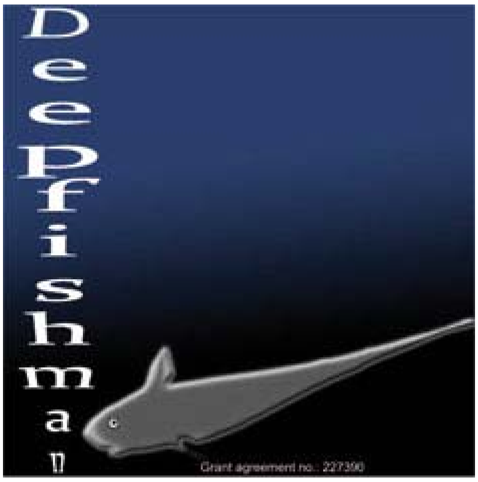


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# Review of assessment and management approaches for deepwater stocks

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## Abstract

## Introduction

Deepwater fish species in general have slow growth rates, extended longevity, late maturity and low rates of natural mortality. As a consequence of their relatively low productive capacity these species are likely to be particularly vulnerable to overexploitation (e.g. FAO 1997). The schooling behaviour and large spawning aggregations of many deepwater species also contribute to their vulnerability, with exploitation of large schools continuing long after declines in overall population abundance have occurred (e.g. Rose and Kulka 1999; Clark et al. 2000). Unfortunately there is a lack of basic biological information and stock structure for most deepwater species. Combined with poor information on abundance, making assessment problematic, this means that knowledge on the status of the stock often lags behind exploitation (Clark 2001; Large et al. 2003). This review provides an introduction to the primary assessment methods currently used for deepwater stocks, and a critical analysis of their strengths and weaknesses. We also review alternative approaches which for given combinations of biological characteristics and data availability could be usefully applied in future. Given inherent data limitations we provide a discussion on ways to represent the uncertainty associated with assessment results and how it can be reduced by drawing on results from related studies and theory.

## Assessment and management

Management consists of three stages: i) the definition of objectives for the fishery, usually in terms of the biological and/or socio-economic returns; ii) the development of policy mechanisms by which these objectives can be reached (e.g. input or output controls); and iii) the implementation of means by which specific policy related decisions are made, given knowledge of the status of the resource. In more well developed management frameworks (Butterworth and Punt 1999; Smith, Sainsbury, and Stevens 1999), the resource assessment method used (along with its data requirements) is also specified as the basis for making management decisions. However it is more common for the resource assessment to encompass a range of different complimentary approaches. Thus a number of different methods may be applied. Here we give some background on management objectives and mechanisms for deepwater fisheries, with more specific details on assessment methods and how they are used to inform management decisions in subsequent sections.

## Management objectives and mechanisms

A universally accepted management goal for fisheries is that described by the FAO (FAO 1995): "to ensure that populations of harvested stocks … are maintained at, or restored to, sustainable levels" – with a similar prescription made regarding deepsea fisheries specifically (FAO 2008). Alongside other socio-economic and ecosystem based criteria, this ethic is enshrined within a number of national legislatures. For example, the Magnuson-Stevens Act (NMFS 1996) and Marine Living Resources Act (MCM 1998) of the USA and South Africa respectively. Management should judge the status of a particular stock and decide on appropriate management measures through the use of "reference points for triggering conservation and management action" (FAO 1995). Reference points are quantities that define operational targets for management, and are usually classified as target or limit reference points, the latter defining a bound within which the stock should remain. Thus achievement of the target reference point would constitute successful management, whereas the limit reference point represents a condition under which remedial action should be taken. Management should be "precautionary", meaning that "uncertainties relating to the size and productivity of the stocks, reference points, stock condition [etc.]" should be accounted for when making management decisions (FAO 1995, 1995). Thus uncertainty should be explicitly considered when making management decisions; an injunction particularly relevant to deepsea fisheries, for which uncertainty is usually large.

Commonly used reference points, particularly within ICES, include: *F limit*; *F target*, *B limit* and *B target* (where *F* refers to the fishing mortality and *B* to the spawning biomass). For example, a recommendation that fishing mortality should not exceed natural mortality (FAO 2008) provides a suitable basis for *F limit*, in stocks for which natural mortality is defined. The maximum sustainable yield (and associated $F^{MSY}$ and $B^{MSY}$) has also been proposed as a universal objective for fisheries management [Johannesburg summit 2002 - ref], although difficulties in estimating MSY for many stocks and failure of the concept to take account ecosystem interactions means that it has not been widely adopted as a management target.

Reference points are used to gauge the status of a particular fish stock, and judge the success of management. However it should be remembered that they are only a proxy for the management goal itself. For example, a particular *F target* level (the reference point) may be desirable because it is associated with sustainable harvesting (the management goal). If reference points are to be used they must therefore be carefully selected to ensure they are consistent with management objectives. In general, suitable reference points will be adequately defined only for those stocks that are well understood. For others, uncertainty makes the definition of reference points problematic. This means that precautionary reference points are often least useful in situations where they are most needed (the "uncertainty paradox": Cadrin and Pastoors 2008).

Reference points can directly influence management through a harvest control rule (HCR), which will set management action according to an agreed algorithm relating status of the stock to the reference point(s) in question. Such reference points can be considered a part of the HCR itself, selected as a formula most likely to achieve management goals. Outside this framework reference points have been criticized as a narrow basis for management, potentially leading to simplistic perspectives of stock status (Sainsbury 2008). We will return to HCRs and how they are selected later in this review. First we detail some of the methods commonly used in assessing the status of deepsea stocks, and which provide a prerequisite for effective management.

## Introduction to assessment methods

### Catch curve analysis

Catch survey analysis assumes that the number of fish of age *a* in a particular cohort can be modelled using Equation T1.1. Given an observation model (Equation T1.2), *Z* can be estimated by fitting the regression: $\ln(C_a) = \ln(RS_a) - Za$ to the catch at age data from a particular cohort (Hilborn and Walters 1992). If cohorts cannot be tracked as they progress through the age classes (e.g. data is only available for a single year) it is necessary to assume the population is at equilibrium (i.e. *Z* and recruitment is constant across years, with no net migration).

Catch-curve analysis is unable to decompose mortality into natural and fishing mortality ($Z = M + F$ ), which requires an age-structured population model (see below). It is therefore of limited use for management, providing no insight on either depletion or fishing mortality, and is generally only applied as a last resort in data sparse situations. Nevertheless it can provide qualitative insights into how exploitation patterns have changed over time, particularly when combined with other observations or analyses. If sufficient data exists from an exploratory survey of an unexploited stock, catch curve analysis can also be used to estimate *M* directly (since *Z* = *M*).

