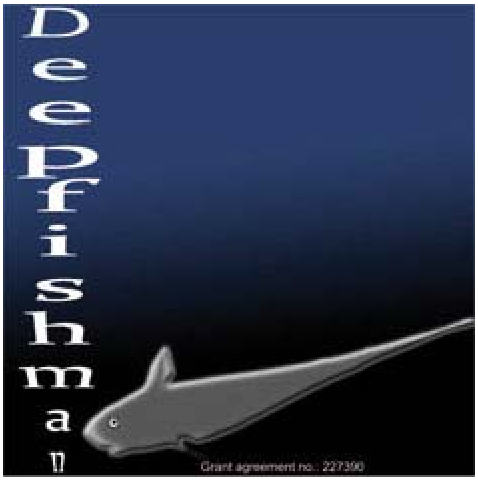

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Review of assessment and management approaches for deepwater stocks

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Abstract

Deepwater fisheries are often characterised by their life history as being susceptible to rapid overexploitation. However it is more generally a lack of data, and a consequentially poor understanding of resource dynamics, that has allowed this overexploitation to take place. This review covers the assessment and management approaches currently being implemented for deepwater fisheries, detailing both their theory and application. Given limitations in the data it is clear that assessments are likely to benefit from the application of derived relationships between life history characteristics and the sharing of this and other information across stocks. It is important that uncertainty in assessment results is represented adequately, and management methods must in turn ensure that decision mechanisms are robust to an incomplete picture of resource dynamics. This requires construction and testing of a harvest control rule within a simulation framework. Harvest control rules themselves need not however be complicated and simple empirical approaches are likely to be adequate for situations in which only relative changes in biomass can be discerned from the data. Development and testing of these control rules is likely to prove a productive area of future research.

Key words: deepwater, stock assessment, management

Introduction

This review provides an introduction to the assessment and management approaches currently implemented for deep water stocks, detailing the methodological backgrounds, providing examples of how they have been applied, and addressing the benefits and shortcomings of each approach. Assessments are generally hampered by a lack of adequate data on the life-history characteristics of the species in question and we review a variety of methods that can be used to supplement the information on which an assessment is based.In addition, appropriate methods for representing uncertainty are described. Finally we review the management approaches that have been applied to deepwater fisheries, and the problems associated with their application to data poor situations.

Characteristics of deepwater fisheries

Deepwater fish species are often characterised as having slow growth rates, extended longevity, late maturity and low rates of natural mortality(Gordon, 2003). As a consequence of their relatively low productive capacity they are likely to be particularly vulnerable to overexploitation. However this is not always the case and some deep water species in fact exhibit life history characteristics comparable to those in shallower waters. In a review of their biological characteristics Gordon (2003) concluded that the squalid sharks, orange roughy (*Hoplostethus atlanticus*) and roundnose grenadier (*Coryphaenoides rupestris*)are the most biologically vulnerable, whilst black scabbardfish (*Aphanopus carbo*) and ling (*Molva spp.*) are more likely to support sustainable fisheries, provided appropriate management measures are in place.

Deep-sea effort has increased rapidly since the 1980’s due primarily to the availability of new technology and surplus fishing vessel capacity (Japp and Wilkinson, 2006). During this time economics and market demand have provided the incentives for deep-sea fisheries development, with technology providing the means to access an increasing range of deep sea habitats, and latent effort capable of rapid exploitation of the resource should the appropriate market or fishing opportunities become apparent.

Despite large amounts of information on a few valuable species, such as orange roughy and toothfish (*Dissostichus spp.*), knowledge of the biology and life history strategies of deep-sea species is generally poor. Our understanding is hampered by a paucity of data, due to the logistical difficulties and costs associated with conducting research and monitoring in deepwater habitats (Japp and Wilkinson, 2006). As such it is more generally a lack of information on life history characteristics, stock structure and population responses to exploitation that make them vulnerable. Unfortunately, this means that knowledge on the status of the resource often lags behind exploitation (Clark, 2001, Large et al., 2003), leading to depletion before catch limits can be reliably estimated.

