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Modelling seamount diversity and biogeography

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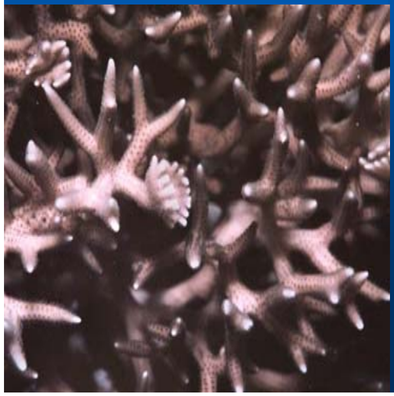


Overview

1. **Modelling patterns of diversity and endemism on seamounts**

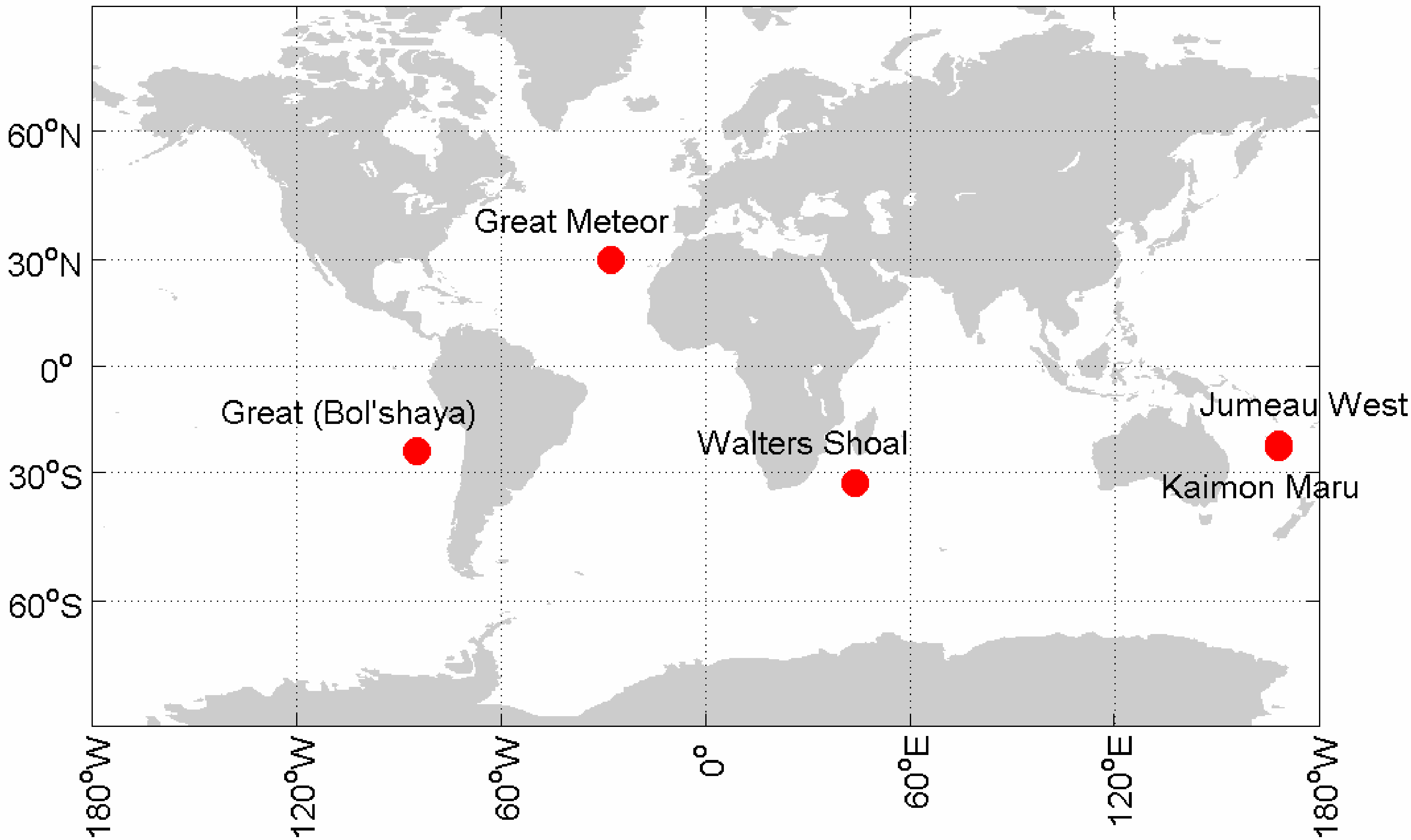
   (pessimism)

2. **Habitat suitability modelling for seamount corals**

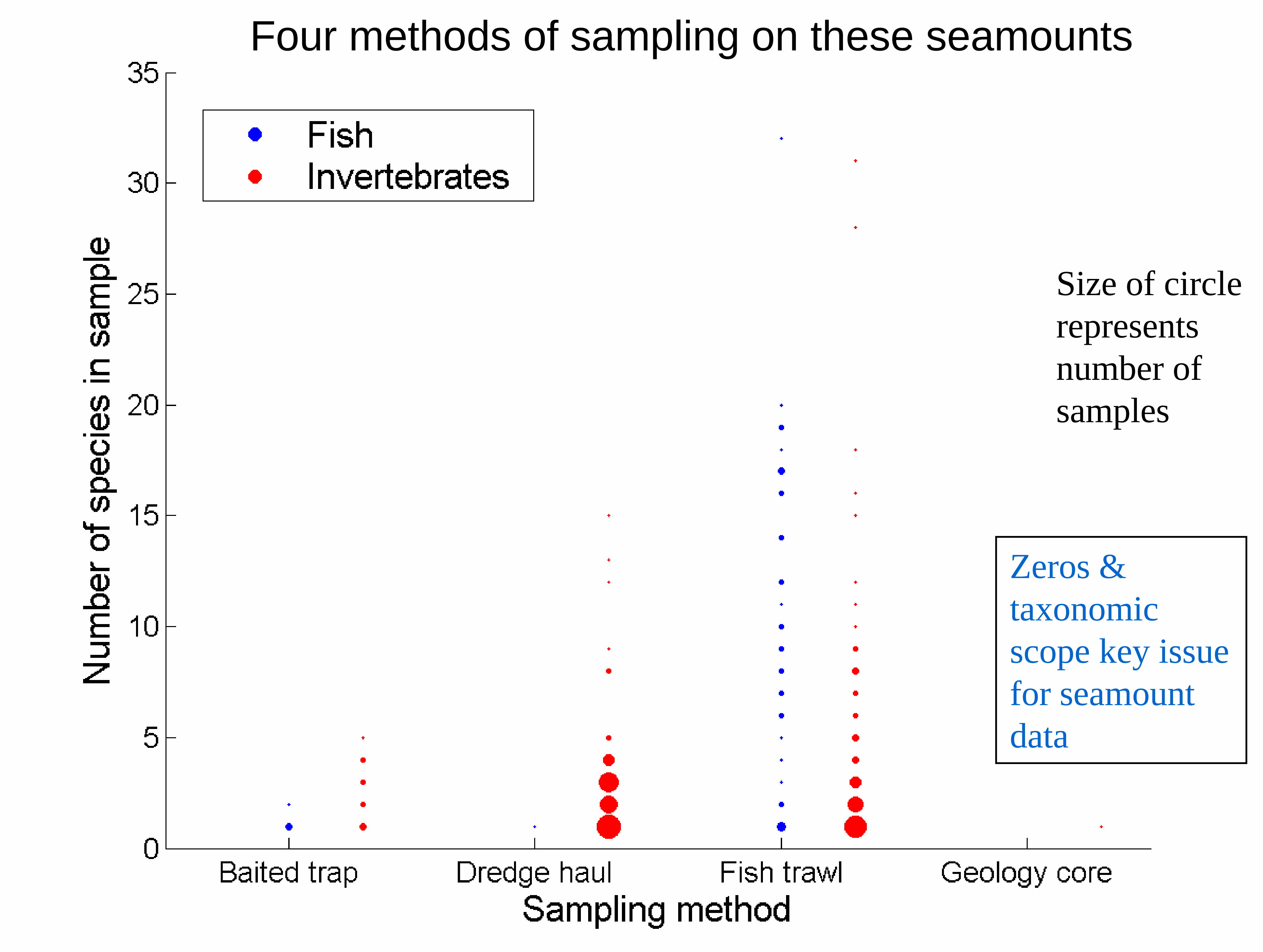
   (optimism)

Section 1: Modelling diversity and endemism

Sampling issues on seamounts



Data originally from Shirshov Institute, Russia. Some of the most comprehensive sampling of fish and invertebrates on seamounts in Seamounts Online (http://seamounts.sdsc.edu/) *using standardised sampling gear* is at these locations


Four methods of sampling on these seamounts
Fish
Invertebrates
Number of species in sample
0
5
10
15
20
25
30
35
Baited trap
Dredge haul
Fish trawl
Geology core
Sampling method
Size of circle represents number of samples
Zeros & taxonomic scope key issue for seamount data

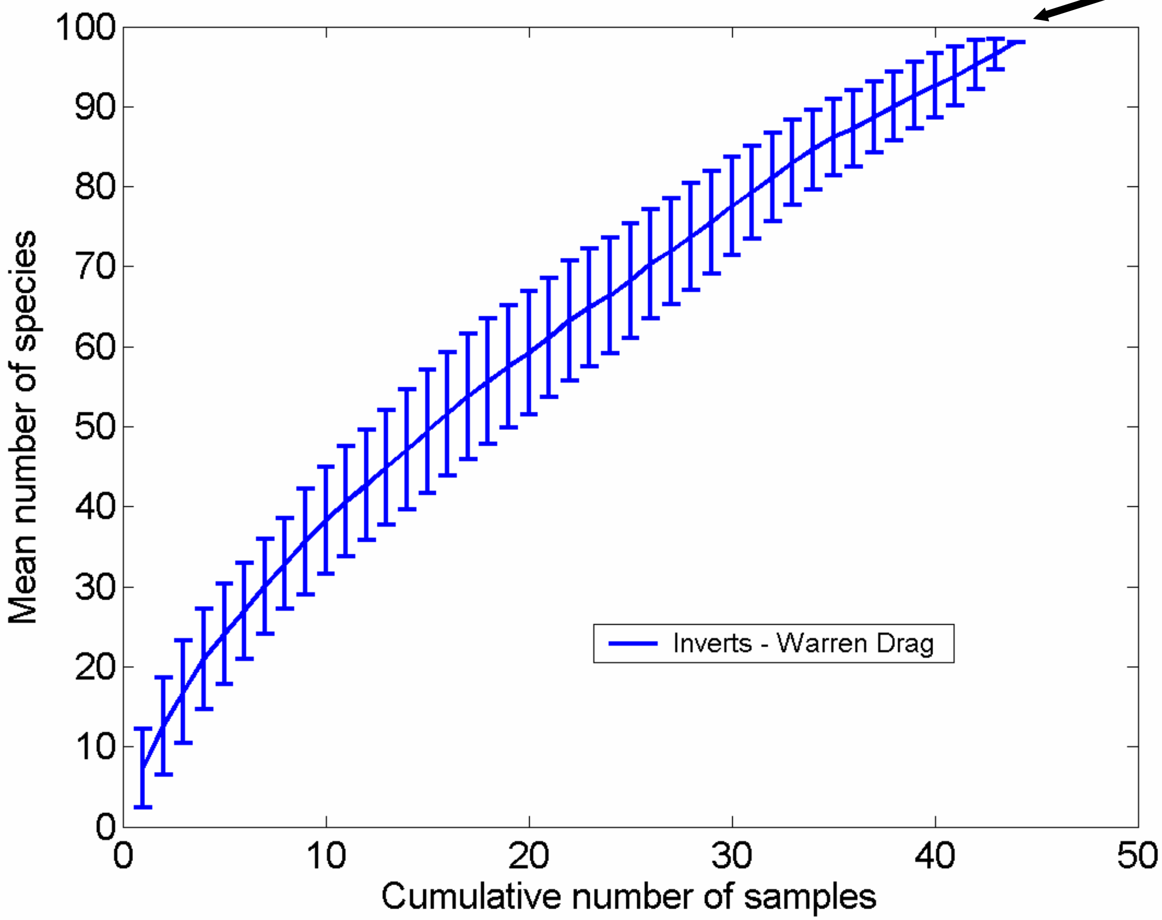
Variation in sampling

- There were ~10 different sampling methods used to collect fish & invertebrates from these seamounts
- This figure doesn't include differences between the same sampling method; e.g. different mesh sizes on nets
- This is one of the biggest challenges when synthesizing seamount data for a large-scale analysis – very difficult to correct for variation in sampling effort

