FAO REPORT

A Review of assessment methods and the development of management procedures for data-poor fisheries.

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ABSTRACT

There are as yet few quantitative measures in place to manage the majority of low-value fish stocks worldwide, mainly due to the lack of reliable data on which to base quantitative assessments. The FAO (2010) has highlighted the need for the development of scientific assessment methods and management procedures for an estimated 90% of the stocks exploited worldwide that are currently not assessed. Formal quantitative stock assessments are generally costly, because they are expertise hungry and demand large quantities of time and information. As such, they do not present a practical management solution for most data-poor stocks, particularly when these are also low value (as is generally the case). Due to the high costs of data collection, these methods and procedures need to be less data-demanding, easy to implement, give reliable estimates of stock status were possible (e.g. abundance relative to some biomass reference point such as B_{MSY}) and provide the quantitative information necessary for providing effective management solutions. This review summarises a suite of approaches when data are limited. These approaches include both simple assessment methods and empirical management procedures (or harvest control rules), grouped according to the data required.

The Report consists of three parts: Part 1 gives an overview of world practices in fisheries assessment and management, followed by Part 2 which reviews existing data-poor assessment methods and their application to provide management advice. The Report concludes with Part 3 which provides two examples of the evaluation of the performance of some simple management procedures when applied to two data-poor stocks.

Acknowledgements

Part 1 A review of world practices in fisheries assessment methods with some comments on their implementation for management

1.1 Current state of world fisheries: a need for improvement

The Mandate

In 1982, the United Nations adopted a "constitution for the oceans" to promote order, stability, predictability and security of the of the world's oceans. Called the United Nations Convention on the Law of the Sea (UNCLOS), it provides a legal framework to guide every aspect of the management of the oceans and the marine environment (Article 61, UN 1982). In particular, with regard to fisheries management, the Convention calls for the adoption of conservation measures to maintain harvested species at, or restore them to, levels that produce maximum sustainable yield (MSY). In 1995, the UN Fish Stocks Agreement (Article 6, UN 1995) and the FAO Code of Conduct for Responsible Fisheries (Article 7, FAO 1995) called for the adoption of a precautionary approach in fisheries management. In 2002, the World Summit on Sustainable Development (WSSD), held in Johannesburg South Africa, called for global marine stocks[1] to be maintained at, or rebuilt to, MSY levels "*with the aim of achieving these goals for depleted stocks on an urgent basis and where possible not later than 2015*" (UN 2002). Some 12 years later, as that recovery period draws to a close, these goals are yet to be achieved.

Overall view

According to the United Nations Food and Agriculture Organization (FAO 2010), just over 10% of the world's exploited fish stocks are assessed, albeit not always regularly. These account for about 80% of the total declared landings, with little or no information being available regarding the stock status for the remaining almost 90% of exploited fish resources worldwide. The state of exploitation of the world's fishery resources had remained relatively stable during the 1990's until about 2004, with 25% of the stocks monitored by FAO estimated to be not-fully exploited, while approximately half of stocks monitored are deemed fully exploited, producing close to their maximum sustainable biological yield, and the remaining 25% are estimated to be overexploited[2]. These estimates have

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[1] Throughout this document, "stock" refers to a management unit, rather than a biological entity: a fish stock encompasses all fish of a particular species in a defined area which are regulated by a specific management agency.

[2] The FAO (2011) currently uses three categories of stock status: not-fully exploited (biomass over 60 percent of pre-exploitation biomass), fully exploited (40-60 percent of pre-exploitation biomass) and overexploited (less than 40 percent of pre-exploitation biomass).

since then been updated to only about 15% of fish stocks considered not-fully exploited in 2009, with an increase in overexploited, depleted or recovering stocks to almost 30% of total stocks monitored (FAO 2012).

The economic perspective

The picture is less positive when seen from an economic perspective. According to a study conducted by the FAO and the World Bank (2009), the majority of the world's marine fish stocks are estimated to be economically overfished. This "Sunken Billions" study reports that marine capture fisheries are an underperforming global asset, with the difference between potential and actual net economic benefits estimated at approximately \$50 billion annually — equivalent to roughly half the global seafood trade. This huge economic loss can likely be recovered by reducing global fishing effort, which in turn would lead in time to an increase in productivity and profitability of the fisheries on the one hand, and to resource recovery to higher levels of sustainable biological and economic yields on the other (World Bank 2009).

The scientific perspective

A study conducted by Worm *et al.* (2009), which estimated current exploitation rates and stock status for 166 assessed fish stocks around the world, confirmed that overfishing remains a problem with 35% of the stocks in the study estimated to lie in the "overfished and subject to overfishing" quadrant of the phase diagram depicted in Figure 1[3]. Of the ten ecosystems studied, average exploitation rates had declined to levels corresponding to, or below, maximum sustainable yield (MSY[4]) in seven systems. To ensure adequate recovery of the 63% of these stocks estimated to be overfished, fishing mortality would need to be decreased somewhat more drastically in order to move stocks from the "stock rebuilding" quadrant, located at the bottom-left of the phase diagram, towards more productive biomass levels.

This study has recently been updated by Ricard *et al.* (2012). Of the 214 stocks in the RAM Legacy Stock Assessment Database[5] for which MSY related reference points could be evaluated, most were

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[3] A stock is considered overfished when the current biomass is estimated to be lower than that which allows maximum sustainable yield (MSY). Overfishing refers to an exploitation rate that would in the long-term deplete the stock below MSY level.
[4] Though it needs to be born in mind that estimates of stock status related to MSY are generally subject to great uncertainty as biological reference points such as B_{MSY} are difficult to estimate, even for data-rich stocks.
[5] The RAM Legacy Stock Assessment Database, inspired by Dr. Ransom A Myers' stock-recruitment database (Myers *et al* . 1995), is a collection in his memory of assessment results for commercially harvested marine species around the world.

found to be overfished: 58% of these assessed stocks were estimated to be below B_{MSY}, the level of biomass at which MSY can be achieved, and 30% subject to continued overfishing with fishing mortality rates exceeding F_{MSY}, the exploitation rate required to achieve MSY.

Of the 81 US stocks investigated by Ricard *et al.*, about half are estimated to be overfished with biomass below B_{MSY}. However, with the aim to rebuild these stocks to MSY level, fishing pressure has been reduced below F_{MSY} with only a third of overfished stocks falling into the upper left-hand "overfished and subject to overfishing" quadrant of Figure 1. A similar picture emerges for Canada, New Zealand and Australia: the majority of stocks assessed in 2012 study are in a fully exploited or rebuilding phase with fishing mortality rates below F_{MSY}. However, the situation is less optimistic for the 48 European stocks investigated in the study. The majority of stocks in this region have been, and are currently, biologically overfished with biomass estimated to be below B_{MSY} and fishing pressure above F_{MSY}.

These statistics correspond to those of the world's stocks with sufficient information on which to base a stock assessment (i.e. considered data-rich) – reliable estimates of stock status and fishing mortality rates for the remaining stocks could not obtained due to lack of data. But what about the majority of the world's fisheries that are not assessed due to lack of data and resources? A recent study by Costello *et al.* (2012) to determine the status of unassessed (data-poor) stocks found that 64% of these stocks were overfished with biomass estimated to be below B_{MSY}.

Given that the goals set out at WSSD (2002) have not been fully achieved in the time allocated, there is a need for better, more effective quantitative management for the majority of harvested fish resources that are currently assessed. Furthermore, there is also an even greater and pressing need for scientific management of the remaining exploited stocks not currently under formal assessment due to lack of adequate data.

The FAO principles and standards

The FAO Code of Conduct for Responsible Fisheries (1995) is a set of principles and standards to ensure the effective conservation, management and development of marine resources. It calls for the adoption of management measures focussed on long-term conservation and the sustainable utilisation of fish resources. These measures "*should be based on the best scientific evidence available and be designed to ensure the long-term sustainability of fishery resources at levels which promote the*

objective of their optimum utilization and maintain their availability for present and future generations".

The overriding objective of fisheries management indicated by these principles is long-term sustainable use. Short-term fishery management concerns are secondary and should not compromise the main objective. Long-term objectives need to be translated into a management plan, or framework, for implementation. Recommendations in the Code pertaining specifically to fisheries management (Article 7 of the FAO Code of Conduct) include *inter alia*:

1) The "*best scientific evidence available*" should be used to evaluate the current stock status as well as the predicted impacts of alternative management actions on the resource: the costs, benefits and effects of different management options need to be fully understood prior to implementation of a chosen management plan.
2) Economic overfishing should be avoided by limiting fishing capacity.
3) Risks and uncertainties associated with alternative management options need to be evaluated to promote informed decision making.
4) Cost-effectiveness and social impact should also be considered when evaluating alternative management measures.
5) On-going (long-term) collection of reliable catch and effort data is a necessary prerequisite for sound statistical analyses to inform decision makers.
6) A precautionary approach to the conservation, management and exploitation of marine stocks should be taken. In particular, the Code of Conduct states that the "*absence of adequate scientific information should not be used as a reason for postponing or failure to take conservation and management measures*".
7) Stock specific target and limit reference points should be determined, as well as actions to be taken if these are exceeded.
8) Once a fisheries management framework is in place, effective fisheries monitoring, control, surveillance and enforcement measures should be implemented to ensure compliance.
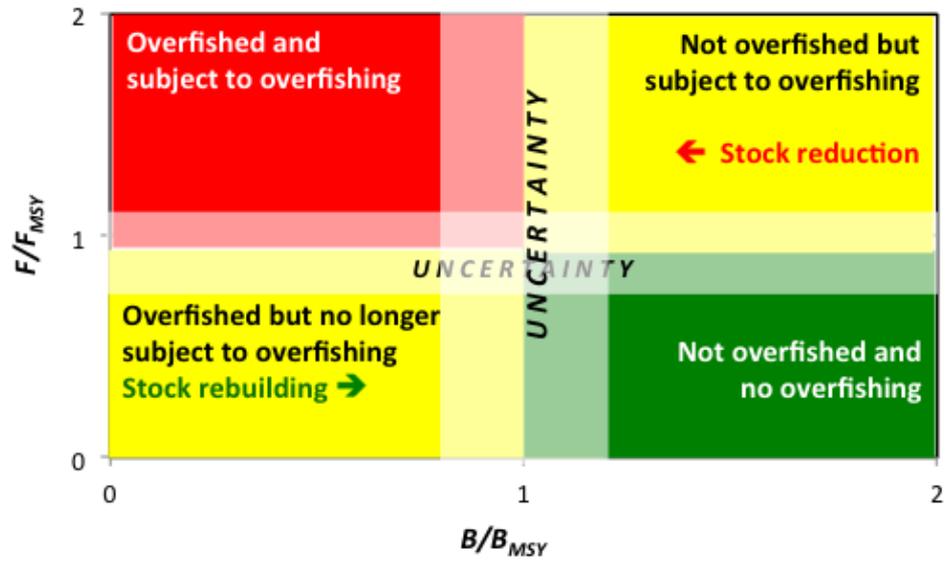
Figure 1: A phase diagram showing quadrants reflecting four possible states of a stock and associated fishing in terms of the biomass, B, and fishing mortality rate, F, compared to the levels at which maximum sustainable yield (MSY) is produced.

1.2 Quantitative fisheries assessment

The traditional and widely used approach for the provision of scientific advice for management (e.g. on catch limits) is stock assessment, where statistical and mathematical models which describe the underlying resource dynamics are fit to fisheries data to produce estimates of current stock abundance (or status, if expressed in terms of some reference level) and sustainable yield.

A variety of stock assessment methods have been developed over the years. Complex age and length based assessment models are typically applied to data-rich stocks (or stock complexes) with reliable age and/or length composition data obtained from commercial fisheries and research surveys which are usually conducted annually. In the absence of reliable age and length composition data, simpler age-aggregated models such as production models, fit to one or more indices of abundance, are typically used to estimate pertinent management quantities. When trend information is not available, simple catch-only methods are sometimes used when assessing data-poor stocks.

The International Council for the Exploration of the Sea (ICES) recently launched the Strategic Initiative on Stock Assessment Methods (SISAM) to identify the best methods on which to base management advice. This ICES initiative included the classification of stock assessment methods according to the amounts and/or types of data required. This classification is intended to guide fisheries scientists in selecting the most appropriate stock assessment methods given the data available for the stock under consideration. In terms of the SISAM (2012) classification scheme, assessment methods are divided into eight core groupings: catch only, time series, biomass dynamics models (production models), VPA based models, statistical catch-at-age models and integrated analysis models. A short discussion of the different models commonly used for fisheries assessment and management is given in Section 1.4.

The choice of assessment method depends largely on the data that are available for the fish stock under consideration. For those data-rich resources that constitute just over 10% of commercially harvested stocks globally, complex statistical models which rely on the availability of comprehensive data sets and high-level scientific expertise are typically preferred. The effort, expertise and time required for data-collection and analyses are substantial, and this level of stock assessment is therefore reserved for the most valuable fish stocks. Less valuable stocks (either in terms of revenue per ton or total tonnage) have less funding available for monitoring, data-collection and analyses. This in turn leads to high levels of uncertainty about resource status, and consequently to greater difficulty in developing appropriate management recommendations regarding sustainable catch levels.

Given fewer quantitative data, there is a need for statistical approaches that admit qualitative information. The Bayesian approach allows information from other species and stocks to be incorporated into the modelling exercise, thus supplementing quantitative data with qualitative information. Generic Bayesian models which incorporate results from meta-analyses have also become popular, particularly when dealing with high levels of uncertainty. Such models have the advantage drawing on the collective knowledge from similar species/ fisheries and offer a way to deal with data-poor stocks.

The following sections provide a brief description of the types of data that are typically required to assess the status of a stock (Section 1.3), followed by a summary of the different assessment methods according to the ICES categorisation (SISAM 2012) (Section 1.4).

1.3   Data

Fisheries management relies on quantitative stock assessments to obtain estimates of stock status and productivity, obtained by fitting a population model (simple or complex, age-aggregated or length- or age-structured) to fishery and research (mainly survey) data in order to estimate model parameters and other pertinent management quantities. The reliability, or otherwise, of these estimates depends on two equally important components: the model (does it describe the underlying population dynamics adequately?) and the data (do they provide sufficient information content and contrast to enable reliable estimation of model parameters?).

A cornerstone of successful modelling is reliable data (e.g. accurate records of past catches). However, for most fish stocks, and particularly for low-value resources, reliable data are in short supply. With the lack of knowledge and greater uncertainty associated with the majority of exploited marine stocks, sustainable resource management becomes even more challenging.

Fisheries scientists typically encounter four main sources of uncertainty. The first is model structure uncertainty due to the lack of knowledge regarding the underlying fish stock and the model that would best describe its population dynamics. A further source of uncertainty is observation error arising from errors in sampling and monitoring of the resource, as well as in data capture (see also below). Process error arises from natural fluctuations about the model relationships related to population dynamics and recruitment. Finally, for those fish resources where harvest control rules are already in place, another important source of uncertainty is implementation error which reflects a lack of compliance with catch/effort limits as can arise due to inadequate enforcement, political interference, market influences and so forth (Hilborn 1996, Butterworth and Punt 1999, Punt and Donovan 2007).

This list of sources of uncertainty omits other key uncertainties regarding the economics of the fishery: harvesting costs, market share and saturation, export costs, taxes, levies, fluctuating exchange rates, etc. – information which is desirable in order to manage a fishery in an economically optimal manner.

As observed by Musick and Bonfil (2005), the data drive the analysis. Applying a complex state-of-the-art model to noisy and/or biased data is more likely to lead to unreliable management advice than applying a very simple model to good quality data (Geromont and Butterworth 2014a). Few reliable data are often far more informative than considerable but noisy data, regardless of the complexity of the model that is applied. Hilborn and Walters (1992) emphasise the need for better quality data, rather than more data or greater precision; they highlight two main concerns that govern the quality of data.

   a) Observation error: random errors and biases in sampling and subsequent data analyses (arising, for example, from systematic errors in ageing) are very important issues in stock assessment and management. Allowance is typically made for random observation error by means of bootstrapping the data, or Monte-Carlo techniques. Sensitivity analysis can incorporate the effects of bias in the data.

   b) Information content: pertinent parameters can be estimated only from information that is embedded in the historical data – if that information is minimal, the parameter estimates will be meaningless.

1.3.1   Catch, effort and abundance data

Total annual catches[6] are particularly important fishery data and are used by nearly all the methods described in the next section. These data are typically collected through logbook records (location, gear and catch), observers (present on commercial fishing vessels) and dockside monitoring (commercial landings data).

Indices of abundance of the stock are one of the primary indicators for the status of a fishery. Abundance indices can be derived from either the commercial catch rate data (CPUE) or from scientific surveys. Index data obtained from fishery independent scientific surveys are often preferred as they provide a relative index of abundance which is hopefully unbiased by design, but typically have high variance. In contrast, the large amount of data available render CPUE indices of low

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[6] Throughout this review, the total catch is assumed to be equivalent to the total removals (landings plus discards), unless otherwise stated.

variance, but GLM standardisation techniques may not be able to remove all sources of bias arising from changes in fishing patterns over time. Methods relying on at least one reliable index of abundance include biomass dynamics models as well as the simple empirical catch control rules used when following an MP approach.

1.3.2 Size/length composition data

Catch composition data provide information regarding stock composition: the relative abundance of different age classes or cohorts within a stock. Ageing is conducted to obtain an age-length key (ALK) which provides estimates of the proportion of each age group in each length class each year. These data are incorporated into age/length based models to provide estimates of fishing mortality rates, selectivity, stock-recruitment relationship parameters etc. Methods that incorporate age and/or length composition data include Virtual Population Analysis (VPA), statistical catch-at-age (SCAA) models, and Integrated Analysis (IA).

1.3.3 Biological data

Biological data such as size/age at maturity, fecundity, growth, spawning and feeding information are collected during fishery independent surveys or other sampling programs related to the fishing operations. The biological characteristics of a stock may change over time due to environmental factors so that continuing sampling programs are required. Reliable biological data are important for age- and length-based models.

1.3.4 Other data

Economic and social data are required if an integrated approach to management is followed where biological, economic and social objectives are incorporated in that approach. These data are typically not included into stock assessment models, but rather introduced at the resource management stage, for example within an integrated Management Strategy Evaluation (MSE) or when a Management Procedure (MP) approach is adopted.

1.4 Methods and models

The choice of "best" population model with which to assess a stock depends not only on the scientific expertise at hand, but more importantly on the type and information content of the data that are available. The Strategic Initiative on Stock Assessment Methods (SISAM 2012) was recently launched to aid scientists in selecting the most appropriate model given the data available. To compare the efficacy of the different methods and draw quantitative conclusions, alternative assessment methods were chosen from the main model categories listed in the sections below, and applied to simulated data generated for a number of key stocks. The simulation-based evaluation of model performance showed that the most appropriate model category depends on the type of data available, and the most appropriate model configuration within a model category depends on the information content of the data. Some initial conclusions drawn from the SISAM workshop, summarised by Deroba *et al.* (2014), are as follows.

a) Different models are consistent with regard to biomass trends, rather than scale of absolute estimates.

b) Similar model types behave similarly: the choice of model type had the biggest effect on consistency across models.

c) Biomass estimates in the most recent years of time-series were least robust to the application of different models.

d) Model uncertainty has important implications when choosing between a "best fit" or ensemble approach.

e) Simulation testing (both self-testing and cross-testing of models[7]) is useful.

A non-comprehensive list of popular stock assessment methods follows below, classified according to data availability, and generally in terms of the broad categories suggested by SISAM (2012).

1.4.1 Catch only methods

Catch only methods rely on the key simplifying assumption that trends in stock abundance can be tracked by trends in total annual catches: catches will at first increase as the fishery develops and later decrease once the stock abundance becomes reduced by exploitation. Generally, no allowance is made for changes in catch arising independent of stock size trends, such as changes in targeting, gear, market influences and fishing regulations.

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[7] A self-test is when the data for the simulation test are generated from the same model used for the assessment. In a cross-test these two models differ.

Examples include studies by Froese and Kesner-Reyes (2002), Worm *et al.* (2006), Pauly (2007) and Zeller *et al.* (2008), who used their various approaches to assess an extensive number of stocks based on their catch histories alone. However, these particular studies were later argued by Branch *et al*. (2011) and Daan *et al.* (2011) to be technically and/or conceptually flawed, resulting in overly-pessimistic estimates of stock status.

Wetzel and Punt (2011) demonstrated that the success of the catch-only method simulation tested in their study relies on good prior (qualitative) knowledge of current depletion – a major drawback for data-poor stocks as such information is unlikely to be available. A simulation study conducted by Carruthers *et al*. (2012) to evaluate and compare the reliability of a selection of catch-only methods showed that additional quantitative or qualitative information is required to obtain reliable estimates of stock status: methods based on catch series data resulted in the misclassification of stocks about two-thirds of the time. In the absence of additional fishery data, catch-only methods are prone to giving overly-pessimistic estimates of stock status.

