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Fisheries Assessment and Management: A Synthesis of Common Approaches with Special Reference to Deepwater and Data-Poor Stocks

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Deepwater fish populations are often characterized by their life-history as being highly susceptible to overexploitation. Moreover, dependent fisheries often develop rapidly, so overexploitation may occur before resource dynamics are quantified sufficiently to assess safe biological limits. It is therefore crucial to employ assessment methods that make the best use of limited data and management procedures that account for large uncertainties. This review provides a critical synthesis of assessment and management approaches for deepwater fisheries. 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 harvest control rules within a simulation framework. Harvest control rules themselves, however, need not be complicated, and simple empirical approaches can 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.

Keywords deepwater fisheries, stock assessment, management procedure

INTRODUCTION

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

Deepwater fish species are often characterized as having slow growth rates, extended longevity, late maturity, and low rates of natural mortality (Gordon, 2003). As a consequence, they are likely to be particularly vulnerable to overexploitation (Koslow et al., 2000; Roberts, 2002). However this is not always the case, and some deepwater 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

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roughy (*Hoplostethus atlanticus*), and roundnose grenadier (*Coryphaenoides rupestris*) are the most biologically vulnerable, while black scabbardfish (*Aphanopus carbo*) and ling (*Molva* spp.) are more likely to support sustainable fisheries, provided appropriate management measures are in place.

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 deepwater species is generally poor. Our understanding is hampered by 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 of the status of the resource often lags behind exploitation, leading to depletion before catch limits can be reliably estimated (Clark, 2001; Large et al., 2003).

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

MANAGEMENT AND ASSESSMENT

Management consists of three stages: (1) the definition of objectives for the fishery, usually in terms of the biological and/or socio-economic returns; (2) the development of policy mechanisms by which these objectives can be reached (e.g., input or output controls); and (3) 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, the method used for making management decisions (along with its data requirements) can also be specified (Butterworth and Punt, 1999; Smith et al., 1999). 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, some background is given 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, Article 7.1.1): "all those engaged in fisheries management should . . . adopt measures for the long-term conservation and sustainable use of fisheries resources"—with a similar prescription made regarding deepwater fisheries specifically (FAO, 2008, 2009). 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 United States 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, 1995, Article 7.5.3). 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, Article 7.5.2). Thus, uncertainty should be explicitly considered when making management decisions, an injunction particularly relevant to deepwater 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 (MSY; and associated F^{MSY} and B^{MSY}) has also been proposed as a universal objective for fisheries management (UN, 2002, Article 31 (a)), 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 be selected carefully 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 the 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). HCRs and how they are selected will be reviewed later. First, some of the methods commonly used in assessing the status of deepwater stocks, and which often provide a prerequisite for effective management, are detailed.

ASSESSMENT METHODS

The goal of stock assessment is to determine the biological status of the fish stock, namely the level of abundance and whether it is being overexploited, and likely effects of management measures, 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. In the most data-poor situations, an assessment may rely solely on commercial catch rates or survey abundance, or on simple indicators of stock size structure. More complicated modeling approaches involve fitting these and other data to dynamical models that capture the underlying temporal trends in the population, determine rates of exploitation, and forecast future stock status under different management scenarios. A range of alternative approaches (from simple to more complex) being used in deepwater fisheries are reviewed.

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 or comparison with general reference points 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 approach to fisheries management (FAO, 2003).

Indicators of Relative Abundance

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 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 modeled statistically (Maunder and Punt, 2004; Venables and Dichmont, 2004) to improve the interpretability of the index.

In the North Atlantic, data availability for deepwater stocks 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 assessment 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 more advanced assessment methods are not applicable (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 stabilize 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). In addition, 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) also 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.

Indicators Based on Catch Size Structure

Several intuitive indications of stock status can be derived from information on catch or population size structure. Mean age, length, or weight of the population will decline as a result of exploitation (assuming no strong recruitment fluctuations). 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. Froese (2004) proposed three simple, size-based indicators: (1) percentage of mature fish in catch, with 100% as target; (2) percent of specimens with optimum length in catch (i.e. the length that maximizes yield per recruit), with 100% as target; and (3) percentage of large or old highly fecund female "mega-spawners" in catch, with 0% as target and 30–40% as representative of reasonable stock structure if no upper size limit exists.

