USING FISHERIES DATA TO IDENTIFY PELAGIC PREDATOR HOTSPOTS IN THE NORTH ATLANTIC

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Introduction

Part 1. Common modelling procedures of Fisheries dependent data

Part 2. Introduction of the MARS modelling procedure as an alternative to commonly used linear and non-linear techniques

Part 3. Comparative test of model performance on a N. Atlantic dataset

Part 4. Usefulness of fisheries data in delineating species hotspots or EFH

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Part 1

Modelling fisheries data

Two main approaches to modelling fisheries data

a) geostatistical; correlational approach and neighbouring effects

b) linear and non linear modelling extensions of regression techniques applied to spatio-temporal data

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$y_i = \mu_i + e_i$

Concerned with explaining the mean effect μ_i with co-located variables

More pertinent to describing the EFH and hotspots of species

Common issues (amongst others) with modelling fisheries data are;

1) Patchiness of data

2) Many instances of zeros

3) Scale dependency

4) Is univariate (1 species/taxa group at 1 time)

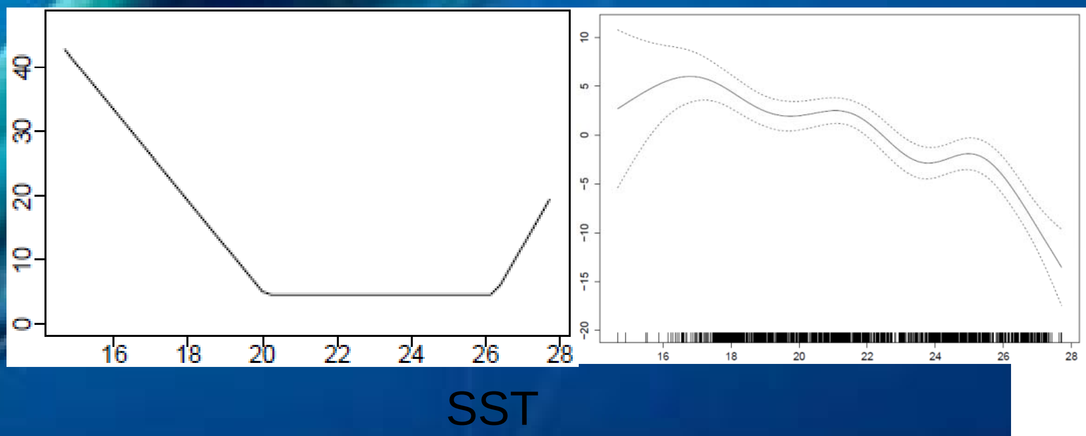
Introducing MARS modelling

Multiadaptive Regression Spline (MARS) Friedman 1991

- non-parametric, non-linear modelling that can model same level of complexity as GAM

- Fits data by fitting piecewise linear segments between knots

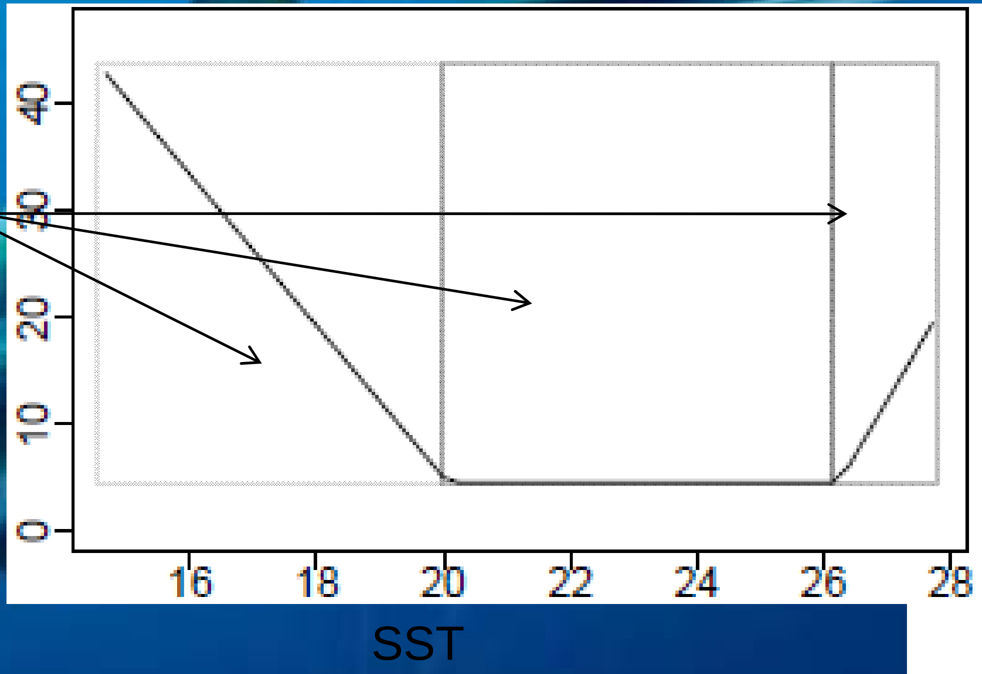
- forward selection: many knots – backward selection; prunes knots to produce parsimonious model



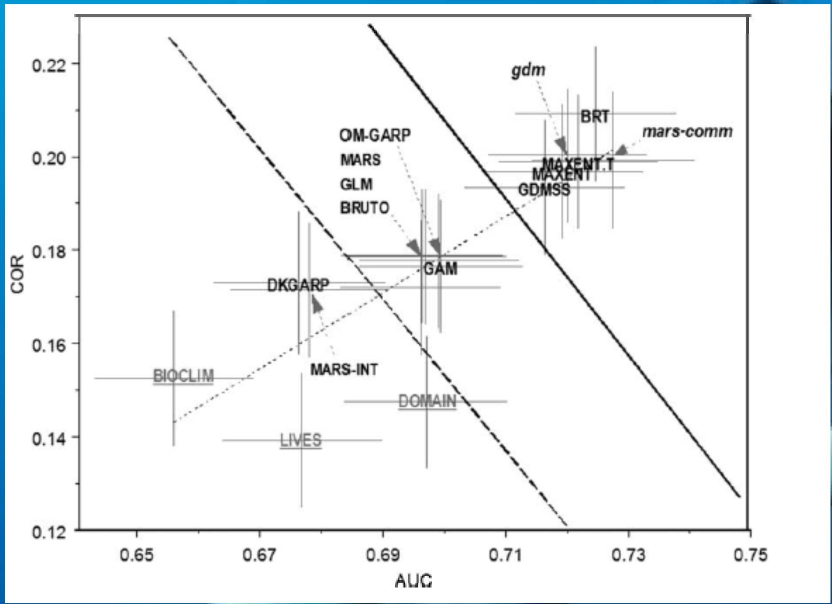
Advantage over other modelling techniques: allows a “multiresponse” approach to be used

