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MULTISPECIES AND ECOSYSTEM INDICATORS, AND BIOMASS-FLEET DYNAMICS STOCK ASSESSMENT: AN INITIAL EVALUATION

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MULTISPECIES AND ECOSYSTEM INDICATORS, AND BIOMASS-FLEET DYNAMICS STOCK ASSESSMENT: AN INITIAL EVALUATION

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PREPARATION OF THIS DOCUMENT

This document reports on the final results and conclusions of a workshop held in Rome, from 23 to 26 October 2006. The objectives of this workshop were to: i) recommend an approach to evaluate ecological indicators of changes in marine ecosystems in data-poor locations; and ii) report on findings for a stock assessment model proposed for data-poor situations where only catch data is available. The group of experts convened for this purpose consisted of Gabriella Bianchi, William Cheung, Kevern Cochrane, Beth Fulton, Paul Medley, Carolina Minte-Vera and Marcelo Vasconcellos.

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ABSTRACT

This publication major objectives are to recommend an approach to evaluate the performance of ecological indicators applicable to the monitoring of the ecosystem impacts of fisheries in data-poor areas, and to evaluate the results of a stock assessment method (biomass-fleet dynamics model) previously proposed for fisheries in situations where only catch data is available.

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APPENDIXES

MULTISPECIES AND ECOSYSTEM INDICATORS (MEI)

1. ECOSYSTEM MODELS

The success of previous studies (e.g. Fulton *et al.,* 2005) has shown the value of the management strategy evaluation approach (MSE Approach) for testing indicators, monitoring and management schemes. The value of such exercises is dependent in part on the match of the model to the questions being asked. As background on this topic and a starting point for further discussion, Beth Fulton (CSIRO Marine and Atmospheric Research, Australia) provided an outline of the ecosystem model types used in Australia.

There has been a wide range of ecosystem models used in Australia, beginning with multispecies models (Sainsbury,1991; LFSIM Little *et al.*, 2004) and more recently including statistical analyses (Norm Hall, Murdoch University, Western Australia), qualitative models and network analysis methods (Dambacher, 2003), through to quantitative whole-of-ecosystem models such as Ecopath with Ecosim (EwE; Christensen and Pauly, 1992; Walters *et al.*, 1997), Atlantis (Fulton *et al.,* 2004) and InVitro (Gray *et al.*, 2006). Each approach has its associated strengths and weaknesses and each provides a useful means of capturing system dynamics, if used with care. Focusing on the most widely used ecosystem models:

1.1 Ecopath with Ecosim

This model type is user friendly and has been widely used around the world, providing many existing models that may be adapted for use in the current study (see www.ECOPATH.org). Numerous EwE modelling exercises have been or are being conducted in the tropics and subtropics in different ocean basins. Its popularity has only grown in the broader resource and ecological modelling community as the software has become more modular and more easily tailored to user needs. The most recent developments have seen the user front end separated from the equations. The equations can now be easily adapted for different models (Christensen, pers. comm.), which facilitates the modification of the existing model as well as allowing the software to be extended. It now has many components, including biological, fisheries and some economics and policy search options (Christensen and Pauly, 1992; Walters *et al.*, 1997). The Ecospace component allows a spatial representation of the ecosystem and fisheries dynamics. These features, the new modularity and careful use of the mediation, forcing, fitting and Ecospace components, means that many of the features of more detailed models (such as non-trophic dependencies, climate and oceanographic changes, non-fisheries anthropogenic impacts) can be represented, at least in some form. Particularly, a coral reef ecosystem model of Indonesia is being constructed, as part of an ecosystem-based management project, which should be one of the most elaborate Ecopath models of coral reef ecosystem that are available so far and can represent some of the detailed interactions in coral reef ecosystem (Pitcher, pers. comm.).

1.1.1 Detailed process models (e.g. Atlantis and InVitro)

These models tackle many processes explicitly and include the representation of the impacts of a wider set of human sectors and each facet of the adaptive management cycle (biophysical system, human activity sectors, monitoring, assessment and management activities). Both of these models are heavily process-based, with Atlantis taking a deterministic approach, while the hybrid model InVitro makes use of an agent-based structure, tying differential equation and individual-based models together. These models are much more complex to implement than EwE, but they can provide payoffs with regard to the flexibility and detailed data they can generate for testing indicators. They have also been written in such a way that components and processes can be easily turned on and off as desired at runtime. Importantly, there are many fewer implementations (only 14 to date), only two of which are tropical (one for an Atlantis spin-off and one for InVitro). The number of applications should increase, so more may be available for adaptation later in the current study.

The noteworthy feature of the ecosystem models developed within Australia (namely Atlantis and InVitro) is the use of the Management Strategy Evaluation (MSE) approach (Butterworth *et al*., 1997, Cochrane *et al.*, 1998, Butterworth and Punt 1999, Sainsbury *et al*., 2000); explicitly detailing each facet of the adaptive management cycle (Figure 1). In particular they include: multiple representations of the main ecological groups and processes found in marine ecosystems; fleet-level to individual-level representation of the dynamics of human sectors (primarily fisheries); a sampling model that reports fisheries statistics and (if desired) the results of fisheries independent data collection exercises, with error structures typical of that found in reality; assessment models (from simple estimates to the explicit assessment models used in reality; such as surplus production models, ADAPT VPA, integrated models); all major management levers (e.g. gear, effort, zoning, seasonal closures, quotas and the like) and management decision models, including lag in implementation of decisions; and simple to complex representations of the socio-economic drivers and considerations, particularly for compliance.

Any model using the MSE approach, or that can be adapted to the approach by the use of supporting plug-in modules, can consider a range of questions. Typical applications are:

- consideration of the ecosystem dynamics (omitting anthropogenic activities); this gives insight into the ecological interactions, bottlenecks and dynamics of the system, such as highlighting unanticipated interactions, such as the use of gelatinous zooplankton as subsistence forage.
- forced historical anthropogenic actions (typically disturbances or extractive actions, liking forcing with known harvests); this not only gives an understanding of how the target species have changed through time, but also gives insight into how the rest of the system has also changed through time, which has feedback implications for the target stock health or may highlight regime shifts.
- dynamically matching historical effort distributions and catches; this can be informative with regard to fleet dynamics in its own right, but is usually a springboard step for predictive applications, which consider the implications and robustness of specific management or monitoring strategies.

The biggest omission in all the existing ecosystem models is the treatment of biodiversity. In EwE, a rule-based algorithm that is based on the biomass changes of the functional groups and the life-history of the species within the groups can be used to determine how depletion can impact at the species level, which in turn can be used to calculate a diversity proxy (William Cheung, UBC, unpubl. data). While other ideas on how this may be tackled using empirical representations exist, they have not seen much use as yet. This may be a problem for testing some potential indicators. Uncertainty and model sensitivity will also present problems, though supplementing the analysis with qualitative and network analysis methods can give a good indication of potential errors due to structural sensitivity (Jeff Dambacher, CSIRO, unpubl. data). However, for the MSE approach as a test for indicators, fine-detail matching is less important than capturing gross non-linearities, so to some degree uncertainty issues are less important. One important feature is to make sure that any ecosystem model used in this study includes (even via simple forcing functions) the impacts of sectors beyond fisheries. The hardest to model, but probably most important, is the use of indicators where there are multiple strong pressures on the system. It is important to make sure that management is aimed at the correct causes of observed changes.