Data requirements: A time-series of total removals (landings and discards) over an extended period that encompasses the development of the fishery (typically more than 10 years), and possibly some qualitative information (reflected by prior distributions) for current depletion and some biological parameters (e.g. the natural mortality rate).

Example of models:

- Depletion Corrected Average Catch (DCAC): A method developed by MacCall (2009) for estimating sustainable yields for data-poor fisheries. Based on the assumption that the historic mean catch over some time period is sustainable if abundance remained unchanged, the model adjusts this average upwards or downwards with an increase or decrease in abundance index (see Section 2.3.5). In addition to an historical catch series, qualitative information is required for pertinent biological parameters such as natural mortality rate. This method provides an estimate of potential yield which is likely to be sustainable and less than MSY for data-poor fisheries. The method is applicable to long-lived species with low natural mortality rates (less than about $0.2yr^{-1}$). The software is available from the NOAA Fisheries Toolbox [nft.nefsc.noaa.gov/DCAC.html].

- Depletion-Based Stock Reduction Analysis (DB-SRA): Developed by Dick and MacCall 2011, this method is a combination of the DCAC and stock reduction methods, and uses each year's catch in a delay-difference production model (see Section 2.4.5). Production is assumed to be lagged by the age to maturity. Input data include a time series of annual catches, as well as knowledge of life-history parameters such as the natural mortality rate, M and age-at-maturity.

- Catch-MSY: This method was developed by Martell and Froese (2013) to obtain MSY estimates (and distributions) using a Schaefer production model (see Section 2.4.2), but here in the absence of an index of abundance. Input data comprise total annual catches (discards included) and the specification of prior distributions for the pre-exploitation biomass, K, and the intrinsic growth rate, r, in addition to knowledge regarding a plausible range for current depletion.

Advantages: These models are typically used for data-poor stocks when other assessment methods fail due to lack of data.

Disadvantages: Catch-only methods rely on key simplifying assumptions that are often difficult to meet. Furthermore, they rely on the incorporation of qualitative information, the reliability of which can be questionable. When very few quantitative data are incorporated into the computations, the qualitative information becomes the driving force in the estimation of model parameters (e.g. the priors in a Bayesian analysis may hardly be informed by other data) which renders parameter estimates and the subsequent management quantities derived of little value.

1.4.2 Time-series

Time-series methods do not model population dynamics explicitly, but rather depend on trends in the catch and or abundance time-series directly. Given adequate information content in a time series, and assuming that time-series data forthcoming in the future will be generated by the same mechanisms as the historic data, these simple methods can be used to track trends in population biomass. However they do not provide estimates of stock abundance in absolute terms.

The simple algorithms underlying these methods are sometimes applied within a formal Management Procedure (MP) approach (Section 3.1), following rigorous simulation trials to show adequate robustness to uncertainty across a suite of (usually age-structured) population models that describe plausible states of nature. For example, simple algorithms based on trends or thresholds in abundance indices have been used in harvest control rules (HCRs) for the management of high-value data-rich stocks in South Africa (Geromont *et al.* 1999, De Oliveira 2003, De Oliveira and Butterworth 2004, Rademeyer 2012) and Namibia (Butterworth and Geromont 2001). In Australia, empirical HCRs for the multi-species Eastern Tuna and Billfish fishery (ETBF) have been developed to set the annual TAEs (Campbell *et al*. 2007). Empirical HCRs that use trend in CPUE data to scale annual TACs for data-poor stocks in the multi-species Southern and Eastern scalefish and shark fishery (SESSF) are

described in Wayte (2009). Empirical HCRs based on the CPUE time series have been adopted to manage the rock lobster fisheries in New Zealand (Starr *et al.* 1997). ICES has recently developed an index-based HCR for category 3 (data-limited) stocks (ICES 2013a)

Data requirements: A time series of total annual catches, at least one relative index of abundance (CPUE and/or survey) and/or mean length/mass of catch.

Examples of models:

- An Index Method (AIM): Developed by Rago, this models the relationship between catch and an abundance time series in order to estimate the catchability coefficient, *q*. It uses a linear model of population growth to measure stock response to different levels of fishing mortality. Given an estimate of the catchability coefficient associated with a relative index of abundance, this method can be used to predict the level of relative fishing mortality at which the population is likely to be stable (Honey *et al.* 2010). The software is available from the NOAA Fisheries Toolbox [nft.nefsc.noaa.gov/AIM.html]

Index-based MPs:

- Threshold-type MPs adjust the TAC up or down in re-specified steps depending on whether threshold values for certain data are crossed. The idea is that unless there is a strong quantitative signal in the data, the TAC is better left where it is so as to avoid the possibility of tracking noise rather than signal in a data-poor situation. When an index of abundance is not available, for example in data-limited applications, simple algorithms based on the mean length of fish caught can be taken to be an indirect index of abundance as illustrated by Geromont and Butterworth (2014a).

- Slope-type MPs utilise the trend in a limited subset of data (typically the most recent four or five years of, say, survey biomass estimates) for input. The annual TAC is simply moved up or down from where it was the previous year, depending on whether the estimated trend is positive or negative (Butterworth and Geromont 2001).

- Target-type MPs move the resource abundance towards a pre-specified target level for some direct or indirect abundance index (survey, CPUE or mean length of catch). The future TAC is adjusted up or down each year depending on whether the average of the most recent surveys is above or below the target survey level (Tier 4 rules in Wayte 2009, Geromont and Butterworth 2014b).

Advantages: These empirical algorithms are simple to apply and easy for all stakeholders in the fishery to understand. Increases/decreases in TAC/TAE follow trends (possibly in relation to thresholds) in an intuitive manner. These simple techniques require few data and offer efficient management tools. Within a formal MP framework, management advice typically includes clear risk-yield trade-offs associated with alternative management actions.

Disadvantages: The key assumption that underpins these methods is that the CPUE or surveys provide a reliable (unbiased) index of abundance. Uninformative data (too much noise in the abundance index), or systematic bias in the data (for example an undetected increase in catchability), render these methods unreliable. Estimates of stock status are not provided by these methods.

1.4.3   Biomass dynamics models

The simplest stock assessment models commonly used, these describe the dynamics of the stock in terms of biomass rather than numbers at age. They are also called surplus production models. The production function can take many forms e.g. Schaefer, Fox and Pella-Tomlinson, although the Schaefer model is the best known (Schaefer 1954, Fox 1970, Pella and Tomlinson 1969, Schnute 1985). Unlike the age-structured models described below, these approaches model the net effects of recruitment, growth and mortality based on information on biomass and catch trends (Hilborn and Walters 1992). As such the data requirements for these models include a time-series of total catches, and one or more time series of relative abundance data (such as CPUE or survey index of relative abundance).

Although simple and relying on few data, Ludwig and Walters (1985) showed that the biomass dynamic models tested generally gave as good, or better, estimates of management parameters than more complex models. They concluded that simple biomass dynamic models should be used in stock assessments based on catch and effort data even when more realistic and structurally correct models are available, and that the choice depends on the contrast in the data rather than on which model structure is more realistic.

Biomass dynamics models have been widely used as the primary basis for management advice for several marine stocks, for example tuna stocks in the Atlantic under ICCAT management.

Data requirements: Historical total catches and a relative index of abundance (CPUE or survey)

Examples of models:

- A Surplus-Production model Incorporating Covariates (ASPIC): The ASPIC framework provides a flexible format for a non-equilibrium biomass production model (Prager 1992, 1994). It fits several forms of surplus-production model (Schaefer, Fox and Pella-Tomlinson) to catch and abundance index data. Estimates of precision are obtained using bootstrapping. The software is available from the NOAA Fisheries Toolbox [nft.nefsc.noaa.gox/ASPIC.html]

- Bayesian Surplus Production (BSP) model: This fits a Schaefer or Fletcher/Schaefer model to CPUE data using the Sampling/Importance Resampling (SIR) algorithm. Bayesian prior distributions can be defined for estimable parameters. Input data are total annual catches and one or more index of abundance, with associated CVs if available (McAllister and Babcock 2006).

Advantages: The simplicity of these models, combined with the modest data requirements, offer a cost-efficient fisheries management option suitable for longer lived species. These models are easy to understand and code, with a limited number of estimable parameters. Standard output includes management quantities such as current biomass (and stock status) as well as typical management reference point estimates.

Disadvantages: These models do not include age-structure and ignore processes such as recruitment, natural mortality and individual growth. This lack of biological reality excludes quantitative and qualitative biological (age/length) data that might be available for the species. The success, or otherwise, of these methods depend on the quality of the data and the information content (Hilborn and Walters 1992): without adequate contrast in the time-series, the estimators cannot distinguish between different possible states of nature. Long time-series, with observations above and below B_{MSY} and periods over which the index of abundance increases, are required (SISAM 2012).

1.4.4 Delay-difference models

These partially age-structured models lie somewhere between the simple age-aggregated biomass dynamics models discussed in the section above and the fully age- length-disaggregated models that follow. The dynamics of the population are represented in terms of equations involving different components of the population. Biological information of the species is incorporated into a simplified model by making some key assumptions about survival, growth and recruitment. Two life stages are typically assumed: one for the pre-recruitment fish and one for the exploitable portion of the stocks. While these models provide a more biologically realistic representation of the dynamics of the fish

stock than the surplus production models described above, they typically still rely on a limited data set only (total catches and, for example, an index of abundance consisting of a recruitment index and a recruited (adult) index).

A delay-difference model has been applied to commercial catch and effort data for tiger prawns in the Australian Northern Prawn Fishery to take account of the weekly timescale of the population dynamics (Dichmont *et al.* 2003). Other applications include a lagged recruitment, survival and growth (LRSG) model used for small coastal sharks on the east coast of the United States (Cortés 2002), and a two-stage biomass dynamic model (CBBM) to assess anchovy in the Bay of Biscay (Ibaibarriaga *et al.* 2008 and 2011).

Delay-difference models are dependent on key simplifying assumptions, and Hilborn and Walters (1992) advise caution when attempting to derive estimates for population parameters from simple time series data. Punt and Hilborn (1996) show that simpler biomass dynamic models perform better that delay-difference models and recommend that age-structured dynamic models be used if a higher level of complexity is sought. Indeed, these models are seldom used at present as recent advances in computing power have allowed for more sophisticated and flexible age-structured models to be implemented efficiently.

Data requirements: A time series of total annual catches and an index of abundance, in addition to quantitative information (perhaps in the form of a prior distributions) for current depletion and biological data on growth (von Bertalanffy parameter estimates) and natural mortality.

Examples of models:
- The Deriso Delay-Difference Model: The population dynamics are described by an age-structured model with knife edge recruitment (Deriso 1980). A stock-recruitment function is incorporated in a simple difference equation to provide a framework to use catch and effort data in conjunction with information on growth, survival and recruitment.
- Lagged recruitment, survival and growth (LRSG): A simple approximation of the Deriso model with biomass in each year given by the sum of the surviving biomass and recruitment less the catch of the previous year (Hilborn and Mangel 1997).
- The Collie-Sissenwine Analysis (CSA): A two-stage stock assessment model to estimate abundance, fishing mortality and recruitment from total annual catches and survey data with associated CVs (Collie and Sissenwine 1983). The two stages are comprised of "recruits" and "post-recruits", with both groups assumed to be available to the fishery. Model parameters are

estimated by maximum likelihood. The software is available from the NOAA toolbox [nft.nefsc.noaa.gov/CSA.html]

Advantages: These models are biologically more realistic than biomass dynamic models and simpler to implement than a fully age-structured approach with fewer parameters to estimate. Their main advantage lies in their ability to incorporate important population dynamics processes in a simple equation while allowing for time-lags due to growth and recruitment. Relatively few data are required.

Disadvantages: The same disadvantages as for biomass dynamics models apply: good quality and contrast in data are essential for successful model parameter estimation. Another disadvantage of these models is the assumption of a time-invariant catchability parameter, *q*: when fishing patterns change, so will selectivity at age, invalidating this assumption. Fully age-structured models are needed to deal with this.

1.4.5   Age-structured production models

Age-structured production models (ASPMs) present a more advanced, biologically realistic, form of the production models described earlier by taking explicit account of biological processes such as recruitment and growth, while avoiding the full complexity of the age-structured models described later. In contrast to the age-aggregated surplus production models, these models are fully age-structured and incorporate a stock-recruitment relationship to predict the number of recruits each year. However catch-at-age data are not essential for parameter estimation purposes (usually only the pre-exploitation biomass, *K*, and the steepness of the stock-recruitment function, *h*, are estimated). In the absence of age composition data, the natural mortality rate and fishing selectivity vector are input (being assumed to be known without error). Various forms of the stock-recruitment relationship can be used, with the Beverton-Holt form generally preferred. The approach can accommodate several fishing fleets. These models can easily be extended to incorporate catch-at-age information, in this manner evolving into the more complex statistical catch-at-age type models. This extension allows for process error to be incorporated by allowing for annual fluctuations about the deterministic stock-recruitment relationship.

De Bruyn *et al*. (2012) compared the performance of an age-structured production model with a non-equilibrium production model applied to albacore tuna in the South Atlantic. They concluded that the benefit of incorporating additional age-structure into the stock assessment was relatively small, and recommended that the simpler surplus production model be used for management advice purposes

instead. However, for data-rich stocks with good quality age composition data, the more complex form of the ASPM is generally preferred.

Data requirements: Total historical catches and at least one index of abundance with an associated fishing selectivity-at-age vector (usually in the form of a logistic ogive), as well as some biological information (values for natural mortality, growth and fecundity-at-age).

Examples of models:

- Age-structured production model (ASPM): Many *ad hoc* versions of ASPM have been coded. Restrepo and Legault (1998) implemented an age-structured production model with stochasticity in recruitment to assess western Atlantic bluefin tuna.

- Stochastic stock reduction analysis (SRA): A stochastic age structured production model with a Beverton-Holt function that simulates changes in biomass over time by subtracting mortality and adding recruits (Walters *et al.* 2006).

Advantages: These models are able to represent the underlying population age-structure while relying on few age-aggregated data, in addition to some biological information on growth and natural mortality. The biomass estimates are "real", so that independent estimates of biomass in absolute terms (e.g. from acoustic or egg-production surveys) can be used in the model fitting or to provide a reality check. Costly catch-at-age data are not required which makes these models a cost-effective assessment option. Model complexity can be added to the basic ASPM as age-disaggregated data become available. Multi-fleets applications are possible. A Bayesian approach can readily be incorporated by defining prior distributions for key model parameters to allow for model uncertainty.

Disadvantages: Care must be taken that the model does not become over-parameterised. In the absence age-composition data, information on key parameters, such as selectivity-at-age, need to be input as there is hardly any information content from which to estimate them, or to update their prior distributions.

1.4.6 Virtual population Analysis

Virtual population analysis (VPA), developed by Gulland in 1965, is widely used as a basis for fisheries management advice for data-rich stocks. The VPA approach entails reconstructing the

population numbers and fishing mortality matrices for each year and age of the assessment period from a full (comprehensive) set of catch-at-age data and the natural mortality rate. Also termed cohort analysis, it makes use of a recursive algorithm that reconstructs each cohort backwards in time from the current year back to the year of recruitment. Population numbers for the most recent years are not well determined due to truncated cohorts, which can result in highly uncertain estimates of current biomass. To estimate the sizes of the cohorts that currently survive in the fishery, simplifying assumptions about terminal fishing mortality must be made. This approach relies on a few key simplifying assumptions: a) no fish survive past a certain age (though more complex formulations can incorporate a plus-group, b) exact knowledge of the natural mortality rate and catches-at-age, and c) no immigration or emigration (Hilborn and Walters 1992). Various estimation methods, sometimes called "tuning", are used to deal with truncated, or incomplete, cohorts in the terminal years.

This assessment approach relies on annual ageing of catch data. VPA methods are not suitable for fisheries with noisy age composition data, and cannot be applied if there are gaps in the ageing time series. Because it is very data demanding and costly, with annual ageing of large catch samples a requirement, VPA has generally been reserved for high value data-rich resources.

VPA methods have been used extensively as the basis for scientific management advice for many data-rich fish stocks globally, in particular by Argentina, Europe and Canada (Ricard *et al.* 2012), as well as by international fisheries agencies such as ICES and ICCAT.

Examples of models:

- ADAPT VPA: Also known as tuned VPA (Gavaris 1988), the catch-at-age data are supplemented by one or more indices of abundance, called tuning indices, to facilitate the estimation of the sizes of the most recent truncated cohorts. Model parameters are estimated by minimising the sum-of-squares over the number of indices of abundance. The two area VPA software package (VPA-2BOX) is based on VPA ADAPT, and has the added capability of analysing two different stocks simultaneously. This software is available from the NOAA Fisheries Toolbox [nft.nefsc.noaa.gov/VPA2BOX.html].

- Extended Survivors Analysis (XSA): Widely used to asses ICES stocks, XSA (Shepherd 1999) differs from VPA ADAPT which uses formal minimisation of the objective function to estimate population numbers. Instead, population numbers-at-age are derived by applying an *ad hoc* algorithm iteratively until convergence is achieved. The tuning is based on age-disaggregated abundance indices.

Data requirements: Catch-at-age data by number for the entire assessment period, along with population and catch weights-at-age and one or possibly more indices of abundance.

Advantages: Assumptions regarding the stock-recruitment relationship are avoided. Given reliable high quality catch-at-age data, good estimates of recruitment can be obtained directly from the data for subsequent use for projections and management advice.

Disadvantages: A complete set of catch-at-age data is required for VPA analyses: annual ageing of large samples of fish from the catch is costly and labour intensive. Catch-at-age data are assumed to be known without error, which is often not realistic: such observation error (in particular systematic biases in ageing), if substantial, can lead to dubious estimates of population numbers. There is seldom sufficient information content in the data for the natural mortality rate to be estimated; it therefore has to be fixed on input which may lead to the systematic under- or over-estimation of cohort sizes. This problem is exacerbated when fishing mortality is relatively low and the total mortality is dominated by the component due to natural mortality.

1.4.7   Statistical catch-at-age methods

Statistical catch-at-age analysis (SCAA), a more complex stochastic form of the traditional ASPM discussed earlier, incorporates age-disaggregated data from the commercial fleets and surveys (if available) into the analysis. SCAA provides an elegant statistical framework to incorporate variability in the data and various population processes (Fournier and Archibald 1982, Deriso *et al*. 1985): observation error in catch-at-age data and relative indices of abundance, and process error (variability in recruitment and mortality).

Compared to VPA which is summarised above, SCAA methods are more flexible and do not require a complete set of age data; they are able to accommodate gaps in the data. These methods provide a statistical framework to estimate population numbers-at-age given incomplete cohort data, and may allow for the estimation of natural mortality rate if there is sufficient contrast in the data. Generally, SCAA methods are considered a subset of integrated analyses; however they are typically simpler to apply than the more complex Integrated Analysis (IA) models described in the next section.

The simplest SCAA methods assume time-invariant fishing selectivity-at-age. For situations where there are indications of change in selectivity, data are typically grouped into blocks corresponding to periods of different selectivity, which increases the number of parameters and usually introduces *ad hoc* restrictions on the extent to which their values may change between blocks. The main problem

with these flexible, highly parameterised statistical models is the danger of over-parameterisation/over-fitting: given the limitations of the input data, there is frequently not enough information content to support the estimation of an extensive range of free parameters. Statistical time-series analysis presents a solution to dealing with parameters that change over time by modelling such changes as random effects, thereby reducing the number of estimable parameters, with the added benefit of providing objective estimates of the variance of the extent of the changes.

Statistical catch-at-age models are commonly used to assess data-rich stocks on the west coast of North America, Australia, New Zealand and South Africa, as well as in international fisheries management organisations such as ICES, CCAMLR, CCSBT and IWC.

Examples of models/software:

- ASAP: ASAP is a SCAA model developed by NOAA that assumes separability of fishing mortality into year and age components to estimate population sizes given observed catches, catch-at-age, and indices of abundance. Discards can be treated explicitly. The code is available from the NOAA Fisheries Toolbox [nft.nefsc.noaa.gov/ASAP.html].

- State-space Assessment Model (SAM): This random-effects model allows for time-variant effects, such as gradual changes in fishing selectivity, while keeping the number of model parameters to a minimum compared to full parametric statistical assessment models (Nielsen and Berg 2014). Software packages such as AD Model Builder (ADMB), developed by David Fournier (Fournier *et al*. 2012), facilitate elegant estimation of random effects within a frequentist framework using Laplace approximation.

