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Executive Summary

In 2010, WGFE (Working Group on Fish Ecology, D. W. Kulka, Chair) met at IFREMER, Sète France, 6–10 September. Nine participants from five countries (Annex 3) addressed five Terms of Reference (Annex 1). As in previous years, the report is structured as a single chapter for each ToR. Below, the results of each of the 2010 ToR are summarized and linked to the Science Plan topics (see Annex 2).

ToR a (Science Plan links: 1, 2, 3, 8, 14): By combining metrics time trends in European fish communities, the results of a simple food web model suggested that there was some compensation between species within functional groups and showed that it is not necessary to focus solely on the complex multi-species size structure models to observe direction of change of populations and community indicators. A wide diversity of impacts, from fishing or resource productivity change was found to have equal evidence at the population level within each community.

ToR b (Science Plan links: 1, 2, 3, 7, 13, 14): A new size-structure metric (size diversity) for fish communities was evaluated using simulated community data, calculated for survey data from various regions and compared to LFI. The North Sea had the lowest size diversity of all communities, in particular in recent years, with an overall decreasing time trend. The highest diversity indicating the most even size spectrum was found for the Eastern Corsica shelf and the Eastern English Channel. Species diversity was higher than size diversity in most communities.

ToR c (Science Plan links: 1, 8, 13, 14, 15, 16): The Swept Area Seabed Impact (SASI) model which estimates adverse affects was used to explore the spatial structure of area swept and determine how well present Essential Fish Habitat Marine Protected Areas (MPAs) do at minimizing adverse affects. Model results illustrated adverse gear effects given the sediment and energy distributions, irrespective of real fishing. Development of this model has also highlighted gaps in knowledge of fish - habitat links and the fishing impacts on habitat and shortcoming in present MPA locations (EFH closures).

Another study emphasized that year-round closures do not have universally positive impacts on the abundance and spill-over potential of stocks. Understanding the spatial distribution of multi-species groups and their habitats is required for designing of area-based strategies that do not inadvertently place rare species, depleted populations and sensitive habitats at risk.

ToR d (Science Plan links: 3, 8, 14): Abundance-occupancy relationships can reflect the susceptibility of a species. Following on a 2009 analysis of residuals in the occupancy-abundance relationships, extinction debt theory (competitive ability and colonisation ability of a species are inversely proportional) was examined. Significant decreases in occupancy over time was observed for species that had both low vigility and low colonisation ability. This agrees with the hypothesis that habitat destruction and fragmentation on Georges Bank may have disproportionately affected these species.

ToR e (Science Plan links: 1, 3, 8): Machine learning approaches and in particular Bayesian networks were used to model fish population interaction based upon biomass data. Approaches such as Bayesian networks offer advantages over traditional modelling approaches, including the ability to exploit human expertise to direct otherwise data-driven models, and uncovering hidden factors that may explain certain artefacts in the data better than measured variables. The identification of species rele-

vant to some event using feature selection and the use of models to capture species dynamics for forecasting future biomass were particularly promising.

1 Introduction

1.1 Terms of reference for 2010

Refer to Annex 1 and at the head of each chapter.

1.2 Participants

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Full contact details of participants are provided in Annex 3.

1.3 Background

Prior to 2003, fish community issues were considered by the Working Group on Ecosystem Effects of Fishing Activities (WGECO). As the demands on that WG increased, the establishment of the Working Group on Fish Ecology (WGFE) allowed a more focused consideration of fish ecology issues including community metrics and the provision of advice on threatened marine fishes. In recent years, the group's terms of reference has expanded to include a broader range of topics within the realm of fish ecology such as ecological aspects related to climate change and regime shifts. Part of this evolution is related to the new ICES structure, described below.

WGECO has traditionally commented on the report of WGFE and asked for specific analyses to be performed thus providing a linkage between the more pure science products of WGFE and the need for advice to inform policy considered by WGECO. Now, with the transformation in the ICES structure, the work of WGFE is guided by the ICES Science Plan (2009–2013, refer to Annex 2). The WGFE parent group under the new structure is SSGEF (SCICOM Steering Group on Ecosystem Function), one of five steering groups reporting to Science Committee.

The mandate of WGFE now relates to many of the sixteen "high priority research topics" (correlated with the ToR in the Executive Summary) that the Science Committee formulated as the basis for the Science Plan (see Annex 2). The WG now focuses its work on those topics that fall under the thematic area entitled "Understanding Ecosystem Functioning" but also addresses topics under "Understanding Interactions of Human Activities with Ecosystems" and to a lesser extent under "Development of options for sustainable use of ecosystems".

Specifically, WGFE has addressed issues on non-commercial fish species, including species of conservation importance, fish communities and assemblages, impacts of climate change and fishing on fish communities and their habitat, and other aspects of fish ecology (e.g. feeding habits and prey rations, habitat requirements), to support ICES advice in areas related to ecosystems, biodiversity, conservation and climate change. In addition to supporting scientific advice, WGFE is a group that can incorporate and germinate scientific ideas related to methodological development and ecological synthesis; thus, WGFE has become a point of initiation into ICES for new

researchers and researchers who have not before been involved in practical applications of their science.

In 2009, WGFE was asked to contribute information on fish to the ICES climate change position paper. Under the heading “Changes in abundance, migration and distributions patterns and sensitivity of marine ecosystems to climate variability and regime shifts”, two sections were produced: a) Changes in abundance, migration and distributions patterns and b) Sensitivity of marine ecosystems to climate variability and regime shifts. In 2010, at the Editorial Workshop for the Position Paper on Climate Change (EWPPCC), the first section was integrated into the position paper as Chapter that is presently under external (final) review. However, the second section (relating to Chapter 10 of the Position Paper) was not used. That chapter can be accessed in the 2009 WGFE report.

For 2010, a lower than normal turnout for the meeting required that a more focused approach to addressing the ToRs be taken. Although all five ToRs were addressed, the degree to which each ToR covered varied. This year's report includes sections dealing with effects of climate and fisheries on fish productivity, metrics to characterize fish communities, spatial methods, abundance/occupancy relationships and state changes in fish communities (see Annex 1). Because the ToRs were not completely addressed in 2010, the WG has extended them to 2011, with only minor alterations.

Given the low ratio (20–30%) of participating membership to total members, a review of the WG membership will be undertaken. A significant number of present members have not participated directly or by correspondence in several years. As with any group, the outcomes depend on the input of group members.

Future work of WGFE will continue to be closely aligned with the ICES Science Plan and SSGEF.

1.4 References

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2 Modelling effects of climate and fisheries on fish productivity and community structure

ToR a) Model the relative effects of climate and fisheries on fish productivity and community structure, including spatial aspects.

2.1 Introduction

The development of the ecosystem approach to fisheries implies the need to take account of multiple pressures on ecosystems. Indicators are widely accepted as tools to monitor changes in ecosystems on different organisational levels (2005; Loh *et al.*, 2005). To address multiple pressures on the many dimensions of ecosystems, it is generally recognized that several indicators are needed. It is important to be able to distinguish between natural environmental variations and human induced stressors (e.g. over-harvesting, habitat destruction and chemical pollution). This requires using a combination of indicators expected to react differentially to various stressors. Analysis of the combined time trends of these specific metrics then allows identification of the most likely driving causes.

There have been some attempts to identify causes of changes by combining changes in indicator species that reacted differently to different sources of pollution in designed experiments (Lenihan *et al.*, 2003), or in population metrics expected to be more sensitive to mortality or to recruitment variations based on theoretical considerations (Trenkel *et al.*, 2007).

Marine food webs are highly connected and characterised by many weak links between species (Link, 2002) and relatively short average path lengths between taxa (Dunne *et al.*, 2004). Short average path lengths between species imply that perturbations (fishing, climate change) are expected to be transmitted more widely throughout marine ecosystems compared to their terrestrial or freshwater counterparts (Dunne *et al.*, 2004). They can also be expected to propagate more rapidly. Indeed, the effects of fishing on cod has found to cascade through four-levels of the Baltic Sea food web (Casini *et al.*, 2008). There are many more empirical examples for cascades through two- or three-trophic levels (Baum and Worm, 2009, Frank *et al.*, 2007). This feature of rapid propagation of perturbations is a prerequisite for studying changes in equilibrium properties of food web models.

Theoretical modelling studies have been carried out for studying effects of fishing and human pressures on marine fish communities. For example FishSUMS, which is a length-structured multispecies fish community model, was developed for modelling past and future trends in the Large Fish Indicator (LFI) in the North Sea (ICES 2009). Similarly, the Size-Based model (SIBmo) of the North Sea fish community was used to explore tradeoffs between fisheries (single-species MSY) and conservation (Large Fish Indicator) objectives for the North Sea and to examine how fish community state indicators respond to changes in fish pressure (ICES, 2009). However, only generic models might be expected to provide general insights, assuming that generic food web properties exist and are understood, which might actually not be the case today (Steele, 2009). Qualitative models are such generic models for which results are presented in the next section.

2.2 Qualitative food-web modelling for predicting the joined directions of change of population and community indicators

2.2.1 System models

We used the simple food chain model with three trophic levels of predator-prey interactions and fishing on the top two levels developed by Dambacher *et al.* (2009). The differential equations describing the dynamics of the system are:

$$\begin{aligned}
 \text{predators: } \frac{dS_1}{dt} &= S_1(\alpha_{12}S_2 - q_4F_4 - \delta_1) + R \\
 \text{preys: } \frac{dS_2}{dt} &= S_2(-\alpha_{22}S_2 + \alpha_{23}S_3 - \alpha_{21}S_1 - q_5F_5 - \delta_2) \\
 \text{resource: } \frac{dS_3}{dt} &= S_3(-\alpha_{33}S_3 - \alpha_{32}S_2 + \beta_3) \quad (\text{eq. 2.1}) \\
 \text{predator fishery: } \frac{dF_4}{dt} &= F_4(e_4q_4S_1 - \delta_4) + V_4 \\
 \text{prey fishery: } \frac{dF_5}{dt} &= F_5(e_5q_5S_2 - \delta_5) + V_5
 \end{aligned}$$

where S_1 are predators, S_2 preys and S_3 the food resource of the preys (or the predators as well, refer to model B in Figure 2.1). Each group of predators and preys includes several species which amounts to assuming that a group of predator species eats a group of prey species, ignoring prey preferences. The model units are abundance, but could also be expressed as biomass. The effort of fleets fishing on predators is F_4 with catchability q_4 . The prey fishery has effort F_5 and catchability q_5 . The transformation of catch revenue into additional effort is modelled by the efficiency coefficients e_5 and e_4 . The α_{ij} are predator-prey interaction coefficients apart from α_{22} and α_{33} which express density-dependent regulation of the abundance of preys and the resource. Density independent birth and death rates are given by β_3 for the resource and δ_1 and δ_2 for the predators and preys respectively. For the fisheries, δ_4 and δ_5 correspond to fleet exits (density-dependent) and V_4 and V_5 to capacity increases (density-independent). Note that in equation 2.1 the predation intakes leading to births, $\alpha_{23}S_3$ for preys and $\alpha_{12}S_2$ for predators, depend on the abundance of their respective preys. Thus by definition this system model is bottom-up driven (Steele, 2009).

The system model in equation 2.1 can be depicted in graphical form using sign di-graphs (Figure 2.1). We refer to it as the food chain model. A model variant consists of allowing the predators to forage on both trophic levels (Figure 2.1b). The dynamics for this omnivorous predator and the resource in the system with omnivory become

$$\begin{aligned}
 \text{omnivorous predators: } \frac{dS_1}{dt} &= S_1(\alpha_{12}S_2 + \alpha_{31}S_3 - q_4F_4 - \delta_1) + R \quad (\text{eq. 2.2}) \\
 \text{food web resource: } \frac{dS_3}{dt} &= S_3(-\alpha_{33}S_3 - \alpha_{32}S_2 - \alpha_{31}S_1 + \beta_3)
 \end{aligned}$$

The linear dynamics of the food chain model (equation 2.1) around the steady state can be written as:

$$\frac{dN^*}{dt} = \mathbf{A}N$$

where N^* represents the levels of the system components at equilibrium and A is commonly called the community matrix; the elements of A its elements are defined by the partial per capita derivatives

$$a_{ij} = -\frac{\partial \left(\frac{dN_i}{N_i dt} \right)}{\partial N_j}$$

The community matrix of the food chain model (equation 2.1) is therefore

$$A = \begin{bmatrix} -R/S_1^2 & \alpha_{12} & 0 & -q_4 & 0 \\ -\alpha_{21} & -\alpha_{22} & \alpha_{23} & 0 & -q_5 \\ 0 & -\alpha_{32} & -\alpha_{33} & 0 & 0 \\ e_4 q_4 & 0 & 0 & -V_4/F_4^2 & 0 \\ 0 & e_5 q_5 & 0 & 0 & -V_5/F_5^2 \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & 0 & a_{14} & 0 \\ a_{21} & a_{22} & a_{23} & 0 & a_{25} \\ 0 & a_{23} & a_{33} & 0 & 0 \\ a_{41} & 0 & 0 & a_{44} & 0 \\ 0 & a_{52} & 0 & 0 & a_{55} \end{bmatrix} \quad (\text{eq. 2.3})$$

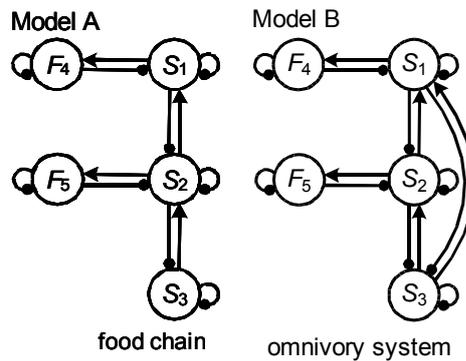


Figure 2.1. Food web models. S1: predators; S2: preys; S3: resource; F4: predator fishery; F5: prey fishery. pointed arrow: positive relationship; round arrow: negative relationship.

2.2.2 Impact of changes in resource productivity and effort management

Climate change will most likely affect primary production through increased temperature favouring plankton blooms, similarly for eutrophication. In the system models, this corresponds to an increase in the productivity β_3 of the resource S_3 in equation 2.1. Fisheries management can regulate fishing pressure on predators and preys by regulating fishing effort changes, δ_4 and δ_5 in equation 2.1. Thus, to study the expected effects of environmental change and fisheries management, we analyse the expected direction of changes in system components to attain a new equilibrium when either the dynamics of S_3 (environment), F_4 or F_5 (fisheries) or combinations of the three change permanently. This takes into account the direct and indirect effects of changes after feeding through the system.

A change in equilibrium levels due to a permanent change in one of the model parameters is obtained through:

$$dN^* = -\mathbf{A}^{-1} \frac{\partial \left(\frac{dN}{N dt} \right)}{\partial p} dp \quad (\text{eq. 2.4})$$

as shown by Dambacher *et al.* (2002). The sign of eq. 2.4 is determined by the inverse of matrix \mathbf{A} (\mathbf{A}^{-1}). As $\mathbf{A}^{-1} = \frac{1}{\det(\mathbf{A})} \text{adj}(\mathbf{A})$, where $\det(\mathbf{A})$ is the determinant and $\text{adj}(\mathbf{A})$ the adjugate of \mathbf{A}

$$\text{sgn } \Delta N^* = \text{sgn} [\text{adj}(-\mathbf{A})]$$

Hence, inspection of the signs of the adjugate of the community matrix \mathbf{A} facilitates determination the expected direction of change for component levels, similarly for changes in life expectancy (Dambacher *et al.*, 2005).

The expected direction of change in both the level of predator and prey abundances and their life expectancies following the permanent change in the parameters of a single process dynamics (F_4 , F_5 or S_3) has been analysed for both models plus three other model variants by Dambacher *et al.* (2009). The results for model A are summarised in Table 2.1. Life expectancy summarises the demographic structure of populations or groups of species. Each process change is predicted to lead to a unique combination of changes in predator (S_1) and prey (S_2) abundance and life expectancy. The predictions for model B are ambiguous in certain cases (values in brackets in Table 2.1). To resolve the ambiguity it would be necessary to parameterise the model.

Table 2.1. Expected direction of change in abundance and life expectancy of predators S_1 and preys S_2 due to the permanent change in the dynamics of a single process (see eq. 2.1) from Dambacher *et al.* (2009). F_4 : predator fishery, F_5 : prey fishery; S_3 bottom resource in food chain. Results are for models A/B in Figure 2.1. Ambiguous predictions in brackets.

Response/ variable	Increased F_4	Increased F_5	Increased S_3	Decreased F_4	Decreased F_5	Decreased S_3
Abundance						
S_1	-/-	-/(-)	+/+	+/+	+/(+)	-/-
S_2	+/+	-/-	+/(+)	-/-	+	-/(-)
Life expectancy						
S_1	-/(-)	+/(+)	-/-	+/(+)	-/(-)	+/+
S_2	+/(+)	-/-	-/-	-/(-)	+/+	+/+

We study the expected direction of change and the conditions for unambiguous predictions if two processes changes simultaneously, i.e. increased or decreased production of S_3 and changed fishing effort for F_4 or F_5 . Table 2.2 summarises the results. For model A, single process changes led to unambiguous predictions for the sign of expected changes in abundance and life expectancy. This is no longer true if two processes change simultaneously. Inequalities for model parameters determining the predicted signs of change are also provided in Table 2.2 for simple cases and some more complex ones in Table 2.3.

We first discuss the results for the simple food chain model (A). In the case of a simultaneous increase of fishing effort on predators (F_4) and increased resource pro-

ductivity (S_3) (first column in Table 2.2), prey abundance (S_2) is expected to increase and the life expectancy of both to decrease as they would if only predator fishing effort F_4 increased (see Table 2.1). The expected direction of change for predator abundance is probably negative given the dominance of negative terms (3 negative vs. 1 positive). If both prey fishing (F_5) and resource productivity (S_3) increase (second column in Table 2.2), positive and negative changes are expected to balance each other leading to a prediction of no change for abundances and predator life expectancy, but prey life expectancy is decreasing. This is not surprising, given that the expected direction of change of the processes in isolation is opposite (Table 2.1). The effect of resource productivity change will be dominant if the contribution of the resource to the abundance increase in S_2 is stronger than the negative impact of fishing ($\alpha_{23}\alpha_{55} > q_5\alpha_{33}$). In this case, the abundance of both predators and prey is expected to increase. In the reverse case ($\alpha_{23}\alpha_{55} < q_5\alpha_{33}$) the effect of increased fishing effort will be dominant and consequently predator and prey abundance is expected to decrease and predator life expectancy to increase. In the case of decreasing fishing effort on predators F_4 and increasing resource productivity, the same changes are expected as if only resource productivity changed. A decrease in prey abundance will happen if $q_4\alpha_{21} > \alpha_{11}\alpha_{44} + e_4(q_4)^2$. For life expectancy of predators to increase, then $q_4\alpha_{21} > (\alpha_{11}\alpha_{44} + e_4(q_4)^2)\alpha_{23}/\alpha_{33}$. Thus the effects of decreased fishing effort on predators happening simultaneously with increased resource productivity is only detectable in certain circumstances. Otherwise the bottom up control will be the dominant feature. A decrease in prey fishing effort F_5 occurring together with increased resource productivity S_3 (last column in Table 2.2) will unambiguously result in an increase of both predators and prey. Life expectancy of predators will decrease, but the direction of change for preys depends on many parameters (see appendix in Trenkel and Rochet 2009). Thus a joint decrease of fishing on predators and an increase and resource can lead to combinations of abundance and life expectancy changes which resemble single process changes of either fishing or resources depending on model parameters.

The results for the model with omnivory (model B) are rather similar to those obtained for the food chain with the exception of the predictions for the case of an increase in fishing effort on prey (F_5) and resource productivity (S_3). Further, in the case of decreased fishing effort on predators (F_5), prey abundance is predicted to decrease rather than increase, though the prediction is not strong and depends on model parameter values.

Overall, when both fishing pressure and resource productivity change simultaneously, the expected direction of changes on the top level, that is for predators, depend on model parameters while those related to fishing on prey are less parameter dependent. In the later case, the general pattern of expected time trends is that predicted for a change in productivity only. Thus bottom-up changes are expected to be dominant. This is not surprising, given the model formulation is that of a bottom-up driven system (Steele, 2009). Top-down pressure changes are more likely to lead to detectable changes if they occur on the top level, i.e. affect the predators of the model system.

Table 2.2. Expected direction of change in abundance and life expectancy of predators S1 and preys S2 due to the simultaneous permanent change in the dynamics of two processes in model A and B (see equation 2.1, figure 2.1). The results are presented as model A/B. The signs for predictions which depend on model parameter values (eq. 2.1) are given in brackets and the determining parts using the notation in eq. 2.1 are provided if they are simple. Certain full terms are given in table 2.3. For example, "A: + if $\alpha_{23}\alpha_{55} > q_5\alpha_{33}$ " means that the prediction is positive if the product of model parameters $\alpha_{23}\alpha_{55}$ is bigger than $q_5\alpha_{33}$ F4: effort of predator fishery, F5: effort of prey fishery; S3 bottom resource in food chain.

Response/variable	Increased F4 and S3	Increased F5 and S3	Decreased F4 and increased S3	Decreased F5 and increased S3
Abundance				
S1	(-)/(0) see table x3	0/+ A: + if $\alpha_{23}\alpha_{55} > q_5\alpha_{33}$	+/+	+/+
S2	+/+	0/(-) A: + if $\alpha_{23}\alpha_{55} > q_5\alpha_{33}$ B: see table x3	(+)/(-) A: - if $q_4\alpha_{21} > \alpha_{11}\alpha_{44} + e_4(q_4)^2$ B: see Table 2.3	+/+
Life Expectancy				
S1	-/-	0/- A: - if $\alpha_{23}\alpha_{55} > q_5\alpha_{33}$	(-)/(-) A: + if $q_4\alpha_{21}\alpha_{33} > \alpha_{23}\alpha_{11}\alpha_{44} + e_4(q_4)^2\alpha_{23}$ B: see Table 2.3	-/-
S2	-/-	-/-	-/-	(-)/(-) see Table 2.3

Table 2.3. Terms for ambiguous sign predictions in press perturbation results of table 2.1. Only terms which depend on model parameters are provided for each model. See eq. 2.3 for the definition of the community matrix terms a_{ij} .

Response/variable	Increased F4 and S3	Increased F5 and S3	Decreased F4 and increased S3	Decreased F5 and increased S3
Abundance				
S1	A: $a_{12}a_{23}a_{44}a_{55} - a_{14}$ ($a_{22}a_{33}a_{55} + a_{32}a_{23}a_{55} + a_{52}a_{25}a_{33}$) B: $a_{44}(a_{12}a_{23}a_{55} + a_{13}a_{22}a_{55} + a_{13}a_{25}a_{52}) - a_{14}(a_{32}a_{23}a_{55} + a_{33}a_{22}a_{55} + a_{33}a_{25}a_{52})$	A: ($a_{23}a_{55} - a_{25}a_{33}$) $a_{12}a_{44}$		

S2		A: (a23a55 - a25a33) (a11a55 + a41a14) B: (a11a44 + a41a14)(a23a36a55- a25a33) - a13a44(a21a36a55 + a31a25)	A: a55a23(a11a44 + a14a41 - a14a21) B: a55(a11a23a44+ a41a23a14) - a55(a21a13a44 + a21a33a14 + a31a23a14)	
Life Expectancy				
S1		A: (a25a33 - a23a55) (a11a44 + a14a41) a12	A: a55a12(a14a21a33 - a11a23a44 - a14a41a23) B: a55a14a31(a12a23 + a12a22) - a55(a11a12a23a44 + a11a13a14a32 + a11a13a22a44 + a12a14a41a23 + a13a14a41a23) - a14a13a25a31a52	
S2				A: a23a25a32(a11a44 + a14a41) - a23(a21a12a44a55+a22a11a44a55 + a22a41a14a55+a25a11a52a44) + a25a41a52a14) B: a23a25(a44a11a32 + a44a13a12 + a41a32a14) - a23a44a55(a21a12 + a22a11) - a23a14a41(a22a55 + a25a52)

2.2.3 Combining metrics time trends to identify process changes in food webs in European fish communities

For identifying changes in food web processes based on time trends in multiple metrics, a certain observed combination of time trends points towards a change in a particular process or several processes using the predictions in Table 2.1 and 2.2. Four time series of metrics are required for this, one each for the abundance of predators and preys and for their life expectancies. Trenkel and Rochet (2010) proposed a statistical approach that calculates the likelihood of each possible metrics time trend combination and uses the log-likelihood ratio with the model with the largest likelihood to determine the evidence in the time series data for each process change. In Rochet *et al.* (2010) a range of abundance and length metrics were calculated from survey data for 14 Mediterranean and East-Atlantic groundfish shelf communities at both population and functional group levels. For this, species were classified as predators or prey looking at their adult diet. Species that could not be classed or were not prey of the retained predators, were discarded. So the number of predators and preys in each community was variable. A wide diversity of impacts from fishing or resource productivity change was found to have equal evidence at the population level within

each community. Consistency between the impacts identified and changes in pressures known from independent information was found at the functional group and community level. The model results suggested that there was some compensation between species within functional groups.

2.3 Incorporating spatial aspects

The models used for exploring the relative effects of climate and fisheries on fish productivity and community structure presented here and in ICES (2009) do not include fully developed spatial aspects. However, it is well known that fish communities are not spatially homogenous nor are the effects of climate or fishing affecting all areas equally (see ToR d below). It seems therefore important to develop modelling approaches that consider spatial aspects.

An attempt is made to include spatial aspects in the SIze-Based model (SIBmo) of the North Sea as described in the 2009 WGFE report (ICES 2009). The model already included a Species interaction matrix based on spatial co-occurrence derived from IBTS data, e.g. when species overlap in space according to the survey then they can pre-date on each other in the model. This is extended by including spatially explicit fishing effort. The modelled non-spatial abundance of the 12 North Sea species in SIBmo is spatially distributed based on the length-class specific distribution in the IBTS survey. On top of this spatially distributed abundance realistic effort by métier along with gear specific catchabilities is placed following the methods described in Piet *et al.* (2009). The Piet *et al.* method (DIMCOM) calculates spatially explicit catches (landings and discards) of the total demersal fish community. In the Piet *et al.* (2009) paper, only two beam trawl and one otter trawl métier were distinguished. This is extended and now four beam trawl, six otter trawl and four static gear métiers are distinguished (Polet *et al.* 2010). This provides the possibility of scenario's with catchability changes in a single métier (e.g. mesh size changes or changes from beam trawl to pulse trawls), or direct effort reduction of a single métier. Some examples can be found in the LOT3 report (Polet *et al.* 2010)

The spatially explicit catches by length derived from DIMCOM, can be summed over the whole North Sea to create a length-specific Fishing mortality. This realistic or scenario derived F-pattern goes back into SIBmo, where it replaces the knife-edge selectivity function that was used to describe the ability of the fishery to catch each species. SIBmo is then used to calculate the LFI indicator and the new abundances of the 12 species. Combining the two methods facilitates testing not only the effect of single métier management measures, but also spatial management measures on the LFI indicator and the other three indicators calculated by SIBmo.

This is a simple step to include, to be able to explore spatial management measures. However, it is not enough to take account of the important spatial aspects driving fish communities, particularly because the smallest spatial scale used is the rather large ICES-rectangles as dictated by the IBTS survey design.

2.4 Recommendations

We recommend the inclusion of spatial aspects, preferably small scale spatial aspects consistent with biological and physical structure to evaluate the effect of spatial management measures on the community indicators. It would make these models useful in evaluating the effects of measures taken within the Natura-2000 areas, and in the upcoming measure to reach Good Environmental Status (see ToR d).

We recommend that spatial aspects of expected climate change and fishing impacts be included in models for evaluating their effects on exploited fish communities and community indicators.

The results of the simple food web model described shows that it is not necessary to focus on the complex multi-species size structure models to come up with answers on directions of change of population and community indicators. We recommend that WGSAM evaluate whether qualitative models and loop analysis provide answers to certain questions dealt with by them.

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3 Metrics for characterising changes in the structure, function and productivity of fish communities

ToR b) Review and evaluate metrics to characterise, monitor and detect changes in the structure, function and productivity of fish communities

3.1 Introduction

In previous years, WGFE has done considerable work on metrics and their relation to fish productivity and community structure. The aim in 2010 was to describe and follow changes in the productivity and community as an indicator of a system's state using a minimal suite of metrics. The metrics should be calculable using regular survey data. The historic observations can be used to show how the metric has performed over time. The current ecosystem management objectives for the North Sea demersal fish community focus on restoring its size structure. When asked by OSPAR to recommend a metric that would best support an Ecological Quality Objectives (EcoQO) for the North Sea fish community, application of the ICES criteria for a good state indicator (ICES 2001a) suggested that size-based metrics would likely perform best (ICES, 2001b, Greenstreet, 2008). Within the Good Environmental Status (GES) framework that is adopted in the European Marine Strategy Framework Directive (MSFD), not only size-based metrics but also metrics for biodiversity and other ecosystem objectives are required. This makes evaluating of metrics even more necessary, especially for areas outside the North Sea.

This year's progress following last year's work on the issue of metric redundancy is described followed by the description of a newly proposed community size-structure metric. This metric is evaluated using simulated community data and calculated for survey data from various regions.