**Table 1. Catch curve model**

| **Data** | |
|---|---|
| $C_a$ | Catches at age |
| $R$ | Recruitment |
| $S_a$ | Selectivity at age |
| **Parameters** | |
| $Z$ | Total mortality per year |
| **Equations** | |
| $N_a = Re^{-Za}$ | (T1.1) |
| $C_a = N_a S_a$ | (T1.2) |

### Depletion methods

Given a closed population (no recruitment, immigration or emigration) then declines in the population biomass *B*, are determined only by fishing pressure and natural mortality. The behaviour of such a population can be described by the Leslie depletion model given in Equation T2.1 (Leslie and Davis 1939), relating the current biomass to the initial biomass and cumulative catches. Combining this with an observation model (Equation T2.2), which relates some biomass index to the population biomass, yields: $I_t = qB_0 - qC_{t-1}$ . This can be fitted to observed catch data to estimate $B_0$ as the x-axis intercept (Hilborn and Walters 1992).

**Table 2. Leslie depletion model**

| **Data** | |
|---|---|
| $C_t$ | Cumulative catches |
| $I_t$ | Abundance |
| **Parameters** | |
| $B_0$ | Initial biomass |
| $q$ | Catchability |
| **Equations** | |
| $B_t = B_0 - C_{t-1}$ | (T2.1) |
| $\hat{I}_t = qB_t$ | (T2.2) |

Alternatively, declines in biomass can be represented in the DeLury depletion model given by Equation T3.1 (DeLury 1947). Assuming the same observation model (Equation T3.2), and taking the natural logarithm, we obtain: $\ln(C_t) = \ln(qB_t) - qE_t$. This can be fitted using regression methods to the within-season data from a particular population, giving $B_0 = e^c/m$, where $c$ is the intercept and $m$ the slope of the regression (Hilborn and Walters 1992). This approach is easily extended to include estimates of natural mortality (the *modified* DeLury model) (Seber 1982).

**Table 3. DeLury depletion model**

| **Data** | |
|---|---|
| $E_t$ | Cumulative effort |
| $I_t$ | CPUE |
| **Parameters** | |
| $B_0$ | Initial Biomass |
| $q$ | Catchability |
| **Equations** | |
| $B_t = B_0 e^{-qE_t}$ | (T3.1) |
| $\hat{I}_t = qB_t$ | (T3.2) |

## Cohort aggregated models

### Catch survey analysis

Catch survey analysis extends the ideas behind the depletion models to include estimates of recruitment. Assumptions regarding the need for a closed population are relaxed at the expense of higher information requirements. Specifically, as well as an abundance index for the recruited population, some data on actual recruitment levels are also required, and are usually provided by surveys. Despite the substantially smaller data requirements of this approach, in comparative assessments it has been shown to produce results similar to those for the more complicated VPA methods described below (González-Yáñez et al. 2006).

**Table 4. Catch survey analysis**

| **Data** | |
|---|---|
| $C_y$ | Catch numbers |
| $R_y$ | Recruitment |
| $I_y^r$ | Recruitment abundance index |
| $I_y^s$ | Population abundance index |

| | |
|---|---|
| **Parameters** | |
| $N_0$ | Initial numbers |
| $q^r$ | Recruitment survey catchability |
| $q^s$ | Population survey catchability |
| $M$ | Natural mortality |
| **Equations** | |
| $N_{y+1} = (N_y + R_y)e^{-M} - C_y e^{-M/2}$ | (T4.1) |
| $\hat{I}^r_y = q^r R_y$ | (T4.2) |
| $\hat{I}^s_y = q^s N_y$ | (T4.3) |

Total population numbers over time are given by Equation T4.1, and estimated by fitting to survey abundance indicies using equations T4.2 and T4.3. A successful fit usually requires a fixed ratio between the two catchabilities (ICES 2008).

**Biomass production models**

Biomass production models are some of the most commonly used in fisheries science, providing a simple biomass dependent growth function for the aggregated population. The most common are the Schaefer (Schaefer 1954, 1957) and Pella-Tomlinson (Pella and Tomlinson 1969) models, both of which were originally developed for Pacific tuna stocks.

Only total catches and an index of abundance (CPUE or tagging data) are required to parameterise these models, which are easily fitted within a likelihood framework provided there is sufficient 'contrast' in the data (Hilborn and Walters 1992). Specifically, some recovery in the stock from a harvested state is required to reliably estimate both the growth rate and carrying capacity (Table 5). This is usually not the case, with only a monotonic decrease in abundance being observed. There is therefore often the need to make use of auxiliary data to estimate the growth rate (McAllister, Pikitch, and Babcock 2001; Myers, Mertz, and Fowlow 1997). Analogous methods also exist to estimate the shape of the production function for the Pella-Tomlinson model (McAllister et al. 2000; Maunder 1996). The incorporation of such information into the assessment is most readily achieved within a Bayesian framework, by generating an informative prior distribution (e.g. Hillary 2007).

**Table 5. Discrete Schaefer biomass production model**

| | |
|---|---|
| **Data** | |
| $C_y$ | Catch biomass |
| $I_y$ | Abundance index |
| **Parameters** | |
| $r$ | Per capita growth rate |
| $B_0$ | Carrying capacity |
| **Equations** | |
| $B_{y+1} = B_y + rB_y\left(1 - \frac{B_y}{B_0}\right) - C_y$ | (T5.1) |
| $\hat{I}_y = qB_y$ | (T5.2) |

## Cohort disaggregated models

Cohort-based models are so-called because they track the movement of age- or length-based cohorts as they progress through the population. Their advantage over cohort-aggregated models is that they allow estimation of recruitment fluctuations, which can exaggerate fluctuations of the available biomass of a population over time, with obvious management implications. The data requirements are large however, substantially so when compared to those needed for parameterisation of biomass dynamic production models. Given these data needs, cohort-aggregated models may sometimes prove more useful for generating management advice (e.g. Ludwig and Walters 1985; Ludwig and Walters 1989), and should at the very least be run in parallel with cohort disaggregated models to verify their output (Hilborn and Walters 1992). Their simplicity means that they can also prove useful for examining conflicts or inconsistencies within the data (specifically catch or catch rate data) within a more intuitive framework (Hillary 2007).

Two modelling approaches are commonly taken, which can broadly be grouped as Virtual Population Analysis (VPA) and Integrated Assessment Models. The latter approach has a variety of incarnations, ranging from Stock Reduction Analysis (SRA) to more complex integrated assessment models, which can statistically combine a wide variety of data sources. The principal difference from VPAs is that such approaches incorporate a more rigorous statistical foundation. Further, more specific differences will become clear in the following discussion.

