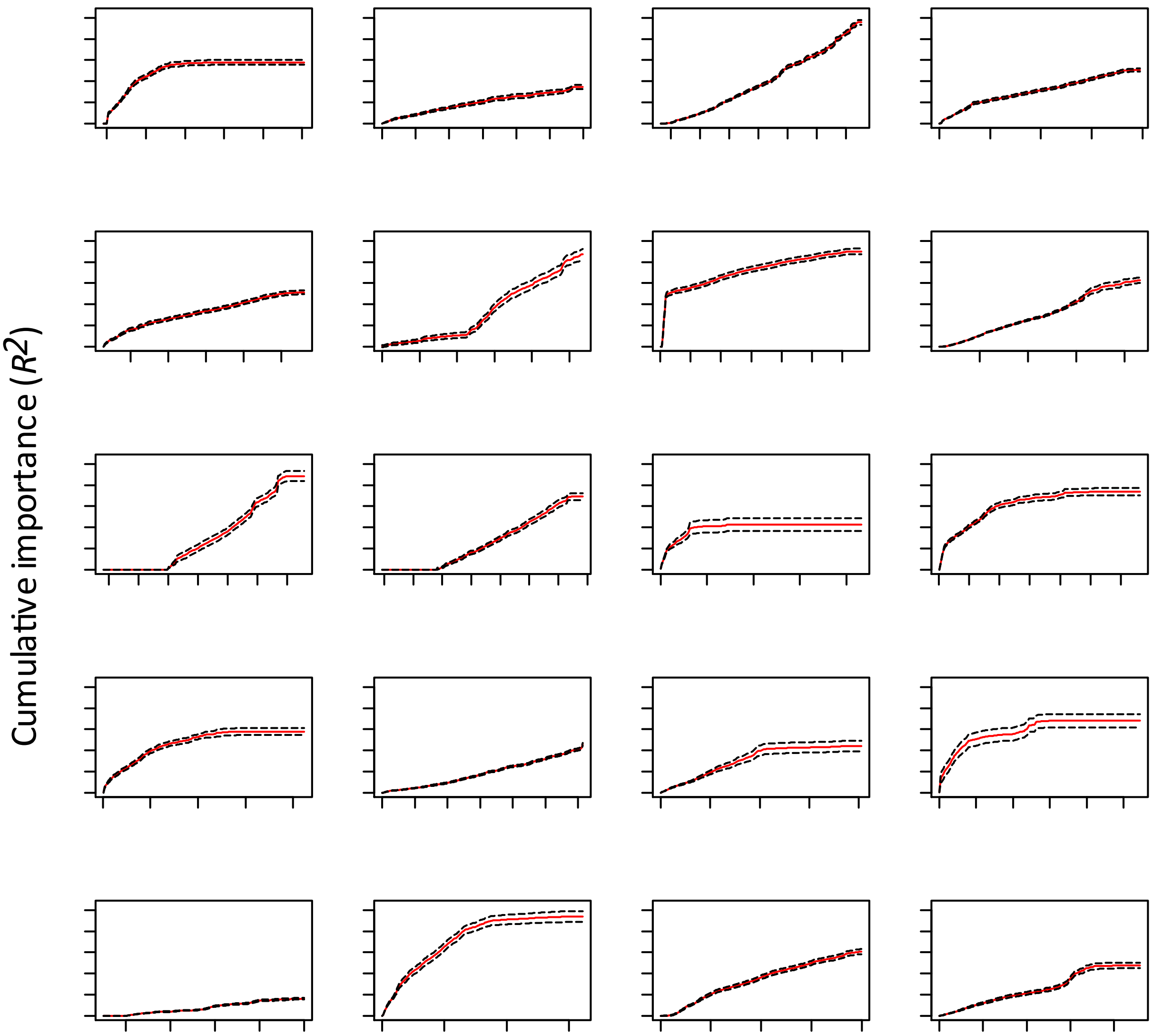

Figure 3-3: Mean (± SD) functions fitted by bootstrapped combined GF models of samples from all biotic groups (R^2). Fitted functions indicate relative compositional turnover along the range of each predictor.

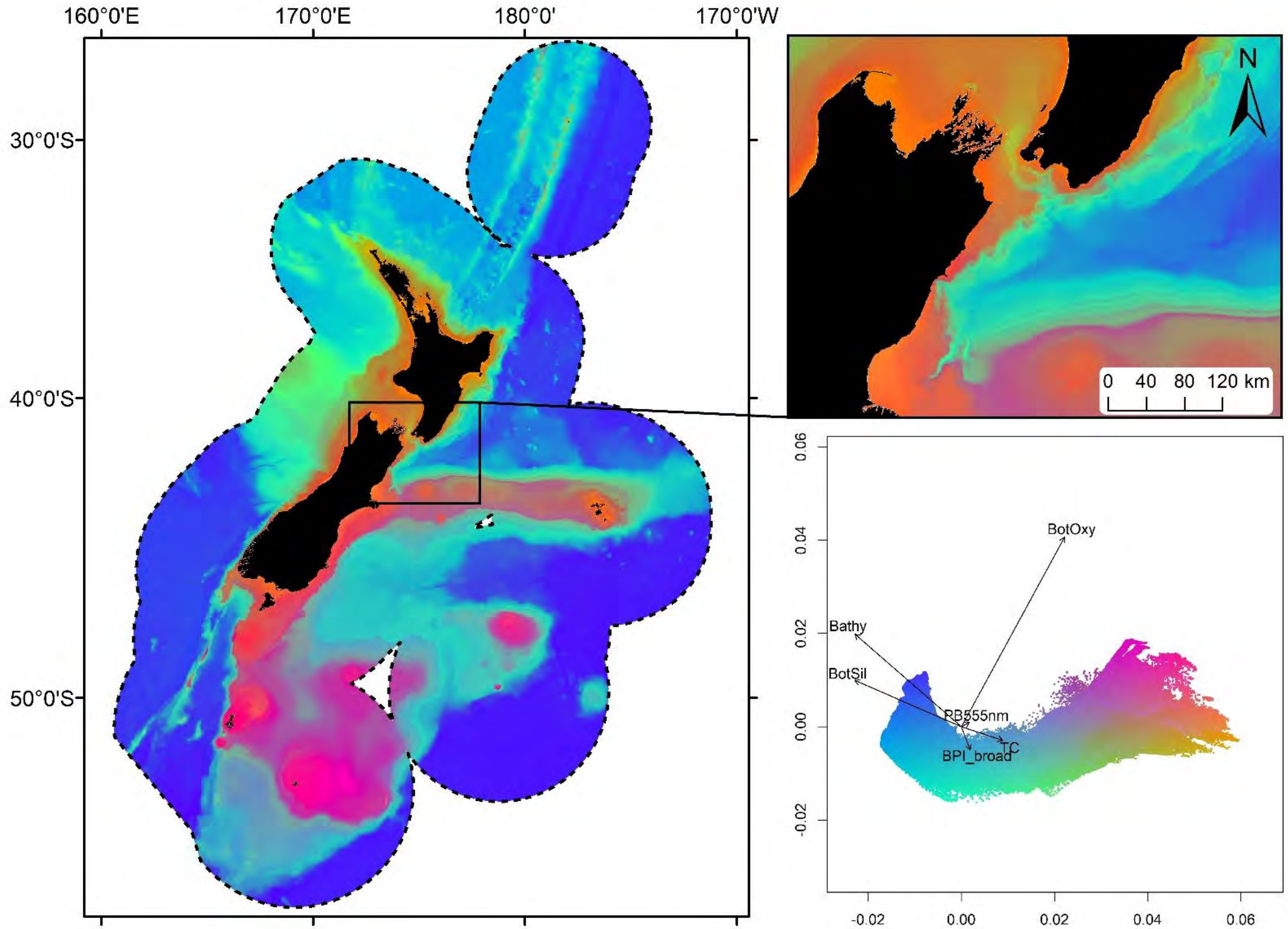

Figure 3-4: Mean predicted compositional turnover in geographic and PCA space derived from 'combined' bootstrapped Gradient Forest model fitted using samples from all biotic groups. Colours are based on the first three axes of a PCA analysis so that similarities/differences in colour correspond broadly to similarities/differences in predicted compositional turnover. Compositional turnover in PCA space, with vectors indicating correlations with the 6 most important environmental predictors (A); Geographic distributions of compositional turnover across the New Zealand marine environment (dashed line)(B); Geographic distribution of compositional turnover at finer scales, centred on Cook Strait (C).

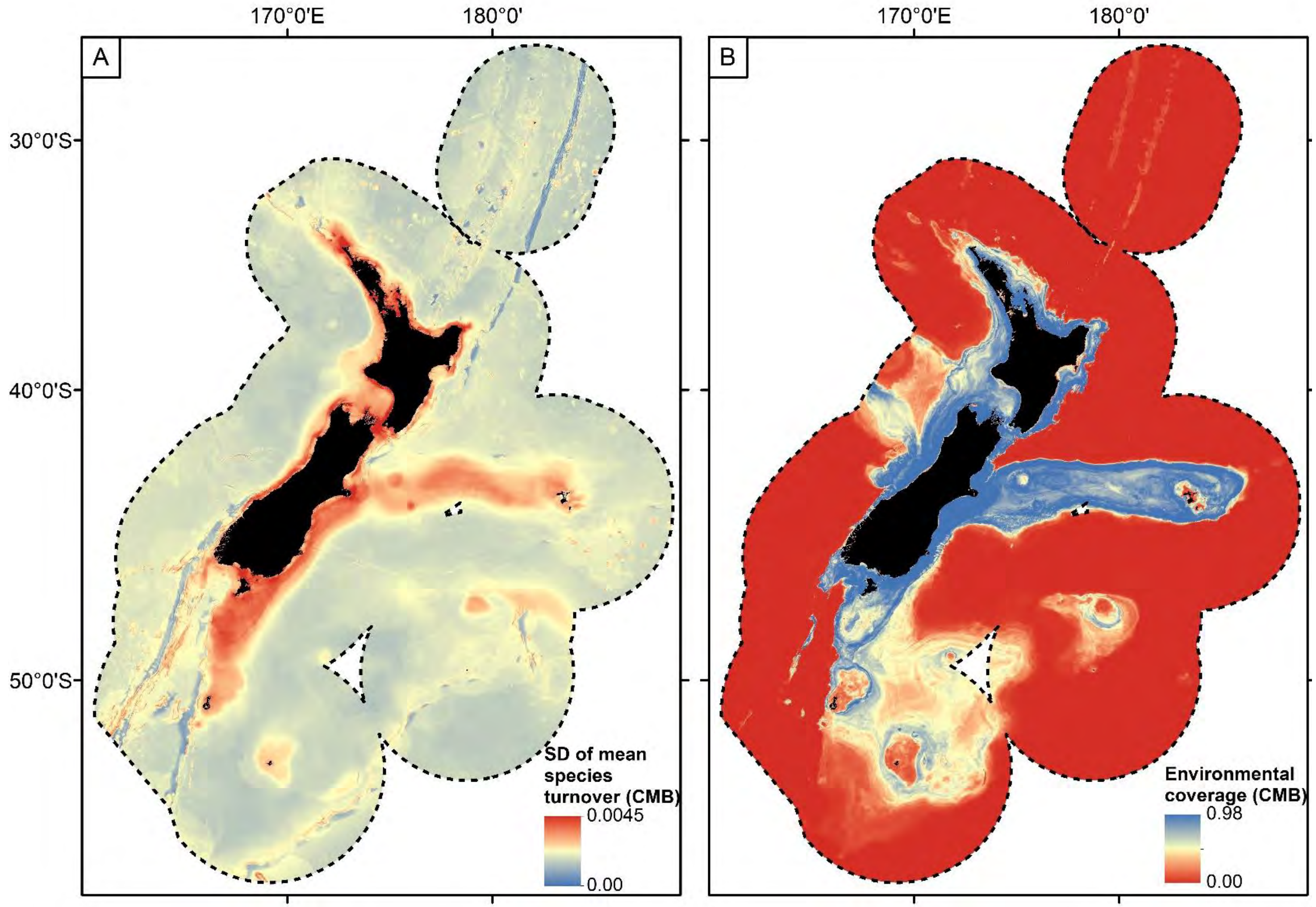

Figure 3-5: Spatially explicit measures of uncertainty for compositional turnover from the 'combined' bootstrapped Gradient Forest model fitted using samples from all biotic groups Uncertainty estimate (SD) of compositional turnover modelled using bootstrapped Gradient Forest model fitted with demersal fish, benthic invertebrate, macroalgae and reef fish samples (A). Predicted environmental coverage depicting the confidence that can be placed in the predictions, ranging from low (i.e., no samples in the dataset with those environmental conditions) to high (i.e., many samples with those environmental conditions) within the New Zealand EEZ (B).

3.2.2 Community classification

Assessment of classification strength

There was adequate benthic invertebrate and demersal fish unique occurrences for more than 70% of all groups (up to 150 groups, Table 5), however, for the more coastally restricted taxa from the macroalgae and reef fish biotic groups, there were fewer groups with adequate occurrences (Table 3-3). All the global ANOSIM R values were significant at the 1% level. The global R values generally increased for all data sets as the classification detail was increased, indicating that finer levels of classification detail defined more biologically distinctive environments (Table 3-3). The ANOSIM R values were higher for demersal and reef fish biotic groups than for the benthic invertebrates and the macroalgae. However, the classification strength became more gradual for all biotic groups, once the number of classification groups exceeded 55 – 75 groups (Table 3-3). Furthermore, pairwise differences between groups (with adequate sample number) declined with increasing classification detail (Table 3-3).

Table 3-3: Results of the pair-wise ANOSIM analysis for the four biological datasets at varying levels of classification detail.

	Classification detail (number of groups)	Proportion of groups ≥ 5 unique occurrences	Proportion of significant inter-class differences	Mean significant ANOSIM R-statistic
Demersal	5	1.00	1.00	0.57
Fish	25	0.84	1.00	0.65
	50	0.82	1.00	0.70
	75	0.76	0.99	0.72
	100	0.73	1.00	0.73
	125	0.74	0.99	0.73
	150	0.73	0.99	0.74
Benthic	5	1.00	1.00	0.22
Invertebrates	25	0.92	0.94	0.21
	50	0.96	0.93	0.23
	75	0.91	0.93	0.25
	100	0.91	0.93	0.27
	125	0.90	0.92	0.26
	150	0.87	0.92	0.26
Reef Fish	5	0.60	1.00	0.20
	25	0.40	0.98	0.32
	50	0.32	0.92	0.41
	75	0.24	0.92	0.41
	100	0.23	0.91	0.49
	125	0.18	0.94	0.49
	150	0.15	0.92	0.49
Macroalgae	5	0.80	1.00	0.01
	25	0.72	0.91	0.03
	50	0.66	0.81	0.04

	Classification detail (number of groups)	Proportion of groups ≥ 5 unique occurrences	Proportion of significant inter-class differences	Mean significant ANOSIM R-statistic
	75	0.55	0.84	0.05
	100	0.50	0.84	0.04
	125	0.44	0.80	0.04
	150	0.45	0.71	0.04

The New Zealand Seafloor Community Classification

The 75-groups defined in the Seafloor Community Classification (SCC) exhibited clear differences in terms of environmental conditions (summarised in Figure 3-6 and Figure 3-7) and in geographic distributions (Figure 3-8 and Figure 3-9). The hierarchical nature of the classification provides a robust description of inter-group relationships, with a number of readily identifiable clusters of related groups (Figure 3-6). Mean environmental conditions, mean model uncertainty estimates and the most frequently occurring taxa in each SCC group are provided in Summary_info_SCC and Mean_Taxa_Occ_SCC respectively (for further information see Table 6-3 in Supplementary materials 1).

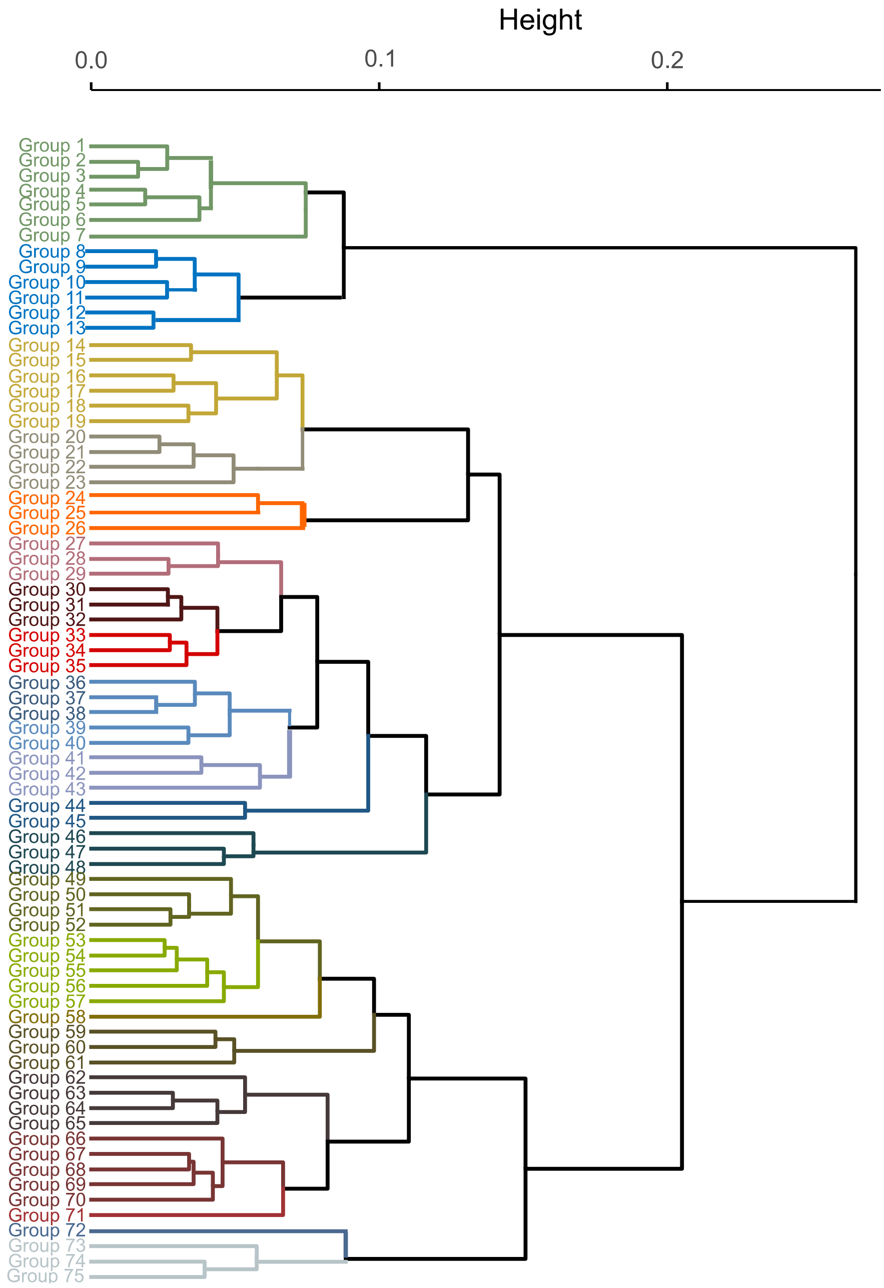

Figure 3-6: Dendrogram describing similarities among the seafloor community classification groups (75 groups) across the New Zealand marine environment. Groups sharing broad similarities are shown as the same colour (groupings assigned visually).