Data requirements: Total annual catches (including discards), some catch-at-age data and an index of abundance such as CPUE or survey. In addition, qualitative information about the biological parameters is useful to define prior distributions if a Bayesian approach is followed.

Advantages: These models are very flexible and can incorporate as much, or as little, age data as are available from various of sources (commercial and/or survey). Unlike VPA methods, catches-at-age are not assumed to be known exactly and sampling variability is incorporated into the model. Depending on data availability, these models can be as simple as ASPMs, with few estimable parameters, or as complex as IA, with many model parameters (e.g. to describe transient effects).

Disadvantages: These methods are complex and require expertise in the fields of mathematics and statistics to understand and implement wisely. Typically, they are used for high-value data-rich stocks only, although flexibility in terms of data requirements may render these models useful in data-limited

cases. Over-parameterisation can be a problem for such flexible and potentially powerful methods: lack of sufficient data, or lack of contrast in the data, can render extensive parameter estimation difficult, if not impossible. Auxiliary information may be required (being incorporated as Bayesian priors), or alternatively the number of free parameters needs to be reduced through use of simplifying assumptions. As with other types of age-structured models (e.g. ASPM and VPA), SCAA cannot easily distinguish between the confounding effects of natural mortality, M, increases in M with age, and asymptotically flat or domed selectivity (Butterworth *et al.* In press).

1.4.8   Integrated analyses

Integrated analysis (IA) provides a flexible statistical framework to model the population dynamics of fish stocks using diverse fishery and survey data, both age and length-based, as well as age-aggregated. SCAA models, summarised in the section above, are generally seen as simpler versions of these fully integrated methods. These models can cater for many other types of data as well, and in their original format without requiring pre-processing, for example the incorporation of length data and age-length keys directly into the likelihood. IA models are highly general (in terms of the types of data that can be incorporated), flexible (in terms of the estimable parameters and management quantities output) and powerful (efficient estimation of large numbers of parameters through use of appropriate software such as ADMB).

Methot *et al.* (2012) divide this category of models into two sub-categories: a) models with length-structured population dynamics, and b) those with age-structured population dynamics, which they describe as follows.

  a) Length structured dynamics using a length-based transition matrix:
     The main advantage, particularly for low-value fisheries, is that length data are easier and less costly to collect than age data. However, length-based models do not perform as well as age-based methods and generally result in less precise estimates of recruitment and mortality compared to models which incorporate age data. This is because, given distributions for length-at-age that are often wider than average interannual growth, the information on cohort strengths is diluted as the different cohorts overlap each other across different length groups. From a management point of view, the lack of accuracy associated with length-based methods can lead to high levels of over-exploitation of the stock unless a very precautionary approach is adopted (Hogarth *et al.* 2006). Length-based models are typically used for lobsters (and other crustacean) fisheries, tropical fish stocks, as well as low-value (data-poor) fisheries for which large ageing programs are too costly.

b) Age-structured dynamics: These models generally cater for multiple areas and growth patterns, as well as for time-dependent effects in population processes. Growth is estimated internally using age-at-length data. As for SCAA, natural mortality rate may be an estimable (free) parameter and recruitment is modelled using a stock-recruitment relationship and allowing for variations about the chosen function. Unlike SCAA, integrated analysis allows for the incorporation of unprocessed data into the model. Taken to one extreme, and given high quality catch-at-age data, this type of model can be configured to resemble a VPA model by allowing for time-dependent effects in fishing selectivity. At the other extreme, when the data do not support the estimation of a comprehensive set of model parameters and key parameters need to be fixed, the IA model can be constrained to become a simple stochastic age-structured production model. Therefore, IA models have the flexibility to be as simple or complex as the data dictate.

IA is gaining popularity worldwide due to the flexibility with which age and/or length composition data may be incorporated into the model. These methods are applied extensively in North America, Australia, New Zealand and to a lesser extent to the stocks assessed by ICES.

Data requirements: Total annual catches, one or more indices of abundance (CPUE or survey), and some age- and/or length-composition data (need not be a comprehensive data set in the sense that gaps in the time-series can be accommodated). In addition, auxiliary information, such as age-at-length data (to estimate growth) and tagging data (to estimate mortality and possibly its age-dependence) can also be incorporated.

Examples of models:

- Stock Synthesis (SS): Developed by Methot (1989, 1990, 2012), SS is an integrated statistical catch-at-age model that can incorporate catch data, survey indices and age and length composition data The latest version, SS3, includes additional options for modelling time-varying parameters and enhanced selectivity features. The software, written in C++ using the ADMB library is available from the NOAA Fisheries Toolbox [NFT.NEFST.NOAA.GOV/stock_synthesis_3.htm].

- Colerain is an Excel-based general statistical age- and sex-structured multi-fleet model developed by Hilborn *et al.* (2001) which can incorporate different sources of information from the fishery and/or surveys. Prior information for model parameters can also be specified. This model allows for temporal changes in the selectivity and catchability of the fishing fleet. The software is available at [fish.washington.edu/research/colerain].

- C++ Algorithmic stock Assessment Laboratory (CASAL) is an advanced software package developed by the National Institute of Water and Atmospheric Research (NIWA) in New Zealand for fisheries assessment and management (Bull *et al.* 2012). It is a flexible age- or length-structured stock assessment model that can be applied to single or multiple stocks, areas, and/or gears, and fitted to data from many different sources. This package is used to assess most of New Zealand's fish stocks, including deepwater (e.g. orange roughy), middle depth (e.g. hoki), inshore (e.g. snapper), and shellfish fisheries. It has also been used to assess Patagonian and Antarctic toothfish, and broadbill swordfish fisheries. The software is available at [www.niwa.co.nz/our-science/fisheries/tools/casal].

- MULTIFAN-CL (Fournier *et al.* 1990, 1998) is a statistical length-based, age-structured model that provides an integrated method of estimating catch-at-age composition, growth and other parameters from catch and effort time series and length-frequency data. This software is aimed at fisheries where length-frequency sampling data are available but in which large-scale age sampling of catches is either too costly or not feasible. This software has been used to assess the status of Western and Central Pacific tunas (Hampton and Fournier 2001). The software is available at [www.multifan-cl.org].

Advantages: An extensive variety of diverse data can be incorporated in its original format, avoiding pre-processing and its attendant problems. Models are highly flexible and can be configured to suit most situations.

Disadvantages: These models can be very complex and are typically only fully developed, understood and applied by highly trained statisticians/mathematicians – a general shortage of the required expertise and skill set has therefore resulted in limited applications. The temptation to over-complicate the model exists, thereby masking the key features of the stock dynamics. No limitations are placed on input data and an all-inclusive approach can be taken regardless of the information content of the data. The quality of the data may not support the estimation of all parameters and effects desired, and care must be taken as subsequent management advice based on over-parameterised models can be dubious at best.

1.4.9   Other

1.4.9.1   Yield per Recruit

This steady state model was first developed by Beverton and Holt (1957) to determine the average yield from a single recruit at different levels of fishing mortality, *F*, given an age at first capture or a selectivity curve. Its utility is based on the assumption that average recruitment will continue regardless of the level of fishing mortality.

This model incorporates some age-structure information in terms of the growth curve and natural mortality. It is particularly useful to ascertain, for example, if fish are being caught from the right age to achieve optimal yield, and to estimate the optimal fishing mortality for a stock. It is not generally used in isolation to serve as a basis for management advice, but rather together with the outputs from an age-structured assessment, for example to estimate reference points for management advice purposes.

However, in the absence of reliable time series data, information on demographic properties (growth, mortality, maturity) may be available for otherwise data-poor species as this allows for the estimation of management targets using per-recruit methods. An example of this method applied in isolation is the South African linefish stocks, considered extremely datapoor, for which management reference points have in the past been estimated using per-recruit analysis (Griffiths *et al*. 1999). However, the reliability of these estimates is questionable as they rely in turn on estimates of natural mortality whose accuracy is debatable.

Data requirements: Biological information pertaining to natural mortality rate and growth information (von Bertalanffy growth function parameters), as well as fishing (gear) selectivity.

Advantages: Yield-per-recruit models are simple and rely on few data (no catch or effort data). These models are useful in terms of direct fishery management recommendations on the optimal size of animals caught to avoid growth overfishing and the optimal fishing mortality to maximise yield.

Disadvantages: These models do not provide estimates of stock status, but rather static management targets and reference points. Yield per recruit methods rely on estimates of natural mortality that are usually not well determined, even for data-rich stocks. In terms of generating management advice, care must be taken when using these models to control catch (TAC) or fishing effort (TAE). Yield per recruit methods exclude a stock-recruitment relationship (no density dependence) and TAC advice based on multiplying the yield per recruit by past average recruitment may fail in circumstances where high fishing pressure causes recruitment overfishing. The problem with generating TAE advice based on this method is the lack of a direct estimate for the catchability coefficient, q, required to

convert fishing mortality rate to effort. Therefore, used in isolation, these methods can result in management advice which is not very reliable.

1.4.9.2   Meta-analyses

This approach uses formal statistical methods for the estimation of parameter distributions based on data from a group of stocks (e.g. stock recruitment parameters and natural mortality rates), and can readily be applied to data stored in some global database. Such analyses have important implications for data-poor fisheries for which traditional assessments are not possible due to lack of data. They are particularly useful for Bayesian-type analyses where prior distributions can be informed by the distribution of the parameter provided by the meta-analysis involving other stocks of the same and/or similar species.

The RAM Legacy Stock Assessment Database, a development of Ransom A. Myer's Stock-Recruitment Database (Myers *et al.* 1995), provides a database for stock assessment results for commercially harvested fish stocks around the world from 21 national and international management agencies for a total of 331 stocks, including nine of the world's ten largest fisheries. These are distributed across 27 large marine ecosystems in the Atlantic, Pacific, Indian, Arctic and Antarctic Oceans (Ricard *et al.* 2012). The database provides data (e.g. catch time series) and assessment results (including biomass, recruits and fishing mortality time series, life history information as well as biological reference points) for data-rich stocks that are assessed regularly.

1.5   Fisheries management

In essence, the aim of fisheries management science is to evaluate different trade-offs in an attempt to maximise the biological and economic yield of which marine resources are capable while at the same time reducing the risk of undue resource depletion due to overfishing. Within this paradigm, it is the role of fisheries management scientists to evaluate these risks and rewards quantitatively. This then leads to scientific management advice to marine resource regulatory bodies on the appropriate management actions (such as appropriate catch or effort levels) required to achieve the desired trade-offs between the biological, economic and social benefits from the fishery one the one hand and the risk to the resource on the other in both the short and long terms.

1.5.1   Management reference points

The role of stock assessment is to estimate current stock status, including whether the stock under consideration is overfished, and if so, to what degree? Is it currently managed to achieve maximum biological and economic yield, with biomass close to the desired target level? Once there is reasonable confidence regarding the estimate of current stock abundance in relation to the desired target level, a management plan can be formulated to achieve long-term biological and economic objectives. In accordance with recommendations of UNCLOS (UN 1982) and the FAO Code of Conduct (FAO 1995) to maintain or restore harvested species at levels which can produce the maximum sustainable yield, fishery management objectives are frequently quantified in terms of MSY reference points.

Figure 1 gives a measure of stock status in terms of biomass (B) and fishing mortality (F) relative to the maximum sustainable biological yield (MSY) related reference points, F_{MSY} and B_{MSY}. This phase diagram illustrates the management actions required in a broad brush manner. Fish stocks are categorised in terms of the four quadrants of the plot. The management action required to move the stock to the desired levels of exploitation can then be determined.

1. Bottom right-hand quadrant: a healthy underfished stock with biomass above B_{MSY} and fishing mortality below F_{MSY}.

2. Top right-hand quadrant: an historically underfished stock with biomass above B_{MSY}, but currently fished at a mortality rate above F_{MSY};

3. Top left-hand red quadrant: an overfished stock, with biomass estimated to be below B_{MSY}, and continued overfishing at levels that exceed F_{MSY};

4. Bottom left-hand quadrant: an overfished stock which is currently in a rebuilding phase with current fishing pressure reduced to allow biomass recovery to MSY level.

In reality, it is very difficult (even impossible) to know exactly where on the plot a stock is positioned because of uncertainty associated with estimates of current abundance, B, current fishing mortality rate, F, and also with the associated reference points in terms of MSY, even for data-rich stocks. Fisheries management is not an exact science and natural fluctuations in resource dynamics (e.g. in recruitment), coupled with high levels of uncertainty regarding assessment models and data, typically result in large variability over time (even from year to year) in estimates of biomass and management reference points. Even with the best management plan in place, the stock biomass cannot possibly be maintained exactly at a level that maximises long-term yield, particularly given fluctuations in recruitment. Rather, the stock will fluctuate about a target biomass, even in the absence of harvesting. B_{MSY} must therefore be considered as a long-term average about which biomass is expected to fluctuate when the stock is fished at F_{MSY}.

Biological reference points and proxies

Biological reference points provide a consistent measure for evaluating stock status and are important for quantitative fisheries management. Methods for estimating stock status and reference points depend on the type and quality of data available. Equilibrium per recruit models are generally used to estimate static MSY related reference points. For data-rich stocks, harvest strategies are typically based on reference points for both biomass and fishing mortality (e.g. B_{MSY} and F_{MSY}) to adjust catch advice in relation to stock size.

However, for cases where reliable estimates of B_{MSY} and F_{MSY} cannot be obtained, proxy-values based on meta-analyses of data-rich stocks, are commonly used. A widely used proxy for B_{MSY} is expressed as a percentage of the pre-exploitation biomass B_0: the percentage depends on the productivity of the species although a default proxy for B_{MSY} of $0.4B_0$ is commonly used (Clark 1993). Proxy-values for F_{MSY} are generally obtained from per recruit analysis. For data-poor stocks which lack adequate quantitative data from which to estimate management reference points, estimates of MSY may be based on average historic catch given a sufficiently long catch time-series. When a reliable index of abundance is available, a target CPUE is sometimes used as a proxy for B_{MSY}.

There are several limitations associated with managing stocks in terms of MSY-based reference points, mainly linked to the high levels of uncertainty about estimates of stock status and such reference points. Given the extent of uncertainty to be expected in fisheries management, a precautionary approach is desirable in which more conservative reference points are adopted so as to avoid stock depletion below B_{MSY} and fishing mortality rates above F_{MSY}.

Precautionary management: limits and targets

United Nations Fish Stocks Agreement (UNFSA) defines management reference points as follows: "*Limit reference points set boundaries which are intended to constrain harvesting within safe biological limits within which the stocks can produce maximum sustainable yield. Target reference points are intended to meet management objectives.*" Furthermore, according to this agreement, the risk of exceeding the fishing mortality limit reference point should be low and the associated target reference point should not be exceeded on average (UN 1995).

Based on the UNCLOS biomass objective (UN 1982) and the FAO Code of Conduct (FAO 1995), B_{MSY} is often chosen as a biomass target. However, the greater the extent of uncertainty associated with estimates of stock status the greater the need to choose a biomass target above B_{MSY}. A precautionary approach to management would therefore correspond to choosing a biomass target, B_{TARGET}, at some percentage above B_{MSY}, with the associated fishing mortality target, F_{TARGET}, below F_{MSY} (see Figure 2). To avoid the possibility of stock collapse due to sustained overfishing, typically limit reference points are also defined. The biomass limit reference point, B_{LIMIT}, chosen at some percentage below B_{MSY}, corresponds to the level of spawning stock abundance below which the reproductive capacity becomes impaired, also called recruitment overfishing (Sissenwine and Shepherd 1987). UNFSA (UN 1995) defines F_{MSY} as the limit above which overfishing occurs and it therefore often serves as a proxy for F_{LIMIT}. In line with the precautionary approach, higher levels of uncertainty regarding stock biomass levels associated with less resource data would in turn necessitate higher associated biomass target and limit reference points and correspondingly lower fishing mortality targets and limits.

Different precautionary management reference points have been developed over the years (Restrepo *et al.* 1998, Brodziak *et al.* 2008, Punt and Smith 2001, Sainsbury 2008, Smith *et al.* 2009, Andersen and Beyer 2013, Maunder 2013). Typical target and limit reference points are shown in Figure 2.
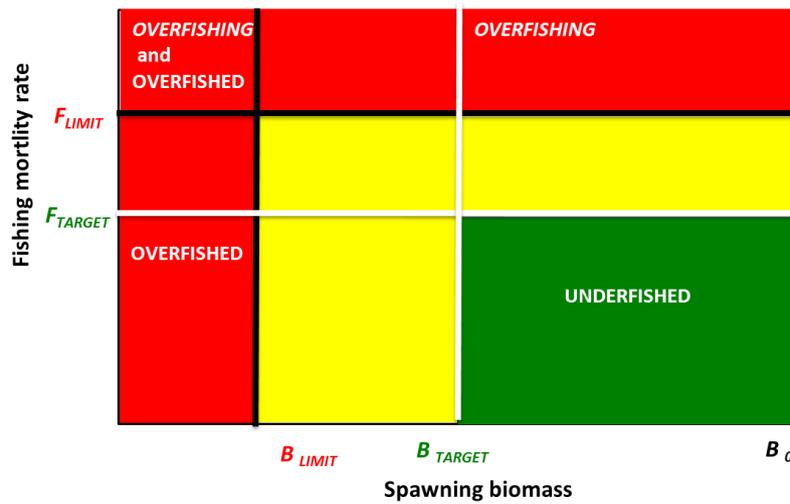
Figure 2: Typical biomass and fishing mortality rate target and limit reference points (adapted from Beddington *et al.* 2007).

With the aim to maximise economic yield (MEY), Australia has adopted a conservative biomass target, well above B_{MSY} (see Figure 3). Target and limit reference points correspond to 20% above and 50% below B_{MSY} for the biomass target and limit reference points respectively (Smith *et al.* 2009). In the absence of reliable estimates of MSY and MEY reference points, proxy values are expressed in terms of the pre-exploitation biomass, B_0. Assuming that B_{MSY} is reached when the stock biomass is approximately 40% of its pre-exploitation biomass, B_0, target and limit reference points correspond to 48% and 20% of B_0, respectively. The corresponding proxy for target fishing mortality is F_{48} which corresponds to the fishing mortality rate that would reduce the biomass to 48% of the pre-exploitation level in the long-term (Haddon *et al.* 2012).

In contrast, in Europe (fisheries under ICES management), F_{MSY} is generally considered a target rather than limit reference point. To safeguard against undesirable low levels of biomass when fishing at F_{MSY}, a biomass trigger is defined: once spawning biomass is estimated to drop below $B_{TRIGGER}$, fishing mortality is reduced from the target fishing mortality F_{MSY} (ICES 2013b), as addressed further below.
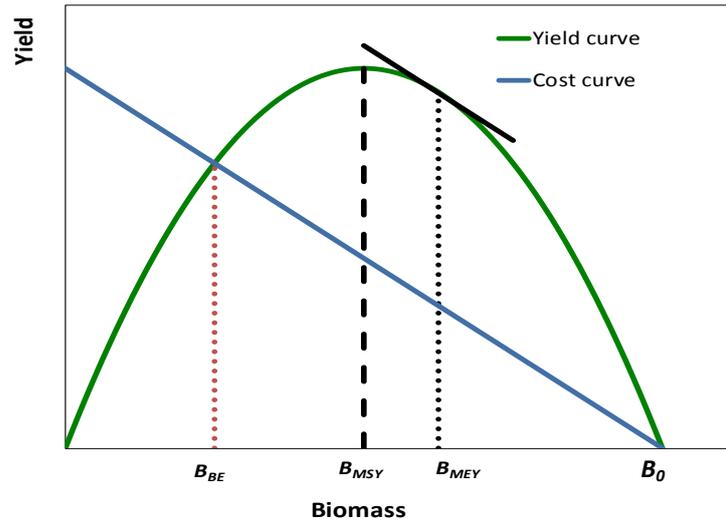
Figure 3: An alternative biomass target corresponds to the biomass that maximises economic yield, B_{MEY}, which is greater than the biomass that maximises biological yield B_{MSY} for fisheries with low discount rates. The bionomic equilibrium, B_{BE}, corresponds to the biomass at which zero net profit is produced and B_0 is the pre-exploitation biomass.

1.5.2 Harvest control rules

Stock assessment methods typically provide estimates of stock biomass and status relative to target, threshold and/or limit reference points, given adequate data. Nevertheless, management failures may occur even when state-of-the-science assessment methods are applied to reliable data, because social or political objectives are not compatible with resource conservation ones. To better formulate management objectives and combat arbitrary catch advice, emphasis has lately been placed on the development and implementation of decision rules. These rules incorporate the results of the stock assessments to provide the scientific advice on which management decisions are based to achieve pre-specified objectives.