3.2 Comparison of large fish indicator (LFI) with other metrics in North Sea

Broader ecosystem management objectives for North Sea demersal fish currently focus on restoring community size-structure. However, most policy drivers explicitly concentrate on restoring and conserving biodiversity and it has not yet been established that simply restoring demersal fish size composition will be sufficient to reverse declines in biodiversity and ensure a generally healthy community. If different aspects of community composition, structure and function vary independently, then to monitor all aspects of community general health will require application of a suite of metrics. This assumes low redundancy among metrics used in any such suite, and implies that addressing biodiversity issues specifically will require explicit management objectives for particular biodiversity metrics. In Greenstreet *et al.* (submitted) following work presented in ICES (2009), the issue of metric redundancy was addressed. Fifteen metrics covering five main attributes of community composition,

structure and function were applied to groundfish survey data. Factor analysis suggested a new interpretation of the metric information and indicated that a minimum suite of seven metrics was necessary to ensure all changes in the general health of the North Sea demersal fish community were properly monitored. Co-variation among size-based and species diversity metrics was low, implying that restoration of community size structure would not necessarily reverse declines in species diversity.

3.3 A new metric: Size diversity

Size is recognized as a key feature in marine ecological processes and, because fishing is size-selective, the size distribution of marine populations and assemblages is often used to monitor fishing impacts at various organization levels (Shin *et al.*, 2005). It was established that aggregated length distributions of fish obtained from scientific surveys are regular and conservative and may therefore be used as indicators for exploited communities in various environments (Pope and Knights 1982; Murawski and Idoine 1992). However, the linearity of size spectra, even in a reduced size range, might be questioned when looking at many data series. A new metric for summarising the community size spectrum was proposed by Rochet and Benoît (submitted) which was not dependent on the linearity of the size spectrum but accounted for its ordered property. The utility of this metric is evaluated here by simulation and by applying it to groundfish survey data.

3.3.1 Metric development

To account for size classes ordered in the size spectrum, a metric including some measure of distance similar to the taxonomic diversity metrics of Clarke and Warwick (1998), is used. Size diversity is defined as:

$$\sum_{x=y} \frac{\sum_{x_{min}}^{x_{max}} \sum_{y_{min}}^{y_{max}} d(x,y)w(x)w(y)}{\sum_{x_{min}}^{x_{max}} \sum_{y_{min}}^{y_{max}} w(x)w(y)} \quad (3.1)$$

where $w(x)$ is the total weight of individuals in the size (weight) class whose mid-point has log-transformed weight x ; $d(x,y) = 1 - \exp(-|y - x|/\delta)$ measures the distance between two classes with log-weight x and y , and δ determines for which difference in log-weight the distance is 1 (Figure 3.1). As d is a function of $y - x$, two fish with a given weight ratio have a similar distance, irrespective of their individual weight. In this definition, the denominator is set so that the index is equal to 1 when all individuals are at distance $d(x,y)=1$. Using the distance between two biomass units rather than two individuals gives more weight to larger individuals in the index calculation. The diversity of a linear biomass spectrum increases as δ decreases. Peaks or gaps in the size spectrum lower its diversity.

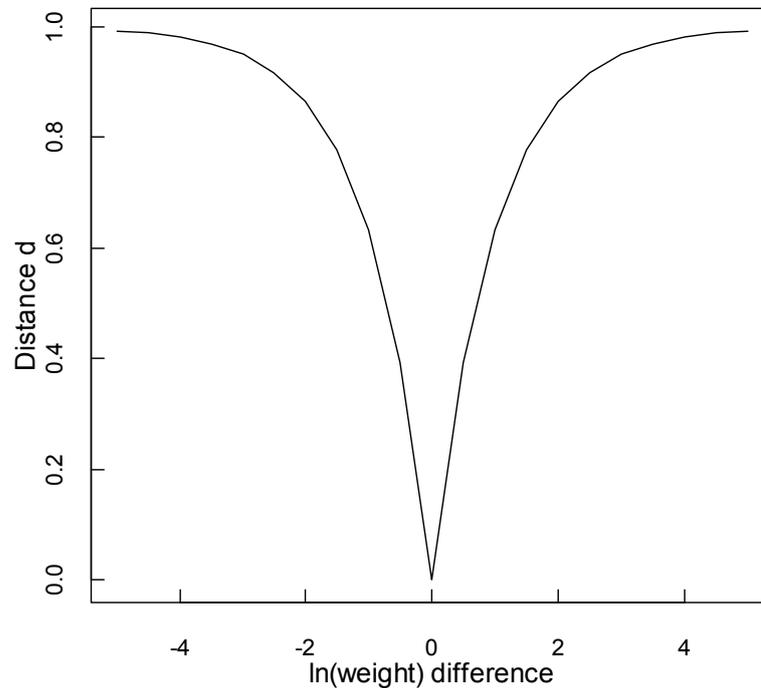


Figure 3.1. Form of distance function $d(x,y) = 1 - \exp(-|y - x|/\delta)$ between log-weight classes x and y as used in size diversity index for $\delta=1$.

3.3.2 Metric testing by simulation

To investigate the properties of the proposed size diversity metric and to compare it to the LFI, a simulation study was undertaken. The LFI was calculated as the proportion in weight of individuals larger than 40 cm. The study consisted of simulating size-structure scenarios of fish communities. The simulation study allowed us to investigate whether, as suggested, a size diversity close to 1 would correspond roughly to an equal distribution of biomass across weight classes, while all biomass in a single size class would lead to a diversity metric closer to zero.

The size diversity index (equation 3.1) is defined in terms of weight but the calculations can also be carried out by converting length to weight assuming a weight-length relationship. Using length makes it more convenient to compare the proposed size diversity index with the LFI. The used virtual communities are by weight per cm-length class (Figure 3.2). The scenarios are arbitrary choices. The last three scenarios are however considered more realistic, the “real” scenario would indicate a realistic community though the current simulation shows big bumps in the size-spectrum which might be more realistic for a population compared to community. However some of communities caught in the IBTS (see real data in the next paragraph) showed similar bumps. The “real bigger” scenario is similar as the “real” scenario but more large fish have been added in the range 30–60 cm and a small extra number of very large fish have been added. The “fished” scenario differs from the “real” as the numbers of fish in the length range of 25–150 cm was decreased.

As expected, the “real bigger” scenario produces the highest value for the size-diversity metrics, while “Fished” gets the lowest metric value. The difference be-

tween the values is however small, especially compared to the results of the LFI. The LFI gives the “Fished” scenario a much lower value than the other two scenarios, while the “real bigger” scenario is even above the North Sea reference value of 0.3. Due to smaller difference between the size-diversity values than for the LFI values it is clear that the size-diversity and LFI are not presenting the same thing of the community size-structure.

There is an issue regarding the minimum size included in the calculations. In size spectrum calculations, fish below a certain size taken by the survey gear are not representative (under-represented) of the population and are generally removed. For IBTS or other survey data collected with the same protocol, a cut-off of 20 cm has been used (e.g. Trenkel and Rochet, 2003). The other factor to be taken into account is the impact of recruitment on the form of the size spectrum and consequently on the size diversity index. Depending on the community, variable recruitment pulses of abundant species might lead to spikes for lower weight classes. To remove undue impacts of recruitment, a cut-off point of 20 cm might also be appropriate. We tested the consequences of a 20 cm cut-off choice by calculating the size diversity index for the full scenarios and by removing individuals below 20 cm from the scenarios. Using this cut-off point not only affects the absolute value of the metric, but also affects the order of the scenarios. It did not change the order in the three more realistic scenarios. But it clearly improved the rank of the “higher”, “1000down” and “low-high” scenarios compared to the other ones.

The 20 cm cut-off is arbitrary and isn't necessary the ideal truncation for all gears and species. Furthermore, it might be necessary to set a different cut-off for different areas (as well as gears). The exact cut-off, if necessary at all, should depend on the size of the recruiting fish. This issue is related to the issues concerning the LFI, where the 40 cm boundary of being a large fish is just as arbitrary. This boundary should potentially also differ between areas, as is tested by WGECO in 2010 while applying the LFI in other areas than the North Sea (ICES, 2010), or should even be set by each species individually (Daan, 2006).

The distance function $d(x,y)$ used in the size diversity index has one parameter (δ) for which a value needs to be selected. Figure 3.1 shows the function for $\delta=1$. This is an arbitrary choice, which causes that the distance between a 20 cm and a 100 cm fish to be almost 1 while lower or higher δ values might be equally valid to use. Clearly, the impact of the δ value will depend on the shape of the size spectrum. To see the impact δ , size diversity was calculated for a range of values $\delta=\{0.5, 1, 2\}$. This changed the absolute value of the size-diversity metric. It however also changed the order of the scenarios, as can be seen for the underlined values in Table 3.1 and in Figure 3.3. With a value of 0.5, the “high” scenario has a higher metric value than the “low_high” scenario, while the opposite is true for a δ of 1 and of 2. This issue however seems of limited concern, looking at the real data analysis shown in the next section.

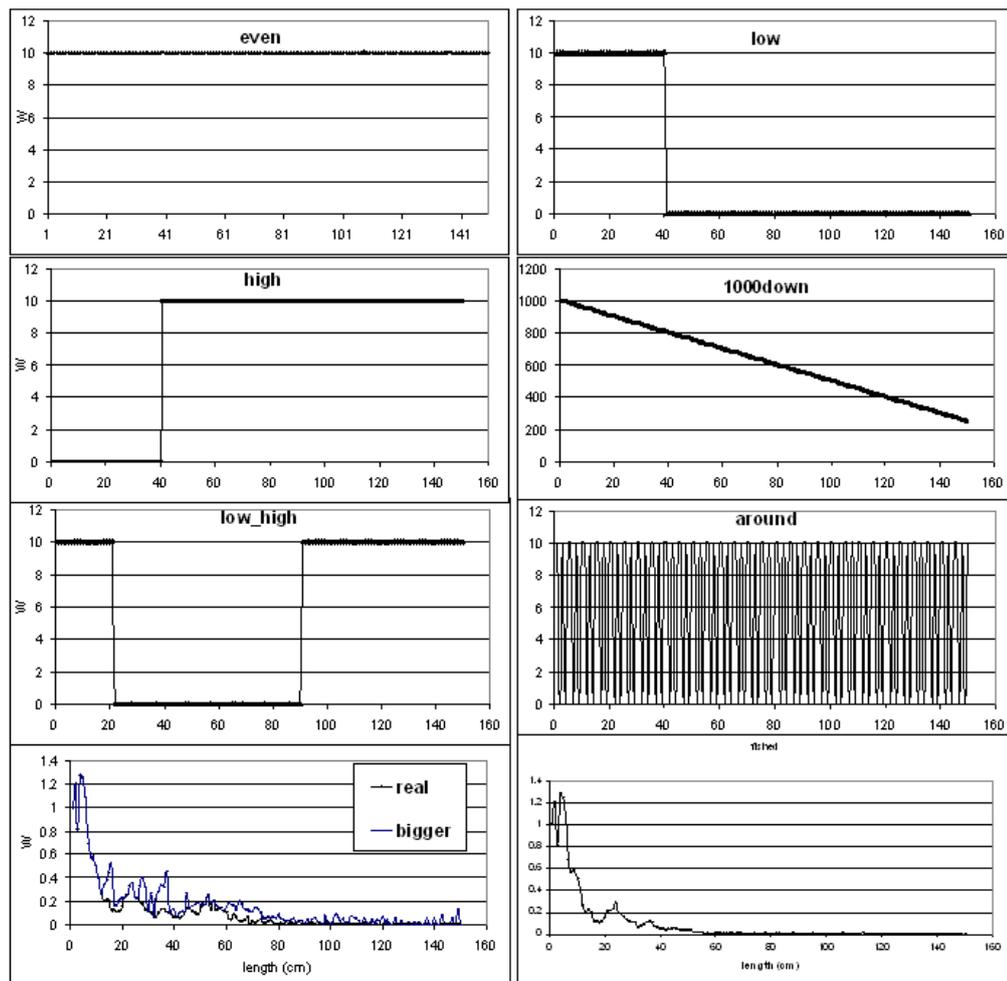


Figure 3.2. Virtual communities in weight used in testing the metrics.

The results of the size diversity metric and the LFI for the different scenarios (Figure 3.2) are presented in Table 3.1 and visualised in Figure 3.3. It can be seen that none of the size-diversity values reaches 1, which would mean evenly distributed biomass. We run a scenario of evenly distributed biomass ($\exp(3\text{Log}(L)) \cdot N=1$ for all length classes), however this resulted as well in a value of the metrics around 0.74.

Table 3.1. Size diversity metric (Size-div.) and Large Fish Indicator (LFI) for simulated size spectrum scenarios (Figure 3.2). Size-diversity using $\delta = 0.5$ and $\delta = 0.2$ and the Size-diversity with a cut-off on 20 cm.

Simulated scenario	Size diversity index				LFI
	All	All	All	>20cm	All
	$\delta = 1$	$\delta = 0.5$	$\delta = 0.2$	$\delta = 1$	
even	0.745	0.854	0.592	0.681	0.733
low	0.730	0.844	0.570	0.450	0.000
High	<u>0.597</u>	<u>0.760</u>	<u>0.410</u>	0.597	1.000
1000down	0.785	0.883	0.637	0.704	0.616
low_high	<u>0.621</u>	<u>0.734</u>	<u>0.515</u>	0.398	0.741
around	0.742	0.852	0.588	0.683	0.733
"real"	0.830	0.903	0.703	0.634	0.197
real bigger	0.842	0.914	0.717	0.693	0.312
Fished	0.805	0.888	0.663	0.551	0.051

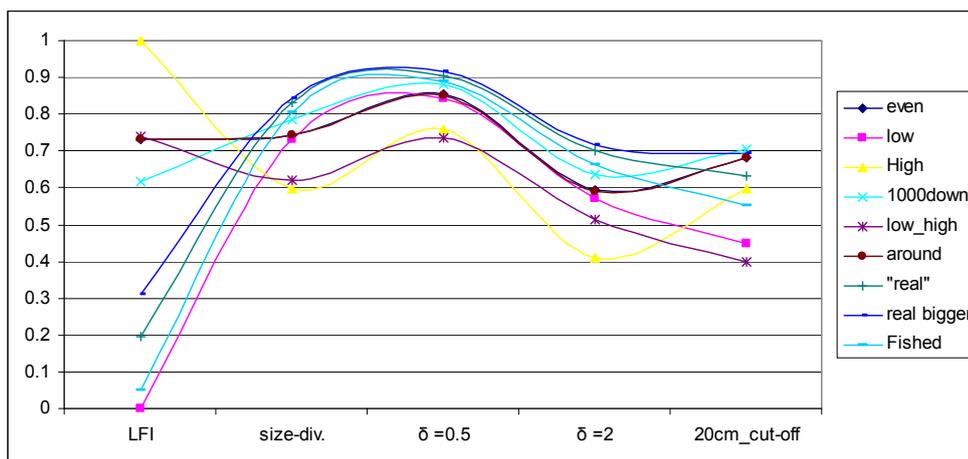


Figure 3.3. Size diversity for simulation scenarios from Figure 3.2 (columns marked “all” in Table 3.1).

3.3.3 Application to survey data

Survey data from seven European fish communities were used to compare size-diversity (for survey details see description in Rochet *et al.* 2005). The calculations employed a 20 cm cut off limit and used $\delta = 1$. For comparison we also calculated the LFI and the species based diversity index Δ_1 proposed by Hurlbert (1971) which expresses the probability of two species taken at random from the community would belong to different species:

$$\Delta_1 = \frac{N}{N-1} \left[1 - \sum_{i=1}^s \left(\frac{N_i}{N} \right)^2 \right]$$

The North Sea (IBTS) had the lowest size diversity of all communities, in particular in recent years with an overall decreasing time trend (Figure 3.4, blue line). The highest size diversity indicating the most even size spectrum was found for the Eastern Cor-

sica shelf (MEDITS-Corse) and the Eastern English Channel (CGFS). Species diversity Δ_1 was higher than size diversity in most communities (black line in Figure 3.4).

For the North Sea (IBTS), Celtic Sea (Evhoe_MC) and the Eastern English Channel (CGFS) we investigated the effects of changing these two parameters. As described above, the δ determines the level of the metric. The question is whether these choices could change the time trend in size diversity. In Figure 3.5, however it can be seen that the effect is limited as the time trends stay more or less the same but the absolute values are shifted. For the IBTS data series, the relative position of some years depends on the value used for δ (highlighted by a circle in Figure 3.5), though the changes are minor. The results obtained for the IBTS data with or without a 20 cm cut off were correlated, though not that strongly (Figure 3.4, right panel). In conclusion, further analyses are required to investigate the sensitivity of the proposed size diversity metric to methodological choices such as the value for δ and the size cut off limit.

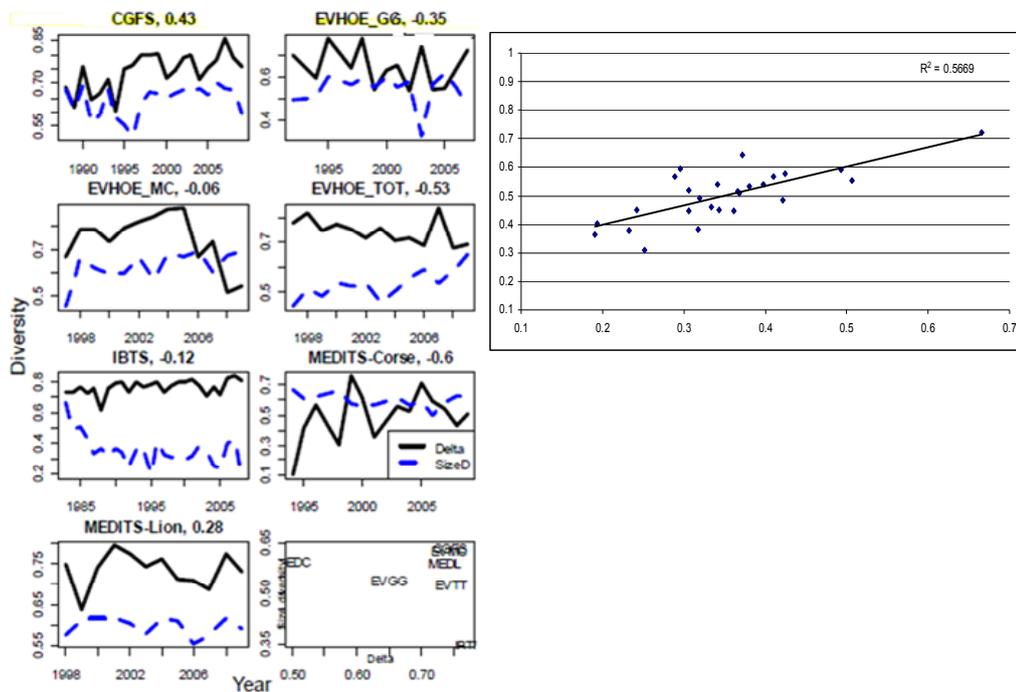


Figure 3.4. Size-diversity metric in the panel on the left (blue) and species based diversity index (black). Numbers in title indicate correlation coefficient between the two metrics. Correlation between size diversity for IBTS data using a cut-off of 20 cm or all data with no cut-off.

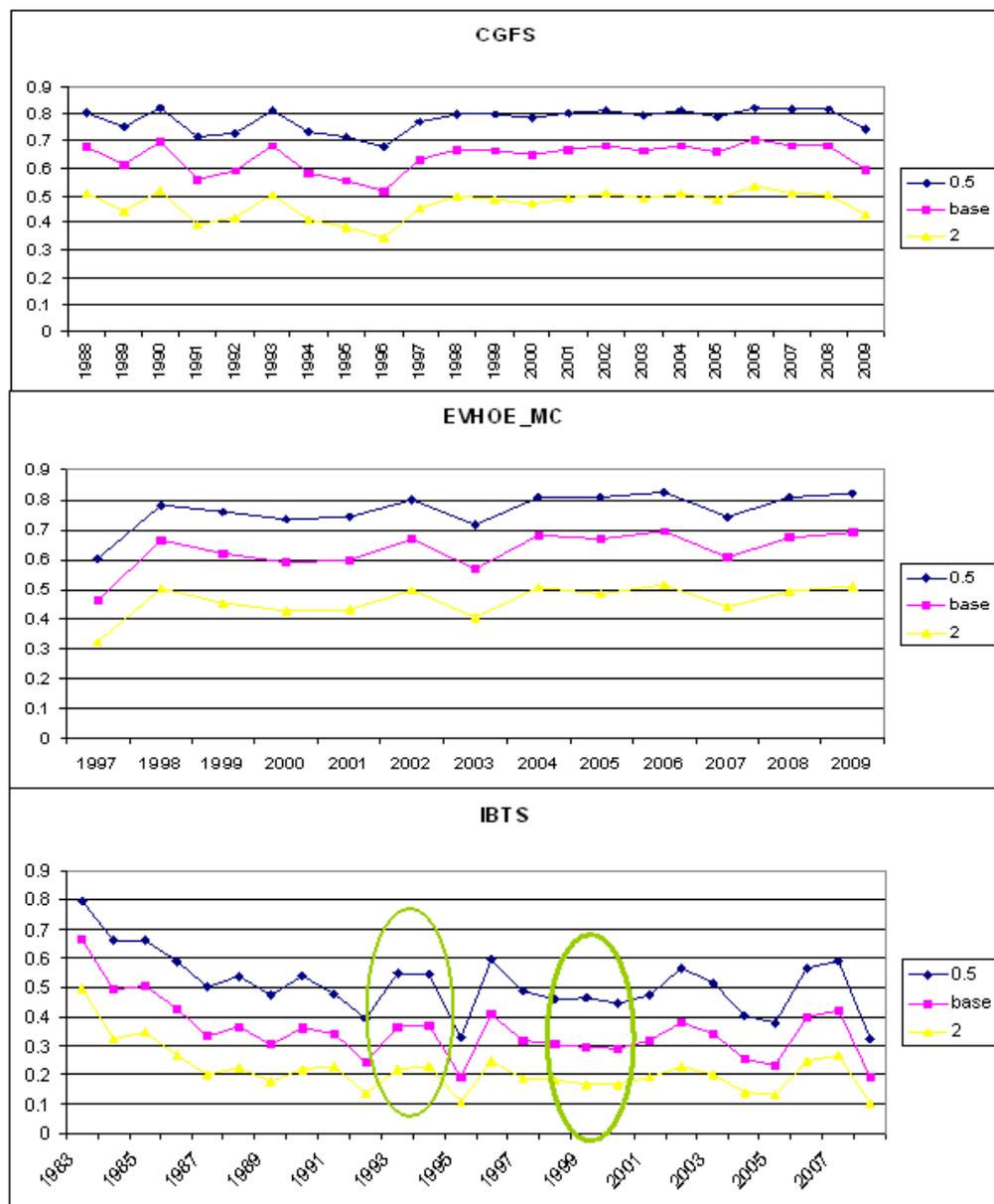


Figure 3.5. Size-diversity metric for the surveys, for different values δ (base = 1). In the green circles you can see a slight change in pattern from better then the year before to worse then the year before.

3.4 Recommendations

Metrics have the potential to be of value in characterising changes in structure, function and productivity of fish communities. Therefore it is recommended to continue the work on metrics within ICES and within this group. This year’s progress has been limited due to the available manpower and a break in continuum in expertise.

However from the progress in last year’s work, and the evaluation of the newly suggested metric, it can be concluded that the work on metrics has yet been finalized. Especially, issues on the choice of arbitrary boundaries for calculation of the metrics as well as on how to use similar issues in different areas need to be explored. For the first issue, it is recommended to evaluate the robustness of the suggested metrics for differences in the arbitrary values. To use similar metrics within different areas it is recommended to evaluate more thoroughly the assumptions of the metric and how

these relate to the community in the specific area. A next step would be suggesting reference-levels for the other areas, based on their unique fish community and environmental conditions.

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4 Spatial methods for comparing and summarising fish and fish community distributions in relation to environment and habitat

ToR c) Develop, explore and apply mapping and other spatial methods for comparing and summarising fish and fish community distributions in relation to environment and habitat

4.1 Introduction

The importance of species-habitat relationships is well established in European, Canadian and USA policy. The European Union Marine Strategy Framework Directive - Good Environmental Status Criteria, Descriptor 1 states "The assessment of species also requires an integrated understanding of the distribution, extent and condition of their habitats... to make sure that there is a sufficiently large habitat to maintain its population, taking into consideration any threat of deterioration or loss of such habitats". The Canadian Species at Risk Act requires assessment and protection of species at risk of extinction and critical habitat for those species at risk. Their Federal Fisheries Act provides Fisheries and Oceans Canada with authority for the conservation and protection of fish and fish habitat essential to sustaining commercial, recreational and Aboriginal fisheries. Federal fisheries in the USA are subject to the Magnuson-Stevens Fishery Conservation Management Act which requires that all fisheries management plans identify Essential Fish Habitat (EFH) and minimized to the extent practicable the adverse effects of fishing on EFH. Federal regulations define EFH as "those waters and substrate necessary to fish for spawning, breeding, feeding, or growth to maturity", and adverse effects as those which are "more than minimal and not temporary".

All of these legislative and policy directives provide measures for protecting the habitats which are important to fish which implies an understanding of **fish and fish community distributions in relation to environmental and habitat factors**. Unfortunately these relationships are often poorly understood and approaches generally rely on assessing proxies (e.g. loss of seabed vertical structure) or indicators (e.g. decreases in biodiversity) to identify where to enact spatial management measures (e.g. Marine Protected Areas - MPAs). Delimiting MPAs to protect such habitats requires mapping and spatial analyses which often use Geographical Information Systems and spatial statistical methods. Examples from the EU and USA are provided to demonstrate applications of mapping and spatial methods presently emanating from the above directives to protect fish habitats, a key part of their ecology.

4.2 Assessment of Existing MPAs using Adverse Effects Criteria: Northwest Atlantic Continental Shelf USA

4.2.1 Background

The Magnuson-Stevens Fishery Conservation and Management Act (MSA 2007) requires USA Federal Fishery Management Councils to **minimize, to the extent practicable, the adverse effects of fishing on fish habitats**. The Swept Area Seabed Impact model (SASI) was developed by the New England Fisheries Management Council Habitat Plan Development Team to 1) assess fishing impacts on Essential Fish Habitat and 2) to develop new spatial fishery management measures (e.g. habitat closed areas) on the Northwestern Atlantic Continental Shelf (640 000 km²). Full documentation of this model is available at NEFMC (2010).

4.2.2 Vulnerability Assessment

A review of the fishing impacts literature (97 papers) relevant to Northeast USA fishing gears and seabed types was organized as a formal vulnerability assessment which quantified both the magnitude of the impacts (susceptibility) that result from the physical interaction of fish habitats and fishing gears, and the duration of recovery following those interactions. **Susceptibility** was defined as the percentage of total habitat features encountered by fishing gear during a hypothetical single pass fishing event that have their functional value reduced. **Recovery** was defined as the time in years that would be required for the functional value of a habitat feature to be restored. Both susceptibility and recovery were scored from 0–3 using the literature and expert knowledge of the fishing gears and habitat features (see Table 4.2.1).

Table 4.2.1. Susceptibility (ω) and recovery (λ) values

Code	Quantitative definition of susceptibility	Quantitative definition of recovery
0	0–10%	< 1 year
1	>10%–25%	1–2 years
2	25–50%	2–5 years
3	> 50%	> 5 years

As a result of the literature review, fish habitat was described in terms of geological and biological structures further subdivided into specific features such as bedforms, biogenic burrows, sponges, macroalgae, etc. The features were selected to reflect published findings that 1) physical alterations of fish habitat occur primarily on the benthos and 2) impacts were strongest on vertical seabed structures (NEFMC 2010). The functional value of the features for fish is not known but generally structure-providing features either provide food (biota on the structure) or shelter for managed species directly, or provide food/shelter for their prey. Therefore, the susceptibility of each feature was taken as the reduction in percent areal coverage within the area swept by the gear. The literature also indicated that natural disturbance levels might affect the habitat features' susceptibility to and recovery from fishing disturbance. Therefore, depth and the model-derived benthic boundary flow (shear stress) estimates were used to define high and low energy environments (Table 4.2.2).

Table 4.2.2. Shear stress model components

Condition	Data source	Parameterization	
		High energy	Low energy
Shear stress	The max shear stress magnitude on the bottom in $N \cdot m^{-2}$ derived from the M2 and S2 tidal components only	High = shear stress $\geq 0.194 N \cdot m^{-2}$ (critical shear stress sufficient to initiate motion in coarse sand)	Low = shear stress $< 0.194 N \cdot m^{-2}$
Depth	Coastal Relief Model depth data	High = depths $\leq 60m$	Low = depths $> 60m$

Vulnerability matrices were used to organize susceptibility and recovery values for each geological and biological feature by fishing gear type and energy level (see Table 4.2.3 for examples).

Table 4.2.3 Susceptibility (ω) values and recovery (λ) scores for dredge effects on high energy cobble including feature-specific gear effects. Susceptibility and Recovery values are defined in Table 4.2.1 (NEFMC 2010).