The length distribution can also be used to estimate total mortality, with the original relationship developed by Beverton and Holt (1957, 1956) and extended to account for a finite maximum length of capture (Ehrhardt and Ault, 1992) and non-equilibrium conditions (Gedamke and Hoenig, 2006).

Table 1 Leslie depletion model. Notational subscript refers to time t

Data	
C_t	Cumulative catch biomass
I_t	Abundance index
Parameters	
B_0	Initial biomass
q	Catchability
Equations	
$B_t = B_0 - C_{t-1}$	Exploitable biomass (T1.1)
$I_t = qB_t$	Predicted abundance index (T1.2)

Aggregated Biomass Models

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 for estimating unexploited stock size and current depletion levels, provided that exploitation has been sufficiently intense to cause a substantial reduction in abundance over the course of the monitoring period.

Given a closed population (no recruitment, immigration, or emigration), declines in the population biomass B are determined only by fishing pressure and natural mortality. The behavior of such a population can be described by the Leslie depletion model given in Equation T1.1 (Leslie and Davis, 1939) in Table 1, relating the current biomass to the initial biomass and cumulative catches. Combining this with an observation model (Equation T1.2), which relates some biomass index to the population biomass, yields: $I_t = qB_0 - qC_{t-1}$. This can be fitted using regression methods to observed catch data to estimate B_0 as the x-axis intercept (Hilborn and Walters, 1992).

Alternatively, declines in biomass can be represented in the DeLury depletion model given by Equation T2.1 in Table 2 (DeLury, 1947). Assuming the same observation model (Equation T2.2), and taking the natural logarithm, $\ln(C_t) = \ln(qB_t) - qE_t$ is obtained. This can be fitted to the within-season data from a particular population, giving $B_0 = e^c/m$, where c is the y-axis intercept and m the slope of the regression (Hilborn and Walters, 1992). This approach is easily extended to include estimates of natural mortality or recruitment (the *modified* DeLury model) (Seber, 1982).

Table 2 DeLury depletion model. Notational subscript refers to time t

Data	
E_t	Cumulative effort
I_t	Abundance index
Parameters	
B_0	Initial biomass
q	Catchability
Equations	
$B_t = B_0 e^{-qE_t}$	Exploitable biomass (T2.1)
$I_t = qB_t$	Predicted abundance index (T2.2)

Depletion methods have been used extensively in deepwater assessments due to the fact that many deepwater fisheries have been monitored for catches and CPUE since the beginning of exploitation and have undergone rapid depletions, hence providing highly informative data for this method (e.g. Perez et al., 2005; Agnew et al., 2009). The modified DeLury method has been widely implemented for ICES deepwater stocks (Large et al., 2003). However, the methods 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.

Depletion models provide information on stock abundance and, if data cover the period since beginning of the fishery, the level of depletion relative to unexploited abundance. However they do not directly provide information on sustainable levels of exploitation or long-term dynamics, because such questions require estimates of the population growth rate and the level of compensatory density dependence.

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. In contrast to depletion models, production models account for compensatory responses that occur in vital rates and, thus, biomass production when a stock is reduced in abundance below its carrying capacity. 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 3). The Schaefer model is equivalent

Table 3 Discrete Pella–Tomlinson biomass production model. Notational subscript refers to time t

Data	
C_t	Catch biomass
I_t	Abundance index
Parameters	
r	Per capita growth rate
B_0	Biomass at carrying capacity
p	Shape parameter
q	Catchability
Equations	
$B_{t+1} = B_t + \frac{r}{p} B_t \left(1 - \left(\frac{B_t}{B_0}\right)^p\right) - C_t$	Biomass (T3.1)
$I_t = qB_t$	Predicted abundance index (T3.2)

to the Pella–Tomlinson model with shape parameter $p = 1$ (Polacheck et al., 1993).

Biomass production models have found use in data limited assessments of deepwater stocks (e.g. Laptikhovsky and Brickle, 2005). Only total catches and an index of abundance (CPUE or tagging data) are required to parameterize 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. 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 (e.g. Gedamke et al., 2007). These and similar approaches (e.g. Myers et al., 1997) are not only beneficial for estimation of the parameters of a 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).