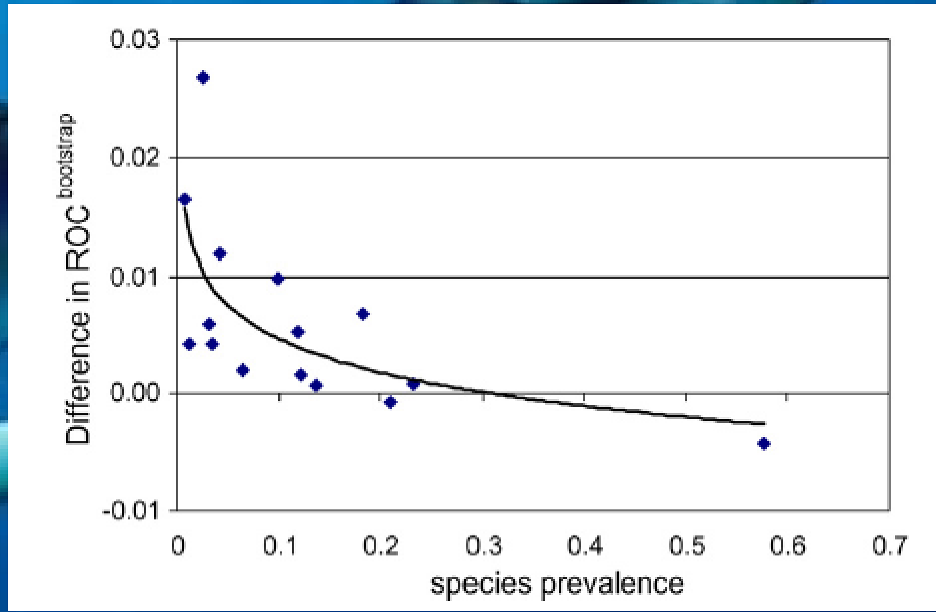
In backward pruning process, knots selected in order to minimize average residual errors averaged across all species

Local relationship between species and independent variable



A number of studies have highlighted the improved predictive capabilities with the Multispecies MARS model



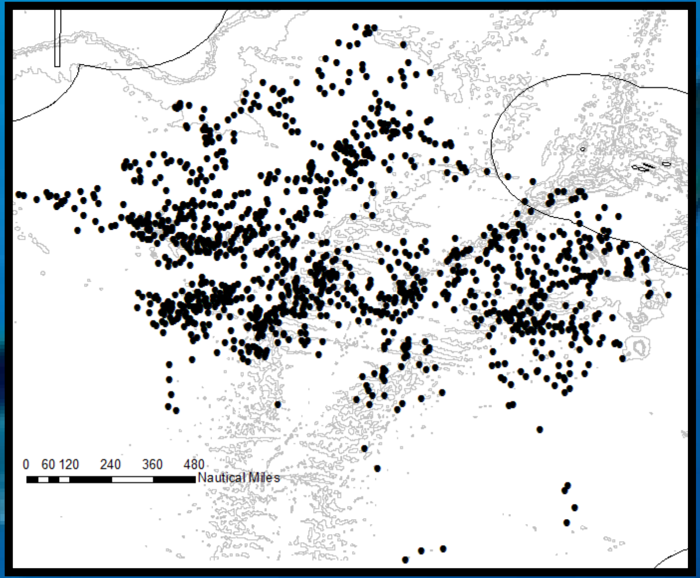


(Elith et al., 2006)

Part 3

Comparative test CPUE data

Fisheries data collected from logs from Spanish LL fishery in N. Atlantic 2008-2011 (n= 1286)



Data tested using GLM, GAM, $MARS_{ind}$ and $MARS_{comm}$

Each method follows same procedures to eliminate errors caused by collinearity etc.

Satellite derived env covariates used include; SST, *chl-a*, PAR, Euphotic depth, SSH