### Virtual population analysis

VPA models are age-based, making the assumption that catch-at-age data are exact (i.e. with negligible error) and require these data to be available for all the years covered by the assessment. Natural mortality is assumed known (for simplicity we have also assumed here that it is constant over ages and years, although this is not necessary). The model usually represents individual cohorts by an approximate linear relationship (Equation T6.1) (Pope 1972), and traditionally assumes a terminal age $A$ at which $N_{yA}$ equals either some pre-determined value, or the numbers associated with some terminal fishing mortality (i.e. the assumed terminal fishing mortality and catch yields the terminal numbers at age). Using this assumption the model works backwards from age $A$ to reproduce the cohort dynamics. This can be done for each cohort that has passed through the fishery (i.e. reached the terminal age), but not for those for which $a < A$ . For these 'incomplete' cohorts, further assumptions are required to generate the 'terminal' $N_{ya}$ values. The terminal $N_{ya}$ (or $F_{ya}$) estimates form the bottom and right-hand sides of a rectangle (with years horizontal and ages vertical) from which the VPA algorithm reconstructs the full matrix of numbers-at-age

Fishing mortality at age is allowed to vary from year to year and is estimated directly from the reproduced dynamics of the 'complete' cohorts (Equation T6.2). For example, given known effort $E_y$, we can then estimate catchability from Equation T6.3. This estimate of $q_a$ from the complete cohorts can then be used to estimate $q_a$ and therefore fishing mortality-at-age in the incomplete cohorts (again using Equation T6.3). This can be achieved through a simple averaging process or more recently through a process of *shrinkage* (see below). Finally numbers for the incomplete cohorts are reproduced by Equation (T6.4).

**Table 6. Virtual population analysis**

| **Data** | |
|---|---|
| $C_{ya}$ | Catch numbers |
| $E_y$ | Fishing effort |
| $S_a$ | Selectivity |
| $M$ | Natural mortality |
| $I_y$ | CPUE |
| **Parameters** | |
| $N_{ya}$ | Numbers |
| $F_{ya}$ | Fishing mortality |
| $Z_{ya}$ | Mortality ($M + F_{ya}$) |
| $q_a$ | Catchability |
| **Equations** | |
| $N_{y+1,a+1} = N_{ya}e^{-M} - C_{ya}e^{-M/2}$ | (T6.1) |
| $N_{y+1,a+1} = N_{ya}e^{-(M+F_{ya})}$ | (T6.2) |
| $F_{ya} = q_a E_y$ | (T6.3) |
| $N_{ya} = \frac{C_{ya}}{1 - e^{-Z_{ya}}}\left(\frac{Z_{ya}}{F_{ya}}\right)$ | (T6.4) |
| $\hat{I}_y = \sum_a F_{ya} N_{ya}$ | (T6.5) |

There are many methods (and associated software packages) available to generate the terminal $N_{ya}$ (or $F_{ya}$) estimates. This process of 'tuning' is achieved using some auxillary data, such as effort, CPUE, survey or mark-recapture data.

The XSA (eXtended Survivors Analysis) (Shepherd 1999; Darby and Flatman 1994) algorithm for example assumes a proportional relationship between abundance indices-at-age and numbers-at-age and uses a simple linear regression to estimate the terminal numbers-at-age predicted by each abundance index (and given the underlying catch-at-age data, $M$ matrix and VPA algorithm). These estimates of terminal numbers are then combined (using inverse-variance weighting) across abundance indices to give a final estimate of the terminal numbers and, subsequently, the final estimates of numbers-at-age (fishing mortality-at-age is estimated given the number-at-age, the catch-at-age and the natural mortality-at-age assuming a Baranov catch equation). Estimates of the most recent numbers (and especially the recent recruitments) are very imprecise (given such limited abundance data to estimate the related terminal numbers) and often *shrinkage* is employed whereby the most recent and youngest estimates of both numbers and $F$ can be shrunk (penalised to lie close to) a recent back-average.

The ICA (Integrated Catch Analysis) (Patterson and Melvin 1996) algorithm is different from XSA in a number of ways. It assumes a separable period at the end of the data (pre-specified) where $F_{ya} = F_y S_a$, where $S_a$ is the selectivity at age. This removes the need for shrinkage (although shrinkage is still allowed) but again the estimates of numbers and fishing mortality in the most recent years remain highly uncertain. Terminal numbers-at-age are estimated directly as model parameters, not derived from multiple estimates as in XSA. Also, in ICA a weighted least-squares objective function is used (as opposed to the *ad hoc* tuning used in XSA) and age-aggregated biomass indices (as well as observation error variance information on the abundance indices) are permitted. The catch-at-age is not assumed to be perfectly known, and can be down-weighted to account for errors in this regards (although not in a complex multi-variate manner). As with XSA only abundance indices are permitted within the estimation (no tagging or other data) and there are still no direct estimates of the most recent recruitment level or parameter uncertainty.

The ADAPT tuned VPA framework (Gavaris 1988) is arguably the most advanced of the tuned VPA algorithms. ADAPT permits a wider array of data than either XSA or ICA: abundance indices (age-structured/aggregated) and mark-recapture data. Also, it has a flexible maximum likelihood framework so alternative and perhaps more sensible probability models can be assumed for the various data. One slight difference between ADAPT and the other main VPA packages is that ADAPT estimates terminal fishing mortality parameters not terminal numbers-at-age (although in conjunction with the catch numbers the two are largely comparable) and an alternative routine for dealing with the plus group. ADAPT also has an in-built set of model decision tools and a bootstrapping procedure much as the one outlined further on in this document. As with all VPA algorithms some shrinkage is permitted and, again, the most recent estimates of *F* and numbers will almost always be the most uncertain.

When projecting forward in time (beyond the current year) an estimate of recruitment is required. This is obtained *post hoc* by fitting a particular recruitment relationship to VPA-based estimates of year class strength, using regression methods (Shepherd 1997).

**Integrated assessment methods**

Although VPA approaches have attracted a great deal of support within ICES, primarily due to the simplicity of the calculations involved, there are problems associated with their implementation (discussed below) which require a more robust statistical approach. Integrated assessment models are so called because they allow the application of multiple data sources (with the error inherent in each accounted for) towards the estimation of implicit model parameters, which provide an indication of the status of the stock. Direct estimation of model parameters in this statistical way is important since it allows insight into the associated levels of uncertainty. Furthermore, integrated assessment methods include the stock-recruitment relationship implicitly within the model, providing a more consistent framework for projections. This facet also makes the estimation of the most recent population levels (in particular recruitment) more robust and precise than VPA methods using the same data.