Structured Population Models

Catch Curve Analysis

If some catch-at-age data are available, they can be used to estimate total mortality using catch curve analysis (Ricker, 1975). The method assumes that the number of fish of age a in a particular cohort can be modeled using Equation T4.1 in Table 4. Given an observation model (Equation T4.2), 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 are 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 4 Catch curve model. Notational subscript refers to age a

Data	
C_a	Catch numbers
R	Recruitment
S_a	Selectivity
Parameters	
Z	Total mortality per year
Equations	
$N_a = Re^{-Za}$	Numbers (T4.1)
$C_a = N_a S_a$	Predicted catch numbers (T4.2)

Catch curves (also known as year class curves) cannot be used to decompose mortality into natural and fishing mortality ($Z = M + F$), which requires an age-structured production model (ASPM; 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 to the current level of fishing mortality (Large and Bergstad, 2003). If sufficient data exist from an exploratory survey of an unexploited stock, catch curve analysis can be used to estimate M directly (since $Z = M$).

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. Although depletion and biomass production models are particularly suited to situations in which aging is difficult (e.g. Carbonell and Azevedo, 2003), they have also been criticized 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 of available biomass directly comparable to that collected from surveys. They also 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 parameterization of depletion and 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 cohort-disaggregated modeling approaches are commonly taken that 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 models that can integrate over a wide variety of data sources in a statistically coherent manner. This statistical consistency sets them apart from VPA approaches.

Table 5 Virtual population analysis. Notational subscripts refer to age *a* and time *t*

Data	
C_{ta}	Catch numbers
E_t	Fishing effort
M	Natural mortality
I_t	Abundance index
Parameters	
N_{ta}	Numbers
F_{ta}	Fishing mortality
Z_{ta}	Total mortality ($M + F_{ta}$)
q_a	Catchability
Equations	
$N_{(t-1)(a-1)} = N_{ta}e^{M} + C_{(t-1)(a-1)}e^{M/2}$	Numbers (T5.1)
$F_{(t-1)(a-1)} = ln\left(\frac{N_{(t-1)(a-1)}}{N_{ta}}\right) - M$	Fishing mortality (T5.2)
$F_{ta} = q_a E_t$	Fishing mortality (T5.3)
$N_{ta} = \frac{C_{ta}}{1 - e^{-Z_{ta}}}\left(\frac{Z_{ta}}{F_{ta}}\right)$	Numbers (T5.4)
$I_t = \sum_a q_a N_{ta}$	Predicted abundance index (T5.5)

Virtual Population Analysis (VPA)

VPA models are age based and require appropriate data to be available for all the years covered by the assessment. Natural mortality is assumed to be known and is usually assumed to be constant over ages and years (although this is not necessary). The model reconstructs cohorts working backward in time, starting from the oldest age class of the cohort represented in the catch and sequentially adding catches and numbers lost to natural mortality. The exact VPA equation is a transcendental equation that needs to be solved iteratively, but in practice, this is often replaced by an approximation due to Pope (1972) (Equation T5.1 in Table 5). Fishing mortality at age is allowed to vary from year to year and is estimated directly from the reproduced dynamics of the "complete" cohorts that have reached the maximum age A (Equation T5.2).

The "terminal" numbers for complete cohorts N_{yA} (i.e., the starting point of cohort reconstruction) are either set to some pre-determined value or to the numbers associated with an assumed terminal fishing mortality. This however cannot be done for cohorts for which the maximum age $a < A$. For these "incomplete" cohorts, further assumptions are required to generate the terminal N_{ya} values. This is commonly achieved by making assumptions about the terminal fishing mortality in incomplete cohorts using the fishing mortality rates estimated for complete cohorts. For example, given known effort E_y, catchability can be estimated 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 (F_{ya}) 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).

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 auxiliary data, such as effort, CPUE, survey, or mark-recapture data, and an observation model (e.g. Equation T5.5).

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, and VPA algorithm – Equation T5.1). These estimates of terminal numbers are then combined (using inverse-variance weighting) across abundance indices to give a synthetic estimate of the terminal numbers and, subsequently, the estimates of numbers-at-age in the final years. Fishing mortality-at-age is estimated given the numbers-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 N_{ya} and F_{ya} are penalized to lie close to a recent back-average.