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 ofpolicy 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 et al., 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, 1995a): "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, and the Harvest Strategy Policy for Australian Commonwealth fisheries (DAFF, 2007). 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, 1995a). 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, 1995a, FAO, 1995b). 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 (World Summit on Sustainable Development – Johannesburg, 2002), although difficulties in estimating MSY for many stocks and failure of the concept to take account of 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

Thegoal of stock assessment is to determine the biological status of the fish stock, namely the level of abundance and whether it is being overexploited, using information on life history and whatever indices of abundance are available. Assessments can be carried out in a myriad of ways, with complexity of the approach adopted depending on the data available. The simplest approaches involve directly estimating indices of abundance from surveys or fishery dependent data and other biological characteristics. These approaches are often used in data poor situations including deepwater. More complicated modelling approaches involve fitting these datato dynamical models that capture the underlying temporal trends in the population, determine rates of exploitation and forecast future stock status under different management scenarios. We review of range of alternative approaches (from simple to more complex) being used in deep water fisheries.

In the most data poor situations a standard formal assessment may not even be possible, relying instead on the direct interpretation of indicators such as commercial catch rates or survey abundance. 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.

It is often the case that data quality will deteriorate moving back in time and it is up to assessment scientists and managers to decide on which data to include. 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.

Simple indicators of stock status

Indicators of stock status refer to some measure of the biological properties of a population, for example, abundance, mean length or mortality (Cotter et al., 2009, Rochet and Trenkel, 2003). In data poor situations where such measures may be the only information available, assessment is based on time series trends of these values and can still provide information useful for management. This approach is becoming widely used to monitor changes in non-target or non-commercial species as part of an ecosystem based approachto fisheries management (FAO, 2003).

Commercial catch per unit effort (CPUE) is probably the most widely used index of abundance and is used to track stock status of many data poor fisheries. Use of CPUE in this way makes make the questionable assumption that commercial CPUE is linearly related to exploitable biomass (Harley et al., 2001, Maunder and Deriso, 2007). If sufficient reliable data are available changes in catchability can be modelled statistically (Maunder and Punt, 2004, Venables and Dichmont, 2004) to improve the interpretability of the index.

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 the commercial CPUE. These data are often sparse, of poor quality and not available to the working groups (Large and Bergstad, 2003). Despite these problems, a simple smoothed 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). 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 et al., 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).

A time series of stock abundance, which may constitute commercial CPUE or survey data, provides a simple index of depletion, provided depletion in the first year of the series is known (Gulland, 1969), or can be approximated (Brooks et al., 2010). If a series of absolute biomass values can be estimated from the index, then it is possible to estimate surplus production for each year of the time series using accompanying data on catches (Hilborn, 2001). Goodyear (2003) showed that use of an abundance index to measure depletion from the unfished state can provide an indication of exploitable biomass relative to that at MSY.

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 in the absence of strong recruitment fluctuation. Mean length in particular is a well established correlate of population size (Beverton and Holt, 1957, Ricker, 1963, Pauly and Morgan, 1987, Ault and Ehrhardt, 1991, Ehrhardt and Ault, 1992). Recruitment fluctuations can be a problem (for example an increase in recruitment can lead to decline in mean age or size) and it is therefore important to consider these indicators alongside those related more directly to abundance.The length distribution can also be used to estimate total mortality, with the original relationship developed by Beverton and Holt (1957, Beverton and Holt, 1956) and extended to account for a finite maximum length of capture (Ehrhardt and Ault, 1992) and non-equilibrium conditions (Gedamke and Hoenig, 2006).

Depletion methods

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.

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 indexto 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 1. 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 2. 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)

The low data requirements of depletion methods mean they have been used extensively within the context of deep-sea fisheries assessments (e.g. Perez et al., 2005, Agnew et al., 2009), with the modified DeLury method being widely implemented for ICES deepwater stocks (Large et al., 2003). However they rely 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 (*Gadus morhua*) (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.