Species accumulation curves

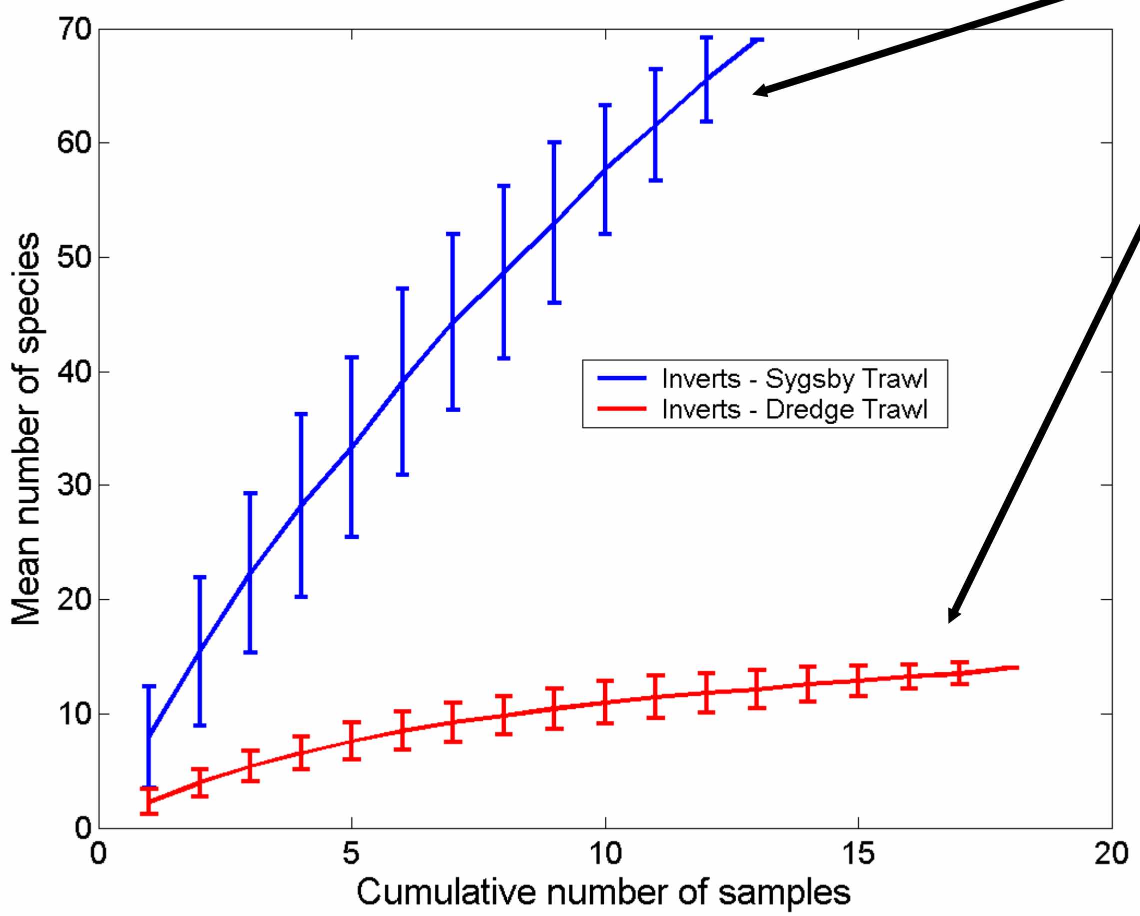
(following Gotelli & Colwell (2001). Ecol. Lett. **4**: 379-391)

No sign of an asymptote



Jumeau West

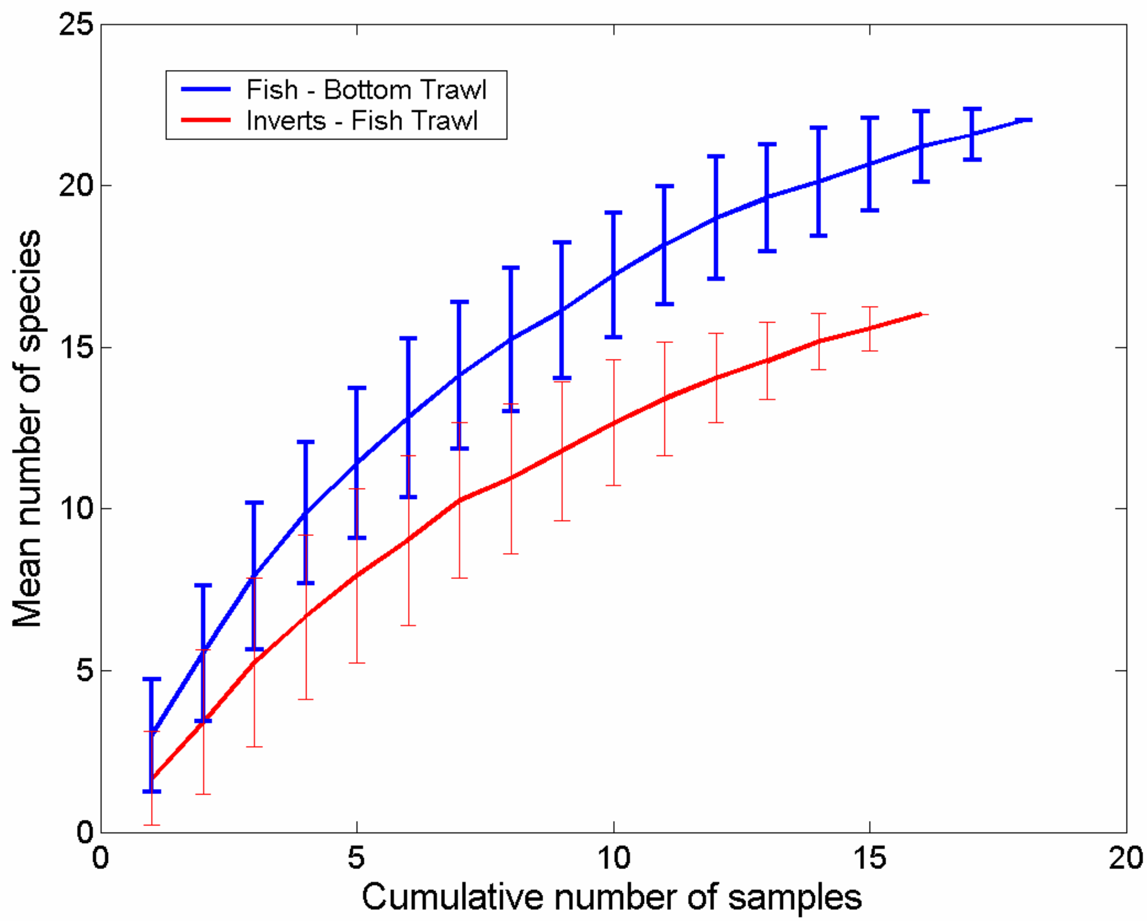
Species accumulation curves



Vastly different number of invertebrates collected by different sampling methods

Great Meteor

Species accumulation curves

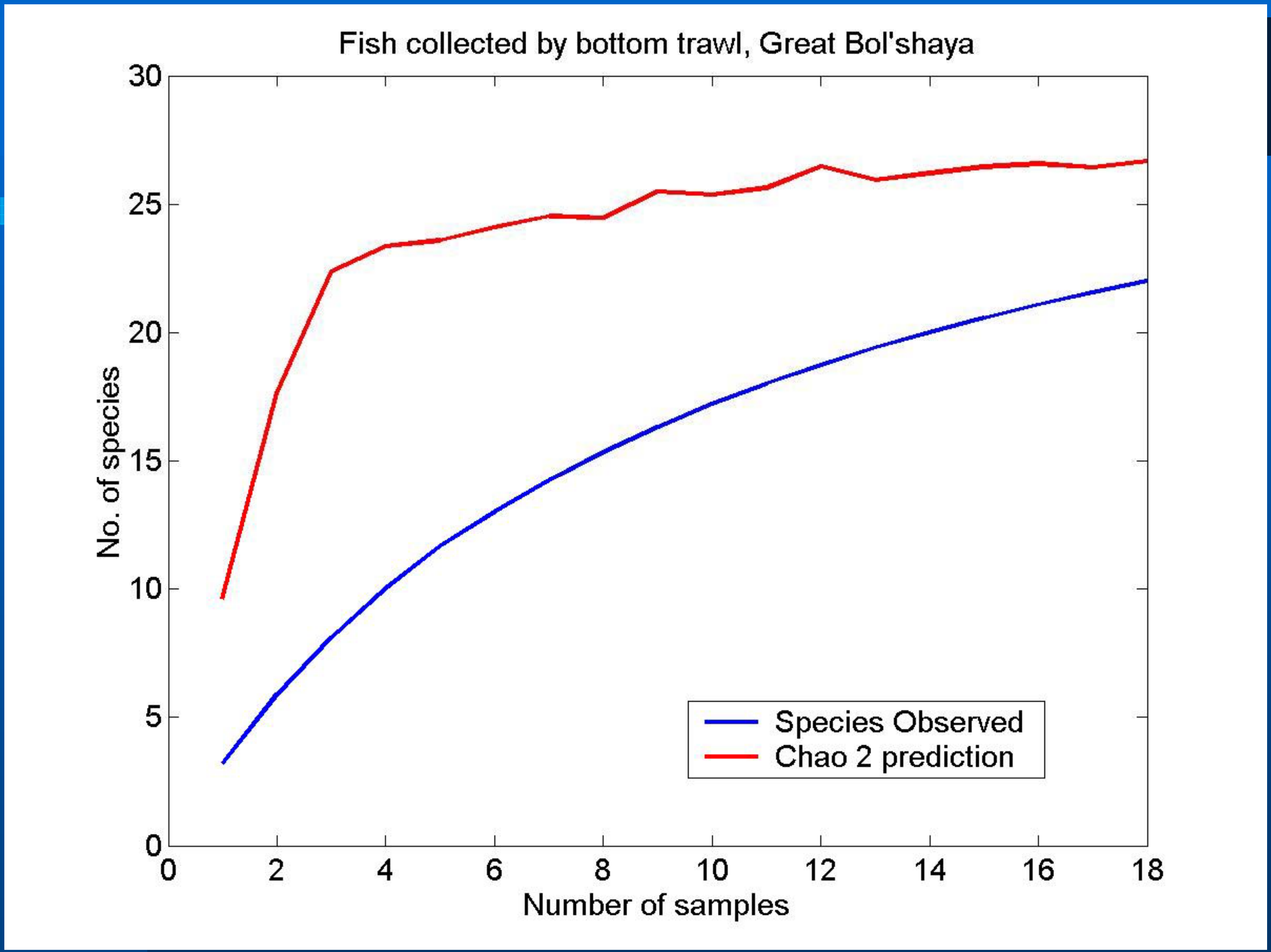


Great Bol’shaya

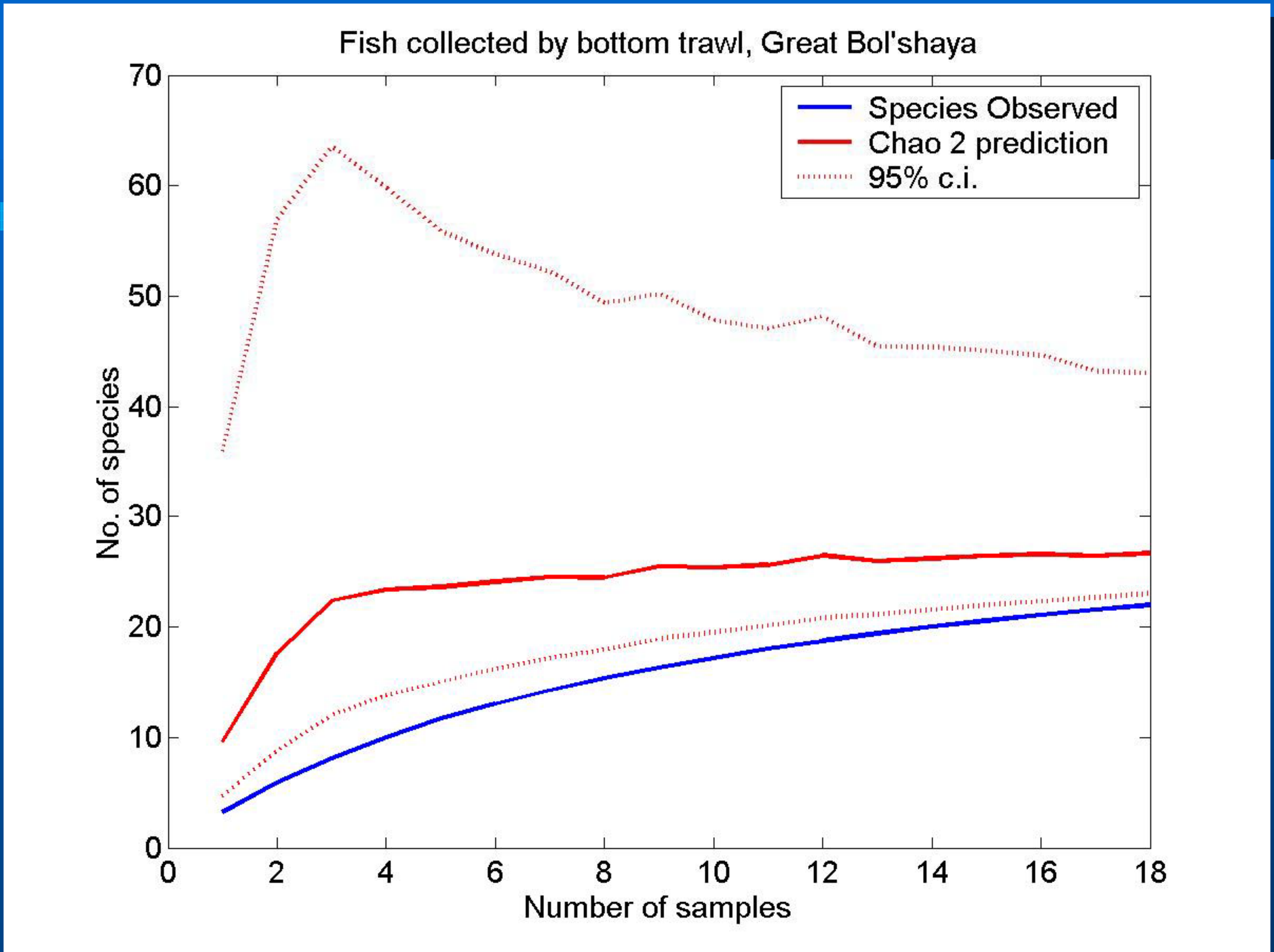
How to work with this data?