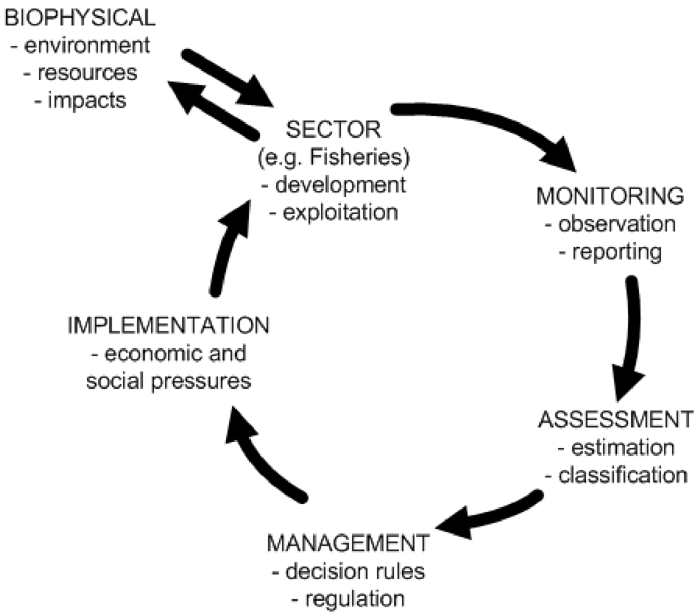

Figure 1: Major components of the adaptive management cycle

2. INDICATORS

There has been a lot of work considering ecological indicators both generally and specifically with regard to the effects of fishing. Many reviews exist (Landres, 1992; Rapport, 1992; Jackson *et al.*, 2000; ICES, 2001; Tegler *et al.*, 2001; Rochet and Trenkel, 2003; Rice and Rochet, 2004; Rochet and Rice, 2004; Cury and Christensen, 2005), but the work on specific indicators and the criteria for their success has also received a lot of intensive interest over the last few years. A useful reference on this is the ICES journal – Volume 62 (2005). Papers in this journal provide a good summary on both of these aspects on indicators. With respect to criteria for success it has been found, both theoretically and empirically (Fulton *et al.*, 2005; Link, 2005;, Rice and Rochet, 2005; Rochet and Rice, 2005), that good indicators are easily measured, cost effective to collect and calculate, and easily interpreted (to avoid confusion about the state of the system they are reflecting). Simple indicators are consistently found to out perform more complex (model-dependent) indicators, which were sensitive to data quality (Fulton *et al.*, 2005; Link 2005). Applied studies have also shown that pragmatism is required in implementation as there will always be some questions of cost, relevance, expertise and existing time series in the local area (Fulton *et al.*, 2004; Link 2005), as well as the need for some degree of regionalization (e.g. inshore-offshore splits were required for best signal detection in a case study based on the Northwest Shelf of Australia [Fulton *et al.*, 2004]). Nevertheless there is consensus on the need for a suite rather than a single indicator and on the types of indicators that perform well regardless of system type. These indicators are:

- **Relative biomass**: specifically of gelatinous zooplankton, cephalopods, small pelagics, scavengers, demersal fish, piscivores, top predators (TL 4+, which synthesise over large temporal and spatial scale), and biogenic habitat (cover forming species). Ease of sampling differs strongly between these groups (for instance external bodies, such as NGOs, often monitor the charismatic top predators, tourism can focus attention on coral reef fishes, snapshots of mangrove forests and shallow benthic habitat may be available from satellite images), but it is possible to find proxies for even some of the most difficult groups. For example, changes in relative biomass of gelatinous zooplankton may be captured by frequency of bloom events, as this is a much more easily obtainable statistic due to the ability to generate it from expert information and fisher interviews.

- **Biomass ratios**: in particular the biomass ratios of piscivore: planktivore (PS:ZP), pelagic: demersal (P:D) and infauna: epifauna. The last of these is probably not feasible in data poor situations, but the other two can be done. More importantly there are existing published values for PS:ZP and P:D that can guide reference direction (if not reference point) definition (Bianchi *et al.*, 2000; Caddy, 2000; Caddy and Garibaldi, 2000).
- **Size spectra**: which give an indication of perturbation in system structure (using the slope of the curve), but can also highlight changes in system productivity (via the intercept).
- **Maximum (or mean) length**: this indicator has been observed to work in practice even if simple rules of thumb regarding L_∞ are used. Caution is needed regarding market driven changing in preferred sizes, however.
- **Total fisheries removals** (catch+bycatch+discards): this indicator considers the total biomass removed from the system versus what is left cycling in the system. While similar in concept to the widely used comparison of primary production vs. removals from the system, there is concern that it will not be suitable for data poor and dispersed small scale fisheries due to the lack of data on removals let alone discards.
- **Diversity** (counts of species): while a highly controversial topic in the ecological and conservation literature, it remains an informative and fundamental piece of information about the system. Alternative measures of diversity or system structure (e.g. Whitakker plots (Krebs, 1998), ABC plots, Kempton Q index (Ainsworth and Pitcher, in press)) may need to be considered too, depending on which operating model is used or what empirical data is available. One possibility is considering the value of changes in species-area curves (e.g. the slope and asymptote of the curve) through time (or spatially if under a perturbation gradient). It is likely that some simple or ordinal data can be collected on this from the fishers themselves given that they are acutely aware of what they catch (Minte-Vera and Medley, pers.comm.). Looking at changes in these rankings could be highly informative.
- **Size at maturity** (weight and length): while this can be a strong means of detecting change in the system and stock structure, it may be too difficult to use in data poor situations.
- **Biophysical** (Chlorophyll a, temperature, dissolved inorganic nitrogen, and level of contaminants): these may be drawn from water quality monitoring programs or remotely sensed data sets, but are needed even if they aren’t already being collected as they are the means of teasing out causation (is a non-fisheries sector producing the changes?). Indicators respond to any system change, including those caused by sectors other than fisheries, so any information that helps elucidate causation is extremely helpful.

While all of these indicators are not equally easily calculated in data poor situations, they are a good “straw-man” to start testing indicators for such fisheries in this study. Regardless of the set that is tested, previous work (Fulton *et al.*, 2005; Link, 2005) has shown that it is critical that:

- a suite of indicators, which are not all highly correlated, is used;
- multiple time and space scales are spanned by the data sets.

It is also critical that data include species that:

- are directly impacted;

- have high turnover rates, which may provide a noisy but early warning;
- define the habitat, as these often have a disproportionate or keystone role in the system; and
- are from the upper trophic level, which are typically both vulnerable in their own right due to their life history characteristics, but also integrative of pressures and patterns at large scales.

It was also noted that there is likely to be differential signal strength in pelagic and demersal systems (Fulton *et al.*, 2004), as pelagic systems are easier to characterize (require fewer parameters), but are more variable leading to longer periods before trends are detected.

Concerns regarding the availability of extended time series at a single location may be addressed by considering snapshots at multiple different locations under differential perturbation (e.g. fishing) pressure, so that it will still be possible get a gradient and contextualization for any individual location. Caution maybe necessary in such a situation though, as there may be problems if a changing environmental (or other) effect is masking the fishing effect.

3. STUDY DIRECTIONS

The high level focus for this study is to consider which ecological indicators of changes in exploited aquatic ecosystems will work in data poor locations; and whether it is actually possible to detect clear ecological signals with the type of information available in these locations. There are many facets to this broad topic: how should the information be collected? Are spatial comparisons sufficient (or even do you get different results in different locations)? How precise does the data used need to be? What frequency of sampling and indicator reporting would be necessary for the indicators to be useful?