Catch curve analysis

If some catch at age data are available then it can be used to estimate total mortality usingcatch curve analysis(Ricker, 1975). The method 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 C_a is often replaced by an abundance index I_a, alongside the assumption that all age classes caught are fully selected.Mortality estimates can be extracted from length data using similar principles, provided the growth curve is known(Gulland and Rosenberg, 1992).

Table 3. 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)

Catch curves (also known as year class curves) are unable to decompose mortality into natural and fishing mortality ($Z = M + F$), which requires an age-structured population model (see below). However they have found use for deepwater stocks within ICES where an estimate of M is available, in many cases providing the only information on changes tothe current level of fishing mortality (without providing absolute estimates) (Large and Bergstad, 2003).If sufficient data exists from an exploratory survey of an unexploited stock, catch curve analysis can be used to estimate M directly (since $Z = M$).

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, Schaefer, 1957)and Pella-Tomlinson (Pella and Tomlinson, 1969)models, both of which were originally developed for Pacific tuna stocks.

Table 4. 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	
$B_{y+1} = B_y + rB_y\left(1 - \frac{B_y}{B_0}\right) - C_y$	(T4.1)
$\hat{I}_y = qB_y$	(T4.2)

Surplus production models have found use in data limited assessments of deep sea stocks (e.g. Laptikhovsky and Brickle, 2005). 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 4). This is a common problem (e.g. black scabbardfish, Large et al., 2003), with only a monotonic decrease in abundance being observed. There is therefore often the need to make use of auxiliary life-history data (e.g. survival rate at age, fecundity at age, age at maturity) to estimate the intrinsic growth rate using demographic methods (Krebs, 1985). These and similar approaches (e.g. Myers et al., 1997) are not only beneficial for estimation of the parameters of a surplus production model, but may provide a first insight into the vulnerability of a stock to exploitation (since stocks with higher growth rates are able to sustain higher catch rates - Cortés, 1998). 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, McAllister et al., 2000, McAllister et al., 2001).

Cohort disaggregated models

Although biomass production 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 disaggregated 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).

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 complexintegrated assessmentmodels, which can statistically combine a wide variety of data sources. The principal difference from VPAsis 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 T5.1) (Pope, 1972), and traditionally assumes a terminal age A at whichN_{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 terminalN_{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 T5.2). For example, given known effortE_y, we can then estimate catchability from Equation T5.3. 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 T5.3). 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 (T5.4).

Table 5. 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	
$N_{y+1,a+1} = N_{ya}e^{-M} - C_{ya}e^{-M/2}$	(T5.1)
$N_{y+1,a+1} = N_{ya}e^{-(M+F_{ya})}$	(T5.2)
$F_{ya} = q_a E_y$	(T5.3)
$N_{ya} = \frac{C_{ya}}{1-e^{-Z_{ya}}}\left(\frac{Z_{ya}}{F_{ya}}\right)$	(T5.4)
$\hat{I}_y = \sum_a F_{ya}N_{ya}$	(T5.5)

There are many methods (and associated software packages) available togenerate the terminalN_{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 $F_{ya} = F_y S_a$, whereS_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).

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 deep sea 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 (ICES, 2009). However its application is often compromised. First, VPA requires an unbroken time-series of catch-at-age data, which is can be very short relative to the history of exploitation. For the Faroese ling, exploitation started in 1904, but catch-at-age data are only available from 1996 onwards (ICES, 2008). For roundnose grenadier, age-length keys are only available for a few years since 1996, despite the initiation of exploitation in 1990 (ICES, 2009). Short time series also have questionably applicability to long lived species, which is a particular concern for many deep sea stocks.

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 which require a more robust statistical approach.

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.

Integrated assessment methods

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 also makes the estimation of the most recent population levels (in particular recruitment) more robust and precise than VPA methods using the same data(Punt et al., 2002, Randomski et al., 2005). The models typically (but not necessarily) project the population cohorts forward from an unexploited equilibrium state and as such have the added benefit of being more inclusive with their data requirements. In particular a complete unbroken time-series of catch-at-age data are not required, allowing longer time trends to be reconstructed, and thus providing more representative estimates of depletion(Butterworth and Rademeyer, 2008). This is one of the main reasons why integrated 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 (*Merluccius paradoxus*) (e.g. Rademeyer et al., 2008a), toothfish (e.g. Hillary et al., 2006a) and orange roughy (e.g. Wayte and Bax, 2002).