- Seamounts are extremely undersampled. Can we do anything about this?
- Rarefaction to standardise sampling effort – but does not provide useful information when sampling methods are different.
- Non-parametric estimators (e.g. Chao1, Chao2). Typically do not converge with data patterns such as those shown.

(pessimism)



Chao 2 non parametric estimator

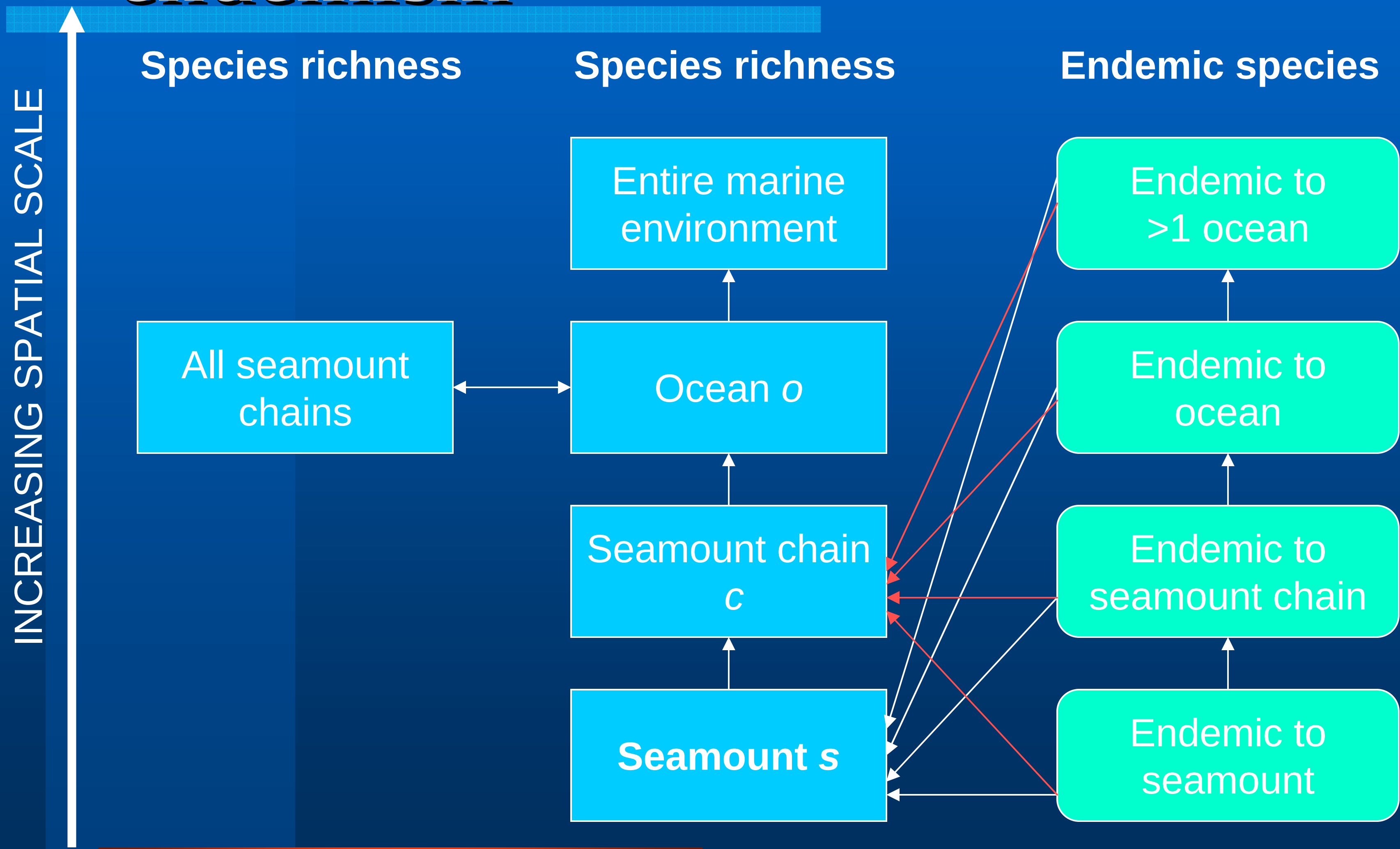


Chao 2 non parametric estimator

Endemism on seamounts

- E.g. Richer de Forges *et al*. (2000). Nature 405: 944-947.
- What are the factors driving patterns of endemism?
- Can we construct theoretical models of endemism on seamounts?

A hierarchical model of endemism



A key question…

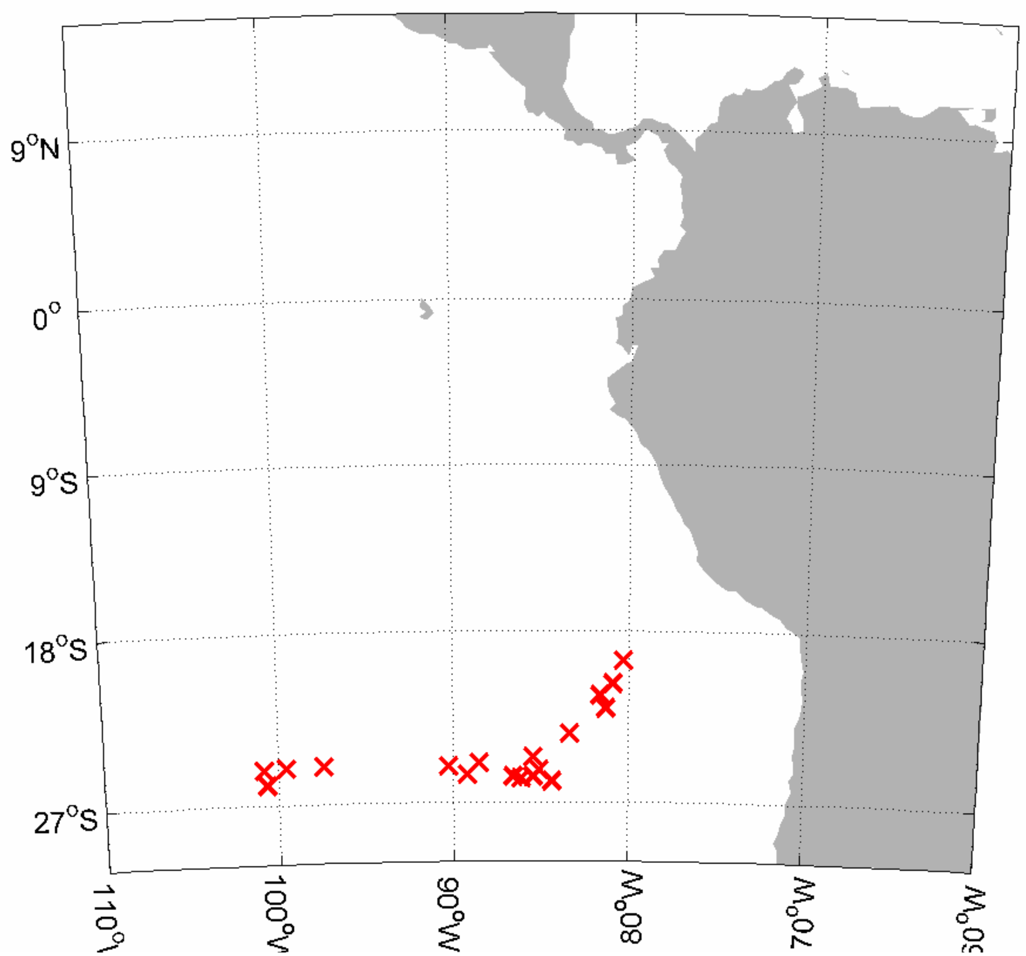
How many of these endemics are true endemics, and how many are a product of incomplete sampling?

Misclassifications will have a big effect on the power of models to explain patterns.

Modelling endemism

- Does terrestrial island biogeography theory provide a suitable testbed for constructing simple models of endemism on seamounts?
- What factors may be important in determining % endemics on seamounts? Isolation, age, depth, size…?

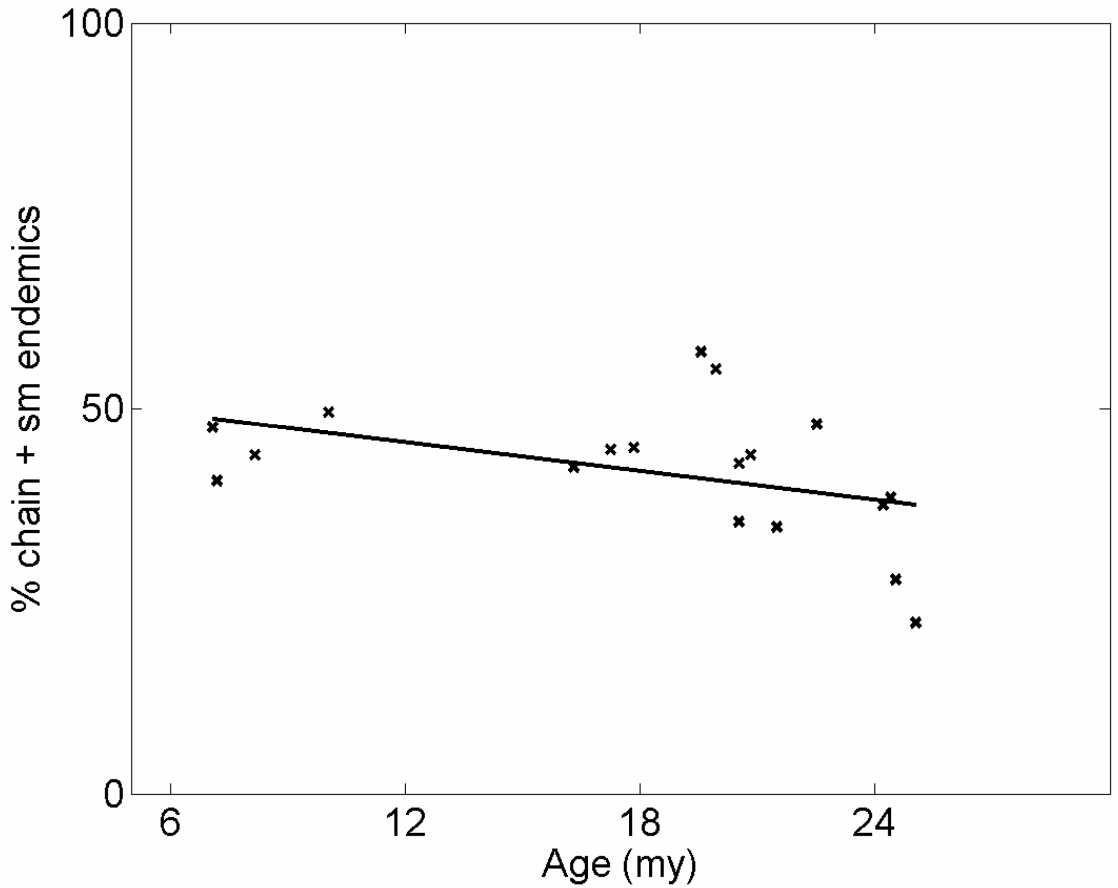
Endemism upon seamounts



Nasca & Sala y Gomez ridges

Simple plots to visually assess the effects of age, depth & geographical isolation