Given the background presented on indicators and models, and the list of areas of interest presented above, a number of objectives have been identified for the current study:

1. To identify which indicators are most likely to be useful in data poor fisheries. The specific set of indicators may well depend on local circumstances including, for example, spatial diversity of the ecosystem and of fishing activities and the extent of fisher community participation. This objective may therefore need to focus more on identifying general rules for selecting indicators depending on local circumstances, including considering the demands and availability of data.
2. To identify the minimum required level of data collection. This should be incorporated into a general strategy for selecting indicators (see above). Related to the minimum data requirement, is the need to identify the minimum required degree of coverage – what proportion of the fishers need to collaborate in data collection for the data to be representative and useful? This question may be dependent on the form of community involvement in fisheries regulation (whether self regulated or not can dictate the degree of engagement), but can also be dependent on cultural and personality driven social interactions. Multiple case studies drawn from different locations should help to identify whether these issues are crippling however.
3. The value of restricted fisheries dependent data sets. In these data poor situations, with many small landing points, market sampling may be the only means of collecting information regarding catch and composition (either species or size structure). This kind of data (as well as the fisheries servicing the markets) can obviously be influenced by market forces. The effect markets have on indicator utility needs to be considered, especially with regard to the issue of how much yield is lost if the indicators are based on uncertain data. Studies in the Solomon islands and the Philippines may help in this aspect of the current body of work.

4. The value of expert information and local knowledge – via surveys of fishers. This kind of data collection poses problems, as explicitly modelling the psychology involved would be an enormous task in itself, but could be represented by considering many different levels of error and then seeing how these levels compare with impressions (e.g. of current state) *versus* fisheries independent data in empirical studies. Literature from psychology, especially on memory studies, should be useful in providing insights on the types and levels of error that may be associated with fishers survey. The location of suitable data sets for this verification need to be identified, but examples (e.g. in Brazil reservoirs [Okada *et al.*, 2005], Gulf of California [Lozano, 2006], the Gulf grouper study [Sáenz-Arroyo *et al.*, 2005] Northern British Columbia [Ainsworth and Pitcher, 2005]) are known to exist. This exercise will be most informative if repeated for different data types (from qualitative to quantitative); as quantitative may be most directly useful for indicator calculation, but may be much harder to collect reliably.
5. The value of benchmarks (reference points) for the most useful indicators. It will be particularly interesting to see if the same points are determined from time series, spatial comparisons and model results. Meta-analysis using data from existing databases may be useful in identifying the benchmark values.

With these objectives in mind there was extensive discussion of sampling exercises and model components required to answer these questions. It was recognized that work would progress much more rapidly if an existing detailed model was taken and used as is, or simplified, rather than spending many months to years developing a new implementation. The time saving associated with existing models would allow for consideration of a much wider range of systems. So long as the models used were of sufficient quality then this approach would have more strengths than weaknesses.

It was agreed that, given the complexity of ecosystem and socio-economic models and the time constraints, development from scratch of either of these model types should be avoided. This means that existing ecosystem models should be used with minimum modification (where possible) and that "painted" scenarios of socio-economics and management actions and feed back should be used to force the models during data generation.

With regard to suitable models, it was agreed that the models used will need to meet certain criteria, which are discussed below. A review of existing models against these criteria would need to form the early phase of the current study. Models to be considered could be drawn from the types recently reviewed by Plagányi (in press), but would need to be supplemented by a potentially wider model set drawn from the ecological literature. For instance it may be worth considering tropical implementations of Ecopath with Ecosim, Stella, bioeconomic Beam models, and models under construction by Les Kaufman (Boston University), InVitro and Atlantis-like models.

The criteria for model selection come in two parts. With regard to immediate use as is, the model must include specific components (listed in the following section), but must also be set up in a rigorous case study and of a reasonable "pedigree" (see model selection criteria in the final study outline detailed towards the end of this document).

Looking beyond immediate use, there is the potential need for model modification, if it does not cover all the needed components listed below or if it can not supply all of the data types needed to calculate the candidate indicators. This means that any model selected for use needs to be easily changeable, preferably tropically focused and reasonably generic. This final point was originally proposed so that the models could be modified to represent "typical tropical" conditions if desired, but if a wide range of model systems are considered then this becomes less of an issue as many case studies would provide as much or more information as a limited number of "generic" applications.

4. CASE-STUDY LOCATIONS

It is important to carefully select potential case study locations so that there is a good coverage of habitat types, fishery and social pressures, particularly in a tropical (and potentially data-poor) context. Related to this is that careful consideration needs to be given to the scales directly considered. An equally important consideration, given time constraints on the study, is to locate the case-study locations that are already being sampled and are (potentially) well known. For instance, the Secretariat of the Pacific Community and the Pacific Regional Oceanic and Coastal Fisheries/Coastal Component (SPC PROCFish/C: www.spc.int/donors/procfish/procfish.html) data collection project in the Pacific Islands makes it an attractive collaborator. That data collection project is collecting fish counts and habitat mapping from a range of islands, with different levels of fishing pressure. While there are no associated fisheries statistics collection or modelling components the empirical data would allow for calculation of many of the indicators listed above. It may also be possible to supplement this data from information collected by researchers at institutes like the University of the South Pacific or via targeted sampling to cover critical gaps. Other potential locations include Indonesia (a modelling study for Indonesia is being conducted at the Fisheries Centre, UBC, led by Tony Pitcher), Brazil, the Philippines and the South China Sea and the tropical areas of Australia (e.g. Torres Strait, Great Barrier Reef or Ningaloo Reef).

Future work envisaged by researchers in the field dovetails well with the objectives of this study. In particular, there is a desire to move beyond the primarily temperate industrialized fishery case studies used to date, and deal with “more difficult” cases (tropical and data poor). Expanding the number of systems considered is also desirable, ideally leading to an investigation including several areas that might have alternative drivers or non-linearities in the time-series. Locations with different time series coverage may also allow for consideration of the ease and feasibility of transitioning from relying on comparisons of spatial snapshots to temporal comparisons and trend calculation based on a time series at a single location. Comparisons across many systems may also allow for estimates of benchmarks and reference points for the indicators, rather than the reference directions that are currently given. This kind of reference setting has not happened a great deal to date (Link [2005] being a notable exception) as model-based values are unlikely to be reliable due to model uncertainties. Reference direction setting is acceptable given the nature of model dynamics *versus* uncertainty, but specific value setting is much more heavily impacted by model uncertainty.

5. MODEL SPECIFICATION

The management strategy evaluation approach envisaged for this study demands some minimum model specifications for best tests of the candidate indicators. The recommendations on these specifications are summarized here.

The biophysical operating model must have some ability to capture spatial dynamics, either explicitly or implicitly. In particular it must have the ability to accommodate a diversity of habitats and potentially extended time periods. The later is necessary so that interannual and large scale changes can be seen in the model dynamics; it is these kinds of strong non-linearities that can impact indicator performance. The importance of the physical environment and its potential to force the biological components should also be considered through an evaluation of the model’s ability to represent the impacts of current flow and advection, nutrient loading or the dispersal of contaminants, along with the model’s representation of more biological environmental features, such as living (biogenic) habitats like corals, sponges and seagrass.

Within the population ecology sections of the biophysical model, there is more flexibility in the exact forms used, but as a common minimum requirement, the model must be able to produce a time series of biomass and some degree of size structure. This suggests that any suitable model must have the ability to represent age structure (either by age classes or stanzas) and potentially include a mix of aggregate groups (e.g. guilds) and species of interest. Finer level details of construction are less of an issue, but it is still worth explicitly considering them when using a model. Topics (and the implications of specific representations) that researchers in the current study should think about when using models, relate to whether the model is mass-balanced; whether differential equation or individual-based representations are used; the form of any recruitment functions (and whether they are explicitly defined or implicitly produced by the model, as in Ecosim); the form of any trophic interaction matrices and whether they are fixed or rule-based (e.g. whether there is gap limitation); the form of any functional feeding responses or feeding behaviour (e.g. whether ratio dependent, foraging arena or Holling type functions are used); whether there are any non-trophic interactions included in the model (or at least the ability to include them via empirical relationships, mediation terms that modify feeding success and predator vulnerability, or specific habitat dependency representations); the form of any movement functions, both daily and seasonal (e.g. at the fine scale, is there diel vertical migration, forage or density dependent movement? or seasonally is there large scale migrations or the formation of spawning aggregations?).