Stock reduction analysis (SRA) represents the simplest form of this type of model (Table 7), using historical catch data in conjunction with estimates of relative stock size reduction due to fishing (usually a catch rate or survey index), to reconstruct possible trajectories of decline (Kimura, Balsiger, and Ito 1984; Kimura and Tagart 1982).

**Table 7. Stock reduction model**

| **Inputs** | |
|---|---|
| $R(.)$ | Recruitment |
| $h$ | Steepness |
| $M$ | Natural mortality |
| $S_a$ | Selectivity |
| $C_y$ | Catch biomass |

| | |
|---|---|
| $w_a$ | Weight |
| $m_a$ | Maturity |
| $I_y$ | Abundance |
| **Parameters** | |
| $N_{ya}$ | Numbers |
| $q$ | Catchability |
| **Equations** | |
| $N_{y1} = R\left(B_y^{sp}, h\right)$ | (T7.1) |
| $N_{y+1,a+1} = N_{ya}e^{-M}\left(1 - S_a H_y\right)$ | (T7.2) |
| $H_y = {C_y}/{B_y^{exp}}$ | (T7.3) |
| $B_y^{sp} = \sum_a N_{ya} w_a m_a$ | (T7.4) |
| $B_y^{exp} = \sum_a N_{ya} w_a S_a$ | (T7.5) |
| $\hat{I}_y = qB_y^{exp}$ | (T7.6) |

Population numbers are projected forward, with each cohort initiated by the assumed stock-recruitment relationship (Equation T7.1). This forward projection allows each cohort to be modelled in a consistent fashion, regardless of whether it has passed completely through the fishery (in contrast to VPA methods). Some prior biological knowledge is required (namely $M$, $h$, $w$ and $m$) and an assumption regarding the commercial selectivity at age. Catchability is typically derived analytically. Importantly however, SRA does not require catch at age data to reproduce cohort dynamics, and as such has minimal data requirements.

As data availability increases, particularly the availability of catch at size and growth information, it is possible to increase the parameterisation to produce a more complicated integrated model. Such models are commonly age-based, and referred to as age-structured population models (ASPMs) or statistical catch at age (SCAA) models. A typical ASPM is outlined in Table 8.

**Table 8. Age-structured population model**

| **Inputs** | |
|---|---|
| *R(.)* | Recruitment |
| $C_{ya}$ | Catch numbers |
| $I_y$ | Abundance |
| $w_a$ | Weight |
| $m_a$ | Maturity |
| $a'$ | Plus group |
| **Parameters** | |
| $N_{ya}$ | Numbers |
| $h$ | Steepness |
| $M_a$ | Natural mortality |
| $F_y$ | Fishing mortality |
| $Z_{ya}$ | Mortality ($M_a + F_{ay}$) |
| $S_a$ | Selectivity |
| **Equations** | |

| | |
|---|---|
| $N_{ya} = R\left(B_y^{sp}, h\right)$ | (T8.1) |
| $N_{y+1,a+1} = N_{ya} e^{-Z_{ya}}$ | (T8.2) |
| $N_{y+1,a'} = N_{ya} e^{-Z_{ya}} + N'_{ya} e^{-Z'_{ya}}$ | (T8.3) |
| $B_y^{sp} = \sum_a N_{ya} w_a m_a$ | (T8.4) |
| $B_y^{exp} = \sum_a N_{ya} w_a S_a \, e^{-Z_{ya}/2}$ | (T8.5) |
| $\hat{C}_{ya} = N_{ya} S_a F_y \left(1 - e^{-Z_{ya}}\right) / Z_{ya}$ | (T8.6) |
| $\hat{I}_y = q B_y^{exp} \square$ | (T8.7) |

These models typically (but not necessarily) project the population cohorts forward from an unexploited equilibrium state. One of their main advantages over SRA, is that they are able to use catch-at-age data to detect recruitment fluctuations, which are important for understanding how the population responds to exploitation. This is achieved by modifying Equation T8.1 to include a stochastic time series component. In contrast to VPA, they are also able to estimate population trajectories without the need for a complete set of catch-at-age data covering all years. This can be a significant advantage, allowing longer time trends to be reconstructed, and thus providing more representative estimates of depletion.

## Management

The means by which assessment results are translated into management action is infrequently specified within the management framework, instead relying on lengthy discussions with the working group charged with reaching a decision on management advice. Such an informal approach is usually neither efficient nor productive (Butterworth 2007). Harvest control rules instead provide a means of automating management decisions: a management recommendation is generated when the HCR is provided with input reflecting the status of the stock - either empirical data (e.g. catch rates and mean length: Brandao and Butterworth 2008) or a derived estimate from the assessment (e.g. spawning stock biomass: Hillary, Kirkwood, and Agnew 2006; SC-CCAMLR 2007). The HCR is agreed upon by all stakeholders at its inception, thus facilitating management action.

Explicit definition of a HCR, associated reference points, inputs and the means by which these inputs are generated, has two advantages. First, it provides the means for efficient management action, as referred to above, which benefits both the fishing industry and the political aspirations of the managers. Second, and perhaps most importantly, a management framework of this type can be tested through computational simulation of how it might perform. This testing results in what is referred to as a management procedure (MP) (Butterworth, Cochrane, and De Oliveria 1997; Kirkwood 1997). The MP selected will be that which is most likely to achieve management goals, taking into account uncertainties in the system. This last point is key: uncertainty can be explicitly accounted for when deriving a HCR and its associated reference points, aiming to ensure that management is robust to limitations in the data, rather than being undermined by it. An MP is therefore by design compatible with the precautionary approach (Butterworth 2007), by making appropriate allowances for scientific uncertainty.

# Critical review of the assessment and management of deep-sea fisheries

## Life history characteristics relevant to assessments

Although deepwater species are often considered to be long-lived, slow growing and of low reproductive capacity, this is not always the case. Some species in fact exhibit life history characteristics comparable to those in shallower waters. Not only are life history parameters important for building model-based representations of a stock but they also provide a good first indication of its likely susceptibility to overexploitation (Clarke 2003; Jennings, Reynolds, and Mills 1998; Brander 1981; Hoenig and Gruber 1990). Within ICES in particular, the lack of reliable assessments has prompted reviews of the life history characteristics of deepwater species in the North-East Atlantic in an attempt to better understand the risks (ICES 2001; Large et al. 2003; Clarke 2003; Clarke et al. 2003).