Stock reduction analysis (SRA) represents the simplest form of this type of model (Table 6), 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 et al., 1984, Kimura and Tagart, 1982).

Table 6. 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	
B_0	Pristine B^{sp}
q	Catchability
Equations	
$N_{y0} = R\left(B_y^{sp}, h\right)$	(T6.1)
$N_{y+1,a+1} = N_{ya}e^{-M}\left(1 - S_a H_y\right)$	(T6.2)
$H_y = {C_y}/{B_y^{exp}}$	(T6.3)
$B_y^{sp} = \sum_a N_{ya} w_a m_a$	(T6.4)
$B_y^{exp} = \sum_a N_{ya} w_a S_a$	(T6.5)
$\hat{I}_y = qB_y^{exp}$	(T6.6)

Population numbers are projected forward, with each cohort initiated by the assumed stock-recruitment relationship (Equation T6.1). 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 7 (note that $Z_{ya} = M_a + F_{ya}$).

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. It is however strongly dependent on assumed parameter inputs to the model, and is unable to use catch-at-age data to detect recruitment fluctuations, which are important for understanding how the population responds to exploitation.

Provided the data contain sufficient information, development of an integrated assessment model is not constrained by the type of data available. This flexibility allows the investigation of a range of model alternatives, which may incorporate different hypotheses on the underlying population processes (e.g. McAllister and Kirchner, 2001). Integrated assessment models can also be extended to account for spatial structure (e.g. New Zealand hoki; Francis et al., 2002), the importance of which for effective management is becoming increasingly well recognised (Lorenzen et al., 2010).

Table 7. Age-structured population model

Inputs	
$R(.)$	Recruitment
C_{ya}	Catch numbers
I_y	Abundance
w_a	Weight
m_a	Maturity
Parameters	
B_0	Pristine B^{sp}
h	Steepness
M_a	Natural mortality
F_y	Fishing mortality
S_a	Selectivity
q	Catchability
Equations	
$N_{y0} = R\left(B_y^{sp}, h\right)$	(T7.1)
$N_{y+1,a+1} = N_{ya}e^{-Z_{ya}}$	(T7.2)
$B_y^{sp} = \sum_a N_{ya} w_a m_a$	(T7.3)
$B_y^{exp} = \sum_a N_{ya} w_a S_a e^{-Z_{ya}/2}$	(T7.4)
$\hat{C}_{ya} = N_{ya} S_a F_y \left(1 - e^{-Z_{ya}}\right)/Z_{ya}$	(T7.5)
$\hat{I}_y = qB_y^{exp}$	(T7.6)

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 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. A good illustration is provided by the assessment of New Zealand hoki, in which results are sensitive to changing the weight assigned to the trawl and acoustic estimates of biomass (Annala et al., 2003).

Life history characteristics and their estimation

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. 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 et al., 1998, Brander, 1981, Hoenig and Gruber, 1990) and can be used to derive appropriate reference points for management. For example, Brooks et al. provide an analytical derivation of SPR-based reference points, based on the maximum lifetime reproductive rate (Brooks and Powers, 2007) or steepness of the stock recruitment relationship (h) (Brooks et al., 2010). Such life-history based approaches provide a useful grounding for management in the data poor situations exemplified by many deepsea fisheries.

One of the most important life history parameters is natural mortality, since high mortality rates generally indicate higher recruitment at equilibrium and therefore productivity. 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). Although natural mortality can be estimated from catch curve analysis of survey data from an unexploited stock (e.g. roundnose grenadier, *Coryphaenoides rupestris*) (ICES, 2009), in the absence of suitable tagging or catch-at-age data, estimates are usually based on empirically derived life history relationships. These require some auxiliary information on longevity (maximum age), mean life-span, individual growth rates or age at maturity. For example, estimates of M can be obtained from knowledge of maximum age (Hoenig, 1983, Hewitt and Heonig, 2005) and age at maturity (Charnov, 1990). Whilst useful, they do however rely on the accuracy of this data, and may lead to poor estimates of M when the ages on which they are based are not properly validated (Clarke, 2003).