The form of the harvest models also needs to be given careful consideration when using an ecosystem model to test indicators. For instance, it will be critical that some degree of subdivision of the fleet structure is possible, so that different motivations and behaviour can be captured. It is likely that in the systems being modelled as a basis of this body of work will be characterized by home port fidelity and the potential for community specific behaviours. It would be preferable for the model to have a dynamic cost function (with some degree of dependency on biomass and the degree of cooperation between and within fleets). This is not an absolute requirement, but the implications of a fixed cost model must be given a good deal of attention to make sure that typical responses to changes in fishing motivation and opportunity costs are not missed. This is important as fleet dynamics is another prime source of non-linearities that could significantly impact indicator performance. Nevertheless the development of a highly detailed explicit socio-economic model is not recommended as part of this study. A more useful compromise would be to use a model that has the ability to reflect the impacts of compliance (or non-compliance), dynamic prices, external social forcing, the opportunity costs associated with non-fishing sectors and to force these with “painted” time series as part of the scenarios.

The sampling (observation) model proposed for this study will be discussed at greater length below, but at its minimum, it must contain all forms of standard data collection as well as the ability to mimic the kinds of data collected from interviews (i.e. local and anecdotal knowledge).

6. KEY COMPONENTS OF THE MODELS

The key components of any tropical ecosystem model used in the model-based indicator testing phase of any future work include environmental, ecological and anthropogenic components. A brief summary of these components is provided here.

6.1 Environmental components

If explicitly spatial, the model needs to differentiate layers defined by wave energy and water clarity. For example any spatially explicit atoll model would need to represent the following depth bands: 0–5 m (wave affected), 5–30 m (where corals dominate), 30–50 m and 50–100 m (where the deepwater zone begins). Any non-spatial models would need to implicitly include some of this spatial structure too, so that trophic and other interactions are accurately captured.

6.2 Habitat types

Multiple habitat types will need to be represented in any tropical model, given the ontogenetic, diurnal and seasonal shifts in habitat preference of many tropical species. For example, a reef model would need to include the lagoon, back reef and fore reef. Another facet of habitat types is the sediments – the distribution of hard and soft sediments would need to be represented in spatially explicit models and in non-spatial models, the webs associated with each sediment type would need to be included. Biogenic habitats would be a critical model component; potential groups of this kind are corals, seagrass, sponges, algae and mangroves. Treatment of these biogenic habitats can pose some complications that require careful consideration. For example, when modelling coral, should the living and skeletal components be treated separately? One potential approach may be to use stanzas to represent the connection between the living zooxanthelle containing biomass (treated as the larval group in the stanza) and the skeleton (treated as the adult group). But the implications of such a treatment would need very careful consideration. Treating all the coral biomass as a single pool and then using facilitation terms may be a more suitable (and typical) representation.

6.3 Other environmental drivers

Temperature is the environmental characteristic that is most easily dealt with, with regard to data and process-driver relationships. For instance, there is a temperature aspect to bleaching and the switch from coral to algae dominated reefs. This driver sensitivity in combination with a representation of the coral habitat dependency of groups (via facilitation or vulnerability) could capture the knock-on effects of changes on refuge for fishes, health of the stocks and the competition for space between coral and algae. Other critical environmental drivers include current, winds, pollutants and nutrients. Currents are important for the flow through and input they bring to reef systems; while the other drivers are usually related to potentially detrimental impacts (e.g. cyclonic storm induced destruction, toxic pollutant contamination and eutrophication).

6.4 Biological components

All aspects of the system need to be represented, though it is possible to obtain a realistic representation with minimal detail in the “supporting” groups and more detail in the dominate groups in the system. At a minimum however the model would need to consider (in some form):

- Primary production; this may be in the form of a simple phytoplankton forcing function, but may need to explicitly include inputs from through flow (as considered by Bulman *et al.* [2002] for seamounts).
- Biogenic habitat types (discussed above).
- Pelagics; these often make up only a small component of the total catch but can give contrast in the indicators (e.g. Pelagic:Demersal biomass ratio captures change in energy flow as demersal predators and competitors are lost and system state changes); in particular it would be important to include planktivores, especially those that are “semi-pelagic” (which feed on the reef part of the time, but inhabit the pelagic realm at other times).
- Demersal fish; in particular the major groups (e.g. reef associated species, groupers, lutjanids and lethrinids) and some other species of interest or concern, like target species. Some size structure (inside and between the groups) is needed to capture the size structure data for the indicator calculations, but also for realistically capturing the size-based (gap-limitation and habitat-use related) changes in mortality.
- Demersal invertebrate groups; again the major groups (guilds) need to be explicitly specified and species of concern (e.g. targeted species including octopus, crab, lobsters, oysters) should be

drawn out separately. Aggregate groups that should be teased out are mobile *vs* immobile, filter feeders, carnivorous forms, target *vs* non–target groups and detritivores (though this last group may be less critical).

- Sharks and other large-bodied piscivores; both for their role in the system and their potential as indicator species it is important that these are represented explicitly.
- Turtles that directly interact with the local system to some degree (e.g. Green Turtles and Hawksbill Turtles) should be included as both indicator species and species of concern; highly mobile and transitory species (e.g. Loggerhead turtles) may be much more problematic to represent and may be better avoided at least initially.

6.5 Human components

At a minimum the model used would need to contain multiple fleet types with alternative gears and degrees of collaboration. It would also be important to have the potential to include the impacts of other human sectors even if the processes of these other sectors are not explicitly represented.

7. PROPOSAL FOR FURTHER WORK

The proposed future work has six components, detailed below. The anticipated time-line for this body of work is approximately two years, potentially running January 2007–January 2009 (dependent on funding constraints).

7.1 Identify EwE models for Indicator Testing

One of the more widely used approaches in modelling tropical and subtropical ecosystems is Ecopath, Ecosim and Ecospace (EwE). The EwE approach is based on a mass-balance assumption and captures a snap-shot of an ecosystem state (Ecopath), from this it initializes biomass dynamic simulations both in time (Ecosim) and space (Ecospace). These simulations can be used to evaluate the outcomes of different scenarios of changes in fishing intensity and behaviour as well as changes in the environment. There are many existing tropical implementations of this model. It is also user friendly, meaning quick progress could be made from preliminary evaluations using existing EwE models and only moving on to more complex versions (or alternative models), if critical gaps in this analysis are identified. Candidate EwE models would need to meet the criteria mentioned above as well as the following specific requirements:

- model pedigree must show that the model is largely based on local data;
- the model should be fitted to time series data;
- there must be an adequate degree of trophic resolution and consideration must be given to whether there is valid group separation;
- a tropical – subtropical focus (as far as possible); and
- stanzas should be used for at least some groups (so that there are sufficient data for size-based and diversity-based indicators).

Candidate models can be drawn from the literature, but also from the model search facilities on the EwE web site. Other potential contacts include Cathy Bulman (CSIRO, Hobart, Australia), Neil Gribble (QDPIF, Cairns, Australia), Villy Christensen (University of British Columbia, Vancouver, Canada), Steve Mackinson (CEFAS, Lowestoft, UK), Steve Martell (University of British Columbia, Vancouver, Canada) and Mary Gasalla (University of Sao Paulo, Brazil).

This review of EwE models should also usefully highlight any drawbacks or limitations of the approach with regard to indicator generation. For example, there may be problems if the facilitation relationships are not enough to model habitat specificity. If the approach proves to have a significant number of problems then alternative models can be considered, from the list provided above, but also from searches of the list of ecosystem models and tools on the Nature Conservancy site www.ebmtools.org.