One of the most important life history parameters is natural mortality. High mortality rates generally indicate higher recruitment at equilibrium and therefore productivity. Indeed, in simulations using a simple yield per recruit model it can be shown that species with high natural mortality have higher rates of sustainable exploitation (Clarke 2003). In the absence of suitable tagging or catch-at-age data, natural mortality estimates are usually based on empirically derived life history relationships (Rikhter and Efanov 1976; Hoenig 1983; Pauly 1980; Jensen 1996; Charnov 1993). These require some auxiliary information on longevity (maximum age), mean life-span, individual growth rates or age at maturity. Whilst useful, they do however rely on the accuracy of this data, and may lead to poor estimates of $M$, particularly when the age estimates on which they are based are not properly validated (Clarke 2003). Alternatively, natural mortality can be estimated from catch curve analysis of survey data from an unexploited stock (as is the case for ICES stocks of tusk and roundnose grenadier).

An additional complication for assessments is that life history characteristics differ with geographical region. Natural mortality for Pacific ocean perch (*Sebastus altus*), for example, has been shown to vary spatially (Gunderson 1977). Orange roughy in the southern hemisphere mature younger, at a lower size and are less fecund compared to those in the North East Atlantic (reviewed in Minto and Nolan 2006). However, inconsistent sampling design and data quality may contribute to these apparent differences – further indication of the need for both accurate and unbiased life-history data with which to estimate $M$ in the absence of more conventional data. A comparison of the various growth curves calculated for Patagonian toothfish (*D. Eleginoides*) shows wide geographical variation, with fish off South America having higher $L_\infty$ values, and more rapid growth, than those from south of New Zealand (Horn 2002). However the reality of such differences are undermined by observations that different data from the same region can yield different results (Horn 2002). There may also be geographical variation in spawning behaviour. For example the roundnose grenadier to the West of Britain appears to have a protracted spawning period with at least two batches per year (Allain 2001), where as in the Skagerrak, the same species appears to have a single well-defined spawning period (Bergstad and Gordon 1994).

In general spawning behaviour is very poorly understood for deep water species. For the orange roughy at least, spawning occurs within a short well defined period (Du Buit 1995; Clark et al. 2000) which most probably accounts for the observed high levels of recruitment variability (Clark 1995).

Such episodic recruitment has also been recorded for the Pacific ocean perch *Sebastes altus* (Leaman and Beamish 1984; Gunderson 1977). In contrast, silver smelt (Magnusson 1988) appear to spawn throughout the year.

The life history characteristics of deepwater species indicate that they may be highly susceptible to overexploitation. However, it is also clear such vulnerability is not universal. This creates additional problems for management since many deepwater stocks are exploited in multispecies fisheries. ICES stocks of roundnose grenadier, for example, are exploited by trawl fisheries that also catch silver smelt, black scabbarfish and blue ling (Charuau, Du Pouy, and Lorance 1995). In such situations there is danger that the local extirpation of the most vulnerable may proceed unnoticed (e.g. Dulvy et al. 2000).

Other aspects that typically differ:

Growth rates

Lower productivity

Spatial aggregation

Recruitment

## Applications

The assessment of harvested populations aims at deriving an estimate of depletion or fishing mortality using information on life history and whatever indicies of abundance are available. As discussed above, the complexity of the approach adopted depends on the data available. In the most data poor situations a standard formal assessment may not even be possible, relying instead on the direct interpretation of commercial catch rates or survey data. At the other extreme, integrated assessment models are able to combine multiple sources of data within a statistically coherent framework to generate accurate estimates of the population indicators required from management.

In the North Atlantic, data availability is generally poor. In particular there is a lack of time-series survey data, so that assessments are forced to rely on commercial catch and effort and make the questionable assumption that commercial CPUE is linearly related exploitable biomass (Harley, Myers, and Dunn 2001; Maunder and Deriso 2007). These data are often sparse, of poor quality and not available to the working groups (Large and Bergstad 2003). Decreases in nominal catch rate immediately indicate that catches may be exerting an influence on stock biomass, particularly given that technological advancements and spatial changes to the fishery often act to stabilise the catch rate even if the stock is declining (Harley, Myers, and Dunn 2001). A declining trend is of particular concern if catches are stable or increasing, suggesting increased effective effort levels or changes in catchability. Such trends are unlikely to be sustainable (Clark 2001). Despite these problems, a simple smoothed CPUE time series is used within ICES as an indication of depletion in situations for which a formal assessment is not possible (Large and Bergstad 2003).

Other intuitive indications of stock status include estimates of mean age, length or weight of the population, which will decline as a result of exploitation and in the absence of strong recruitment variation. Such indicators are particularly useful for situations in which data are limited and have been developed for application to some of the heavily exploited tuna stocks (Maunder and Deriso 2007). In a recent application to management of toothfish in the Prince Edward Islands, mean fish length and CPUE are used to set catches (Brandao and Butterworth 2008).

In addition to CPUE, the only other time-series data available are usually total landings, meaning that only the most rudimentary assessment methods can be applied. Depletion methods are a particularly suitable approach, providing a simple means of approximating unexploited stock size and current depletion levels. Their low data requirements mean they have been used extensively within the context of deep-sea fisheries assessments (e.g. Perez, Pezzuto, and Andrade 2005; Agnew et al. 2009), with the modified DeLury method being widely implemented for ICES deepwater stocks (Large et al. 2003).

Depletion models depend on a complete time-series; otherwise population sizes will be underestimated. Furthermore they make a number of questionable assumptions, namely that the population is a single stock, which is not always well established, and that catchability does not change over time or space. This assumption is clearly violated for aggregating species such as orange roughy (Clark et al. 2000) and cod (Rose and Kulka 1999) so that sequential depletion of fish aggregations can occur unnoticed by the analysis. The modified DeLury model also assumes constant recruitment over time, the realism of which must be considered in light of what is known about the stock being assessed.

Surplus production models have also found use in data limited assessments of deepsea stocks (e.g. Laptikhovsky and Brickle 2005). A common problem is a lack of contrast in the CPUE data (e.g. black scabbardfish, Large et al. 2003), preventing the reliable estimation of both *r* and *K* parameters (Hilborn and Walters 1992). Although such models are particularly suited to situations in which ageing is difficult (e.g. Carbonell and Azevedo 2003), they have also been criticised precisely due to their lack of data inclusivity, which can lead to the discarding of what small amounts of data are available (Punt 2003).