For example, if a stock is estimated to be overfished with a biomass well below B_{MSY} (or a proxy thereof), some rebuilding plan to move the stock towards the target biomass within a pre-specified number of years is desirable. This would involve decreasing fishing pressure to first move a stock from the top to the bottom left-hand zone of Figure 2, followed by a gradual biomass recovery to B_{MSY}, or above, to move the stock to the target zone in the phase diagram. To aid management decisions, rebuilding plans are formulated in terms of a well-defined (and simulation tested) decision rules that include management reference points as well as realistic time-frames in which to realise pre-specified objectives.

A harvest control rule (HCR) is an algorithm that determines how the annual catch is adjusted each year according to stock indicators, and in relation to management reference points and the perceived extent of uncertainty about the stock. With the aim to rebuild stocks to, or maintain them at, at their most productive biomass levels, so as to maximise yield while minimising the risk of stock depletion to levels that might impair future recruitment levels, HCRs typically incorporate target and limit reference points, sometimes with pre-specified thresholds between the two.

To better link the choice of the HCR to be applied to the quality and quantity of data available, some management authorities have developed tier systems (Punt *et al.* 2013). For example, one of eight regional councils in the United States, the North Pacific Fishery Management Council (NPFMC), has adopted a tiered system to better define harvest control rules according to the type of information available (NPFMC 2014). For the Tier 1 rule, the fishing mortality rate that gives acceptable biological catch (ABC) is decreased linearly from a maximum value of 0.75% of F_{MSY} to zero in relation to a decrease in biomass below B_{MSY} (Figure 4). Details of this tier system are given in Appendix A.1.
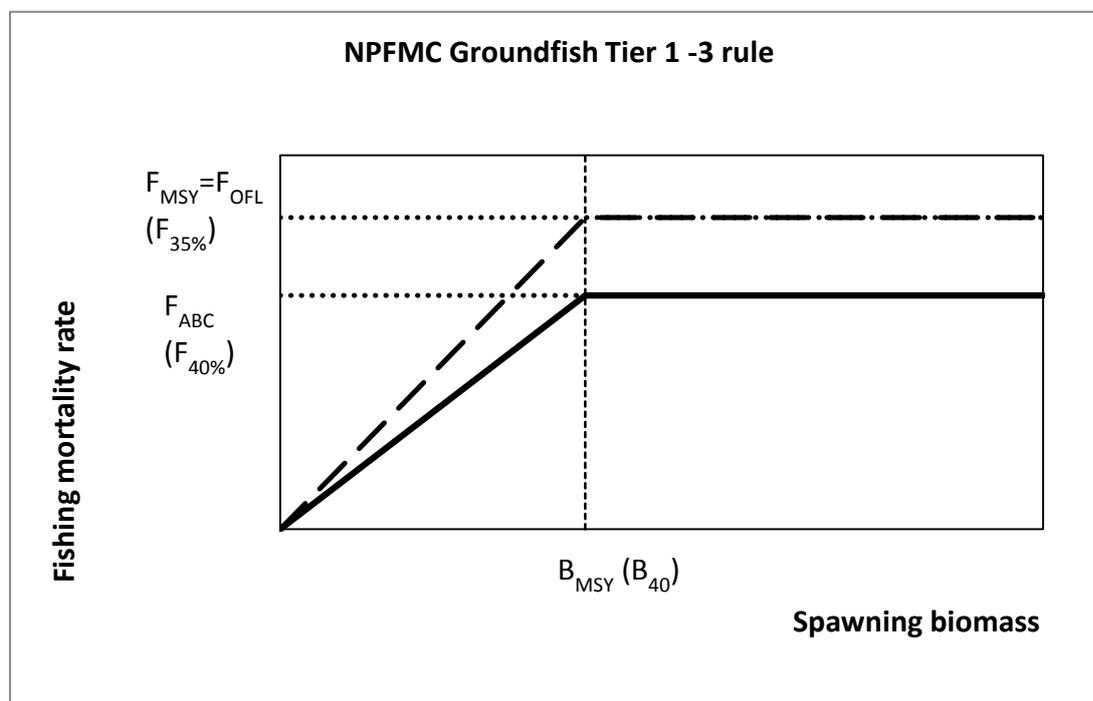
Figure 4: The Tier 1 HCR adopted by the North Pacific Fishery Management Council (NPFMC) to set annual catch limits (ACLs) for North Pacific groundfish. The upper (dashed) and lower (solid) lines correspond to fishing mortality rates associated with the overfishing limit (OFL) and acceptable biological catch (ABC), respectively (see Appendix A.1 for details).

To prevent overfishing in all Commonwealth fisheries, a Harvest Strategy Policy (HSP) was introduced in Australia in 2007 to set limit and target biomass reference points to achieve risk-related sustainability objectives (Smith *et al.* 2009). An objective of this HSP is to ensure that harvesting strategies meet risk thresholds even in circumstances when data availability is compromised as in the case for data-poor stocks. The policy specifies explicit management reference points with the biomass target and limit fixed at 48% (a proxy for B_{MEY}) and 20% (a proxy for half of B_{MSY}) of pre-exploitation biomass, respectively. In addition, the policy also specifies an acceptable level of risk: stock biomass must exceed B_{LIMIT} at least 90% of the time (Smith *et al.* 2013).

Based on the approaches adopted for Alaskan fisheries, the Australian Fisheries Management Authority (AFMA) organise harvest strategies for Southern and Eastern Scalefish and Shark Fishery (SESSF) species according to a tiered system in terms of types of data, methods of assessment and decision rules (see Appendix A.3 for details). Stocks with sufficient data and robust stock assessments are managed according to the Tier 1 decision rule where target fishing mortality rate is set equal to F_{MEY} when stock biomass is above B_{MSY}, and zero when biomass drops below B_{LIMIT} (Figure 5).
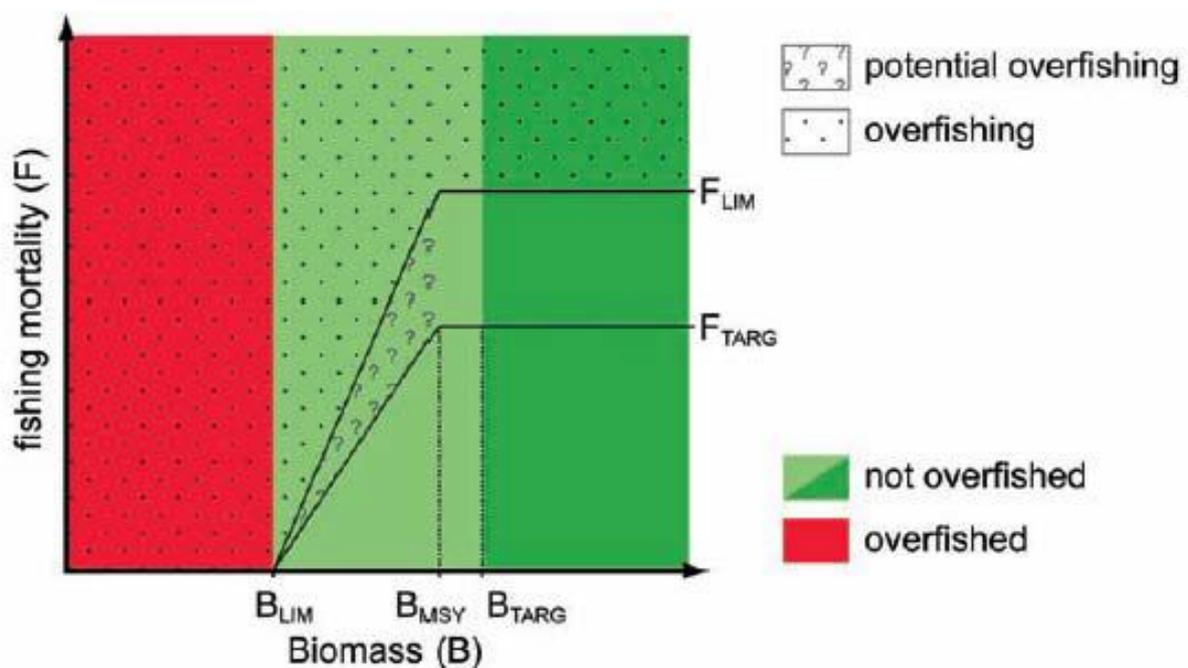
Figure 5: The SESSF HCR with biomass target, MSY and limit reference points indicated by B_{TARG}, B_{MSY} and B_{LIM}. Australia's HSP specifies a biomass target of B_{MEY}, the biomass at which maximum economic yield is achieved. According to this rule the target fishing mortality rate, F_{TARG}, is progressively reduced to zero once the biomass decreases below MSY level (from Smith *et al.* 2009).

In contrast, the ICES harvest control rule is based on reference points F_{MSY} and $B_{TRIGGER}$ (ICES 2013b). An estimate of B_{MSY} (the value around which stock size fluctuates when $F = F_{MSY}$) is not incorporated in the HCR explicitly as recent stock size trends may not be informative about B_{MSY}. Rather, a threshold reference point, $B_{TRIGGER}$, is adopted which corresponds to the lower bound of spawning biomass fluctuations about B_{MSY} when fishing at F_{MSY}. It serves to trigger a reduction in fishing mortality to allow the stock to recover and fluctuate about B_{MSY} (see Figure 6).
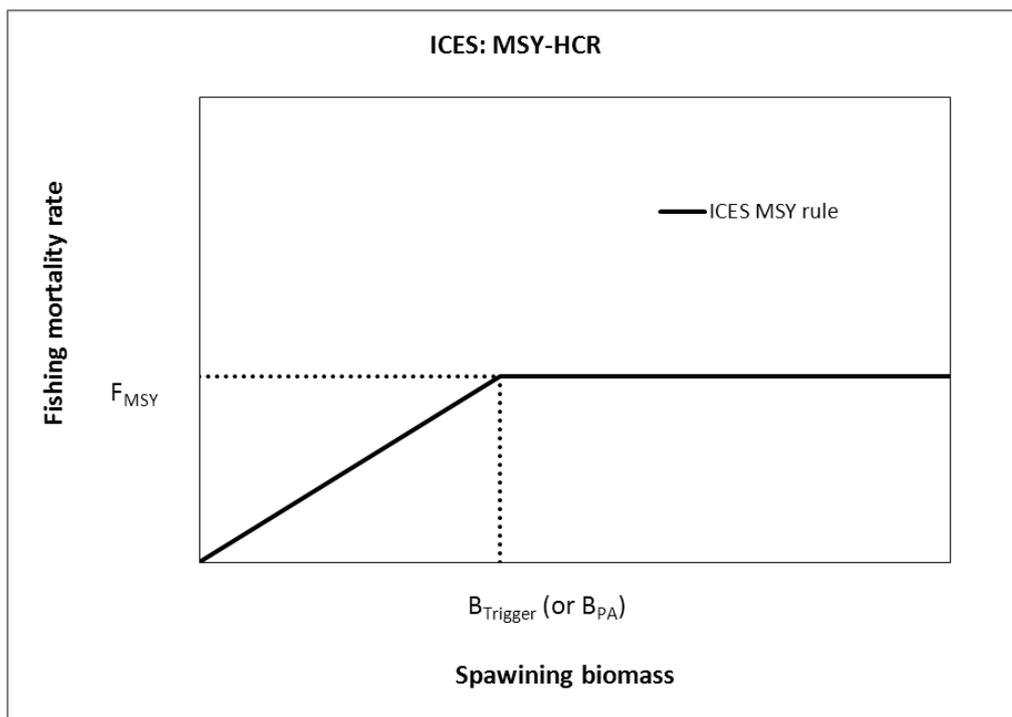
Figure 6: The HRC adopted by ICES. F_{MSY} is considered a target rather than a limit reference point and $B_{TRIGGER}$ serves as a precautionary threshold point (equivalent to B_{PA} adopted by ICES previously).

1.5.3   The Management Procedure Approach

The Management Procedure (MP) approach, first developed by the International Whaling Commission's (IWC's) Scientific Committee (Punt and Donovan 2007), places the emphasis on long-term management of the resource and has found favour with marine scientists and fisheries managers seeking a comprehensive and inclusive resource management approach.

Rather than base management advice on a "best" assessment, this approach integrates over a variety of different plausible population models, called the operating models, representing different hypotheses regarding the resource. Different harvesting strategies are then simulation tested to ascertain which harvest control rule (HCR) would best ensure that the desired long-term management goals are met in practice across this range of alternative population models. While an assessment approach typically allows for only one possible representation, or reality, of the resource, the MP approach incorporates different plausible states of nature, represented by a range of assessment (operating) models drawn from the range discussed in Section 1.4 above.

The MP approach has established itself as a powerful fisheries management tool to assist meeting multiple management objectives in a manner that checks robustness to uncertainty for compatibility with the Precautionary Approach (De Oliveira *et al.* 2008). An advantage of this approach is related to the important resource management concern of long-term trade-offs between, for example, the mutually conflicting objectives of maximizing catch and minimising the risk of overexploitation of the resource. Another important advantage is the inclusive nature of this approach where key stakeholders participate in setting management goals and in deciding strategy to achieve them. However, the key advantage of the MP approach is its ability to incorporate uncertainty in the modelling exercise explicitly, thereby ensuring consistency with the precautionary approach (Butterworth 2007).

For this reason, *inter alia*, this approach has been, and remains, favoured over that of annual stock assessments as the basis for the provision of management advice for the most valuable data-rich fish stocks in South Africa (Geromont *et al.* 1999). In New Zealand, the MP approach has been adopted to provide TAC recommendations for their rock lobster fisheries (Starr *et al.* 1997). More recently, an MP approach has been adopted for Southern bluefin tuna (CCSBT 2012) and is planned for North Atlantic bluefin tuna (ICCAT 2006). Initiatives are underway to introduce the MP approach in Europe and the USA (De Oliveira *et al.* 2008), with MPs having been formally adopted in Iceland to manage Icelandic cod (ICES AGICOD Report 2009), haddock (ICES 2013c) and saithe (ICES 2013d). A more general form, known as Management Strategy Evaluation (MSE), is popular in Australia where

it has been applied by the Australian Fisheries Management Authority (AFMA) partnership to ensure stakeholder involvement in all key areas of fisheries management (Smith *et al.* 1999).

The MP approach, to date used only for the management of high-value data-rich marine resources, could lend itself well to data-poor stocks in order to better address the uncertainty and risk associated with lack of data, in a framework that is "closely linked to fisheries management and the decision making process", as stipulated by the FAO (2010). Furthermore, motivation to collect extra data is part and parcel of an MP approach in which the collection cost of and yield obtainable from extra data are quantified as standard management statistics. As such, the MP approach may present a plausible management solution for the vast number of data-poor resources that are currently not under any formal assessment (Geromont and Butterworth 2014a).

1.6   Discussion

1.6.1   Methods: complex or simple

With advances in computer power, assessment models have become more complex. Hilborn (2003) lists some disadvantages with the current trend to use ever more complex models:

a) Lack of transparency: The complexity of these models render them "black boxes" which are difficult to understand, even by the analysts, and even more difficult to explain to fishery stakeholders.

b) Lack of access: Complex models exclude all but the skilled analysts. With the shortage of trained scientists, assessments may be performed by people who are unable to understand the underlying statistical methods and software. More complex models, with fewer people who understand them, might lead to the abandonment of these state-of-the-art methods in favour of simple (and untested) "rules of thumb" whose application is understood by all.

c) The models overshadow the data: Most effort goes into modelling and analysis, and scientists become out of touch with the fishery, with the consequence that models are becoming more technical and less relevant to the fishery to be managed.

For these reasons, Hilborn predicts that there will be a move towards using management procedures (MPs) which employ rules that use data directly or very simple models, with complex models relegated to the role of providing the operating models (different states of nature) on which the MPs are simulation tested for robustness.

1.6.2   Management: science or solution?

A typical problem associated with stock assessment is model uncertainty: how to choose the "best" model to apply to the data available for the species/stock under consideration. An important conclusion drawn from the 2012 SISAM workshop was that, while application of multiple models may help to evaluate model uncertainty, having more than one model does not facilitate management advice when estimates of stocks status differ. Furthermore, applying multiple models to real data cannot distinguish performance as they cannot be calibrated against the "truth" (Deroba *et al.* 2014). Wentzel and Punt (2011) conducted a comparative study to evaluate model performance of different methods when estimating appropriate harvest levels for data-poor stocks. They concluded that simulation testing is essential to evaluate the risks associated with alternative methods to provide

decision makers with the necessary information to set precautionary reference points and acceptable biological catches that account for uncertainty. Millar *et al.* (2014) suggest a move away from "best" assessment type management towards "model averaging" (Claeskens and Hjort 2008) to incorporate a range of plausible hypotheses. However, as Hogarth *et al.* (2006) point out, "*stock assessment is not the purpose of management, but one step in a much larger process intended to achieve management objectives under conditions of uncertainty.*"

An alternative methodology, the Management Procedure (MP) approach (Section 3.1), follows a more holistic approach to fisheries management and presents a formal framework to take full quantitative recognition of underlying uncertainty by integrating over a range of assessment models, called operating models, as well as including all stakeholders (scientists, industry and managers) in the management process, thereby ensuring that diverse plausible hypotheses and objectives are evaluated. Bentley and Stokes (2009) compare the two management paradigms and highlight the potential of the MP paradigm for application to data-poor stocks characterised by high levels of uncertainty in cases where the assessment paradigm has difficulty to provide fisheries management advice due to limited data.

1.6.3   From science to policy to implementation: a partnership approach

Consider three very distinct stages in traditional fisheries management: science, policy, and implementation. These three stages frequently do not give the same weight to different objectives: while the scientist focuses on biological objectives, the policy maker concentrates on socio-political issues and the fisherman keeps an eye on economic targets. Once catch advice is recommended by the scientists to the policy makers, the advice will likely be re-configured to better suit a different set of objectives. The resultant catch advice is then repackaged into smaller units before being converted to currency by one or more fishing fleets, from one or more countries, competing for one or more resources, with catches often not being well monitored. It comes as no surprise then that the resultant catch (removals) may well be very different from the TAC advised by the scientists. Policy decisions that differ from underlying the scientific advice constitute a source of uncertainty that is often ignored in the scientific evaluation of harvesting strategies. Termed "institutional uncertainty" by Hogarth *et al.* (2006), it is a measure of:

i)   how well key stakeholders communicate with each other;

ii)   how well the scientific information is understood by different stakeholders; and

iii)   to what extent participants in the process can evaluate trade-offs and are willing to compromise if necessary.

The main reason for this divergence in scientific and policy advice is entrenched in the compartmentalising of the different management stages. On the one hand, the fishery scientists who provide scientific advice are unlikely to be fully cognizant of pertinent social, economic and political factors that drive policy. On the other hand, resource managers who must decide on the economic and social constraints of rebuilding strategies are unlikely to fully grasp the implications of the assessments. This division of focus may lead to a management failure because different trade-offs are not fully evaluated. This leads to the impossible task of deciding future strategy without giving decision makers a choice of feasible (simulation tested) options together with the risk/reward trade-offs associated with different management actions.

A formal MP approach (Punt and Donovan 2007), and more generally MSE as practiced in Australia (Smith *et al.* 1999), presents a framework to combine expertise and insight from scientists, policy makers and industry representatives who seek to streamline fisheries management:

i) scientists are exposed to the realities of fisheries management and attendant uncertainties, economic objectives and social constraints;

ii) industry members are informed regarding the risk-return trade-offs and potential long-term gains associated with healthy biomass levels; and

iii) policy makers get insights into the biological and economic implications of alternative strategies.

Within this framework, scientists are aware of social and economic objectives when designing harvesting strategies, and members of industry better understand the short- and long-term catch/catch rate trade-offs of the strategy that they themselves will endorse prior to implementation.

Part 2 A review of existing data-poor assessment methods for data-poor stocks and their application to management

Contributing reviewers:

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2.1 Introduction

There are as yet few quantitative measures in place to manage the majority of low-value fish stocks worldwide, mainly due to the lack of reliable data on which to base quantitative assessments. The FAO (2010) has highlighted the need for the development of scientific management methods and procedures for an estimated 90% of the stocks exploited worldwide that are currently not assessed. Due to the high costs of data collection, these methods and procedures need to be less data-demanding, and give either or both reliable estimates of stock status (e.g. abundance relative some biomass reference point such as B_{MSY}) and provide the quantitative information necessary for designing effective management approaches. The FAO (2010) further states that uncertainty and risk need to be incorporated in an assessment process that is "closely linked to fisheries management and the decision-making process", including some form of motivation to collect further data based on the exploitation rate where "intensively exploited fisheries will require more intensive and frequent data collection and monitoring than moderately exploited ones".