For a rigorous evaluation of the performance of the candidate indicators, the selected operating model should have a good representation of the ecosystem state and its dynamics. As the ideal indicators should be widely applicable, candidate ecosystem models should also cover a range of different fisheries, habitat types and geographic areas. The following is a list of criteria for model selection, focusing on judging whether an existing EwE implementation meets the studies requirements. The final ranking of the suitability of a EwE model as an operating model for indicator testing can be developed from these criteria. If models that meet the minimum criteria are shown to be insufficient in number, it may be possible to do some minimum modification of existing models, – dividing existing groups into stanzas or age-structure, for instance – to improve the quality of the model for the purpose of testing indicators.

7.1.1 Parameter quality

The EwE approach depends on the mass-balance Ecopath model, as this provides the initial conditions and parameter set used to initialize the Ecosim and Ecospace simulations. Therefore, the quality of the parameters of the Ecopath model is an important criterion for model selection. Fortunately there are existing means for evaluating this quality.

Ecopath has a routine called “Pedigree” that allows systematic categorization of the source of the input parameters – specifically the biomass (B), production to biomass ratio (P/B), consumption to biomass ratio (Q/B), and ecotrophic efficiency (EE) or each group; as well as the diet composition matrix and the catch of each group by each fleet. In the pedigree routine, a coded statement categorizing the origin (data type and associated uncertainty) of a given input can be given to each parameter for each of the modelled groups. The key is that inputs are rated based on how they have been derived: local data, other locations, “best guesses”, empirical relationships, other Ecopath models or estimated by the current model. Associated with each of these categories is an index of data quality which ranges from 0 to 1, with 0 being the lowest quality (estimated by the model while solving the mass-balance equations) while 1 being the highest quality (e.g. data from a quantitative study conducted in the study area). By summing across these pedigrees, an index (*P*) of the overall quality of the input information in Ecopath can be calculated:

$$P = \sum_{i=1}^{n} \sum_{j=1} \frac{I_{ij}}{n} \qquad (1)$$

where I_{ij} is the pedigree index for model group *i* and parameter *j*, *n* is the total number of modelled groups. A measure of the degree to which local data was used to produce the input parameters (*LD*) can also be estimated, using:

$$LD = P \bullet \frac{\sqrt{n-1}}{\sqrt{1-P^2}} \qquad (2)$$

This index summarizes quite simply how well a given model is rooted in local data (Christensen *et al.*, 2004).

7.1.2 Model structure

As mentioned in the earlier sections, certain ecosystem structures are considered important for the representation of a tropical or subtropical ecosystem model for the purposes of capturing system state and generating the kinds of information needed for calculating the candidate indicators. These structures include:

- presence of age structure in some form (whether via juvenile-adult splitting, multi-stanza representations or explicit age-structure), at least for those groups with important ontogenetic differences. Detailed age structure may be required for species where maximum or mean length is being monitored;
- inclusion of both the pelagic and demersal system components (including fishes and invertebrates);
- inclusion of known key ecosystem groups;
- presence of K-selected (or "charismatic") groups (e.g. large predators, turtles, marine mammals, and seabirds);
- the division of groups based on size (e.g. small, medium and large demersal fishes);
- presence of biogenic habitat forming (structural) groups (e.g. coral, sponges, seagrass and mangroves);
- representation of major fishing fleets.

7.1.3 Peer review

While not an absolutely key criterion, if a model is published in a primary or other peer-reviewed literature, there may be more confidence associated with its structure and dynamics. A model review may also have been conducted through other means. Through review, criticisms or weaknesses are more likely to be documented.

7.1.4 Geographic or system representations

The candidate models should cover a range of habitat and system types and be drawn from different regions. The systems that should be covered include estuaries, coral reefs, sections of continental shelf and deltas. Given the differences in driving forces and degree of closure between reefs in the Caribbean and south Pacific, for example, it is also important to draw examples from each of the major ocean basins.

7.1.5 Spatial and temporal simulations

It is critically important that simulations using Ecosim (and preferably Ecospace) have been conducted. An Ecopath model that has not transitioned is of no value in this study.

7.1.6 Time-series fitting

The utility and rigor introduced by good time series fitting of Ecosim models means that it should be one of the criteria in model choice. Fitting with time-series data is one of the most objective ways to test the performance of an Ecosim model. It also allows for the estimation of some of the more uncertain parameters (e.g. vulnerability parameter). Therefore, a model that has been rigorously and thoughtfully fitted with time-series abundance or relative abundance should be considered of a higher quality.

Moreover, if time-series data are used to estimate environmental anomalies that affect the ecosystem, it would be particularly useful for indicator testing.

7.2 Scenarios to be run

A range of scenarios will need to be run to cover many alternative perturbation types and system dynamics. These scenarios may be run by the model developers or directly by the current research team. Scenarios considered should include:

- light, moderate and heavy fishing intensities.
- eutrophication and other forms of large scale system change, particularly different forms of climate change and pollution.
- gear specific questions, such as changes in gear type with different selectivity and incidental impacts (e.g. from lines to gillnets).
- habitat degradation; including perturbations such as sedimentation, but also destructive fishing techniques; it would be interesting to see whether destructive fishing practices can be detected by indicators.
- market based scenarios, such as a switch from subsistence to commercial fishing.
- pulses in recruitment or other noisy ecological events, such as regime change and switch to algal domination.

These scenarios should be run independently and in combination so that synergistic and differential impacts can be discerned. Use of network analyses (e.g. those developed by Jeff Dambacher, CSIRO Marine and Atmospheric Research) can also be used to augment these scenarios as well as the use of multiple models so that the potential for structural sensitivity to significant impact the results can be judged.

7.3 Generate time series for use by sampling model

This may be done by the people who have developed the models based on standardized data requests from the research team in this study. Alternatively the models will be run directly. Regardless, the desirable outputs from the models (so that the candidate indicators can be calculated is):

- time series of biomass by component;
- catch time series; this should include discards, so that total removal estimates can be made;
- diversity indices; this is unlikely to be available directly from the models and may need to be calculated in the sampling model (see below);
- time series of size composition; this may in part be calculated from the biomass time series of groups with different body sizes. However, the time series of maximum (or mean) length implies that a fairly detailed age-structure will need to be needed for a number of key groups;
- size at maturity; this may not be universally available, but may be available for age-structure or multi-stanza components.

7.4 Sampling model

This would need to be constructed as part of the current study and would need to be a plug-in for a package (e.g. R, Excel), a DLL or built as stand alone software. By building this as a stand alone plug-in or piece of software that takes in time series generated by the operating (ecosystem) models to generate the data and calculate the indicators, the inefficiency of re-implementing for each operating model is avoided. It is also an ideal approach if existing models are simply to be used off the shelf.

The objective of the sampling model is to compute the candidate indicators with perfect information and then again using the data generated with differing degrees of error. This contrast should highlight the minimum requirement on accuracy needed for the data to remain useful. It can then be judged whether such a CV is achievable in practice. More specifically, the sampling model will generate data, with realistic levels of measurement uncertainty (bias and precision), from the time series output from the selected ecosystem models. This data generation will be repeated under a range of levels of uncertainty, but also using simple models of different data collection methods (from quantitative surveys in specific, but constrained locations, through to qualitative interviews). Capturing the error structure correctly is an important part of sampling models used in management strategy evaluation. These models must represent errors from data gathering, but also observational error (which may be proportional to data coverage) and bias (e.g. it may well be the case that only the most productive fishers agree to collaborate in data collection exercises). It will be important to get a real world handle on these different forms of error, particularly those to do with fisher surveys. There is promising work in this area already, in the form of studies like those considering fisher perceptions regarding the best remembered catches of Gulf Grouper (Sáenz-Arroyo *et al*., 2005) and sampling exercises aimed at comparing trends from memory and those from surveys (e.g. Ainsworth *et al*., 2005).

In the later stages of the exercise (if and when spatially dynamic models are brought on line), then the issues of spatial coverage and whether it can be a substitute for a time series in a single location will be considered.