Seamount age vs. endemics

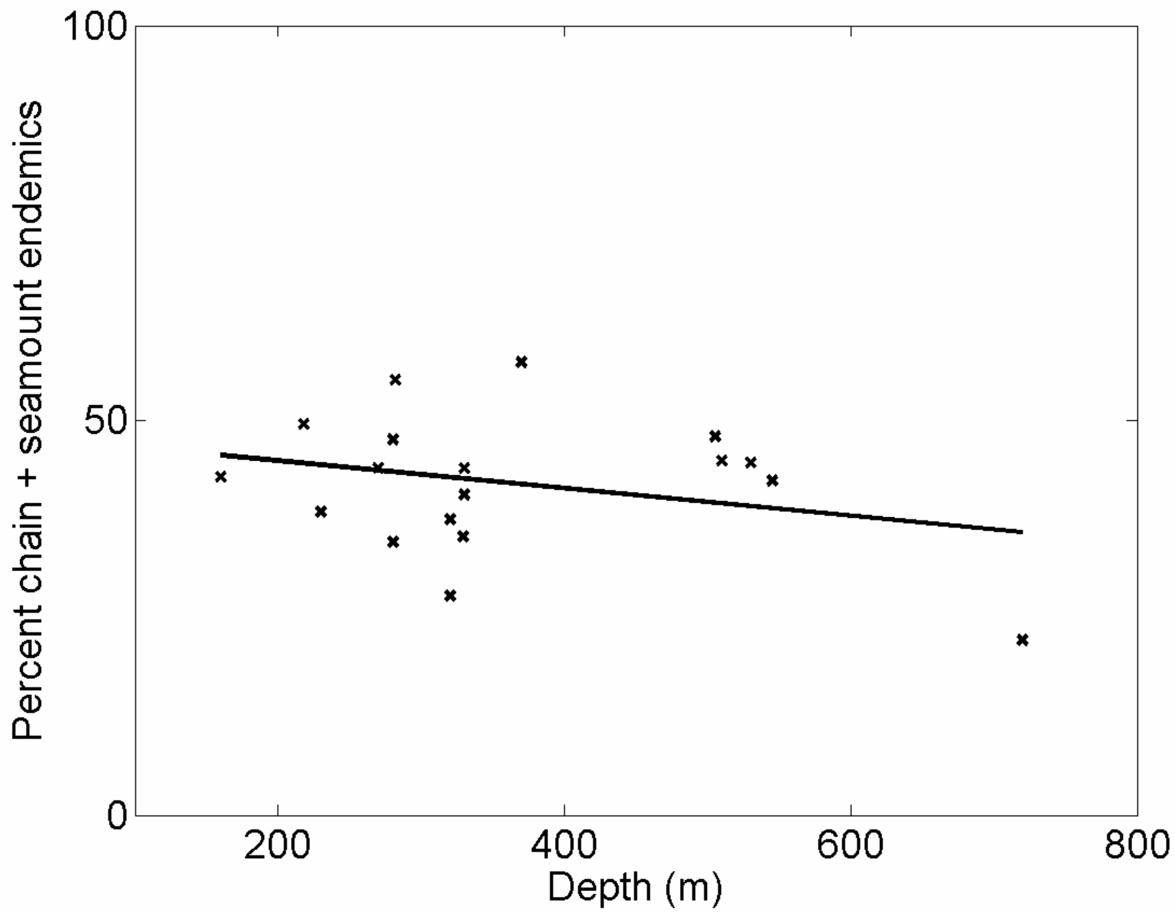


Percent endemics - fish and invertebrates

Needs a GLM to properly assess fit

These plots will change if endemics are reclassified

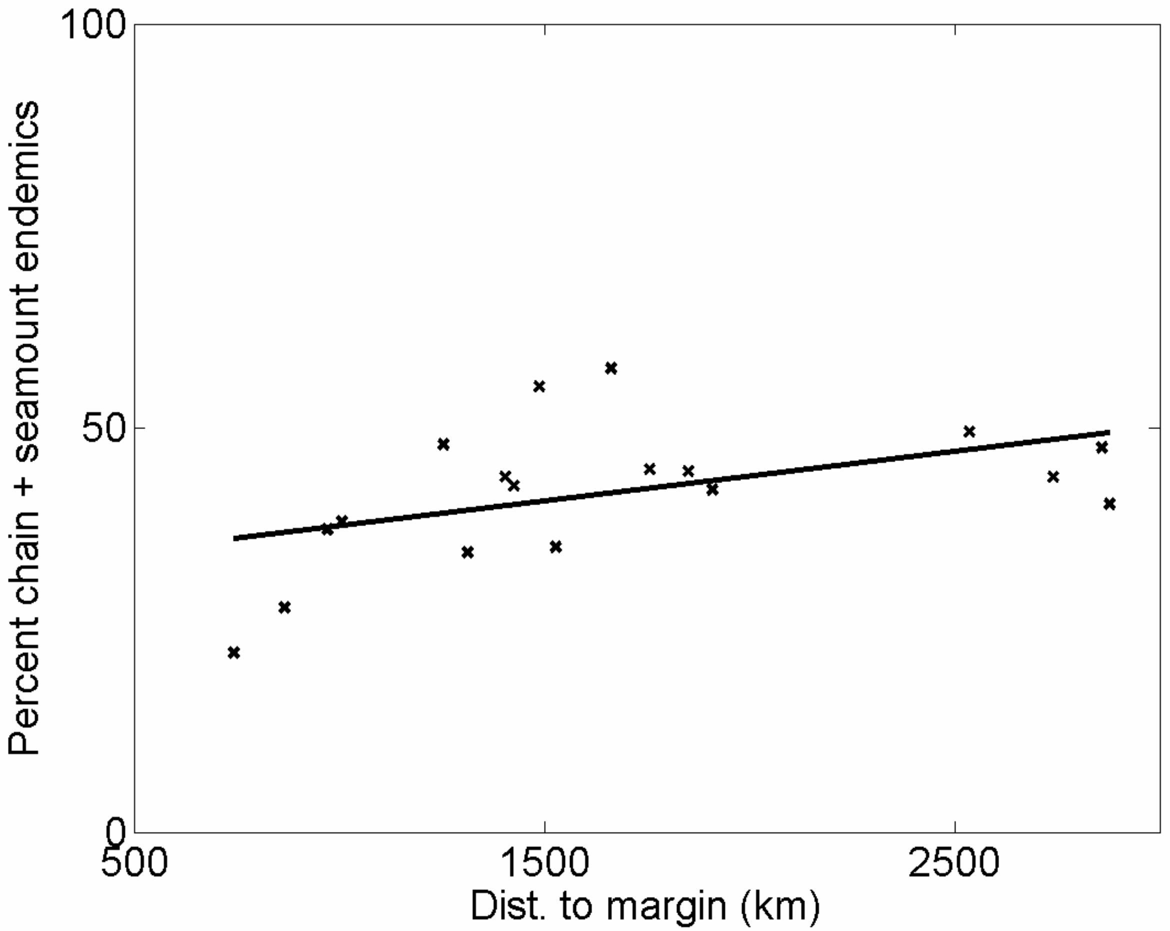
Seamount depth vs. endemics



Percent endemics - fish and invertebrates

Needs a GLM to properly assess fit

Distance from continental margin (geographic isolation) vs. endemics



Percent endemics - fish and invertebrates

Needs a GLM to properly assess fit

Certainly not the full story

e.g. Tasmanian Seamounts

IBGT does not appear to be a good fit.

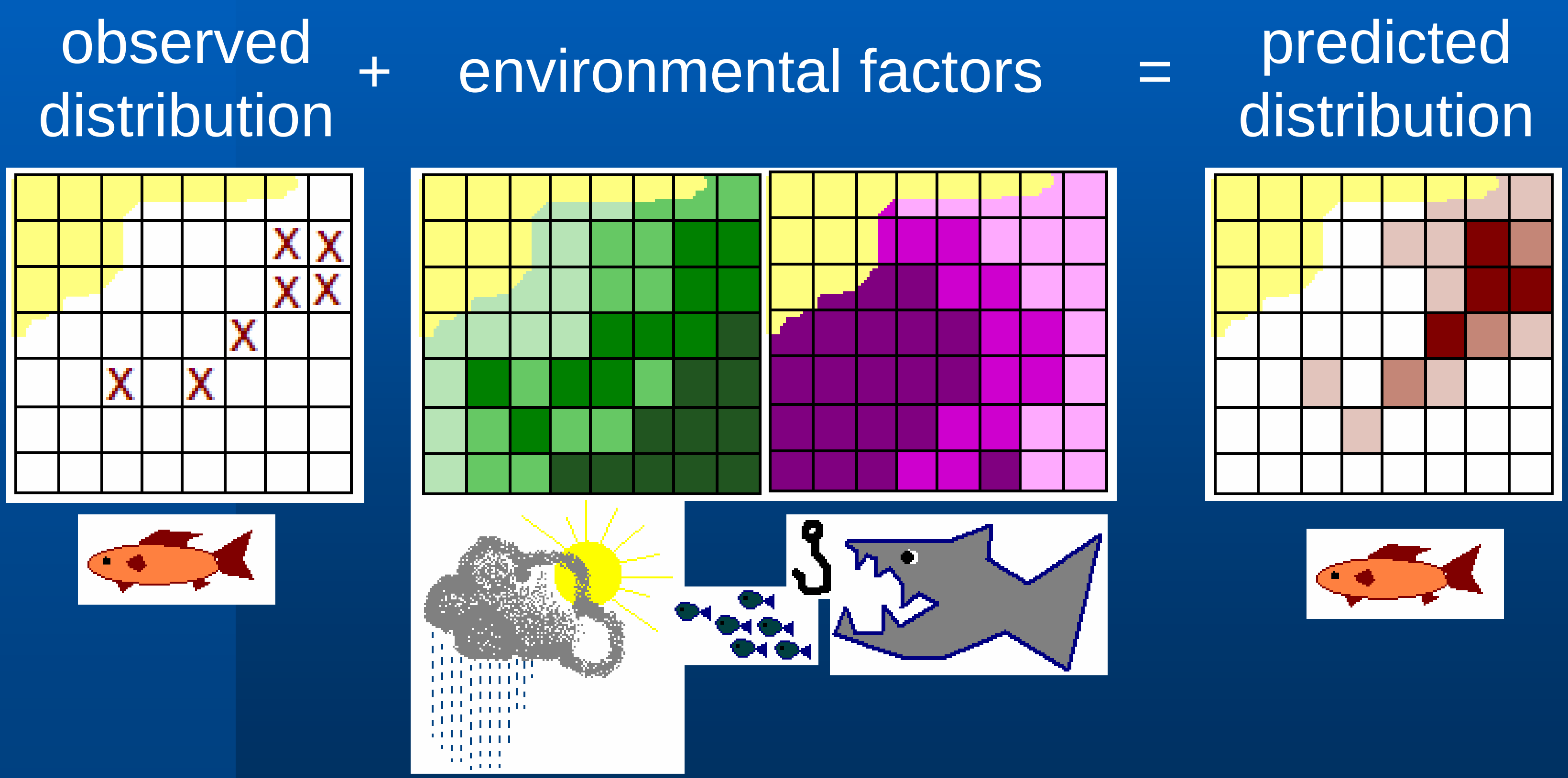
To summarise

- Problems with correcting for sampling effort. This is a major issue.
- General patterns of endemism & the factors responsible are difficult to establish.
- These simple models (based on island biogeography) do not appear to provide a good fit to seamounts. Very data limited.

(pessimism)

Section 2: Modelling global habitat suitability for Scleractinian corals on seamounts