Traditional stock assessment methods such as Virtual Population Analysis (VPA) and Statistical Catch-at-Age (SCAA) are generally not a viable option for data-poor stocks because there are rarely sufficient reliable data from which to estimate population-model parameters. Furthermore, formal quantitative stock assessments are generally costly, expertise hungry and demand large quantities of time and information. As such, do not present a practical management solution for most data-poor stocks, particularly when these are also low value (as is generally the case).

There are many causes for sparse data. The reason a stock is data-poor is usually because of its relatively low-value (and therefore it is often discarded), or simply because catches are low. Management of low-value data-poor stocks can be particularly difficult due to high discard rates which are hard to estimate reliably. The lack of data, and consequent lack of stock assessment, poses a great challenge for fishery managers and also creates a serious risk of biological and economic

overexploitation for data-poor fisheries. Rather than attempt to collect and compile comprehensive data-sets with which to perform complex (e.g. age-structured) assessments, simple methods are required for data-poor stocks that use relatively few but often readily available data, where these methods are easy to implement.

In the past, data-poor management has generally based catch advice on proxies (e.g. fixing the fishing mortality, F, equal to the natural mortality rate, M) or the historical average catch... Catch-only methods have also become popular for stocks with a reliable catch time series, when used together with some biological information (MacCall 2009, Dick and MacCall 2010). In the absence of a reliable catch time series, length-based methods have been proposed (Gedamke and Hoenig 2006, Prince 2011, Hordyk 2014b), or simple methods that rely on some index of abundance (ICES 2012, Geromont and Butterworth 2014a).

A number of workshops have been held globally to identify data-poor (or data-limited) stock assessment methods associated with different levels of data availability as well as harvesting strategies to ameliorate the lack otherwise of effective management for such species/stocks. For example, a workshop was held in California in 2008 to discuss various challenges for managing data-poor stocks. This summarised then current approaches used around the globe (Honey *et al.* 2010).

In Australia, a Harvest Strategy Policy (HSP) was introduced in 2007 to set limit and target biomass reference points to achieve risk-related sustainability objectives even in circumstances when data availability is compromised (Smith *et al.* 2009, Punt *et al.* 2011). An objective of this HSP is to ensure that harvesting strategies meet risk thresholds even when the level of uncertainty is high, as is the case for data-poor stocks. In particular, Smith *et al.* (2009) propose that information from data-rich stocks/fisheries could be used when developing harvest control rules to manage data-poor stocks/fisheries, either by applying the "Robin Hood" approach of using data/information of data-rich stocks to inform analyses for demographically similar data-moderate or data-rich stocks, or by simply grouping similar (bycatch) species in "baskets" and basing management decisions on one member of such a group. Based on applications in Australia, Smith *et al.* (2009) recommend that objective harvest control rules be developed to manage data-poor stocks/fisheries in the absence of stock assessments due to insufficient data. Geromont and Butterworth (2014a) propose a generic Management Procedure (MP) approach for data-poor stocks to better account for the high levels of uncertainty typically associated with these stocks. The MP approach also provides a formal framework for all aspects of the management process, from stakeholder participation when prioritising objectives, to data-collection and finally automating catch advice.

Based on experiences around the world, and particularly in Oceania, Prince (2010) recommends a collaborative approach where local fishers are involved in data collection, assessment and management. He suggests that simple transparent decision rules based on resource indicators collected directly from catch data (e.g. size-based indices of abundance) are required.

In an effort to develop methods to better inform decision makers on stocks without analytical assessments, ICES (2012) has evaluated and implemented a suite of data-limited methods. For those fisheries where an index of abundance (direct or indirect, such as provided by mean the length of the catch) is available, catch advice is generated by applying a simple control rule that adjusts the catch up/down if the average index for the most recent years is higher/lower than the previous average.

In early 2014, the Natural Resources Defence Council (NRDC) convened a Data-Limited Methods (DLM) Workshop in Miami, USA, to investigate appropriate methods to set catch limits when data are lacking. The workshop – which was comprised of scientists from the US National Marine Fisheries Service, state and international fishery management organizations, and academia – reviewed current and emerging methods, evaluated their efficacy for different fisheries and data situations, and developed recommendations for improving the science and management of data-limited fisheries, including through the use of a "Data-Limited Fisheries Toolkit" (Carruthers 2014). The Toolkit, which was unveiled at that workshop, facilitates the use of management strategy evaluation (MSE) to identify optimal data-limited methods depending on species, fishery, and data quality, and then allows for the rapid application of the best available data-limited methods for each situation. A summary of current methods to set catch limits for data-limited fish stocks in the United States is provided by Newman *et al.* (2014).

To the review emerging data-poor methods and provide an overview of their performance, *Fisheries Research* has dedicated a special issue, currently in press, to the "Development, testing and evaluation of data-poor assessment and management methods". A number of scientific papers that have been accepted for publication in this Special Issue are referenced in this document.

A summary of data-poor methods follows (Table 1). These methods encompass traditional stock assessments and extend to harvest control rules (HCRs) for providing management advice in the form, for example, of catch limits. The reason is that in the data-poor area, the methods available range from one end of the spectrum to the other, with some overlap between simple assessments and control rules. There are many ways these methods/approaches could be arranged. The decision taken for what follows was to do this on the basis of the type of data available, as this will probably provide the most user-friendly basis for readers seeking practical advice for their fishery.

Data type	Method type	Method
Qualitative and semi-quantitative (Section 2.2)	Assessments	Fisher's Knowledge (FK)
		Productivity and Susceptibility Analyses (PSA)
		Length-based decision trees
		Traffic-light framework
Per-recruit and length-based (Section 2.3)	Assessments	Beverton-Holt
		Length-Based Spawning Potential ratio (LB-SPR)
		Length-based per-recruit
		length-based indicators $P_{mat}, P_{opt}, P_{mega}$
	Harvest control rules	Stepwise constant-catch
		Length target
		$L_{F=M}$ Reference point
Catch-based (Section 2.4)	Assessments	Catch classification method
		Catch-MSY
		Catch-Only Model (COM)
		State-Space Catch-Only Model (SSCOM)
		Depletion-Based Stock Reduction Analysis (DB-SRA)
		Catch-Curve Stock Reduction Analysis (CC-SRA)
	Harvest control rules	Depletion Adjusted Catch Scalar (DACS)
		Shepherd's Hang Over TAC (SHOT)
		Depletion-Corrected Average catch (DCAC)
Index-based (Section 2.5)	Assessments	An Index Method (AIM)
		Replacement-yield model
		Surplus production model
	Harvest control rules	Index adjusted status quo
		Index slope
		Index target
		Index distribution
MPA-based (Section 2.6)	Harvest control rules	Density Ratio Control Rule (DRCR)

Table 1: This table categorises data-poor methods into six broad categories according to the type of data available, although there is unavoidable overlap between these methods and categories.

2.2 Qualitative and semi-quantitative methods

In very data-poor situations where quantitative methods fail, semi-quantitative approaches are useful to perform a rudimentary risk assessment and vulnerability analysis. These methods should not be seen as a substitute for stock assessment or MP/MSE approaches as they do not generate quantitative catch advice or estimate of stock size.

2.2.1 Fishers' Knowledge (FK)

Fishers' knowledge can be incorporated in all aspects of fisheries assessment and management and has particular potential if there is little other information on which to base management advice. For example, local knowledge, based on fishers' experience, can be used to reconstruct basic indicators of abundance or set up a local survey programs involving fishermen.

Prince (2010) argues that data-poor fisheries can be managed successfully only by involving local fishers in all aspects of the fishery including data collection, assessment and management: the solution to data-poor fisheries is to adapt simple fisher-based processes locally by involving fishers "to fish for data as well as profit" and recruiting and training "barefoot ecologists" to support the implementation of fishery based systems for data collection and assessment. He suggests that local FK and expert knowledge can be combined to develop simple management strategies for conserving local spawning biomass, for example the length-based decision tree applied to abalone stocks in Australia (Prince 2010).

Orensanz *et al.* (2013) investigate different methods to use FK in various components of a fishery, including social, cultural, economic and governance aspects. They emphasise that regular collaborative partnerships involving fishers, scientists and managers are the most effective way to engage FK in fisheries assessment and management. Some methodological guidelines to promote successful collaboration are:
1. Establish a framework to facilitate interaction and collaboration among all stakeholders of the fishery;
2. Promote collaborative research projects;
3. Provide rules of engagement to promote mutual respect and transparency;
4. Prioritise stakeholder objectives;
5. Identify realistic (and practical) methods and solutions;
6. Assist in obtaining financial support;
7. Provide training to stakeholders;

8. Encourage stakeholder participation and discussion at different stages of management process from design to implementation, as well as feedback;

9. Examine standards and protocols and experimental and survey designs;

10. Establish protocols for data validation;

11. Communicate and disseminate project results to all stakeholders.

Advantages:

A partnership approach presents an ideal framework to combine expertise and insight from managers, scientists and fishers and to promote cross-fertilisation between experience-based and research-based knowledge. FK can be used to inform prior distributions when adopting Bayesian-type assessment methods. FK is indispensable when reconstructing a time series of total removals.

Disadvantages:

The high levels of variability typically associated with catch rates derived from FK make it difficult to distinguish a real trend in stock abundance from noise in the data. Bias and discontinuities (non-comparability) in data series are unavoidable when attempting to reconstruct an historical time-series from FK. More generally, one must guard against the provision of biased information to support hidden agendas regarding the outcome.

Applications and reviews:

Some examples of collaborative initiatives between fishers, scientists and managers are listed below (Orensanz *et al*. 2009).

- Formal stakeholder participation is part of the lobster fishery management process on the Pacific coast of central Baja California, where the fishery authority collaborates with cooperatives (represented by the fishing federation FEDECOOP) to monitor the lobster fishery (Ponce-Diaz *et al.* 2009) to provide time series data for stock assessments. The federation was integral to the MSC certification of the lobster fishery, the first artisanal fishery from a developing country to be MSC certified.

- Further south, off the Chilean coast, the lobster fishers of Juan Fernandez Archipelago, collaborated with scientists to design and implement a cost-effective sampling program. The resultant standardised index of relative abundance was in turn used to develop harvesting strategies that were compatible with the traditional tenure system already in place for the lobster fishery (Ernst *et al.* 2010).

- In California, fishers from a trap fishery participated in a monitoring program which in turn provided a cost-effective catch-based indicator of crab abundance. This collaborative monitoring program served as a foundation for many recommendations including the definition of objectives, training of participants, validation and review of collected data (Culver *et al.* 2010).

- On the east coast of Canada, a partnership between fishing associations and scientists collaborate in regional sentinel fishing programs with the main objective being to develop and maintain continuous and consistent indices of abundance to be used in cod stock assessments. The sentinel programs were established in 1994 by the Fisheries Resource Conservation Council (FRCC) to monitor the evolution of cod stocks following the closure of the northern cod fishery in the Gulf of St. Lawrence. The program requires training of fishermen, specifically on the sampling protocols for sentinel fisheries (GSP 2002).

- In the Australian abalone fishery, divers are taught to assess abalone reefs using shell morphology to distinguish between sub-adult and fully fecund abalone. This Rapid Visual Assessment (RVA) (Prince *et al.* 2008) provides a crude yet powerful tool to gauge stock status and develop reef-scale harvest policies. This technique is particularly valuable to identify and avoid growth and recruitment overfishing. Decision trees, which codify the qualitative information, are used to categorise reefs into exploitation categories, each with its pre-agreed harvesting policy (see Section 2.2.3 for details).

2.2.2 Productivity and Susceptibility Analysis (PSA)

Originally developed to classify bycatch sustainability in the Australian prawn fishery (Stobutzki *et al*. 2001), this approach determines stock vulnerability to overfishing in a broad brush manner. Subsequently, in the US, PSA was identified as the best approach to evaluate the productivity of data-poor stocks and their susceptibility to over-exploitation based on a flexible semi-quantitative methodology that is applicable broadly (Patrick *et al.* (2009). PSA is an integrated risk approach and gives a measure of stock vulnerability to overfishing of a stock in relation to other stocks and, as such, can aid management recommendations when data are limited.

The method involves giving a score (1=low, 2=moderate, 3=high) for the stock's productivity and susceptibility attributes (for example 22 attributes in total for the case considered in Patrick *et al.* (2009)). The productivity of a stock is an indication of its capacity to recover once depleted, while the

susceptibility is a measure of the stock's availability to the fishing fleet (catchability). The stock's vulnerability score is then calculated by inspecting a plot of the weighted average of these scores. Stocks with a low productivity score and a high susceptibility score are the most vulnerable, while those with high productivity and low susceptibility are less vulnerable.

Method:

The overall vulnerability is measured as the Euclidian distance from the plot origin:

$$v = \sqrt{(p-3)^2 + (s-1)^2}$$

where p is the productivity score (ranging from 3 to 1) and s is the susceptibility score (ranging from 1 to 3). Therefore, a high productivity and low susceptibility combination places the attribute close to the origin of the (p, s) plot corresponding to low vulnerability, while a low productivity score and high susceptibility score implies that the stock is very vulnerable to overexploitation (see Figure 7).
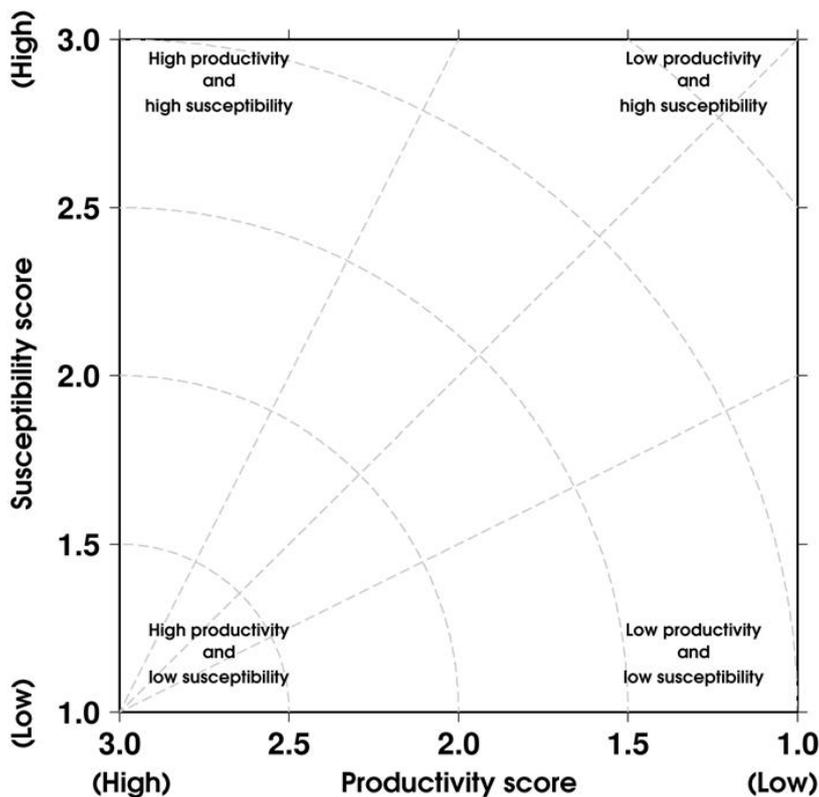
Figure 7: A PSA plot with showing a reversed productivity scale from high to low productivity (plot taken from Patrick *et al.* (2009).

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Patrick *et al.* (2009) selected ten productivity and twelve susceptibility attributes for their study. Not all attributes are equally important when assessing the vulnerability of a fishery/stock. They therefore suggest that a default weight of 2 be given to all attributes, and recommend that these weights are then adjusted from 0 to 4 to better reflect the vulnerability of the fishery. Note that the same weighting system should be applied to all stock within a fishery to ensure consistent results.

Productivity attributes (high=3, moderate=2 and low=1):

1. Intrinsic growth rate (r): Patrick *et al.* (2009) recommend that this attribute be given a maximum weight of 4 as this parameter combines of a number of processes/attributes. A high score of 3 is given when $r > 0.5$, while a low ranking is given to a low-productive species with $r < 0.16$

2. Maximum age (t_{max}): The higher the maximum age the lower the natural mortality rate. A high score of 3 is given to a short-lived species with a maximum age of less than 10 years, while a low score of 1 is given to a long-lived species with a maximum age greater than 30 years.

3. Maximum size (L_{max}): The presence of larger fish generally reflects a lower level of productivity. A high score is given to a species with maximum length less than 60cm, while a low score is accorded to large species with maximum length in excess of 150cm.

4. Growth coefficient (κ): A long-lived, low-productivity stock generally has a low value for κ. The inverse relationship between the maximum age and κ can be approximated by $\kappa = 3 / t_{max}$ (Froese and Binohlan 2000). A high score of 3 is given when $\kappa > 0.25 \, yr^{-1}$ while a low score of 1 is given when $\kappa < 0.15 \, yr^{-1}$.

5. Natural mortality rate (M): Stock with higher M require high production levels to maintain stock abundance. Conversely, low production is associated with a low M. Therefore, a high score of 3 is given to a species when $M > 0.4 \, yr^{-1}$, while a low score of 1 is given when $M < 0.2 \, yr^{-1}$.

6. Fecundity: Fecundity, measured as the number of eggs per spawner, fluctuates highly with spawner size and age, and Musick (1999) suggests using data from fish at age of first maturity. A low value for fecundity is typically taken to indicate low productivity. However, this metric is difficult to interpret as fecundity also depends on survival.

7. Breeding strategy: This attribute gives an indication of juvenile mortality rate. A score of 1 to 3 is based on the extent of parental protection of larvae, the length of gestation period and nutritional contribution.

8. Recruitment pattern: This attribute distinguishes between stocks with sporadic recruitment patterns (corresponding to a higher risk of subsequent year-class failures) and those stocks with stable recruitment. A high score of 3 is given for a stock for which recruitment is frequently successful and a low score of 1 for stocks for which recruitment success is rare.

9. Age-at-maturity (t_m): Long-lived low productivity stocks generally mature at older ages. Therefore, a high score of 3 is given for stocks with an age at 50% maturity less than 2 years, while a low score of 1 is given to stocks that take longer than 4 years to reach 50% maturity.

10. Mean trophic level: More productive stocks generally fall in lower trophic levels and *vice versa*. A high score of 3 is given when the trophic level is judged to be less than 2.5 while a low score of 1 is given when the trophic level above 3.5.

Susceptibility attributes (low=1, moderate=2 and high=3):

1. Areal overlap: Greater overlap of the stock and the fishery implies greater susceptibility.

2. Geographic concentration: Highly aggregated stocks, or "hot spots", render a stock susceptible to the fishery if there are areal and vertical overlaps.

3. Vertical overlap: similar to 1) above, but here refers to the vertical position of the stock in the water column in relation to the fishing operation (e.g. Demersal, mid-water or pelagic).

4. Seasonal migration: This attribute may or may not impact the susceptibility of the fishery depending on the overlaps of the distribution with the fishery at different times of the year.

5. Schooling, aggregation, and other behaviour (in response to fishing): Behavioural responses such as herding that would affect gear catchability.

6. Morphology affecting capture: This attribute concerns selectivity to fishing gear based on fish shape (rotundity, spiny versus soft ray fins). Conventionally selectivity is assumed to be related to fish length, but having taken that into account, a species with bony spines will be retained by a given mesh size to a greater extent than a soft spined species.

7. Desirability/value of fishery: The higher the value of the stock, the more susceptible it would be to overfishing. A low score of 1 is given to a non-targeted bycatch and/or discard species, while a score of 3 is given to a high-value targeted stock.

8. Management strategy: A low score of 1 is given if the target stock is under formal management, while a high score of 3 is given to a targeted stock in the absence of catch limits or accountability measures. Data-poor stocks will typically receive a high score until formal management measures are in place.

9. Fishing mortality rate: Overfishing is defined as fishing mortality relative to natural mortality rate: a low score of 1 is given if $F/M < 0.5$, while a high score of 3 is given if $F/M > 1$

10. Spawning biomass: A low score of 1 corresponds to a spawning biomass (or proxy) in excess of 40% of the pre-exploitation level, whereas a high score of 3 is given to stocks with SSB falling below 25% of the pre-exploitation level.

11. Survival after capture and release: This attribute scores the likelihood of the fish surviving after being discarded. A low score corresponds to a resilient fish with a 67% probability of survival, while a high score is given to a species with a survival rate of less than 33%.

12. Fishery impact on habitat: A low score is given when the fishery has minimal (or temporal) adverse effects on the habitat. A moderate score is given if these effects are more than minimal, but mitigated, while a high score is given when such effects are not mitigated.

The software is available from the NOAA toolbox [nft.nefsc.noaa.gov]

The PSA also incorporates a tier-based data quality index (five tiers ranging from data-rich (1) to data-poor (5)) to provide a measure of data uncertainty. In this manner, for those data-poor stocks which lack life-history parameter estimates, stocks/species with similar demographic parameters could be used, in association with a low data quality score.