Another important life history characteristic that is usually poorly described, even for data rich stocks, is that of the stock recruitment relationship. This relationship is usually referred to by a single parameter equal to the recruitment when spawning biomass is 20% below pristine levels (the steepness h). In line with life history based approaches to approximate M, Mangel et al. (2010) showed how steepness can be predicted if information on natural mortality, maximum per capita productivity, maturity and biomass growth are available.

There are many methods that describe relationships between key life-history parameters of a species and which could be used to inform data-poor deepwater fisheries assessments (e.g. Rikhter and Efanov, 1976, Pauly, 1980, Jensen, 1996, Mangel et al., 2010, Charnov, 1993). Complementary to these approaches, there are usually well developed assessments and well studied populations of deepwater fish that provide a potentially useful array of pre-existing information (Hilborn and Liermann, 1998). This type of meta-analytic approach can augment the obvious need for more data collection. Informative priors can be developed for Bayesian assessment models through hierarchical meta-analysis in which data from several independent stocks or species are represented as a probability distribution of the parameter of interest. Originally introduced by Liermann and Hilborn

(1997) to represent depensation at low stock sizes, this approach has since been implemented in a variety of settings (e.g. Michielsens et al., 2006, Myers et al., 2002, Myers et al., 1999, Myers et al., 2001, Hillary et al., 2009), including the estimation of steepness of the stock-recruit relationship for deepwater Pacific Ocean perch (Dorn, 2002).

In using a meta-analytical approach, strong information is shared across stocks with weak information to improve estimation. However, sharing data in this way is open to criticism for the assumed similarities that exist between the assessed stock and those used to inform the assessment. The issue of representativeness is perhaps more problematic for deepwater species as these species tend to be data-poor. The results of Bayesian assessments are affected more by the choice of the prior distributions and are therefore more readily biased by the use of information from more productive stocks. It is therefore appropriate to assume, *a priori*, that productivity of deepwater species is low (Punt, 2003). This can be incorporated into assessments through the selection of prior distributions that give greater *a priori* weight to low productivity scenarios. In the absence of data suggesting otherwise, the posterior assessment results will be based primarily on this assumption of lower productivity.

Given the lack of data available 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. Acomparison of the various growth curves calculated for Patagonian toothfish shows wide geographical variation, with fish off South America having higher L_∞ 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. An exception is orange roughy, for which spawning occurs within a short well defined period (Du Buit, 1995, Clark et al., 2000), probably accounting for the observed high levels of recruitment variability (Clark, 1995). Such episodic recruitment has also been recorded for the Pacific ocean perch (Leaman and Beamish, 1984, Gunderson, 1977), where as silver smelt (*Argentina silus*) appear to spawn throughout the year (Magnusson, 1988).

The life history characteristics of some deepwater species indicate that they may be highly susceptible to overexploitation. However, it is also clear that such vulnerability is not universal. Differential responses to exploitation create problems for management since many deepwater stocks are caught in multispecies fisheries. For example, ICES stocks of the more vulnerable roundnose grenadier are exploited by trawl fisheries that also catch the more productive black scabbardfish and blue ling (*Molva dypterygia*) (Charuau et al., 1995). In such situations there is the danger of local extirpation of the most vulnerable, necessitating the need for species specific monitoring of abundance (Dulvy et al., 2000). The risk of local extirpation highlights the importance of accurate information on life-history characteristics so that the most vulnerable species can be identified. To this end, reviews of the life history characteristics of deepwater species in the North-East Atlantic have been undertaken in an attempt to better understand the risks associated with exploitation (ICES, 2001, Large et al., 2003, Clarke, 2003, Clarke et al., 2003). Such information improves the prospects for sustainable management. In the Australian Western deepwater trawl fishery, for example, the shovelnose lobster (*Ibacus* spp.) is caught alongside the more vulnerable deepwater dogfish (*Centrophorus* spp.), identified as such through an ecological risk assessment (Wayte et al., 2007). To prevent depletion of this and other vulnerable species trigger catch limits are set to prompt more detailed assessment and potentially limit fishery development if they are in danger of overexploitation (Dowling et al., 2008).