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Comparative test CPUE data

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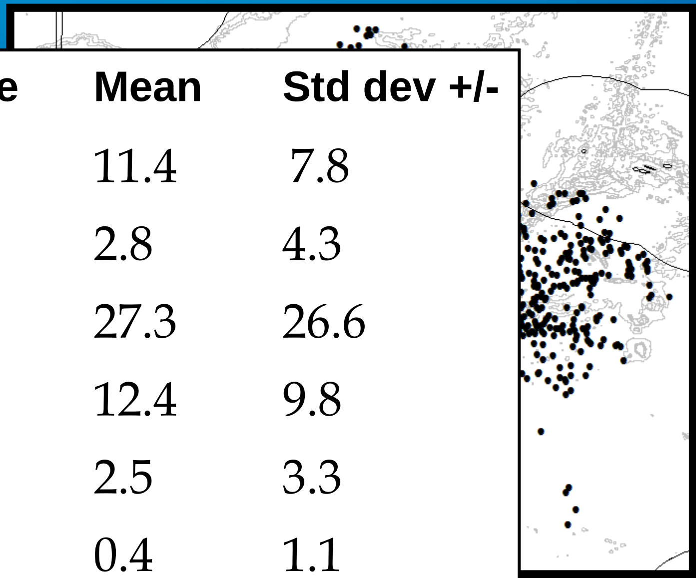
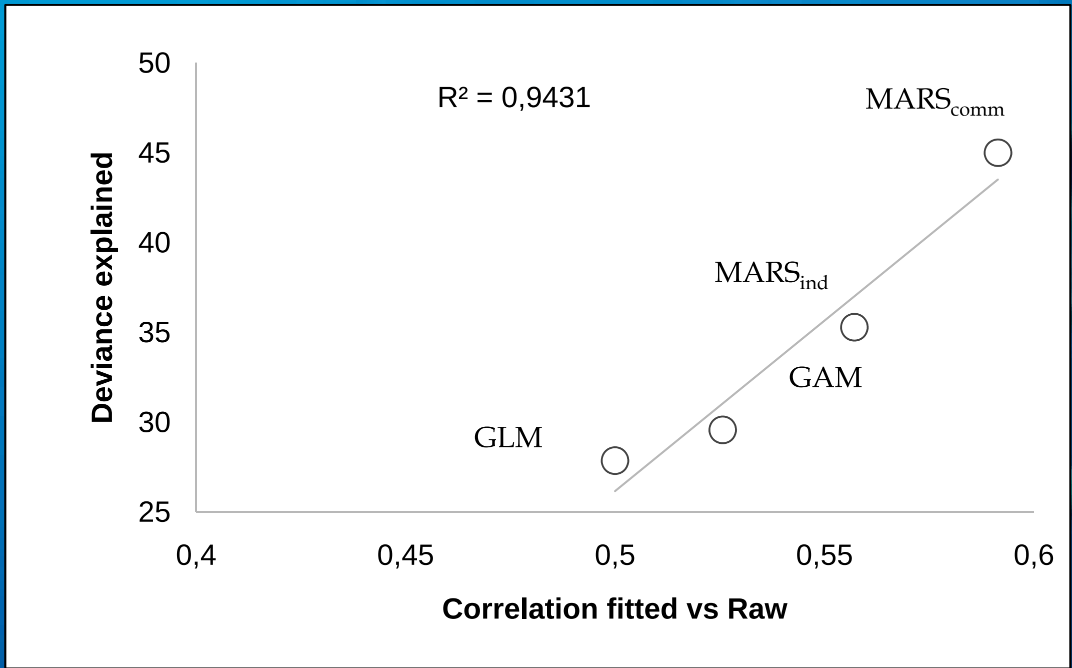
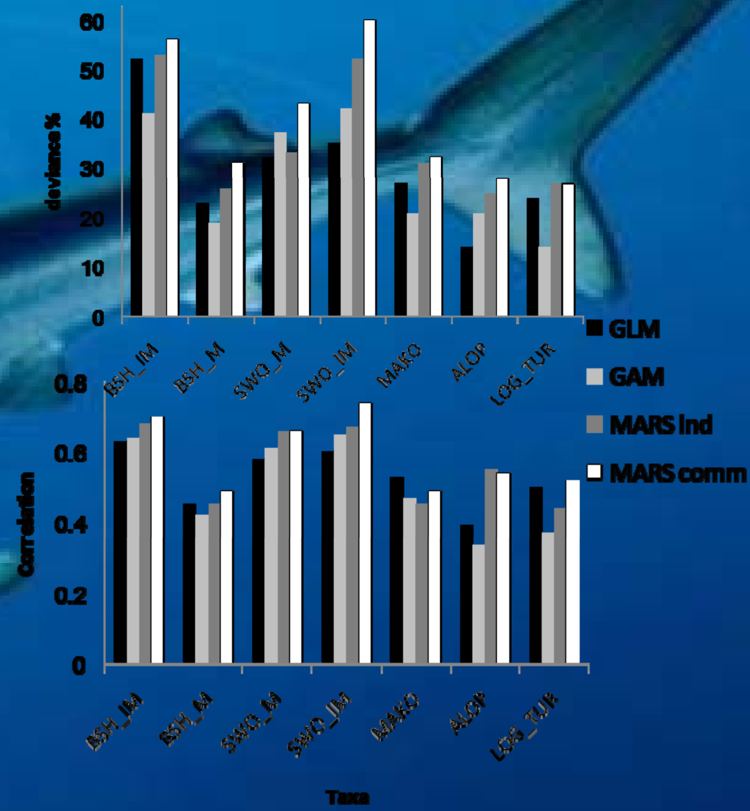


Species	n	Prevalence	Mean	Std dev +/-
Swordfish$_m$	1281	0.99	11.4	7.8
Swordfish $_l$	733	0.57	2.8	4.3
Blue Shark$_m$	1263	0.98	27.3	26.6
Blue Shark $_l$	1261	0.98	12.4	9.8
Mako (Shortfin)	999	0.77	2.5	3.3
Thresher Shark	247	0.19	0.4	1.1
Loggerhead	168	0.14	0.3	1.2

Comparative test CPUE data

$MARS_{comm}$ consistently outperformed other methods in terms of deviance explained and correlation





Comparative test CPUE data

Variable	*gcv*
SST	100
V.1	88.2
V.2	78.9
Lat	69.9
Long	62.4
V.3	50.4
V.4	43.9
V.5	38.7
Quarter	32.6
PAR	29.4
Euphotic	12.9

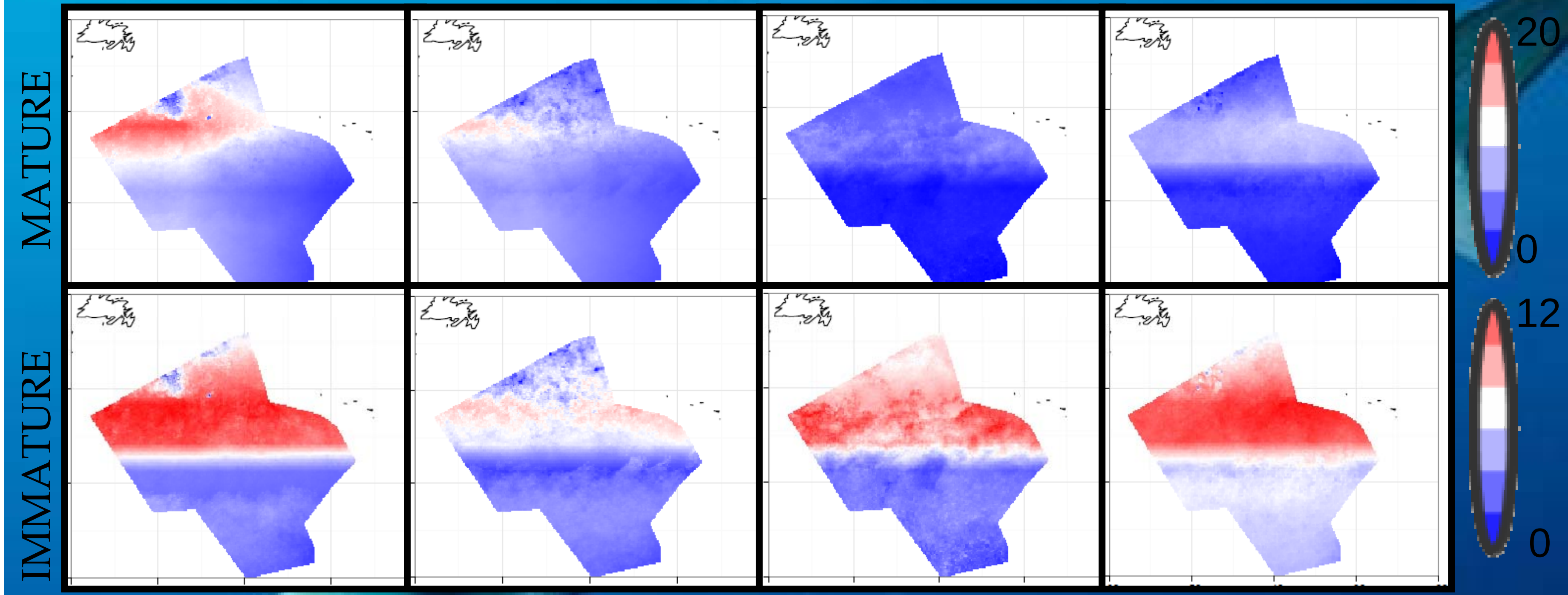
Importance of variables determined by generalized cross validation