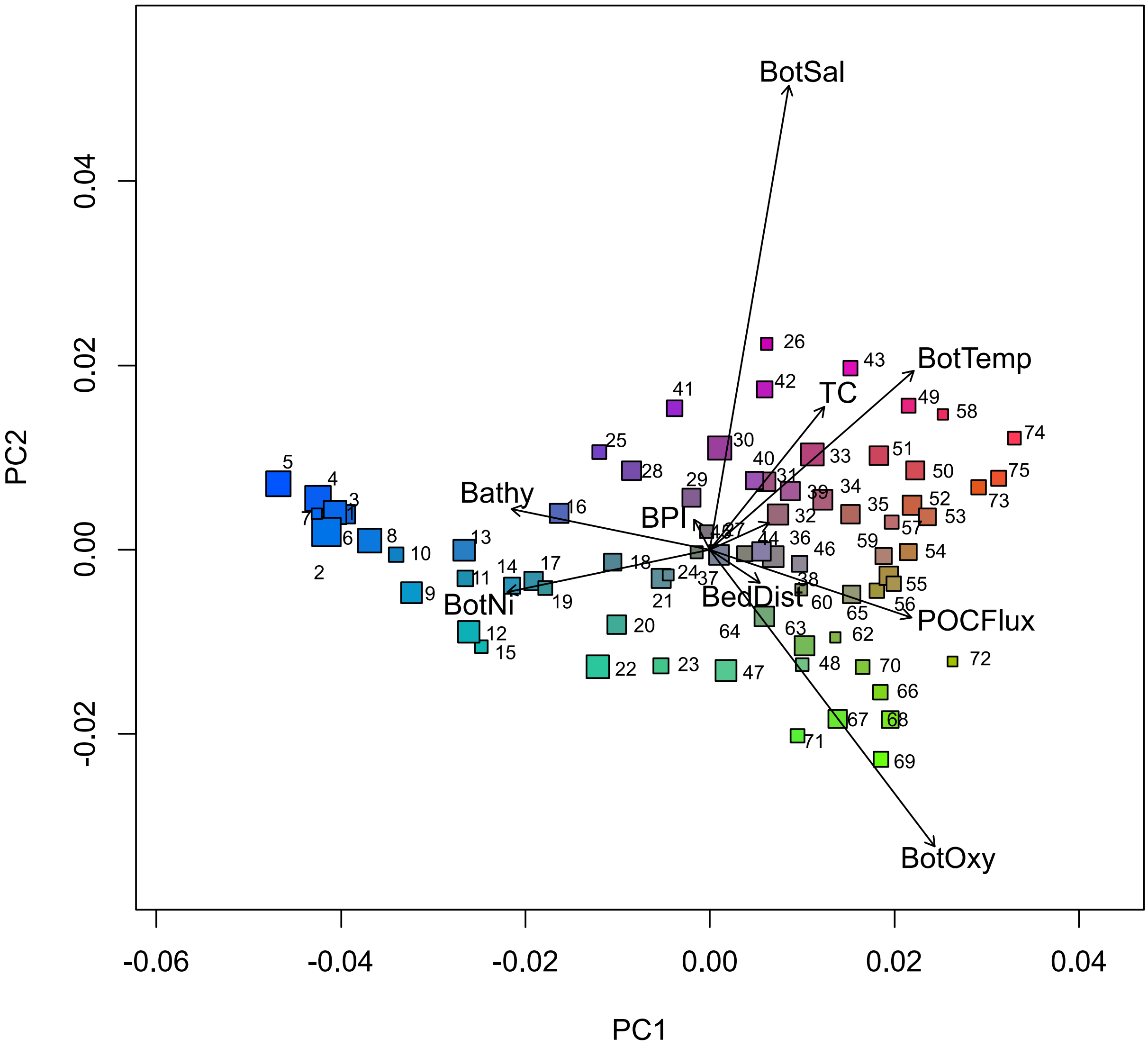

Figure 3-7: Principle Component Analysis (PCA) of the seafloor community classification groups (75 groups) for the New Zealand marine environment. Vectors indicate correlations with the nine most important environmental predictors and symbol size indicates the relative spatial area represented by the group. Colours are based on the first three axes of the PCA analysis applied to the group means for each of the transformed predictor variables, so that similarities/differences in colour correspond broadly to similarities/differences in predicted compositional turnover (Figure 3-4).

Geographic and environmental patterns of the SCC closely reflect the patterns of the combined compositional turnover on which the SCC was based. At broad scales, SCC groups were differentiated primarily according to oceanographic conditions such as depth (along PC1 in Figure 3-7) and bottom temperature (co-linear with bottom salinity and bottom oxygen, along PC2 in Figure 3-7). Environmental differences among SCC groups in deep water (groups 1 – 19, mean depths between 4156 and 537 m) were relatively muted, but greater environmental differences were evident among SCC groups at intermediate depths (group 20 – 48, primarily mean depths between 537 and 52 m), particularly with respect to bottom temperature, bottom oxygen concentration and bottom salinity. These more pronounced environmental differences among groups at intermediate depths were aligned with well-defined oceanographic patterns observed in New Zealand's oceans, with a clear latitudinal separation along the boundaries of the Subtropical Front (STF). Intermediate depth groups to the north of the STF included groups 27-35; 41-43 and south of the STF included 20-23; 36-40; 46-48. Environmental differences became even more pronounced at shallow depths (groups 49 -75, primarily mean depths between 54 and 1 m), where variation in more localised environmental conditions such as productivity (POCFlux), seafloor topography (BPI broad and Slope), seabed disturbance (BedDist) and tidal currents (TC, Figure 3-7) were important differentiating factors.

As with previous classifications based on estimates of compositional turnover (e.g., Stephenson et al. 2020c), environmental differences between SCC groups were mirrored by differences in biological composition. SCC groups varied in their characterising taxa with many taxa occurring in several groups sharing similar environmental characteristics (e.g., orange roughy (*Hoplostethus atlanticus*), and smooth oreo (*Pseudocyttus maculatus*) were most frequently observed in deep cold-water groups), whereas a large number of species occurred infrequently or in a small number of groups (see mean frequency occurrence of all taxa sampled within each group in Mean_Taxa_Occ_SCC). A more detailed description of the characterising demersal fish, benthic invertebrate, macroalgae and reef fish characterising taxa is provided in Petersen et al. (2020).

In addition, mean values for the two spatially explicit estimates of uncertainty differed between biotic groups and between SCC groups (Summary_info_SCC; see Table 6-3 in Supplementary materials 1). Mean environmental coverage was low across all biotic groups for all very deep-water SCC groups (groups 1 – 8) reflecting the lower confidence that can be placed in predictions of these largely unsampled parts of the New Zealand marine environment. Broadly, with decreasing depth, the mean environmental coverage increased, although some small localised SCC groups with few biological samples had low environmental coverage (e.g., group 26). Mean environmental coverage for demersal fish and benthic invertebrates was consistently higher than for macroalgae and reef fish across most SCC groups, possibly due to the more restricted distributions of the latter and the more spatially extensive sampling of the former, although this varied between SCC groups (especially groups very close to shore where macroalgae had higher environmental coverage in some cases). Several SCC groups had low or variable number of samples across biotic groups, but moderate to high combined environmental coverage (e.g., shallow coastal groups 58 – 60, 66, 72), suggesting sampling in similar environmental conditions had occurred for these taxa in other SCC groups. Mean variability (SD) in compositional turnover differed between biotic groups but was generally low compared to the compositional turnover (e.g., spatial patterns in uncertainty reflected those described in section 3.2.1). Detailed descriptions including mean environmental values, characterising taxa and mean uncertainty measures (standard deviation of compositional turnover and predicted environmental coverage) for individual SCC groups are provided in Petersen et al. (2020).

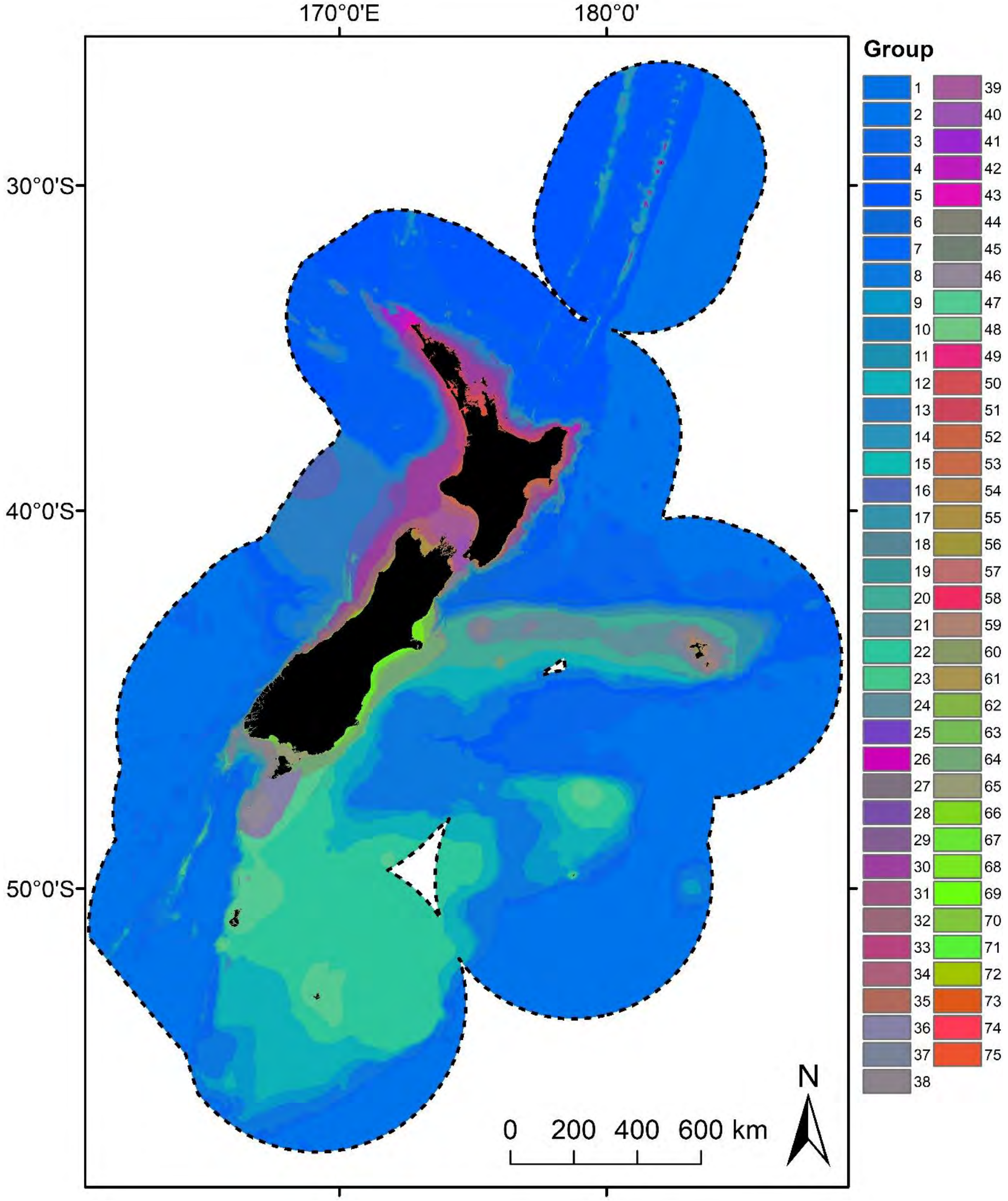

Figure 3-8: Geographic distribution of the Seafloor Community Classification (75 groups) derived from 'combined' bootstrapped Gradient Forest model. Colours are based on the first three axes of the PCA analysis applied to the group means for each of the transformed predictor variables, so that similarities/differences in colour correspond broadly to similarities/differences in predicted compositional turnover.

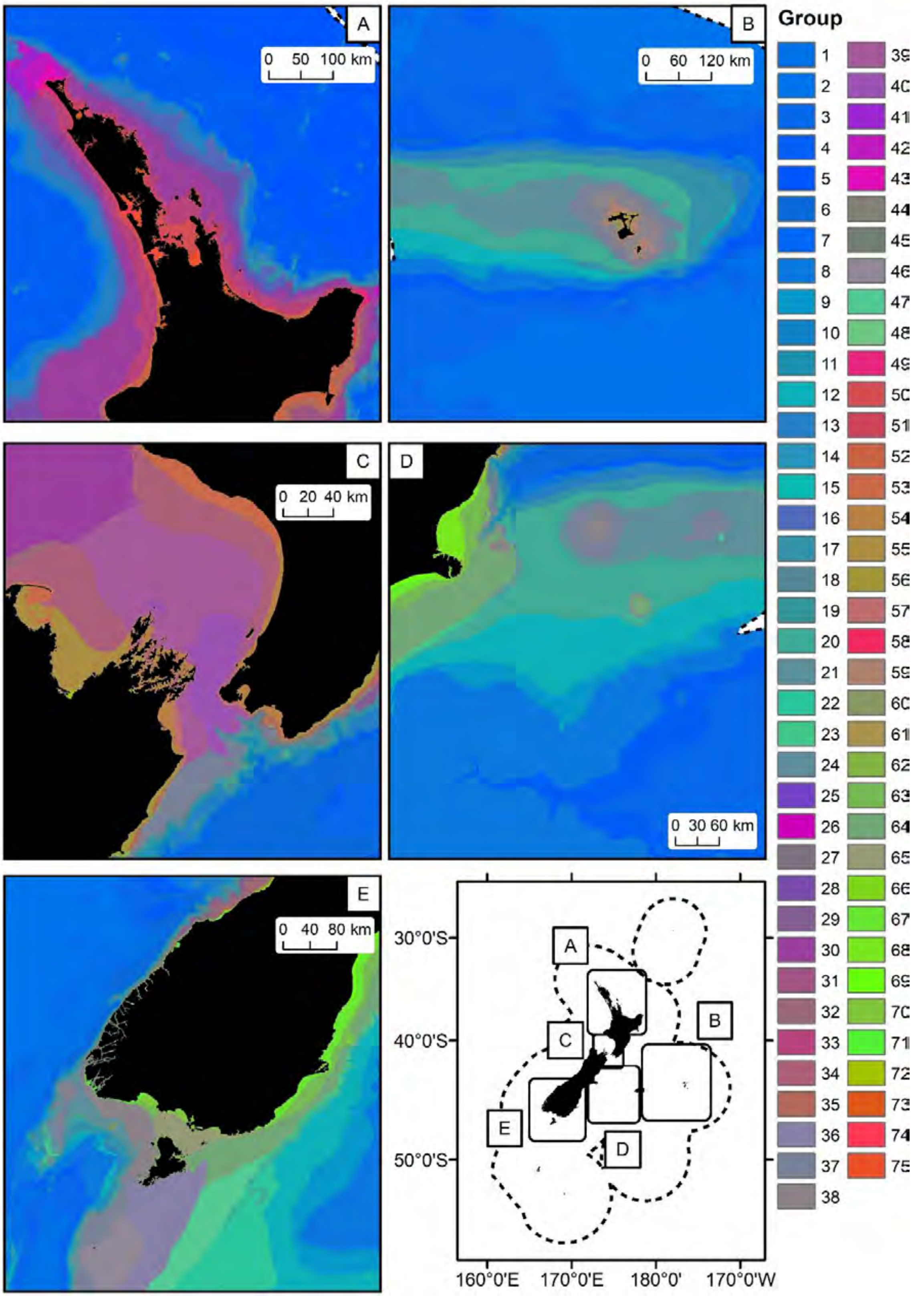

Figure 3-9: Closeup views of parts of the geographic distribution of the Seafloor Community Classification (75 groups) derived from 'combined' bootstrapped Gradient Forest model. Colours are based on the first three axes of the PCA analysis applied to the group means for each of the transformed predictor variables, so that similarities/differences in colour correspond broadly to similarities/differences in predicted compositional turnover.

4 Discussion

Following a workshop with experts and members of the MSAG held on the 9th August 2019, it was decided Gradient Forest models would be used to develop a fit-for-purpose marine environmental classification (Objective 1). The relevant environmental and biological datasets required for GF modelling were collated (Objective 2). This data collation included extensive grooming and error checking of sample data from multiple sources for four biotic groups occurring on or near the seafloor (i.e., demersal fish, reef fish, benthic invertebrates and macroalgae). The final taxonomic datasets consisted of 630,997 records of 1,716 taxa occurring at 39,766 unique locations. Gridded environmental data (available at two resolutions: 250 m grid resolution within the Territorial Sea and a 1 km grid resolution within the Exclusive Economic Zone) were collated from multiple sources. Many of these environmental data layers were updated in the process and extensive metadata was created to ensure reproducibility and ease of use of these in future projects.

Bootstrapping techniques were applied to the analysis of spatial patterns of compositional turnover for taxa in each of the four biotic groups. This approach allowed for measures of model uncertainty (a measure of variability in compositional turnover) to be produced in a spatially explicit manner. In addition, an added measure of uncertainty – coverage of the environmental space – was produced to further highlight geographic areas where model predictions may be less certain due to low sampling. Finally, the estimates of compositional turnover for each biotic group were combined to represent overall compositional turnover in seafloor communities, and then classified using a hierarchical procedure to define groups at different levels of classification detail, i.e., 30, 50, 75 and 100 groups (Objective 3). Here, a concise and comprehensive report is presented, detailing all environmental and biological datasets, methodology used and overview of the 75-group classification – termed the 'New Zealand Seafloor Community Classification' (SCC) (Objective 4). A detailed environmental and biological (community) description of the SCC (e.g., as in Stephenson et al. 2020c) is provided as a separate report (Petersen et al. 2020) (Objective 5). Here we critically appraise the SCC (section 4.1) and briefly summarise considerations for future use in spatial conservation and resource management planning (section 4.2).

4.1 Critical appraisal of the Seafloor Community Classification

The methods and data used to develop the SCC build on those used in previous classifications of New Zealand's marine domain: the New Zealand Marine Environment Classification (MEC, Snelder et al. 2007) and the Benthic Optimised Marine Environment Classification (BOMEC, Leathwick et al. 2012). Although the classification is environment-based, in broad terms the classification can be understood as a spatial summary of variation in seafloor community composition and turnover in the New Zealand marine environment (Stephenson et al. 2020c). Overall, the spatial distribution of the SCC is consistent with the MEC and BOMEC which identified depth, and to a lesser extent, water temperature and water mass, and major oceanographic features as important drivers of taxa composition. However, the SCC also identified finer scale environmental differences for inshore groups (at shallow depths), where variation in more localised environmental conditions such as productivity (POCFlux), seafloor topography (BPI broad and Slope), seabed disturbance (BedDist) and tidal currents (TC) were important differentiating factors.

The SCC is a significant advance on previous numerical classifications in New Zealand, in terms of the availability of a much larger number of taxonomic records, spanning multiple biotic groups combined with a more comprehensive, recently updated, set of environmental predictor variables in a flexible machine learning modelling framework that can incorporate non-linear relationships between taxa and environment (Pitcher et al. 2012; Stephenson et al. 2020c). Furthermore, spatial estimates of confidence were provided for the predicted compositional turnover, which can in turn partially be used to assess the confidence that can be placed in the individual SCC groups (see section 4.2 for further details on how these estimates could be useful for spatial planning as well as their limitations).

The SCC groups represent groups of taxa that share the same suite of environmental preferences, and therefore inhabit the same locations. These groups can be considered communities as they describe groups of spatially and temporally co-occurring taxa, which may interact to some extent with one another (Morin 2009). Some of these taxa will have different ecological niches (e.g., demersal predators versus benthic invertebrate filter feeders) and may only be 'associated' because they inhabit the same volume of water. Although some species in a community interact either directly (e.g., through predator-prey interactions) or indirectly (e.g., by feeding on the same organisms), other taxa may not necessarily interact with each other (Francis et al. 2002). There is still a paucity in information with regards to species interactions at the spatial scales of the communities identified by the SCC. Regardless, the inferred communities from the SCC provide useful descriptions of habitat and biotic assemblages for resource management and conservation planning, particularly when considered alongside the estimates of confidence for each of the groups.