Representing uncertainty in the assessment results

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, 1995b), 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 from inversion of the Hessian matrix. Approximate uncertainty in derived quantities (such as biomass) can be obtained via the analytic Delta method (Needle and Hillary, 2007) but a simpler 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. Statistical theory states that these provide an unbiased estimate of the true distribution of model parameters. Estimates of derived quantitiescan then be obtained through iteration of the model. 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 for 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):

$$\mathrm{p}(\theta | D) \propto \mathrm{p}(D|\theta)\mathrm{p}(\theta)$$

where θ 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 (*Macruronus novaezelandiae*)(Francis et al., 2002) and South Georgia toothfish (*Dissostichus eleginoides*)(Hillary et al., 2006b).

Management

The Management Procedure

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, 2009) or a derived estimate from the assessment (e.g. spawning stock biomass: Hillary et al., 2006b). 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 (Cooke, 1999). This testing results in what is referred to as a management procedure (MP) (Butterworth et al., 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. A MP is therefore by design compatible with the precautionary approach (Butterworth, 2007), by making appropriate allowances for scientific uncertainty.

Reference points

Reference points generally represent either targets for management, or triggers for management action (see earlier discussion). But the reference points themselves must also be easy to estimate from the available data. For example, although B^{MSY} and F^{MSY} are often stipulated as suitable target reference points, MSY is very difficult to estimate for most stocks, since it is dependent on the stock-recruitment relationship. In situations where recruitment either appears independent of stock size (Myers, 2001), or there is insufficient contrast to estimate the relationship, a proxy for MSY must be used (Restrepo and Powers, 1999). For example, fishing mortality based reference points such as those associated with the maximum yield per recruit (F_{MAX}), or a 10% gradient in the yield per recruit curve($F_{0.1}$). Another useful proxy is given by $F_{x\%}$, which is the fishing mortality associated with a spawning potential ratio (SPR) of x percent. The SPR is defined as the productivity per recruit over the productivity in the absence of fishing. Thus it gives an indication of the proportional reduction in productivity of the stock as a consequence of fishing. An appropriate $F_{x\%}$ can be selected through simulation (Clark, 1991, Clark, 1993, Clark, 2002, Mace and Sissenwine, 1993, Mace, 1994).

Harvest control rules

Harvest control rules, broadly defined, specify the fishing mortality to which the exploited population should be subjected to meet management objectives. This fishing mortality can be controlled through either input (effort) versus output (catch) based management, with corresponding specification of a total allowable catch (TAC) or total allowable effort (TAE). The relationship between catch and fishing mortality is dependent on the resource biomass, whereas the relationship between effort and fishing mortality is dependent on the catchability. Broadly speaking, the appropriate management approach will depend on how well the biomass and catchability (the relationship between effort and fishing mortality) are defined, or specifically the uncertainty associated with estimates of each.

If stock biomass is highly uncertain relative to catchability, which is either well estimated or at least stable over time, then effort controls are usually more appropriate. The advantage being that under constant catchability and effort, catch will change with resource biomass. Thus the fleet will benefit from productive years whilst catch in unproductive years will be naturally curtailed. If the converse is true, so that catchability is poorly defined compared to resource biomass, effort controls are problematic and direct specification of the catch is more likely to lead to an appropriate level of fishing mortality.

Effort controls are therefore more appropriate for situations in which recruitment to the fishery is inherently unpredictable, usually due to strong environmental drivers. However, even in such situations, performance can be undermined by changing technical capacity, which increases the catchability (e.g. Vasconcellos, 2003, Ulrich et al., 2002, Kompas et al., 2004).The problem of a changing relationship between effort and fishing mortality has undermined the ubiquity of effort based management, and for this reason much of the literature on control rules has focused on setting TAC's. In most deepwater situations HCRs of this type are likely to form a central component of any mature management regime. But it should nevertheless be borne in mind that input based control may be necessary for situations with a highly uncertain stock status, and when spatio-temporal management is required.