The underlying principle of habitat modelling

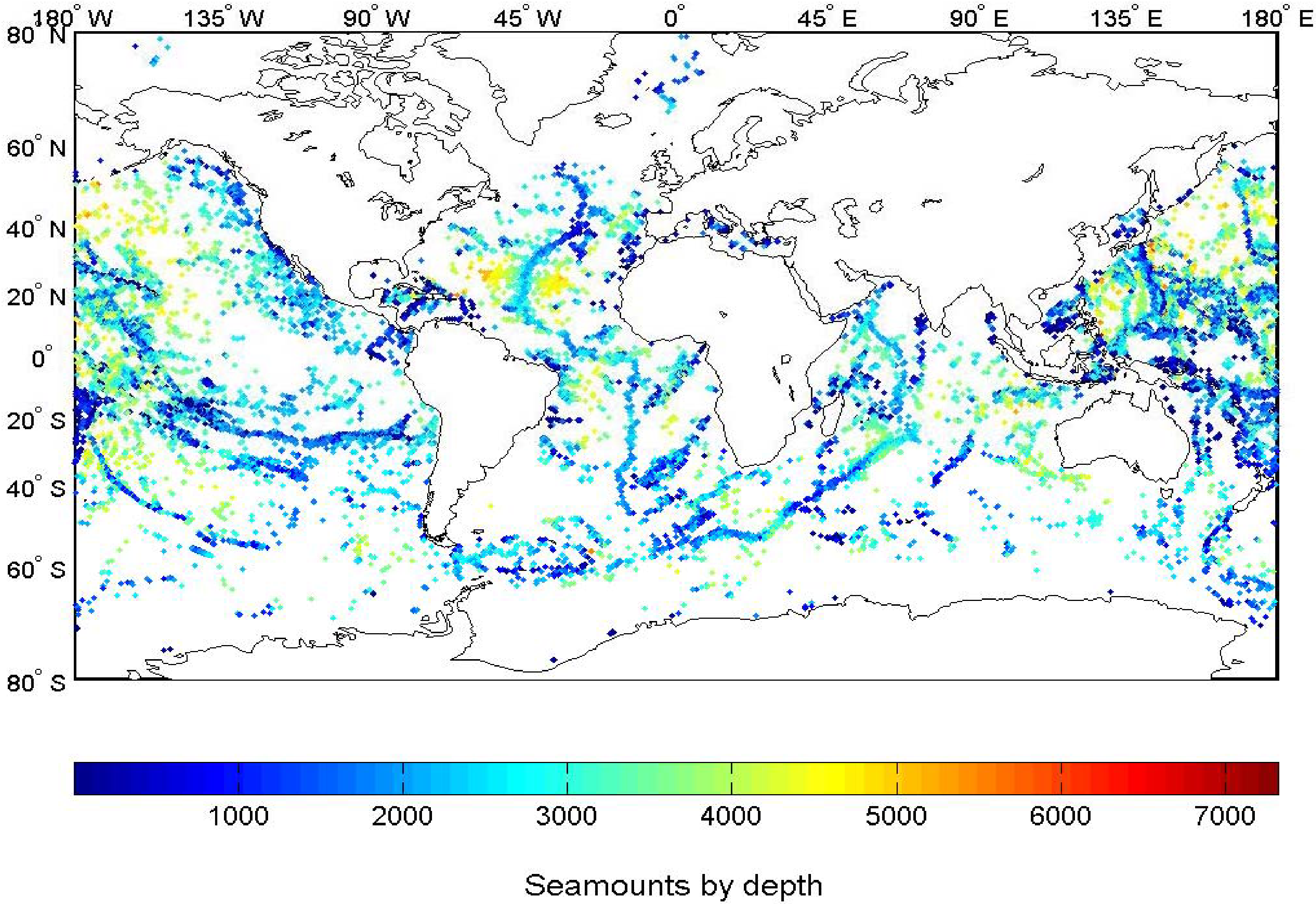


J. McPherson

Modelling deep-sea coral ranges

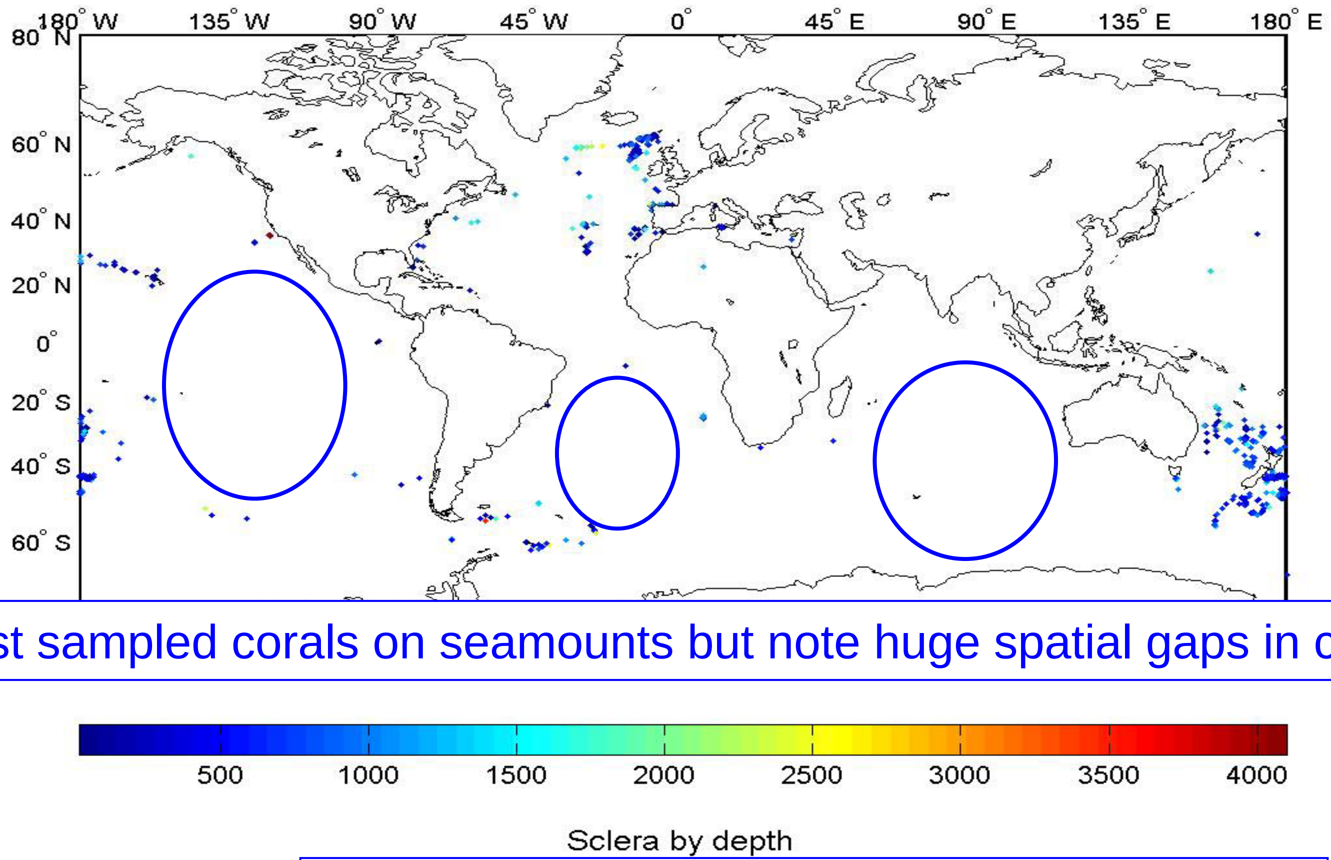
- Central question:

  Can we predict seamounts likely to provide suitable coral habitat?



Data from SAUP

Scleratinia by depth



Best sampled corals on seamounts but note huge spatial gaps in coverage

… are depths merely reflecting sampling bias?

Modelling methods

We only have presence data; no absences. The zeros problem again

Envelope Models

- BIOCLIM, DOMAIN, Mahalanobis distance

Canonical Methods

- ENFA, discriminant analysis

Regression Techniques

- GLM, GAM, generalized dissimilarity models, (boosted) regression trees, MARS

Machine learning methods

- GARP, artificial neural networks, MAXENT

ENFA – Environmental Niche Factor Analysis

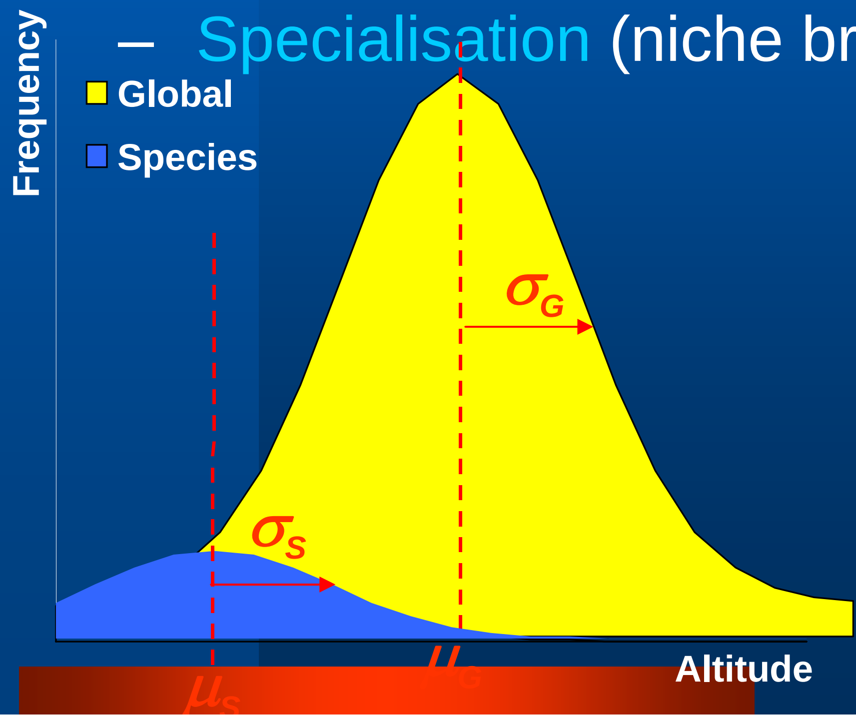
- **Inputs: ecogeographical variables (EGV's) such as temperature, salinity, chlorophyll; and a species presence map.**
- **Summarises all variables into a few uncorrelated factors.**
- **Takes only presence data into account.**
- **Compares the species distribution to the 'global' (available) environmental habitat distribution.**

Hirzel *et al*., Ecology (2002)

ENFA

e.g. Brotons *et al*. 2004 Ecography 27: 437-448

- Species niche is a subset of the global environment.
- Species set of EGV's differs from global set by:
  - Marginality (deviation from the global mean)
  - Specialisation (niche breadth)



$$\text{Marginality} = \frac{\left|\mu_G - \mu_S\right|}{1.96\sigma_G}$$

$$\text{Specialisation} = \frac{\sigma_G}{\sigma_S}$$

Hirzel *et al*., Ecology (2002)

ENFA - continued

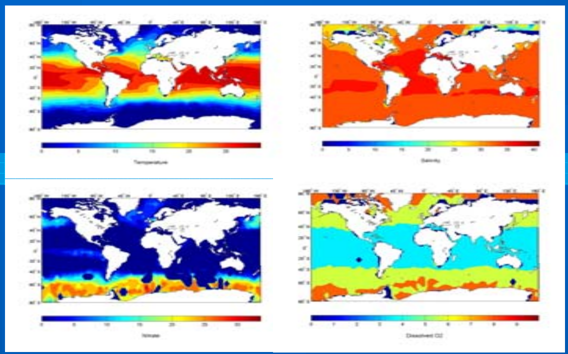
- In many respects similar to a PCA, but eigenvectors are assigned ecological meaning: first represents 100% of marginality, others the remaining specialization.

LIMITATIONS OF ENFA

- Assumes that ecogeographical variables (EGV's) are multinormally distributed & represent important factors.
- Threshold selection for model is not simple (converting from habitat suitability % to p/a).
- *Sample range must reflect actual species range*.

Hirzel *et al*., Ecology (2002)

The general idea

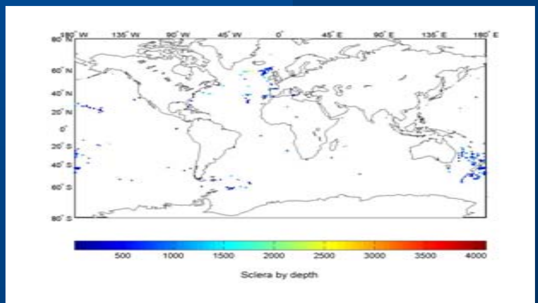


Globally 1 degree gridded data for 0 – 5500m from the World Ocean Atlas, GLODAP project & elsewhere

Ecogeographical variables

Suitable habitat prediction

Species presence



Scleratinia by depth on a 1 degree grid

Coral habitat prediction

- Model suitable locations for Scleratinia globally against an environmental background of the global ocean down to 5500m.
- Then restrict it only to those locations that are known to have seamounts in the appropriate depth range. Cannot map directly to seamounts due to SAUP and coral data mismatches.

- Remember, we are only predicting suitable Scleratinia habitat. We do not know if it will actually contain coral.

Scleratinia Results

Eigenvalues

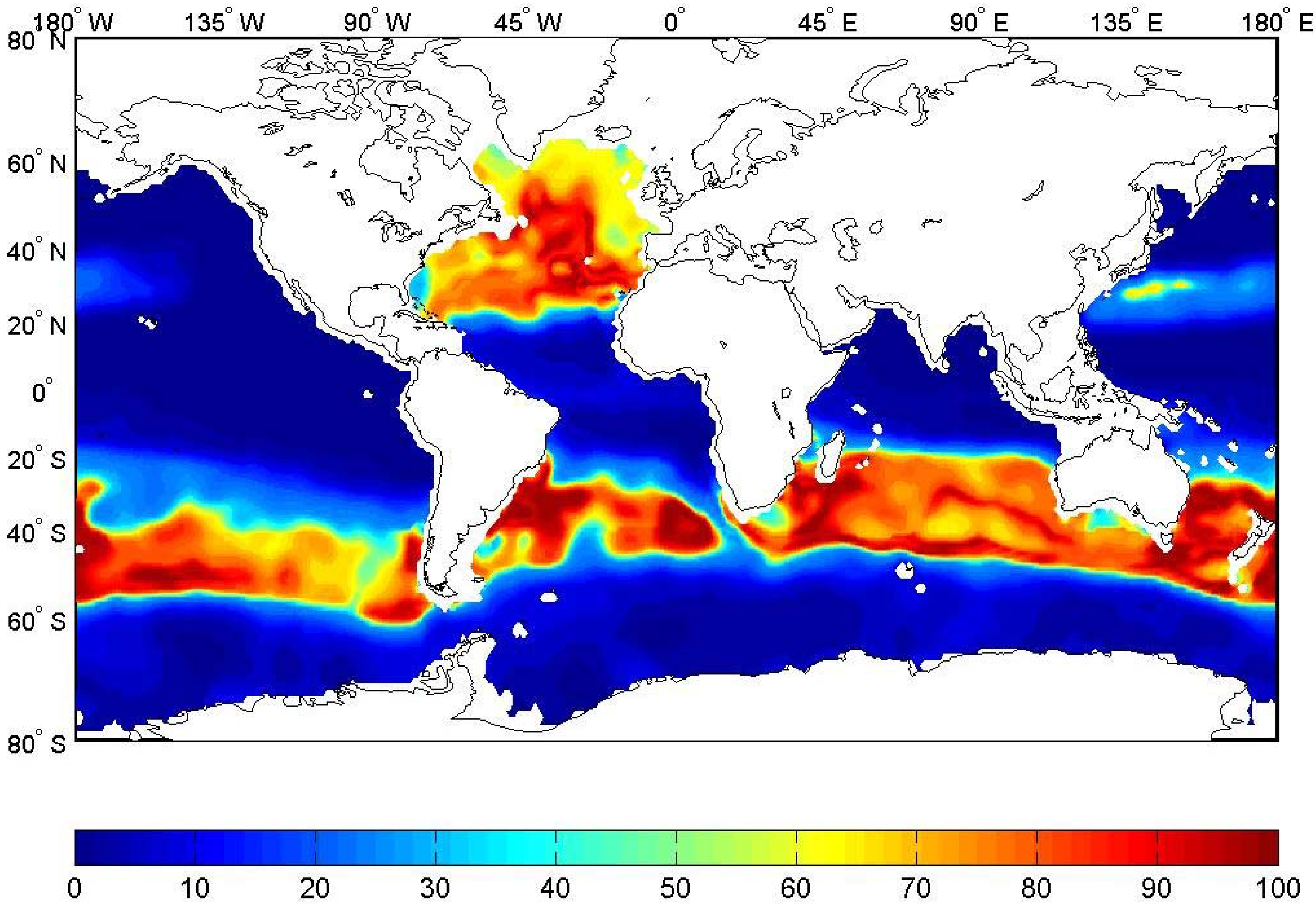
	Value	Expl.Spec.	Cum.Expl.Specialisation
1	8.657	0.343	0.343
2	8.741	0.346	0.689
3	3.086	0.122	0.811
4	1.936	0.077	0.888
5	1.265	0.050	0.938