One challenge with numerical classifications, such as the SCC, is the communication of results from a statistically complex product in a way that facilitates their use by management agencies and others involved in spatial planning processes (Rowden et al. 2018). Building on methods developed by Stephenson et al. (2020c), individual group descriptions for the SCC are provided in Petersen et al. (2020). These descriptions are provided to facilitate use of the classification by both managers and stakeholders and, at least in part, help bridge the gap between the typical output from numerical classifications and the readily understandable habitat and assemblage descriptions that result from thematic classifications (Rowden et al. 2018). As new data become available, the underlying numerical methodology underpinning the classification could be re-run, thus the SCC lends itself to being continually improved and refined over time (the locations and descriptions for all data files and R code are available in the Supplementary materials 1, Table 6-3).

Despite the large datasets collated for the development of the SCC, there remain limitations associated with the classification, which at least in part, can be attributed to the available biological and environmental data. The long temporal span over which taxa samples were collected means that there is a mismatch between the temporal window of biological data and that of the environmental variables which were mostly compiled from data collected in the last few decades. This mismatch means that the compositional turnover presented here should be interpreted as a spatially and temporally smoothed representation (Stephenson et al. 2018a). The ability of the classification to represent variation in taxa composition at different scales using independent or newly collected data (e.g., as in Bowden et al. 2011; or as in Stephenson et al. 2018a) would be of interest in order to independently validate the accuracy of the SCC.

Although the species occurrence data we used mostly provided adequate spatial coverage of our study area close to shore and further offshore on the Chatham Rise and the Challenger and Campbell Plateaus (as assessed by the coverage of the environmental space), several large, outlying sections had few or no biological samples, notably the vast majority of waters deeper than 2500m. For deeper waters where few samples are available, lower confidence can be placed in the predictions of compositional turnover that underpin the SCC.

The ‘quality’ of the available biological data varied by biotic group based on differences in sampling gear and method. Records for demersal fish and reef fish were collected using (relatively) consistent sampling gears and methods (Smith et al. 2013; NIWA 2014, 2018). Abundance estimates were available for both these biotic groups, and few assumptions were required to use these data as presence / absence in GF models to make them consistent with benthic invertebrate and macroalgae group data. In contrast, multiple sampling gears and methods were used to collect benthic invertebrates, which required division of these data into gear catchability categories. However, it should be noted, that there was a high proportion of unique taxa associated with each gear type and therefore it was deemed important to include each of these because they sampled differing parts of the community. Information on sampling methods for macroalgae were not easily available but given their localised nature (collected on or close to shore), this was not deemed to be critical. Neither the benthic invertebrate nor the macroalgal data here can be considered true presence / absence (because of variations in the survey designs used to collect these data), and therefore the classification results from these biotic groups should be used with greater caution (although care was taken to account for differences in the biases associated with sampling method as per Phillips et al. (2009)). Abundance estimates were not available in a consistent manner for benthic invertebrate and macroalgal data. Further, the effect of using genus records on predictions of benthic invertebrate compositional turnover (especially at a fine scale) is not clear (e.g., some genera may contain many species whereas others may only contain a single species within the New Zealand marine environment). Despite this uncertainty, the use of genera data instead of species is likely to provide more accurate representations of broad-scale patterns due to the more comprehensive spatial sampling represented by the genus-level data. Future iterations of the SCC may benefit from being tuned using abundance estimates and, for benthic invertebrates, records at the species level (e.g., using data from comprehensive surveys as in Bowden et al. 2019). Despite these limitations, the taxa data used here form a valuable dataset that will have uses outside the development of the SCC (e.g., see Lundquist et al., 2020) and represents the best available compiled biotic information at present for the New Zealand marine environment.

At the scale of the New Zealand marine environment, the quality of environmental data may vary spatially, i.e., some layers may be most robust close to shore. For example, the sediment classification layer (Sed.class) will be more robust inshore due to higher sampling underpinning the spatial data layers (Bostock et al. 2019). Despite the large influence that substrate is expected to have on demersal and benthic species composition (Ruiz et al. 2009), this environmental predictor variable had relatively low influence on seafloor community compositional turnover, most likely due to incomplete substrate distributions, for example, incomplete information on the distribution of hard substrata such as rocky reefs.

In prior spatial analyses using a subset of taxa records analysed here (e.g., Leathwick et al. 2006; Compton et al. 2012; Compton et al. 2013; Wood et al. 2013), the inclusion of many environmental variables was avoided because they generally only provide small improvements in predictive accuracy and complicate interpretation of model outcomes (Leathwick et al. 2006). However, here the interpretation of model outcomes (i.e., the drivers of distribution) was of secondary interest, the primary focus being on maximising the predictive accuracy of the model. For certain taxa the inclusion of a broad range of environmental predictors in this manner can result in modelled relationships that are not easily explained ecologically. For example, macroalgal compositional turnover along the gradient of bottom silicate concentration in this analysis. However, in this case, bottom silicate is assumed to be a proxy for other unmeasured variable(s) (e.g., as bathymetry is often used in similar spatial models, Dunstan et al. (2012)). For model prediction into well-sampled environmental space this use of a unknown proxy variable is not likely to affect prediction accuracy (interpolation) but this may not be the case when predicting into poorly sampled space (extrapolation) where the environmental variable may no longer be viable as a proxy (Elith & Leathwick 2009).

The lack of consistent spatially explicit abundance information, coupled with the incomplete information about substrate type, means that despite the comprehensive SCC group descriptions of the environmental and biotic characteristics, SCC groups may still lack some of the key features that stakeholders may more readily associate with, or understand as habitats and communities. For example, the lack of abundance information means there is no spatial information about the locations of biogenic habitats, despite biogenic habitat forming taxa being present (and identified as characterising taxa) in several groups (e.g., bivalves, stony corals – see Petersen et al. (2020) for further information). Additionally, further discrimination within groups based on a more detailed and reliable substrate layer would allow finer-scale biodiversity patterns to be more easily communicated. These limitations may be addressed by using other spatial layers or classifications, for example, a thematic classification may provide adequate descriptions at these finer scales if such information is available in a particular area , e.g., The Coastal and Marine Habitat and Ecosystem Classification (MFish and DOC 2008) – or an improvement of this current thematic classification.

4.2 Considerations for using the Seafloor Community Classification in spatial planning

Description of spatial variation in species compositional turnover and richness is central both to our understanding of the scaling of diversity, and for identification of priority sites for conservation (McKnight et al. 2007). SCC groups are based on estimated taxa compositional turnover, which allows spatially explicit measures of (predicted) within-group and between-group similarity in taxonomic composition to be produced (Stephenson et al. in review). That is, the transformed environmental space can be used to represent biological similarity. In turn, these similarity metrics can allow identification of environments that are likely to host rare or unusual communities as well as identifying geographic areas (which may consist of multiple SCC groups) that are most representative of New Zealand seafloor communities as a whole, for example, in a spatial conservation prioritisation analysis (Leathwick et al. 2011).

A recent analysis by Stephenson et al. (in review) compared the efficacy of a demersal fish GF-based classification with increasing group number (10; 20; 30; 50 and 100 groups) against individual species distribution layers (derived from species distribution models) for use in conservation planning (using the prioritisation software Zonation). The best-performing GF-based conservation ranking used continuous spatial layers describing the within-group and between-group similarities of a 30-group classification together with species richness (all layers with equal weighting). Conservation outcomes from this ranking were only marginally less efficient (7%) than those from a more conventional ranking that used 217 individual species distribution layers, despite using only half of the available species' occurrence data in the individual species distribution models. The authors concluded that despite only using a 30-group classification, GF models were more likely to capture information across a broad range of species, allowing for representation of both common and rare species when describing spatial variation in species composition and turnover. In addition, the reduced number of groups (e.g., for the present work this would be 75 SCC groups compared to 1600 species layers) facilitates the understanding and communication of spatial biodiversity patterns and may be of use for decision-making in participatory stakeholder processes (Stephenson et al. in review).

Given the hierarchical nature of the SCC classification, consideration will be required as to what constitutes the most appropriate level of classification detail for conservation planning purposes. At the scale of the New Zealand marine environment, the 75-group SCC may be appropriate. Using a higher number of classification groups (100 – 200 groups) is likely to be more appropriate for a regional scale analysis (e.g., at the scale of the Hauraki Gulf), particularly for inshore areas where there is a greater heterogeneity in environmental conditions (Stephenson et al. 2018a). As part of any spatial planning analysis, information from the SCC could be supplemented with the inclusion of other spatial layers to facilitate selection of areas of particular importance (e.g., see Stephenson et al. (2018b); Lundquist et al. (2020b) for a comprehensive list and description of spatial layers available in New Zealand to inform the identification of Key Ecological Areas). However, the SCC aims to represent seafloor communities but to achieve comprehensive representation for conservation planning, information on other species, including pelagic species, not captured in the SCC will most likely be required. This is especially the case given that it is unlikely that the SCC would be an appropriate proxy for pelagic species distributions (Hewitt et al. 2015).

A spatial conservation prioritisation analysis using the 75-group SCC would benefit from the inclusion of classification uncertainty measures because failure to acknowledge sources of uncertainty can lead to poor management decisions (Regan et al. 2005; Link et al. 2012). Here we provide two spatially explicit measures of uncertainty: model variability and environmental coverage, which provide two complementary measures to be considered by managers. The environmental coverage provides an indication of the parts of the environmental space which, for example, contain many samples - meaning we can be more confident of the relationships and the predictions for compositional turnover and SSC groupings in such areas (Smith et al. 2013; Stephenson et al. 2020a). The uncertainty estimates of compositional turnover (i.e., standard deviation of the mean (SD) compositional turnover averaged across each environmental variable) provide an important indication of the variability in the modelling estimates. Given that uncertainty estimates of compositional turnover will only vary in areas where samples are present, we suggest that the uncertainty associated with individual SCC groups first be assessed by examining the number of samples and environmental coverage values. Where these values are adequate (e.g., environmental coverage > 0.05 as in (Stephenson et al. 2020a) or another suitable cut-off), the uncertainty estimates of compositional turnover will provide further insight into the variability (and therefore the confidence) of the underlying models used for the classification. However, it should be noted that both these uncertainty estimates are not propagated through the model to include any uncertainty in the classification. That this, here we only quantify parts of the model uncertainty (albeit arguably the most important parts); there are no estimates of classification uncertainty per se (Hill et al. 2020). This means that for parts of the environmental space our estimate of uncertainty will be an under-estimate of the actual uncertainty (i.e., particularly for those parts of the environmental space that could be classified as either in one group or another similar group). However, spatial predictions of inter- and intra-group (biological) similarity can be generated from the classification which can be used to highlight those areas in the classification groups which may be classified in one group or another and therefore may represent less certain classifications (e.g., see methods and use of these layers in Lundquist et al. 2020a; Stephenson et al. in review).

Finally, uncertainty estimates can be used in combination as part of a gap analysis to highlight areas that would most benefit from increased sampling by targeting of underrepresented assemblages for further sampling and/or protection (Ferrier et al. 2007; Pitcher 2007).

4.3 Conclusion

To the authors' knowledge, the SCC uses the largest number of taxa records and the most comprehensive, and highest resolution, set of environmental predictor variables used to date to develop a numerical classification globally. The SCC and associated spatially explicit uncertainty layers are particularly well suited as inputs for marine protection planning and reporting at a national scale. Firstly, spatially explicit estimates of within and between group similarity of the SCC make it particularly well suited to support developing a representative network of marine protected areas (objective 10.6.3 of the New Zealand Biodiversity strategy, Department of Conservation (2020)) and complement work to develop Key Ecological Areas mapping for New Zealand. Secondly, the development of two spatially explicit measures of uncertainty allow a nuanced use of these layers for spatial planning. The SCC summarises a large and complex taxa dataset spanning four biotic groups in a single classification layer which could greatly facilitate communication of complex spatial biodiversity patterns during participatory stakeholder processes. Despite the advances and utility of the SCC for conservation planning there remain several limitations, including a lack of abundance data, and a lack of some of the key features that stakeholders may more readily associate with, or understand as, habitats and communities (e.g. communities associated with rocky reefs, pelagic species). These limitations can, at least in part, be overcome through the use of other spatial layers to supplement the distributional information of other important biodiversity features (e.g. as collated for the identification of Key Ecological Areas, Stephenson et al. 2018b; Lundquist et al. 2020b) such as, distributions of fish spawning grounds, biogenic habitats. An additional advantage of numerical classifications such as the SCC is that these can be evaluated and updated as and when new biotic data become available.

Finally, it is important to note that adopting the SCC is just the first step towards the effective application of this classification for spatial planning purposes. New Zealand conservation and management agencies will need to commit to actively engage long-term in a structured feedback process to help maintain, modify and improve the SCC, as well as promoting and facilitating its application via open-access online data portals and tools. Part of this commitment includes sufficient resourcing to achieve this essential underpinning infrastructural support. None of the aforementioned was provided for previous classifications of New Zealand's coastal and marine environments, and is one of the reasons that, for example, the MEC has been underutilised, and the development of a regional MEC and a final BOMEC did not progress beyond examples (Rowden et al. 2018).

5 Acknowledgements

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We acknowledge prior research and the methodological developments by New Zealand researchers on which this work builds on. Namely, the Marine Environment Classification (MEC – Snelder et al., 2007) and the Benthic Optimised Marine Environment Classification (BOMEC – Leathwick et al., 2012).

We acknowledge the contributions of data and advice from many sources including: the National Institute of Water and Atmospheric Research (NIWA) for collections data and spatial environmental variable layers; Auckland and Te Papa Museums for providing collections data; the Department of Conservation for spatial data layers; the OTOT programme for providing the estuarine benthic invertebrate data collected by several New Zealand regional authorities (Northland Regional Council, Auckland Regional Council, Waikato Regional Council, Bay of Plenty Regional Council, Hawkes Bay Regional Council, Horizons Regional Council, Greater Wellington Regional Council, Marlborough District Council, Nelson City Council, Tasman District Council, West Coast Regional Council, Environment Canterbury, Christchurch City Council, Otago Regional Council and Environment Southland); MODIS data were used courtesy of NASA Goddard Space Flight Center, MODIS project. Ocean colour satellite data were accessed via the NASA Ocean Biology Distributed Active Archive Center (OB.DAAC). Coastal ocean colour data were processed courtesy of Simon Wood (NIWA).

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6 Supplementary Materials 1 – Filepaths and metadata

6.1 Biological data

Table 6-1: Filepaths and description of biological data.

Home folder	sub folder	Files	Filetype	Description
Biological data	Benthic invertebrates	BI_matrix_LLG.LMG_unique_GN	CSV	Benthic invertebrate genera matrix used in Gradient Forest Models: X, Y locations (projection: EPSG:9191). Genera presence/absence sampled using LLG.LMG gear types are provided from columns 4 - end
		BI_matrix_MMG_unique_GN	CSV	Benthic invertebrate genera matrix used in Gradient Forest Models: X, Y locations (projection: EPSG:9191). Genera presence/absence sampled using MMG gear types are provided from columns 4 - end
		BI_matrix_SMG_unique_GN	CSV	Benthic invertebrate genera matrix used in Gradient Forest Models: X, Y locations (projection: EPSG:9191). Genera presence/absence sampled using SMG gear types are provided from columns 4 - end
		BI_matrix_SSG_unique_GN	CSV	Benthic invertebrate genera matrix used in Gradient Forest Models: X, Y locations (projection: EPSG:9191). Genera presence/absence sampled using SSG gear types are provided from columns 4 - end
		BI_Names_Genera	CSV	List of unique genera across all gear types used in GF analysis
		BI_SDM	CSV	Records (n = 94 035) of benthic invertebrate genera with > 70 unique locations used in Species Distribution Models (SDM)
		CombinedDatabase_Benthic Invertebrates	CSV	Groomed, benthic invertebrate records
	Demersal fish	DF_Names_species	CSV	List of unique species used in GF analysis
		DF.matrix_all_years_unique_SP	CSV	Demersal fish species matrix used in Gradient Forest Models: X, Y locations (projection: EPSG:9191). Species presence/absence are provided from columns 4 - end
		DF_allyears_SDM	CSV	Records of demersal fish species with > 70 unique locations used in Species Distribution Models (SDM)
		TRAWL_demersal_fish_1979_2018	CSV	Groomed, demersal fish records
	Macroalagae	MA_Names_species	CSV	List of unique species used in GF analysis
		MA_matrix_unique_SP	CSV	Macroalagal species matrix used in Gradient Forest Models: X, Y locations (projection: EPSG:9191). Species presence/absence are provided from columns 4 - end
		MA_SDM	CSV	Records of Macroalgal species with > 50 unique locations used in Species Distribution Models (SDM)

Home folder	sub folder	Files	Filetype	Description
		MA_AllRecords_Sp	CSV	Groomed, macroalgal records
	Reef fish	Reef_fish_list	CSV	List of unique species used in GF analysis
		SampSitesFish_SPname	CSV	Reef fish species matrix used in Gradient Forest Models: X, Y locations (projection: EPSG:9191). Species presence/absence are provided from columns 4 - end

6.2 Environmental data

Table 6-2: Filepaths and description of environmental data. Files referred to in the main of the text are highlighted in grey.

Home folder	sub folder	Files	Filetype	Description
Environmental data		env_pred_metadata.xlsx link: [Environmental data\env_pred_metadata.xlsx]()	Excel (.xlsx)	**Metadata** for each environmental variable, including information on: environmental variable abbreviation used throughout the text; full name; spatial projection of the layers; temporal range of the data used to generate the layers (can be static if this layer does not vary over time, e.g., bathymetry); description of the environmental variable and any brief methods used to generate the layers; native resolution of the spatial grids; method for modifying the resolution (if any); units; source/reference; notes/comments; the year layers were last updated (if known); name and contact for any further enquiries.
Environmental data	1 km	Bathy Beddist BotNi BotOxy BotOxySat * BotPhos BotSal BotSil BotTemp BPI_broad BPI_fine carbonate Chl-a Chl-a.Grad DET DynOc Ebed fluxSeabed Gravel Kpar MLD Mud OxyUt PAR PB Reef Rough sand SeasTDiff Sed.class Slope SST SstGrad SuspPM TC TempRes VGPM	TIFF	Geospatial raster (.tif) files at a 1 km grid resolution across the New Zealand Exclusive Economic Zone (spatial projection: EPSG:9191).

Home folder	sub folder	Files	Filetype	Description
	250m	Bathy Beddist BotNi BotOxy BotOxySat * BotPhos BotSal BotSil BotTemp BPI_broad BPI_fine carbonate Chl-a Chl-a.Grad DET DynOc Ebed fluxSeabed Gravel Kpar MLD Mud OxyUt PAR PB Reef Rough sand SeasTDiff Sed.class Slope SST SstGrad SuspPM TC TempRes VGPM	TIFF	Geospatial raster (.tif) files at a 250m grid resolution across the New Zealand Territorial Sea (spatial projection: EPSG:9191).

6.3 Model outputs

Table 6-3: Filepaths and description of GF model outputs. Files referred to in the main of the text are highlighted in grey.