The integrated catch analysis (ICA) (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 it 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 regard (although not in a complex multivariate 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 rather than terminal numbers-at-age (although in conjunction with the catch numbers, the two are largely equivalent) and has an alternative routine for dealing with the plus group. ADAPT also has an in-built set of model decision tools and a bootstrapping procedure, similar to the one outlined later in this article. As with all VPA algorithms, some shrinkage is permitted and, again, the most recent estimates of fishing mortality 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).

VPAs have found favor within ICES where they are used in the assessment of European deepwater 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 utility as an assessment model is often compromised. VPA requires an unbroken time series of catch-at-age data, which 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 onward (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 have questionable applicability to long-lived species, which is a particular concern for many deepwater stocks.

Although VPA approaches have attracted a great deal of support within ICES, primarily due to the simplicity of the calculations involved, there are several problems associated with them. First, the classical VPA relies on the assumption that catch-at-age data are exact (i.e., with negligible error), though this assumption can be relaxed, for example in "separable" versions. Second, 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. Finally, a VPA does not include an internally estimated stock–recruitment relationship. This undermines the statistical consistency of the model, because covariation in model parameter estimates is not considered. All these criticisms are dealt with effectively by integrated assessment models.

Integrated Assessment Methods

Integrated assessment models are so called because they allow the contribution of multiple data sources (with the error inherent in each accounted for) towards the estimation of implicit model parameters. The population is projected forward from an initial estimated state, which thereby provides an indication of the status of the stock. Direct estimation of model parameters is important, since it allows insight into the associated levels of uncertainty. Furthermore, integrated assessments include the stock–recruitment relationship implicitly within the model, providing a statistically consistent framework for future 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 do not require unbroken time series of catch-at-age data, allowing longer time trends to be reconstructed, and thus providing more representative estimates of depletion (Butterworth and Rademeyer, 2008). These advantages mean that integrated assessment models are 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., 2006), 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). Population numbers are projected forward, with each cohort initiated by the assumed stock–recruitment relationship (Equation T6.1). This forward projection allows cohorts to be modeled in a consistent fashion, regardless of whether they have 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, SRA does not require catch-at-age data to reproduce cohort dynamics and, as such, has minimal data requirements.

Initial steps toward 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).

Table 6 Stock reduction analysis. Notational subscripts refer to age a and time t

Inputs	
$R(.)$	Recruitment function
h	Steepness
M	Natural mortality
S_a	Selectivity
C_t	Catch biomass
w_a	Weight
m_a	Maturity
I_t	Abundance index
Parameters	
B_0	Pristine B^{sp}
q	Catchability
Equations	
$N_{t0} = R\left(B_t^{sp}, h\right)$	Recruitment (T6.1)
$N_{t+1,a+1} = N_{ta}e^{-M}\left(1 - S_a H_t\right)$	Numbers (T6.2)
$H_t = C_t / B_t^{\exp}$	Harvest rate (T6.3)
$B_t^{sp} = \sum_a N_{ta} w_a m_a$	Spawning biomass (T6.4)
$B_t^{\exp} = \sum_a N_{ta} w_a S_a e^{-\frac{M}{2}}$	Exploitable biomass (T6.5)
$I_t = q B_t^{\exp}$	Predicted abundance index (T6.6)

They have also been applied historically to orange roughy in New Zealand waters (Clark, 1996). SRA is 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 predicting how the population may respond to exploitation.

Provided the data contain sufficient information, development of an integrated assessment model is not constrained by the type of data available. As data availability increases, particularly the availability of catch-at-size and growth information, it is possible to increase the parameterization to produce a more complicated integrated model. Such models are commonly age based and referred to as ASPMs or statistical catch-at-age (SCAA) models. A typical ASPM is outlined in Table 7 in which observed numbers at age (usually expressed as a proportion) and total catch biomass are compared to model predictions (Equations T7.5 and T7.6) during fitting, alongside a comparison of the observed and predicted abundance indices (Equation T7.7).

The flexibility to include different data types 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 is becoming increasingly well recognized for effective management (Lorenzen et al., 2010).

There has been an increasing trend toward integrated assessments that has tracked the computational resources available for model fitting. Integrated models can often be supported by external estimations of population parameters in relation to mortality, growth, or recruitment. Increasingly however, all the available data are being integrated into a single analytical framework, thus ensuring statistical consistency. A recent study involving several deepwater rockfish stocks shows that even natural mortality parameters, which are critical to assessments but notoriously difficult to estimate, may be estimated internally in integrated models (Lee et al., 2011). Likewise, in one assessment of New Zealand orange roughy, for example, the growth curve is now estimated internally (Smith et al., 2002). 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 minimization 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).