SST – most important environmental variable in predicting patterns in species' CPUE

Part 3

Comparative test CPUE data

Swordfish CPUE



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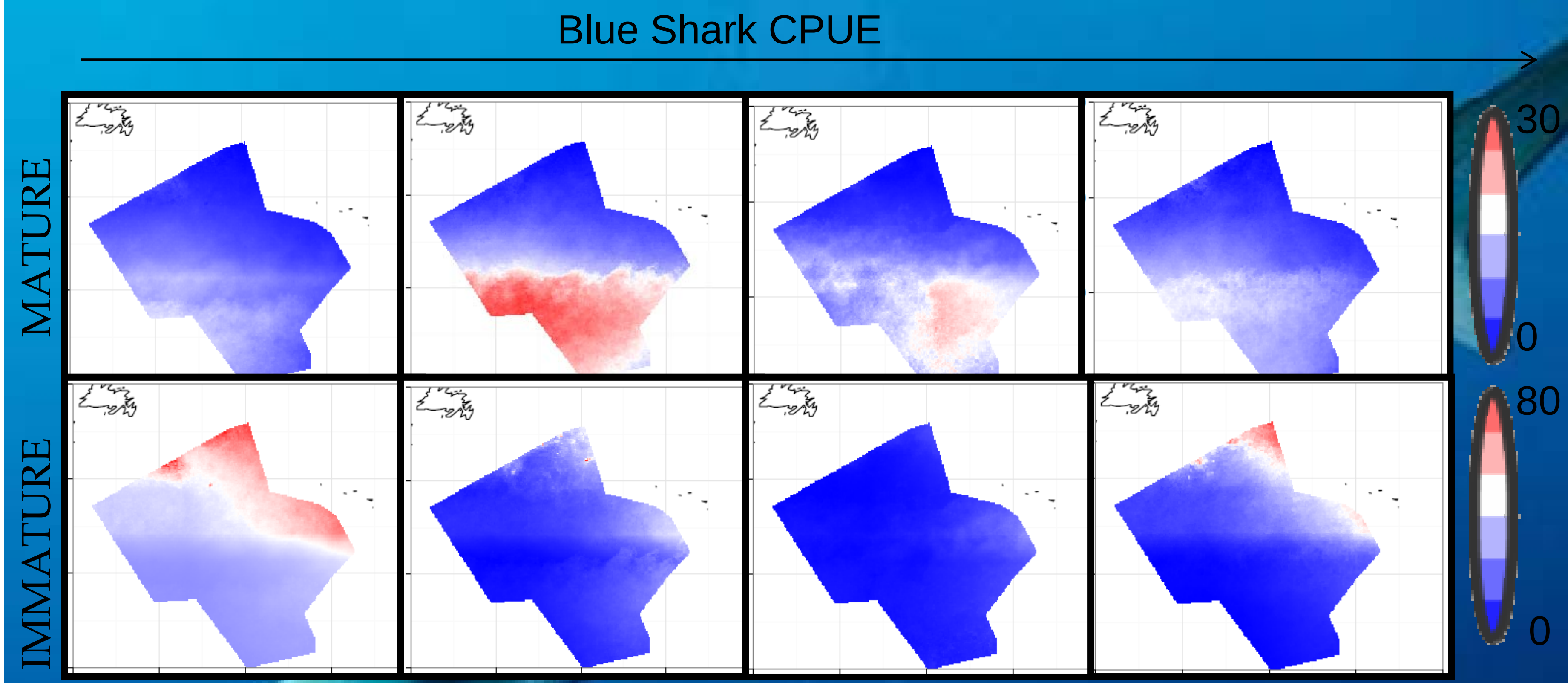

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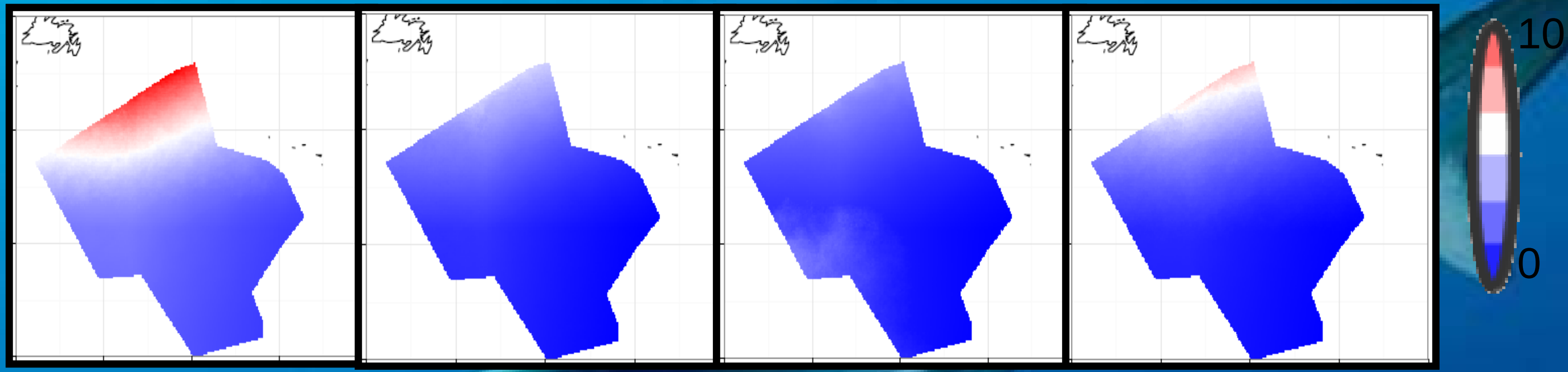
Mako CPUE