Moving to a cohort structured model can not only make use of whatever catch-at-age data are available, but has the advantage of properly accounting for time lags in the population (from spawning to recruitment) and can predict an abundance index directly comparable to that collected from surveys (available biomass). Virtual population analyses are frequently used to accommodate available catch-at-age data, and have found favour within ICES where they are used extensively in the assessment of European deepsea stocks for which there are sufficient data. The tuned VPA model XSA (Shepherd 1999; Darby and Flatman 1994) is the model of choice and is applied, for example, to the Faroese Ling (*Molva molva*) and roundnose grenadier (*Coryphaenoides rupestris*) (ICES 2009). However its application is often compromised. First, it requires an unbroken time-series of catch-at-age data, which is often very short with questionably applicability to species that have very long life-spans, or have been exploited for long time periods. For the Faroese ling, exploitation started in 1904, but catch-at-age data are only available from 1996 onwards (ICES 2008). For ICES stocks of roundnose grenadier, age-length keys are only available for a few years since 1996, despite the initiation of exploitation in 1990 (ICES 2009). In this particular case, it was decided to create an average ALK and apply it to catch-at-length data for all years, which undermines the ability to track recruitment cohort strength through the population.

Whether short time series of data are suitable for assessments also depends on the objectives of management. It is often the case that data quality will deteriorate moving back in time. If the stock is known to be in a depleted state, so that the primary objective is for recovery, using only data for more recent years to better ensure comparability of abundance indices and hence to obtain unbiased estimates of trend becomes paramount. In contrast, if management is to be based on measures of depletion or absolute biomass (e.g. $B_{MSY}$) then longer time series are more desirable (NRC 1998), allowing a more accurate representation of the stock in its pristine state.

There are however more fundamental problems relating to the use of VPA analysis, which pertain to the methodology itself. First, VPA does not provide a reliable representation of stock dynamics for recent years, since it relies on information from ancestral cohorts that have already passed through the fishery. The use of shrinkage within XSA for example, will lead to an overestimation of abundance for a declining stock, and underestimation if the stock is increasing. Second, a VPA does not include an internally estimated stock-recruitment relationship, which undermines the statistical consistency of the model. Both these criticisms are dealt with effectively by integrated assessment models (SCAA or ASPM), which have the added benefit of being able to be more inclusive with their data requirements. In particular a complete unbroken time-series of catch-at-age data are not required. This is one of the main reasons why integrate assessment models are the most widely applied in deepwater assessments conducted in Australia, New Zealand, South Africa and the United States (Punt 2003). Examples include deepwater stocks of hake (e.g. Rademeyer, Butterworth, and Plaganyi 2008), toothfish (e.g. Hillary, Kirkwood, and Agnew 2006) and orange roughy (e.g. Wayte and Bax 2002).

Initial steps towards an integrated assessment approach have been made by ICES through application of SRAs to stocks of orange roughy, yielding results similar to those from surplus production model and depletion estimates (Large and Bergstad 2003), and in a more tentative fashion to blue ling fisheries around Iceland and the Faroe islands (ICES 2008). They have also been applied historically to orange roughy in New Zealand waters (Clark 1996). SRA does not require catch at age data to reproduce cohort dynamics, and as such has minimal data requirements. This makes it an attractive approach for deepwater fisheries.

Provided the data contain sufficient information to parameterise the model, development of an integrated assessment model is not constrained by the type of data available. This allows the investigation of a range of model alternatives, accounting for alternative relationships between predicted and observed values (e.g. McAllister and Kirchner 2001). Integrated assessment models can also account for spatial structure (Francis, Cordue, and Haist 2002), the importance of which is becoming increasingly well recognised.

There has been an increasing trend towards integrated assessments that has tracked the computational resources available for model fitting. Integrated assessment models can often be supported by external estimations of population parameters in relation to mortality, growth or recruitment. Increasingly however, all the available data is being integrated into a single analytical framework, thus ensuring statistical consistency. In one assessment of New Zealand orange roughy for example, the growth curve is now estimated internally (Smith et al. 2002), rather than externally as has previously been the case (Francis 2001). An important by-product of this increasingly integrated approach is that it allows for the identification of conflicts within the data and limitations in the model structure. Model fitting involves the minimisation of an objective (likelihood) function which receives a weighted contribution from all the data sources. If the outcome of the model fit depends on this weighting (e.g. Clark 2003) then it indicates a conflict between the various data sources or (more correctly) a misrepresentation of the data by the model. This can prompt model revisions to create a more accurate picture of stock dynamics,

## Estimation and the importance of uncertainty

There has traditionally been a tendency for management advice to be based on the best available estimates of stock status. However this approach has been gradually overtaken by the need to take account of the bias and imprecision that surrounds these estimates (Punt 2003). This uncertainty is often considerable, leading Walters and Pearce (1996) to suggest that estimating the biomass of a stock should be considered successful if within 40% of its actual value. The recognition that assessment results are both biased and imprecise led in part to the precautionary approach to fisheries management (FAO 1995), which has in turn placed a greater emphasis on risk, its quantification and how it can be accounted for by management decisions.

The estimation of uncertainty within the assessment models defined in this document covers a multitude of approaches, where often the particular assessment method has an associated algorithm for deriving this uncertainty. It is not our intention to propose an optimal method, merely to provide a review and advice as to what methods are available, their relative ease of use and applicability, and their potential drawbacks.

### Residual bootstrap approach

This approach is well suited for all types of models where least-squares objective functions (and not likelihoods) are employed (e.g. VPA). The theory is as follows: let be $I_{...}$ an observed data value (at some resolution ...) and $\hat{I}_{...}$ be the model-predicted value, with associated residual $\varepsilon = I_{...} - \hat{I}_{...}$ . Re-sampling these residuals (e.g. using an appropriate stratified bootstrap or by simulating from an estimated distribution), “new” data can be generated by adding the re-sampled residuals to the model-predicted values. Model parameters can then be re-estimated with the “new” data and the process repeated until one obtains a suitably large sample of the estimated parameters and associated derived quantities (Needle and Hillary 2007).

This approach is particularly useful for exploring the uncertainty in VPA assessments – residuals are re-sampled along years (but not ages) to obtain samples of the numbers and fishing mortality matrices at relatively low computational cost. Such approaches have been developed for the VPA methods used in the FLR assessment framework (Kell et al. 2007), namely XSA and ICA, and is also in the ADAPT framework.

### Approximate Monte Carlo approaches

When likelihood functions (not least-squares objective functions) are employed, as is often the case with the integrated assessment models, an approximate covariance matrix of the maximum likelihood parameter estimates can be obtained. Standard errors and CVs for estimated parameters are thus easily obtained and approximate uncertainty in derived quantities can be obtained via the Delta method (Needle and Hillary 2007). A more simple approach (that is also useful in management strategy evalution) is to use the maximum likelihood estimates and covariance matrix to generate multi-variate normal samples of the parameters (with related samples of the derived quantities). Statistical theory states that these provide an unbiased estimate of the true distribution of model parameters. Generating multi-variate normal deviates is computationally simple, making this a convenient Monte Carlo approach to both estimating the uncertainty and deriving samples of key population variables. These can be used assessing stock status or deriving reference points in a quasi-probabilistic framework.