As shown in the general cycle of the sampling model given in Figure 2, the kinds of sampling methods that will be mimicked include:

- fisheries independent surveys,
- catch sampling,
- market sampling,
- fisher interviews (covering qualitative changes along with categorical and quantitative estimates),
- some post-processing generation of data for the calculation of diversity indices. No ecosystem model can easily output this, so it will need to be generated via proxies based on biomass and size structure or life history information generated by the ecosystem models; one possibility is to consider whether composition can be explained using species abundance models.

This sampling model will be run repeatedly for each scenario, as the observation and reporting errors will be generated stochastically so multiple runs will be necessary to produce a reasonable indication of the distribution of possible results.

One of the issues which the sampling model will need to consider is how data for environmental indicators might be obtained. For example, how would the fisheries managers, which could be the local community, monitor temperature, pollution, eutrophication or habitat change? This may need creative thinking and/or consultation to identify feasible approaches for inclusion in the sampling model.

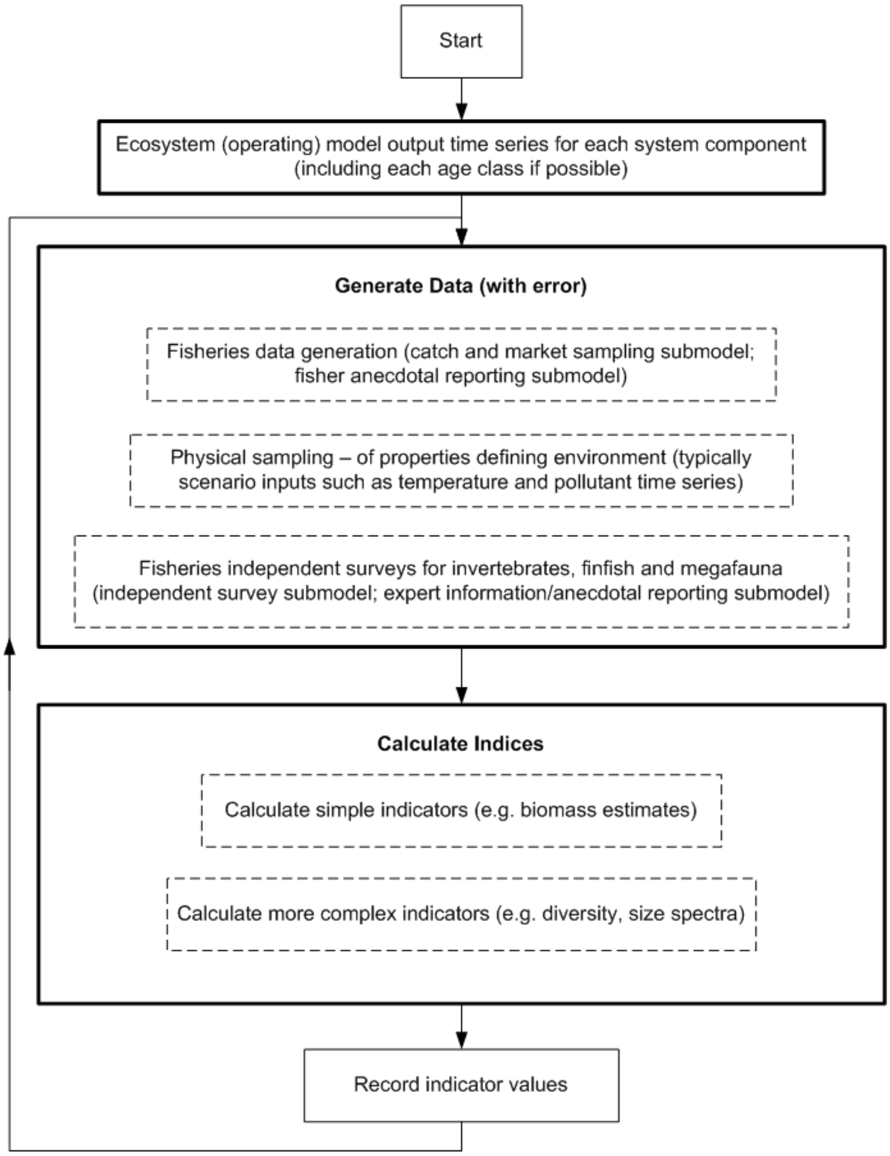

Figure 2: Schematic diagram of the form of the sampling model of indicator calculation.

7.5 Model extension and development

If there is a gap in the available model types then it will be necessary to modify an existing model so that it provides a reliable representation of a missing system type. This phase of the study will only be necessary if the earlier review and preliminary analyses do not unearth one (or more) examples of an adequate model of each the main tropical system types (atoll, continental, and estuarine systems). In the first place any modified model may be of the EwE type; but if major limitations are found with the EwE approach then these additional models may need to be completed in one of the other types of model identified using the review and search engines described in phase 1 above. Essential components of the other approaches may also be adapted into the EwE approach if that is proven to be more cost-effective.

7.6 Field testing and data collection

Field studies will be used to obtain real data to test indicators. This task will be undertaken simultaneously with the modelling tasks above. Field testing would make best use of existing data collection exercises (e.g. SPC PROCFish/C, the Indonesian project, Marine Management Area Science Project in Abrolhos) supplemented by targeted data collection designed by this study to cover critical gaps in the existing data collection efforts. Given the likely timeframe for this study and the existing data collection exercises it is important that this phase begin quickly.

REPORT ON FINDINGS FOR THE BIOMASS-FLEET DYNAMICS MODEL

A. REVIEW OF RESULTS TESTING/FITTING

Vasconcellos and Cochrane (2005) proposed two models for the stock assessment of fisheries which only have catch data. Annual time series of catch data are more common than other types of data due to the requirement of many government statistics departments which emphasize outputs from economic sectors, and to the support from FAO and other organizations in collecting the appropriate data to report landings.

The assessment models are based on the logistic population model, but without a time series of fishing effort or an index of abundance. To fit the population model, an additional assumption has to be made on how the exploitation rate (fishing effort) develops. The biomass-fleet dynamics models that have been suggested follow two effort scenarios. The first allows a linear change in effort (a fixed quantity of effort) requiring one parameter and the second a proportional change (logistic effort model) requiring two parameters.

Several simulation tests were performed on the biomass-fleet dynamics models (Minte-Vera, 2006), in order to test the accuracy of the model, and sensitivity to observation error, priors, parameterization, the choice of likelihood function and the robustness to model mis-specification.

The main conclusions from those tests were:

1. Both the linear and the logistic effort dynamic models seemed unable to estimate the model parameters accurately when fit to data generated from the same fitting model and with no observation error, unless provided with adequately informative priors. However, the models were able to provide acceptable estimates of management quantities even with less informative priors. These findings suggest that the model could be used to generate robust management advice.
2. The fits were in general insensitive to the addition of observation error over the range tested here.
3. The management quantity that had the most precise and accurate posteriors was B/B_{MSY} for either data with and without observation error for both linear and logistic effort dynamic models.
4. The use of informative priors on all the parameters produced the best fits as expected. However, the fits were substantially improved when using informative priors on some parameters. The fits for the linear model were improved by including informative priors on r – the intrinsic rate of population growth – while the fits for the logistic model were improved by including informative priors on x – the rate of increase in harvest rate over time.
5. Alternative parameterizations of the model further improved the fits. Models fitted using uniform prior on the natural logarithm of the unexploited biomass produced less biased posterior distributions for several parameters and derived quantities than those fitted with uniform priors on the unexploited biomass.
6. Fits performed using lognormal and normal likelihood functions produced similar posterior distributions.
7. The logistic model was more robust than the linear model to model mis-specification. The logistic model produced accurate posteriors when fit to either data generated from the linear or logistic model, whereas the linear model produced highly biased posteriors even for the management quantities when fit to data generated from the logistic model.