Harvest control rules fall into two groups: empirical and model-based (Rademeyer et al., 2007). Empirical rules take direct data inputs, whilst model-based HCR's have an intermediary step that provides some estimated inputs, usually the biomass or fishing mortality, for the HCR.

Empirical HCRs will set the TAC for year *y* directly and usually take the form

$$TAC_y = f(TAC_{y-1}, \ldots, TAC_{y-p}, I_{y-1}, \ldots, I_{y-q})$$

where *I* is a population index(such as abundance or mean length), and *p* and *q* are integer values. For example a TAC may be set based on an average of previous years TACs, weighted by historic changes in CPUE (Apostolaki and Hillary, 2009b); or be a function of slope in the CPUE over previous years and the current TAC (Rademeyer et al., 2008b, Brandao and Butterworth, 2009). Importantly, such an HCR can only dictate changes in the TAC in response to relative changes in the population. Absolute TAC values are a product of historic precedent. Thus to determine whether management objectives for the fishery are reached requires it to be tested using a simulation model of the resource dynamics, and 'tuned' accordingly.

A simple example of a model based HCR would be to choose a TAC such that $F_y = F_{TARGET}$, where F_y is the fishing mortality in year y. F_{TARGET} can either be a constant value or a function of some reference points. Typically, F_{TARGET} is a stepwise function of spawning biomass, so that fishing mortality is reduced as the biomass declines below the target biomass reference point. Above the target reference point, and assuming F_{TARGET} is correctly specified, the harvest control rule will naturally yield catches consistent with management objectives. This type of 'threshold' control rule is popular within ICES, and has also been applied by the Pacific Fishery Management Council (PFMC) to the management of deepwater stocks on the continental slope of the United States West coast (PFMC, 2008).

Harvest control rules in practice

If the assessment itself needs to be tailored to the data available, then development of a harvest control rule is similarly dependent on a reliable representation of the resource. This representation is necessary for the implementation of model based HCRs, and although empirical HCRs do not need an assessment to be implemented, they usually require an assessment model for development and testing. In general therefore, harvest control rules are only implemented for those deepwater stocks that are relatively data-rich and for which reliable assessments exist. Harvest control rule for deepwater stocks are therefore rare, although examples do exist.

A notable set of model based harvest control rules exist for deepwater stocks of rockfish (*Sebastesaltus* and *Sebastes crameri*) and sablefish (*Anoplopoma fimbria*) caught on the continental slope of the United States West coast. These are managedby the Pacific Fishery Management Council

(PFMC) using a thresholdmanagement strategy which aims to manage the fish stock at MSY, with a target reference point of B^{MSY} and associated F^{MSY}(PFMC, 2008). Since F^{MSY} is not known (because density dependence in the recruitment relationship is unquantified)proxies of $F_{50\%}$ (rockfish) and $F_{45\%}$ (sablefish) are used, with a B^{MSY} proxy of 40% of the unfished biomass (0.40B). Below this target biomass fishing mortality is reduced linearly. Below a biomass of 0.25B, rebuilding plans are implemented.Importantly, knowledge of these stocks is sufficient for the harvest control rules tobe tested extensively within a simulation framework(Punt et al., 2008).

Well developed harvest control rule also exist for some of the toothfish fisheries of the Southern Oceans, within the remit of CCAMLR. The objectives of CCAMLR management are expressed as a three part rule based on a constant harvest rate γ and the pre-exploitation biomass B^0:

(i) choose γ_1 so that the probability of the spawning biomass dropping below 20% of B^0 over a 35-year harvesting period is less than 10%;

(ii) choose γ_2 so that the probability of the spawning biomass dropping below 50% of B^0 over a 35-year harvesting period is less than 50%; and

(iii) select the lower of γ_1 and γ_2 as the appropriate TAC.