Assumptions: This method assumes that the qualitative or semi-quantitative rankings are unbiased and the criteria are appropriate for the stock/fishery under consideration.

Input: In-depth knowledge and understanding of the species and fishery, with particular regard to stock productivity and susceptibility to fishing gear and practices. Qualitative and semi-quantitative knowledge needs to be quantified in terms of parameters such as: $r, t_{max}, L_\infty, \kappa, M, F/M$.

Advantages: This method is used to rank data-poor stocks in terms of their vulnerability and so identify and prioritise stocks in terms of their research and management requirements. This methodology could prove very useful in combination with other data-poor approaches. For example, prior distributions could be derived using this method to be applied subsequently in other data-poor methods such as DCAC and DB-SRA (Cope *et al*. In press).

Disadvantages: The main disadvantage is that the rankings are subjective and therefore cannot be rigorously simulation tested. In the absence of reliable quantitative estimates of the life-history and fishery parameters, this method relies on qualitative estimates of stock productivity and susceptibility which can lead to unreliable rankings. For data-poor stocks, many attributes will be unknown resulting in default scores that are unlikely to reflect the true productivity and susceptibility of the stock. The two attributes related to stocks status and fishing mortality rate are generally not known for

data-poor stocks – given this knowledge, a more quantitative approaches may be more desirable. The attributes scored are not always independent of each other and assigning appropriate weights can be difficult. The PSA does not provide management reference points, but merely indicates high risk stocks that require management intervention.

Applications and reviews:

- Stobutzki *et al.* 2001 applied PSA to assess the sustainability of some 411 fish bycatch species in the Australian northern prawn fishery. Each species was ranked in terms of its susceptibility to mortality in prawn trawling and its capacity to recover after depletion. The ranking determined the relative capacity of the species to be resilient to trawling, thereby prioritising species for research and management interaction.

- Simpfendorfer et al. (2008) used this approach to assess the risk of over-exploitation for data-poor pelagic Atlantic sharks. Results were compared to PSA scores for the blue shark, a data-rich ICCAT managed species that is estimated not to be over-exploited at present. All shark and ray species investigated in this study were found to have higher risk levels than those associated with the blue shark, mainly due to the lower levels of productivity associated with these species compared to blue shark.

- Patrick *et al.* (2009, 2010) applied PSA to six US fisheries consisting of 166 stocks following the Vulnerability Evaluation Work Group (VEWG) held in 2008 to provide a methodology for determining the vulnerability of stocks for which there were insufficient data to conduct quantitative modeling. The PSA was identified as the best approach for this. The stocks/species investigated in this study exhibited varying degrees of productivity and fishing susceptibility, with different levels of data quality. The PSA was able to distinguish between stocks, with appreciably higher susceptibility scores accorded to stocks that were known to be overfished or undergoing overfishing. However, the susceptibility of non-target stocks was not notably different from target stocks, highlighting the need for re-examination of vulnerability thresholds for bycatch stocks.

- ICES (2012a, 2012b) is currently evaluating the application of PSA for Category 5 and 6 stocks characterised by having only landings data available (ICES 2012b). The WKLIFE Workshop (ICES 2012a) notes that attributes scored should be as independent from each other as possible to maximise the amount of information drawn on. To increase the level of precaution, a default high risk level score is recommended if the score for an attribute is unknown.

- Cope *et al*. (2011) used PSA to measure the vulnerabilities of 90 managed groundfish stocks, 64 of which are currently managed within stock complexes. These stock complexes are re-evaluated by first using a partitioning cluster analysis to group the stocks by depth and

latitude. Vulnerability reference points are then established based on the PSA results to determine vulnerability groups of low, medium, high and major concern within each ecological group. This method is a simple and flexible approach to incorporating vulnerability measures into stock complex designations while providing information with which to prioritize stock and complex-specific management.

- Chato Osio *et al.* (in press), applied PSA to 151 Mediterranean demersal fish species. Out of 151 species, 58 displayed low vulnerability, 20 medium vulnerability, 25 high vulnerability and 48 were considered of major concern. More than half showed a vulnerability, e.g. risk of being overfished, greater than the stocks currently assessed in the Mediterranean Sea. Most of the cartilaginous fish fell in the high and major concern areas. With generalized mixed models the exploitation ratio (F/F_{MSY}) of assessed stocks was regressed against PSA scores and area, and a statistically significant correlation was found. Using this result, assessed stocks were used as a training set to predict the exploitation of un-assessed stocks. The prediction relies on a number of assumptions on targeting, representativity of the assessed stocks and number of available stock assessments.

- Cope *et al.* (in press) developed and introduced a prior on relative stock status using PSA vulnerability scores. Data from U.S. west coast groundfish stocks (*n*=17) were used to develop and then test the performance of the new relative stock status prior. This predictive relationship, as well as the default prior was then used to test the performance of these stock status priors in data-reduced applications conducted within a common age-structured framework.

- Sustainability Assessment for Fishing Effects (SAFE), originally developed for risk assessment of bycatch species in the Australian Northern Prawn Fishery (Brewer *et al*. 2006, Zhou and Griffith 2008, Zhou *et al*. 2009), has been extended to other fisheries by Zhou *et al.* (2011). SAFE uses similar data (but fewer attributes) as in the PSA method and may be regarded as a quantitative version of PSA. It has been recommended as the first choice (over PSA) for assessment of bycatch species in Australia (Smith *et al.* 2014). The method consists of two major components: indicators and reference points. SAFE focuses on one single indictor, the fishing mortality rate, because of a lack of data for estimating biomass for the majority of bycatch species. The impact reference point represents the level of mortality that would theoretically cause a population to eventually equilibrate to the associated population reference point level. Instead of using time series of catch data and age composition, the SAFE derives fishing mortality rate through estimation of spatial overlap between species distribution and fishing effort distribution. For the second component, the biological reference points (BRPs), SAFE derives these from life-history parameters that are widely available for many species rather than from time-series of fisheries data (Zhou *et al.* 2012b). SAFE has

been applied to sustainability assessment of more than 400 fish bycatch species in the prawn trawl fisheries in Australia (Brewer *et al*. 2006, Zhou and Griffiths 2008, Zhou *et al*. 2009a, Zhou 2011). In addition, the method has been applied to sea snakes impacted by prawn trawling (Milton *et al*. 2007, Zhou *et al*. 2012a). After its initial application in the prawn fisheries, SAFE has been extended to a dozen major fisheries in Australia involving hundreds bycatch species (Zhou *et al*. 2007, 2009b, 2011, 2012c, 2013; Zhou and Fuller 2011).

2.2.3 Length Length-based decision tree

Prince (2010) developed a reef assessment decision tree for the western abalone fishery of Victoria, Australia. This decision tree assigns a population status to each reef and is used for setting harvests. The initial tier of the decision tree is based on medium to long-term trends (5-15 years) in catch or effort data for each reef, with subsequent tiers based on the shape and appearance of the abalone shells by using rapid visual assessment (RVA).
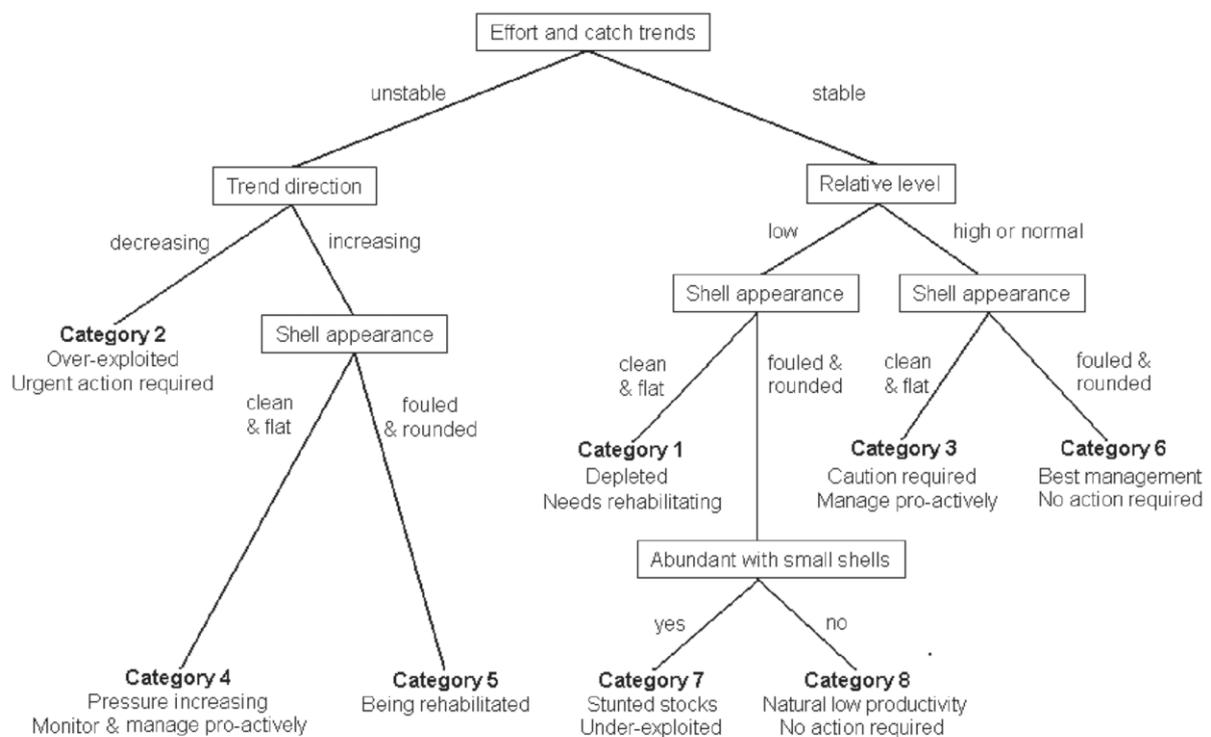
Figure 8: The decision tree used to categorise abalone stocks in Australia based on shape and size of harvested abalone (taken from Prince 2010).

Assumptions:

Input: Reef-code effort and catch and the appearance of the abalone shells

Advantages: The rapid visual assessment (RVA) is a crude yet powerful tool for judging population status and developing harvest policies. It motivates the abalone divers to engage directly in the management process. RVA allows for the rapid assessment of reefs by interviewing divers or organising workshops.

Disadvantages: The main disadvantage is that the method generates qualitative outcomes that are difficult to translate into quantitative management advice. The method relies on the memory and power of observation of abalone divers. This type of survey poses questions about potential bias, for example the effect of spatial range of observation relative to the stock.

Application and reviews:

- Prince (2010) reports that the reversal of the typical "top-down" approach to fisheries management, where the reef is assessed by industry, is gaining popularity for setting regional TACCs and used more widely through the Australian abalone fisheries. Based on the implementation success of this method, he strongly recommends the collaborative involvement of local fishers in data collection, assessment and management.

2.2.4   Traffic-light framework

Caddy (1999, 2002) developed a simple semi-quantitative approach to precautionary fishery management that is suitable for application to data-poor stocks. Precautionary management objectives are prioritised according to a list of qualitative and semi-quantitative criteria organised into four tables: landings trends, environment and ecosystem, the stock(s) and the fishery. The scoring of the characteristics allows for a semi-quantitative comparison between stocks/fisheries and can be used to identify which stocks/fisheries are most in need of research and management action. The Table also suggests simply formulated precautionary reference points, e.g. size-based reference points that are readily understood by the fishery stakeholders. The traffic-light system incorporates a suite of limit reference points to provide progressively precautionary management response to the status of multiple criteria and indices.

The harvest control rule is based on the outcomes of multiple limit reference points (LRPs) that represent agreed limits to dangerous conditions. If contravened, these manifest as "red lights". With each additional LRP contravention, or red light, the management response becomes increasingly severe.

Examples of simple reference points are provided below based on knowledge of the von Bertalanffy growth parameters and some idea of fishing selectivity that is typically incorporated in the size-based LRPs. Using the per-recruit approximations developed by Beverton and Holt (1957), total mortality rate, Z, can be expressed in terms of the mean length of fish in the catch:

$$Z = (F + M) = \frac{\kappa(L_\infty - \bar{L})}{(\bar{L} - L_c)} \qquad (2.1)$$

where L_∞ is the maximum length at maximum age, L_m is the mean length of the fish in the catch, L_c is the length at first capture, and κ is the growth coefficient. Substituting L_m for $\bar{L}$, a suitable LRP is given by:

$$Z_{LRP} = \frac{\kappa(L_\infty - L_m)}{L_m - L_c} \qquad (2.2)$$

If current total mortality exceeds the LRP ($Z \geq Z_{LPR}$), the light turns red and management response becomes more restrictive.

If $\bar{L} < L_m$, the size of first capture needs to be increased. An appropriate size limit is given by:

$$L_c > L_m - \frac{L_\infty - L_m}{M}\kappa \qquad (2.3)$$

If five or more LRPs are contravened (activating five red lights), the fishery is closed until three or four lights turn green again.

Assumptions: The criteria will be scored objectively and without bias. The LPRs are realistic and based on reliable parameter estimates,

Input: Qualitative and semi-quantitative knowledge of the fishery and of the life-history parameters of the stock.

Advantages: The method is geared towards data-limited fisheries and aids prioritising management options. The method is simple and the list of semi-quantitative criteria can accommodate direct observations of fishers and promotes involvement by all stakeholders. This approach can be used in conjunction with quantitative methods.

Disadvantages: Management decisions based on qualitative criteria are difficult (perhaps impossible) to simulation test so that it becomes difficult to ascribe any extent of reliability. Combining (and assigning suitable weighs to) multiple indicators in a harvest control rule may be difficult: not all criteria are equally important, or independent.

Applications and Reviews:

- Halliday *et al*. (2001) investigated the use of a traffic light method as a framework for precautionary fishery management. The method was applied to Northwest Atlantic shrimp stocks and some DFO Scotia-Fundy Region groundfish stocks.

Qualitative and semi-quantitative methods	
Assumptions	Qualitative information and/or scoring of attributes and rankings are objective and unbiased.
Advantages	Qualitative and semi-quantitative methods promote a partnership approach between all stakeholders.
	Expertise from different disciplines can be combined and integrated.
	Qualitative information from various sectors can be used to reconstruct time series data and to inform qualitative assessment model assumptions and parameter choices (e.g. for catchability).
	Qualitative knowledge and methods can be used to construct Bayesian priors.
Disadvantages	The feedback is primarily subjective rather than mainly objective.
	It is difficult to quantify qualitative information and outcomes.
	Misinformation and hidden agendas may render these methods unreliable.
	These methods are generally associated with high levels of variability and bias.
	Qualitative approaches are difficult, if not impossible, to simulation test.

Table 2: Summary of general assumptions and advantages/disadvantages associated with qualitative and semi-quantitative methods.

2.3   Per-recruit and length-based Methods

To evaluate if a stock is subject to over-exploitation, it is desirable to compare current spawning stock biomass and fishing mortality estimates to their corresponding values at MSY. However, for data-poor stocks, such estimates are not usually available. This section explores per-recruit methods that can be used when biological data such as growth, natural mortality and maturity are available, in addition to possibly some length composition data to estimate management reference points.

2.3.1   Beverton-Holt

The analytic methodology described below is the standard per-recruit analysis first developed by Beverton and Holt (1957).

For continuous fishing, we have:

$$\frac{dN}{dt} = \begin{cases} -MN & \text{for } t < t_c \\ -(F+M)N & \text{for } t \geq t_c \end{cases} \tag{2.4}$$

where F and M are the instantaneous fishing mortality and natural mortality rates, and t_c is the age at first capture.

The equilibrium population numbers at age are then given by

$$N_t = \begin{cases} Re^{-Mt} & \text{for } t < t_c \\ Re^{-Mt_c}e^{-(F+M)(t-t_c)} & \text{for } t \geq t_c \end{cases} \tag{2.5}$$

where R is the number of recruits.

Assume a von Bertalanffy (1938) form for the growth of fish in terms of length:

$$L_t = L_\infty(1 - e^{-\kappa(t-t_0)}) \tag{2.6}$$

where L_t is the length at age t, L_∞ is the asymptotic length, κ is the growth coefficient, and t_0 is the age corresponding to zero length.
Assume further a length-weight relationship of the form:

$$w_t = a(L_t)^b \tag{2.7}$$

where a and b are the length-weight coefficients (a cubic relationship between length and mass with $b = 3$ is assumed here).

Let t_m the age at maturity be such that $t_m \geq t_c$, then the equilibrium spawning biomass is given by:

$$SSB = \int_{t_m}^{\infty} w_t N_t dt \qquad (2.8)$$

After integration the equilibrium spawning biomass per recruit is given by:

$$SSB / R = w_{\infty} e^{-Mt_c} e^{-(M+F)(t_m - t_c)} g(F, t_m) \qquad (2.9)$$

where

$$g(F, t_m) = \frac{1}{F+M} - 3\frac{e^{-\kappa(t_m - t_0)}}{F+M+\kappa} + 3\frac{e^{-2\kappa(t_m - t_0)}}{F+M+2\kappa} - \frac{e^{-3\kappa(t_m - t_0)}}{F+M+3\kappa} \qquad (2.10)$$

Similarly, the equilibrium yield is given by:

$$Y = \int_{t_c}^{\infty} w_t F N_t dt \qquad (2.11)$$

Integrating over the interval from t_c to infinity gives the yield per recruit:

$$Y / R = w_{\infty} F e^{-Mt_c} g(F, t_c) \qquad (2.12)$$

where

$$g(F, t_c) = \frac{1}{F+M} - 3\frac{e^{-\kappa(t_c - t_0)}}{F+M+\kappa} + 3\frac{e^{-2\kappa(t_c - t_0)}}{F+M+2\kappa} - \frac{e^{-3\kappa(t_c - t_0)}}{F+M+3\kappa} \qquad (2.13)$$

The number (per recruit) of fish caught is given by:

$$C = \int_{t_c}^{\infty} F N_t dt = \frac{F e^{-Mt_c}}{(F+M)} \qquad (2.14)$$

so that the mean length (per recruit) of fish caught is:

$$\bar{L} = \int_{t_c}^{\infty} L_t F N_t dt / C \qquad (2.15)$$

and after integrating it follows that:

$$\bar{L} = L_{\infty} \left[1 - \frac{(F+M)e^{-\kappa(t_c - t_0)}}{(F+M)+\kappa} \right] \qquad (2.16)$$

After substitution, the total mortality rate, Z, in terms of mean length is given by:

$$Z = (F+M) = \frac{\kappa(L_{\infty} - \bar{L})}{(\bar{L} - L_c)} \qquad (2.17)$$

Input: Life-history parameters, M, L_{∞}, κ, t_m

Assumptions: The main assumption is that the stock is equilibrium, i.e. recruitment and mortality are time-invariant. For the Beverton-Holt formulation, the somatic growth curve is assumed to follow a von Bertalanffy form, and the weight is proportional to length cubed. In addition, selectivity is assumed to be knife-edged with uniform selectivity above the age at first capture, t_c.

Advantages: Per recruit methods can be applied when fishery data are sparse and only growth parameters are available for the species (or a similar species). They provide basic management reference points, for example a minimum length at first capture, that could be incorporated in harvest control rules.

Disadvantages: Equilibrium conditions are unlikely to hold in most circumstances. In particular, this method is not suitable for stocks with high recruitment variability.

Applications and reviews:

- Per recruit analysis is commonly applied to both data-poor and data-rich stock assessments. Yield per Recruit (YPR and YPRLEN) software is available from the NOAA Fisheries Toolbox. The latest version allows the user to incorporate uncertainty in weights-at-age, natural mortality, maturity and fishing selectivity. The software also provides equilibrium estimates for management quantities such as MSY, F_{MSY} and B_{MSY} if a stock-recruit relationship is specified. [nft.nefsc.noaa.gov]

- O'Farrell and Botsford (2005) applied the per-recruit model to estimate the Fractional Change in Lifetime Egg Production (FLEP) from length frequency data from pre-exploitation (or early) and current period of the fishery in addition to the life-history parameters for the species. The fractional change is the ratio of the lifetime egg production (LEP), or equilibrium egg-production per recruit, from the early compared to that of the late period.

- Gislason *et al.* (2008, 2010) investigated the relationship between natural mortality, *M*, and the von Bertalanffy growth parameters, κ and length.

- Le Quesne and Jennings (2012) developed an age-structured population model based on Beverton-Holt life-history invariants to establish reference points and the sensitivity of a species in the Celtic Sea to fishing mortality.

- ICES (2012a) applied per recruit models to stocks to estimate yield and spawning biomass per recruit reference points based on the assumption of knife-edged recruitment to the fishery at age 1 and 2. Reference points calculated for WKLIFE stocks were based on the life-history relationships of Le Quesne and Jennings (2012) and a von Bertalanffy κ / L_∞ relationship of Gislason (2008). They show that the per recruit reference points are sensitive to the assumed selectivity pattern, highlighting the need for stock and fishery specific selectivity patterns.