The biomass-fleet dynamics model appears to provide a robust assessment of fisheries where only a total catch time series is available. The assessment method appears to do well in estimating indicators important for management advice, even where parameters are not estimated accurately and with bias due to structural error.

The model was tested on real data of ten previous stock assessments (Medley, 2006). In terms of management advice, the model did not fail on any assessment out of the ten tested, albeit in many cases the model fit was fairly poor. The general advice extracted from the model was in line with advice given based on the full assessments. These tests represent worse-case scenarios, where the model is being fit to data where the population model and effort models do not hold. The priors were generally not very informative unless there was strong justification. The model fully fitted five parameters in each case, one more than in the original test assessment.

In all the test cases, it was expected that the priors could be improved with better background data. While some methods for generating priors were tested, there was clearly a need to develop a strategy for obtaining priors as informative as possible, but without bias.

The analysis also developed an alternative method for robust fitting. The model has also proved very difficult to fit as it is non-linear both in effort and biomass dynamics. A robust fitting strategy will be required to ensure good, unbiased management advice even where data are poor and fit are poor.

B. SUGGESTED IMPROVEMENTS

From the results of the simulation and fitting, as well as from the discussions during the workshop, the following improvements were thought necessary and should be implemented as soon as possible.

B.1 Estimation of initial state

The management advice is sensitive to the initial state of the stock. The initial state of the stock could be better estimated either by reconstructing approximate catches to the start of the fishery, or extrapolating the model back to the start, when effort and catch were at a known low fixed point. While the former approach may yield better results, it will frequently be difficult to attain with an acceptable degree of accuracy in data poor fisheries. In such cases the latter approach may be useful and should be straight forward to implement in many cases without requiring additional information other than an estimated starting year for the fishery. A global database on catches, effort, catch prices and fishing costs (an effort and cost database is currently being developed; Gelchu, 2006; Sumaila, pers. comm.) would be useful to provide extra information. Both approaches should be explored.

B.2 Diagnostics

Diagnostics are required to indicate when the model fit is poor, and provide clues on what can be done to correct it. A simple diagnostic of observed and expected catches needs to be obtained from the model fit. Not only would this diagnostic allow assessment of how well the model fits, more importantly, it might suggest ways to improve the fit and where the problems might lie.

B.3 Prior density functions

There are various improvements that could be made to the use of priors. Prior probability density functions (pdfs) are an important component of the analyses where data are uninformative on one or more parameters of the model. This is very likely to be the case with this model. In these assessments, with more time, improved priors might have been developed and applied. However, care needs to be taken as a poor prior can bias results and make assessments worse rather than better. The findings and recommendations are:

- Priors for the population parameters r and B_∞ may be developed based on the biology and ecology of the species and ecosystem being exploited. Some attempt has been made with reasonable success in the test assessments, but further improvements are necessary. Using some of these techniques suggested below, it might be found that r and B_∞ are not independent and a joint prior is necessary.

    - Population models are a useful way to generate priors, but only when there is good information for all the parameters. Using meta-analyses, it might be possible to provide standard parameter pdfs for broad ranges of species to fill out gaps in demographic models (see for instance Myers *et al*., 1999 and McAllister *et al*., 2001).
    - Ecosystems models may be a useful way to generate priors for unexploited stock size and r across a range of fishery habitats and for a range of species groups. It would be useful to consider how this might be done with current ecosystem models.
    - For the unexploited biomass, it could be useful to consider typical population densities for different types of fish. This may be related to habitat, ecosystem productivity and so on. Defining these as priors means that exact values are not required, but ensure probabilities cover the most likely densities, which can be raised by the fishing area. Fishing areas can be determined relatively easily from maps and satellite imagery.
    - A more widely available method would be to use simple relationships among life history parameters. For example, r was assumed proportional to M in a few assessments tested (Medley, pers.comm.) and maximum population growth rate (an index of r) was found to be correlated to maximum body size (Denney *et al.,* 2002). It would be useful to have a meta-analysis to identify appropriate relationships to use.

- The test assessments lacked reasonable priors on the rate of effort change and bioeconomic equilibrium. It is suggested that a number of methods be tried so that they can be compared. This also gives fisheries scientists options as to the approach they might use, with different approaches being appropriate in different fisheries. Using some of these techniques, it might be found that x and a are not independent and a joint prior may be necessary.

    - Methods developed for ParFish might be used to obtain fisher opinion on the value of these parameters. Given that they are directly related to fisher behaviour, it is likely that informative priors can be developed in this way. Appropriate questions will need to be developed and tested. Questions could include, for example, vessel age, dates when fishers have entered and left the fishery, level of CPUE when they enter or leave, and so on. Answers would need to be interpreted through a simple model to generate a prior.
    - More complex bioeconomic models, such as Beam 5, may also be able to suggest generic priors for these parameters in much the same way as ecosystem models might be used to estimate priors for the population model. A monte carlo simulation of the economic model might be developed which allows generation of simple parameter values.
    - x and a might be fitted to data which include effort time series. If a large enough number of fisheries are analysed in this way, this may indicate minimum informative priors which can be used for these parameters.

- Prior generation might be helped by improving data sharing. FishBase can be used to generate growth parameter priors for particular species. Similar data sharing might be used for other parameters with the express aim of facilitating priors for stock assessment, including the biomass-fleet dynamics model. Such a database could be used to store results from meta-analyses.

Alternative parameterizations of the model should be tested as well in order to make the model more robust and of wide application. Useful parameterization would be those that reduce correlation among parameters, and will facilitate the estimation of the joint posterior distribution, and those that are biologically or economically meaningful and thus easier to construct informative priors for, from either published information or from fishers' observations. For example, the models should be fit using priors on a log rather than linear scale for unexploited biomass.

It may be useful to construct priors for the observation error scale parameter in the likelihood function, the initial harvest rate, and the initial depletion level rather than treat them as fixed. This will add significantly to the fitting problems, and should be considered when a robust fitting procedure has been completed.

B.4 Improvements in the harvest dynamics modelling

- Adding a time series of pseudo-data, perhaps based on subjective information, that adjusts for changes in effort known to occur. For example, effort may be known to have doubled or halved at a particular time due to a specific management action or event, such as loss of vessels to a hurricane or exclusion of foreign fishing vessels.
- Adding an autoregressive or moving average term to one of the existing parameters. For example, *a* could be allowed to adjust for opportunity costs changing for fishers. However, this type of model extension adds complexity and can make a fit worse, and therefore remains a lower priority.

B.5 Fitting procedures

There are a number of improvements in the fitting procedure which could be considered. Each would require further research.

- Software to fit the model could be developed to take advantage of the model structure as part of the fitting process. The fitting process could include a systematic search for posterior modes to ensure results would not be biased as well as generally ensuring robust numerical algorithms were used which could cope with non-linearities in the likelihood.
- A rejection sampling method should be developed to fit the model. While testing the method, an adaptive approximating function was used to fit the model. The method could be used for the SIR algorithm, but was inadequate for the superior rejection sampling algorithm. It was found that the logistic model likelihood can exhibit severe non-linearities across the range of parameters. Some improvements were obtained by re-parameterization and transforming the parameter to reduce non-linearities. Further work could make the fitting procedure more efficient and reliable. A significant advantage of the approach is for the user to be able to view and apply manual corrections to the approximating function, making the method easy to understand, flexible and easy to correct.
- Diagnostics are required for the fitted model, to see how good the fit is. While even a poor fit might have to be accepted as the best available, diagnostics would allow users to discriminate between different fits, sources of information, corrections and so on.
- The catch observation error scale parameter was fixed. In some cases, the maximum posterior mode was at a point where this parameter was so large that the likelihood becomes uninformative (the model does not fit the catch data). Although a prior on this parameter would cure this problem, the added complexity in the analysis would make fitting difficult unless the procedures

can be improved. The mode at unrealistic values for this parameter may also indicate the model fails to fit.