Home folder	sub folder	Files	Filetype	Description
GF_outputs	R code	1.Species_Env_prep 2.GF_tuning 3. BOOTSTRAPPING_GF_MODELS 4. COMBINING_GF_MODELS_BOOT_F 5. CLASSIFICATION_SPECIES_ENV_INFO 6. CLASSIFICATION_UNCERTAINTY_INFO	Rdata	Annotated R code used to prepare and run GF models and subsequent analyses from Stephenson et al., 2020. Files are numbered in the order that they were used.
	R objects	BI_LLG.LMG.source BI_MMG.source BI_SMG.source BI_SSG.source boot_array_EnvTran_CMB1.source DF.source EnvRanges.BI.source EnvRanges.CMB.source EnvRanges.DF.source EnvRanges.MA.source EnvRanges.RF.source imp.vars.BI.source imp.vars.CMB.source imp.vars.DF.source imp.vars.MA.source imp.vars.RF.source MA.source Pred_1km.BI.source Pred_1km.CMB.source Pred_1km.DF.source Pred_250m.BI.source Pred_250m.CMB.source Pred_250m.DF.source Pred_250m.MA.source Pred_250m.RF.source Pred_EEZ_MA1.source RF.source species.BI_LLG.LMG.source species.BI_MMG.source species.BI_SMG.source species.BI_SSG.source species.DF.source species.MA.source species.RF.source	Rdata Source	R objects used for GF analysis
	Results	Mean_Taxa_Occ_SCC.xlxs Link: GF_outputs\Results\Mean_Taxa_Occ_SCC.xlsx	Excel workbook (xlsx)	**Mean occurrence of taxa within each group of the Seafloor Community Classification (SCC).** Information is organised by taxa (tab 1: Demersal Fish; tab 2: Benthic invertebrates; tab 3: Reef fish; tab 4: macroalgae). Colours provide an indication of the relative ranking of each taxa **within** groups (blue = low frequency occurrence and red indicates high frequency occurrence within groups).

Home folder	sub folder	Files	Filetype	Description
		SP_R2.xlxs Link: GF_outputs\Results\Sp_R2.xlsx	Excel workbook (xlsx)	**Mean (± SD) R^2_f values for individual taxa from GF models**. (BI: Benthic invertebrates, DF: Demersal fish, MA: Macroalgae, RF: Reef fish).
		Summary_Info_SCC.xlsx Link: GF_outputs\Results\Summary_info_SCC.xlsx	Excel workbook (xlsx)	**Mean and range (25 – 75 quantile) of environmental variables (tab 1), uncertainty measures (tab 2) and most frequently occurring taxa (tab 3) within each Seafloor Community Classification group.** For the mean environmental variable values, colours provide an indication of the relative ranking within each group (blue = low value and red indicates high value within groups).
		Petersen et al 2020 - Seafloor Community Classification: Group descriptions	Word document (docx)	**Individual group descriptions for the Seafloor Community Classification.**

6.4 Seafloor Community Classification, example group description

Following methods developed by (Stephenson et al. 2020c), individual group descriptions for the Seafloor Community Classification are provided in Petersen et al. (2020). This included the location of the SCC group within the New Zealand marine environment; information on environmental characteristics (mean values for a subset of the available environmental variables, termed “characterising environmental conditions”); description of species’ assemblages (mean frequency occurrence and contribution of individual taxa to intra-group similarity for a subset sampled taxa, termed “characterising species”); and a summary of model uncertainty (mean measures of GF model confidence). For further details on methods and qualitative descriptions see Petersen et al. (2020). An example of a group description for Group 30 is provided below.

Group 30

1. Geographic location

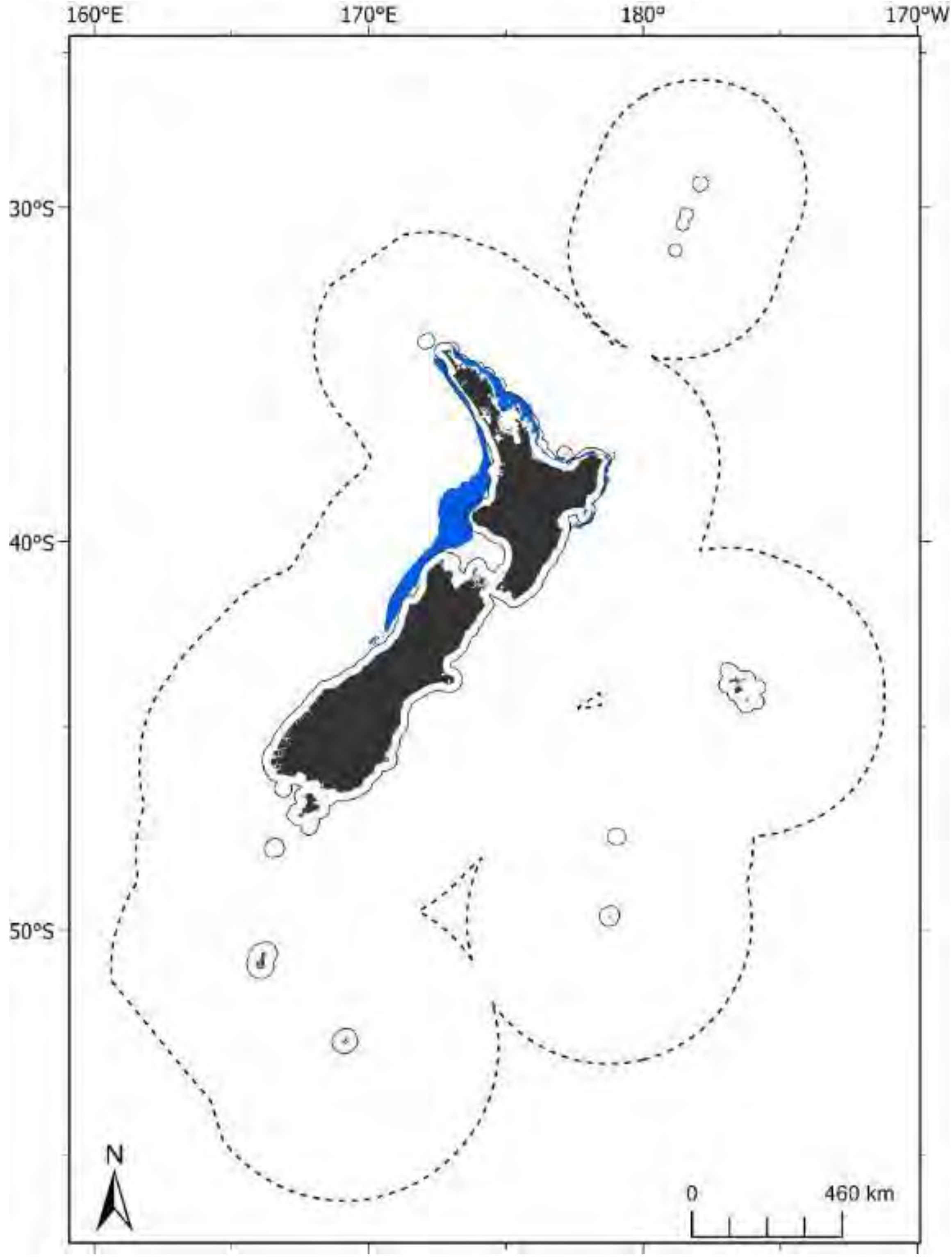

Figure 6.1 Geographic distribution of group 30 from a 75-group seafloor community classification (SCC) in the New Zealand marine environment (dashed line).

2. Group Description

Group 30 is a large widespread group (Figure 6.1) occurring on the continental shelf north of the Subtropical Front in warm, moderate productivity coastal waters (Table 6.5). This group is characterised by moderate oxygen concentrations and low dissolved silicate and nitrate concentrations at depth (Table 6.5). Benthic invertebrate assemblages are diverse and are characterised by high frequency occurrence of the squid Nototodarus, multiple coral species, and low frequency bivalve, brachiopod and gastropod occurrence (Table 6.6). Fish assemblages are diverse, with ~130 demersal fish taxa and ~50 reef fish taxa. Demersal fish assemblages are characterised by high frequency tarakihi, barracouta, jack mackerel and school sharks, and reef fish assemblages are characterised by very high frequency occurrence of nearly 20 taxa including perch, damselfish and morwong (Table 6.6). This group has a very high number of samples for benthic invertebrates and demersal fish and very low samples for macroalgae and reef fish (Table 6.6). Overall confidence in modelled relationships is moderate – high for this group (high confidence for 'combined' biotic group environmental coverage and moderate for model variability (SD), Table 6.7). Note, there is low sample number and low confidence associated with model variability of reef fish (Table 6.7).

3. Similar groups

Closely related to group 31; more loosely related to group 32.

4. Characterising environmental conditions

Table 6.5: Group 30 characterising environmental conditions

Environmental variable	Mean value	Qualitative description
Bathymetry	129 m	Shelf depth
Slope	0.34 °	Low slope
Bottom silicate	4.91 µmol l^{-1}	Low concentrations of silicate at depth
Dissolved oxygen at depth	5.21 µmol l^{-1}	Moderate concentrations of oxygen at depth
Temperature at depth	14.15 °C km^{-1}	High bottom water temperature
Downward vertical flux of particulate organic matter at the seabed	41.22 mgC m^{-2} d^{-1}	Moderate productivity
Turbidity	0.002 m-1	Low turbidity

5. Characterising Species

Table 6.6: Species name, mean frequency occurrence and % contribution to group 30 similarity for those species contributing to a total of 70% of the group similarity or > 4 % to the group similarity. Groups with no species present or where data was insufficient to run analyses are reported as na.

Taxa type	Sampling gear	n samples	Unique taxa	Scientific name	Common name/broad descriptor	Mean frequency occurrence	% contribution to similarity
Benthic invertebrates	LLG.LMG	1271	154	*Nototodarus*	Squid	0.92	99.06
	MMG	65	191	*Lyreidus*	Crab	0.4	15.8
				Heteromolpadia	Sea cucumber	0.31	10.71
				Ophiozonoida	Brittle star	0.31	10
				Monomyces	Coral	0.32	7.15
				Peronella	Sea cucumber	0.26	5.21
	SMG	70	154	*Monomyces*	Coral	0.13	11.8
				Saccella	Bivalve	0.11	10.51
				Caryophyllia	Coral	0.1	7.98

Taxa type	Sampling gear	n samples	Unique taxa	Scientific name	Common name/broad descriptor	Mean frequency occurrence	% contribution to similarity
				Pratulum	Bivalve	0.09	6.14
				Splendrillia	Gastropod	0.06	5.37
				Neothyris	Brachiopod	0.07	4.68
				Tethocyathus	Coral	0.07	4.24
				Balanophyllia	Coral	0.06	4.11
	SSG	33	17	*Dittosa*	Crab	0.33	48.72
				Neothyris	Brachiopod	0.3	27.12
Demersal fish		1414	129	*Nemadactylus macropterus*	Tarakihi	0.75	13.05
				Thyrsites atun	Barracouta	0.7	11.48
				Trachurus declivis	Jack mackerel	0.59	8.22
				Galeorhinus galeus	School shark	0.56	7.19
				Zeus faber	John Dory	0.55	7.14
				Chelidonichthys kumu	Red gurnard	0.5	5.94
				Lepidopus caudatus	Frostfish	0.48	5.18
				Squalus acanthias	Spiny dogfish	0.48	5.01
				Lepidotrigla brachyoptera	Scaly urnard	0.45	4.66
				Chrysophrys auratus	Snapper	0.4	4.1
Macroalgae**		3	3	*na*	*na*	*na*	*na*
Reef fish		3	49	*Centroberyx affinis*	Nannygai	1	4
				Caprodon longimanus	Perch	1	4
				Hypoplectrodes sp B	Perch	1	4
				Pseudocaranx dentex	Trevally	1	4
				Pagrus auratus	Snapper	1	4
				Scorpis violaceus	Sea chub	1	4
				Amphichaetodon howensis	Butterflyfish	1	4
				Chromis dispilus	Damselfish	1	4
				Parma alboscapularis	Damselfish	1	4
				Aplodactylus arctidens	Marblefish	1	4
				Cheilodactylus spectabilis	Morwong	1	4
				Nemadactylus douglasii	Morwong	1	4
				Pseudolabrus luculentus	Wrasse	1	4
				Bodianus vulpinus	Hogfish	1	4
				Odax pullus	Butterfish	1	4
				Forsterygion flavonigrum	Triplefin	1	4
				Parablennius laticlavius	Blenny	1	4
				Parika scaber	Leatherjacket	1	4

**** No samples with species present, ** insufficient data to run simper analysis***

6. Uncertainty ranges

Table 6.73: Mean uncertainty values for group 30 by biotic group and 'combined'.

Taxa	Mean SD	Confidence (SD)	Mean Env. Cov	Confidence (Env. Cov)
Benthic invertebrates	0.002	Moderate	0.642	High
Demersal fish	0.003	Moderate	0.606	High
Macroalgae	0.002	Moderate	0.138	Moderate
Reef fish	0.004	Low	0.322	Moderate
Combined	0.003	Moderate	0.623	High

7 Supplementary Materials 2 – Maps of biological samples

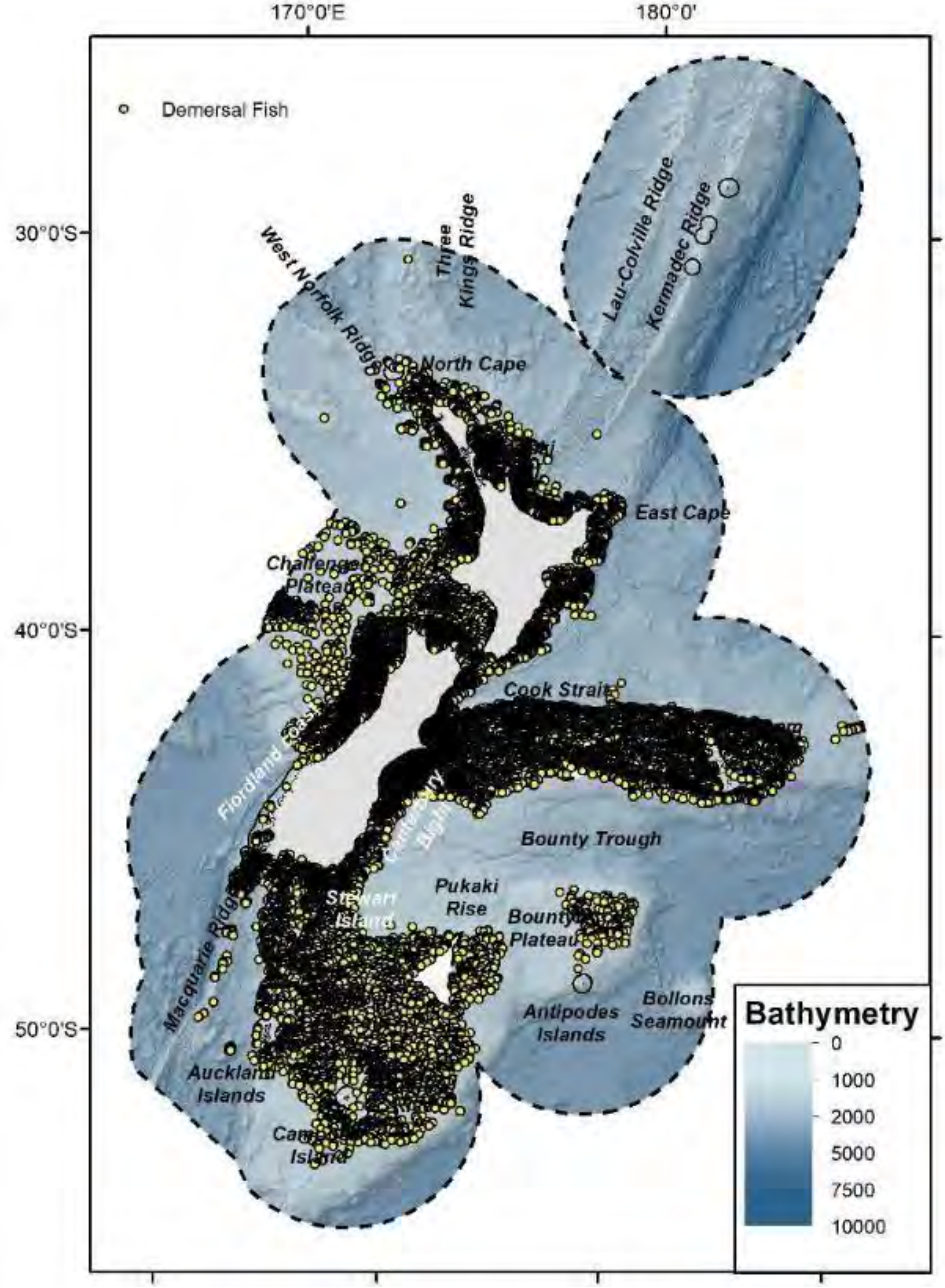

Figure 7-1: **Map of study region with unique locations of demersal fish used in GF analysis.**

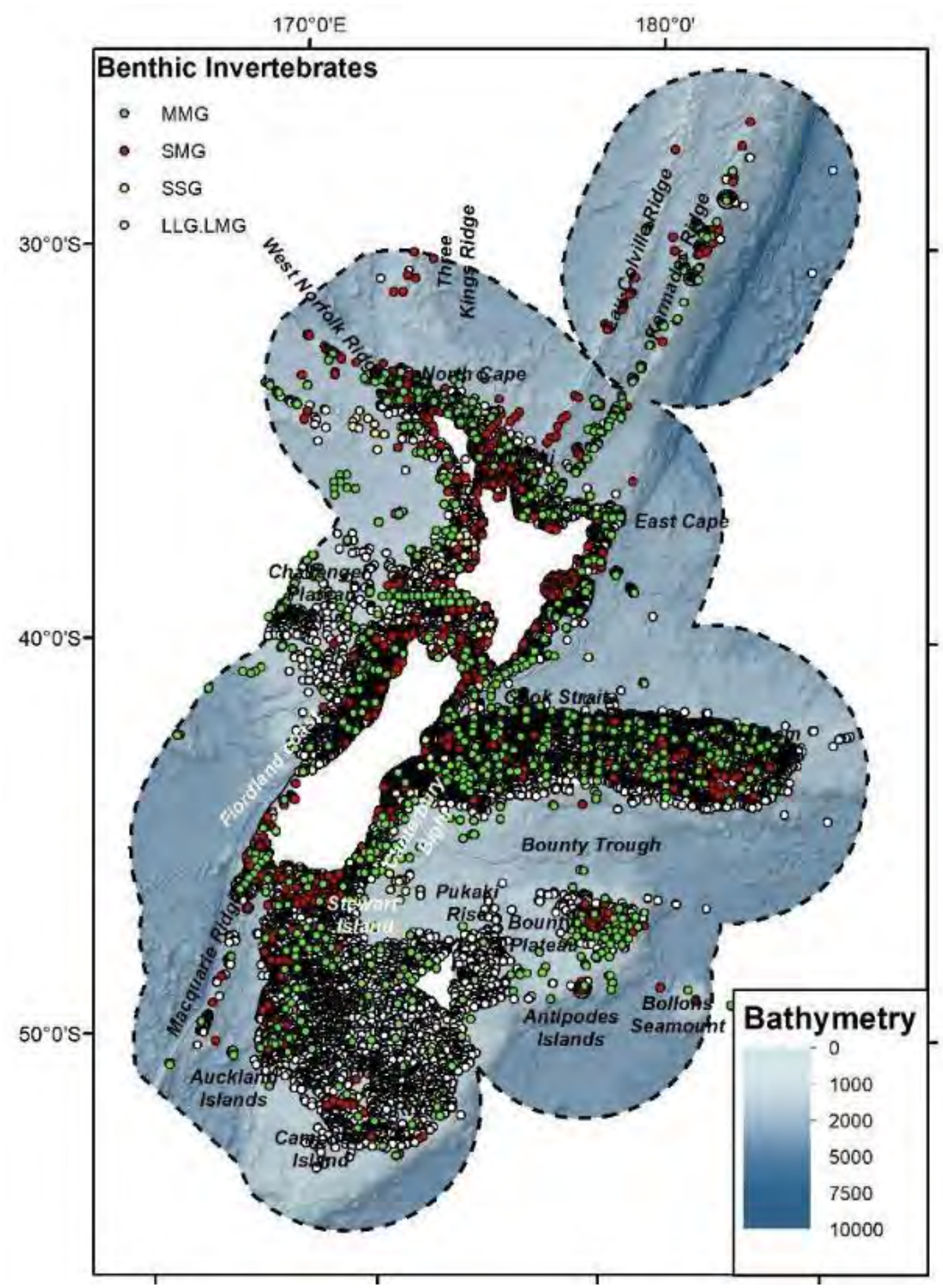

Figure 7-2: Map of study region with unique locations of benthic invertebrates (by sampling gear type) used in GF analysis.