WKLIFE demonstrated that F reference points can be generated for data-poor stocks on the basis of very limited life-history data.

2.3.2 Spawning Potential Ratio (LB-SPR)

Beddington and Kirkwood (2005) explored how the life-history ratios can be used to assess data-poor stocks when adopting the simplifying Beverton-Holt invariants. Hordyk *et al.* (2014a) developed a more general model to provide a link between the M / κ, L_m / L_∞, and F / M ratios and the equilibrium length composition, the spawning biomass-per-recruit and the spawning potential ratio (SPR) of the stock.

The unfished population numbers per recruit can be approximated by:

$$N_x / R = \exp(-Mxt_{max}) \tag{2.18}$$

where R is the equilibrium number of recruits, M is the natural mortality rate (assumed to be age and time invariant) and $x = t / t_{max}$ is the age of the fish expressed as a ratio of the maximum age t_{max}.

The natural mortality rate is inversely proportional to longevity, so that:

$$M = -\ln P / t_{max}$$

where P denotes the proportion of fish that survive to the maximum age. In terms of P, the population numbers per recruit is simply: $N_x / R = P^x$.

Assuming von Bertalanffy growth (see equation (2.6)) with $t_0 = 0$ and $t_{max} = -\ln P / M$, the growth equation can be expressed in terms of M / κ:

$$L_x = L_\infty (1 - P^{x/(M/\kappa)}) \tag{2.19}$$

Similarly, the equilibrium numbers per recruit can be expressed in terms of the M / κ ratio:

$$N_x / R = (1 - L_x / L_\infty)^{M/\kappa} \tag{2.20}$$

The corresponding biomass per recruit in terms of the M / κ ratio is given by:

$$B_x / R = (1 - L_x / L_\infty)^{M/\kappa} (L_x / L_\infty)^b \tag{2.21}$$

where b is the weight exponent.

The length at which the biomass per recruit is a maximum is given by (Beddington and Cooke 1983):

$$L_{opt} = L_\infty \left[\frac{b}{(M / \kappa) + b} \right] \tag{2.22}$$

where b is usually set equal to 3. Assuming knife edged maturity and that length-at-maturity occurs at L_{opt}, then the L_m / L_∞ ratio can be derived from the M / κ ratio:

$$L_m / L_\infty = b / (M / \kappa + b) \tag{2.23}$$

or inverting:

$$M / \kappa = b / (L_m / L_\infty) - b \tag{2.24}$$

Under these assumptions, the spawning potential ratio (SPR) in terms of the M / κ, F / M and L_m / L_∞ ratio is given by:

$$SPR = \frac{\sum_{x=x_m}^{1} (1 - L_x / L_\infty)^{M/\kappa[F/M+1]} (L_x / L_\infty)^b}{\sum_{x=x_m}^{1} (1 - L_x / L_\infty)^{M/\kappa} (L_x / L_\infty)^b} \tag{2.25}$$

Given an estimate for M / κ, the F / M ratio can be estimated from the length composition of the catch by minimising the negative of the log-likelihood (assuming a multinomial distribution):

$$-\ln L = \sum_i O_i \ln(P_i / O_i^P) \tag{2.26}$$

where O_i and O_i^P are the observed number and proportion of the catch in length class i, respectively, and P_i is the predicted proportion in the catch calculated by multiplying the age structure of the vulnerable portion of the population by the transpose of the catch age-length transition matrix and standardising (Hordyk *et al.* 2014a).

Input: Length composition data in addition to the life-history ratios M / κ and L_m / L_∞.

Assumptions: The main model assumption is that the stock is in equilibrium with constant recruitment and total mortality.

Advantages: LB-SPR can potentially provide a cost-effective assessment method for data-poor fisheries: length frequency data are cheap to collect and generally available for data-poor fisheries. This method does not require time series data such as total historical catches or an index of abundance which are often lacking (or unreliable) for data-poor fisheries. The two life-history ratios required as input (M / κ and L_m / L_∞) have been shown to be conservative across family groups and can

typically be derived from similar (data-rich) species. This method, linked to a harvest control rule that generates catch advice, has been simulation tested within a MSE framework.

Disadvantages: The population size structure is not sufficiently informative for low M/κ species which have many adult age-classes of the same size – for such species/stocks a direct index of abundance is required for management purposes. Furthermore, the model does not account for changes in fishing mortality (e.g. sudden changes in response to management regulations).

Applications and reviews:
- Using life-history ratios, Beddington and Kirkwood (2005) developed techniques to allow for the estimation of MSY and F_{MSY} from the growth parameters, the length at first capture and the steepness of the stock-recruit relationship in data-poor situations.
- Andersen and Beyer (2013) developed a framework to assess the exploitation status of data-poor stocks based on the life-history invariants and size information in the catch. A single parameter, the asymptotic size, is used to characterise the life-history parameters describing growth, mortality and recruitment. This framework incorporates stock-recruitment function to estimate fishing mortality, F, and the biological reference point, F_{MSY}.
- Prince *et al.* (2014) performed a meta-analysis of the relationship between the size, age and reproductive potential of 123 species. The results of this study do not support the common assumption of unique values for the life-history ratios (the so-called Beverton-Holt life-history invariants BH-LHI) and that assuming a M/κ ratio of 1.5 leads to overestimating the productivity of long-lived species. Rather, they observed considerable but predictable natural variation in the life-history ratios of different species. However, there is potential to "borrow" knowledge from well-studied data-rich species and apply these life-history ratios to similar data-poor species.
- Hordyk *et al.* (2014b) evaluated the performance of LB-SPR through simulation testing under a variety of conditions and assumptions: data are simulated for four species with diverse life-history parameters and M/κ in the range 0.53 to 3.05, based on the meta-analysis of Prince *et al.* (2014). In particular, they investigated sensitivity of the model to recruitment variability and dome-shaped selectivity, as well as error in input parameters. They suggest that the precision of the SPR estimate can be improved by increasing the sample size of the length measurements (bins) and propose a sample size of at least 1000 to capture the size composition of the stock.
- Kokallis *et al*. (2014) conducted a simulation study based on the framework developed by Andersen and Beyer (2013) with direct estimation of asymptotic size. The simulation study compares the reliability of the assessment under varying degrees of data availability: no prior

knowledge of the life-history parameters at one extreme, to scenarios where one or more parameters are known. Without prior knowledge of the life-history parameters, it is possible to correctly assess if fishing mortality is below F_{MSY} in more than 60% of cases, and almost always correctly classify if the stock is subject to overfishing. Performance is greatly improved with knowledge of the ratio of age-dependent natural mortality and growth (i.e. the age-dependent equivalent of the M/κ ratio). Their study demonstrates that it may be possible to classify if data-poor stock is subject to over- or under-fishing, although the extent to which F is above/below F_{MSY} can only be determined with substantial uncertainty.

2.3.3 Length-based per-recruit

Gedamke and Hoenig (2006) extended equilibrium model described in Section 2.3.1 to incorporate a sudden and permanent change in total mortality from Z_1 to Z_2. The mean predicted length d years after the change in mortality, at age $g = t_c + d$ is given by:

$$\bar{L} = \frac{\int_{t_c}^{g} N_t(Z_2)L_t dt + \int_{g}^{\infty} N_t(Z_1, Z_2)L_t dt}{\int_{t_c}^{g} N_t(Z_2)dt + \int_{g}^{\infty} N_t(Z_1, Z_2)dt} \quad (2.27)$$

where $N_t(Z_2)$ denotes the number of fish younger than age g, and $N_t(Z_1, Z_2)$ are the number of fish of age g and older. After integration and simplification, the mean equilibrium length d years after the change in mortality is:

$$\bar{L} = L_\infty - Z_1 Z_2 (L_\infty - L_c) \left\{ \frac{(Z_1 + \kappa) + (Z_2 - Z_1)\exp(-(Z_2 + \kappa)d)}{(Z_1 + \kappa)(Z_2 + \kappa)[Z_1 + (Z_2 - Z_1)\exp(-(Z_2)d]} \right\} \quad (2.28)$$

The total mortality rates can be estimated by minimising the negative of the sample-size-weighted log-likelihood:

$$-\ln L = \sum_y m_y (\bar{L}_y^{obs} - \bar{L}_y)^2 / 2\sigma^2 + \ln \sigma / \sqrt{m_y} \quad (2.29)$$

where $\bar{L}_y^{obs}$ and $\bar{L}_y$ are the observed and model predicted mean length in year y, m_y are the number of fish in the sample greater than L_c, and σ is the estimated standard deviation of the residuals.

Input data: The mean length of catch time series, $\bar{L}_y^{obs}$, the von Bertalanffy growth parameters, and if applicable, the year(s) in which mortality changed, identified by sudden changes in observed mean length.

Assumptions:

The assumptions are the same as those listed in Section 2.3.1, but here one or more changes in mortality are allowed:

1. Deterministic asymptotic growth, with κ and L_∞ known.

2. Constant recruitment over time.

3. Mortality-at-age is constant for all fish aged t_c and older.

4. Selectivity is knife-edged, with all fish larger than L_c fully selected by the fishery.

Advantages: This method allows for the estimation of total mortality from mean length data that are usually readily available for most fisheries. Accounting for one or more changes in mortality renders this method more realistic and allows for the incorporation of longer time series of length data.

Disadvantages: This method is only applicable if selectivity is knife-edged, i.e. fish larger than the size of first capture, L_c, are all equally available to the fishery. This method is in this form not reliable if the fishing gear targets age-classes selectively, but can be generalised to take that into account. From a numerical point of view, this method is very time-intensive (searching for the most likely combination of F breaking points) which makes it difficult to simulation test.

Applications and reviews:

- Gedamke and Hoenig (2006) assessed two goosefish stocks in the north-eastern United States based on 40-year mean length time series derived from the NMFS groundfish trawl survey length-frequency data. A single change in total mortality was assumed for the southern stock resulting in estimates for the pre- and post-1977 fishing mortality rates of 0.31yr⁻¹ and 0.6 yr⁻¹ respectively. The method detected two changes in fishing mortality for the northern goosefish stock: an increase from 0.14 yr⁻¹ to 0.29 yr⁻¹ in 1978, and a further increase to 0.55 yr⁻¹ in 1987.

2.3.4   Length-based indicators P_{mat}, P_{opt} and P_{mega}

To avoid undue depletion of stocks, Froese (2004) proposes three simple fishery indicators based on length composition data:

1. the proportion of mature fish in the catch (P_{mat}), with a target of one,

2. the proportion of fish of optimum length corresponding to highest yield from a cohort (P_{opt}), with a target of one, and

3. the proportion of large mature "mega-spawners" in the catch (P_{mega}), with a target of zero although 0.3 to 0.4 is considered a reasonable proportion.

These three quantities provide some measure of the sustainability of catches. Froese argues that, to ensure sustainability, the catch should consist mainly of mature fish of a size that maximises the yield from a cohort, while the very large mature animals should rather be conserved to maximise future spawning.

The three catch-by-length proportions are given by:

$$P_{mat} = \sum_{L_{mat}}^{L_{max}} P_L \tag{2.30}$$

$$P_{opt} = \sum_{0.9L_{opt}}^{1.1L_{opt}} P_L \tag{2.31}$$

$$P_{mega} = \sum_{1.1L_{opt}}^{L_{max}} P_L \tag{2.32}$$

where P_L is the proportion of the catch in length class L,

   L_{mat} is the length at 50% maturity,

   L_{max} is the maximum length, and

   L_{opt} is the length at which the biomass of a cohort is maximised.

A combined indicator, $P_{obj} = P_{mat} + P_{opt} + P_{mega}$, is introduced to differentiate amongst selectivity patterns (Cope and Punt 2009):

a) $P_{obj} < 1$ distinguishes a fishing selectivity pattern associated with growth and recruitment overfishing,

b) $1 < P_{obj} < 2$ corresponds to a (logistic) selectivity pattern that includes some immature fish of suboptimal length, and

c) $P_{obj} = 2$ is indicative of sustainable catches of optimally-sized fish and bigger.

Given L_{mat} and L_{opt} and estimates for the three indicators (2.30), (2.31) and (2.32), Cope and Punt (2009) construct a decision tree to indicate when a stock is above or below the management reference points in the absence of direct estimates of fishing mortality rate, F, spawning biomass, B^{sp}, and recruitment compensation characterised by steepness h.
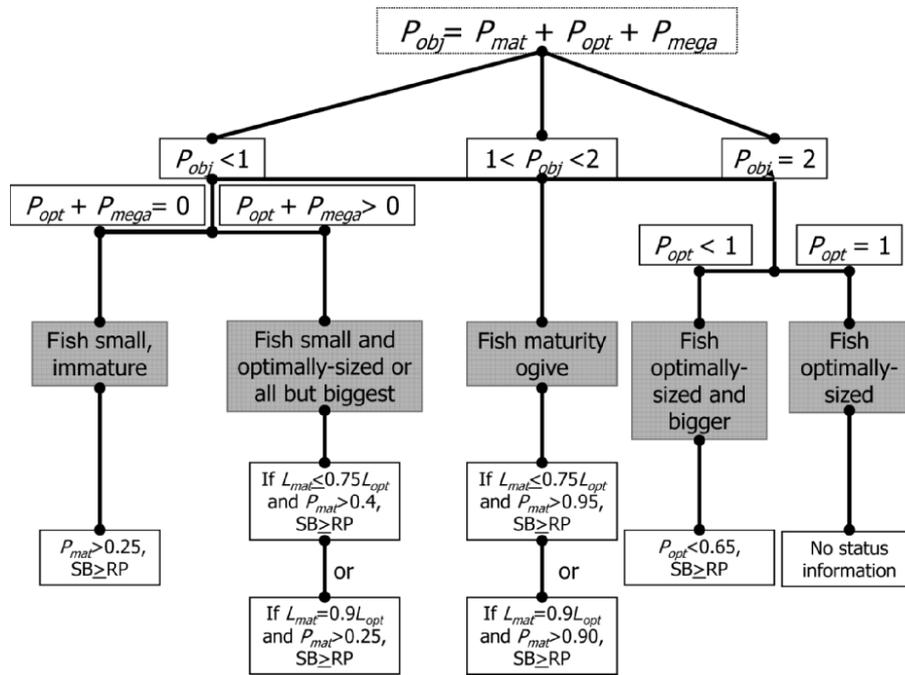
Figure 9: The decision tree (taken from Cope and Punt 2009) to aid determination of stock status in data limited situations. The combined metric, P_{obj}, distinguishes the selectivity pattern of the fishery (grey boxes). The P_{mat} or P_{opt} values are then used to indicate if the spawning biomass of the stock is at or above the target reference point of $0.4 B_0$. Note that a P_{opt} value of one is non-informative about stock status.

Note that, according to the decision tree above, stocks with P_{mat} and P_{opt} values less than one can theoretically be harvested sustainably, while a P_{opt} value of one (i.e. harvesting only fish of optimal size) could potentially lead to major (undetected) decreases in population biomass.

From a fisheries management point of view, these metrics can be incorporated in a HCR that adjusts catches up or down in relation to perceived stock status and spawning biomass target and limit reference points. For example, a L_{opt} strategy could be adopted where $P_{obj} = 2$ and $P_{mat} = 1$ are both heavily enforced. This rule would ensure that only mature and optimally sized fish are caught.

Similarly, a penalty can be incorporated to discourage fisheries from catching primarily juvenile fish ($P_{obj} < 1$).

Assumptions: The main assumption is that the catch-at-length data is representative of the entire catch of the fishery.

Input:

Input data consist of catch-at-length data from the fishery and estimates of L_{mat} and L_{opt} .

Advantages: Length composition data is easy to collect and usually readily available. These simple and intuitive indicators encourage participation by all stakeholders. They can potentially be used (both individually and in combination) in HCRs to provide a basis for TAC advice, although this would require prior MSE or, more specifically, an MP approach to determine robustness of such a control rule.

Disadvantages: This method does not provide catch advice. The targets are unlikely to be practical for some fishing sectors. Caution should be taken when using mean size and size composition data as indicators for stock depletion due to their potentially imprecise albeit informative nature. Cope and Punt (2009) show that there is little contrast between estimates of the length-based indicators at different depletion levels when *h* (steepness) is low. This is problematic as *h* is unknown (not well estimated) for most species, and more so when data are limited. This lack of contrast will negatively affect the performance of HCRs based on these length-based indicators.

Applications and reviews:

- This method was initially introduced by Froese (2004) to avoid growth and recruitment overfishing. Froese also considered that application of these simple indicators would encourage participation of all stakeholders in the fishery, including fishers, managers and politicians.

- Cope and Punt (2009) investigate the performance of monitoring stock exploitation in terms of these length-based indicators via simulation testing. They develop Froese's concepts further by exploring the link between these length-based indicators and fishing mortality and spawning biomass with the aim to develop simple harvest control rules (HCRs) for data-limited stocks. Their study demonstrates insensitivity of results to different life-history

parameters, thereby rendering this method suitable to a wide range of stocks. The decision tree aids the interpretation of stock status to provide flexible management advice.

- Babcock *et al.* (2013) applied the length-based indicators in combination with the Beverton-Holt life-history parameter estimates to determine if the most common species caught at Glover's Reef marine reserve, Belize, were overfished ($B < B_{\text{target}}$) and experiencing over-fishing ($F > M$). In particular, they investigated the importance of uncertainty about stock status estimates based on poor estimates of the life-history parameters by using Monte Carlo simulations. For example, estimates for the life-history parameters typically span a broad range for data-poor reef species which in turn leads to high levels of uncertainty about the management status of the species (Cummings *et al.* 2014).

2.3.5   Length-based Harvest Control Rules (L-HCRs)

For data-poor fisheries for which no reliable index of abundance exists, data may be available for the average individual length or mass of the fish caught each year. Length-based methods are attractive in data-poor situations as these data are easy and cheap to collect. Based on the per-recruit analysis, the mean length of fish harvested may be used as an indicator of the level of depletion of the resource to set yearly catches or some similar management control measure. However, the mean length of fish caught does not provide a direct index of abundance and a time lag is to be expected before a decrease in biomass is reflected in the length data. These control rules therefore need to incorporate additional precautionary measures to ensure early detection of over-fishing and stock depletion and to adjust catch advice accordingly. The challenge for these rules is to react fast to perceived trends in fishing mortality and abundance while ignoring the noise component in the length data.

2.3.5.1   Stepwise Constant Catch HCR

This HCR is a simple constant catch strategy with a step up or down depending on whether some threshold is reached in terms of the recent mean length of fish caught (Geromont and Butterworth, 2014). The rationale underlying this type of MP arises from considerable uncertainty regarding the status of the resource coupled with the fact that mean length data do not constitute a direct index of abundance and can be very noisy (consequently having limited information content). It is therefore not defensible to adjust the catch up or down annually as the mean length increases/decreases because these fluctuations could bear little relation to resource population size, but rather arise from effects

such as observation errors. For this HCR, the catch is left unchanged until strong evidence (in terms of a large change in mean length of the resource harvested) suggests that the catch should be increased or decreased. Given this inertia in the interests of stability, clearly such HCRs need to be tuned to be conservative (risk averse).

No restriction on the inter-annual change in catch advice is suggested for this class of HCRs as the step-size should remain fixed, and large decreases in terms of double step downs may be necessary for severely depleted resources.

$$C_{y+1} = C_y \pm step \qquad (2.33)$$

where C_y is the total catch in year y, $step$ is typically defined as a percentage of the recent average catch,

$$C^{ave} = 1/y_1 \sum_{y'=y-y_1}^{y-1} C_{y'}$$ for the preceding y_1 years (e.g. Geromont and Butterworth (2014a) suggest a

step size of $step = 5\% C^{ave}$).

For the first year of the projection period an appropriate "starting level" must be chosen (which is not necessarily equal to the actual catch of the previous year).

The catch for the next year is increased/decreased only if the recent mean length is more than a predetermined percentage higher/lower than the average of historic mean length of catch. For example, let:

$$L_y^{ratio} = \frac{L_y^{recent}}{L^{ave}} \qquad (2.34)$$

where

$$L_y^{recent} = \frac{1}{y_1} \sum_{y'=y-y_1+1}^{y} L_{y'}$$ is the average mean length over the most recent y_1 years, and

$$L^{ave} = \frac{1}{y_2} \sum_{y'=n-y_2}^{n-1} L_{y'}$$ is an average historical mean length (which remains fixed over the projection

years).