Remember that first factor accounts for all of the species marginality

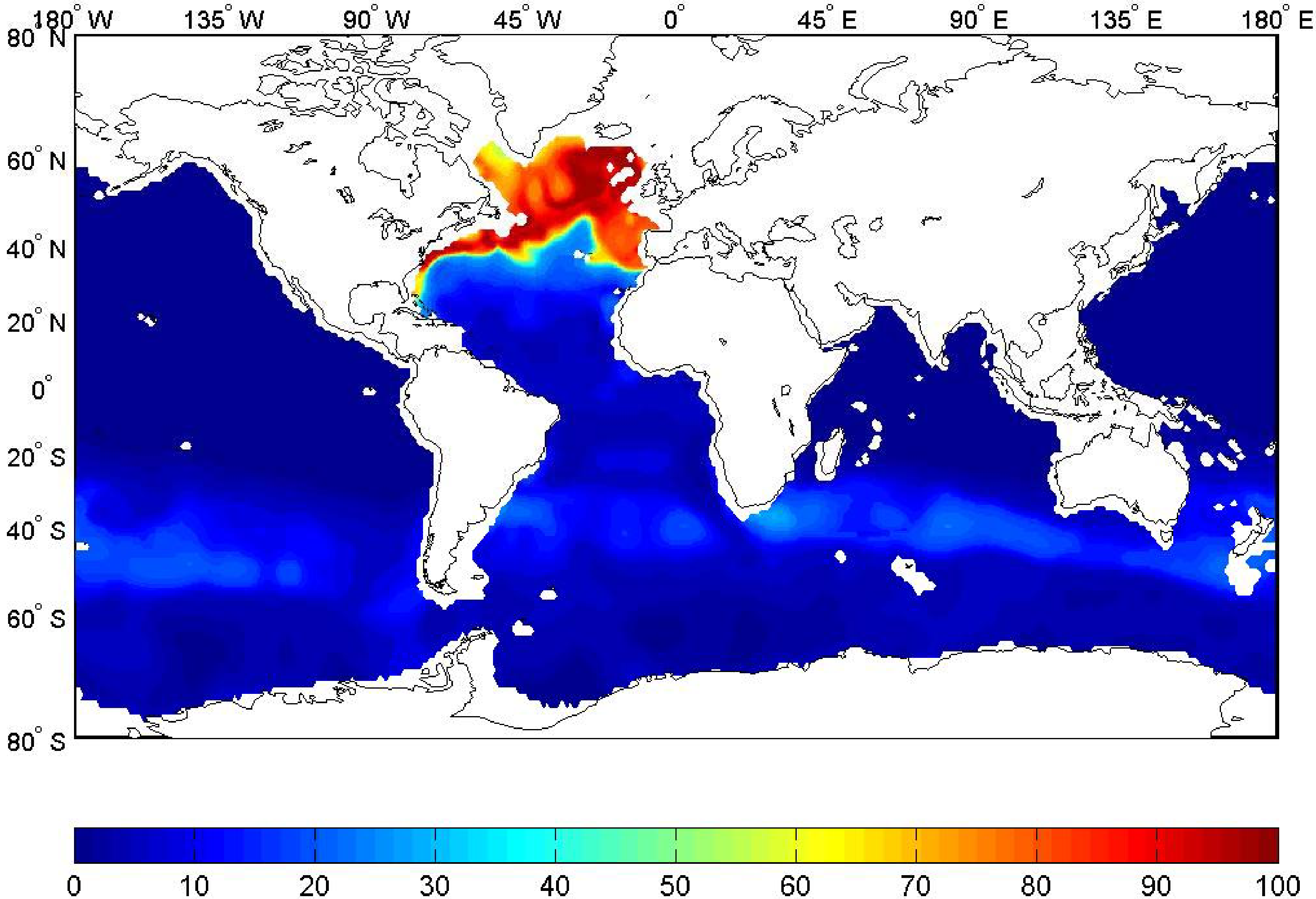
Score matrix

	Marginality	Specialisation	
	1 (34%)	2 (35%)	3 (12%)
Total CO2	-0.43	0.24	-0.44
Depth	-0.43	0.21	0.10
Temperature	0.41	-0.13	0.02
% O2 sat.	0.39	0.85	-0.75
Alkalinity	-0.33	-0.08	0.00
Sfc. Chloro.	0.29	-0.02	-0.03
Dis. O2	0.27	-0.39	0.48
Salinity	0.23	-0.03	0.08

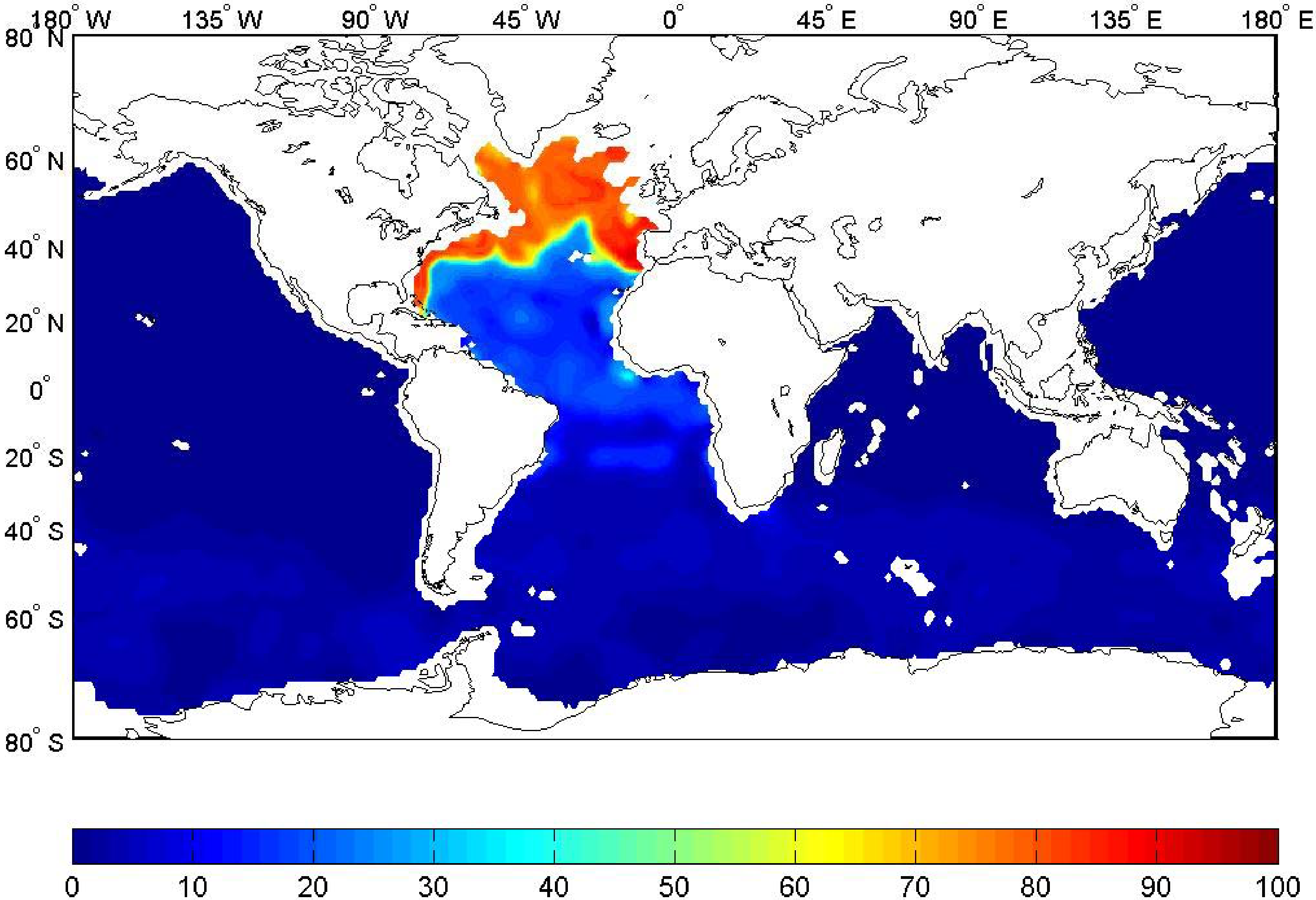
Marginality: 1.411
Specialisation: 1.776



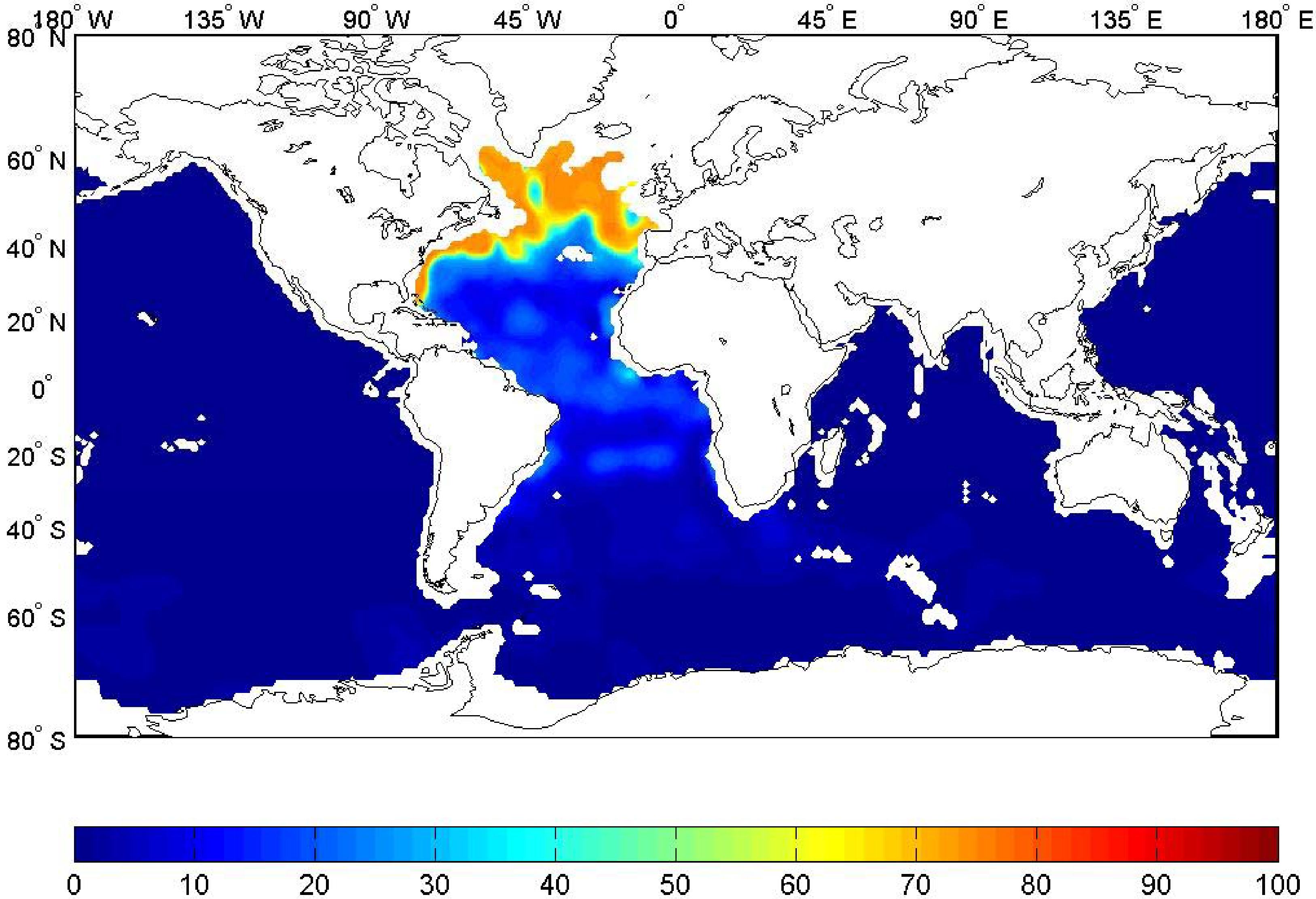
Predicted habitat suitability at 500m, Scleractinia