Table 7 Age-structured production model. Notational subscripts refer to age a and time t

Inputs	
$R(.)$	Recruitment function
C_{ta}	Catch numbers
C_t	Catch biomass
I_t	Abundance index
w_a	Weight
m_a	Maturity
Parameters	
B_0	Pristine B^{sp}
h	Steepness
M_a	Natural mortality
F_t	Fishing mortality
S_a	Selectivity
Z_{ta}	Total mortality ($M_a + S_a F_t$)
q	Catchability
Equations	
$N_{t0} = R\left(B_t^{sp}, h\right)$	Recruitment (T7.1)
$N_{t+1,a+1} = N_{ta} e^{-Z_{ta}}$	Numbers (T7.2)
$B_t^{sp} = \sum_a N_{ta} w_a m_a$	Spawning biomass (T7.3)
$B_t^{\exp} = \sum_a N_{ta} w_a S_a e^{-Z_{ta}/2}$	Exploitable biomass (T7.4)
$C_{ta} = N_{ta} S_a F_t \left(1 - e^{-Z_{ta}}\right)/Z_{ta}$	Predicted catch numbers (T7.5)
$C_t = \sum_a w_a C_{ta}$	Predicted catch biomass (T7.6)
$I_t = q B_t^{\exp}$	Predicted abundance index (T7.7)

LIFE-HISTORY CHARACTERISTICS AND THEIR ESTIMATION

Life-history parameters are 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 and Powers (2007) and Brooks et al. (2010) provide analytical derivations of data-poor reference points, based on life-history information. Such approaches can provide a useful starting point for management in the data-poor situations exemplified by deepwater fisheries.

Life-History Strategies

Winemiller and Rose (1992) developed an empirical typology of fish life-history strategies that provides a useful framework for gauging vulnerability to exploitation, as well as identifying aspects of population dynamics pertinent to fisheries assessment. The typology is based on an empirically derived, trilateral continuum with three endpoints: opportunistic, equilibrium, and periodic life-history strategies. Most deepwater fish stocks are likely to fall within either the equilibrium type (low fecundity, large egg size) or the periodic type (long-lived, high fecundity, high recruitment variation). Both types are characterized by high levels of compensatory reserve. Periodic types are subject to high environmentally driven variation in recruitment success, often with long periods of very low recruitment. Maintaining an appropriate age structure and spawning stock biomass is particularly important in periodic type populations (Winemiller, 2005; King and MacFarlane, 2003).

Natural Mortality

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). Unfortunately, natural mortality rates are difficult to estimate. Direct estimates of the natural mortality rate may be obtained from catch curve analysis of survey data from an unexploited stock (e.g., roundnose grenadier, *Coryphaenoides rupestris*) (ICES, 2009), from tagging data, or from a regression of total mortality estimates on fishing effort (Brodziak et al., 2011). In the absence of such data, mortality 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). While useful, they rely on the accuracy of these data and may lead to poor estimates of M when the ages on which they are based are not properly validated (Clarke, 2003). Estimating natural mortality directly within integrated assessment models is becoming the preferred option, where sufficiently informative data and suitable models are available (Lee et al., 2011; Brodziak et al., 2011). Where a wide range of fish sizes and ages are harvested, size/age dependence of natural mortality should be accounted for, as is becoming standard practice in many stock assessments (Brodziak et al., 2011; Lorenzen, 2000).

Stock–Recruitment Relationship

The stock–recruitment relationship is an important life-history characteristic because it provides information on the level of compensatory density dependence in the population and, thus, its resilience to exploitation (Rose et al., 2001). The level of compensatory reserve is usually referred to by a single parameter equal to the proportion of maximum recruitment that occurs when spawning biomass is 20% of pristine levels (the steepness h). The closer h is to one, the more resilient the population is to exploitation. Steepness can be estimated directly, where stock and recruitment data are available for different levels of spawning stock biomass, but this is rarely the case unless the stock has been exploited and monitored for a long period of time. 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.