Scallop Dredge / Cobble / High energy			
Feature name and class – G (Geological) or B	Gear effects	ω	λ
Cobble, pavement (G)	burial, mixing, homogenization	1	0
Cobble, piled (G)	smoothing, displacement	3	3
Cobble, scattered in sand (G)	burial, mixing, displacement	1	0
Anemones, actinarian (B)	breaking, crushing, dislodging,	2	2
Ascidians (B)	breaking, crushing, dislodging,	2	1
Brachiopods (B)	breaking, crushing, dislodging,	2	2
Bryozoans (B)	breaking, crushing, dislodging,	1	1
Hydroids (B)	breaking, crushing, dislodging,	1	1
Macroalgae (B)	breaking, dislodging	1	1
Mollusks, epifaunal bivalve, <i>Modiolus modiolus</i>	breaking, crushing, dislodging,	2	3
Mollusks, epifaunal bivalve, <i>Placopecten magel-</i>	breaking, crushing	1	2
Polychaetes, <i>Filograna implexa</i> (B)	breaking, crushing, dislodging,	2	2
Polychaetes, other tube-dwelling (B)	crushing, dislodging	2	1
Sponges (B)	breaking, dislodging, displacing	2	2

4.2.3 The Model

The Swept Area Seabed Impact (SASI) model components, including fishing effort, the input and output model grids, and habitat feature vulnerability, are combined as depicted in Figure 4.2.1.

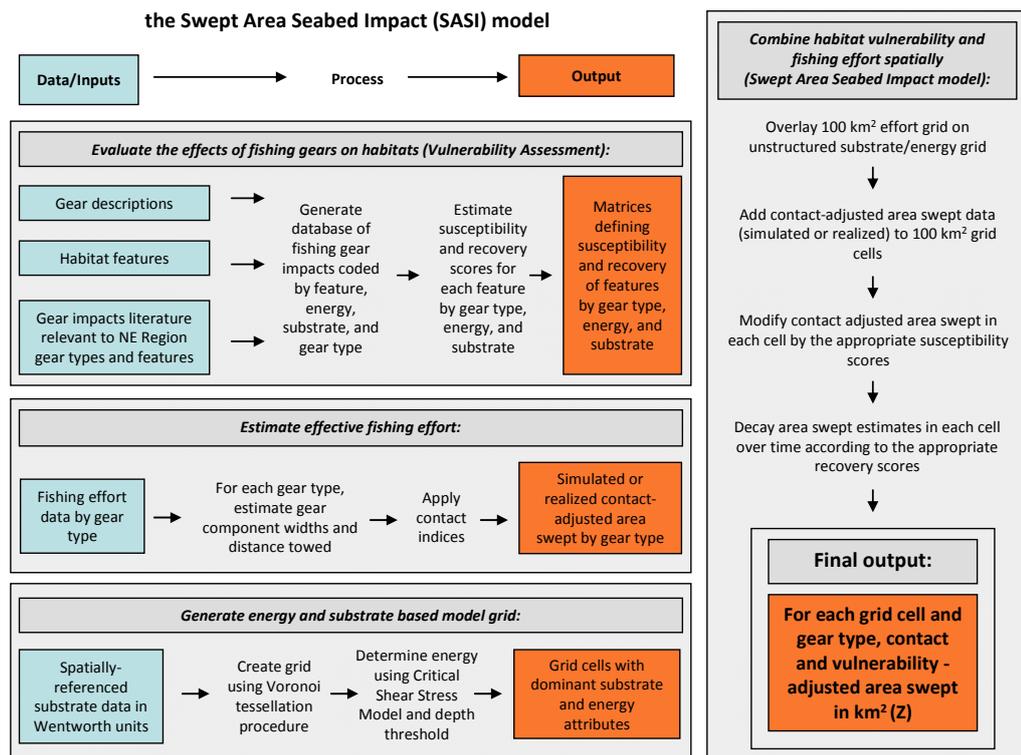


Figure 4.2.1. SASI model components flowchart.

The SASI model estimates adverse effect (Z) in km² by modifying the nominal area swept by the gear based on the degree to which the gear components (e.g. foot rope, doors) contact the seabed and the vulnerability of the habitat features to such contact. Therefore, one unit of fishing effort will generate an impact on benthic habitat that is equal to the area swept by that unit of effort, A , scaled by the assessed vulnerability of the underlying habitat type to that type of fishing gear.

The susceptibility parameters initially modify area swept, and the recovery parameters determine the rate of decay of that adverse effect in the years following the impact. Incorporating this recovery vector requires a discrete difference equation. Let the basic equation be:

$$Z_{t+1} = Z_t [1 + (X_t - Y_t)],$$

where Z_t is adverse effect going into year t , X_t is the positive effect of year of habitat recovery, and Y_t is the adverse effect of one year of fishing activity (i.e., A modified by the susceptibility parameters). If adverse effect in a given year (Y_t combined with Z_t) is greater than recovery, X_t , Z_{t+1} will be negative.

The positive effect term X_t is the proportion of Z_t that recovers within a year, and is estimated using a linear decay model:

$$X_t = \frac{[\lambda(A\omega)_{t_0}] \Delta t}{Z_t}$$

The recovery parameter, λ , represents the decay rate and is calculated as $1/\tau$ where τ is the total number of years over which the adverse effects of fishing will decay. t_0 is the initial year when the effect entered the model, and Δt is the contemporary time step, such that $\Delta t = t - t_0$ where t is the year for which the calculation is being made.

A , the contact-adjusted area swept by one unit of fishing effort, can be decomposed into:

$$A = (w\chi)d,$$

where, w is the linear effective width of the fishing gear and χ is a constant representing the degree of bottom contact a particular fishing gear component may have. The variable d is the distance travelled in one unit of fishing effort.

The adverse effect term Y is the proportion of Z that is introduced into the model at time t :

$$Y_t = \frac{(A\omega)_t}{Z_t}$$

Indexing this dynamic model across all units of fishing effort (j) by nine fishing gear types (i) and a matrix of habitat types determined by combinations of five sediments (k), two energy environments (l) and 27 individual habitat features (m) (see Table 3 for example) leaves us with:

$$Z_{t+1} = Z_t + \left[\sum_{i=1}^9 \sum_{j=1}^n \sum_{k=1}^5 \sum_{l=1}^2 \sum_{m=1}^{27} \left[\left(\lambda(A_{i,j}\omega_{k,l})_{t_0} \Delta t \right) - (A_{i,j}\omega_{k,l})_t \right] \right]$$

4.2.4 Mapping and Spatial Interpolation

Area swept fishing effort data and vulnerability information were spatially referenced using fishing vessel trip reports and a model-domain-wide map of surficial sediments. The sediment map was generated using 68 968 sediment samples from the US Geological Survey's usSEABED database (Reid *et al.* 2005) and University of Massachusetts Dartmouth School for Marine Science and Technology (SMAST) continental shelf video survey database (Stokesbury *et al.* 2004, 2010). Sediments were classed based on particle size (using the Wentworth scale) into mud, sand, granule/pebble, cobble, and boulder and the dominant sediment type in each sample was estimated based on volume, area or frequency of occurrence in local replicates. As this required amalgamating several data sources, a Voronoi tessellation of the sampling locations was used to create an unstructured map grid (Figure 4.2.2, Isaaks and Srivastava 1989) which did not smooth the data values and allowed direct query of the data sources during the analysis. Each of unstructured grid cells was then classified as having a high or low energy level using literature-based shear stress and depth-based criteria corresponding to the critical shear of coarse sand (Table 4.2.2). This threshold was selected because the sediments in 92% of the shelf area (depths $\leq 300\text{m}$) were sand (68%) or mud (24%). Finally, a 100 km² grid was overlain on the unstructured grid, and the area-weighted sediment composition of each 100 km² grid cell calculated based on the attributes of the corresponding unstructured cells. This procedure is equivalent to Sibson's Natural Neighbor Interpolation but yields a distribution rather than a weighted average value (Sibson 1981).

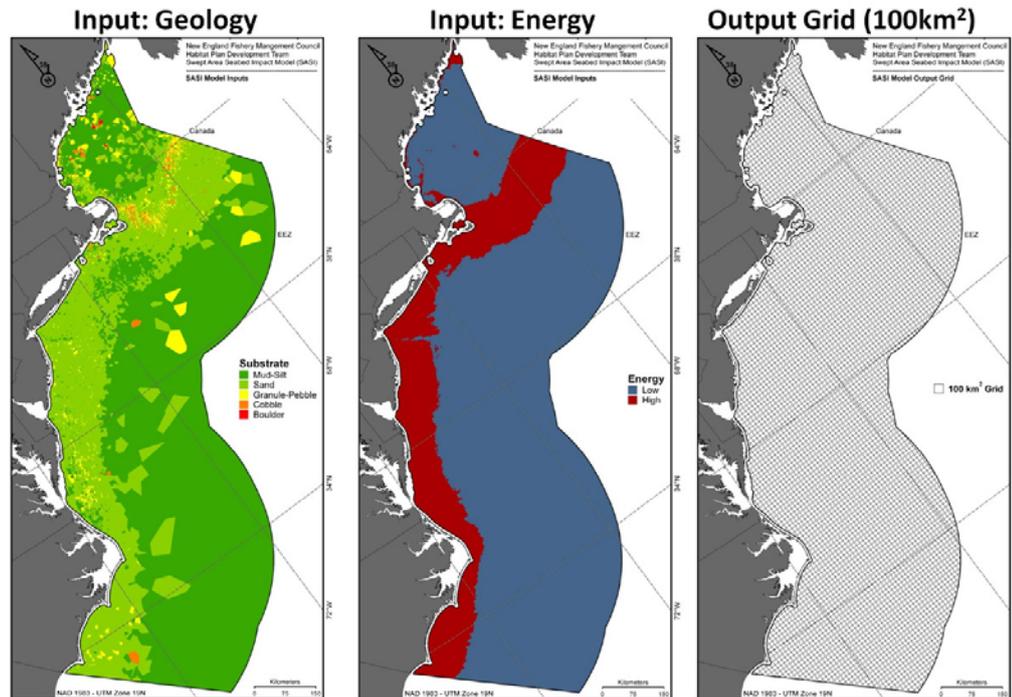


Figure 4.2.2. Model grids. From left: Voronoi diagram of sediment samples ($N = 68,968$), showing mud (green), sand (light green), granule-pebble (yellow), cobble (orange), and boulder (red); Energy, with low energy in blue and high in red; Structured 100 km² grid for fishing effort data.

4.2.5 Fishing gears evaluated

Only seabed impacts from bottom-tending gears that account for substantial landings, revenue, and/or days at sea were evaluated. According to the National Marine Fisheries Service Vessel Trip Reports (VTR) from 1996–2008 federal or state-managed species were harvested with 45 gears. However, only eight gear types accounted for roughly 99% of fishing: ocean quahog/surf clam dredge, sea scallop dredge, sink gill-net, bottom longline, bottom otter trawl (combining fish, scallop, and shrimp), mid-water otter trawl, lobster pot, and purse seine. Of these, midwater otter trawls and purse seines were not evaluated in the Vulnerability Assessment due to low or no bottom contact.

4.2.6 Spatial and Temporal observations and Modelling Scales

Ecological studies should clearly define the components of their sampling and analysis scales (Dungan *et al.* 2002). Most importantly, no spatial or temporal structure can be detected that is smaller than the sampling grain or larger than the extent (Legendre and Legendre, 1998). The scale of sampling and analysis includes three primary levels; the *grain* is the elementary sampling unit (most basic measurement scale), the *lag* is the distance or time between samples and *extent* is the sampling domain (Dungan *et al.* 2002).

The decision to use a 100 km² model output grid was based on the spatial scales of the input data (Table 4.2.4). The most poorly resolved data were the vessel trip reports (VTR) which vary in accuracy from the tow level to the trip level. Therefore the fishing effort data were aggregated at the 100 km² cell level and the distribution of habitat features in each cell determined as described above.

Table 4.2.4. Spatial Scales

Input	Data Source	Spatial Scale		
		Grain	Lag	Extent
Geology	Video Survey	100 m ²	1 km	70 000 km ²
Geology	usSEABED	0.1–0.5 m ²	3.1 km	598 089 km ²
Geology	Combined	0.1–100 m ²	1.96 km	598 089 km ²
Energy	NOS Depth	1–10 m ²	0.35 km	598 089 km ²
Energy	FVCOM CSS	–	5.9 km	308 976 km ²
Fishing	VTR	3–11 000 km ²	2–100 km	598 089 km ²
SASI Output		100 km²	100 km²	598 089 km²

4.2.7 Simulated Fishing Model Runs

Simulated outputs are based on running the SASI model with a hypothetical, uniformly distributed amount of fishing (area swept) applied to each 100 km² grid cell for each gear type. During the model run 100 km² of nominal area swept (A) was added in each annual time step. At each time step, the susceptibility and recovery values for the habitat features in each model cell were randomly drawn from the ranges defined in the vulnerability assessment. The model was run 100 times and the median feature Z_{∞} (Z infinity) values were assessed. The model reached asymptotic equilibrium in year 11 because the maximum recovery time assigned to the habitat features was 10 years. The amount of area-swept remaining in year 11 is thus referred to as Z_{∞} . The results and maps show the adverse effects of a particular gear type given the sediment and energy distributions irrespective of real fishing. This informs assessments of the vulnerability of a given location to fishing and allows the comparison of areas which are presently open or closed (Figure 4.2.3).

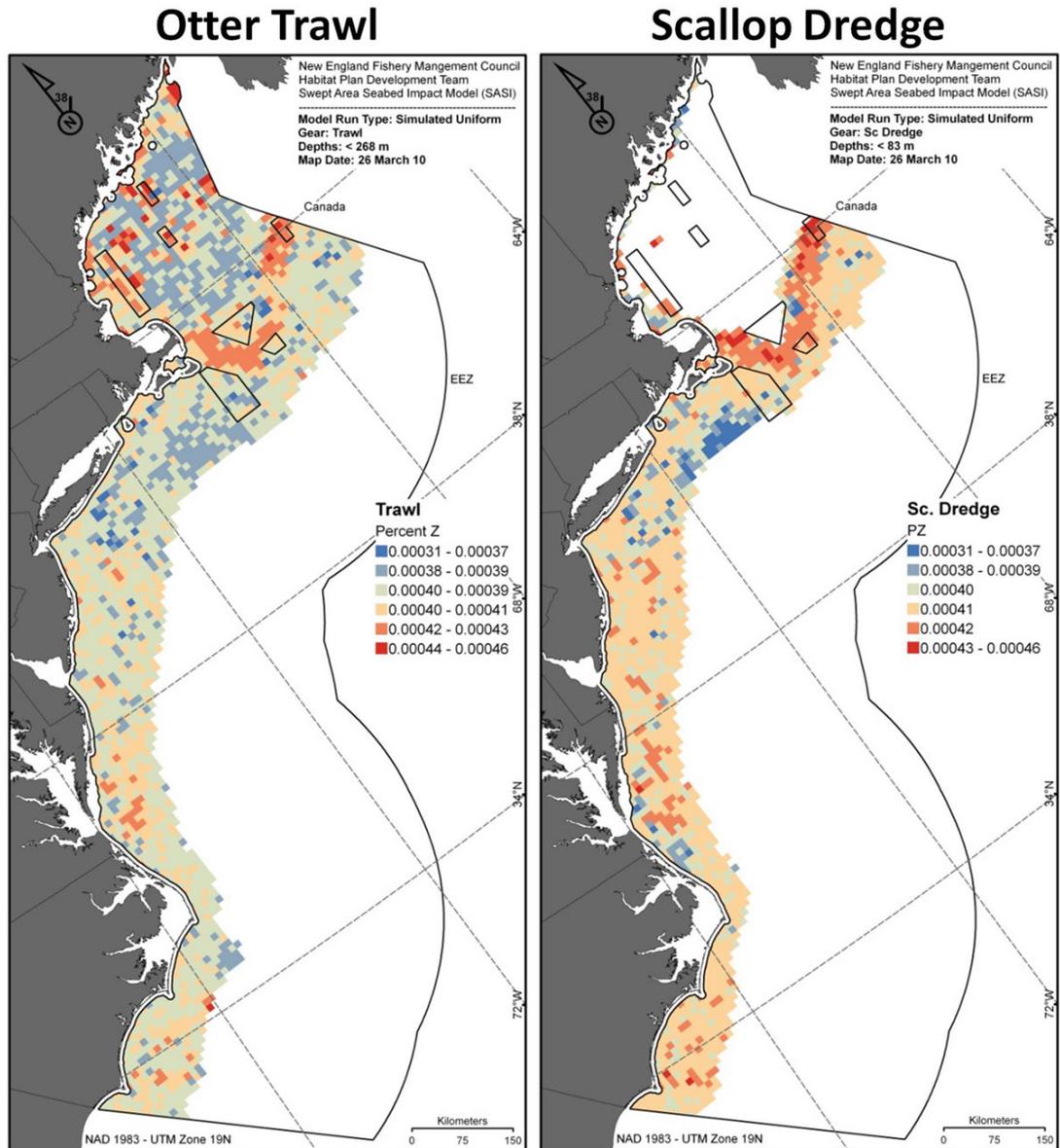


Figure 4.2.3. Simulated uniform fishing outputs for Otter trawl and Scallop dredge. The black boundaries are present MPAs (EFH closed areas).

4.2.8 Realized Fishing Model Runs

Realized model runs estimated the impact of real fisheries on the seabed. The model configuration was identical to the simulated runs except area swept (A) was based on VTR data from 1996–2008. As with the simulation, realized area swept was added in annual time steps. However, realized outputs were mapped annually to show changes in fleet activity over time (Figure 4.2.4). To ensure that the annual Z values reflected fishing prior to 1996, a 10 year burning period based on 1996 fishing was used.

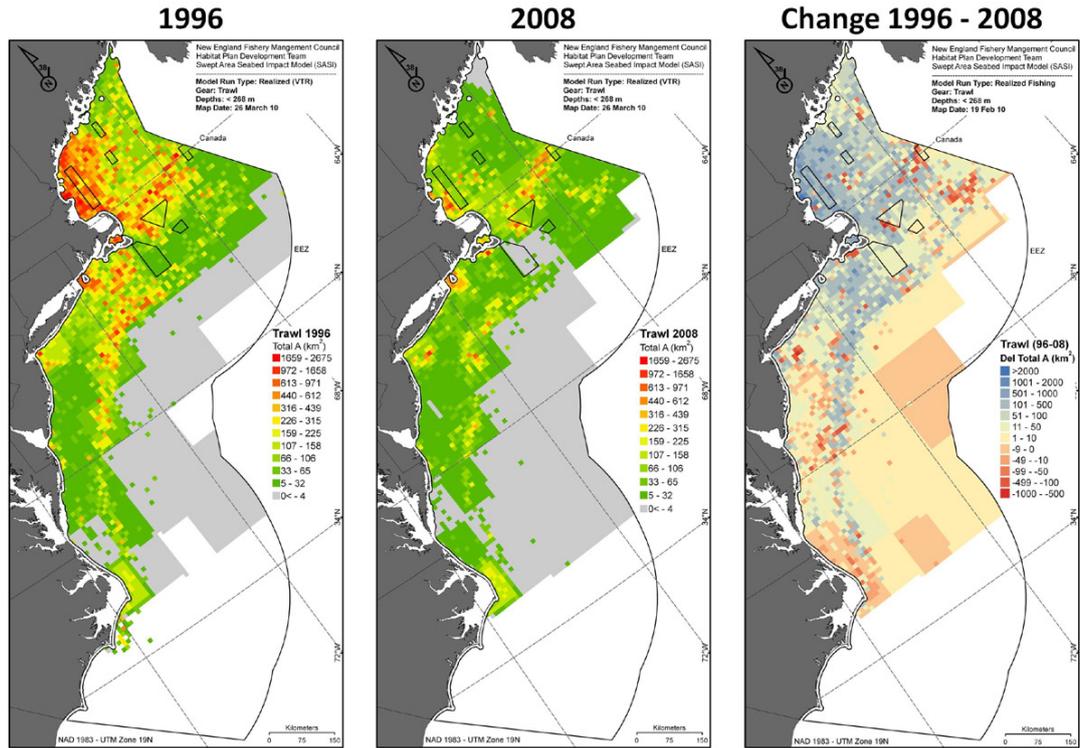


Figure 4.2.4. Realized fishing model output for years 2008 (left) and the change in fishing between 1996 and 2008 (right). The black polygons are present MPAs (EFH closed areas). In the right-hand panel (Change 1996-2008) blue indicates less and red indicates more area swept.

Trawl area swept accounted for the majority of fishing effects and by 2009 total area swept declined to near half of 1996 levels due to regulatory fishing effort reductions (Figure 4.2.5).

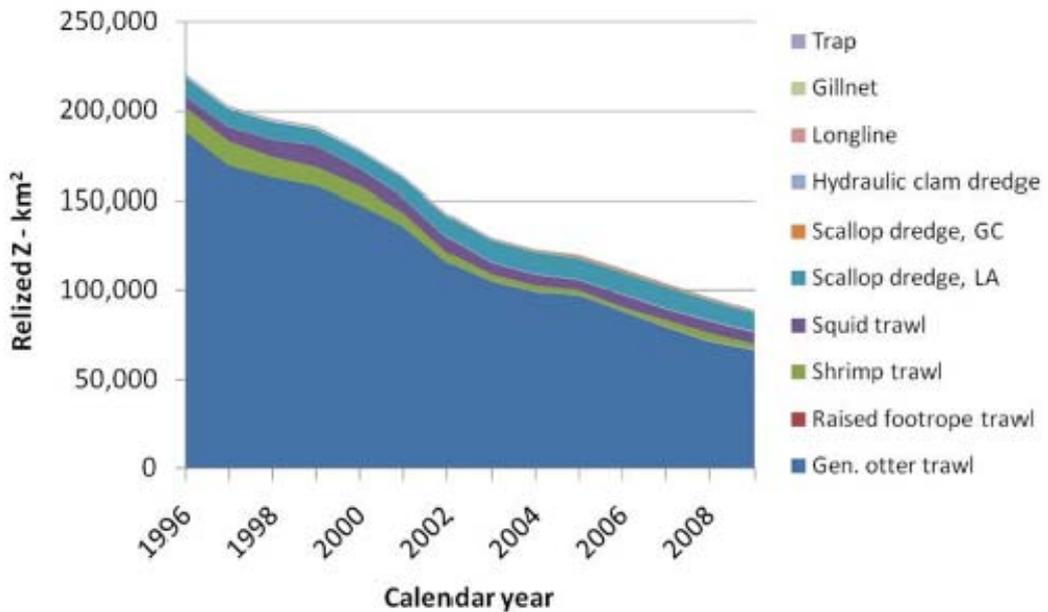


Figure 4.2.5. Realized model output for years 1996–2009.

4.2.9 Hotspot and Cluster Identification

Fishery managers identified the following objectives for the SASI model results assessment: 1) explore the spatial structure of the asymptotic area swept and find clusters of high and low Z_{∞} for each gear type, 2) determine how well present Marine Protected Areas (MPAs) do at minimizing Z_{∞} , and 3) identify areas with similar or higher Z_{∞} values than the present EFH MPAs. These MPAs all prohibit the use of mobile fishing gears.

4.2.10 Spatial Structure and Cluster Analysis

Local Indicators of Spatial Association (LISA) statistics including Moran Scatterplots and Local Moran's I were used to explore the spatial structure of Z_{∞} and to determine if each SASI grid cell was a member of a high or low Z_{∞} cluster. The LISA statistics were developed by Anselin (1995) and are designed to test individual sites for membership in clusters. These tools differ from commonly used global statistics such as Moran's I , Geary's c , and Matheron's variogram which were designed to describe the general autocorrelation characteristics of a dataset. Cressie's (1993) "pocket plot" can identify outliers but does not provide a formal test of significance. Variograms can be used to dissect spatial patterns into their directional components, but are not designed for single spatial foci as are local statistics. Recently, Harris and Stokesbury (2010) used these methods to assess the spatial structure of local surficial sediment characteristics on Georges Bank, USA.

The spatial association of each SASI model grid cell with its neighbors was estimated with the Local Moran's I_i (Anselin 1995):

$$I_i = \frac{x_i}{Q_i^2} \sum_{j=1, j \neq i}^n w_{i,j} x_j,$$

where

$$Q_i^2 = \frac{\sum_{j=1, j \neq i}^n w_{i,j}}{n-1} - \bar{X}^2.$$

Where $x_i = Z_{\infty i} - \bar{Z}_{\infty}$, $Z_{\infty i}$ is the asymptotic area swept accumulated for cell i , and \bar{Z}_{∞} is the overall mean asymptotic area swept accumulation value for the model domain. The neighbourhood weights $w_{i,j}$ were determined using Queen Contiguity (i.e. the 8-neighbor rule). When $I_i > 0$ there is positive local autocorrelation, i.e., the cell is in a neighbourhood of cells with similar characteristics, but which deviate (positively or negatively) from the overall mean cell characteristics. Negative autocorrelation ($I_i < 0$) occurs when the cell is in a neighbourhood with dissimilar Z_{∞} characteristics. When $I_i = 0$ the cell is in a neighbourhood with random characteristics, or when the cell and its neighbours have characteristics equal to the overall mean (Boots 2002).

The null hypotheses that Z_{∞} was globally or locally random (I and $I_i = 0$) were tested by estimating p -values for I and I_i using 9,999 permutations of a spatially random Z_{∞} reference distribution (GeoDa® software, Anselin *et al.* 2006). These p -values are one-sided *pseudo*-significance values: $p = (M + 1) / (R + 1)$ where R is the number of permutations and M is the number of instances where I or I_i are greater than or equal to the observed value for positive autocorrelation, or less than or equal to the observed value for negative autocorrelation.

A Moran scatterplot is a bivariate plot of w_i as a function of x_i , and the slope of a line fit to the scatterplot gives global Moran's I (Anselin 1996). The four quadrants of the

scatterplot indicate an observation's value relative to its neighbours with cluster significance defined by the p-values associated with each cell's I_i . Cells with higher than average values ($x_i > 0$) with neighbouring high values ($w_i > 0$) are in the High-High quadrant and together with those in the Low-Low ($x_i < 0, w_i < 0$) quadrant indicate positive local spatial autocorrelation. The High-Low (H-L) and Low-High (L-H) quadrants indicate negative local spatial autocorrelation. The objective of this spatial analysis is to identify clusters of high Z_∞ so the High-High (H-H) and High-Low (H-L) clusters were mapped.

Local spatial statistics are particularly susceptible to Type I errors then the data are global autocorrelated because multiple comparisons are being made among many values some of which are clearly not independent (Ord and Getis 2001, Boots 2002). Therefore, a range of p-values ($p \leq 0.1, 0.05, \text{ and } 0.01$) were examined as the criteria for systematically defining clusters of Z_∞ .

Asymptotic area swept (Z_∞) for all gear types demonstrated strong global and local spatial autocorrelation (Table 4.2.5, Figure 4.2.6).

Table 4.2.5. Global Morans I statistic and p-value for each gear type.

Gear	Global Morans I	p
Trawl	0.4748	≤ 0.0001
Dredge	0.465	≤ 0.0001
H. Dredge	0.8281	≤ 0.0001
Gillnet	0.4029	≤ 0.0001
Longline	0.4052	≤ 0.0001
Trap	0.6868	≤ 0.0001

The Moran scatterplots show the strong degree of global and local spatial autocorrelation for each gear type and identify the quadrant location of every SASI grid cell and neighbourhood in the model domain (Figure 4.2.6).

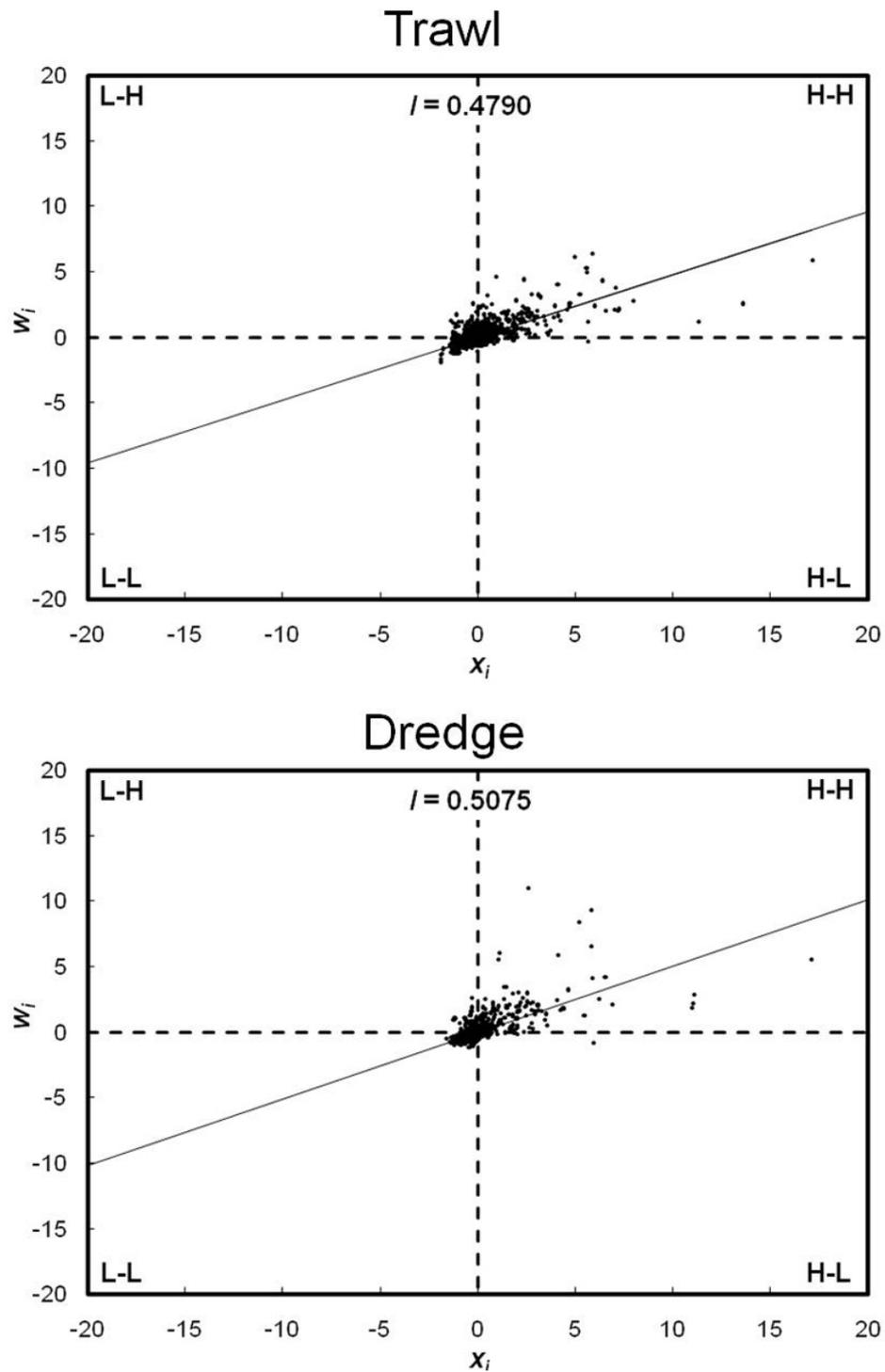


Figure 4.2.6. Moran scatterplots for trawl and dredge gears.