Predicted habitat suitability at 1000m, Scleractinia



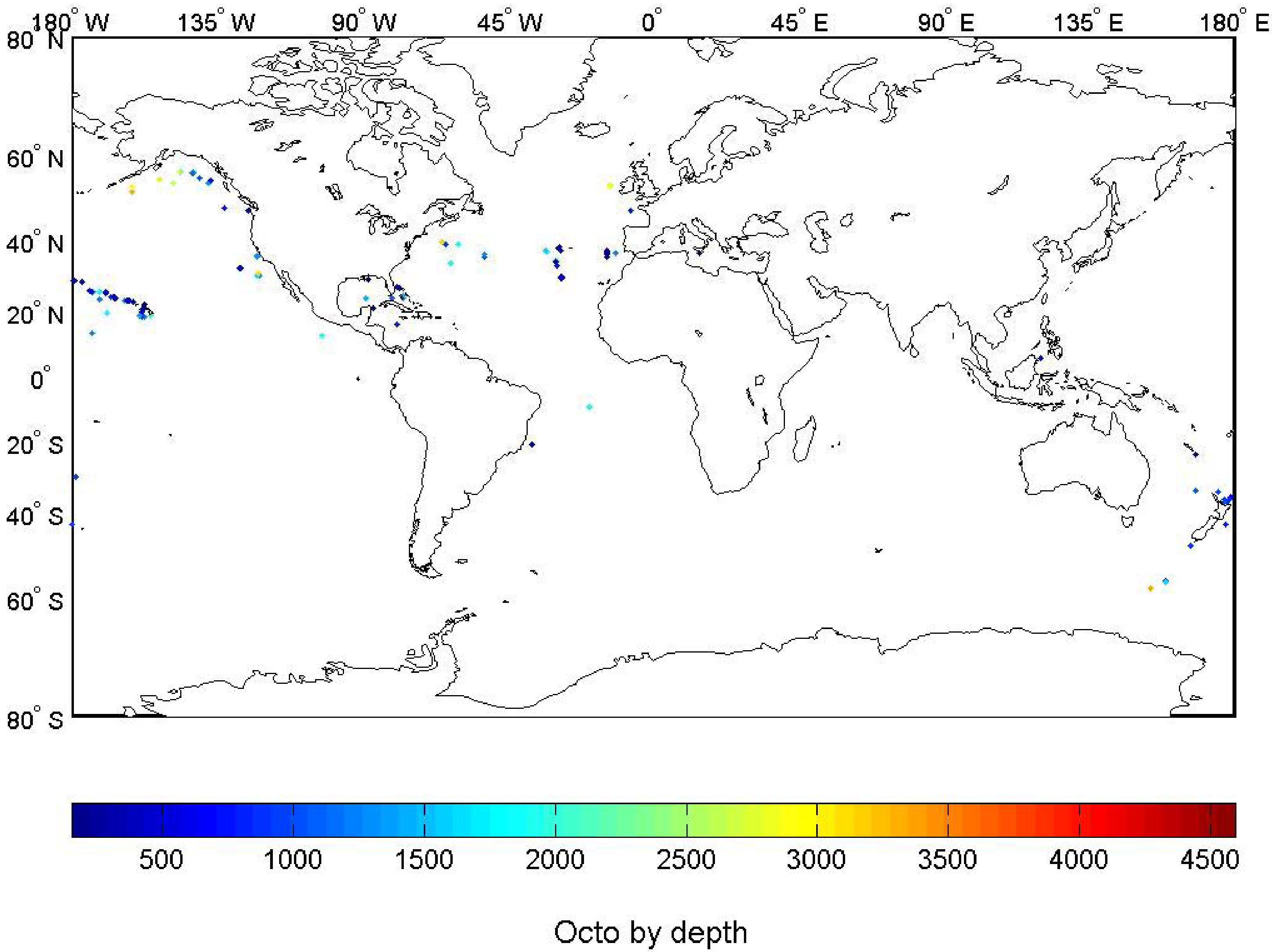
Predicted habitat suitability at 1500m, Scleractinia



Predicted habitat suitability at 2000m, Scleractinia

Octocorallia

- Presence data much more limited
- Model likely to have less power
- Model at a *very* preliminary stage


180° W
135° W
90° W
45° W
0°
45° E
90° E
135° E
180° E
80° N
60° N
40° N
20° N
0°
20° S
40° S
60° S
80° S
500
1000
1500
2000
2500
3000
3500
4000
4500
Octo by depth

Octocorallia Results

Eigenvalues

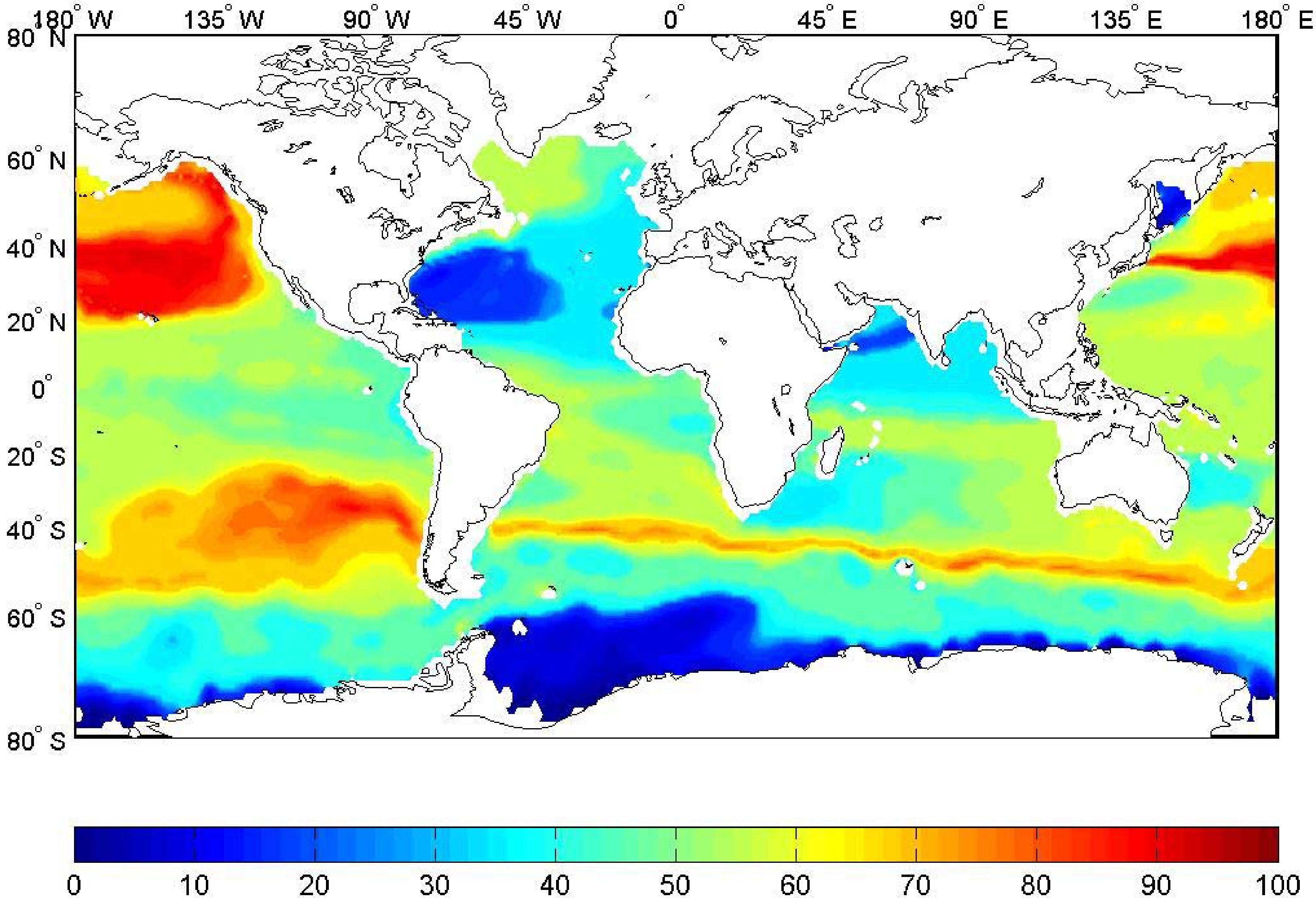
	Value	Expl.Spec.	Cum.Expl.Specialisation
1	7.916	0.305	0.305
2	8.838	0.341	0.646
3	5.521	0.213	0.859
4	1.502	0.058	0.917
5	0.897	0.035	0.952

Remember that first factor accounts for all of the species marginality

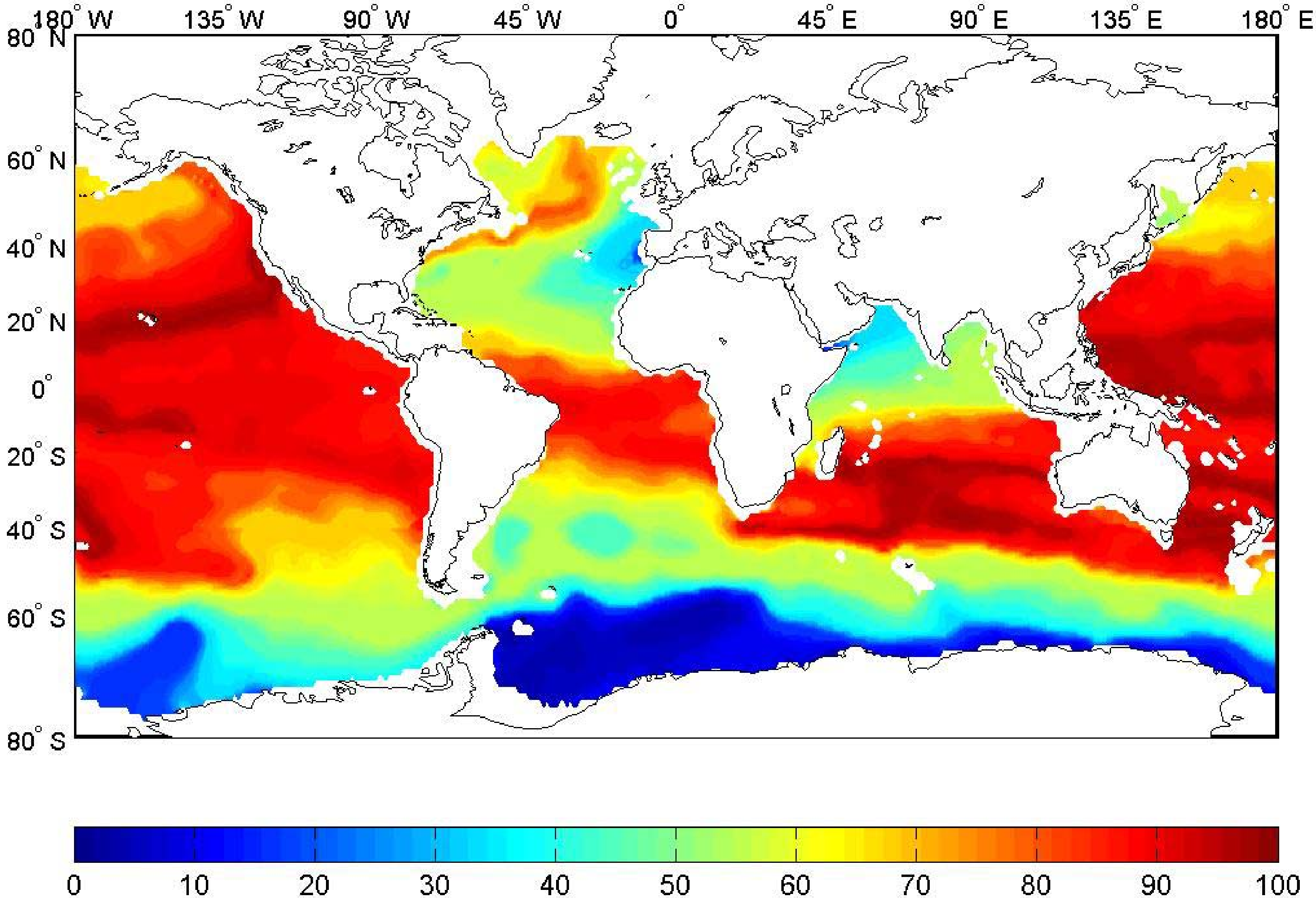
Score matrix

	Marginality	Specialisation	
	1 (31%)	2 (34%)	3 (21%)
Temperature	0.62	-0.53	0.33
Depth	-0.51	-0.77	-0.04
Salinity	-0.43	0.07	-0.16
Dis. O2	-0.29	0.19	0.65
Total CO2	-0.26	0.23	-0.17
Alkalinity	-0.13	-0.17	0.32
% O2 sat.	-0.04	-0.05	-0.55
Sfc. chloro	0.03	0.02	0.01

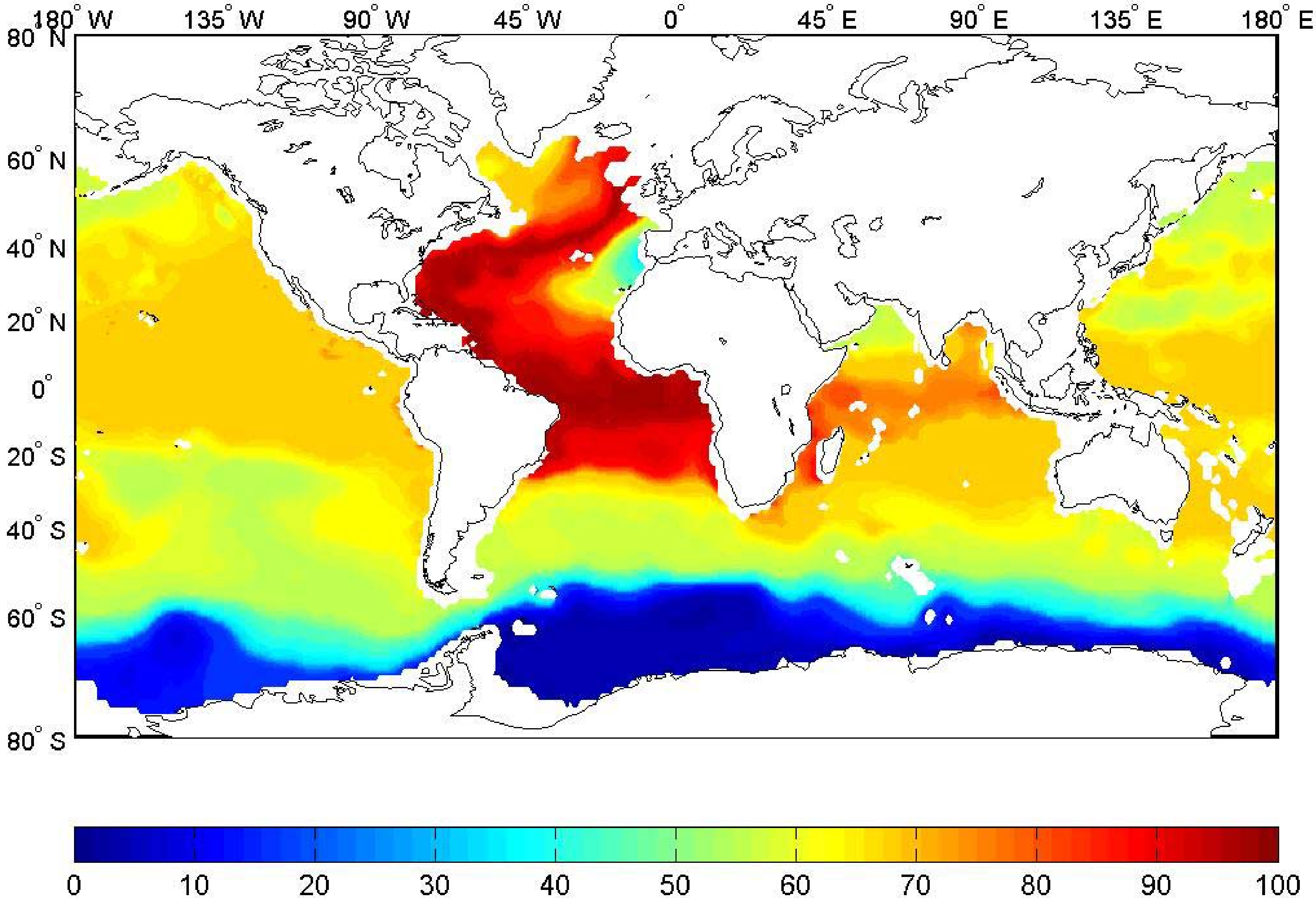
Marginality: 0.769
Specialisation: 1.800