Meta-Analytic Approaches

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; Peterson and Wroblewski, 1984). 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 prior 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., 2012), 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 precisely for the assumed similarities that exist between the assessed stock and those used to inform the assessment. The issue of representativeness is problematic for data-poor species, since the results of Bayesian assessments may be affected more by choice of the prior distributions than by the stock specific data, and are thus more readily biased. 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 weight to low productivity scenarios. In the absence of data suggesting otherwise, the posterior assessment results will therefore be based primarily on this assumption of lower productivity.

A complication for meta-analytic approaches is that life-history characteristics can 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 Northeast Atlantic (reviewed in Minto and Nolan, 2006). However, inconsistent sampling design and data quality may contribute to these apparent differences. For example, even though growth curves calculated for Patagonian toothfish show wide geographical variation, with fish off South America having higher L_∞ values and more rapid growth than those from the South of New Zealand (Horn, 2002), the reality of such differences is undermined by observations that different data from the same region can yield different results (Horn, 2002).

A further consideration for meta-analyses is that there may also be geographical variation in spawning behavior. 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), whereas in the Skagerrak, the same species appears to have a single well-defined spawning period (Bergstad and Gordon, 1994). In general, spawning behavior is very poorly understood for deepwater 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), whereas silver smelt (*Argentina silus*) appear to spawn throughout the year (Magnusson, 1988).

Mixed Fisheries

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 multi-species 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 Northeast 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).

ESTIMATING AND 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, 1996), 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 the particular assessment method often has an associated algorithm for deriving this uncertainty. The intention of the authors is not to propose an optimal method, but merely to review what methods are available and advise on their relative ease of use, applicability, and 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 I be an observed data value and $\hat{I}$ be the model-predicted value, with associated residual $\varepsilon = I - \hat{I}$. Resampling these residuals (e.g., using an appropriate stratified bootstrap or by simulating from an estimated distribution), "new" data can be generated by adding the resampled 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 resampled 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 Fisheries Library for R (FLR) assessment framework (Kell et al., 2007; Hillary, 2009a), 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. Approximate uncertainty in derived quantities (such as biomass) can be obtained via the analytic Delta method (Needle and Hillary, 2007), but a simpler approach is to use the maximum likelihood estimates and covariance matrix to generate multivariate normal samples of the parameters. Generating multivariate 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 it is also the most powerful. The Bayesian approach allows the probability distribution of the parameters (and derived quantities) to be defined 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, or the prior parameter distribution updated by the data and the likelihood (probability model):

$$p(\theta|D) \propto p(D|\theta)\, p(\theta)\,.$$

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 an inference about the parameters (and derived quantities) from this sample. Importantly, the Bayesian approach is specifically defined in terms of probabilities, allowing the use of decision analysis tools and risk to be spoken of 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., 2006).

MANAGEMENT

The Management Procedure (MP)

The means by which assessment results are translated into management action is infrequently specified within the management framework; instead relying on lengthy discussions within 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 (HCRs) 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: Brandão and Butterworth, 2009) or a derived estimate from the assessment (e.g. spawning stock biomass: Hillary et al., 2006). The HCR is agreed upon by all stakeholders at its inception, thus facilitating management action.

An explicit definition of an HCR, associated reference points, inputs, and the means by which these inputs are generated has two advantages. First, it provides the foundation 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 an HCR and its associated reference points, aiming to ensure that management is robust to limitations in the data, rather than being undermined by them. An 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, the 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 the mortality 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 $x\%$. 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

HCRs, 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 the 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. 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 is that under constant catchability and effort, catch will change with resource biomass. Thus the fleet will benefit from productive years, while catch in unproductive years will be naturally curtailed. If the converse is true, 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, the attainment of management objectives 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 prevented the uptake of effort-based management, and for this reason, much of the literature on control rules has focused on setting TACs. In most deepwater situations, HCRs of this type are likely to form a central component of any mature management regime. But, nevertheless, it should 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.

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

Considering output based management only, empirical HCRs will set the TAC for year y directly and usually take the form

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

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, 2009), or be a function of slope in the CPUE over previous years and the current TAC (Rademeyer et al., 2008b; Brandão 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 likely to be reached requires the HCR 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 HCR 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 U.S. west coast (PFMC, 2008).