### Bayesian approach

This approach is arguably the most difficult to implement, but also the most powerful. The Bayesian approach allows us to define the probability distribution of the parameters (and derived quantities) directly in terms of the likelihood (the probability model for the data, given the parameters) and the prior distribution (the probability model for the parameters in the absence of any data). The multiplication of the likelihood and the prior yields the *posterior* distribution: the prior parameter distribution updated by the data and the likelihood (probability model):

$$\mathbf{p}(\vartheta|D) \propto \mathbf{p}(D|\vartheta)\mathbf{p}(\vartheta)$$

where $\vartheta$ is the parameter vector and $D$ is the data. Markov chain Monte Carlo (MCMC) or other techniques can be used to sample from this distribution directly (not approximately as for the previous method) and make inference about the parameters (and derived quantities) from this sample. Importantly, the Bayesian approach is specifically defined in terms of probabilities, allowing us to use decision analysis tools and to speak of risk in a well-defined manner.

Bayesian methods are used for a number of deepwater assessments, including Namibian orange roughy (McAllister and Kirchner 2001), New Zealand hoki (Francis, Cordue, and Haist 2002) and South Georgia toothfish (Hillary, Kirkwood, and Agnew 2006). Other toothfish populations managed by the Commission for the Conservation of Antarctic Marine Living Resources (CCAMLR) provide further examples (SC-CCAMLR 2007).

## A role for meta-analysis?

A common problem for deepwater assessments is the absence of key life-history information for a specific stock: growth, maturity, natural mortality or key stock-recruit parameters are often lacking. However, there are usually well developed assessments and well studied populations of deepwater fish that provide a potentially useful array of pre-existing information. This type of meta-analytic approach has been used many times – the “Robin Hood” approach where one takes from data rich stocks to share with data poor ones.

Bayesian hierarchical meta-analysis has been used to estimate stock-recruit parameters (particularly the steepness) for a range of “similar” stocks of salmon (Michielsens et al. 2006), Pacific groundfish (Dorn 2002), and EU herring (Hillary et al. 2009). In these cases strong information is shared across stocks with weak information to improve estimation. Parameters such as $M$ and growth are also likely to be similar in "similar" stocks and this type of approach offers a way of improving the information we apply in data situations.

As well as sharing information of direct relevance to the assessment, other life-history parameters may also be useful. Estimates of *M* for example, can be obtained from knowledge of maximum age (Hoenig 1983; Hewitt and Heonig 2005) and age at maturity (Charnov 1990), information on which can therefore be usefully shared between stocks. There are many other methods for obtaining preliminary estimates of key life-history parameters (e.g. Rikhter and Efanov 1976; Pauly 1980; Jensen 1996) which can benefit from meta-analytical approaches. These are likely to prove extremely valuable to data-poor deepwater fisheries assessments, and assessment scientists should therefore always be prepared to incorporate available information from similar stocks.

A few thoughts:

Maybe divide critical review section into groups where particular methods could be helpful or more appropriate for certain cases (vulnerable life-histories; recruitment variability; spatial aggregation; incomplete information (i.e. abundance indices for juveniles or adults only); lack of particular combinations of survey/effort/catch data)

Maybe worth having a table of approaches typically used, their data requirements and strengths/weaknesses in each circumstance and then some text on promising approaches which could be useful?

A bit more about what the consequences are for BRPS say for comparing R versus K strategists (what did the Clarke paper show not just the method), or simply across a range of Linf or Winf due to life history invariants

Other alternative approaches:

Probably need to say something about EAF methods? given that the ecosystem is considered vulnerable and that is what we need to move towards

Use of ecological indicators for fish populations, communities, and indicator species

Multispecies/life history and ecosystem modelling approaches

Simulation tools for evaluating HCRS

Some interesting ideas:

> Reference points based on maximum lifetime reproductive rate (Brooks et al 2009)
>
> FISBOAT papers useful for cases where fishery-independent data are available including spatial indicators
>
> e.g. CUMSUM method for HCRS based on multiple indicators

Discussion of what longer term data collection should comprise, monitoring

## Harvest Control Rules

Harvest control rules have been used to streamline decision-making process and reduce the influence of short-term political goals; to make management decisions more transparent and more clearly dependent upon fresh evidence.

Finally, both reference points and harvest control rules fit with the risk based approach to management enabling decision makers to account for scientific and other sources of uncertainty. It is possible to explicitly take risks into account by specifying reference points and generating harvesting recommendations through HCRs based on probability to avoid undesirable outcomes.

However, certain conditions are necessary for constructing reference point used with harvest control rules type of a management system. Foremost, there must be a consensus over management objectives and that consensus must be possible to express in terms of reference points. Most reference points are based on models that have a high demand for data if they are realistic in taking complexity of species biology into account and biological knowledge. For the cases where neither data nor biological knowledge are present in sufficient quantities to develop informative models, reference points might still be used but their choice would be more dependent on stakeholder consensus and expert opinion. This is the approach implied in FAO (2008) paragraph 77 quoted above which states that harvest rate for some deep-sea species should not exceed “inferred” natural mortality, since many deep-sea species are long-lived natural mortality is low and a safe level of harvest rates therefore is still lower.

In addition to consensus over management objectives, there must be an informed decision over the scope and detail of risk management framework for each fishery to which reference point/ HCR regime is to apply. Although such risk framework are often implicit in the definition of the reference points, e.g. avoid biomass decline to a low level with high probability, for deep water species it is even more pertinent to have a formal risk assessment if only a qualitative one before narrowly focusing on specific risks to be avoided and formulating reference point/HCR risk mitigation framework.

Nonetheless, HCR based management can be suitable for deep-sea species as it has improved management for many different kind of fisheries. Harvest control rules or management procedures are used extensively by the management authorities in most fisheries in New Zealand, Australia and South Africa, and in some fisheries of USA and in a few fisheries in Europe. Harvest control rules can be tested in simulations first, the approach pioneered by the International Whaling Commission. The idea is to create different versions of reality (operating models) based on the processes that are believed to be important in determining the dynamics of the resource. Including different models is vital, not only because model uncertainty being an important source of uncertainty in general, but also because it can accommodate diversity of opinions among stakeholders, and thus help to reach a consensus over potentially controversial management decisions. Further, as in IWC, stakeholders can be invited to suggest various management rules.

These are tested in simulations and those that are shown to be robust to different uncertainties, i.e. different operating models, and perform well with regard to management objectives are implemented.

Not all HCR require specification of reference points or even presuppose stock assessments. HCR by definition is just a pre-agreed management rule, the rule can be based directly on observations or ecological indicators instead of species specific stock assessments.