The LISA analysis delimited clusters of high and low Z_{∞} for all gear types at the $p \leq 0.1$, 0.05 and 0.01 levels. Using $p \leq 0.1$ criteria resulted clusters which were nearly identical to $p \leq 0.05$ (11 additional cells, see Figure 4.2.3) so only $p \leq 0.05$ and 0.01 results are presented (Figures 4.2.2–4.2.6). Regardless of gear type most of the cells in the model did not form significant clusters (Figure 4.2.7). Where clustering occurred, between 85 and 99% of cells were in Low-Low (L-L) or High-High (H-H) clusters consistent with strong spatial autocorrelation. Outliers High-Low (H-L) and Low-High (L-H) were rare.

Seven clusters were identified for both trawls and scallop dredges. These clusters corresponded to known geomorphological features (Table 4.2.6).

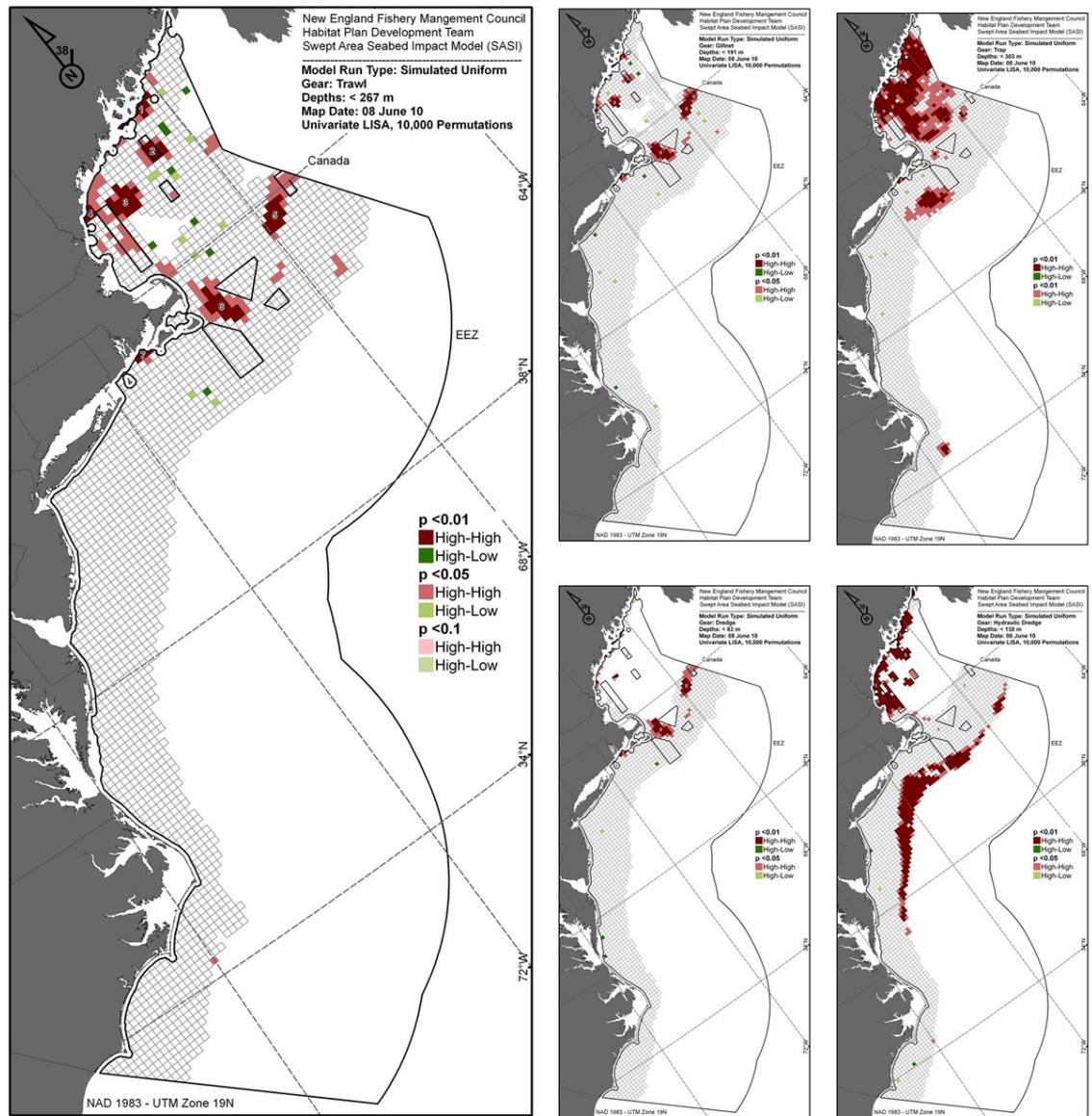


Figure 4.2.7. Maps of Z_{∞} H-H (High-High) and H-L (High-Low) clusters defined by $p \leq 0.1$, 0.05 and 0.01 levels for each gear type.

Table 4.2.6. Name, mean and sum z and the area of each $p \leq 0.01$ cluster identified for Trawl gear.

Trawl $p \leq 0.01$ Clusters				
Number	Name	Mean Z_{∞}	Sum Z_{∞}	km ²
1	South of Mt Desert Island Cluster	67.828	474.797	470
2	Jeffrey's Bank Cluster	60.898	487.185	800
3	Platts Bank Cluster	57.369	917.911	1600
4	Cape Neddick Cluster	51.416	154.247	283
5	Georges Shoal Cluster	57.404	746.251	1300
6	Great South Channel Cluster	55.580	833.696	1500
7	Brown's Ledge Cluster	55.785	223.138	273

4.2.11 Assessment of Present MPAs

Equal Area Permutation tests (EAP) were used to determine the levels of Z_{∞} in present MPAs relative to the model domain. The area-weighted mean Z_{∞} for each MPA was compared to a permutation distribution of values calculated using 9,999 randomly placed areas equal in size to the tested MPA. The percentile of the tested area's Z_{∞} value and number of areas with $Z_{\infty} \geq$ to the tested area were identified. These permutation-based areas were mapped along with the 100 highest mean Z_{∞} value areas (99th percentile of the permutations distribution, Figure 4.2.8).

The shapes and orientations of the tested MPAs vary. To construct consistent permutation distributions for all areas and gears circles were used because they are isotropic and their areas can be calculated simply using radii ($\text{Area} = 2\pi \times \text{radius}^2$).

The EAP results are presented in a summary table (Table 4.2.7) in histograms indicating the position of the tested areas in their respective EAP distribution, and in maps. For example, Closed Area I South, a 584 km² Essential Fish Habitat Closed Area, falls at the fiftieth percentile in the permutation distribution indicating the MPA is not likely minimizing Z_{∞} and may be displacing fishing effort to more vulnerable seabed (Figure 4.2.8).

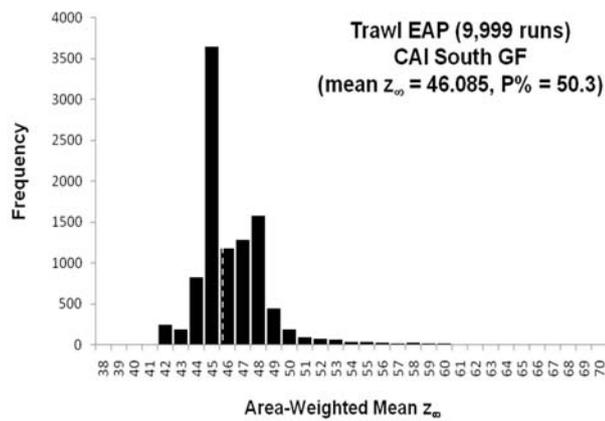
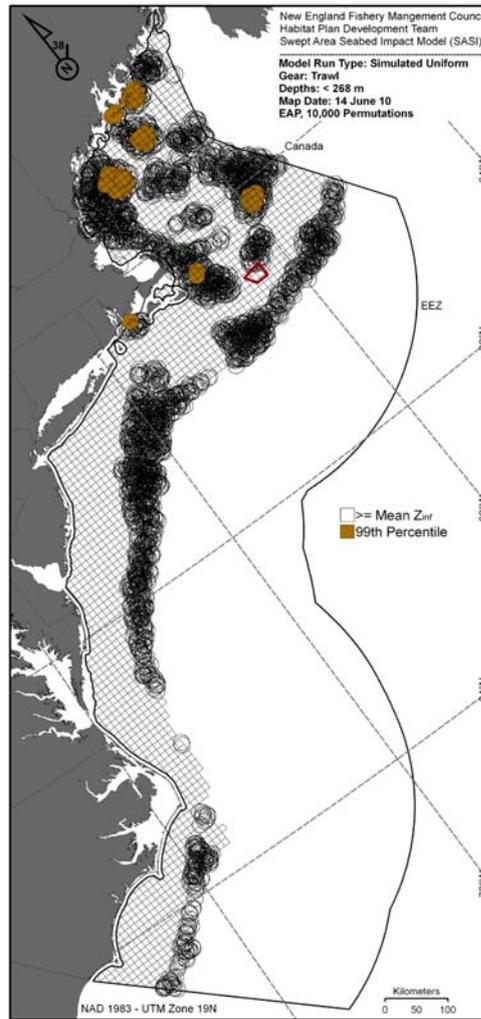


Figure 4.2.8. Trawl EAP map and histogram for CAI South EFH Groundfish Closed Area (red polygon). Open circles are permutation areas with $z_w \geq$ than the tested area, and solid orange circles show the locations of the highest 100 z_w permutation values. The histogram indicates the position of the tested area in the EAP distribution (dashed line), and shows the z_w (mean z_w) and permutation percentile (50.3 P%).

Table 4.2.7. Trawl EAP results with tested areas, their size, \bar{z}_W permutation percentile (P%) and number of permutation areas with $\bar{z}_W \geq$ than the tested area.

Closed Area	Tested area result			Permutation results		
	km ²	AWM z_{∞}	Sum z_{∞}	P%	Areas with \geq Mean z_{∞}	
Groundfish (Amendment 13) EFH Closed Areas	Cashes L. EFH GF	443	51.437	588.06	96.00%	400
	Jeffreys B. EFH GF	499	57.667	510.13	99.10%	90
	WGOM EFH GF	2272	50.114	1777.55	95.10%	490
	CAII EFH GF	641	49.425	844.79	92.20%	780
	CAI N. EFH GF	1937	45.186	1287.93	12.80%	8721
	CAI S. EFH GF	584	46.085	609.67	50.30%	4970
	NLCA EFH GF	3387	46.787	2205.24	56.80%	4320

4.2.12 Model assumptions and limitations

Any model is necessarily a simplification of reality and should be interpreted with a full understanding of the underlying data sources and assumptions. The primary assumptions of SASI are 1) **that area swept, when adjusted for gear contact with the seabed, is a proxy for seabed impact**, and 2) **seabed impact as defined is a suitable proxy for the adverse effect of fishing on fish habitat**. These assumptions reveal the major limitation of the model: **the relative importance of geological and biological habitat features to fish is not known**. Investigations of these critical relationships should be a research priority.

Other assumptions relate to the way fishing effort is combined in the model. Foremost among these is the assumption that fishing area swept is additive. As the model runs over time, units of fishing area swept are continually added in annual time steps. This area swept decays based on the appropriate feature recovery values for that substrate and energy type. Auster (1996) illustrates a linear decline in physical attributes due to fishing impacts, consistent with this assumption, but also discusses the issues of threshold and feedback effects. He hypothesized that an alternative to the “first pass” scenario is one that approaches a linear, arithmetic decline based on increased rate of impacts with feedback loops to an earlier state due to recovery/recruitment and the physical processes that reset the clock to some earlier state.

Another important assumption is that each of the geological and biological features impacted contributes equally to the modification of area swept. This equal weighting strategy was selected because no more well supported alternative was available. This further highlights the lack of information on the relationship between habitat features and fish.

A major limitation in this modelling work was the spatial resolution of fishing effort data. For example, vessel trip reports provide a single latitude/longitude coordinate for a fishing trip and the locations of all tows are inferred to this single point. Using the 100 km² structured grid allows the SASI model to bridge between low resolution effort data and the more finely resolved unstructured substrate grid. As the within-cell location of the fishing events are not known the area-swept is apportioned evenly over the cell and the impacts accrue based on the cell-wide distribution of habitat features.

Another model limitation relates to the availability of substrate data. Due to sampling with core and grab devices data on substrate classes larger than granule-pebble are unavailable in the waters outside the domain of the SMAST continental shelf video survey. For example, spatial distributions of hard substrates in the canyon areas along the edge of the continental shelf are not well known so these locations are not well resolved in the model grid due to lack of sampling. To ensure managers interpreting the spatial analysis results keep these limitations in mind a map of spatial data support was also created (Figure 4.2.9).

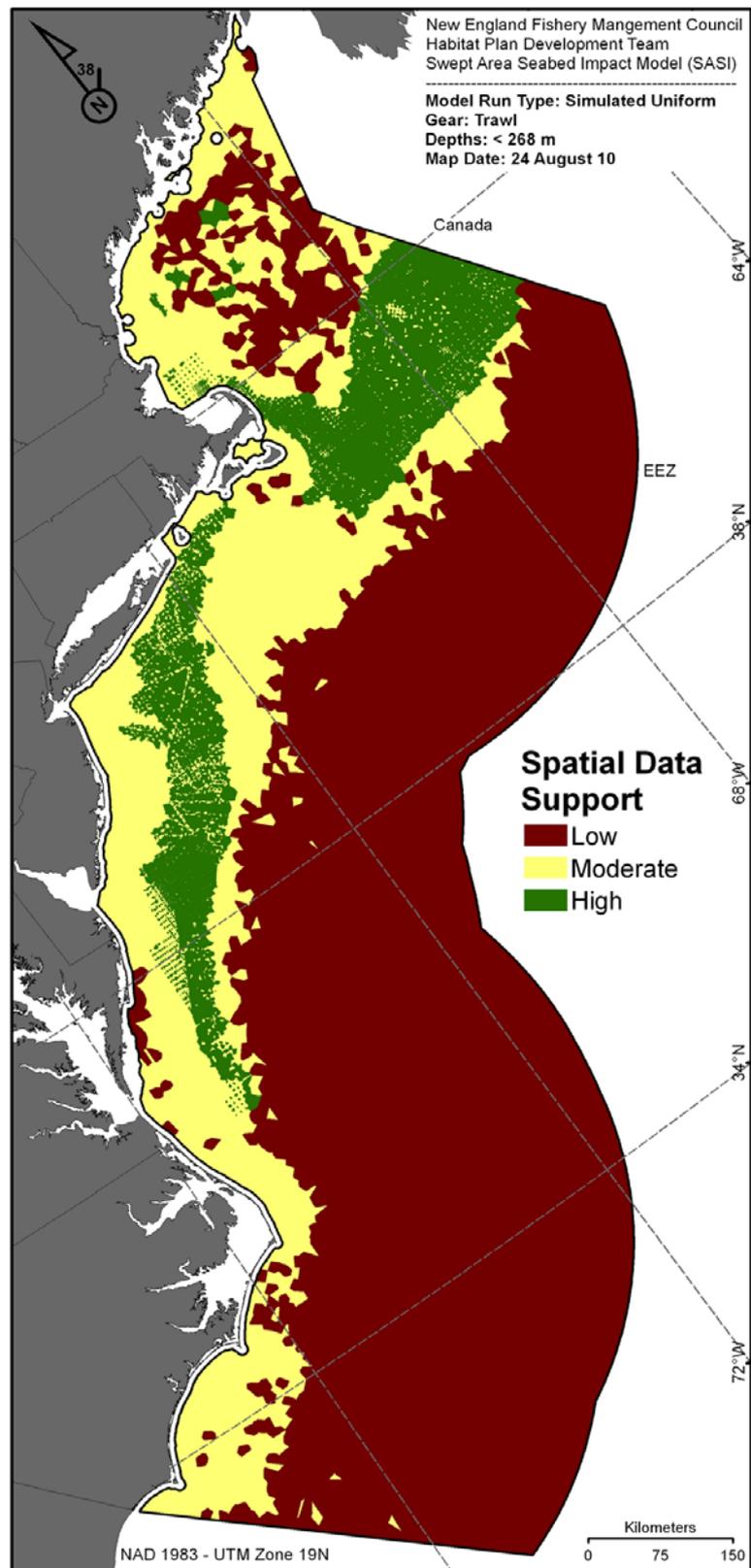


Figure 4.2.9. Spatial data support map showing regions with high, medium and low levels of supporting data. High = full range of substrates detectable, high sampling frequency, Moderate = only mud- granule pebble detectable or low sampling frequency, Low = only mud- granule pebble detectable and low sampling frequency.

4.2.13 Recommendations/ Future work

The development of this model has highlighted gaps in our knowledge of fish - habitat links and the fishing impacts on habitat. Goals for future work include:

- 1) Developing regionalized models (e.g. Gulf of Maine, Georges Bank) to account for localized feature distributions.
- 2) Use of vessel monitoring system (VMS) data to estimate area swept.
- 3) Testing geological and biological component weightings, or feature weightings within each component, using empirical data. This will require additional fieldwork and analysis.
- 4) Developing sediment-specific fishing gear contact indices.
- 5) Shortening the model time step to allow for estimation of seasonal effects (this might require seasonal estimation of vulnerability parameters as well).
- 6) Quantify the trade-off between habitat recovery gained in closed areas and correspondent increases in adverse effects in open areas due to the redistributed fishing effort.

4.3 Criteria-based MPA Evaluation: Biodiversity and the Georges Bank Essential Fish Habitat Closed Areas

4.3.1 Essential Fish Habitat closures and regions of high biodiversity

Since December 1994, closed areas have protected nearly 30% of on Georges Bank (NE USA) from commercial gears capable of catching (e.g. trawls and scallop dredges, Fogarty and Murawski 1998). Additional regulation was added in 2003 when large parts of these already closed areas were designated as Essential Fish Habitat (EFH) closures (Figure 4.3.1).

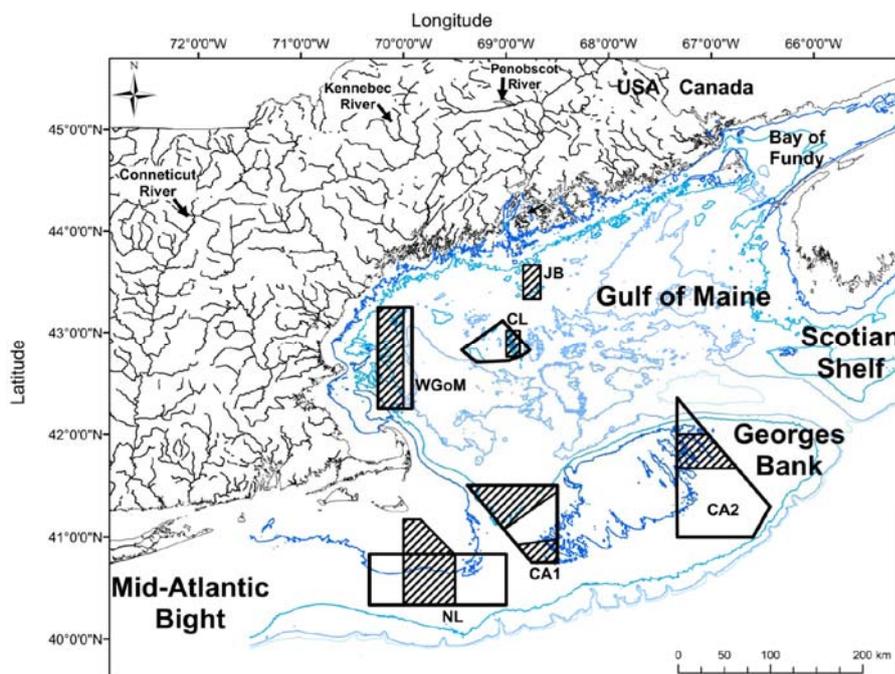


Figure 4.3.1. Georges Bank/Gulf of Maine region with closed areas (polygons) and EFH closures (hatched polygons). Only year-round closures are shown. WGoM = western Gulf of Maine, CL = Cashes Ledge, JB = Jeffery's Bank, NL = Nantucket Lightship, CA1 = closed area 1, CA2 = closed area 2.

Presently, the Gulf of Maine and Georges Bank are assessed as two distinct stock areas. The approach was adopted based on oceanographic and bathymetric differences justified during the previous era of single-species management. However, division amongst fish assemblages within the region does not conform simply to bathymetric changes and thus the legacy of past decisions is a significant issue. Recent analysis of NMFS trawl survey data (see Box 4.3.1 for analysis summary) provides some details about how biodiversity, and specific assemblages of fish, are spatially structured (Figure 2, Jordaan *et al.* in review). Initially, the division by PC1 roughly follows the conventional stock separation of Georges Bank and the Gulf of Maine (Figure 4.3.2) and, if only those two assemblages are considered, the current closures do indeed contain some of each assemblage. However, further assemblage divisions (Figure 4.3.2, PC2-PC6) combined with fishing effort (Figure 4.2.4; Figure 4.2.7) leave significant gaps in coverage indicating that areas particularly rich in assemblages types (biodiversity hotspots) are not being covered (Figure 4.3.3) and even PC1 demonstrates that one cannot treat either the Gulf of Maine or Georges Bank as a single species assemblage or “ecosystem unit”.

Box 4.3.1 – PCA technique

The analysis of NMFS trawl survey data follows procedure outlined by Jordaan *et al.* (2010) for analyzing bootstrapped PCA (PCA_{BTSP}) and a “normal” PCA (PCA_{NRML}) with three steps:

- (1) Evaluate PCA_{BTSP} eigenvalues and establish stopping rules using 95% confidence intervals to divide PCs between those that provide a meaningful dissection of the data and those which are considered trivial components (Jackson 1993). Only relevant PCs are included in further analyses
- (2) Using the relevant PCs, species eigenvector 95% confidence intervals are compared to one another, and to a score of 0. This allows a determination of both which species are correlated in abundance (i.e.: form assemblages) and which (groups of) species are driving the patterns for PCs (significantly different from 0).
- (3) Relate relevant PC scores at each site to spatial data and map spatial biodiversity indices. An inverse distance weighting (IDW) interpolation technique established assemblage areas.

Incoherence between EFH closures and underlying fish assemblage structure becomes greater at finer scales of analysis, such as when analysis is restricted to the Maine-New Hampshire Inshore Trawl Survey (Jordaan *et al.* 2010), whose region only receives habitat protection from Jeffery’s Bank and a small part of the western Gulf of Maine closure (JB and WGoM, Figure 4.3.1). Thus, neither coastal patterns, nor the patchily distributed fish assemblages throughout coastal regions (Jordaan *et al.* 2010), are considered in the present closure system. At even finer spatial scales, trends in assemblages are driven by estuarine and wave-energy generated ecological gradients along the coastline of the inner Gulf of Maine (Jordaan 2010). Management policy

must not only involve multiple jurisdictional organizations, but also recognize different scales of assemblage structure and the different ecological drivers responsible for their persistence.

4.3.2 Legacy Conservation Measures

Loss of biodiversity, in particular, has been used to promote marine spatial restrictions in fishing effort. However, this often results in a significant conundrum; modern fisheries management has shifted to a more ecosystem-based or multi-species perspective, but both historical policy and present day fisheries allocations are species-specific. The legacy of species-by-species management policy has left the present-day Gulf of Maine -Georges Bank region with a series of closed areas that do not appear to (and were never intended to) protect biodiversity.

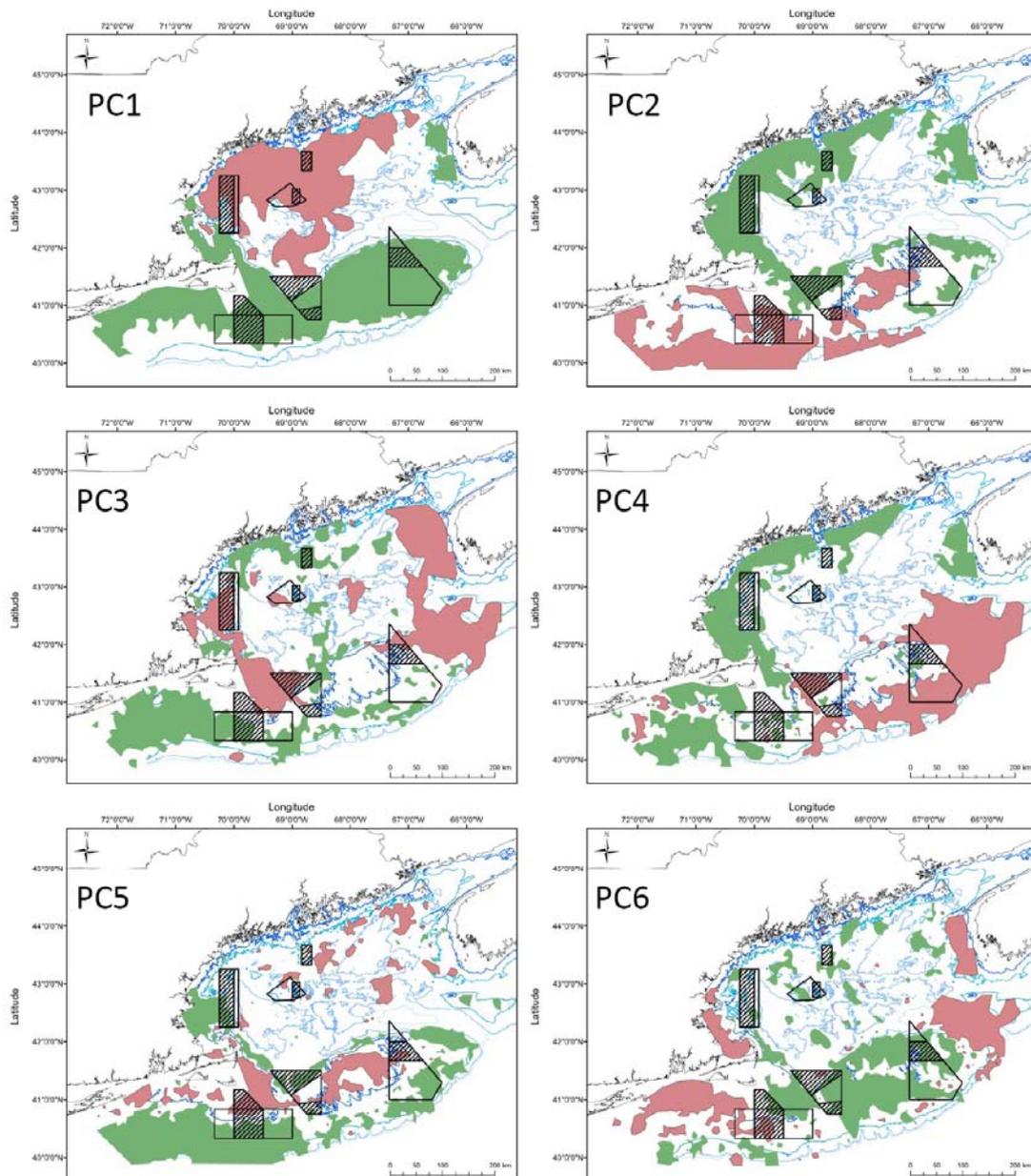


Figure 4.3.2. Patterns in species assemblages using NMFS trawl data and PCA-Bootstrap evaluated analysis (see Jordaan *et al.* 2010 for details of technique). Each figure represents two contrasting assemblages of species. Hatched polygons=EFH closures, polygons= closed areas.