HCRs in Practice

If the assessment itself needs to be tailored to the data available, then development of an HCR 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, HCRs are only implemented for those deepwater stocks that are relatively data rich and for which reliable assessments exist. HCRs for deepwater stocks are therefore rare, although examples do exist.

A notable set of model-based HCRs exist for deepwater stocks of rockfish (*Sebastes altus* and *Sebastes crameri*) and sablefish (*Anoplopoma fimbria*) caught on the continental slope of the U.S. west coast. These are managed by the PFMC using a threshold management strategy that 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. Below this target biomass, fishing mortality is reduced linearly. Below a biomass of 25% of the unfished biomass, rebuilding plans are implemented. Importantly, knowledge of these stocks is sufficient for the HCRs to be tested extensively within a simulation framework (Punt et al., 2008).

Well-developed HCRs 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: (1) choose γ_1 so that the probability of the spawning biomass dropping below 20% of B_0 over a future 35-year harvesting period is less than 10%, (2) choose γ_2 so that the probability of the spawning biomass dropping below 50% of B_0 over a future 35-year harvesting period is less than 50%, and (3) select the lower of γ_1 and γ_2 for 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 γ_1 and γ_2, selected to ensure that the above criteria are met (e.g. Hillary et al., 2006). The algorithm used to select γ through this process of simulation therefore constitutes the HCR. Notably, it has been applied even in exploratory situations where knowledge of the stock is poor (Hillary, 2009), albeit in an illustrative context. A different HCR, based on recent trends in the CPUE and mean length, is applied to the Prince Edward Islands, and it has been evaluated by extensive simulation in light of its performance against the CCAMLR criteria (Brandão and Butterworth, 2009).

The work by Brandão and Butterworth (2009), provides a good example of the application of a simple indicator-based HCR to a deepwater fishery. However, it required evaluation of the HCR 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 in these cases it is difficult to develop such a control rule.

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 deepwater management systems. Nevertheless, there is clearly scope for further work. Recently, progress has been made toward development of relative HCRs within the context of survey dependent assessments (Apostolaki and Hillary, 2009). 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 can therefore only provide relative indications of abundance. Nevertheless, this may be sufficient information for an appropriately constructed HCR. The development of such HCRs is likely to be fruitful for data-poor deepwater situations, perhaps allowing integration of some of the simpler indicator-based assessment methods into a more robust management framework. It is also possible that HCRs of a generic form may be developed for application to data-poor stocks. In such cases, a conservative guess at the HCR tuning parameters (based on experience from other stocks) may provide an immediate interim solution to the problem of management.

SYNTHESIS AND CONCLUDING REMARKS

The assessment and management of deepwater and other newly developing, data-poor fisheries is challenging for three reasons.

1. Many deepwater stocks are innately vulnerable to over-exploitation due to their life-history characteristics (high longevity, slow growth, highly variable recruitment)
2. Fisheries may develop rapidly once a stock has been discovered and fishing technology and markets developed, so that stocks may already be heavily exploited by the time a first assessment is completed.
3. Data availability is often poor, particularly but not exclusively during the early phases of development of the fishery.

It is crucial, therefore, to take account of these issues in the choice of assessment method and management framework (reference points and HCRs) and in the design of data collection programs (Large et al., in press).

Even under very data-poor situations, certain approaches, such as simple structural indicators of stock status or depletion models, can provide an indication of exploitation status. More sophisticated and informative approaches are also available, even though they may require great reliance on secondary data, such as those from meta-analyses. In such situations it may be best to use multiple approaches, with simpler methods used to cross-check basic results from more complex methods that rely on meta-analyses.

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 auxiliary information and the representation of uncertainty in estimated stock status. However it is important that prior information is carefully selected from stocks with a known similar biology or alternatively biased toward low levels of productivity so that management is conservative.

Research should be directed towards development of appropriate HCRs given limitations in the data and the simplicity of assessment models that can be applied in the majority of data-poor situations. Empirical HCRs can 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, 2009) and have been effectively applied to deepwater stocks (Brandão 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 be extracted. This would require simulation testing against hypothetical stocks with a range of alternative life-history traits, depletion levels, and observation uncertainty.

The assessment and management of data-poor and deepwater fisheries is therefore a fertile area for the development of techniques that will allow a more sustainable exploitation of vulnerable 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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