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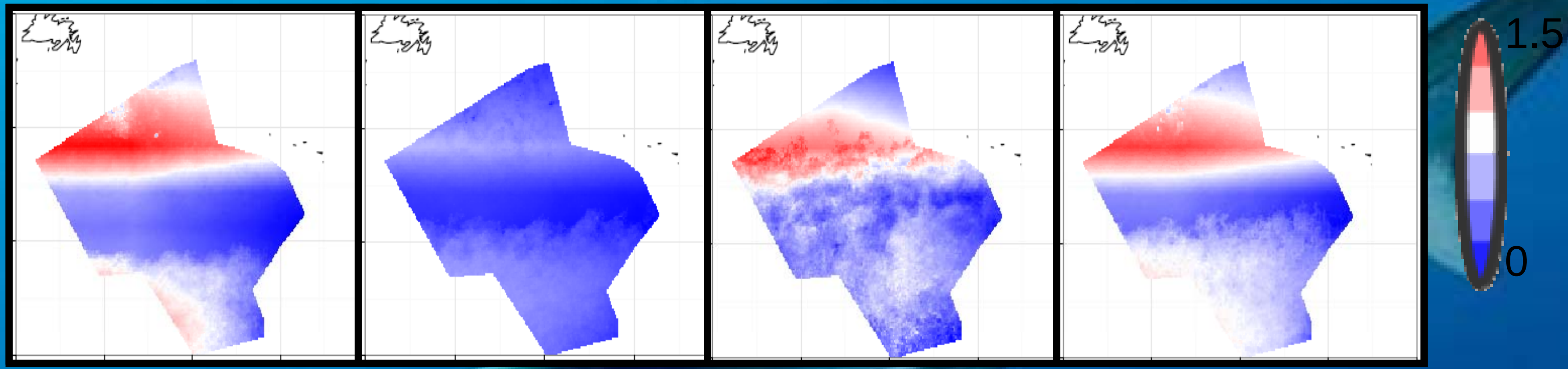
Thresher Shark CPUE



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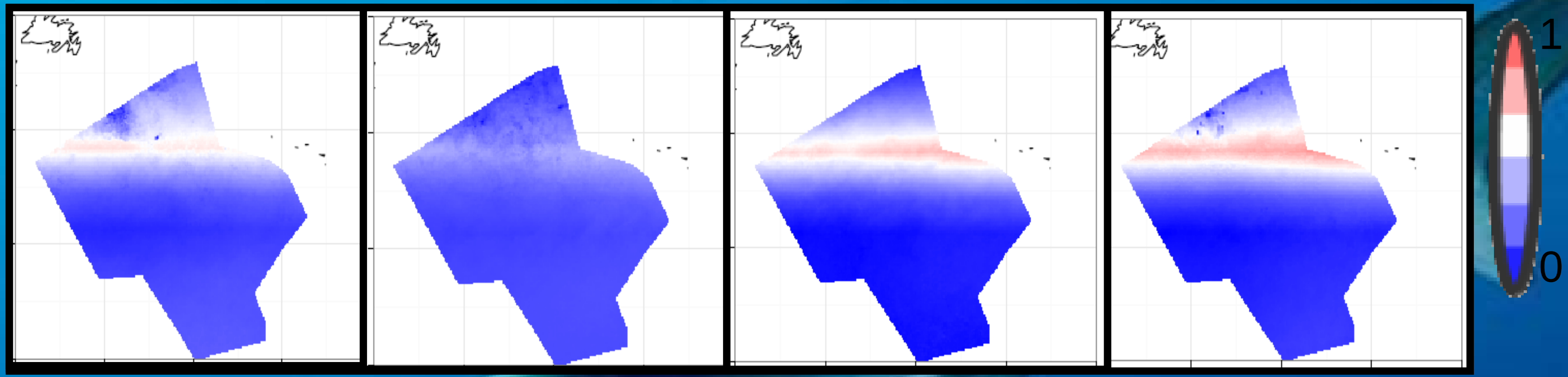
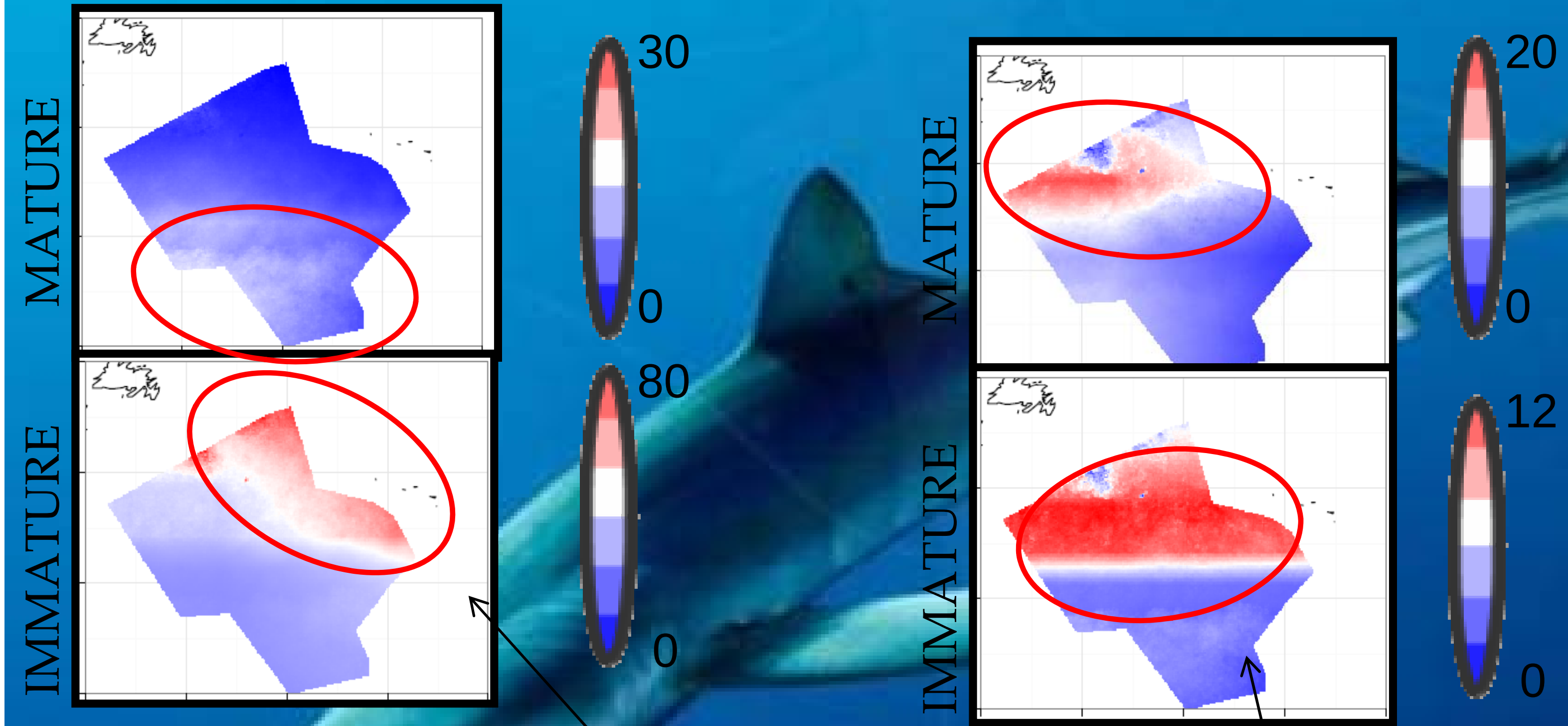
Comparative test CPUE data