In this case 50% B^0 and 20% B^0 constitute the target and limit reference points respectively. The annual TAC is usually set through a process of simulation, whereby the stock is projected forward under constant values of $\gamma_1$and γ_2, selected to ensure that the above criteria are met (e.g. Hillary et al., 2006b). The algorithm used to select γ through this process of simulation therefore constitutes the harvest control rule. Notably, it has been appliedeven in exploratory situations where knowledge of the stock is poor (Hillary, 2009), albeit in an illustrative context. A different harvest control rule, based on recent trends in the CPUE and mean length, is applied to the Prince Edward Islands, and has been evaluated by extensive simulation in light of its performance against the CCAMLR criteria (Brandao and Butterworth, 2009).

The work by Brandao and Butterworth (2009), provides a good example of the application of a simple indicator based harvest control rule to a deepwater fishery. However it required evaluation against a well developed assessment model capable of predicting absolute levels of biomass. Although the indicators themselves may be easy to derive, such a model is not available for many data poor stocks and thus it isimpossible to develop such a control rule for many deep water stocks.

The problem of MP evaluation for a data poor stock is not one that is easily resolved. Unless suitable meta-analytical approaches can be used to construct an appropriate operating model (for simulation testing of the control rule), a fully developed MP is beyond the reach of most deepsea management systems. Nevertheless, there is clearly scope for further work. Recently, progress has been made towards development of relative harvest control rules within the context of survey dependent assessments(Apostolaki and Hillary, 2009b). Such assessments (e.g. Beare et al., 2005, Bogaards et al., 2009, Porch et al., 2006, Trenkel, 2008) do not make use of catch information (either because it is absent or unreliable), and therefore can only provide relative indications of abundance. Nevertheless this may be sufficient information for an appropriately constructed harvest control rule. The development of such HCRs based on empirical data or limited estimation for input is likely to be fruitful for data poor deepsea situations, perhaps allowing integration of some of the simpler indicator based assessment methods into a more robustmanagement framework.

Synthesis and concluding remarks

Although this paper has focused on the assessment and management of deep water stocks, many of the problems and shortcomings reviewed are typical for data poor fisheries. What makes deep water fisheries particularly difficult to manage is that this data poor status is often associated with a high level of vulnerability to over-exploitation.

There is an obvious need to collect more data, but it is nevertheless important that appropriate assessment methodsbe developed and applied to remedy current shortcomings. These are likely to make extensive use of meta-analyses to approximate the life-history parameters of poorly described stocks and allow the application of more advanced assessment models. Theoretical and empirical life-history relationships are likely to prove an important complement to this approach. Meta-analysis could also be used to improve the inclusivity of the data, for example by applying posterior estimates of catchability for trawl surveys (Harley and Myers, 2001, Millar and Methot, 2002) to other data poor stocks.

Meta-analytical approaches applied within a Bayesian context can provide an appropriate framework for the inclusion of auxillary information and the representation of uncertainty in estimated stock status. It is important that prior information is carefully selected from stocks with a known similar biology or alternatively biased towards low levels of productivity, so that management is conservative.

Research should be directed towards development of appropriate harvest control rules given limitations in the data and the simplicity of assessment models that can be applied in the majority of data poor situations. Empirical harvest control rules can however themselves be simple, and there is not necessarily any advantage or need for added complexity. Such control rules may only require relative indications of changes in stock biomass (Apostolaki and Hillary, 2009a) and have been effectively applied to deep water stocks (Brandao and Butterworth, 2009, Rademeyer et al., 2008b). Although a thorough evaluation requires testing against a well developed assessment model, it may be that general features of these control rules can beextracted. This would require simulation testing against hypothetical stocks with a range of alternative life-history traits, depletion levels and observation uncertainty.

Deepwater fisheries assessment and management is therefore a fertile area for the development of techniques that will allow the sustainable exploitation of vulnerable, data poor stocks. However this requires that the rate of exploitation does not continue to exceed our understanding so that the eventual application of these techniques is ensured.

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