The EFH closures (Figure 4.3.1) are single species-centric since characteristics used to determine placement was based on Atlantic cod (particularly juvenile) habitat. Closed Area II, for example, was defined as the boundaries of the existing habitat areas of particular concern (HAPC) for cod based on the presence of gravel/cobble substrate. In contrast, Groundfish Amendment 13 states that industry credits Closed Area I for rebuilding haddock, with stock assessments showing a modest increase, but does not provide much benefit for cod except that it contains a spawning area. Thus, management success can be measured by benefits to single species but biodiversity is often overlooked, poorly understood in relation to oceanographic processes, and not quantitatively considered in management plans.

4.3.3 Negative effects of single-species focused spatial planning

Closing areas with a single-species focus and vague stock rebuilding objectives can have negative impacts which may be equivalent to or greater than not closing areas. Consider the impacts of the Georges Bank closures on areas with high biodiversity. There is a direct relationship between increasing fishing intensity, declines in diversity, and loss of secondary production (Hinz *et al.* 2008; Hinz *et al.* 2009). While geographically-based management needs to include area-based restrictions, such measures displace and concentrate fishing effort to the open areas. Thus, species and habitats not considered in planning may experience increased risk of overexploitation and consequent adverse impacts (Hilborn 2003, Murawski *et al.* 2005, Hiddink *et al.* 2006, Harris and Stokesbury 2010). For example, fishing effort displaced by the Georges Bank closures has concentrated along protected area boundaries (Murawski *et al.* 2005, Kellner *et al.* 2007). Nearly 10% of trawling effort now occurs at distances 1 km from the year-round closures, with about 25% of effort located within 5 km (see Figure 4.2.4 above, Murawski *et al.* 2005). Some species (haddock, yellowtail) appear to be benefitting from protected areas with catches and measures of profit per tow increasing closer to closed areas, while other species show no relationship between catch rates and distance from closed areas. As depicted clearly in Figure 1.2.4 above displaced fishing effort has become concentrated along the west and northern boundaries of CAI and CAII (Murawski *et al.* 2005). This displaced fishing effort now overlaps with some of the biodiversity hotspots (Figure 4.3.3) and is heaviest west of CAI in what is probably important habitat for the cod species assemblage (Figure 4.3.2, PC3-red hue).

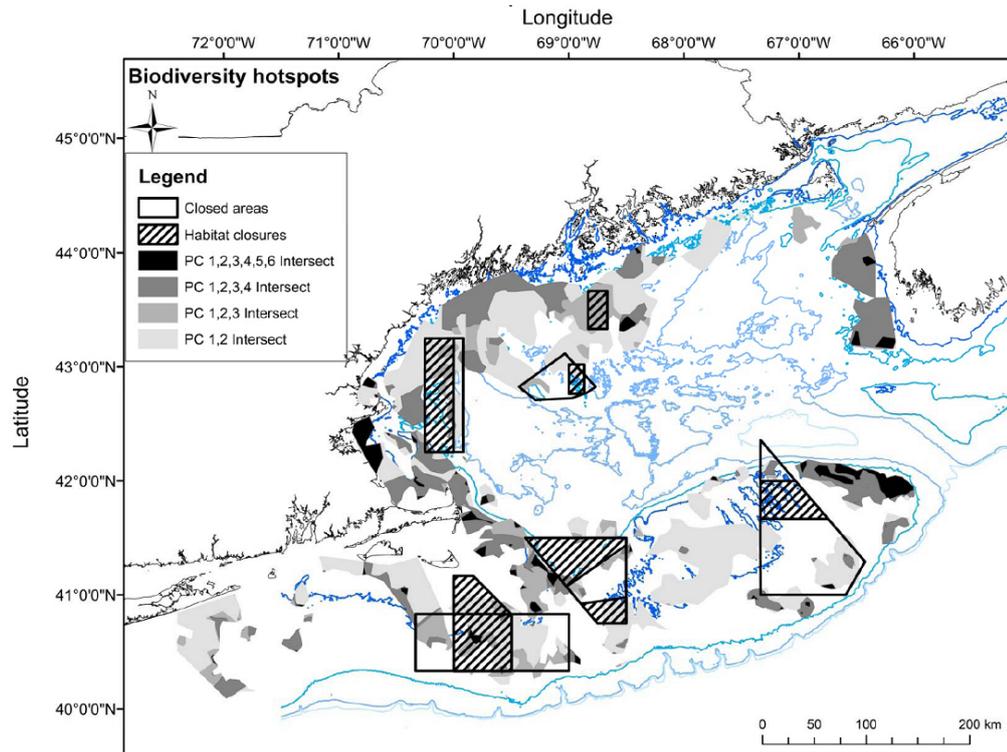


Figure 4.3.3 Georges Bank/Gulf of Maine region closed areas and biodiversity hotspots (from Jordaan *et al.* in review).

This corresponds with the sediment maps produced by Harris and Stokesbury (2010) which show that a majority of Georges Bank's cobble and boulder habitats occur outside the closed areas. Thus fishing has inadvertently been concentrated on the very habitats that the EFH closed areas sought to protect.

4.3.4 Conclusions and Future Work

These findings emphasize that year-round closures will not have universally positive impacts on the abundance and spill-over potential of all groundfish stocks until there is a more systematic and comprehensive design approach. Understanding the spatial distribution of multi-species groups and their important habitats is required for designing of area-based strategies that do not inadvertently place rare species and depleted populations and sensitive habitats at risk (Hinrichsen *et al.* 2009, Suuronen *et al.* 2010). Because of the multi-scaled nature of ecological systems a fittingly hierarchical organization of reserves, with varying degrees of protection, is required to simultaneously meet species-specific and system-wide conservation objectives.

4.4 Criteria-based MPA Selection: North Sea – Dutch EEZ

4.4.1 Background

The European Marine Strategy Framework Directive 2008/56/EC (MSFD) establishes a framework within which Member States shall take the necessary measures to achieve or maintain 'good environmental status' in the marine environment by the year 2020 at the latest. This objective is to be pursued through the progressive elaboration of strategies for their marine waters. 'Good environmental status' shall be determined at the level of the marine region or subregion (specified in MSFD Article 4) on the basis of eleven qualitative 'descriptors' specified in Annex I of the MSFD.

One of these descriptors involves biodiversity and is defined as:

"Descriptor 1: Biological diversity is maintained. The quality and occurrence of habitats and the distribution and abundance of species is in line with prevailing physiographic, geographic and climatic conditions."

Full text on the criteria for good environmental status that are relevant to this descriptor is given in the European Commission Decision of 1 September 2010 on criteria and methodological standards on good environmental status of marine waters (COM: 2010/477/EU). The Commission Decision states that:

"Assessment is required at three ecological levels: species, habitats (including their associated communities, in the sense of biotopes), and ecosystems."

Three criteria have been defined for the assessment of any species, which are i) species distribution, ii) population size, and iii) population condition. Criteria for the assessment of habitats are their i) extent, ii) distribution, and iii) condition (for the latter, in particular the condition of typical species and communities). The criterion for the ecosystem level is a combination of both species and habitats. An overview of the criteria and the indicators related respectively to them is given in Table 4.4.1.

Table 4.4.1. Criteria for good environmental status relevant to Descriptor 1: Biological diversity.

Ecological level	Criterion	Indicator	
Species	1.1 Species distribution	1.1.1 Distributional range	
		1.1.2 Distributional pattern within the latter, where appropriate	
		1.1.3 Area covered by the species (for sessile/benthic species)	
	1.2 Population size	1.2.1 Population abundance and/or biomass, as appropriate	
	1.3 Population condition	1.3.1 Population demographic characteristics (e.g. body size or age class structure, sex ratio, fecundity rates, survival/ mortality rates)	
		1.3.2 Population genetic structure, where appropriate	
Habitat	1.4 Habitat distribution	1.4.1 Distributional range	
		1.4.2 Distributional pattern	
	1.5 Habitat extent	1.5.1 Habitat area	
		1.5.2 Habitat volume, where relevant	
	1.6 Habitat condition	1.6.1 Condition of the typical species and communities	
		1.6.2 Relative abundance and/or biomass, as appropriate	
		1.6.3 Physical, hydrological and chemical conditions	
	Ecosystem	1.7 Ecosystem structure	1.7.1 Composition and relative proportions of ecosystem components (habitats and species)

4.4.2 Research question

The Dutch government (Ministry of Agriculture, Nature and Food Quality) has initiated a study to explore the use of the "Descriptor 1 - Biological diversity criteria for defining ecological valuable areas in the Dutch EEZ that may qualify for protection

(i.e. MPAs) on the basis of GES-criteria". In this section we present an explorative study to illustrate some challenges to using criteria for identifying hotspots of declining fish diversity.

4.4.3 Data

Data describing fish distributions (including elasmobranches) in the North Sea were taken from the first quarter International Bottom Trawl Survey (IBTS). The surveys use a standard bottom-trawl net (chalut à Grande Ouverture Verticale, GOV-trawl) that is specifically designed to sample fish that live at and above the seabed (Heessen *et al.* 1997). The IBTS sampling is stratified according to a grid of ICES rectangles (0.5° latitude; 1° longitude; approximately 56 x 56 km). Details of the gear and sampling strategies can be found in the manuals for the survey (ICES 2006). The data were extracted from the ICES DAtabase for TRAWl Surveys DATRAS, downloaded 9 August 2010.

Catch rates were raised to number of individuals caught per 60-min tow. Data from 1983–2010 were used in the analysis because all the participating countries followed the same sampling strategies during this period. To avoid the introduction of temporal trends that may be related to differences in the sampled survey area over time, only rectangles fished in at least 75% of the years were used. Fish were identified to the lowest possible taxonomic level, which was mostly to species level; however, for consistency we refer to all taxa as species. Corrections for misidentifications were made following the approach of ter Hofstede & Daan (2008). In addition, some fish were only identified to the family level (families Myctophidae, Serranidae, Percichthyidae, Blenniidae, Stichtaeidae, Callionymidae, Gobiidae, Bothidae and Rajidae). To avoid misinterpretation for non-existing species these family-level records were not included in the analyses. Gear selectivity is always an issue and survey catches never represent the complete fish community present in an area. Selectivity is particularly poor for smaller species so those with $L_{\max} \leq 10$ cm were excluded. There are also selectivity issues with large fish which may be able to escape capture by out swimming the gear, or pelagic species, which may be underrepresented in a bottom trawl survey. Since several of the analyses focus on the edges of the fish community, such as large fish (see below), these were kept included in the selected data set. Of course, the outcomes of these preliminary analyses may lead to adjustment of these data selections. The list of taxa to be initially explored includes 128 fish species.

4.4.4 Selection of indicators

A decline in the biological diversity of fish communities is considered to be a decay of the good environmental status, and will occur when species disappear from the system. The chance for species to disappear is highest when abundance is low and increases when the capacity for adaptation is limited. Changes in biological diversity can be determined using indicators. Several indicators have been selected based on their application in relation to the criteria for good environmental status relevant to spatial biological diversity of fish communities. These are given below and the method for obtaining insight in the spatial fish diversity is described.

- **Declining trends**, contributes to GES-criteria 1.1 and 1.2

When abundance of fish species declines over time, e.g. as a result of fisheries or climate change, local biodiversity of the fish community is expected to decline. A declining trend can occur both spatially by means of a decrease in the distribution range (relates to criterion 1.1 - species distribution) and/ or a decrease in abundance (relates to criterion 1.2 - population size). Thus areas with large numbers of species with de-

clining distribution and abundance trends may potentially qualify as marine protected areas.

- **Large fish species**, contributes to GES-criteria 1.1 and 1.2

Under the influence of fishing large fish species may disappear from the ecosystem, both through targeting and as a result of bycatch. The areas that are still occupied by the large fish species in relatively high numbers, or perhaps even more the areas from which the species have disappeared, could qualify as potential MPA's.

- **Large fish individuals**, contributes to GES-criterion 1.3

An important feature of a healthy fish population is a balanced age-structure or size-structure. Fishing pressure may result in fewer large fish in the population via targeting and or bycatch. A truncation in length structure within a population falls under criterion 1.3 (population condition). The areas that are still occupied by the large fish individuals in relatively high numbers, or perhaps even more the areas from which the older fish have disappeared, could qualify as potential MPA's.

- **Rarity**, contributes to GES-criteria 1.1 and 1.2

The concept of rarity unites two aspects: distribution (criterion 1.1) and abundance (1.2). Changes in local biological diversity will most likely occur in the areas inhabited by rare species, and on the edges of the distribution range of species where the abundance is lowest.

4.4.5 Caveats to consider

The usefulness of the selected indicators for meeting GES criteria relevant to biological diversity has only marginally been explored during this WGFE meeting. However, more work will be done intersessionally with the outcomes discussed during the 2011 WGFE meeting. During this years' meeting, a discussion was held on the caveats that need to be considered when using the indicators at varying spatial analysis scales.

4.4.5.1 Spatial Scaling

Working at a particular spatial scale raises variance and analysis power issues. Generally, increasing the spatial resolution reduces the number of samples available for grid-level calculations. This increases the influence of outliers and zero catch values. Conversely, decreasing the spatial resolution of the analysis leads to the need for broader scale data aggregation which may wash out important spatial features: coarse spatial analyses may be too broad for use in management advice (MPA selection). In the case of the North Sea IBTS dataset, the sampling design is stratified according to ICES rectangles with each rectangle sampled at least twice per year. If annual trends are calculated at the species level within each rectangle then only a few samples are available per year. This issue is more pronounced for the less abundant species. The issue may be solved by combining rectangles and thereby decreasing the resolution, however the spatial detail available for defining MPA's will decrease. Careful consideration of the resolution of the sampling grid in relation to the amount of available data is therefore necessary before performing the analysis. Further, the limitations of the spatial analysis scales should be clearly identified. It may also be appropriate to conduct the analysis using several scales for comparison.

4.4.5.2 Spatial unit fungability

Spatial hotspots are by definition relative measures which identify something out of the ordinary. It is therefore critical that the features being assessed are spatially fungible (i.e. equivalent measures). When comparing the biodiversity of different areas samples must be standardized to account for the maximum potential number of species in each location. Meaning, one should interpret the results for an area relatively to its capacity: if a certain number of species is found to display a certain trend in an area, it is essential to know the total number of species that is present in the area, in order to be able to judge to value of the area relatively to a larger region.

4.4.5.3 Temporal unit fungability

Another issue to take into account is the selection of the time period when analyzing temporal changes. Many species do not show straightforward linear change, but often display fluctuations, such as decadal variance. In order to avoid such confounding patterns one may consider comparing fixed periods with each other, instead of looking at trends over time. The choice of these periods needs thorough consideration and the reasoning for selection of these periods should be well justified. Also, when looking at change over time or between periods in indicators that describe components of biodiversity, one should not only study declines or decreases, but information on increases is equally important when defining potential protected areas.

4.4.5.4 Caveats, an example: Method for use of the indicator Declining trend

To illustrate the challenges to using indicators to meet biological diversity criteria for GES, we have performed an exercise by use the Declining trend indicator. There are many ways to display declining trends of fish species. In this exercise the species from the North Sea that have a significant decline in annual geometric mean CPUE over the selected series (1983–2010) were identified using linear regression. The species that appear to be having a significant decrease in abundance are listed in Table 4.4.2. **As discussed above, one needs to consider whether the selected period makes sense in relation to the question to address and also whether it is justified to expect linear trends in species abundance over time.**

Table 4.4.2. Fish species showing a significant decline in CPUE in the North Sea, based on IBTS-Q1 data for the period 1983–2010.

Species		Lmax	Estimate	P-value
<i>Anarhichas lupus</i>	wolffish	125	-0.103	<.0001
<i>Clupea harengus</i>	herring	40	-0.068	0.0019
<i>Dipturus batis</i>	grey skate	250	-0.062	0.0053
<i>Gadus morhua</i>	cod	190	-0.104	<.0001
<i>Melanogrammus aeglefinus</i>	haddock	112	-0.054	0.0172
<i>Merlangius merlangus</i>	whiting	70	-0.072	0.0008
<i>Molva molva</i>	ling	200	-0.056	0.014
<i>Platichthys flesus</i>	flounder	50	-0.051	0.0269
<i>Sebastes viviparus</i>	small redfish	35	-0.064	0.0043
<i>Squalus acanthias</i>	spurdog	105	-0.087	<.0001
<i>Trisopterus luscus</i>	bib	45	-0.071	0.0011
<i>Zoarces viviparus</i>	viviparous blenny	52	-0.048	0.0361

The number of species with a significant declining trend was calculated by ICES rectangle. Clusters of rectangles with high numbers of species in decline indicate a hot-spot for potential or actual biodiversity reduction. **As discussed above, the statistical power of these regression analyses low when applying at the resolution of ICES-rectangles, since only on average 2–3 samples are taken per rectangle. Combination of rectangles should therefore be considered.**

The results are presented in Figure 4.4.1 which indicates the number of species with a declining trend (range 0 to 5) per rectangle. Visual interpretation of the figure indicates that the centre of the North Sea generally has a higher number of declining species per rectangle. However, **as discussed above, the figure may be misleading since it lacks information on the maximum possible potential of an area.** Out of the 12 selected species, the number of species showing a decline is presented by rectangle, but it is unknown whether all 12 species have the potential to occupy the rectangle.

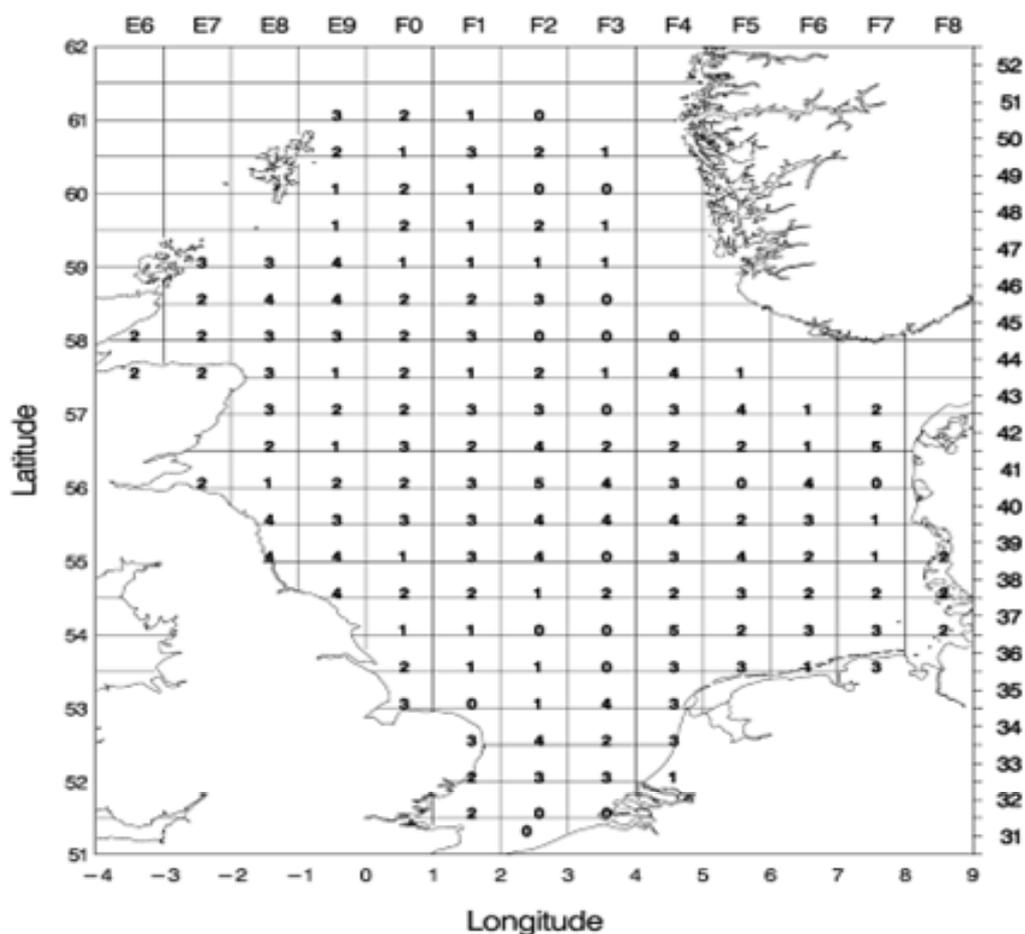


Figure 4.4.1. Numbers (out of 12) of declining species by ICES rectangle having a decline in CPUE over the period 1983–2010.

4.4.6 Future work

The study described above is still very much preliminary and purely intended to illustrate potential shortcomings when performing spatial analyses. However, it does present an initial outline of the research question for management purposes and speculates on methods to fulfil the request. Intersessionally, the work will continue and methods will be explored in order to develop a sound approach to use the crite-

ria for GES relevant to biological diversity of fish communities to define areas in the Dutch EEZ that may qualify for protection.

4.5 General Conclusions

Limited sampling coverage and the *post hoc* nature of many spatial fisheries management questions mean that these mapping and spatial analyses routines often require merging data from various sources, and interpolating information to unsampled locations and times. Therefore it is practical to use methods which maintain continuity between final data products and inputs, and to minimize the use of smoothing interpolation methods and data transformations which mask raw trends. Analysts should also provide users with measures of spatial data support. Two recommendations are 1) "Don't use graphics programs or GIS spatial analyses unless you are in complete control and you know they do what you want them to" (p. 292, Webster and Oliver 2001) and 2) "report all components of observation and analysis scales to increase the possibility of cross-study comparisons" (p. 262, Dungan *et al.* 2002).

4.6 Recommendations

- Continue to investigate mapping and spatial methods for comparing and summarizing fish and fish community distributions in relation to environmental and habitat factors including how these tools are applied in spatial management (e.g. MPAs) and how uncertainties in these relationships are characterized.
- The expected outcomes of MPAs may rely on relationships between fish and fish communities and their habitats. Given the state of science these relationships are often hypothetical. Such relationships should be clearly stated and dedicated research initiated to investigate them.
- MPAs should have clearly stated purposes and goals including timescales for expected outcomes (e.g. measurable increases in biodiversity by 2020).
- The MPA designation, assessment and refinement process should be dynamic and take account of new information. This may mean boundary refinement or MPA relocation.

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5 Abundance/ distribution relationships within species, and groups of species in different ecosystems in relation to habitat, environment and in relation to anthropogenic impacts

ToR d) Examine abundance/ distribution relationships within species, and groups of species in different ecosystems in relation to habitat, environment and in relation to anthropogenic impacts

5.1 Introduction

Theoretical and empirical research has linked trends in species occupancy, abundance and extinction with habitat alteration and community structure in a wide range of animal taxa. The idea that geography interacting with ecological processes leads to the structuring of communities over time was developed in the late 1960s and 1970s (see Malanson, 2008 for a review). Accordingly, an equilibrium number of species emerges, and is maintained by the balancing of inputs (local immigration) and outputs (local extinction). The theory is often applied to colonization of unoccupied habitat, such as a new island, and was termed “island biogeography”. Early in the development of island biogeography, the importance of the time needed to reach equilibrium was recognized as was the importance of habitat fragmentation (Brown, 1971). Specifically, over time, habitat fragmentation can result in increased abundance

of rapidly dispersing species and the local extinction of sedentary species (Diamond *et al.*, 1976). The extinction debt hypothesis by Tilman *et al.* (1994) introduced the counter-intuitive idea that the order of extinction with continued permanent habitat destruction would start with species that are the best competitors which are also usually the most abundant species in equilibrium conditions (Malanson, 2008). At the same time, the poorer competitors but better dispersers or colonizers would increase in relative abundance and spatial occupancy. For example, if a community experiences habitat fragmentation and destruction, a “time delayed” extinction debt is realized that will result in the species with the greatest competitive ability and weakest colonizing ability to trend toward local extinction over multiple generations.

Hanski and Ovaskainen (2002) pointed out that under the extinction debt hypothesis the frequency of all species will include a “transient” period with increased prevalence of rare species. This results because of the time-lag between fragmentation and eventual extinction and is especially important for species close to their extinction threshold (Hanski and Ovaskainen, 2002). Thus, evaluating the present conditions in an ecosystem may not reflect the total extinction debt accrued and future local extinctions resulting from habitat destruction (Hanski and Ovaskainen, 2002). A little unexplored feature of habitat fragmentation is that as habitat is altered from a spatially structured system, to a fragmented and eventually homogenized system, species richness may actually increase during the transient period before extinctions occur (Figure 5.1). As spatially structured habitat is fragmented, boundaries between heterogeneous habitat types are blurred and competitors requiring specific niches are forced to occupy suboptimal habitat. The key feature that emerges is that a greater number of species will occupy a greater proportion of area increasing the overall system richness per habitat unit.

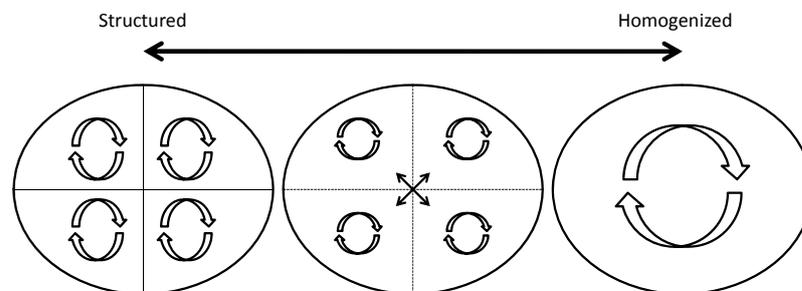


Figure 5.1. Spatially structured habitat is depicted in A, fragmented habitat in B and homogenized habitat is shown in C. As structure breaks down optimal habitat is fragmented and boundaries are blurred eventually leading a homogenized system where structure is absent and movement is not restrained by structure or optimal habitat choice.

The extinction debt hypothesis has been applied to habitat destruction for many terrestrial ecosystems but relatively few examples exist for marine communities. Frisk *et al.* (in press) studying the Georges Bank finfish and shellfish community, and the related concept of occupancy and abundance (O-A) relationships, found that the strengths and slopes of the relationship declined between 1963-2006 and was correlated to trawling effort. The changes in O-A relationships are consistent with habitat fragmentation as has been well documented for terrestrial systems (Frisk *et al.*, in press, Freckelton *et al.* 2006, Gaston *et al.* 2000); however, these concepts are not as commonly applied in marine systems. Further, a key assumption of extinction debt theory may not hold for marine systems: the theory assumes a hard trade-off between

competitor skills and dispersal in that highly specialized strong competitor species have poor dispersal (Banks, 1997). This distinction may not be as clear for marine species which have a wide range of life histories and dispersal levels from passive large-scale pelagic eggs, to nesters, live bearers and mouth brooders. The need for a better understanding of the resilience of marine species is highlighted by recent research indicating that marine species are more vulnerable to extirpation than previously assumed (Duvly *et al.*, 2003). Duvly *et al.*, (2003) identified 133 extinction events, mostly local or regional, and argued high fecundity and large scale-dispersal do not make marine animals more resilient to extinction compared to other taxa.

In the marine environment habitat destruction, for example by bottom trawling, has been found to reduce benthic biodiversity (Thrush *et al.*, 2002). Thrush *et al.*, explain this observation by habitat specific species richness - if some particular habitats such as soft sediments get destroyed leading to habitat homogenization, the overall species richness decreases. The expected effects of habitat homogenization on fish are more complex compared to physical removal of benthic species. Population dynamics of mobile species depend on a range of habitats critical for successive life stages. For example, the reproductive success of spotted spiny lobster has been found to be reduced in fragmented habitats with smaller patch sizes (Robertson and Butler IV, 2009). Caddy (2008) reviews the various ways habitat structures including epifauna are essential at different life stages of fish and other mobile marine fauna in particular early life stages as they provide cover from predation, reduce foraging success and provide nesting and resting sites etc. Unfortunately, certain habitats are more vulnerable to destruction by fishing than others, e.g. boulder habitats and areas with low natural physical disturbance (NEFMC 2010).

Our goal is to apply the extinction debt hypothesis to the Georges Bank finfish and shellfish community from 1963–2008. The spatial distribution of bottom trawl fishing on Georges Bank has changed over time with the implementation of no go fishing zones and regulated access zones. These regulated zones disproportionately consist of sandy habitat and to a lesser extent gravel and boulder habitat, while a large proportion of vulnerable boulder, pebbles and gravel habitats remain unprotected (Figure 5.2). Areas outside protected areas have seen increased fishing effort to take advantage of spillover effects and as a result of effort displacement potentially increasing effort in more vulnerable gravel, pebbles and boulder habitat (see Murwaski *et al.*, 2007). Additionally, use of rockhoppers has allowed the fishery to move into rougher ground over recent decades. Bellman *et al.* (2005) showed that on the west coast of the United States regulation reducing rockhopper size led to spatial displacement of fishing effort. No information regarding this is available for Georges Bank but it might be suspected that a similar process of spatial changes and adaptation of fishing gear occurred over time in adaptation to the implementation of access regulated areas.

For evaluating the extinction debt hypothesis for Georges Bank, we will estimate (1) long-term changes in species richness in the western Atlantic and (2) occupancy trends for competitors, intermediate and colonizing species. Further, we expand the theory to include adult dispersal in model development. The overall objective is to determine if long term trends in the finfish and shellfish community are consistent with a system experiencing extinction debt from habitat alteration.