Loggerhead Turtle CPUE



Blue Shark CPUE



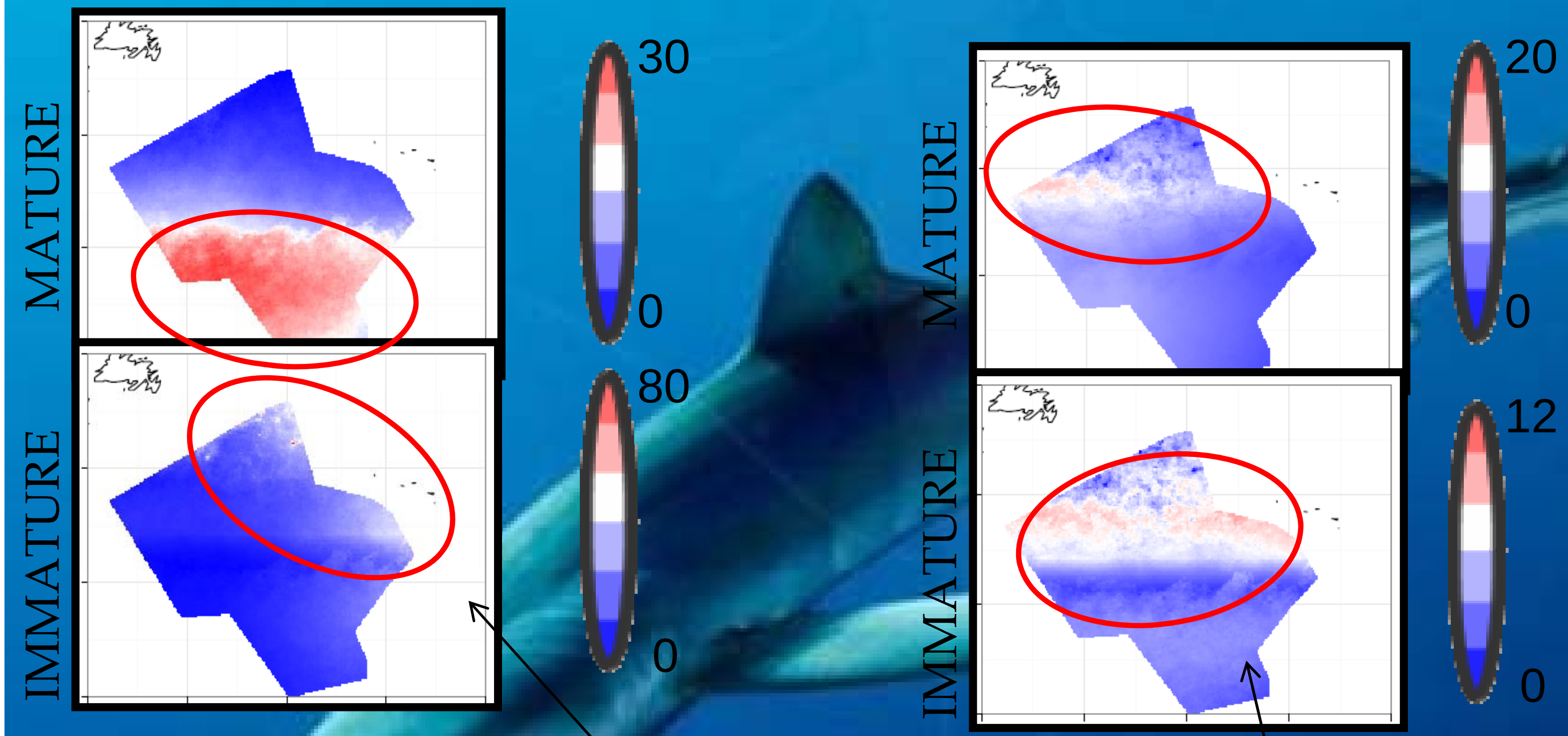
Coarse distinction in catch rates; Persistent across seasons

Coarse alignment in catch rates; Persistent across seasons

Part 4

Fisheries data and hotspots

Blue Shark CPUE



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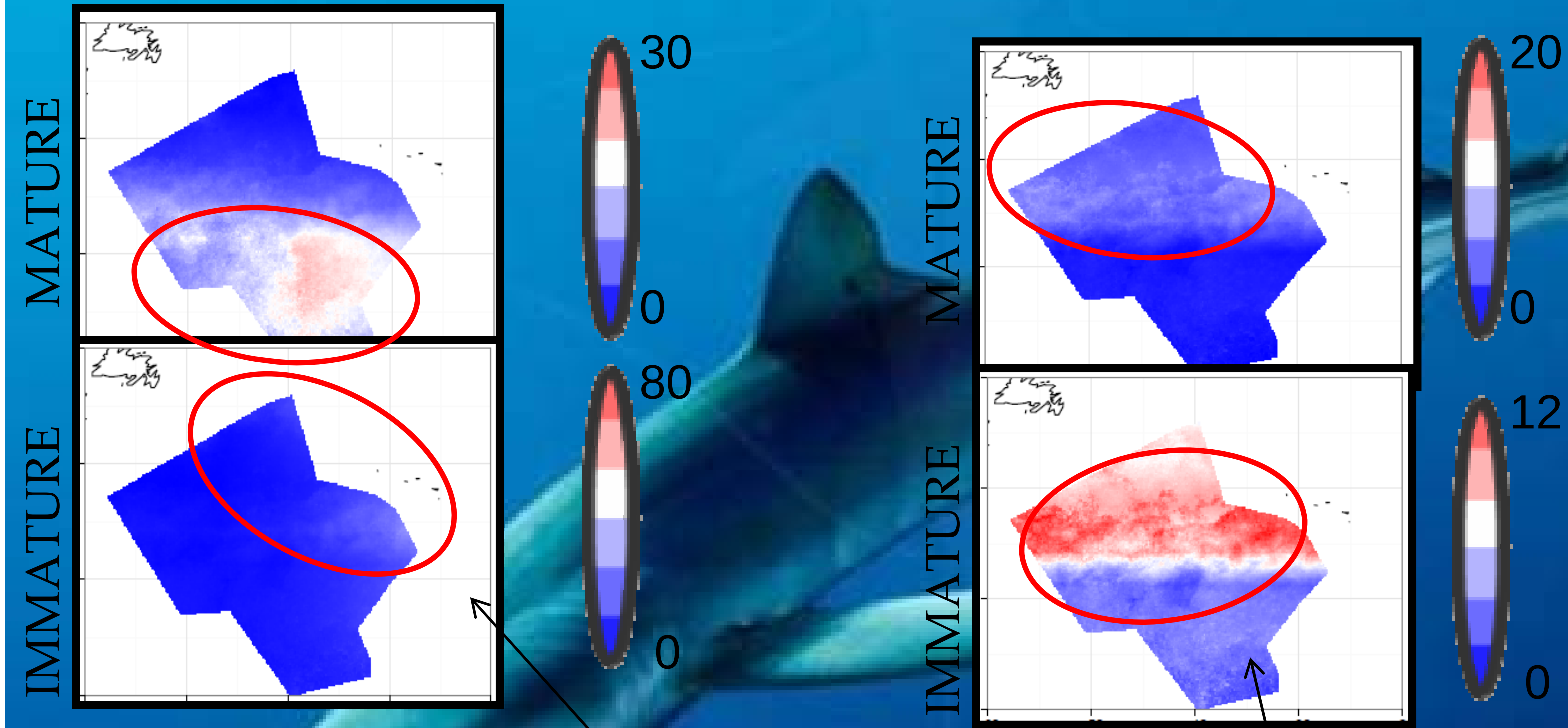