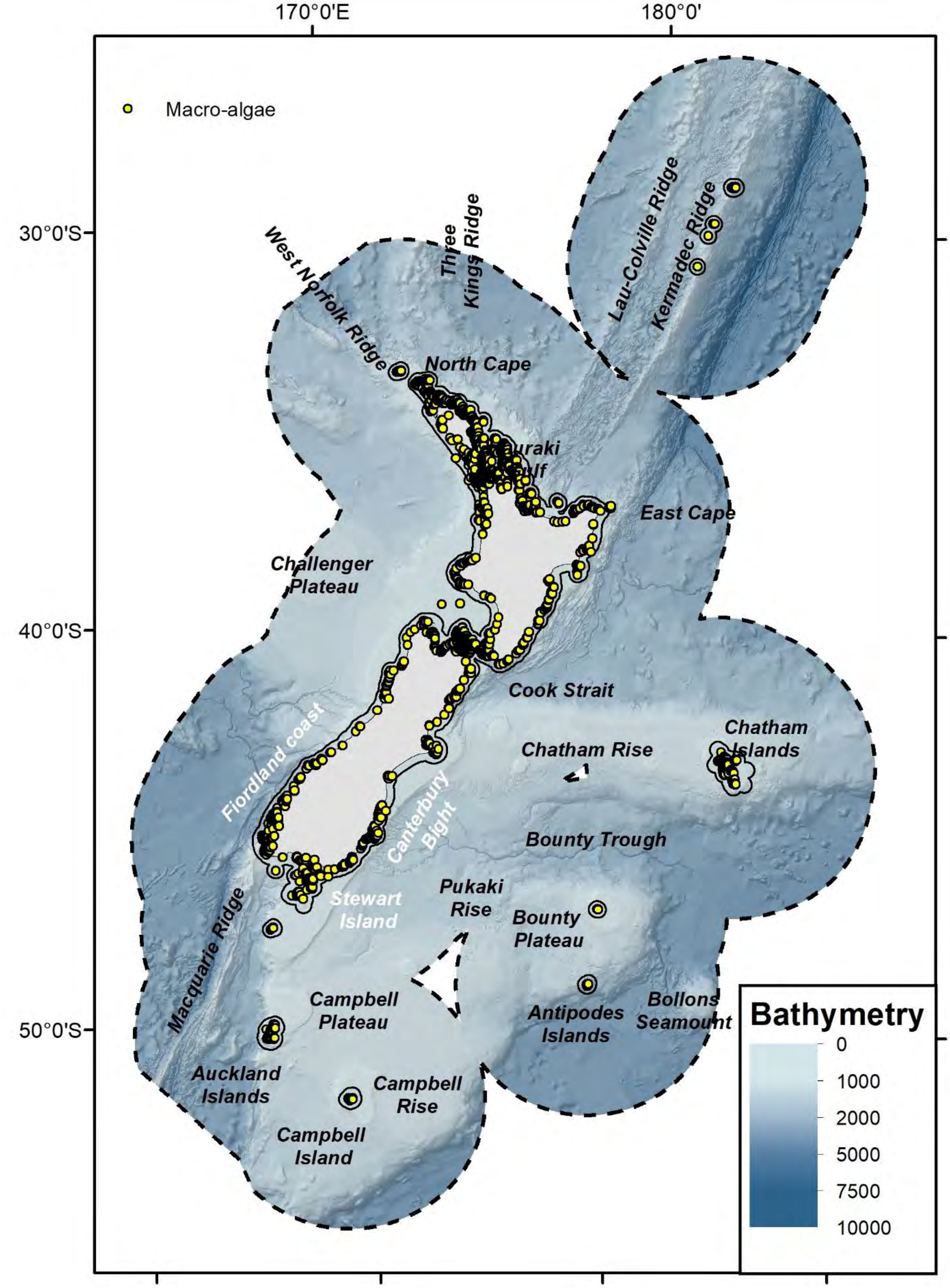

Figure 7-3: Map of study region with unique locations of macroalgae used in GF analysis.

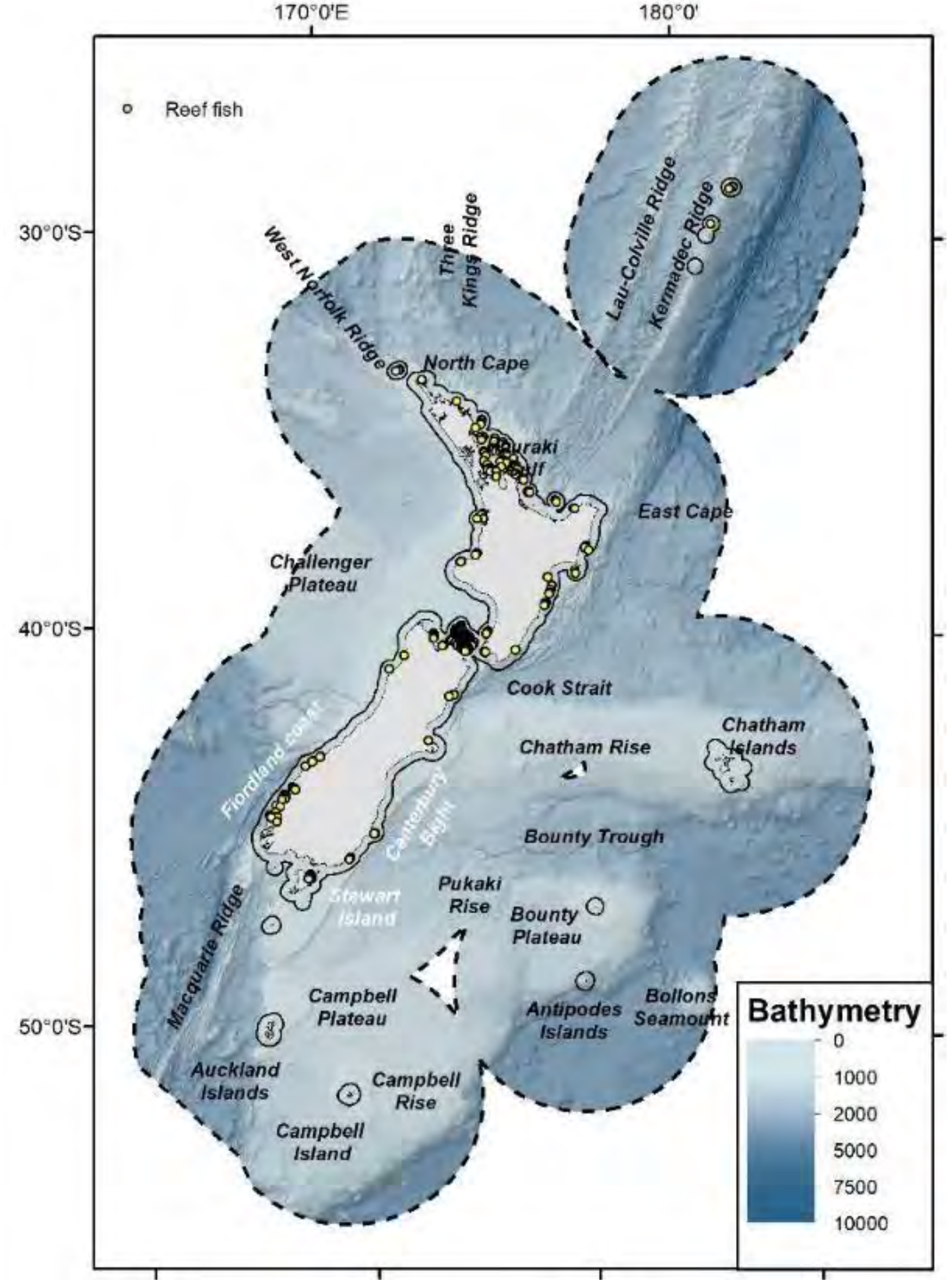

Figure 7-4: Map of study region with unique locations of reef fish used in GF analysis.

8 Supplementary Materials 3 – Estuarine benthic invertebrates

8.1 Data and methods

Although the estuarine benthic invertebrate dataset comprises some of the best data in New Zealand regarding paired biological-environmental samples, the environmental predictors used for the SCC were thought to be less robust in estuaries and therefore would not produce useful predictions. In addition, despite the availability of environmental variables at a 250 m spatial scale, predictions at this spatial scale may still be too coarse to reflect the sharp environmental gradients present in none but the largest estuaries. Therefore, only paired biological and environmental data within this dataset were used for further modelling.

Data retrieved from the National Estuary Dataset and used in this analysis included macrofaunal abundance data and paired physico-chemical sediment data, as well as Sea Surface Temperature (SST) and Salinity (Sal.Fac). Macrofauna cores were sieved through 0.5mm mesh, with all taxa included. In most cases a standard core size (13 cm dia x 15 cm depth) was used. Paired sediment data was available for grainsize (< 63 µm, 63 µm–2 mm, > 2 mm) (here 'Mud' (< 63 µm) was retained for analysis) and Total Organic Carbon (TOC) content for all data points. Variability in the taxonomic resolution of the species identifications was apparent between regions/organisations. In addition, methods used to measure grainsize analysis and Total Organic Carbon content was also variable. For the macrofauna data, clumping of biotic groups was undertaken to standardise the results based on the methodology suggested by Berthelsen et al. (2020), with small further modifications based on expert opinion within NIWA's benthic ecology team (such as removing terrestrial insects and freshwater species). For the sediment data, grainsize analysis methodologies varied between wet sieving and laser diffraction, the laser based only on < 2 mm particle size, while wet sieve measures all fractions. The percent grainsize for each fraction < 2 mm was therefore adjusted in the wet sieved samples to account for this difference (i.e., % of < 63 µm out of the < 2 mm fraction). Total Organic Content was either directly measured or estimated based on known relationships with ash-free dry weight, depending on which method was used. Sea Surface Temperature (SST) is a measure of the average SST for a location just offshore of the estuary for the month/year that the site was sampled. Salinity was calculated based on a distance weighted flow of freshwater input from streams within a 1 km radius of each sampling location (Sal.fac, where a high Sal.fac indicates low salinity). In addition to data retrieved from the National Estuarine Dataset, an exposure metric was calculated for each sampling location. Exposure (Exp.Wind) was calculated based on measuring the distance from each sampling point to the land in 1 degree intervals (over 360 degrees in total), multiplied by the total number of days the predominant wind was from that direction (binned into 45 degree intervals) and the average wind speed for those days. Predominant wind direction and speed was extracted regionally from the nearest regional airport weather station over 3 years of records.

Despite spatial and temporal variability in the dataset, all log transformed abundance of estuarine benthic invertebrate taxa were used in the analysis (without spatial aggregation) in order to maximise the amount of data available for the analysis and avoid introducing additional confounders (such as the loss of regional data from the NRC where only 3 replicates were sampled per site).

As for other biotic groups, species compositional turnover of estuarine benthic invertebrates was estimated using bootstrapped GF models as described in section 2.4.1. Predicted compositional turnover between samples was summarised using principle components analysis (PCA). The colours used in the PCA were based on the first three axes of the PCA analysis so that similarities/differences in colour corresponded broadly to pairwise similarities/differences in the transformed environmental space. Predicted compositional turnover between samples was classified into 10 groups using K-means clustering.

8.2 Results and discussion

Most estuarine benthic invertebrate taxa were effectively modelled (i.e., approx. 147 out of 188 taxa had $R^2_f > 0$ – Table 8.1). Individual taxa R^2_f ranged from a min 0.01 to 0.94, with a mean 0.51 (Table 8.1). To put these results into context, these R^2_f were similar to values for other biotic groups despite the R^2_f for estuarine benthic invertebrate taxa representing the explained deviance in abundance, which tends to be lower than R^2_f from presence/absence models.

Table 8.1 Mean (±SD) model fit metrics of individual taxa (R^2_f) from bootstrapped GF models.

Measure	Species modelled (total possible: 188)	Min R2	mean R2	max R2
Mean	146.63	0.01	0.51	0.94
Standard deviation	5.90	0.01	0.03	0.03

All environmental variables contributed to predicting compositional turnover of estuarine benthic invertebrates (Fig 8.1). Wind exposure was the most important variable for predicting compositional turnover of estuarine benthic invertebrates followed closely by SST, Salinty, Mud content and organic matter (Fig 8.1). Inspection of the fitted functions for the environmental variables indicated that SST, Mud, TOC had broadly linear relationships with compositional turnover, whereas Exp.Wind and Sal.fac showed a levelling off in compositional turnover at higher values (e.g., Exp.Wind > 5,000,000) (Fig 8.1).

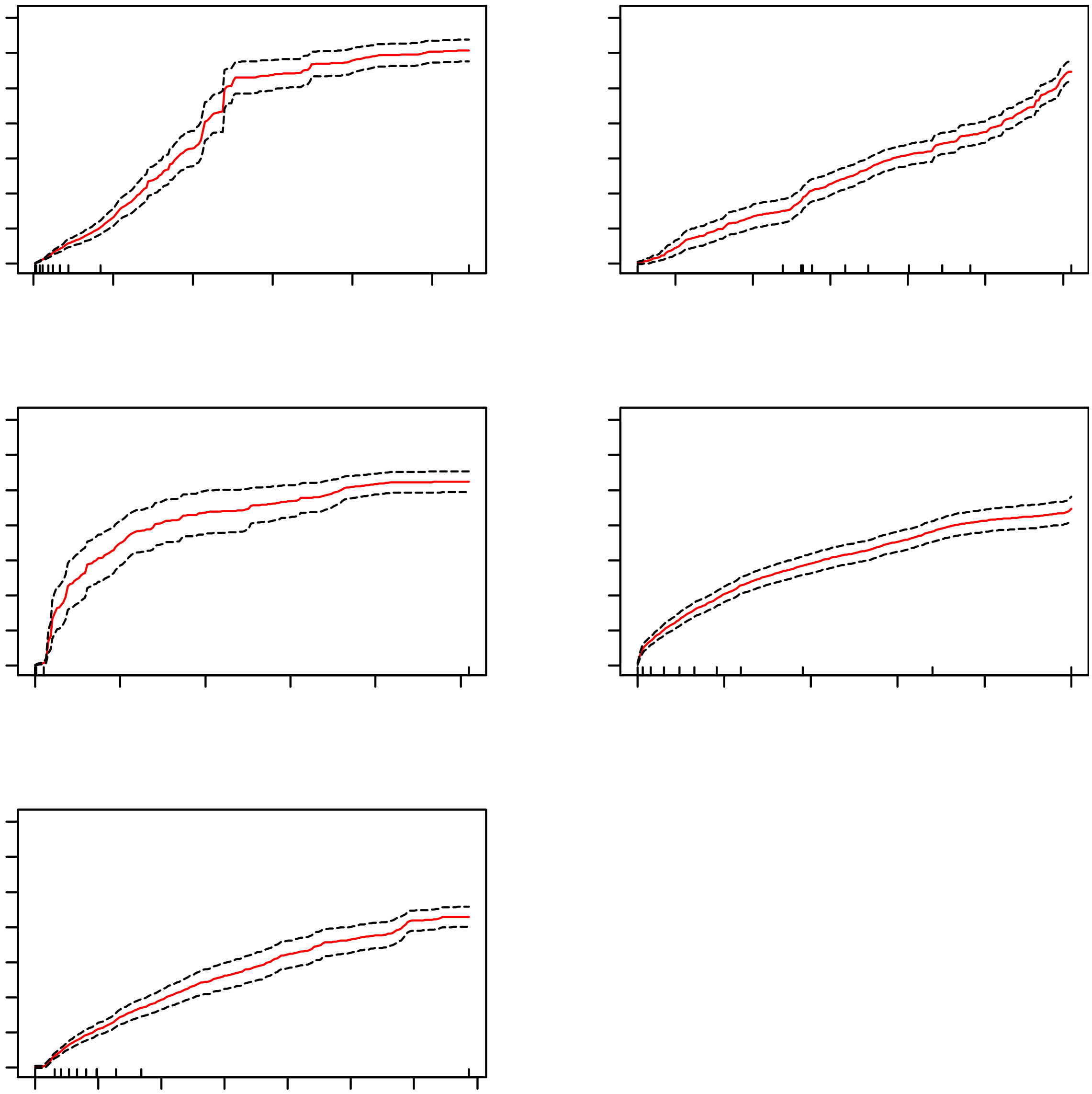

Fig 8.1. Mean (± SD) functions fitted by bootstrapped GF models of estuarine benthic invertebrates. Fitted functions indicate relative compositional turnover along the range of each predictor.

Estuarine benthic invertebrate samples were well spread in environmental space, and at a 10 group classification level showed clear environmental preferences (Fig 8.2, Table 8.2). For example, group 10 was characterised by low Mud content, moderate TOC and very high SST (Fig 8.2, Table 8.1).