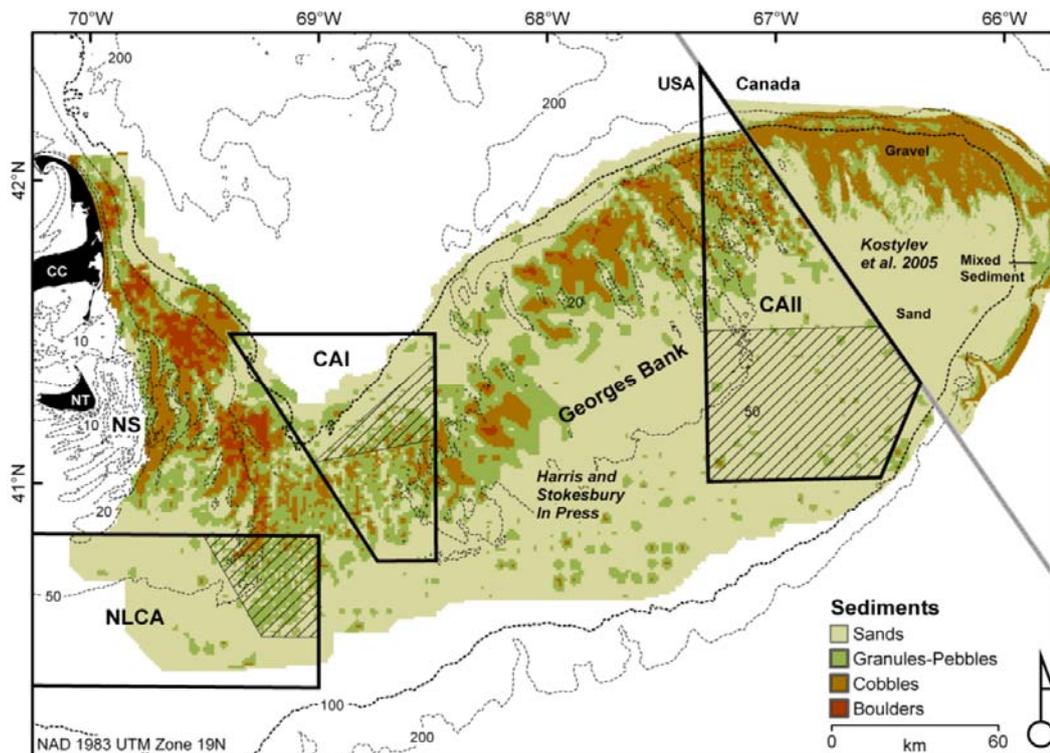


Figure 5.2. Map of superficial sediments (maximum size) redrawn from Harris and Stokesbury (2010). No trawling has been permitted in the Nantucket Lightship Closed Area (NLCA), Closed Area I (CAI) and Closed Area II (CAII) since 1994. The hashed ones indicate sea scallop dredge fishery access areas which are fished on a rotational schedule.

5.2 Methods

5.2.1 Data

We analyzed data from the autumn National Marine Fisheries Service's (NMFS) bottom trawl survey (autumn: 1963–2009). The survey utilized a Yankee 36 bottom trawl equipped with a 1.27-cm mesh liner and 450 kg doors (Sosebee and Cadrin, 2006). A standard tow was 30 minutes (timed from winch lock to winch unlock) at 3.8 knots. In 2009, gear, vessel and sampling protocol changed considerably: a new vessel was introduced, the gear was changed to a 4 seam trawl with 550 kg doors, a standard tow was changed to 20 minutes ground time (touch down until lift-off) and vessel speed reduced to 3.0 knots. In addition, many new stations were added in 2009. These changes in the survey are apparent in many analyses (especially species richness) therefore our analyses here include data only until 2008. We standardized all tows to 1 nm based on trawling time and vessel speed.

5.2.2 Species filtering criteria

The NMFS database for Georges Bank (here defined as trawl sets in the box demarcated by 40.5 to 42.5 N; 66 to 69 W) has recorded the presence of 219 different categories of catch. Some of these are not living organisms such as "TRASH" while others represent broad groupings of several species such as "SHRIMP UNCL". For the present analyses, it was necessary to apply appropriate filtering criteria to obtain subsets of the 219 categories that reduce the possibility of survey catchability or species rarity leading to spurious conclusions.

For analyses that required analysis of abundance trends, we needed to confine the species to groups that were both well caught by the survey and thus relative abun-

dance and occupancy differences could be considered real. We therefore applied a filter following Frisk *et al.*, (in press) to the dataset where the only groups that were considered in the analysis were:

- 1) The species must have been caught in more than 40 of the 46 years
- 2) There must have been more than 1000 individuals caught over the survey time series (1 nm tow standardized).
- 3) Categories not discriminated to the species level were excluded.
- 4) Shrimp were excluded because they often not well caught and are sometimes partially destroyed by the gear.

This filter resulted in a dataset which included 39 species (Table 5.1).

Table 5.1. Thirty-nine species in the filter in order of their relative long term abundance.

Species
Longfin Squid
Silver Hake
Butterfish
Haddock
Sea Scallop
Spiny Dogfish
Red Hake
Longhorn Sculpin
Atlantic Herring
Windowpane
Acadian Redfish
Northern Shortfin Squid
Little Skate
Yellowtail Flounder
Winter Skate
Northern Sand Lance
American Plaice
Moustache Sculpin
Fourspot Flounder
Atlantic Mackerel
White Hake
Atlantic Cod
Winter Flounder
Sea Raven
American Lobster
Lady Crab
Thorny Skate
Gulf Stream Flounder
Atlantic Rock Crab
Pollock
Blackbelly Rosefish
Witch Flounder
Ocean Pout
Longfin Hake
Goosefish
Smooth Skate
Cunner
Fourbeard Rockling
Cusk

For analyses of species richness distributions over stations, we need only to be confident in presence/absence thus the filter was relaxed to allow rarer species into the

analysis. It is necessary, however, to limit the number of species included in these analyses to reduce the potential for “species-creep” artefacts. Species creep is often present in older multispecies surveys where there is a trend toward increasing species richness over time as the survey become more sophisticated and the ability of workers to identify rarer species and the interest in rarer species increases over time. In the present survey dataset for George’s Bank, there is on average 0.7 more species recorded each year between 1963 and 2009. Some of this may be a true increase in richness while some of the increase is likely due to species creep. Accordingly, filtering criteria for richness analyses were:

- 1) The species must have been caught in more than 40 of the 46 years
- 2) Categories not discriminated to the species level were excluded.

5.2.3 Colonizer-Competitor group classifications

The reduced species dataset, consisting of 39 species meeting the filtering criteria above were classified as colonizers (Col, n=9), competitors (Com, n=9) or mixed (M, n=21). These qualitative designations were determined through examination of Fishbase.org as well as primary publications and DFO and NMFS species information sheets. Group classifications were used for mapping as well as in data analysis described below. In addition, the adult dispersal mode was characterised by two vigility levels: high vigility for species moving around, including on and off Georges Bank and low vigility for those staying on Georges Bank all year round.

5.3 Analyses

5.3.1 Data analysis

Occupancy-abundance data were fitted with both a model free spline curve and a log-linear curve to examine the pattern of residuals by year for the spline and compare to the annual fits from log-linear curve slopes. We examined the distribution of species richness over stations and time if there were temporal trends in mean and variance of richness at stations over time. Generalized additive models were fitted to the occupancy trends over time by species groups to uncover any changes in the occupancy that might occur in particular colonizer-competitor groups relevant to expected trends predicted by extinction debt theory. To complement the GAM analysis visually, we constructed maps showing the temporal trends in occupancy of colonizer-competitor groups in 1*0.5 degree boxes from the NE USA continental shelf.

All analyses were conducted in R (R Development Core Team 2010) using contributed libraries.

5.3.2 Occupancy and abundance

Occupancy and abundance was calculated as the proportion of stations per year in which at least one individual of a species was caught. Abundance was defined as the mean catch per station in a standard tow (1.85 km). Before any analyses were performed on occupancy data, they were logit transformed which is a common transformation for proportions and is particularly useful for occupancy proportions (Williamson and Gaston 1999).

5.3.3 Occupancy-Abundance relationship

O-A was estimated for 39 species for each year with a cubic spline fitting and residuals were examined by year. The residuals patterns are thus assessed by the proportion of points above or below the spline curve for anyone year, i.e. it is not a check on

the validity of a fitted relationship by examining residual pattern for all points. Further, results are displayed when the spline was fitted to species colonization-competitor groups: competitors, mixed and colonizing species.

For ease of comparison of OA relationships between years, parametric OA relationships $Logit(O) = s \cdot \log(A) + C$ were also fitted and trends in the slope s and the r^2 value expressing the strength of the fit examined following the methods of Frisk *et al.*, (in press).

5.3.4 Species richness

We define species richness as the total number of species captured in a single tow among the 164 species retained. Density plots and estimation of the 10th and 90th quantile and the interquartile range (IQR) of the species richness distribution per haul was performed for each year.

To combine trends in the OA relationships with trends in mean richness we estimated the relationship between the proportion of positive residuals of the OA relationship to both the mean richness and interquartile range in the density distribution of species richness. We analyzed the 39 species selected based on our filtering to estimate OA relationships to avoid species that may not have adequate data to estimate the relationship. However, richness was estimated based on the 164 species dataset.

5.3.5 Temporal changes in occupancy

Temporal trends in occupancy of colonization groups were modelled using Generalized additive models (GAM) with the following model structure:

$$Logit(E[O]) = a_s + s_g(\text{year})$$

where *Logit* indicates logit transformation, $E[O]$ is expected occupancy, a_s is the species constant and s_g is a smooth function for each group. Two models were fitted including one with the three primary competitor-colonization groups and a second model expanded to include species with high and low vigility leading to six groups.

To combine trends in the OA relationships with trends in mean richness we estimated the relationship between the proportion of positive residuals of the OA relationship to both the mean richness and interquartile range in the richness density distribution. We analyzed the 39 species selected based on our filtering to estimate OA relationships to avoid species that may not have adequate data to estimate the relationship. However, richness was estimated based on the 164 species dataset.

5.3.6 Spatial analysis of abundance and richness

The slopes of linear models fitted to average abundance (number per haul) per year per rectangle (1 degree longitude by ½ degree latitude) were plotted on a map for competitor-colonizer groups for the following areas: Gulf of Maine, Georges Bank and southern New England. Maps for slopes in changes in species richness were prepared in the same way. An expanded geographic range was chosen to view trends in competitor-colonizer groups over a broader region.

5.4 Results

5.4.1 Occupancy and abundance

A smoothing spline fitted to the OA data for all species and years shows a non-linear increase in occupancy with abundance (Figure 5.4.1). This curve is the expected community OA ($E(OA)$) relationship though it does not represent the OA for any one species though it is broadly representative of the relationship for the three colonization groups. The proportion of positive residuals for each year decreased over the time series from 0.72 early in the series to 0.36 in more recent year (Figure 5.4.1 inset). The proportion of positive residuals represents the deviation in occupancy of species from the $E(OA)$. The decrease in the proportion of positive residuals over time means that species occupancy decreased over time from expected regardless of their abundance and the fact that the $E(OA)$ is broadly representative of different colonization groups indicates that this changing occupancy is not simply a result of changing dominance of groups with different OA relationships. However, spline fits to the OA data for each competitor-colonizer group shows some variation in the shape of the OA curve (Figure 5.4.2). The OA curve for the competitor and mixed group shows a steep increase that continues over the abundance range, while the colonizer OA curve becomes flatter at higher abundances. A decrease in the proportion of positive residuals was observed for the competitor and mixed group, while no trend was apparent for the colonizer group.

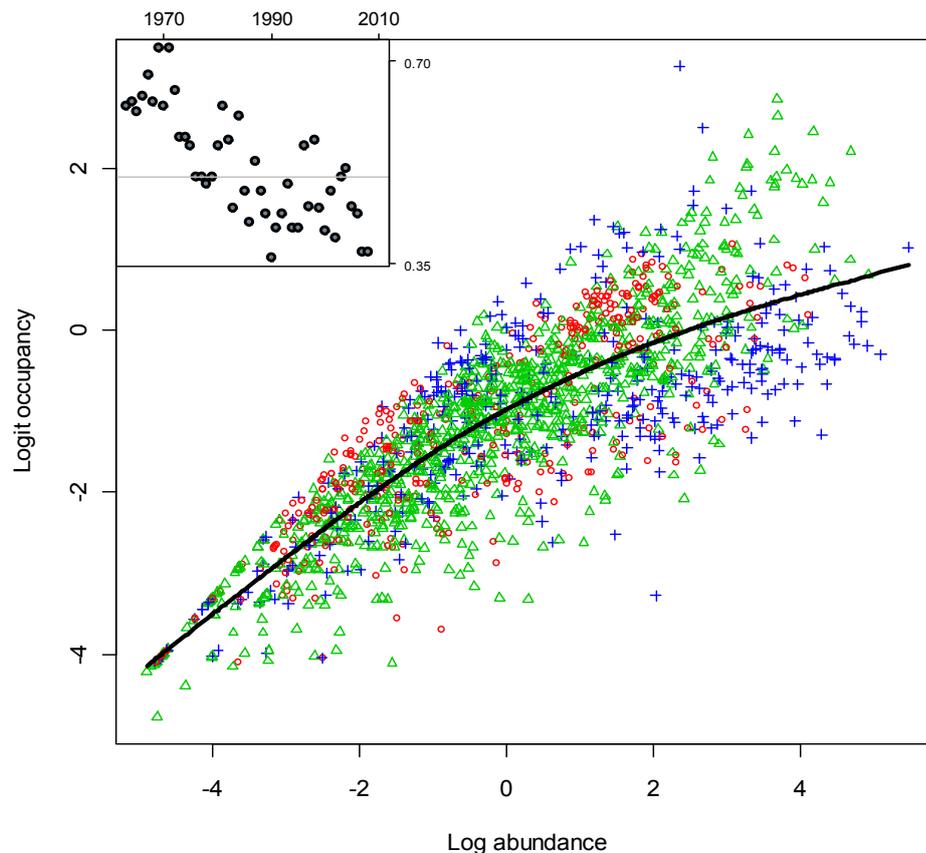


Figure 5.4.1. Expected occupancy-abundance for the 39 species Georges Bank fish community. The solid line is a cubic spline smooth to all points and thus can be considered the expected community OA relationship. Red circles represent colonizer-group species, blue crosses represent competitor-group species and green triangle symbols represent mixed-group species. Not all plotting symbols are visible owing to overlap in the 1732 points. Individual group plots can be found in the appendix.

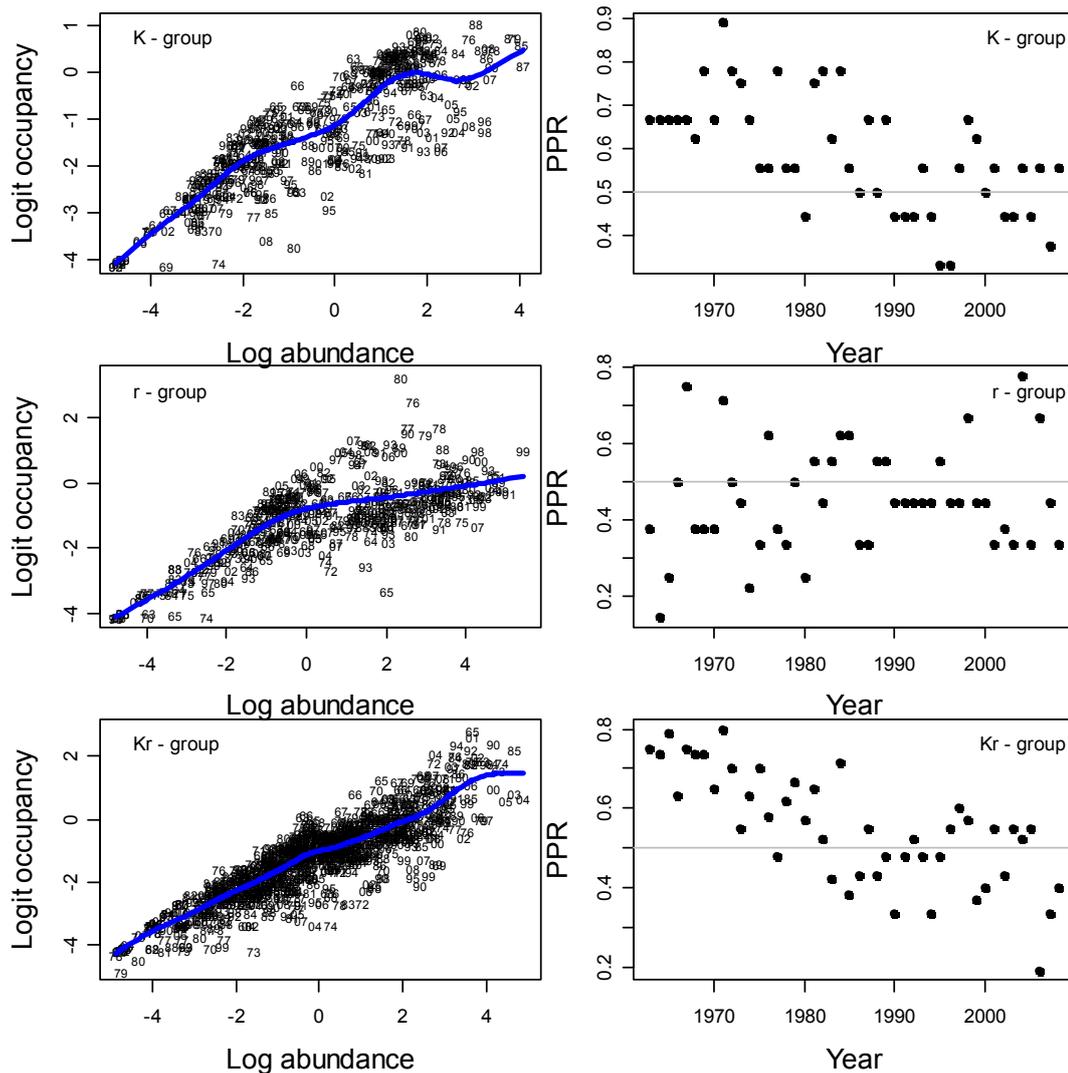


Figure 5.4.2. Expected occupancy-abundance for the 39 species Georges Bank fish community for each competitor-colinizer group. The solid line is a cubic spline smooth to all points and thus can be considered the expected community OA relationship. Also shown is the proportion of positive residuals for each year (1963 to 2008) from the expected OA relationship for the 39 species dataset for each competitor-colinizer group.

5.4.2 Species richness

Density of species richness over stations for the 164 species dataset showed an increasing mean over the time series and also an increasing interquartile range (IQR) which suggests that more species were found at a greater number of stations; but also that variation in species richness over stations was greater (Figure 5.4.3, 5.4.4, 5.4.5; IQR vs. year, $n = 46$, $r^2 = 0.3$, $p = 0.001$; Q10 vs. year, $n = 46$, $r^2 = 0.53$, $p = 0.001$; Q90 vs. year, $n = 46$, $r^2 = 0.53$, $p = 0.001$). The proportion of positive residuals from the E(OA) plotted against mean and IRQ from the richness density (Figure 5.4.4) shows a decreasing relationship, i.e. as richness and its variance over stations increased the abundance standardized occupancy decreased. The increasing richness suggests a homogenization towards the mean community where species are appearing together more frequently in the same area than they were earlier in the series. Together, the increase in IQR of richness and decrease in the proportion of positive residuals in the OA relationships suggests there are more stations with fewer and greater species

than before with an overall increase in the mean. Thus, there are more species in suboptimal places while there are more areas with no occupancy.

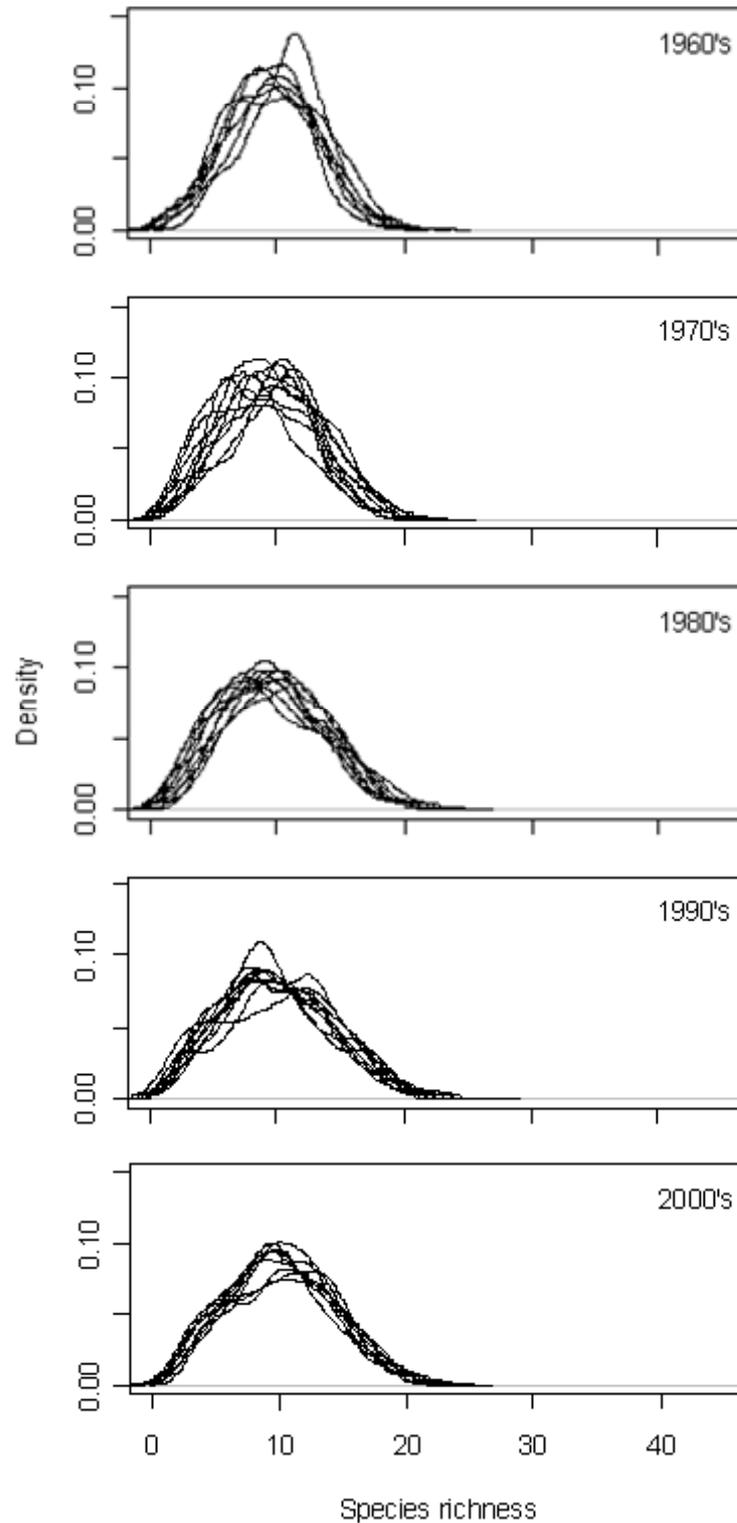


Figure 5.4.3. Species richness density for the 164 species dataset from Georges Bank 1963-2008. The number of stations with high species richness is increasing over time. Note: Richness is calculated per station.

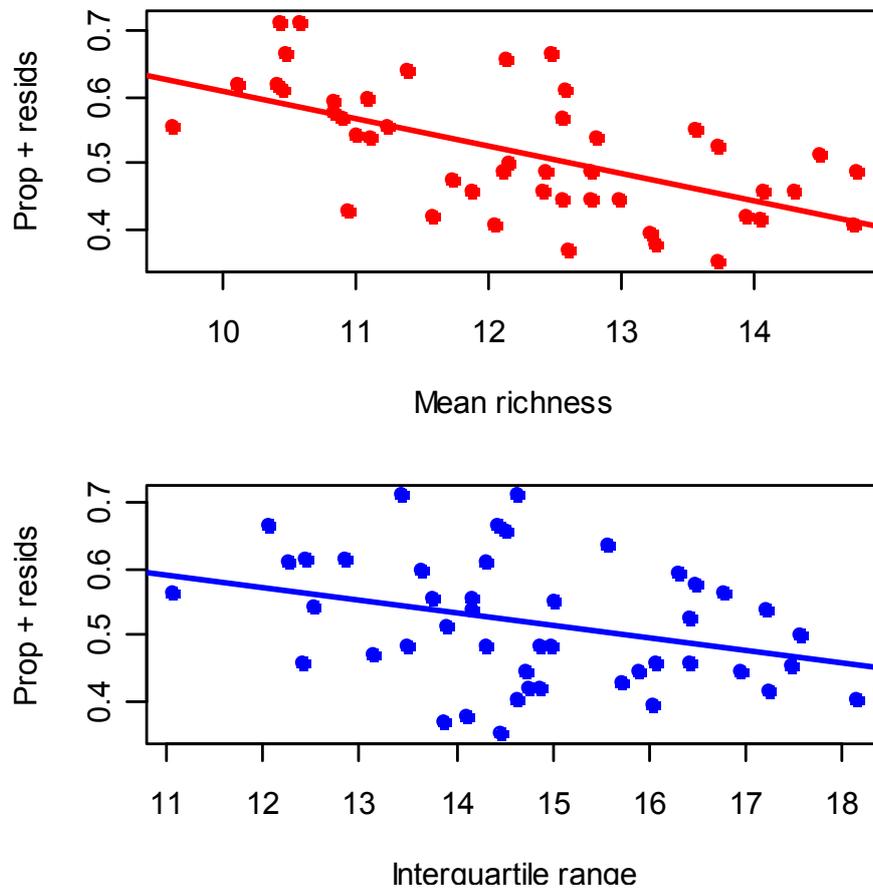


Figure 5.4.4. The proportion of positive residuals for the 39 species OA relationship regressed against the mean richness of the 164 species dataset (A) and the proportion of positive residuals for the 39 species OA relationship is regressed against the inter quartile range for the 164 species dataset.

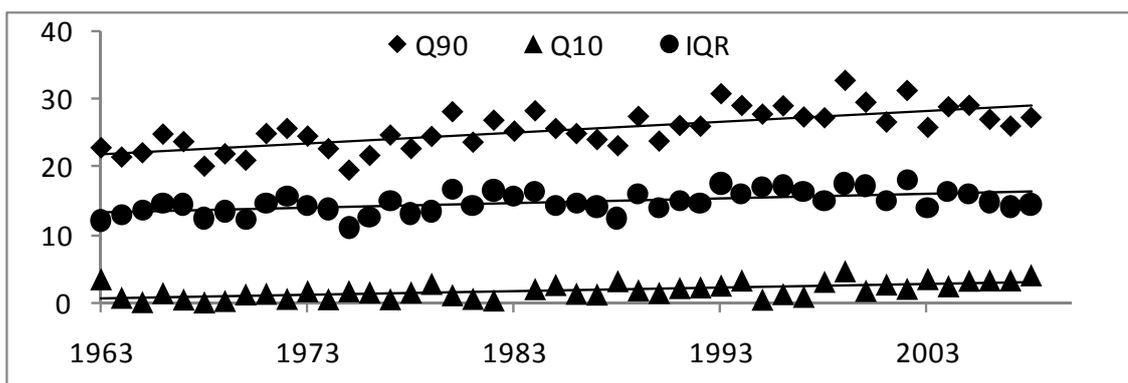


Figure 5.4.5. The 10th, IQR and 90th percentiles are plotted for the species richness density distributions.

5.4.3 Trends in occupancy of colonization groups

The trend towards increasing homogenization is apparent in the GAM analysis on occupancy by colonization-competition group which shows significant decreases in occupancy of competitors but more profound increases in occupancy of colonizers over time (n=1732, r²=0.74, Figure 5.4.6, Table 5.4.1). The large increase in occupancy

of colonizer species with a smaller decrease in occupancy of competitor suggests that something has occurred in the George's Bank fish community since the 1960s that favours the latter group of species over the former. The GAM fitted to the expanded groups with adult vigility levels indicated similar overall trends ($n=1732$, $r^2=0.77$, Figure 5.4.7). However, competitors with high vigility actually increased while competitors with low vigility showed an even stronger decline in occupancy. Colonizer species also show differences by vigility group with low vigility species increasing at a higher rate.