- It may be possible to improve the likelihood by considering the autoregressive residuals. This may allow the method to favour fits where the residuals appear independent and random rather than only considering the size of the residuals.
- Other formulations of the model may be considered in future, although in most cases this would mean more parameters would be fitted. For example, a process error as well as observation error may be considered more realistic particularly where the exploitation rate is being modelled as well. However, in data poor situations, fewer parameters generally mean the model is more robust, and more parameters fitted to little data could lead to worse results. Therefore, it is recommended to focus on the current logistic model rather than develop further complications.

C. OVERALL ROBUST PROCEDURE

A robust procedure needs to be developed, based on information that most fisheries scientists would be able to get for any fishery to augment a catch time series. The procedure should include:

C.1 Use of logistic model

Unless there are strong indications that the linear model is the best representation of the harvest rate changes over time, the logistic model should be preferred, because it appears to be more robust to model mis-specification than the linear model and it could be used in a wider range of situations. The model would also be amenable to applying simple corrections. From fisher interviews, it might be concluded that the harvest dynamics assumption does not hold, but the same information might be used to generate covariates, which could be used to represent different harvest phases in the fisheries.

C.2 Guidance for the construction of priors for each of the parameters

Interaction with the fishers and a review of available information could improve the fits of the models. The Bayesian approach used for fitting is flexible enough to include this information either as prior or as penalty functions.

A priority should be given to the parameters describing the harvest dynamics, which had the most influence on the fit in the simulation testing. For the harvest dynamics parameters, examples of use of the supplementary information to construct the priors have been outlined above. The simplest and easiest to implement would be interviews with fishers and others, which could be used to derive opportunity costs, entry and exit rates, necessary adjustments to the model of the catch time series (such as management or other interventions), as well as the state of the fishery when the time series begins.

The catch data collection might have begun in an arbitrary date along the fisheries history. This implies that data is not available since the start of the fisheries which may affect the estimation of the parameters. In this case, it is suggested that interviews should be carried out to try to establish when the fisheries started, reconstruct catches, and ascertain when the fisheries might have been at the approximate bioeconomic equilibrium in its history. The model can be used to extrapolate across periods of missing data, and in particular towards the start of the fishery when the stock was only lightly exploited. All these might help prevent poor management advice in giving a good general idea as to the state of the stock and fishery.

For the stock dynamics parameters, the priors could come from combinations of the following strategies:

- Where life history information is complete, a simple population model can be used to estimate *r* (Leslie matrix).
- Heuristic relationships between life-history parameters might be used to estimate *r*.
- Meta-analysis for species or species groups might indicate typical *r* parameters.
- Unexploited stock size (B_∞) might be estimated by typical densities for the species or species group and the area of the fishery. The analyst should be wary what habitat the densities apply to and whether the area only covers this habitat.
- Meta-analysis of primary production – will provide an upper bound for the unexploited biomass and *r* at any trophic level.

Non-parametric kernel smoothing can be used to estimate prior densities where a number of point estimates are available, rather than fitting parametric distributions. This avoids having to make assumptions about an appropriate parametric probability density.

Many of the prior parameters are hyperparameters scaling for the dispersion of the prior pdfs. These might be chosen based on the source information (non-parametric method) or defined based on a heuristic categorical method (set depending on whether the user is very sure, sure, unsure or very unsure, for example).

C.3 Management procedure evaluation

The model should be used to provide management advice based on estimated management quantities rather than to attempt to obtain accurate estimates of the model parameters. Several management quantities should be reported, so to provide different options for the managers, such as current depletion, B/B_{MSY}, replacement yield, MSY, and relative exploitation rate (F/F_{MSY}). It has been found that the management quantities that should be preferred for producing management advice should be based specially on relative quantities, such as B/B_{MSY} or depletion (B/B_∞).

The use of the models in this context should be further tested in a management procedure evaluation. Management procedures or management strategy evaluations have been found very useful in fisheries, because they recognize the uncertainties in the population-assessment-management systems, but the need to produce robust advice despite those uncertainties. The whole fisheries system is simulated, including the data-collection, assessment, management advice and implementation of the management advice in an iterative process. The overall system is then appraised to see whether it would lead towards the desired targets.

C.4 Improved robust, fitting methods

Although the concept of the model is good, among the problems that are likely to be encountered are the numerical problems regarding the integration of the joint posterior density function. Several algorithms for the numerical integration should be tested, in order to make the model safe for final user applications. SIR algorithms (used in Minte-Vera, 2006 and Medley, 2006) and rejection sampling (tried in Medley 2006) seem to be more appropriate than MCMC (initially used by Minte-Vera [pers. comm.*]* with no success), which appears difficult to adapt to complex non-linear likelihoods. Since the parameter space is highly correlated in this model and contains discontinuities, the standard MCMC jumping functions appear to be unable to cope and are either too slow or fail to converge to a solution. It is possible that improvements in the informative priors and likelihood (e.g. using autocorrelation of the residuals) could make fitting easier. However, a good approximating function to the posterior pdf should be possible, given the small number of parameters, and lead to sufficient accuracy using either rejection sampling or SIR algorithms.

C.5 Implementation platform

The method would be best distributed along with supporting software. Access to the software could exist on a number of platforms, but it would be ideal to limit the software to a specific language. Options would include R, Visual Basic, or coded DLLs in C++ or Delphi. Preference should be given to free, open source software, which could allow advanced users to improve/customize the models and which will not require the purchase of software licences by users.

C.7 Interpretation of the results

Guidance will be needed on how to interpret the results. This would include diagnostic tools to check whether the numerical algorithm was successful in estimating the posterior distribution, the degree to which the likelihood agrees with the priors, and the use of the results in decision analysis, such as ParFish. It would also be useful to check the information content of the data by comparing the fit using only the priors and fits using the priors and the likelihood.

D. MINIMUM REQUIREMENTS FOR SAFE APPLICATION

We considered that at least four requirements should be attain in order to apply the model safely:

1. Availability of catch time-series. One of the advantages of the model is that it does not treat the catches as a forcing function of the model, but rather as data, so in theory even incomplete time-series of catches could be used. However, the more complete the time-series, the better.

2. Robust estimation procedure implemented in a widely available platform.

3. **Availability of information on the start of the fisheries.**

4. Informative prior information on all parameters generated from valid methodology.

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APPENDIX 1

Objectives of the Workshop on Multispecies and Ecosystem Indicators, and Biomass-fleet Dynamics Stock Assessment (Rome, 23–26 October 2006)

The objectives of the above workshop were twofold:

i) to recommend an approach to evaluate the performance of ecological indicators applicable to the monitoring of the ecosystem impacts of fisheries in data-poor areas, and
ii) to evaluate the results of a stock assessment method (biomass-fleet dynamics model) previously proposed for fisheries in situations where only catch data is available.

During the workshop, the participants reviewed the types of ecosystem models that could be used in a management strategy evaluation approach (MSE) for testing ecological indicators of changes in marine ecosystems. Potential ecological indicators to be evaluated were proposed, including the relative biomass of ecosystem components, size spectra, maximum (or mean) length, total fisheries removals, species diversity, size at maturity, and a range of biophysical parameters. The workshop also proposed a study outline to consider which ecological indicators of changes in exploited aquatic ecosystems will work in data-poor locations; and whether it is actually possible to detect clear ecological signals with the type of information available in these locations.

The workshop also reviewed several tests performed with the biomass-fleet dynamics model in order to test the accuracy of the model, and sensitivity to observation error, priors, parameterization, the choice of likelihood function and the robustness to model mis-specification. Preliminary results indicate that the model appears to provide a robust assessment of fisheries where only a total catch time series is available. The assessment method appears to do well in estimating indicators important for management advice. Suggested improvements to the model were elaborated.

APPENDIX 2

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