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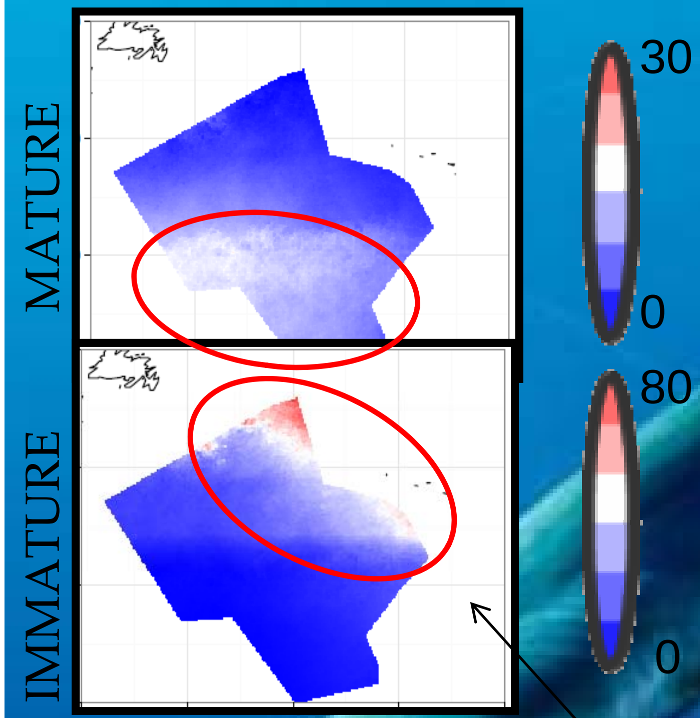

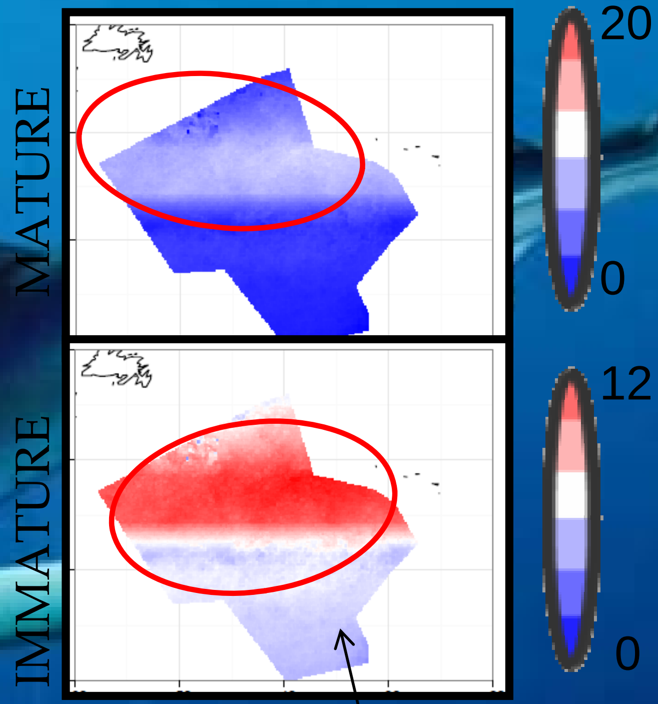

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Coarse alignment in catch rates; Persistent across seasons

Fisheries data and hotspots

- How effective can Fisheries data be?

Obvious limitations in data coverage and resolution

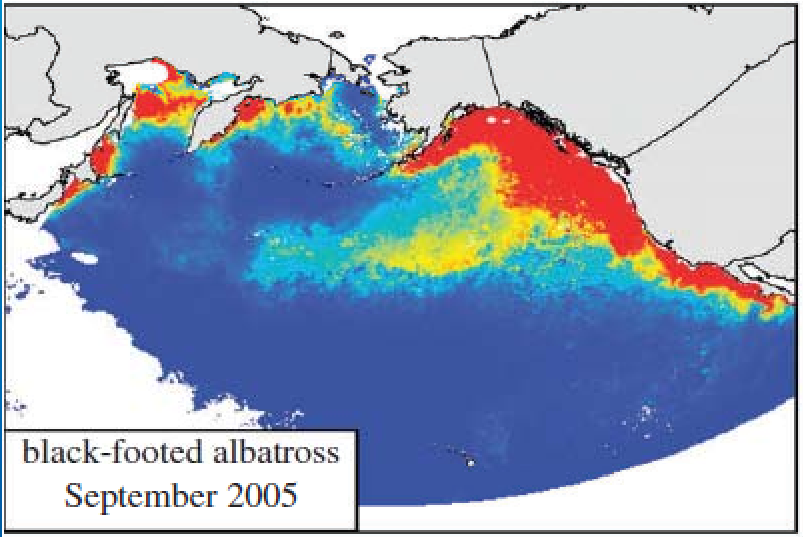
- How much does bycatch correspond to actual aggregation areas of species multitaxa?