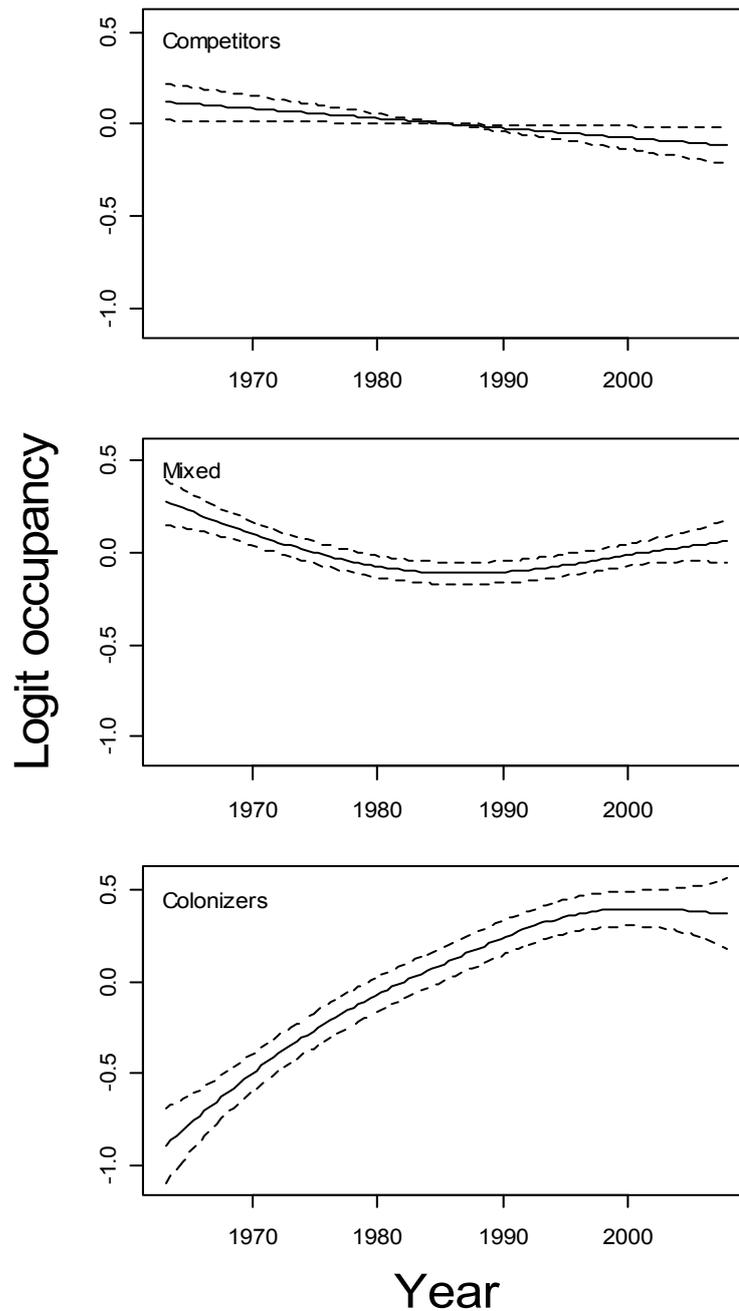


Figure 5.4.6. Generalized additive model fitting of occupancy trends by colonizer-competitor groups described by extinction debt theory implicit in island biogeography. The GAM model fitted was $\text{logit}(\text{occupancy}) \sim \text{species} + \text{s}(\text{year})$. An additive year effect was included initially but removed because it showed no trend and makes interpretation of the group effects more difficult. All trends were significant ($p < 0.05$).

Table 5.4.1. Results for GAM model where A is the competitor-colonizer group model, Com is competitor, M is mixed, Col is colonizer, B is the expanded competitor-colonize and vigility model, HV is high vigility and LV is low vigility.

A			
Groups	F	P-value	
Com	6.8	0.009200	
M	9.137	0.000005	
Col	20.635	0.000000	

B			
GroupS	F	P-value	
Com-HV	2.572	0.043110	
Com-LV	4.228	0.000067	
M-HV	10.099	0.000021	
M-LV	3.709	0.014580	
Col-HV	14.643	0.000000	
Col-LV	6.228	0.000000	

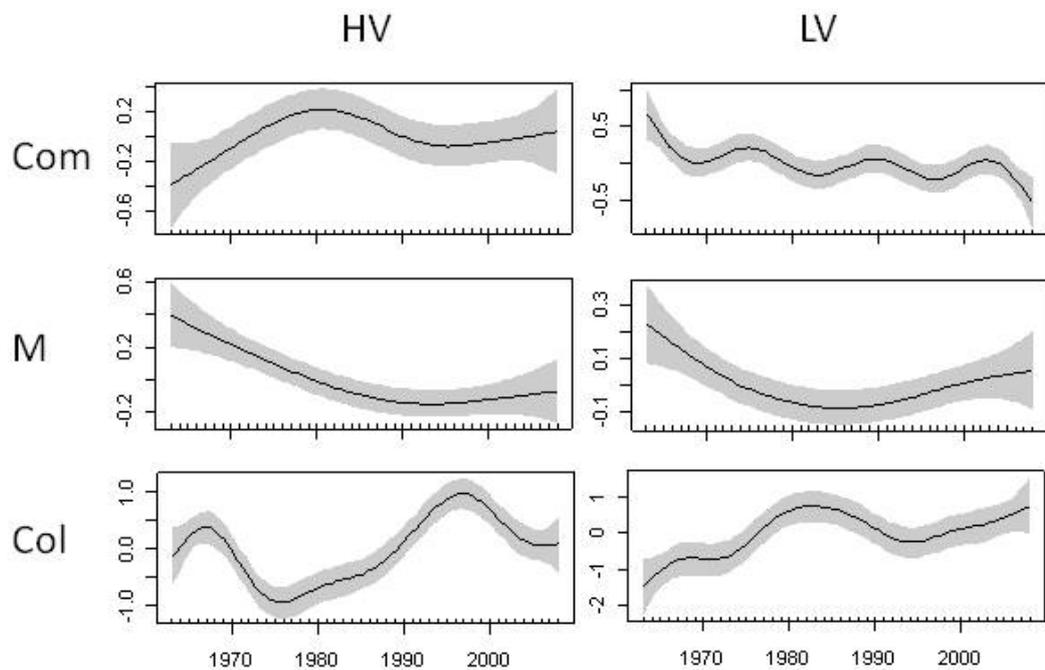


Figure 5.4.9. Generalized additive model fitting of occupancy trends by colonizer (Col)-competitor (Com) and adult (M) vigility groups where HV is high vigility and LV is low vigility. Note Y-axis is scaled to magnitude of change.

5.4.4 Spatial analysis of abundance and richness

Slopes fitted to the trend in abundance indicate a steady trend on GB and a slight increase in the GOM and SNE for competitors, the mixed group shows a slight increase overall and colonizers show a large increase in SNE (Figure 5.4.8). Slopes fitted to species richness showed occupancy of the competitor group would suggest a force

has been acting on the Georges Bank fish community since the 1960s that favours the latter group of species over the former.

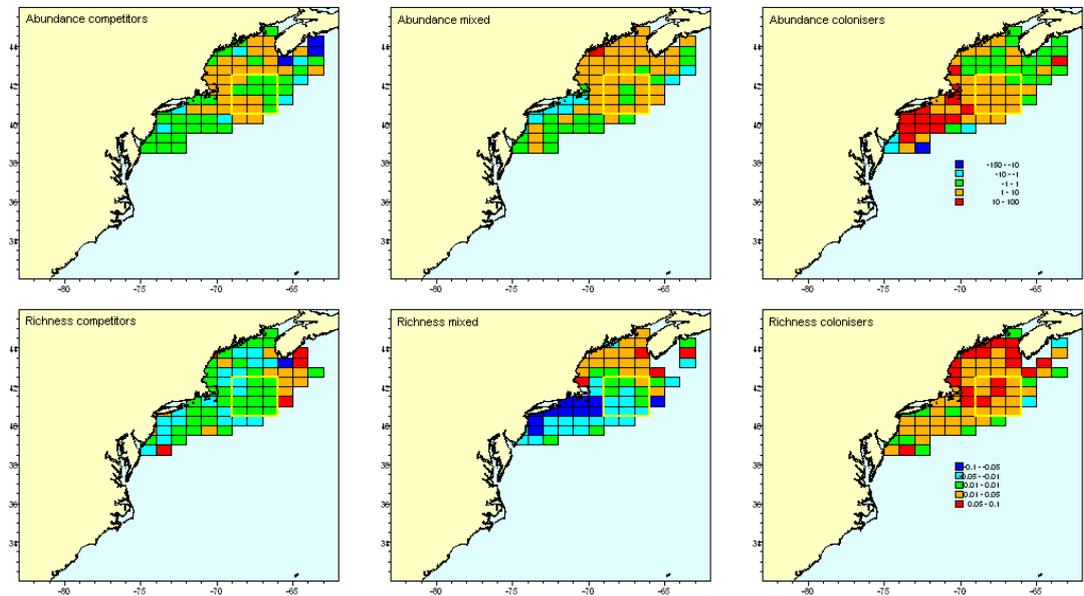


Figure 5.4.8. Slopes of linear models fitted to mean abundance per haul (top row) and richness (bottom row) decadal averages per rectangle for three colonization-competition groups. The slopes indicate the magnitude and direction of the temporal change for each group and rectangle. Rectangles measure 1 degree longitude by $\frac{1}{2}$ degree latitude.

5.5 Discussion

Extinction debt theory is a relatively simple concept arising directly from island biogeography theory developed in the 1960s. Tilman's (1984) articulation of the theory necessitates the very strong assumption that competitive ability and colonisation ability of a species are inversely proportional. This strong assumption may be more valid in terrestrial ecosystems rather than aquatic ones where dispersal strategies for most species have a large element of passive dispersal in the water. We have attempted to add some subtlety to the strong competition-colonisation trade-off by accounting for some other behaviours of marine organisms for movement and colonisation. The result of this is that we were able to find significant decreases over time in occupancy for species that had both low vigility and low colonisation ability. This accords with the hypothesis that habitat destruction and fragmentation on Georges Bank may have disproportionately affected these species.

Despite the fact that our analyses show patterns of changing occupancy for species that are consistent with extinction debt phenomena, we have yet to find the smoking gun of habitat destruction and fragmentation. Many habitat related theories in community ecology derive from terrestrial studies where habitat is often much more easily identified, quantified and destruction and fragmentation easily documented. We are only just beginning to be able to do this in marine systems but there remains the issue that marine species view their habitats as combinations of long term benthic (e.g. corals) and short term in the water (e.g. seasonal temperature fields). So, although it is well known that some fishing gears are destructive to certain benthic structures, they do not destroy relatively transient pelagic habitats.

Further work using this extinction debt theory as means of developing hypotheses is necessarily going to involve seeking this holy grail of defining habitat associations,

quantity and quality of habitat, and the destruction and fragmentation of habitat. Further lines of study could be to use various statistical designs incorporating established marine protected areas on Georges Bank to try to disentangle habitat destruction owing to fishing from natural variability or direct impacts of fishing on species via removals.

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6 Fluctuations and Interactions within fish communities

ToR e) Evaluate fluctuations within fish communities:

- i) What constitutes regime shifts in fish communities. Can mechanisms be identified detected?
- ii) State changes - Cycles vs. regime shifts
- iii) Are anthropogenically induced changes alterable?

6.1 Using Machine Learning Techniques to Model and Explain Fish Population Interactions

6.1.1 Introduction

Some spectacular collapses in fish stocks have occurred in the past 20 years, the most notable being Northern cod off eastern Newfoundland has experienced a 99% decline in biomass. Cod is not alone as there are populations of various species that have been reduced to only a small percentage of stock sizes in recent history. Much of this effect is due to direct mortality on fish through fishing and subsequent indirect effects and weak linkages to other species. It has been hypothesized that the region has moved to an alternative “stable state” and is unlikely to return to a cod dominated community without some chance event beyond human control.

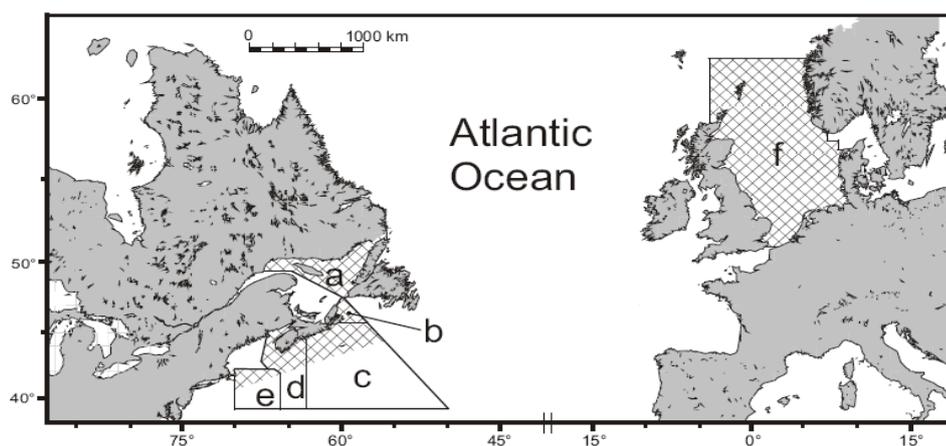


Figure 6.1. The Northern Gulf (a) and East Scotian Shelf (c) – The focus of the initial experiments.

This section aims to uncover key relationships between species by modelling the complex interactions using probabilistic networks. Modern machine learning approaches (Bishop 2006) such as Bayesian networks offer numerous advantages over traditional modelling approaches, including the ability to exploit human expertise to

direct otherwise data-driven models, and uncovering hidden factors that may explain certain artefacts in the data better than measured variables. The focus is the Northern Gulf (region a in Figure 6.1) between the years 1984 and 2005, and the East Scotian Shelf (region c in Figure 6.1) between the years 1970 and 2006 using fish biomass data.

A number of questions are asked of different machine learning techniques within the context of modelling fish interaction. These are documented below. The final question represents the key novelty of the research which is a focus on critical sub-systems through the exploration of the functions of species across different populations. Different species may have similar functional roles within a system depending on the region. For example, one species may act as a predator of another which regulates a population in one location, but another species may perform an almost identical role in another location. If we can model the function of the interaction rather than the species itself, data from different regions can be used to confirm key functional relationships, to generalise over systems and to predict impacts of forces such as fishing and climate change. The approach concerns functional network topology and avoids the necessity of describing the specifics of network nodes. Our results so far are promising, demonstrating that similar functional roles can indeed be discovered using simulated data with relatively small sample sizes. Initial results on biomass data from the Northern Gulf and the East Scotian Shelf also point to some interesting discoveries between the two geographical locations, in particular identifying similar competing-predator combinations and predator-prey interactions.

Questions posed are:

- 1) Can we use machine learning (in particular, feature selection) to identify species that are relevant to some “event”?
- 2) Can we use Bayesian networks to combine human expertise with data to build better models?
- 3) Can we model the temporal and dynamic nature of fish interactions?
- 4) Can we identify species in different oceans that perform similar functions?

6.1.1.1 Can we use machine learning (in particular, feature selection) to identify species that are relevant to some “event”?

Models that are learned from data to predict a discrete event (or class) are known as classifiers (Langley 1992) and prior to inducing these from data, it is common to identify the relevant features. There are two main approaches: Rank feature selection and Wrapper feature selection (Inza *et al.* 2004). The former attempts to identify relevant variables through the use of a metric that scores how well a variable ‘separates’ the two classes. The latter scores variables based upon how well they classify variables with the use of a chosen classification model. This offers the advantage of exploring how well variables interact but also risks bias due to the choice of classifier. For this paper, we apply both techniques, a rank approach using both information gain and chi-squared as the scoring metric and a wrapper approach using a Bayesian classifier and a Decision Tree. Here we explore the use of feature selection to identify relevant species to predict the collapse in cod in 1990 in the Northern Gulf. Both filter and wrapper feature selections were applied and the relevant species are reported in Figure 6.2 where all species are ranked in order of relevance and in Figure 6.3 where the difference between pre and post 1990 correlations are reported. Figure 6.2 illustrates that both methods identify similar species as being most critical (including haddock, white hake, witch flounder and thorny skate). However, other species such as redfish

become much more relevant when species interaction is taken into account, jumping from 31st place to 20th place when using the wrapper feature selection. Figure 6.3 demonstrates how the relationship of some of the species to cod, identified through feature selection, have indeed changed after 1990, in particular sea raven, white hake, redfish and shrimp.

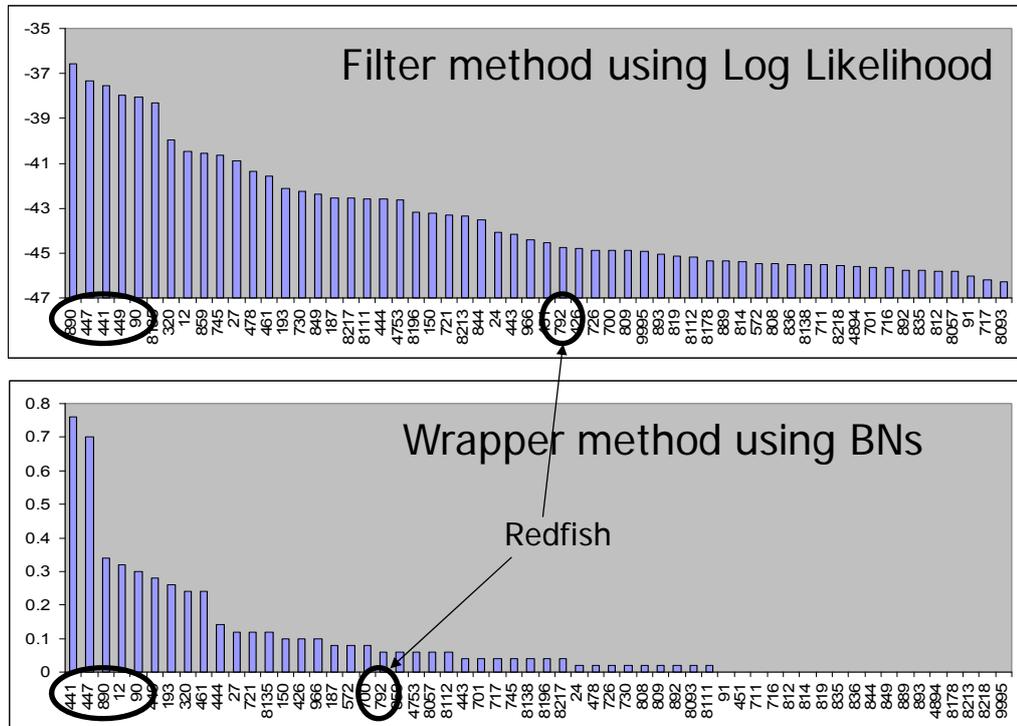


Figure 6.2. Feature Selection results. Rank selection which simply scores species based on their predictive power is shown on the top and Wrapper selection which takes into account interaction between species is illustrated below. Similar top ranking species are circled as is the redfish which rises considerably in ranking when interaction is taken into account.

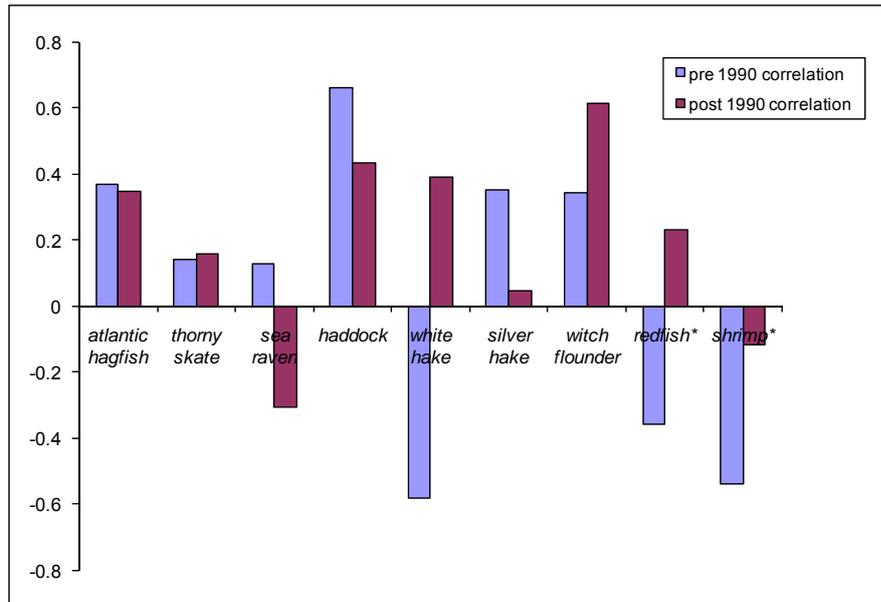


Figure 6.3. A comparison of correlations of species identified using feature selection, prior to and post the 1990 collapse in cod. Notice how the relationship between cod and some species has changed dramatically – some from strong positive to strong negative and vice versa.

6.1.1.2 Can we use Bayesian networks to combine human expertise with data to build better models?

Bayesian Networks (BNs) are probabilistic models that can be used to combine expert knowledge and data using prior information (Pearl 1988, Heckerman 1996, Milnes 2010). They facilitate the discovery of complex relationships in large datasets and enable non-statisticians to query resultant models. For this reason they are particularly useful in the analysis of fish population data when trying to understand underlying relationships between different species. A BN consists of a directed acyclic graph, made up of links between nodes that represent variables in the domain. The links are directed from a parent node to a child node, and with each node there is an associated set of conditional probability distributions. A Bayesian network thus consists of the following: a set of N nodes, representing the variables in the domain and directed links between the nodes. Associated with each node, there is a conditional probability table representing the probability distribution for each variable given the values of that node’s parents. See Figure 6.4 for an example BN for five species.

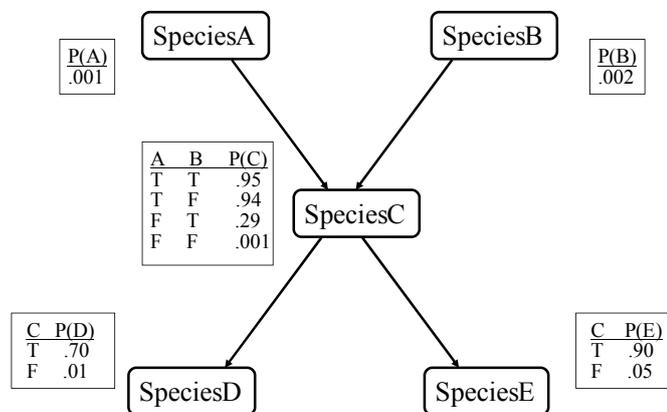


Figure 6.4. An example of a Bayesian Network with five species. Species C renders species A and B conditionally independent of species D and E. Associated with each node is a conditional probability distribution.

Learning the structure of a BN from data (Cooper 1992, Suzuki, 1996) is a nontrivial problem due to the large number of candidate network structures. As a result there has been substantial research in developing efficient algorithms within the optimisation communities.

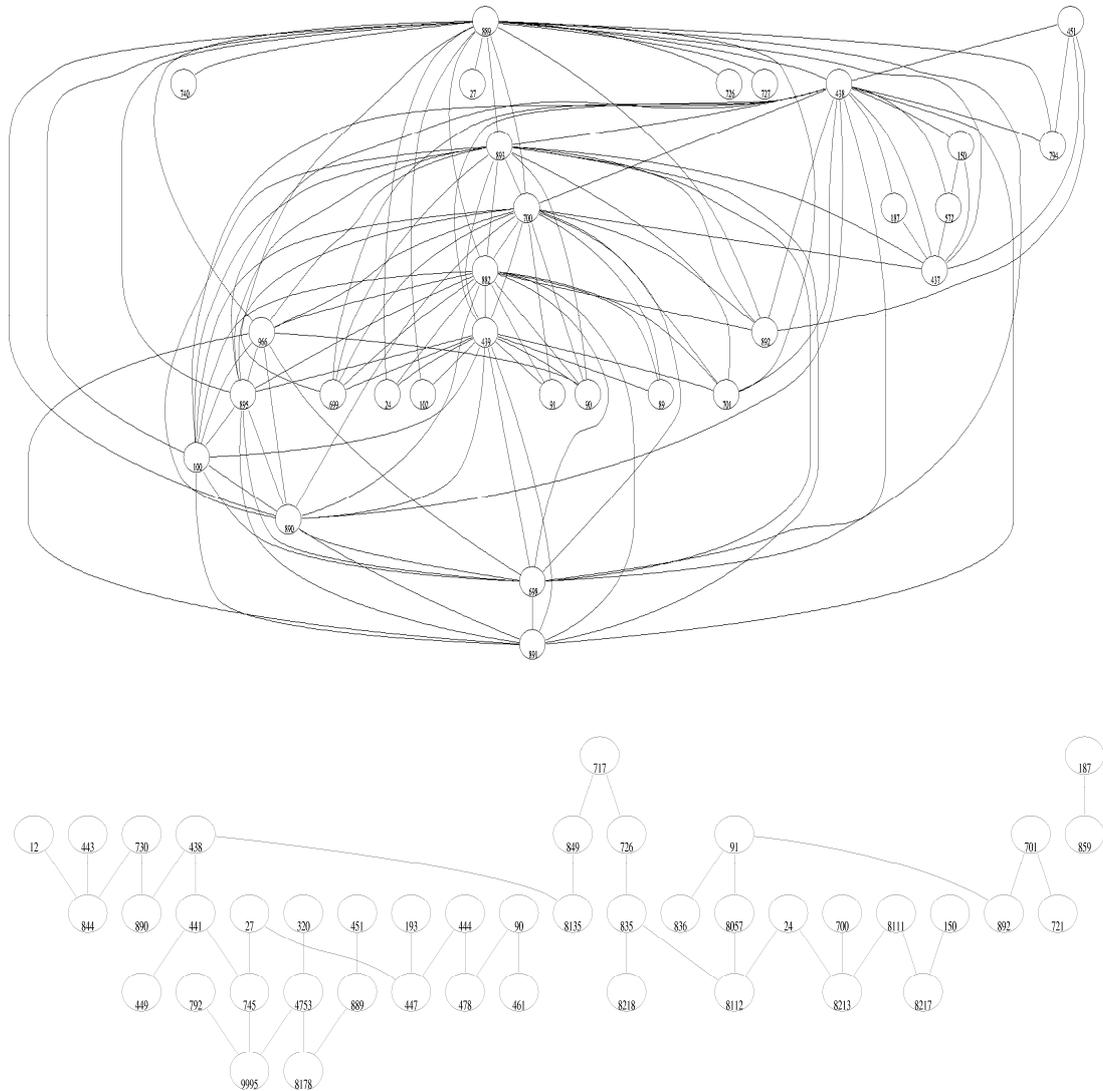


Figure 6.5. Top - a network derived from a human expert and bottom - a Bayesian Network learned from the N Gulf data. Notice how much less “connected” the BN is compared to the expert constructed one. This is very likely to be due to the limitations of the available data: the relationships found in the Bayesian Network are only those that can be found with significance.

Figure 6.5 shows two networks, one a network drawn up based on human expertise of fish interactions and one a Bayesian network learnt directly from the N Gulf data. Notice how far fewer connections there are in the Bayesian network likely to be due to data quality issues. More data is needed due to issues such as missing data (30% has been imputed) and limited sample size. Nevertheless, the next question explores to what extent models can be learnt from this data to make predictions about the future states of species with some success.

6.1.1.3 Can we model the temporal and dynamic nature of fish interactions?

In order to explore the dynamics of species interaction and also to enable the forecasting of future states of communities we also explore the use of Dynamic Bayesian Networks (DBNs) (Friedman, 1998a). A DBN is a Bayesian network where the N nodes represent variables at differing time slices. Therefore links occur between nodes over time and within the same time lag. Figure 6 shows an example of a DBN where each node represents a variable at a certain time slice and each link represents a conditional dependency between two nodes. Given some evidence about a set of variables at time t , we can infer the most probable explanations for the current observations. We can also make use of hidden (or latent) variables which represent unmeasured data using the EM algorithm (Friedman 1998b) to explore whether they can capture important events (e.g. changes in fishing) or species that are missing from the available data.

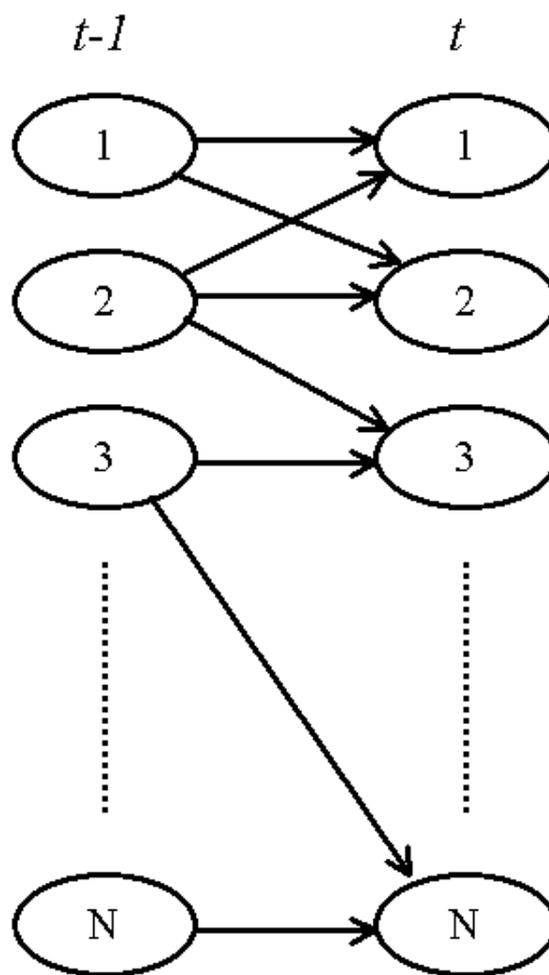


Figure 6.6. A dynamic Bayesian network for modelling the temporal nature of data. Nodes represent variables at a particular point in time, t and links can occur within one time slice or from previous time points to future ones.

The experiment involved learning DBN structure and parameters with hidden state variables from the NG dataset to see if relevant species could identified and used to forecast cod biomass in the future. The hidden state was also explored to see if the information it conveyed could be interpreted.