HCR can be defined either with regard to output, so that catches are controlled, or the inputs into the fishery, so that effort is controlled (this can include gear specification, time and space based control measures). Here are some examples of harvest control rules.

**HCR 1. Constant TAC (model-free)**

The simplest example of a harvest control rule is to keep either TAC or total effort constant at some level, for instance:

$$TAC_y = TAC_{MSY}$$

**HCR 2. TAC based directly on observations (model-free)**

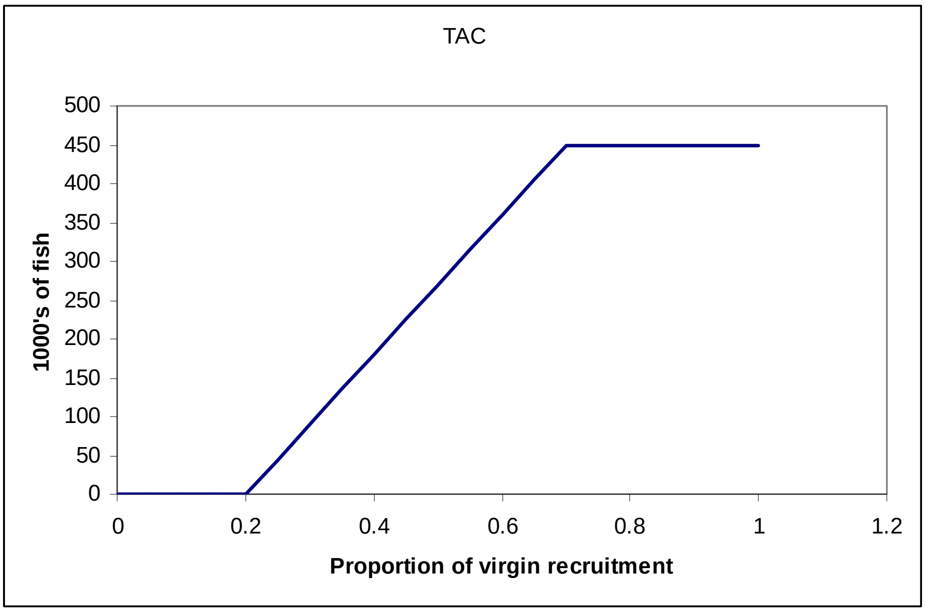
Another simple harvest control rules is to allow TAC to fluctuate with some index of abundance, based on fishery independent data, such as estimates/observations of spawner escapement or spawner biomass or even recruitment projections. For example,

$$TAC_{y+1} = TAC_y \frac{S_y}{S_{y-1}}.$$

**HCR 3. TAC as a step-linear function of some index (model – based)**

Another way to set a harvest control rule is to make it a function of some index, for example a proportion of virgin recruitment as depicted in 0. This is a kind of HCR that is entirely defined by management reference points and thus could be expected to be susceptible to biases in the estimates of those reference points, as well as the particulars of the model used to estimate where the stock is relative to the reference point (Cooke 1999).

In an example of such a harvest control rule depicted in 0 no catches are allowed, if assessed recruitment is below 20% of the estimated carrying capacity in the index stock unit; TAC depends linearly on the estimated (from observations) proportion of the carrying capacity, if those estimates fall between 20 and 75%; and maximum catch is allowed, if it is found that the recruitment exceeds 75% of the carrying capacity.




**An example of a harvest control rule**

### HCR 4. Multi-annual harvest control rules

One of the desirable qualities of a management procedure, from the industry's point of view, is stability. Multi-annual management strategies where advice is stabilized over years are therefore of interest (Geromont *et al.* 1999; Kell *et al.* 2006). Such advice can have a generic form:

$$TAC_{y+1} = TAC'''_{y+1}(1-\beta) + \beta TAC_y .$$

In the equation above, TAC for the future year is a linear combination of the TAC set by some harvest control rule, $TAC'''_{y+1}$, and the TAC from the previous year. If the beta parameter equals to zero, then the TAC from last year has no influence on the TAC for the next year. If beta is equal to 1, then the TAC is kept constant at the level of the initial setting.

Operating models enables comparison in simulations of output vs. input based controls. Several other studies have compared output (TAC) based controls with input (effort) based controls (McAllister and Kirkwood 1998; Hjerne and Hansson 2001; Ulrich *et al.* 2002; Vasconcellos 2003). The preference seems to depend on the circumstances of the fishery, such as the relationship between abundance and CPUE. The choice of output vs. input control depends on management objectives - industry/processors/fisherman might prefer stable catches that are associated with output controls rather than higher long term yield that can be a result of input management (Hjerne and Hansson 2001).

For the short lived species, where recruitment is strongly influenced by environmental factors, such as Brazilian sardine, the preference as to input or output controls, in terms of minimizing the probability of stock collapse, depended on the accuracy of stock assessment. Different HCR rules evaluated in the case study of Brazilian sardine by Vasconcellos (2003), among which were effort, catch control, and constant escapement rules, performed differently depending on the ability to measure precisely the true status of the stock. The value of perfect information about the true status of the stock was evaluated in the same study (Vasconcellos 2003). It is possible that the same is true of the deep-sea species, and that the preference for a particular control rule will depend on the kind of uncertainties that characterise a fishery with respect to ageing or assessment in general, recruitment and aggregation behaviour, productivity and life-span.

Other harvest control rules that have been evaluated attempt to closely mimic actual management procedures used in practice. These are usually more computationally intensive as they mimic stock assessments that rely on sophisticated population models and can involve stochastic stock projections under different catch options. For example, in evaluating management strategies for Southern bluefin tuna, one of the harvest control rules to be evaluated was such that the TAC was set according to the level that resulted in high probability of the stock remaining above the threshold value for a given time frame in projections based on simulated catch at age data (Polacheck *et al.* 1999).

For data-poor species simpler HCRs might be desirable, such a constant catch or effort management regime set at a precautionary level. Further, the burden of proof should be reversed: industry must demonstrate that a particular HCR will not create unacceptable risks before securing permission to exploit a resource of which little may be yet known.

Apostlaki and Hillary (2009) propose a generic framework for setting harvest control rules based on fishery independent data and ecological indicators. Essentially, in this case a harvest control rule becomes a potentially complex function of a range of relevant observations/indicators relative to reference points which specify the desired range of those observations/indicators. One of the potential problems in applying this approach to deep-sea species is the slowness with which many indicators change in reaction to unsustainable exploitation. This is due to longevity, aggregation behaviour, and intermittent recruitment. Also a general lack of knowledge about biology and ecology and habitat ranges of many deep-sea species is an obstacle in choosing good indicators.

## Conclusions

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