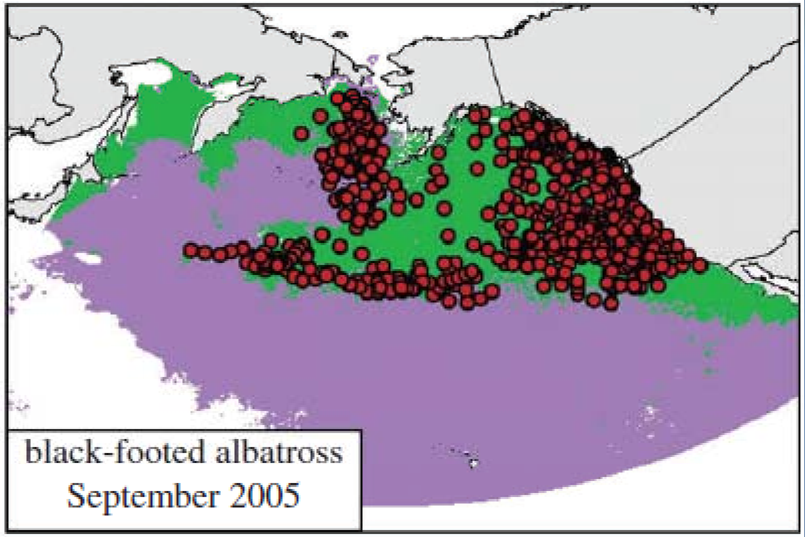
Combine information derived from fisheries "population" level with telemetry data "individual" level

Dynamic habitat modelling for highly mobile species

Allows identification of potential "hotspots" from an oceanographic perspective

e.g. – black footed albatross, North Pacific



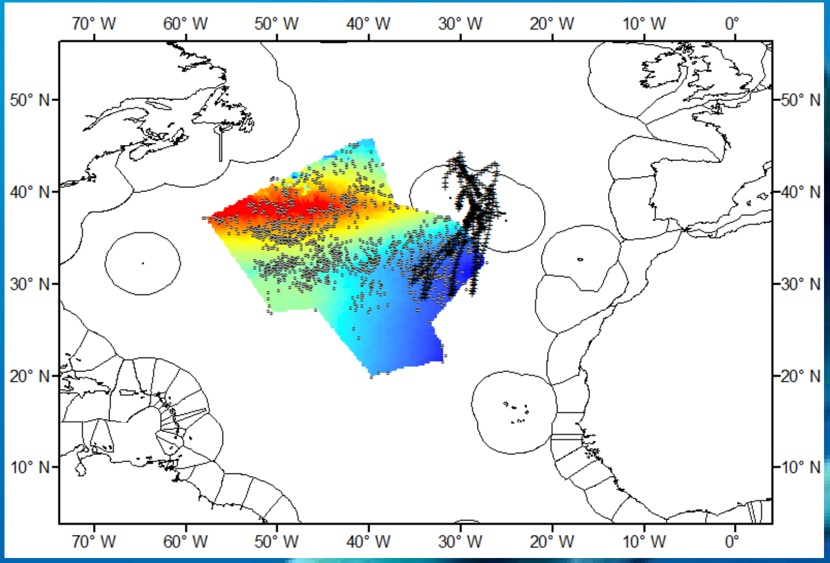


(Zydelis et al., 2011)

Part 4

Fisheries data and hotspots

Adopting a similar approach for highly mobile pelagic predators



Problems with spatial overlap

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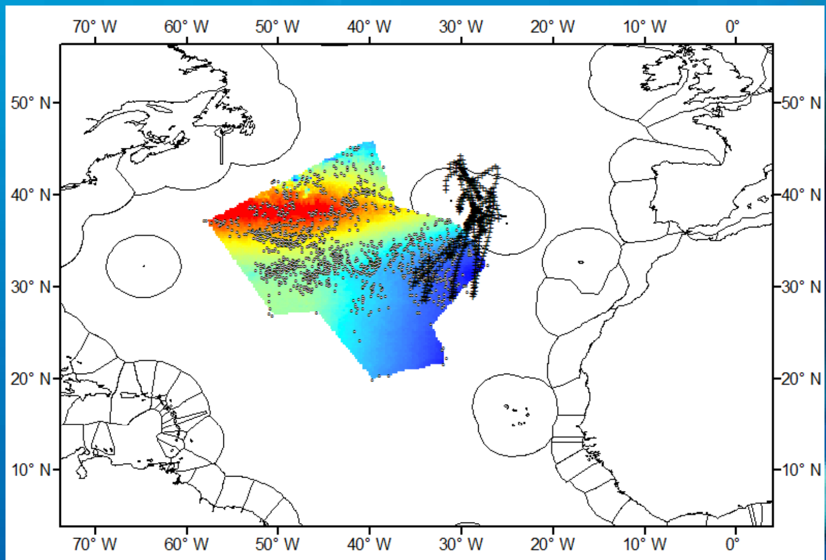

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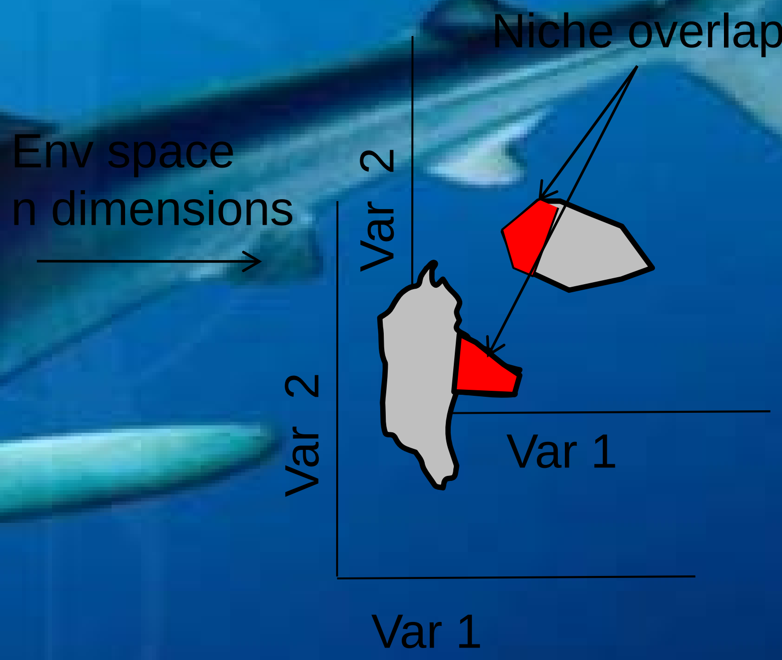

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SEVENTH FRAMEWORK PROGRAMME

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