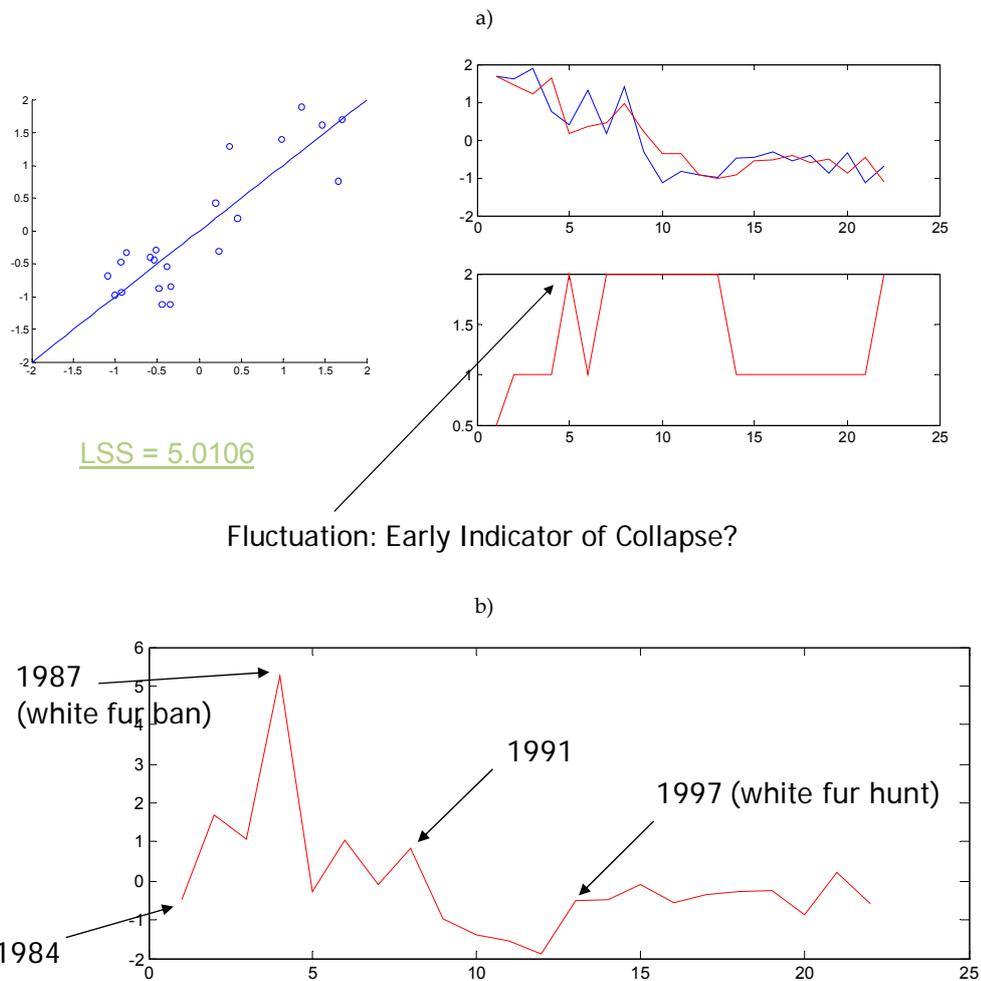


Figure 6.7. A DBN learned from NG Data with a discrete 2-state hidden node (a) and a continuous hidden node (b) with dates at key fluctuations.

Figure 6.7a shows the results of learning the DBN and testing it on forecasting the future biomass of cod. The prediction is surprisingly good as shown in the scatterplot with a least sum square error of 5. The line plots show the cod biomass over time in blue along with the predicted values from the DBN in red. The fit is good and at least some drop in biomass is predicted at the key collapse (time points 9 and 10) though not as extreme as what actually occurred. The hidden state is interesting as it predicts a distinct change in the state of the community with a fluctuation that occurs well before the collapse. The species that were associated with predicting cod in the DBN structure were hakes, redfish, witch flounder, shrimp, thorny skate and haddock, many of which are known to be influential on the cod population. A linear dynamic system was also used where the hidden state variable was continuous and certain key dates were observed in the fluctuations of this variable. Fluctuations could be due to changing temperature, fishing levels, or predator populations. See Figure 6.7b for some of these details.

6.1.1.4 Question: Can we identify species in different oceans that perform similar functions?

The "Wasp Waist" effect is found in populations in the Northwest Atlantic (a) and the Northeast Atlantic (b) as shown in Figure 6.8 (Jorda *et al.* 2005). A number of nodes represent the larger species which determine the population of the wasp waist species, capelin or sandeel, which in turn determines the populations of the smaller

species. Notice that the same functional structure is applicable to different sets of species depending on the geographical location and this is what our approach attempts to model. This is similar to the approach used in (Thrush 2008) but focuses on integrating datasets from different fish communities and uses the Bayesian network paradigm rather than neural networks.

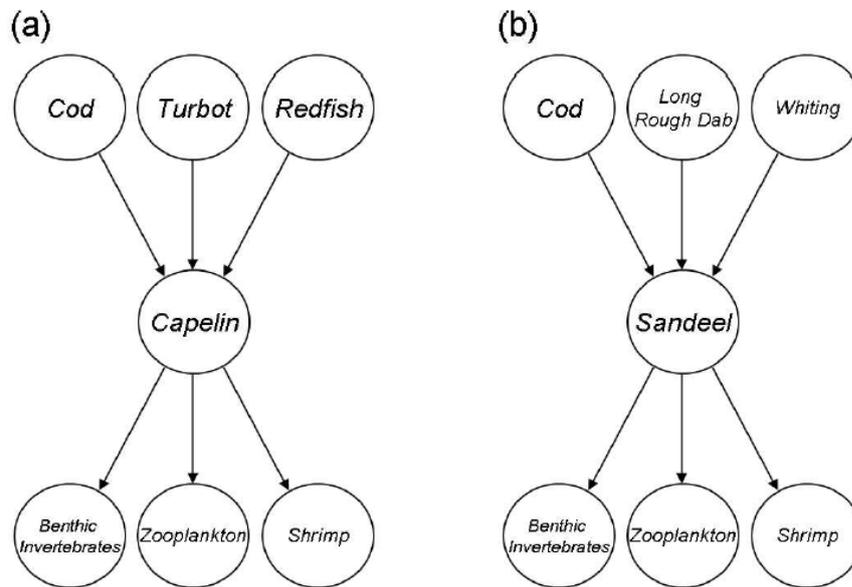


Figure 8. The Wasp Waist: An example of a functional model that is comparable between two fish communities, one in the Northwest Atlantic (a) and one in the Northeast (b). The species differ but the structure of the relationships between species is the same.

The proposed functional model approach (Algorithm 1) searches for a set of species, *vars2*, that fit a predefined function such as the Wasp Waist. Here, a predefined Bayesian network, *BN1*, is used that has been parameterised from predefined species in the NG data, *vars1*. This model is used to search for species in the ESS data that best fit. Algorithm 2 uses the species discovered in Algorithm 1 from the ESS data integrated with the NG data to build a more robust functional model. It uses a k-fold cross validation approach to test the predictive accuracy of the model parameterised with the newly associated data. The functional approach is compared to a standard leave one out cross-validation where the data from ESS is not integrated. The experiments always ensure that the test data is unseen and has been used to neither select the variables nor parameterise the model.

Algorithm 1 The FnBN search algorithm

```

1: Input:  $t_{start}$ ,  $iterations$ ,  $data_1$ ,  $data_2$ ,  $vars_1$ ,  $BN_1$ 
2: Parameterise Bayesian Network,  $BN_1$  from  $data_1$ 
3: Generate randomly selected variables in  $data_2$ :  $vars_2$ 
4: Use  $vars_2$  to score the fit with selected model  $BN_1$ :  $score$ 
5: Set  $bestscore = score$ 
6: Set initial temperature:  $t = t_{start}$ 
7: for  $i = 1$  to  $iterations$  do
8:   Randomly switch one selected variable in  $dataset_2$  and rescore:  $rescore$ 
9:    $dscore = rescore - bestscore$ 
10:  if  $dscore \geq 0$  OR  $UnifRand(0, 1) < \exp^{(dscore/t)}$  then
11:     $bestscore = score$ 
12:  else
13:    Undo variable switch in  $vars_2$ 
14:  end if
15: end for
16: Output:  $vars_2$ 

```

Algorithm 2 Using the discovered functional variables to build models

```

1: Input:  $data_1$ ,  $vars_1$ ,  $data_2$ ,  $vars_2$ 
2: Apply k-fold cross validation to build  $k$  training and testing sets on  $data_1$ 
3: For each training phase incorporate the data from  $data_2$  using  $vars_2$  identified in Algorithm 1
4: Test on the test sets from  $data_1$ 
5: Output: Predictive Accuracy

```

a) Simulated Data

Firstly, simulated data was used to test the approach. A structure that captures two competing predators was used (predator1 \rightarrow prey \leftarrow predator2) to generate two datasets, $d1$ and $d2$. A predefined BN structure was used and parameterised using selected “species” in $d1$. The algorithm was used to search for “species” in $d2$ that best fit this model. It was expected that the correct associated variables from $d2$ would be discovered. Algorithm 2 was also used to explore how the identified “species” from $d2$ could be used to build better models by combining the data with that from $d1$. Different sample sizes were used for $d1$ and $d2$ and prediction accuracy compared using models learnt from $d1$ data only and models learnt using a combination of $d1$ with discovered species data from $d2$. Figure 9 shows the results of these experiments. It is clear that for smaller sample sizes ($d1 < 40$) the correct species can be identified (over 90% of the time) in that the resulting predictive accuracies of models learnt on the combined data were considerably better than those using $d1$ only. This effect becomes less and less as the sample sizes of $d1$ and $d2$ become larger. It was hypothesised that if $d1$ was too small, the pre-defined model would not be well parameterised and that if $d2$ was too small, the new data would not be rich enough to identify similar functions. However, even for samples of size 10, an improvement in accuracy was observed.

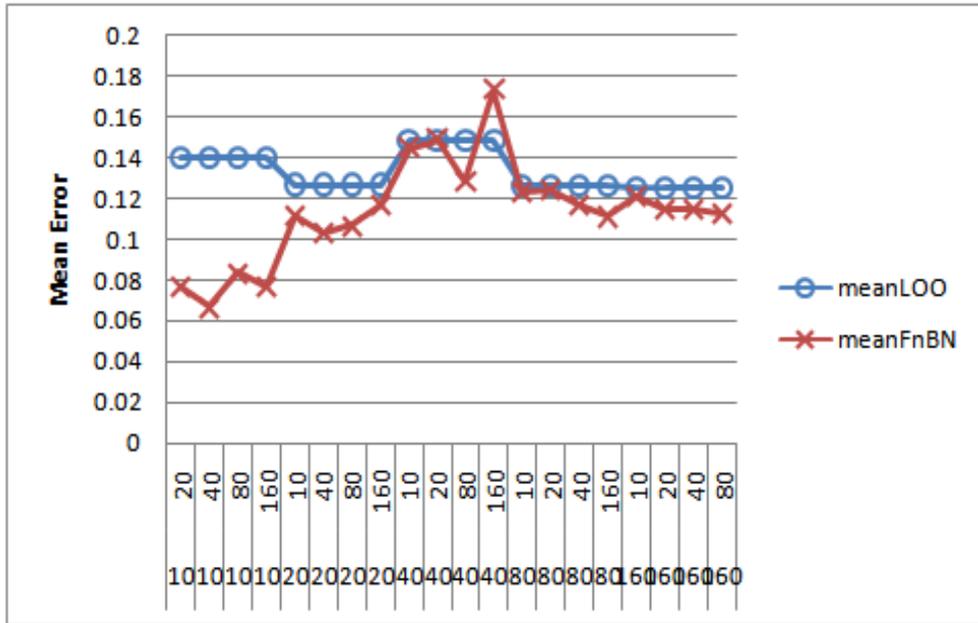
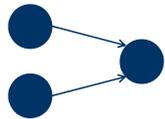


Figure 9. The mean error of the predictive model learnt from d1 only and tested using simple leave one out cross validation (blue), and the FnBN approach using the species identified in d2 integrated with the d1 data (red). As the sample size of d1 and d2 increase the effect becomes less pronounced as enough data is supplied in d1 to learn a good model.

b) Real Data

Competing Predators



Northern Gulf			
Cod (438)	Halibut (829)	Northern Shrimp (8111)	
East Scotian Shelf			Frequency
boreal red shrimps	white hake	monkfish	17
capelin	smooth skate	thorny skate	14
Atlantic argentine	Atlantic herring	Greenland halibut	14
Greenland halibut	spiny dogfish	white hake	10*
Greenland halibut	Atlantic Cod	pollock	6*
Atlantic poacher	haddock	white hake	6
Atlantic herring	Atlantic halibut	Atlantic Cod	5*
	LOO	FnBN	
Mean % Error	0.306	0.216	
SD Error	0	0.006	

Northern Gulf			
Cod (438)	Redfish (Rockfish 792)	Northern Shrimp (8111)	
East Scotian Shelf			Frequency
pollock	longfin hake	at halibut	10
American plaice	at halibut	boreal red shrimps	9
white hake	smooth skate	at herring	8
cod	spiny dogfish	snake blenny	6
at halibut	smooth skate	pollock	5
at herring	snake blenny	marlin-spike	4
smooth skate	monkfish	boreal red shrimps	4
monkfish	Atlantic wolffish (striped)	spiny dogfish	4
white hake	thorny skate	at halibut	3
haddock	at halibut	at hagfish	2
white hake	pollock	lumpfish	2
	LOO	FnBN	
Mean % Error	0.297	0.251	
SD Error	0	0.016	

Predator / Prey



Cod	Capelin	Frequency
smooth skate	thorny skate	25
thorny skate	smooth skate	24
gr halibut	at poacher	21
at poacher	gr halibut	15
longfin hake	white hake	6
white hake	longfin hake	5
marlin-spike	longfin hake	3
longfin hake	marlin-spike	1
LOO % Error = 0.162	FnBN % Error = 0.162	

Redfish	Capelin	Frequency
smooth skate	thorny skate	32
thorny skate	smooth skate	25
at poacher	gr halibut	15
gr halibut	at poacher	15
white hake	longfin hake	3
longfin hake	white hake	2
longfin hake	marlin-spike	2
marlin-spike	longfin hake	2
monkfish	thorny skate	1
smooth skate	monkfish	1
thorny skate	monkfish	1
witch flounder	sea raven	1
LOO % Error = 0.162	FnBN % Error = 0.162	

GrHalibut	Capelin	Frequency
Capelin	American Plaice	38
Capelin	thorny skate	37
boreal red shrimps	monkfish	23
daubed shanny	thorny skate	2
LOO % Error = 0.405	FnBN % Error = 0.216	

Applying an identical set of experiments to the two datasets, Northern Gulf and East Scotian Shelf, the mean errors and the identified species in the ESS were explored for different functional structures and predefined species. The tables on the left were the results of searching for similar species in the ESS as competing predators identified in the NG: cod and halibut competing for shrimp and cod and redfish competing for shrimp. The tables document the predictive error for using the NG data alone compared to the FnBN approach which integrates the new data from ESS. It can be seen that both sets of experiments for competing predators result in better models with lower mean errors. The species identified in 100 repeated experiments are documented as frequencies. There are some species which seem to make sense having common predators, in particular halibut and dogfish, halibut and cod, and halibut and herring. There are also some unlikely species combinations which may be due to the functional models finding relationships due to spurious and implicit correlations. Whilst it was promising to see that shrimp appear in the competing predators function as prey it is odd that it is sometimes confused as a predator. These results imply that the associated species are indeed in some way functionally similar (or at least predictive of the original specified function) but some of the spurious relationships could be due to shifts in dominance in entire systems from fish to invertebrates or perhaps a reaction to a changing (cooling) environment which favoured shrimp growth. The competing predators function appears to benefit more than the simple predator prey function with more improved accuracies. This could be a result of a better fit of model and problems with spurious correlations. Indeed, many predator prey pairs seem to be associated with competitors (due to implicit correlations – e.g. Smooth and Thorny skate).

6.1.2 Conclusions

In this report, a number of questions have been asked about fish population interaction based upon biomass data from two regions in the Atlantic. Machine learning approaches and in particular Bayesian networks have been used to model these relationships with varied success. The identification of species relevant to some event using feature selection and the use of models to capture species dynamics for forecasting future biomass were particularly promising. There is still much work to be done on exploring the integration of expert knowledge with Bayesian network models using Bayesian priors and the functional model approach to integrating data from different species needs to be investigated further, though very promising results have been collated on simulated data and to a lesser degree on the East Scotian shelf and Northern gulf data where more robust models were generated and similar functions were observed for predator-prey-pairs and competing-predator functions.

Future work will involve several themes:

- 1) Incorporating prior expertise using network priors based on similar work in (Steele *et al.* 2009).
- 2) Continuing the functional Bayesian network modelling approach using more complete datasets from a larger number of locations and modelling more complex functions.
- 3) Continuing the hidden state based approaches to modelling the dynamics. In particular exploring when certain relationships and functions appear to break down over time.

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Annex 1: WGFE Terms of Reference 2009

- a) Model the relative effects of climate and fisheries on fish productivity and community structure, including spatial aspects.
- b) Review and evaluate metrics to characterise, monitor and detect changes in the structure, function and productivity of fish communities
- c) Develop, explore and apply mapping and other spatial methods for comparing and summarising fish and fish community distributions in relation to environment and habitat
- d) Examine abundance/distribution relationships within species, and groups of species in different ecosystems in relation to habitat, environment and in relation to anthropogenic impacts
- e) Evaluate fluctuations within fish communities:
 - i) What constitutes regime shifts in fish communities. Can mechanisms be identified detected?
 - ii) State changes - Cycles vs. regime shifts
 - iii) Are anthropogenically induced changes alterable?

Long Term Terms of Reference

- Examine climate change processes and predictions of impacts

WGFE will report by 15 October in 2010 (via SSGEF) for the attention of SCICOM.

Annex 2: ICES Science Plan topics

Thematic Area 1: Understanding Ecosystem Functioning

1. Climate change processes, and predictions of impacts
2. Fish life history information in support of EAM
3. Biodiversity and the health of marine ecosystems
4. The role of coastal zone habitat in population dynamics of commercially exploited species
5. Top predators (marine mammals, seabirds, and large pelagics) in marine ecosystems
6. Sensitive ecosystems (deep sea corals, seamounts, Arctic areas), as well as rare and data-poor species
7. Integration of surveys in support of EAM

Thematic Area 2: Understanding Interactions of Human Activities with Ecosystems

8. Impacts of fishing with marine ecosystems
9. Carrying capacity and ecosystem interactions associated with mariculture
10. Influence of development of renewable energy resources (e.g. wind, hydro-power, tidal and waves) on marine habitat and biota
11. Population and community level impacts of contaminants, eutrophication, and habitat changes in the coastal zone
12. Introduced and invasive species, their impacts on ecosystems and interactions with climate change processes

Thematic Area 3: Development of Options for Sustainable Use of Ecosystems

13. Marine living resource management tools
14. Operational modelling combining oceanographic, ecosystem and population processes
15. Marine spatial planning, including the effectiveness of management practices (e.g. Marine Protected Areas (MPAs), and its role in the conservation of biodiversity
16. Socio-economic valuation of ecosystem goods and services, and forecasting of the impact of human activities

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Annex 4: Agenda

Work days begins 9:00 at IFREMER

Lunch (12:30 – 13:30)

Day ends ~18:00 to 19:00

Monday, 6 September 2010:

Introductions – Institute, country, interests

Startup, connection to the server and other logistics performed by IFREMER Staff.

Low participation issue in 2010 – Discussions around how to improve participation by WGFE members and the need to revisit membership

Final formulation of groups for each ToR and assignment of a coordinator who will be responsible for pulling together the corresponding report chapter.

Presentation - Verena Trenkel

Other

Tuesday, 7 September 2010:

Group and individual work

Plenary consultation on ToR (a) analysis

Wednesday, 8 September 2010:

Group and individual work

Plenary presentation of work and text

Thursday, 9 September 2010:

Group and individual work

Plenary presentation of work and text

Friday, 10 September 2010:

Plenary on suggested ToRs for 2010

Group and individual work

Plenary presentation of work and text

Compilation of report

Annex 5: WGFE draft resolution for the next meeting

The **Working Group on Fish Ecology (WGFE)**, chaired by Dave Kulka, Canada, will meet in **Hamburg Germany**, **DATE** (to be confirmed) on:

- a) Present new results on modelling the interacting effects of climate and fisheries on productivity and community structure, including spatial aspects"
- b) Review and evaluate metrics to characterize, monitor and detect changes in the structure, function and productivity of fish communities;
- c) Develop, explore and apply spatial methods for comparing and summarizing fish and fish community distributions in relation to environment and habitat;
- d) Examine abundance/distribution relationships within species, and groups of species in different ecosystems in relation to habitat, environment and in relation to anthropogenic impacts;
- e) Evaluate fluctuations within fish communities:
 - i. What constitutes regime shifts in fish communities? Can mechanisms be identified detected?
 - ii. State changes - Cycles vs. regime shifts
 - iii. Are anthropogenically induced changes alterable?
- f) Review, report on and develop the outputs of the ICES SIBAS Workshop on 'Biodiversity indicators for assessment and management'¹

¹Review the outputs of the ICES SIBAS Workshop on 'Biodiversity indicators for assessment and management' (available February 2011) and, based on the indicators that have been proposed and the reporting processes they are intended to support, report on:

- The strengths and weaknesses of the proposed indicators for fishes and fish communities;
- Recommended modifications to the indicators;
- The process that would be used for data acquisition, analysis and reporting of the indicators;
- The tradeoffs between fishing and the status of fish populations and communities that need to be considered when setting targets for biodiversity indicators;
- The information, data and tools that are available to assess and quantify these tradeoffs;
- How the indicators, targets and tradeoffs might be presented as advice;
- The additional data, information and science needs to quantify tradeoffs.

Long Term Terms of Reference

- g) Examine climate change processes and predictions of impacts

WGFE will report by **DATE** 2011 (via SSGEF) for the attention of SCICOM.

Supporting information

Scientific Justification and Relation to the 16	Refer to the Executive Summary for a cross match of ToRs and SCICOM high priority topics. a) ToR a is a more general phrasing of the traditional WGFE work on indicators of fish
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High Priority Topics (Hpt) of the Science Plan and Strategic Initiatives (Si)	<p>community structure, dynamics, production and function and human and climate impacts. This ToR relates mainly to Science Plan Theme 1 and high Priority Topics (HPT) points 1, 2, 3, 8, 14</p> <p>b) WGFE is continues to develop and test new community and viodvierty indicators in support of an ecosystem approach to management. ToR b relates to the data part of the modelling work described in ToR a. ToR b therefore in relevant to all of the same sections of the science plan, with additions: 1, 2, 3, 7, 13, 14. This work also has direct relevant to the Strategic Initiative on Biodiversity</p> <p>c) Objective methods for spatial andalysis is an essentialto examining changes in fish distributions in relation to forcing such as climate and fishing effort. Thus, this work could be important in the future for SSICC and HPT 1. Sophisticated objective mapping tools are are essential in developing strategies for marine spatial planning and therefore relevant to SICZSP and HPT 15. 1, 8, 13, 14, 15, 16</p> <p>d) Changes in spatial distribution (occupany) of fish in relation to external (climate, fisheries, habitat) and internal (density dependence) forces and the separation of the two remains and important research area in WGFE. This work relates to HPT 3, 8, 14. This work can provide some theoretical back for work on marine spatial planning especially regarding sensitivity of species groups to habitat destruction and fragmentation with is important for SICZSP.</p> <p>e) This ToR is an open call to examine the concept of state changes, including regime shift (and like processes) in marine fish communities. Considerable confusion and contention revolves around this issue currently and WGFE has a range of expertise that can shed light on the issuers. This work relates to most topics under the Ecosystem Function thematic area and HPTs 1, 3, 8. Because there is considerable interest and expertise on this topic in academia, it is hoped that this ToR may be an incentive for this segement of the research community to attend in greater numbers.</p> <p>f) This ToR contributes to the delivery of the SCICOM/ACOM Strategic Initiative on Biodiversity (SIBAS).</p>
Resource requirements	
Participants	The group is normally attended by 15–20 members and guests.
Secretariat facilities	None.
Financial	No financial implications.
Linkages to SCICOM Steering Groups	SSGEF, SSGSUE, SSGHIE, SSGESST
Linkages to other groups	<p>Work on simulation in fish communities for the testing of EcoQOs is closely related to the development of multispecies modelling in WGSAM</p> <p>EcoQO work is an important component of advice provided by ACOM</p> <p>The work of this group is an important information source for WGECO (Ecosystem Effects of Fishing)</p> <p>This group has provided key scientific products to the Strategic Initiative on Climate Change (SSICC)</p>
Linkages to other organizations	Work on indicator modelling and specifically EcoQO projections are the result of OSPAR requests to ICES.

Annex 6: Recommendations

The following Recommendations have been generated by the work of WGFE in 2010. They will be used, along with the Science Plan to guide the formulation of ToRs and work topics within the ToRs for the group. They can also be used more generally, at the discretion of ICES to formulate future directions.

RECOMMENDATION (FROM WGFE REPORT)	ACTION
ToR a - Include spatial aspects consistent with biological and physical structure to evaluate the effect of spatial management measures on the community indicators, useful in evaluating the effects of measures taken within the Natura-2000 areas, and in the upcoming measure to reach Good Environmental Status, for example.	WGFE
ToR a - Spatial aspects of expected climate change and fishing impacts should be incorporated into models for evaluating their effects on exploited fish communities and community indicators.	WGFE, SIBAS
ToR a - The results of the simple food web model described in the 2010 WGFE Report (Chapt. 2) shows that it is not necessary to focus on the complex multi-species size structure models to come up with answers on directions of change of population and community indicators. We recommend that WGSAM evaluate whether qualitative models and loop analysis provide answers to certain questions dealt with by them.	WGSAM
ToR b - Continue the work on metrics within ICES and within this group as metrics have the potential to be of value in characterising changes in structure, function and productivity of fish communities.	WGFE
ToR b – On the issues of choice of arbitrary boundaries for calculation of the metrics, evaluate the robustness of the proposed metrics for differences in the arbitrary values. Evaluate more thoroughly the assumptions of the metric and how these relate to the community in specific areas. Propose reference-levels for the other areas, based on their unique fish community and environmental conditions.	WGFE
ToR c - Develop regionalized models to account for localized geological, biological and perturbation feature distributions.	WGFE
ToR c - Continue to investigate mapping and	WGFE, SIASM

<p>spatial methods for comparing and summarizing fish and fish community distributions in relation to environmental and habitat factors including how these tools are applied in spatial management (e.g. MPAs) and how uncertainties in these relationships are characterized.</p>	
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Eight Recommendations were received by WGFE one week prior to the 2010 meeting. Thus the Recommendations were dealt with accordingly, as items that WGFE could deal with in 2011.

RECOMMENDATION (FROM ICES)	ACTION
<p>WKMOR - Mechanistic simulations of the early life stages of marine organisms should be developed where mortality is an emergent property, as opposed to being prescribed.</p>	<p>WGFE undertakes work on all life stage of fish and thus as part of its mandate, examines early life stage mechanisms. WGFE will endeavour to take into account emergent as well as prescribed properties went working on mechanistic simulations.</p>
<p>WKMOR - Experimental research should identify the characteristics of survivors and non-survivors, and quantify levels and variability in parameters required for modelling mortality in the sea.</p>	<p>Characteristics of survivors and non-survivors and parameter variability will be taken into account when modelling mortality of fish.</p>
<p>WKMOR - Adequately controlled experiments should be carried out to quantify the importance of less well known sources of mortality, e.g. investigating the effect of disease by replicating the pathogen environment in the sea, and studying individual developmental competence and variability in intra-cohort survival</p>	<p>This recommendation does not have a direct application to the work of WGFE as disease and pathogens are not directly dealt with except under the broader topic of natural mortality (undifferentiated)</p>
<p>WKMOR - A comprehensive listing of mortality estimation methods, with a careful articulation of their sensitivities and biases, should be compiled</p>	<p>Compilation of a list of mortality estimation methods in fish is more directly applicable to species assessment groups. However, estimation of mortality is done within some of the modelling work of the group.</p>
<p>WKMOR - Providing guidance (e.g. for fishery managers and scientists) should also include recommending valid correlation tools, with relevant caveats about their limitations with respect to predictions.</p>	<p>In the conduct of modelling, limitations with respect to predictions should always be considered as is the case for any work done within WGFE.</p>
<p>WKMOR - There is a need for coordinated research on fish early-life stages and on zooplankton to evaluate mortality, its magnitude, variability, and causes to further our understanding of how mortality operates in pelagic ecosystems</p>	<p>Evaluation of mortality in early life history stages is part of the conduct of WGFE.</p>

<p>WGECO - WGECO recommends that WGFE be made aware of the suggested ToR a) for 2011 which will continue work on the proportion of large fish indicator.</p>	<p>WGFE is continuing its work on community metrics.</p>
<p>SGIMT - ICES should request regional species lists from expert groups, notably the WGPME, WGHABD, WGZE, BEWG, WGFE and WGBIODIV, these lists should be compared / checked against WoRMS to provide standard nomenclature and synonyms using the new tool (http://www.marinespecies.org/aphia.php?p=match).</p>	<p>This is a large project that may be considered in the future by WGFE. However, it is best coordinated by taxonomically based WGs.</p>