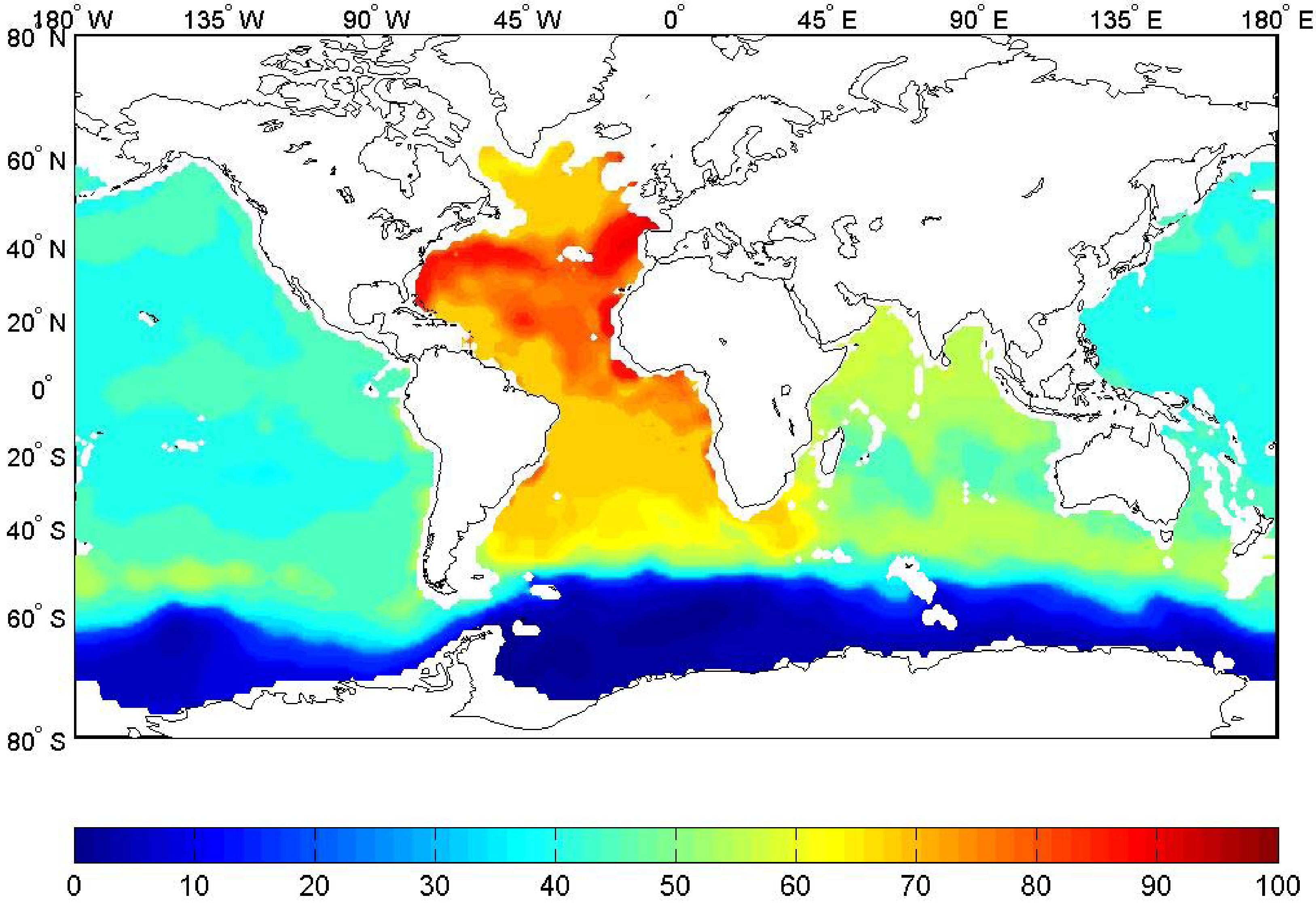
Predicted habitat suitability at 500m, Octocorallia



Predicted habitat suitability at 1000m, Octocorallia



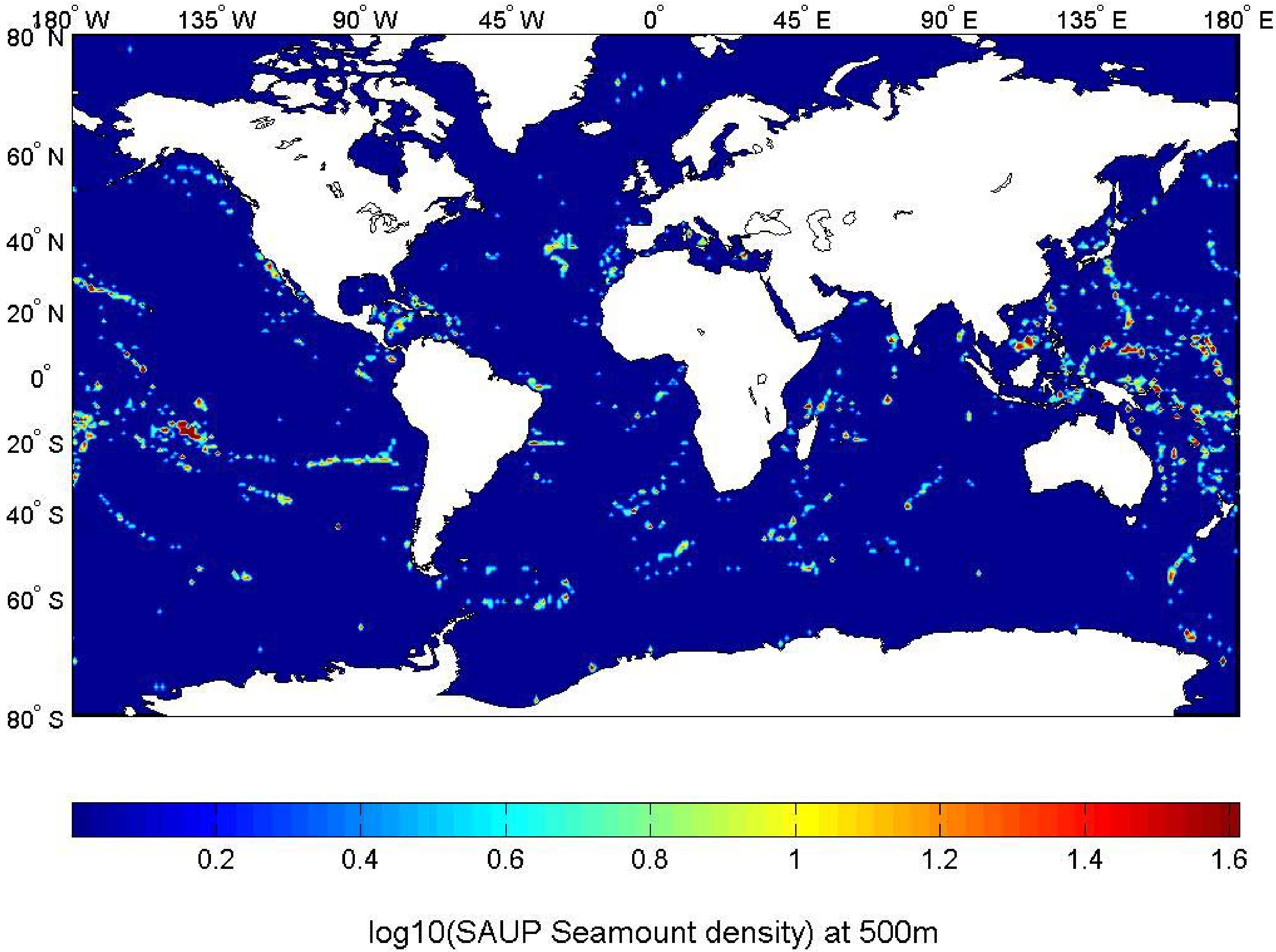
Predicted habitat suitability at 1500m, Octocorallia



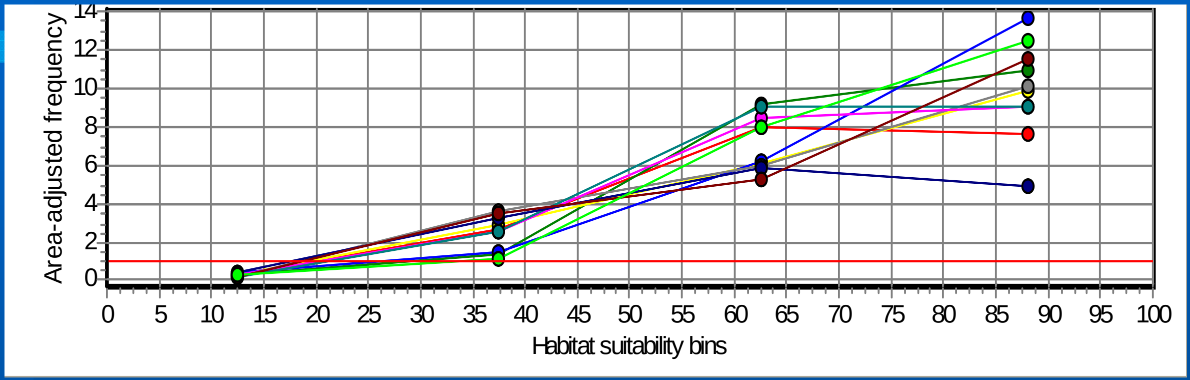
Predicted habitat suitability at 2000m, Octocorallia

The next steps…

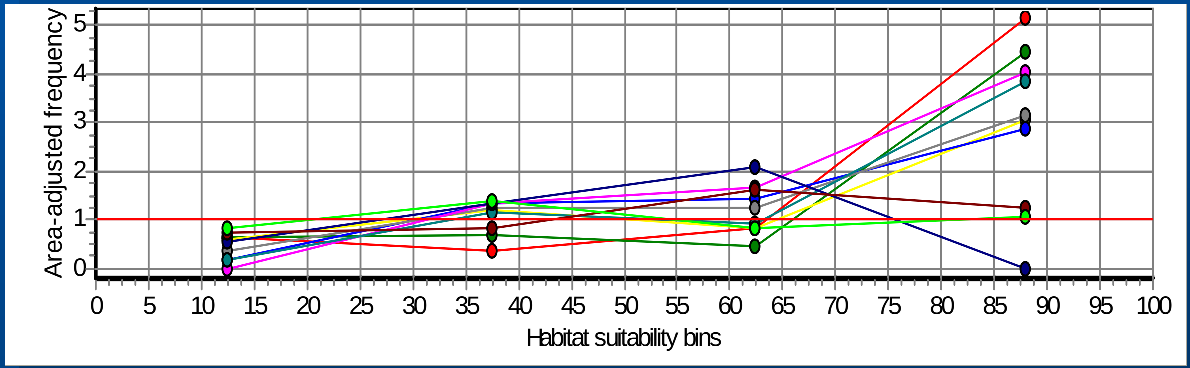
- This workshop is a perfect opportunity to ‘ground truth’ these models
- Match to fishing effort & seamount density. (Spatial autocorrelation issues – can deal with these in a mixed-model spatial regression).


180° W
135° W
90° W
45° W
0°
45° E
90° E
135° E
180° E
80° N
60° N
40° N
20° N
0°
20° S
40° S
60° S
80° S
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
log10(SAUP Seamount density) at 500m

Model calibration and verification



Scleractinia



Octocorallia

Cross-verification: 4 bins, 10 replicates

Other potentially important factors

- Current velocity – filter feeders. There may be a scaling issue here as small-scale turbulence may be v. different from regional current average
- Substrate type
- Seamount diameter/height as a measure of patch size
- Distance to nearest seamount chain
- Many other possibilities

What else can we do?

- Compare outputs from multiple appropriate models (e.g. maximum entropy models for absence only data) for verification purposes (model averaging)

- Compare to data from other (non-seamount) deep sea Scleractinia; differences, similarities

- Community based models use commonly associated species as a ‘proxy’ for presence records

(optimism)

In Conclusion

- Data quantity and differences in sampling methodology are two key limiting factors for modelling diversity on seamounts
- Need to further develop statistical tools for these kinds of data
- Having data with presence/absence (i.e. zeros) opens up a much wider variety of modelling techniques
- Apply appropriate analysis techniques for the quality and quantity of the data available

Acknowledgements

- FMAP – Future of Marine Animal Populations
- CenSeam (especially DAWG)
- ISA
- Tony Koslow