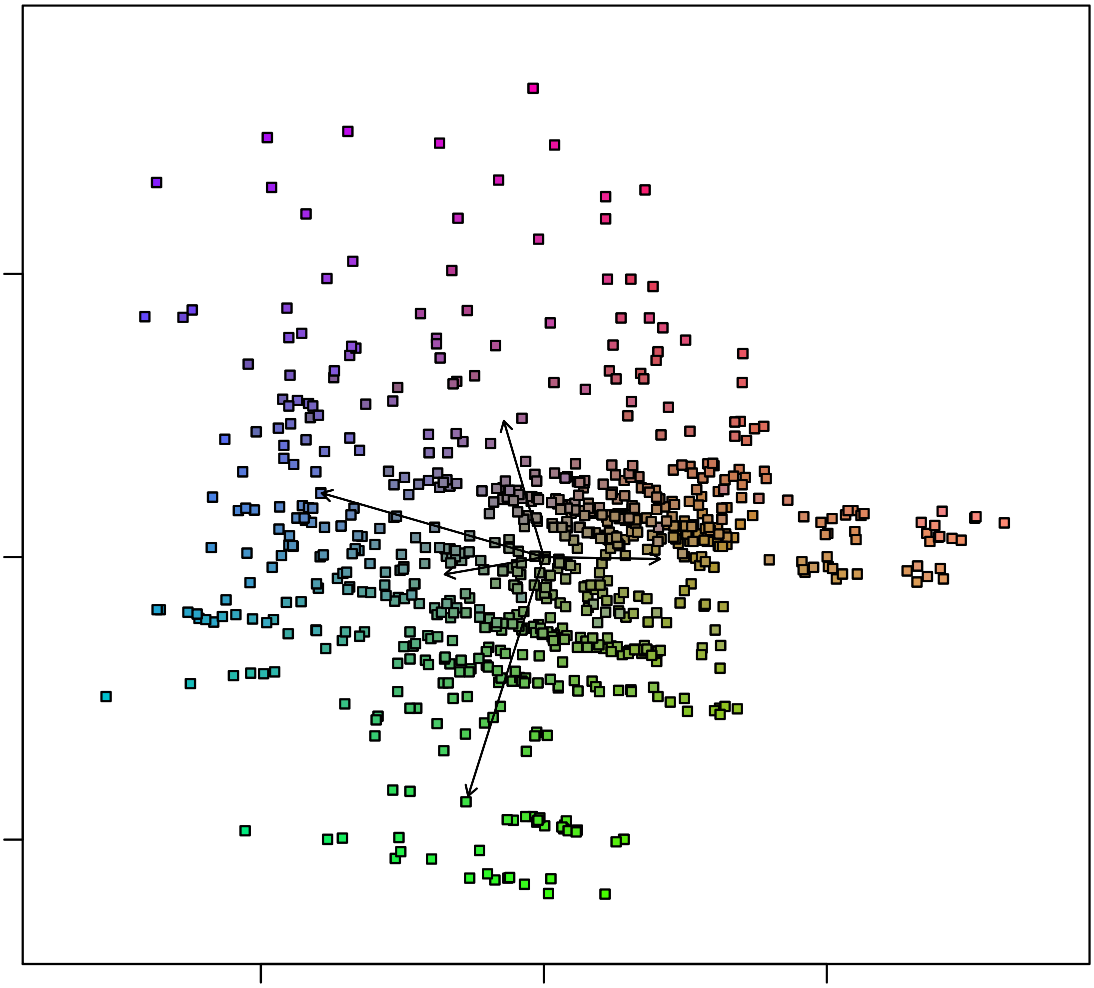

Fig 8.2. Distributions in PCA space of 10 groups defined by classification of transformed environmental layers derived from bootstrapped Gradient Forest models fitted using estuarine benthic invertebrate records. Colours are based on the first three axes of a PCA analysis so that similarities/differences in colour correspond broadly to similarities/differences in group taxonomic composition. Vectors indicate correlations with the five most important environmental variables.

Table 8.2. Number of samples and mean value of environmental variables for estuarine benthic invertebrate classification at a 10-group level.

Group	n.samples	Mud	TOC	Sal.fac	SST	Exp.Wind
1	131	10.85	0.32	0.00	15.27	588932.10
2	100	2.29	0.20	0.01	14.68	583887.80
3	78	69.25	0.56	0.01	17.19	250295.60
4	72	29.97	0.53	0.00	15.45	428929.40
5	34	40.11	0.51	0.37	15.24	79215.67
6	45	79.64	1.71	0.01	17.61	351204.80
7	68	4.48	0.35	0.00	18.26	1038544.00
8	142	19.82	0.53	0.00	18.34	502250.00
9	47	2.08	0.15	0.00	15.52	4426073.00

10	41	7.90	0.57	0.00	21.75	139486.60

The classification worked well at describing groups across broad environmental conditions (Table 8.2). For example, for Auckland Council (AC), the larger more exposed estuaries (such as Kaipara and Manukau) were dominated by group 9, which was associated with high Exposure. Upper Waitemata was characterised primarily by groups 3, 4 and 8, which are associated with the muddier more organically enriched environments often observed in the upper arms of estuaries. Regional trends also emerged, for example HBRC, NRC, and TDC were primarily characterised by groups 8 and 10, diverging from other regions through differences in SST (Table 8.3).

Despite regional separations of groups, some large estuaries also contained at least some samples in almost all groups (e.g., Kaipara contained samples classified into 7 of the 10 groups). Whether this reflects the large size of the estuary (and therefore it's likelihood to contain many of the communities found across the country), or whether this high number of groups is linked to sample size (Kaipara contained almost half of the samples available in the Auckland Council area) is unclear. Our inability to spatially extrapolate the estuarine dataset in a comparable way to other classifications within this report highlight how current estuarine modelling efforts are limited by lack of fine scale environmental data collected for the purpose of spatial extrapolation. In addition, many of environmental data layers being used in offshore applications are considerably less robust and reliable at the estuarine scale. This means that models to help with spatial conservation planning and management cannot be used to their full potential in areas where they are urgently needed—the coastal and estuarine environments that New Zealanders use and value every day. Moving forward, we recommend prioritising the collection of a national estuarine dataset for the purpose of spatial extrapolation (i.e., using standardised sampling methods and a single central parataxonomic clearinghouse to ensure data integrity and cross-comparability).

Table 8.3. Number of estuarine benthic invertebrate samples assigned to each classification at a 10-group level shown by Council and Estuary.

	Group										
Council / Estuary	1	2	3	4	5	6	7	8	9	10	Total
AC	**62**	**86**	**63**	**164**		**114**	**133**	**160**	**369**		**1151**
centralwaitemata	10	16		4							30
kaipara	4		15	4		84	133	72	207		519
mahurangi	12			36							48
mangemangeroa	4			28							32
manukau									162		162
okura	7	12		24							43
orewa	5	10		4							19
puhoi	5	8		8							21
turanga	3	6		12		6					27
upperwaitemata			48	20		24		88			180
waikopua	7	4		8							19
waiwera	2	14		16							32
whangateau	3	16									19
BOPRC	**2**		**6**	**8**		**6**	**238**	**296**			**556**
ohiwa	2			8							10

	Group										
Council / Estuary	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Total**
tauranga			6			6	238	296			546
ECAN	**23**	**10**	**45**	**56**	**5**	**12**	**21**	**112**			**284**
akaroa	10	8									18
avonheathcote	10		30	36	5		21	104			206
lyttelton			15	12		12					39
okainsbay	3	2		8				8			21
ES	**13**	**80**		**12**		**48**	**7**				**160**
awarua	1	2									3
bluff	1	2									3
fortrose	1	8									9
freshwater		8									8
haldane	1	2		12							15
jacobsriver	4	22				24					50
newriver	2	26				24	7				59
waikawa2	3	10									13
GWRC	**20**	**14**	**9**	**20**	**55**		**21**	**8**	**36**		**183**
hutt					10						10
lakeonoke					5						5
makara	1	6									7
porirua	19			20			21	8			68
tikotu		4									4
waikanae					15				36		51
whareama			9		15						24
wharemauku		4									4
whareroa					10						10
HBRC			**27**		**25**		**7**	**272**		**40**	**371**
ahuriri							7	272		40	319
porangahau			27								27
wairoa					25						25
HRC				**4**	**5**						**9**
manawatu				4	5						9
MDC			**12**	**4**		**12**	**7**	**64**			**99**
havelock			3			6		48			57
shakespeare							7	8			15
waikawa1				4							4
wairau			6			6					12
whangarae			3					8			11
NCC	**1**		**3**				**14**	**16**			**34**
delaware			3				7	8			18
nelsonhaven	1						7	8			16
NRC			**24**		**5**	**60**		**24**		**370**	**483**
kerikeri						18					18
mangonui						6				140	146

	Group										
Council / Estuary	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Total**
ngunguru										210	210
ruakaka			6								6
waitangi1			9			24					33
waitangi2					5						5
whangarei			6			12					18
whangaroa			3					24		20	47
ORC	**3**	**4**	**15**	**8**	**75**	**18**					**123**
catlins	2		6								8
kaikorai		2	3	4	5	12					26
kakanui					10						10
owaka				4	5						9
shagriver			3		15						18
taieririver		2			5						7
tokomairiro					20	6					26
waikouaiti	1		3		15						19
TDC	**4**		**12**	**12**				**104**			**132**
moutere								48			48
ruataniwha	3										3
waimea	1		12	12				56			81
WCRC			**6**								**6**
orowaiti			6								6
WRC	**3**	**6**	**12**				**28**	**80**	**18**		**147**
firth							14	48	18		80
raglan			12					16			28
tairua	3	6					14	16			39

9 Supplementary Materials 4 – Compositional turnover for individual biotic groups

9.1 Demersal fish

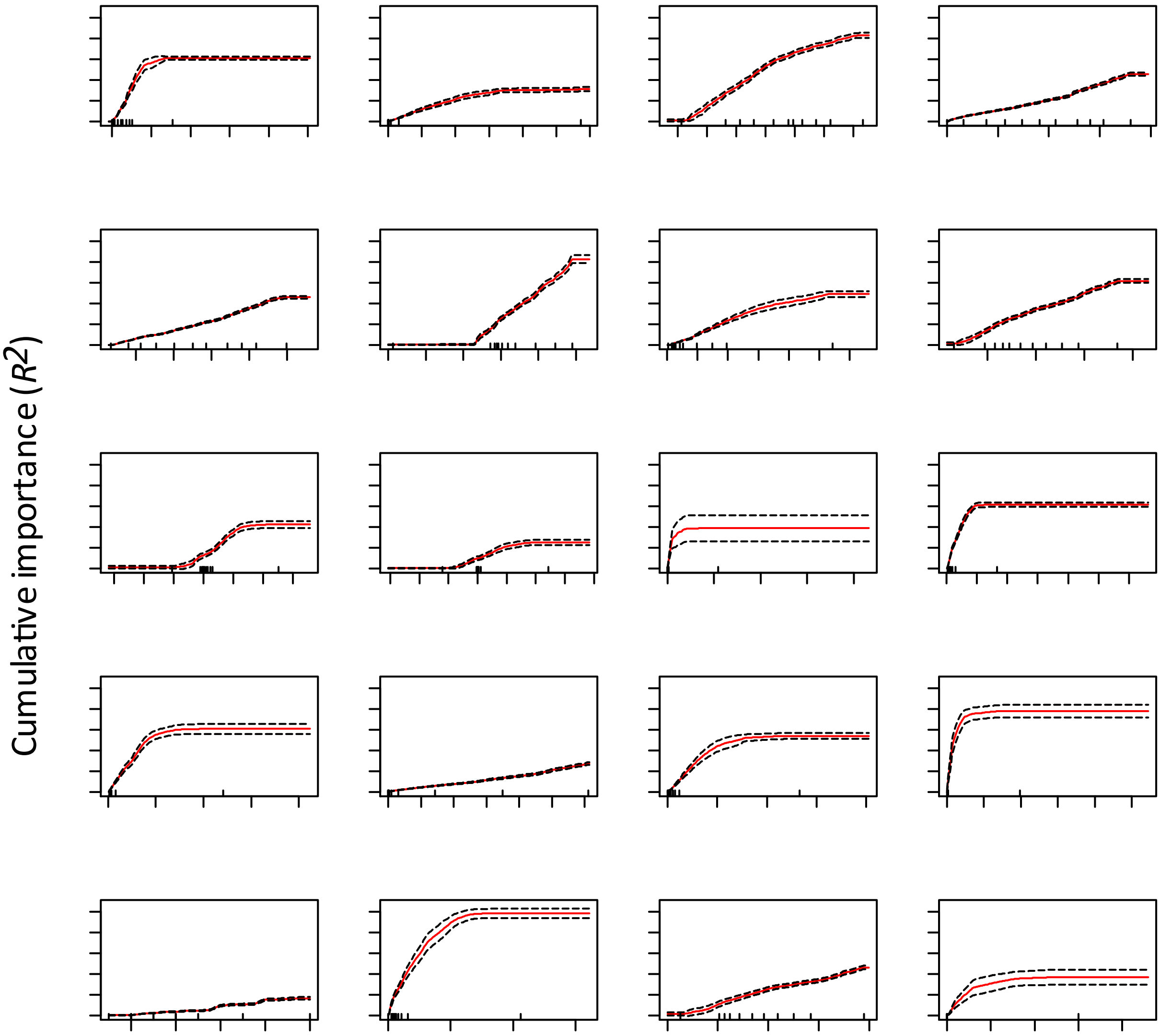

Figure 9-1: Mean (± SD) functions fitted by bootstrapped GF models using demersal fish samples (R^2). Fitted functions indicate relative compositional turnover along the range of each predictor.

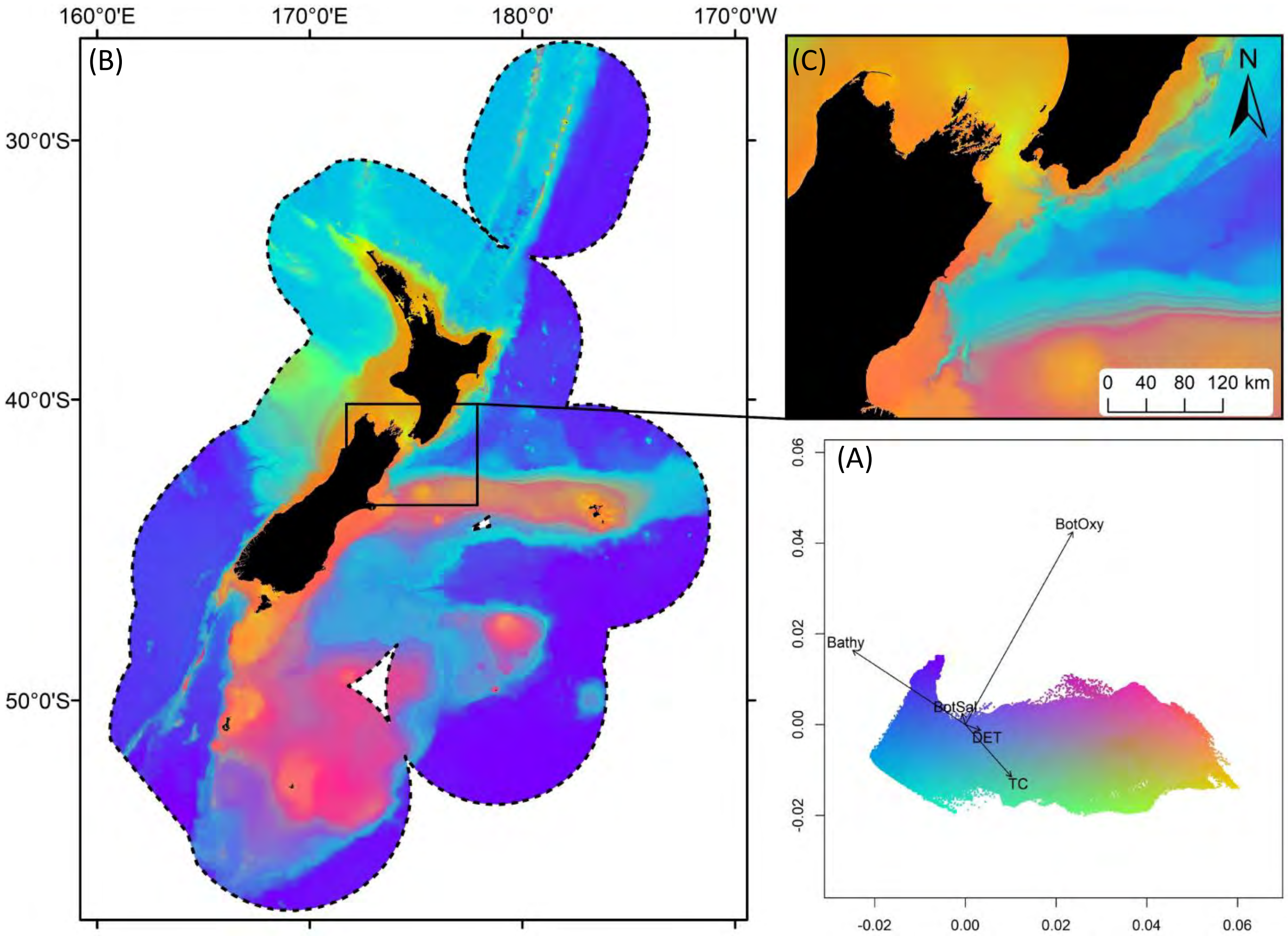

Figure 9-2: Mean predicted compositional turnover in geographic and PCA space derived from bootstrapped Gradient Forest model fitted with demersal fish samples. Colours are based on the first three axes of a PCA analysis so that similarities/differences in colour correspond broadly to similarities/differences in predicted compositional turnover. Compositional turnover in PCA space, with vectors indicating correlations with the 6 most important environmental predictors (A); Geographic distributions of compositional turnover across New Zealand's marine environment (dashed line)(B); Geographic distribution of compositional turnover at finer scales, centred on Cook Strait (C).

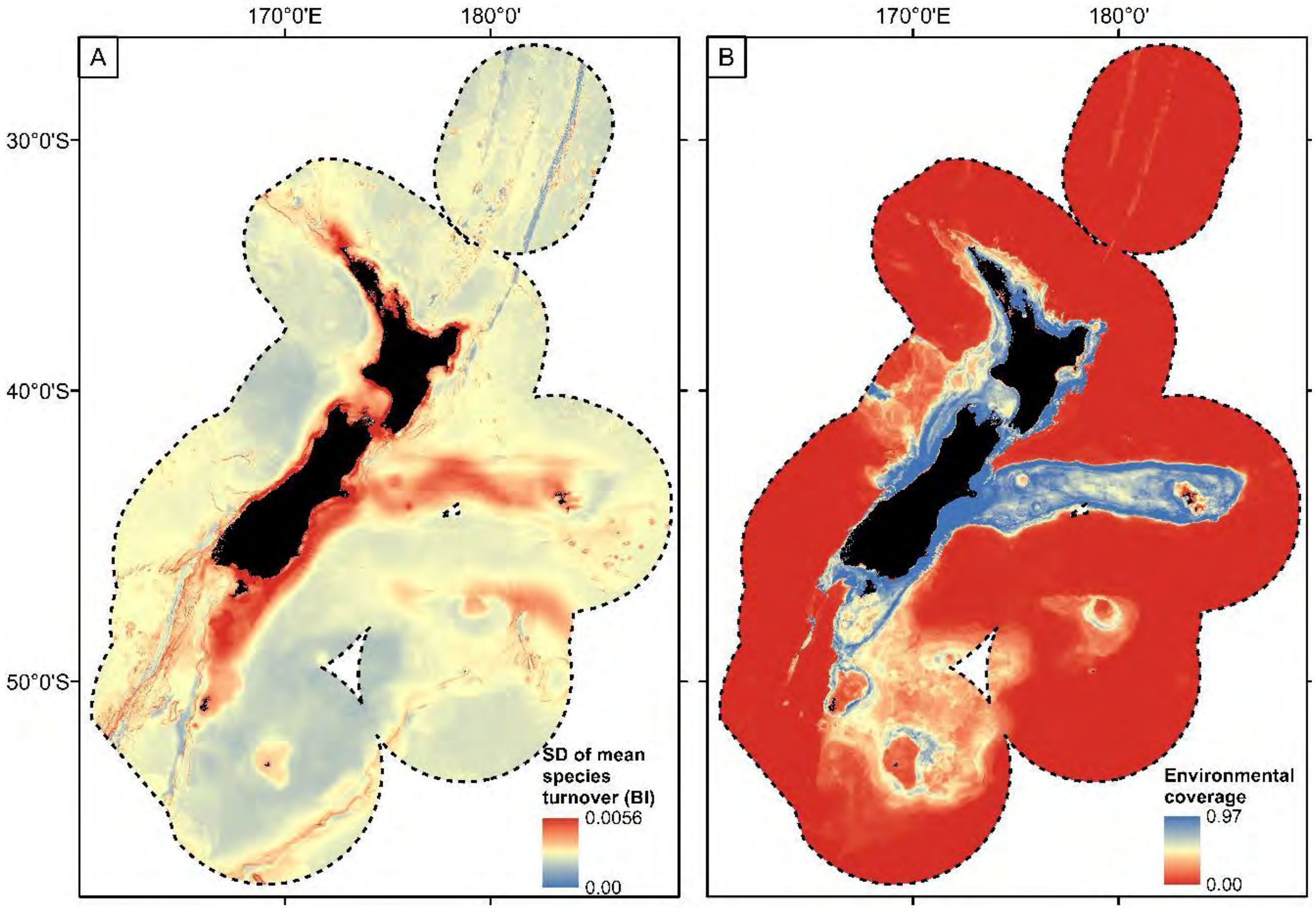

Figure 9-3: Spatially explicit measures of uncertainty for compositional turnover modelled using bootstrapped Gradient Forest model fitted with demersal fish samples. Uncertainty estimate (SD) of compositional turnover modelled using bootstrapped Gradient Forest model fitted with demersal fish samples (A). Predicted environmental coverage depicting the confidence that can be placed in the predictions, ranging from low (i.e., no samples in the dataset with those environmental conditions) to high (i.e., many samples with those environmental conditions) within the New Zealand EEZ (B)

9.2 Benthic invertebrates

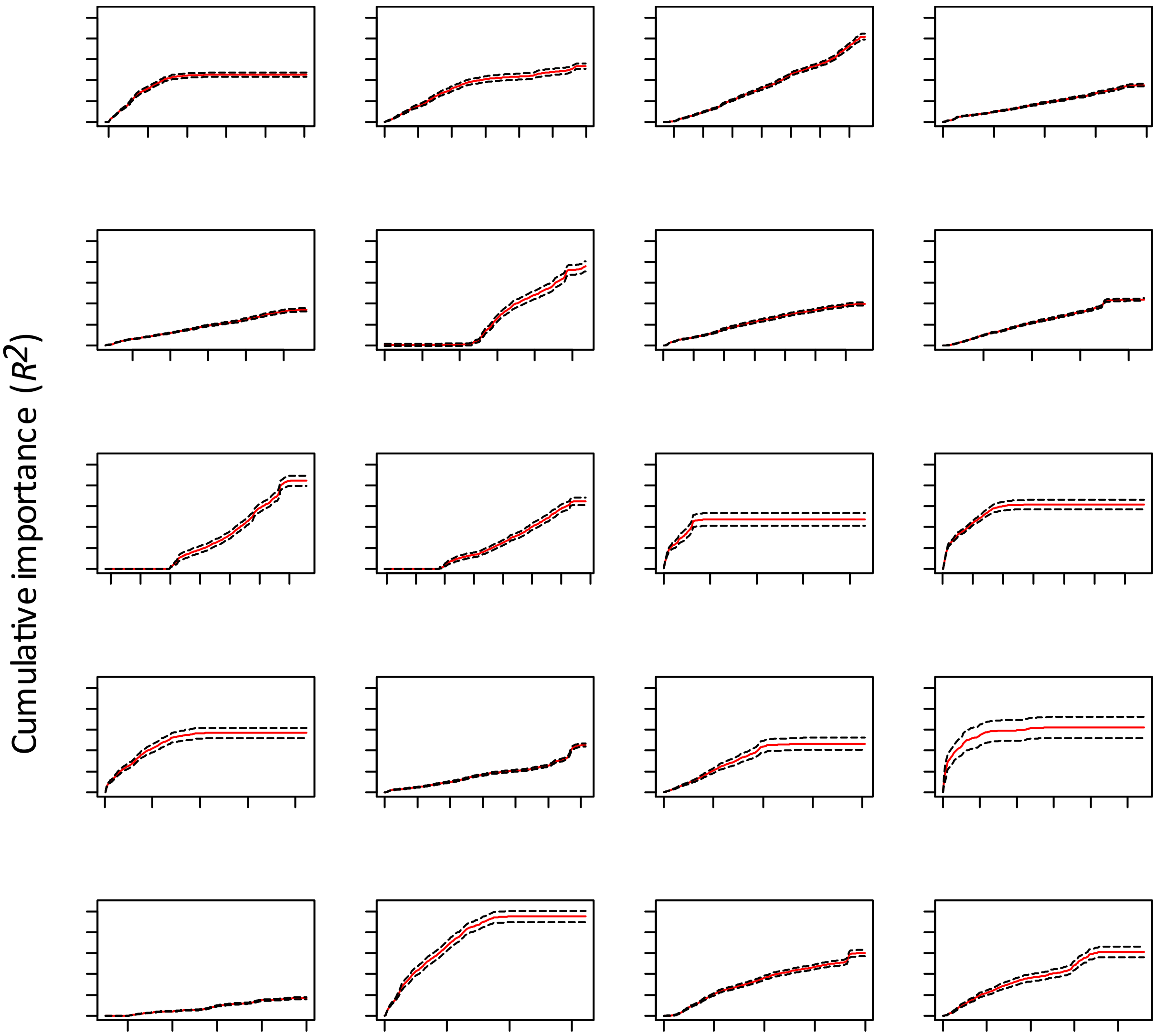

Figure 9-4: Mean (± SD) functions fitted by bootstrapped GF models using benthic invertebrate samples form combined gear types (R^2). Fitted functions indicate the relative compositional turnover along the range of each predictor.

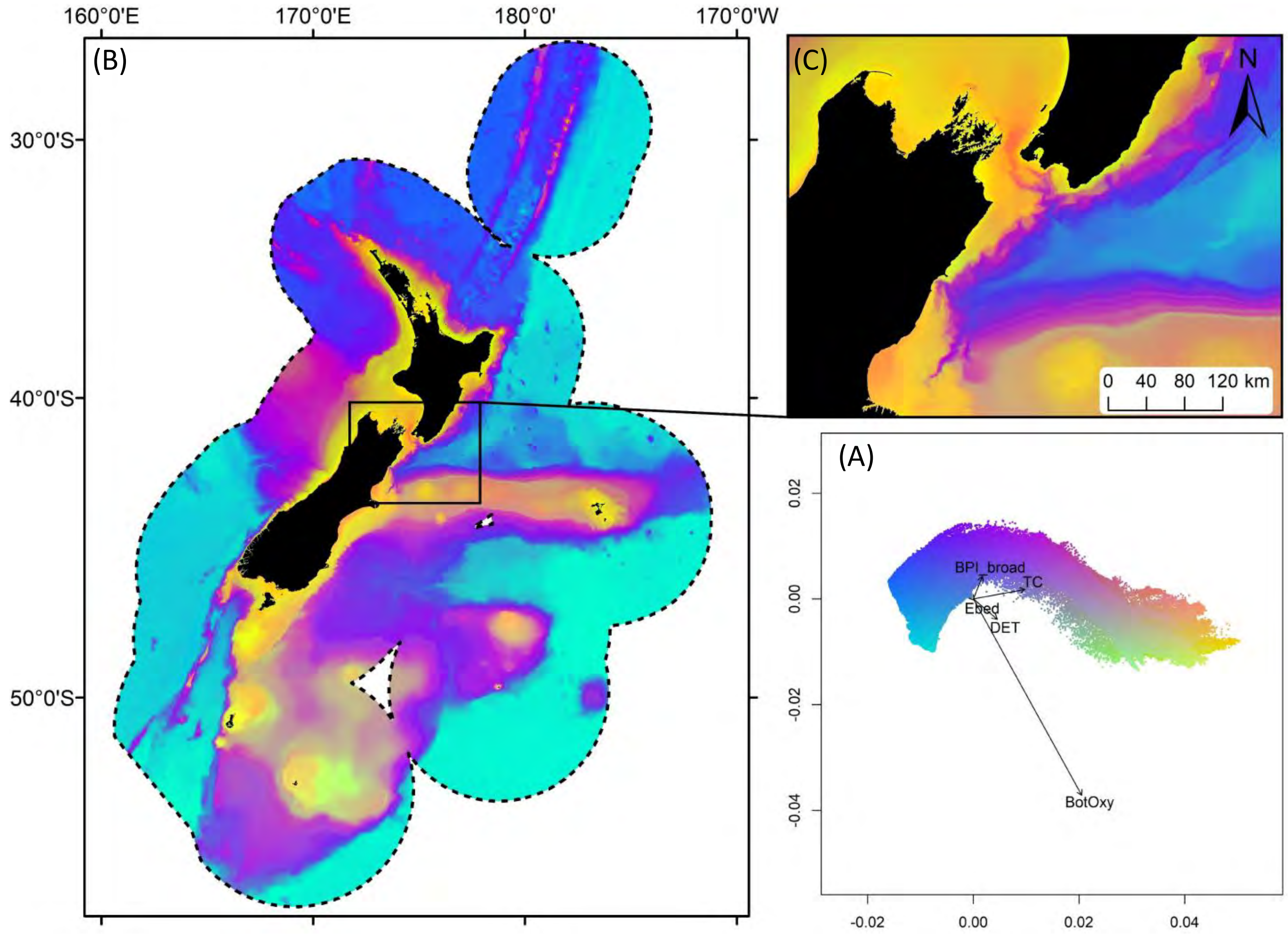

Figure 9-5: Mean predicted compositional turnover in geographic and PCA space derived from bootstrapped, combined, Gradient Forest model fitted with benthic invertebrate samples. Colours are based on the first three axes of a PCA analysis so that similarities/differences in colour correspond broadly to similarities/differences in predicted compositional turnover. Compositional turnover in PCA space, with vectors indicating correlations with the 6 most important environmental predictors (A); Geographic distributions of compositional turnover across New Zealand's marine environment (dashed line)(B); Geographic distribution of compositional turnover at finer scales, centred on Cook Strait (C).

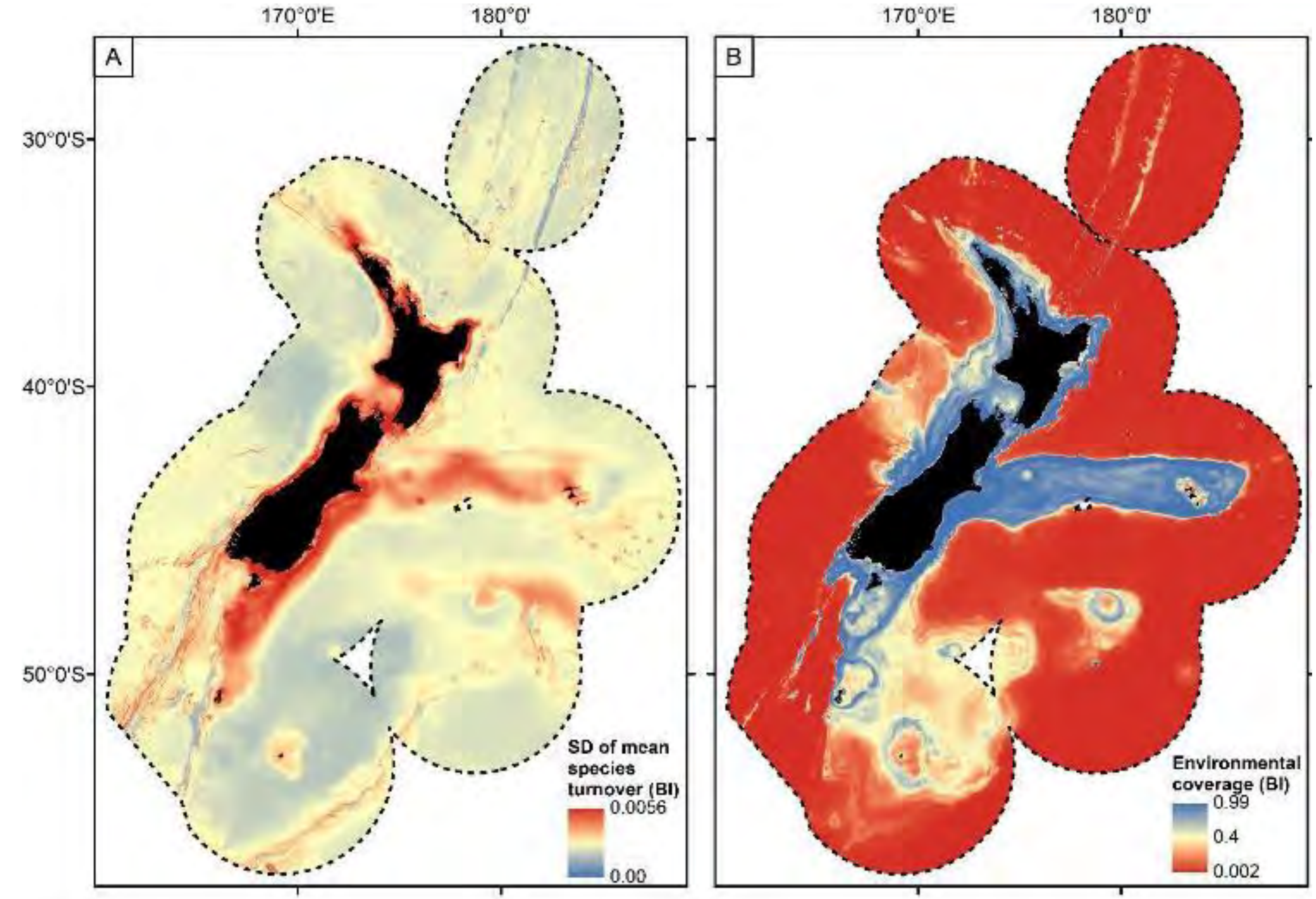

Figure 9-6: Spatially explicit measures of uncertainty for compositional turnover modelled using bootstrapped Gradient Forest model fitted with benthic invertebrate samples. Uncertainty estimate (SD) of compositional turnover modelled using bootstrapped Gradient Forest model fitted with demersal fish samples (A). Predicted environmental coverage depicting the confidence that can be placed in the predictions, ranging from low (i.e., no samples in the dataset with those environmental conditions) to high (i.e., many samples with those environmental conditions) within the New Zealand EEZ (B).

9.3 Rocky reef fish

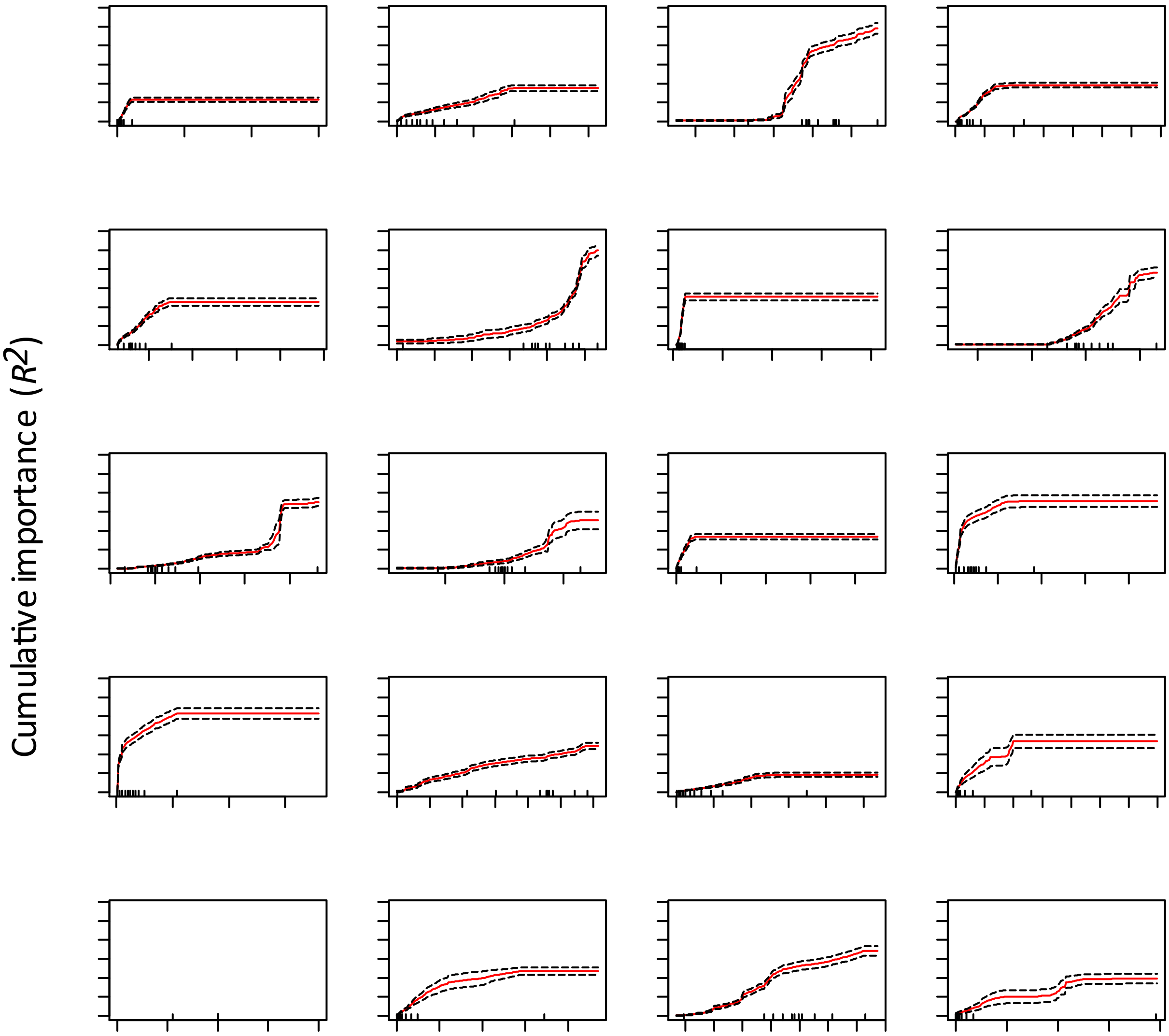

Figure 9-7: Mean (± SD) functions fitted by bootstrapped GF models using reef fish samples (R^2). Fitted functions indicate relative compositional turnover along the range of each predictor.

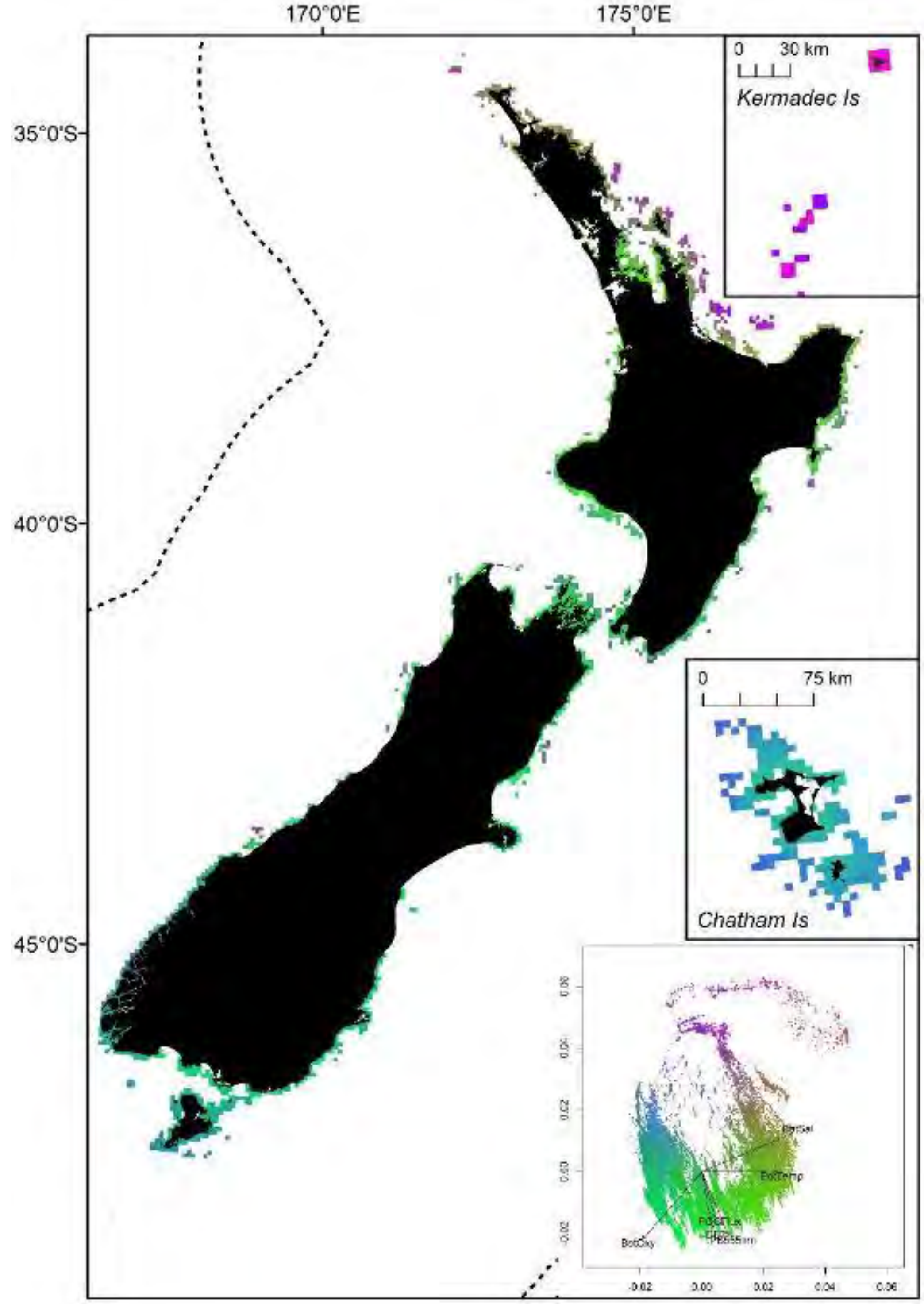

Figure 9-8: Mean predicted compositional turnover in geographic and PCA space derived from bootstrapped Gradient Forest model fitted using reef fish samples. Gridded predictions produced at a 250 m scales were aggregated to a 5 km scale for easier visualisation and clipped to areas representing rocky reef layers. Colours are based on the first three axes of a PCA analysis so that similarities/differences in colour correspond broadly to similarities/differences in predicted compositional turnover. Compositional turnover in PCA space, with vectors indicating correlations with the 6 most important environmental predictors (A); Inset maps show the Kermadec Islands and the Chatham Islands.

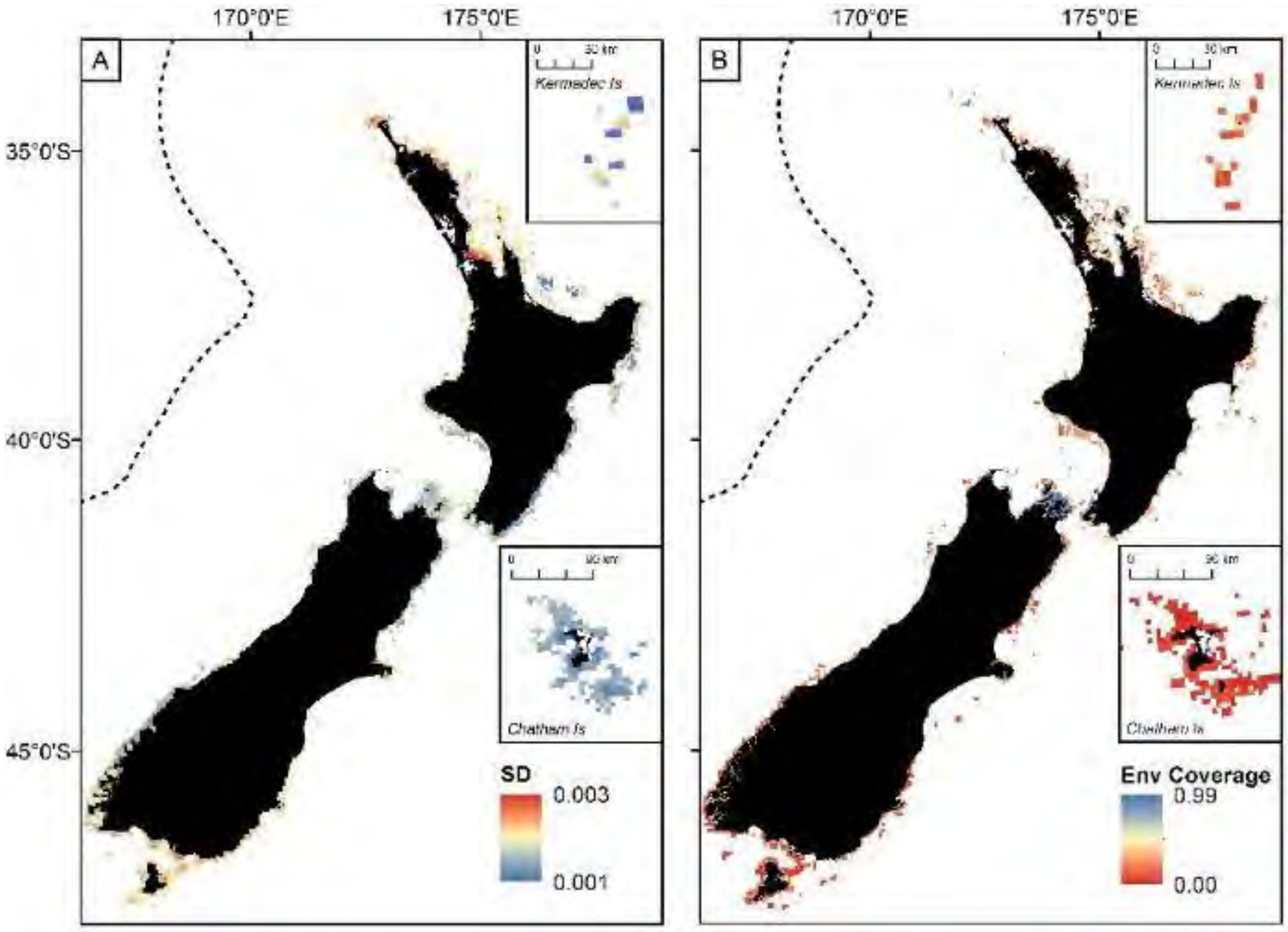

Figure 9-9: Spatially explicit measures of uncertainty for compositional turnover modelled using bootstrapped Gradient Forest model fitted with reef fish samples. Gridded predictions produced at a 250 m scales were aggregated to a 5 km scale for easier visualisation Uncertainty estimate (SD) of compositional turnover modelled using bootstrapped Gradient Forest model fitted using reef fish samples (A). Predicted environmental coverage depicting the confidence that can be placed in the predictions, ranging from low (i.e., no samples in the dataset with those environmental conditions) to high (i.e., many samples with those environmental conditions) within the New Zealand marine environment (B). Inset maps show the Kermadec Islands and the Chatham Islands.

9.4 Macroalgae

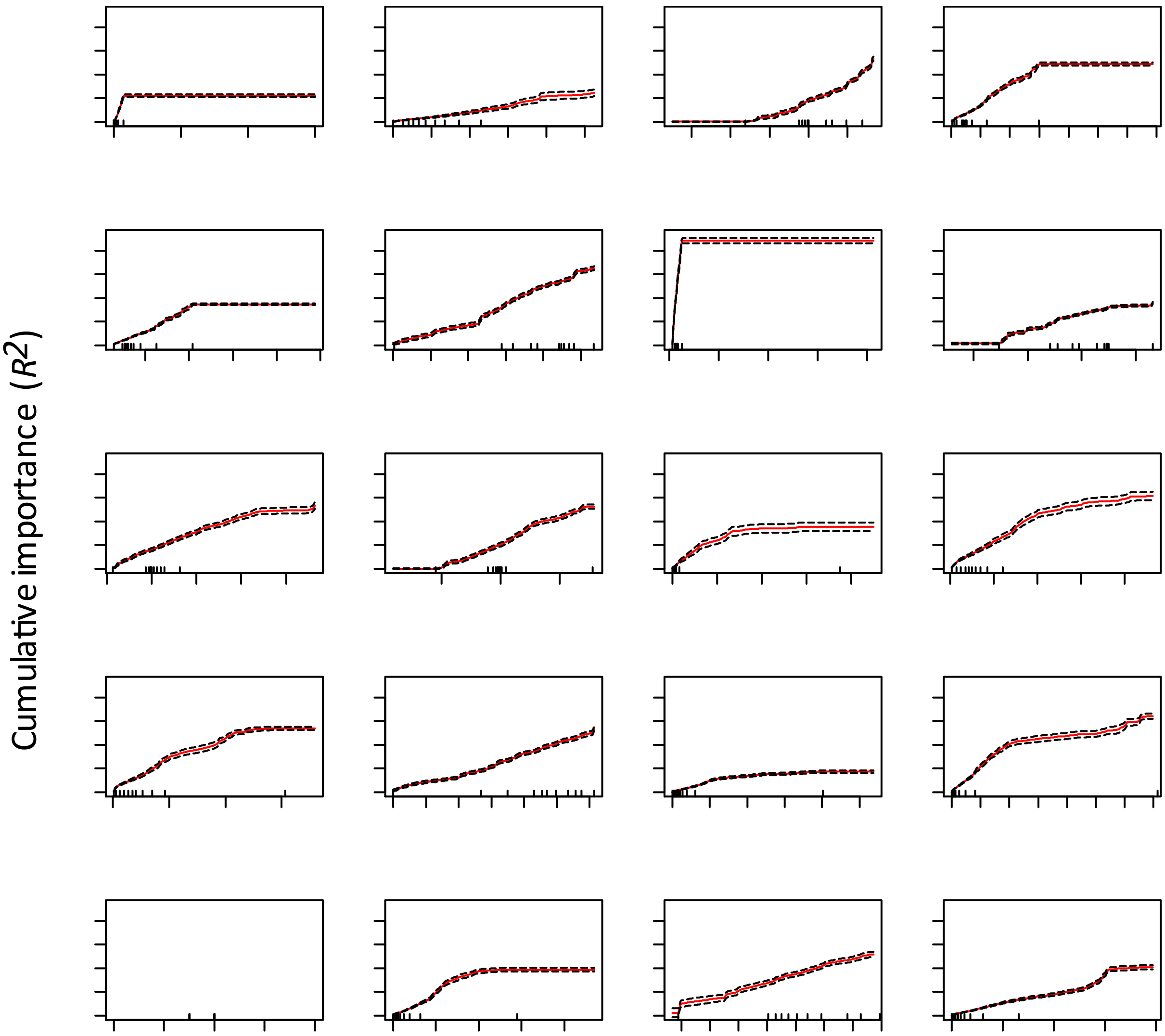

Figure 9-10: Mean (± SD) functions fitted by bootstrapped GF models using macroalgae samples (R^2). Fitted functions indicate relative compositional turnover along the range of each predictor.

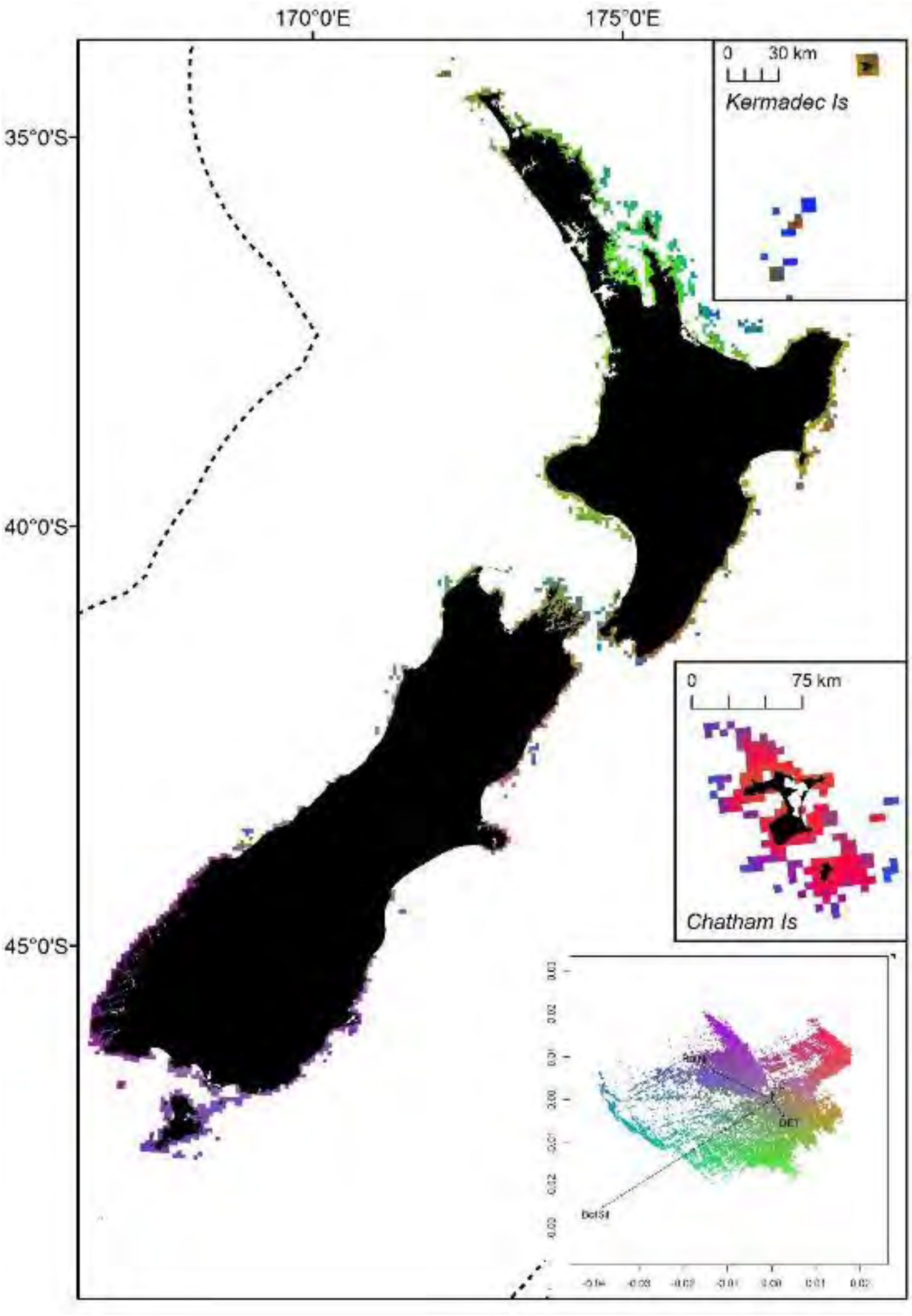

Figure 9-11: Mean predicted compositional turnover in geographic and PCA space derived from bootstrapped Gradient Forest model fitted using macroalgae samples. Gridded predictions produced at a 250 m scales were aggregated to a 5 km scale for easier visualisation and clipped to areas representing rocky reef layers. Colours are based on the first three axes of a PCA analysis so that similarities/differences in colour correspond broadly to similarities/differences in predicted compositional turnover. Compositional turnover in PCA space, with vectors indicating correlations with the 6 most important environmental predictors (A); Inset maps show the Kermadec Islands and the Chatham Islands.

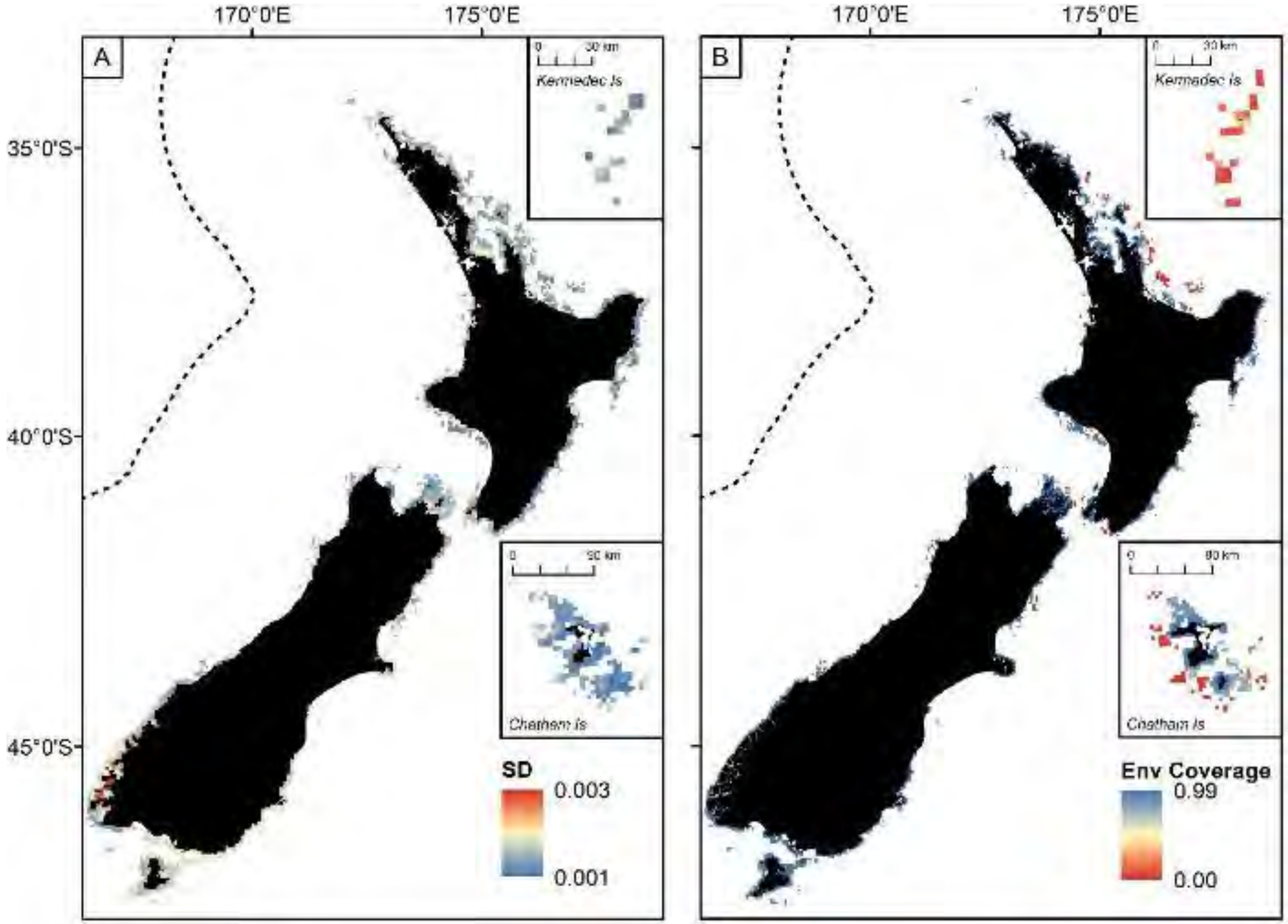

Figure 9-12: Spatially explicit measures of uncertainty for compositional turnover modelled using bootstrapped Gradient Forest model fitted using macroalgae samples. Gridded predictions produced at a 250 m scales were aggregated to a 5 km scale for easier visualisation Uncertainty estimate (SD) of compositional turnover modelled using bootstrapped Gradient Forest model fitted using macroalgae samples (A). Predicted environmental coverage depicting the confidence that can be placed in the predictions, ranging from low (i.e., no samples in the dataset with those environmental conditions) to high (i.e., many samples with those environmental conditions) within the New Zealand marine environment (B). Inset maps show the Kermadec Islands and the Chatham Islands.

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