The catch advice is only increased by a single step for year $y+1$ if L_y^{ratio} is greater than the upper threshold On the other hand if L_y^{ratio} falls below the lower threshold, the catch is decreased by a step. As a precautionary measure multiple step-downs are permitted. For this HCR a greater upper threshold is typically chosen to ensure that the catch does not increase too rapidly, which runs the risk

of unintended resource overexploitation (e.g. lower/upper thresholds of 0.98 and 1.05 were selected by Geromont and Butterworth 2014a). Symmetrical lower/upper threshold values may be appropriate for a resource for which the status is judged to be healthy given a coarse preview of the history of the fishery. However, to ensure adequately low inter-annual variability in annual catches, higher thresholds for both increasing and decreasing the annual catch may be necessary.

Input: Mean length of the catch data and the recent average catch.

Advantages: Under stable conditions, this rule is simple constant catch strategy with some precautionary limits built in, so adds industrial stability.

Disadvantages: This rule may not be able to reduce catches quickly enough at very low biomass levels. Choosing the appropriate thresholds can be tricky: if the lower threshold is chosen too high, the HCR might react to noise rather than signal in the data; if too low, the rule will react too slowly, with very negative consequences for the resource.

Reviews and applications:
- Geromont and Butterworth (2014a) simulation tested this HCR for a depleted stock of medium productivity. This rule showed promise, but further testing and tuning is required to ensure adequate precaution is applied at low biomass levels.

2.3.5.2 Length target HCR

This HCR is similar to the Tier 4 control rule for Australian fisheries, which is based on a target CPUE level as tested in Wayte (2009); here, however, annual mean length of fish caught is used as an indirect index of resource abundance in the absence of a CPUE or survey index. A target mean length, L^{target}, is chosen with the intention to achieve some associated target level of abundance. The TAC advice for the next year is given by:

$$TAC_{y+1} = \begin{cases} C^{\text{target}} \left[w + (1-w) \dfrac{L_y^{\text{recent}} - L^0}{L^{\text{target}} - L^0} \right] & \text{if } L_y^{\text{recent}} \geq L^0 \\ \\ wC^{\text{target}} \left[\dfrac{L_y^{\text{recent}}}{L^0} \right]^2 & \text{if } L_y^{\text{recent}} < L^0 \end{cases} \quad (2.35)$$

where $0 \leq w \leq 1$ is a smoothing parameter, C^{target} is a target catch associated with the target length (chosen as an average over a period of stable catches), L_y^{recent} is the average mean length over the most recent years, L^{target} is the target length (informed by equilibrium per-recruit analysis), and L^0 is the limit mean length below which future catches are reduced quadratically rather than linearly with L.

Input: Mean length time series, L_y.

Advantages: The HCR is intuitive and defined in terms of target and limit reference points. Given a long mean length time-series, the target length can be derived from a stable period in fishery, or alternatively, it can be determined by applying per-recruit analysis.

Disadvantages: There is a lag time between a decline in biomass and a decrease in mean length. This rule therefore needs additional precautionary measures to avoid undetected depletion.

Reviews and applications:

- Geromont and Butterworth (2014a) simulation tested this HCR for application to data-poor stocks with alternative choices for the control parameters to optimise risk-yield performance and achieve quick recovery for "severely depleted" stocks. Summary statistics showed that this length-based rule performed adequately compared to HCRs that rely on a direct index of abundance.

2.3.5.3 $L_{F=M}$ **Reference point HCR**

Jardim *et al.* (2015a in press) developed and simulation tested this rule on 50 stocks (pelagic, demersal, deep sea and Nephrops) assuming two exploitation scenarios (development and over-exploitation). This HCR adjusts the catch advice up or down if the current mean length in the catch is above or below the mean length when fishing at $F = M$. The catch advice for the next year is given by:

$$C_{y+1} = C_{y-1}\left(\frac{L_{SQ}}{L_{F=M}} \right) \tag{2.36}$$

where C_{y-1} is the total catch in the previous year, L_{SQ} is the status quo (current) mean length in the catch given by:

$$L_{SQ} = \frac{\sum_a C_{a,y} L_a}{\sum_a C_{a,y}}$$

and $L_{F=M}$ is the mean length in the catch associated with a fishing mortality rate F that is equivalent to the natural mortality rate M, approximated by:

$$L_{F=M} = 0.75 L_c + 0.25 L_\infty$$

where L_c is the length at first capture.

These length-based reference points L_{SQ} and $L_{F=M}$ serve as proxies for current fishing mortality, F_{SQ} and the fishing mortality rate required to achieve MSY, F_{MSY}.

Input: Mean length time series, L_y, and growth parameters estimates L_c and L_∞.

Advantages: The rule is simple and based on readily available data.

Disadvantages: This type of length-based control rule is not always able to adjust catch advice effectively, particularly at low biomass levels. The length data are generally very noisy with limited information content regarding biomass trends. The $L_{F=M}$ reference point would require stock-specific tuning (and take depletion levels into account) to achieve adequate risk-averse performance.

Reviews and applications:

- Jardim *et al.* (in press) simulation tested this HCR and found that it was able to reverse decreasing trends in biomass at catch levels well below MSY. However, the rule did not prevent over-exploited stocks declining further. No implementation error was incorporated in this simulation study.

Per-recruit and length-based methods	
Assumptions	Per-recruit methods assume equilibrium conditions hold, with recruitment and natural mortality constant. Length composition data are representative of the total catch distribution. The mean length index is a reliable indicator of trend in biomass.
Advantages	*Per-recruit methods:* These methods are typically applicable in cases where time-series data are sparse or non-existent, as long as there is knowledge of the life-history parameters. As such they provide cost-effective management options for data-poor stocks. They provide an estimate of total mortality and also basic management reference points. These methods may often be used in combination with other approaches. *Length-composition methods:* Length data are easy and cheap to collect. Length-based indices, and their use in harvest control rules, are simple to understand and intuitive to implement. These simple approaches encourage the participation of stakeholders.
Disadvantages	*Per-recruit methods:* These methods do not take dynamic effects into account. Equilibrium conditions are unlikely to hold. These methods are not suitable for species with high recruitment variability. They rely on accurate estimates of growth parameters and natural mortality, which are difficult to estimate. *Length-composition methods:* Mean length is usually a rather imprecise indicator of stock depletion. There is a lag in feedback from the mean length data. Extra precaution is required at low levels of depletion. Control rules are often not able to distinguish between noise and trend in the mean length time series.

Table 3: Summary of general assumptions and advantages/disadvantages associated with per-recruit and length-based methods.

2.4 Catch-based methods

A number of data-poor assessment methods that rely on catch-data alone to estimate stock status have been proposed and applied in the past. Also termed ORCS (Only Reliable Catch Stocks) methods, in their most rudimentary form, these methods typically assign different fishery development stages to a stock associated with levels of catch in relation to the maximum historical catch. However, these methods have since been subjected to a critical evaluation and shown to be biased when applied in the absence of additional information (Branch *et al.* 2011, Daan *et al.* 2011 and Carruthers *et al.*, 2012). As a consequence, a number of model-based methods have been proposed to assess data-poor stocks when a reliable catch time series is available, in addition to supplementary data, for example some knowledge of current depletion and/or information of the life-history of the species/stock, or similar species/stock.

The subsections that follow list a number of catch-only methods according to their data requirements and model complexity.

2.4.1 Catch classification method

Introduced by Froese and Kesner-Reyes (2002), this method involves examining the catch time series to classify the status of a stock/fishery according to five development stages: undeveloped, developing, fully exploited, overfished and collapsed. This method is based on the assumption that catches are initially low for a developing (and unregulated) fishery, rise until the fishery is fully exploited, then decline due to overfishing, and finally decline further until stock collapse.
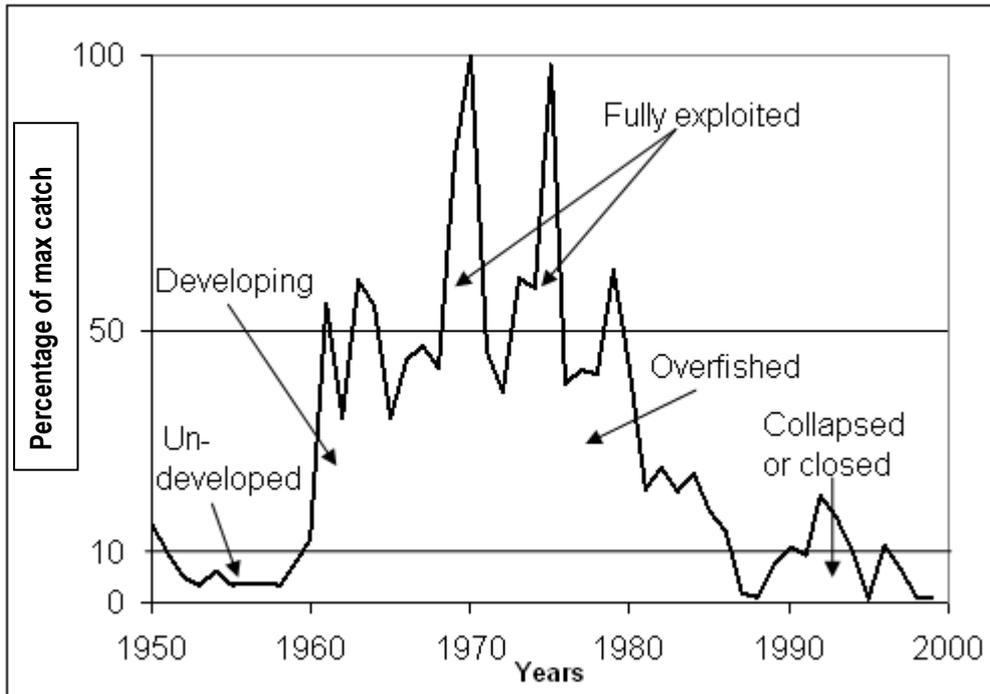
Figure 10: Transition phases of a typical fishery. This plot is copied from Froese and Kesner-Reyes (2002).

The criteria used to assign the different phases are:

1. Underdeveloped: $\qquad y < y(\max P), P < 0.1$

2. Developing: $\qquad y < y(\max P), 0.1 < P < 0.5$

3. Fully exploited: $\qquad P > 0.5$

4. Overfished: $\qquad y > y(\max P), 0.1 < P < 0.5$

5. Collapsed: $\qquad y > y(\max P), P < 0.1$

where P denotes the production expressed as a percentage of the maximum, max P, and $y(\max P)$ refers to the year at which max P occurs.

Assumptions: After the maximum catch is reached, the trend in catch is assumed reflect the trend in biomass. Furthermore, this method assumes that the fishery developed in the absence of catch/effort regulations and other effects (targeting, gear, market changes) that may affect the level of catch.

Input: A complete catch time series, C_y, from the start of the fishery.

Advantages: The method simplifies complex dynamics. Apart from a catch time series, no other data are required.

Disadvantages: The catch time series alone is not informative about stock productivity and size: total annual catches are influenced by factors other than the stock biomass. This method has been shown to give an overly pessimistic assessment of stock status.

Applications and Reviews:

- Froese and Kesner-Reyes (2002) classified the fishing status of over 900 species into undeveloped, developing, fully exploited, overfished and collapsed by investigated their catch time series.

- Worm *et al.* (2006) predicted that all commercially exploited stocks will have collapsed by 2048 according to stock status estimates based on this method of classification. Accordingly, a stock is classified as collapsed if the current catch is less than 10% of the historical maximum. However, the methodology used in this study has since elicited numerous rebuttals (Branch *et al* (2011, Daan *et al* (2011) and Carruthers *et al.* (2012)).

- Branch *et al*. (2011) applied this method to simulated catches fluctuating about a mean value to demonstrate that the method was biased toward assessing stocks as developing in early years and as collapsed in later years. This is because stocks can only be classified as developing before the maximum catch is achieved, and as over exploited or collapsed after the maximum catch. This method therefore excludes a more positive view of current stock status.

- Daan *et al*. (2011) argue that this method is both technically and conceptually flawed and that any predictions about stock status derived from it represent flawed prophecies.

- Carruthers *et al.* (2012) simulation tested this method for a number of fisheries development and overfishing scenarios, and found that it was error-prone and generally provided overly pessimistic estimates of stock status. According to this study, the method misclassified a stock two-thirds of the time.

- Froese *et al.* (2012) responded to the previous three studies, showing that the applied simulations were not appropriate for testing of this method, that maximum catches are highly correlated with MSY, and that the biomass trends of fully assessed stocks in the Northeast Atlantic are consistent with the trends derived from catch classification of these stocks. Furthermore, they also stress that this method was developed to better understand trends in the global catch data provided by the FAO, and not for application in single stock management.

2.4.2   Catch-based MSY

Biomass dynamic models may be applied when an index of abundance is available. However, a data-poor application which relies only on a catch time series, in addition to qualitative information regarding the resilience of the stock, has been developed by Martell and Froese (2013) to obtain estimates of MSY. Termed a Catch-MSY method, this employs the Schaefer form of the surplus production function where MSY is achieved when the biomass is reduced to half the virgin biomass, K, i.e. employing a fairly conservative production function (compared to, say, a Fox production function with $B_{MSY}/K = 0.37$).

The dynamics of the population is described by the Schaefer model:

$$B_{y+1} = B_y + rB_y\left(1 - \frac{B_y}{K}\right) - C_y \tag{2.37}$$

where B_y is the biomass at the beginning of year y, r is the intrinsic growth rate, K is the pre-exploitation equilibrium biomass, and C_y is the total catch (including discards) in year y.

In the absence of an index of abundance from which to estimate the model parameters, the input data consist only of a time series of total annual catches, in addition to prior distributions for model parameters, r and K, and depletion in the first and final year of the time series. The method involves randomly drawing r and K combinations from uniform distributions and assuming a Bernoulli distribution to accept/reject (r, K) combinations if the biomass in the final year falls inside/outside the range assumed for final depletion. Each viable (r, K) combination provides an associated estimate of MSY ($rK/4$ in terms of the Schaefer production model). The method relies on the premises that the observed catches are produced either by a large population with high K and low productivity, r, or alternatively a highly productive but small stock (high r, low K). For the case where the historical catches are too small to distinguish the level of productivity and size of the stock (the (r, K) combination), MSY is likely to be underestimated (Martell and Froese 2013).

Parameter prior distributions:
Fairly wide plausible ranges need to be defined for the model parameters, for r and K as well as initial and current depletion. The type of prior distribution adopted depends on the best available information for the stock under consideration. In the interest of generality, Martell and Froese (2013) propose the following default distributions.

1)   A uniform distribution is assumed for intrinsic growth rate r. Each stock is categorised according to one of four overlapping resilience groups:

- high resilience: $r \sim U[0.5, 1.5]$

- medium resilience: $r \sim U[0.2, 1]$

- low resilience: $r \sim U[0.05, 0.5]$

- very low resilience: $r \sim U[0.015, 0.1]$

2) A uniform distribution for the pre-exploitation biomass, K, is developed from the maximum historical catch:

$$K \sim U[\max(C_y), 100 \times \max(C_y)]$$

3) Uniform distributions for initial and final depletion are based on the catch time series:

Initial: $B_1 / K \sim U[0.5, 0.9]$ if $C_1 / \max(C_y) < 0.5$

$B_1 / K \sim U[0.3, 0.6]$ if $C_1 / \max(C_y) \geq 0.5$

Final: $B_n / K \sim U[0.3, 0.7]$ if $C_n / \max(C_y) > 0.5$

$B_n / K \sim U[0.01, 0.4]$ if $C_n / \max(C_y) \leq 0.5$

Input: A catch time-series, C_y, and information regarding the resilience of the stock to construct a prior for *r*.

Advantages:

Martell and Froese (2010) show that only a surprisingly narrow range of (r, K) combinations result in viable stock biomass trajectories. The Catch-MSY method is well suited to provide preliminary estimates and distributions of MSY in cases when abundance data are lacking. From a management point of view, these MSY distributions can potentially be incorporated in simple harvest control rules based on some lower percentile of the interval.

Disadvantages:

The reliability of estimates for MSY depends on the plausibility of the prior distributions chosen for *r* and *K* and initial and final depletion, all of which require careful consideration. Knowledge of the distribution for MSY is less valuable from a stock management point of view than the distribution assumed for depletion, which is required as an input for this method. Data-poor stocks are typically associated with limited monitoring of catches and poorly estimated (and often short) catch time series with little information about stock productivity and size. Furthermore, this method is not recommended for developing fisheries, or lightly fished stocks, as the associated time series of catches will not be informative.

- Martell and Froese (2010) applied this method to 146 stocks worldwide for which independent MSY estimates, based on comprehensive stocks assessments, were available and found good agreement with their results: most of the catch-MSY estimates fell within a range of 0.5 to 1.5 of the independent estimate.

- Simulation results from a comparative study conducted by Rosenberg *et al.* (2014) indicate that catch-MSY performed the best of the catch-only methods considered (panel regression, catch-MSY, COM-SIR and SSCOM) across the majority of scenarios tested. In particular, catch-MSY was better able to estimate stock status over short time scales than the other methods evaluated.

2.4.3   Catch-Only Model (COM)

Based on a combination of a Schaefer biomass dynamic and a logistic effort model, this Bayesian approach was developed by Vasconcellos and Cochrane (2005) to predict catches over time under assumptions about effort trends, and use this as a basis to estimate the values of parameters of the Schaefer model. Based on assumptions about temporal trends in fishing effort, this method incorporates only a catch time series in the likelihood function to assess the status and dynamics of a stock. In an unregulated fishery, trends in historical catches are primarily a reflection of changes in the fishing effort as the fishery evolves: there is typically a rapid increase in effort during the developing stage, stabilising as the fishery reaches maturity, which is followed by a decrease in effort once the senescent stage is reached. This method is therefore applicable to data-poor fisheries that were/are not under any formal management (i.e. no external effort/catch controls), or that portion of the catch time series before effective management was introduced.

In terms of a linear effort model, fishing effort, E_y, is assumed to increase linearly from the start of the fishery:

$$E_{y+1} = E_y + xE_0 \tag{2.38}$$

where E_0 is the effort at the first year of the fishery, and x is a multiplier that defines the rate of increase in effort over time.

When employing a logistic-like model, the annual fishing effort is assumed to increase from the start of the fishery until the bionomic equilibrium is reached:

$$E_{y+1} = E_y[1 + x(\frac{B_y}{B_{BE}} - 1)] \tag{2.39}$$

where $B_{BE} = aK$ denotes the bionomic equilibrium, given as a proportion of the pre-exploitation biomass, K, and B_y is the stock biomass in year y.

A Schaefer model is used to describe the stock dynamics:

$$B_{y+1} = B_y + rB_y(1 - \frac{B_y}{K}) - C_y \qquad (2.40)$$

where r is the intrinsic growth rate, and C_y is the observed catch in year y.

Finally, the standard assumption is made that the estimated catch in any year is directly proportional to the product of biomass and effort so that:

$$\widehat{C}_y = qE_y B_y \qquad (2.41)$$

where q is the constant of proportionality, so that substituting (2.39) and (2.40) into (2.41) gives:

$$\widehat{C}_{y+1} = qE_y[1 + x(\frac{B_y}{aK} - 1)][B_y + rB_y(1 - \frac{B_y}{K}) - C_y] \qquad (2.42)$$

Assuming that the stock was at carrying capacity at the start of the fishery ($B_0 = K$), and that expected and observed catches are identical for the first year $qE_0 = C_0 / K$ at the start of the time series. Under these circumstances, the number of estimable parameters are reduced to three when assuming a linear effort model (r, K and x), or four when using the logistic model (r, K, x and a). The negative of the log-likelihood function to be minimised is:

$$-\ln L = \sum_{y=1}^{n} \left[(\ln C_y - \ln \widehat{C}_y)^2 / 2\sigma^2 + \ln(\sigma C_y \sqrt{2\pi}) \right] \qquad (2.43)$$

where n is the number of years in the catch time series, C_y and $\widehat{C}_y$ are the observed expected catch for year y, and σ is the coefficient of variation. Vasconcellos and Cochrane (2005) used a Markov Chain Monte Carlo (MCMC) method to obtain posterior probability distributions of model parameters.

Assumptions:

The main assumption is that the fishery is unregulated so that increases in fishing effort were not constrained given the absence of management restrictions. Furthermore, the effort dynamics are assumed to follow the model. The catch time series is assumed to be complete with data from the start

of the fishery when the stock was at virgin biomass. Furthermore, catchability is assumed to remain constant over time, i.e. no increase in q associated with advancements in technology.

Input:

C_y over the period when the fishery was largely unregulated. In addition, information about the dynamics of the stock/species, or similar stocks/species, is required to construct priors for parameters.

Advantages:

This method, based only on catch data and prior information about the dynamics of similar species/stocks, provides posterior probability distributions of population model parameters and fisheries management quantities such as F / F_{MSY} and B / B_{MSY}.

Disadvantages:

The main assumption is that the time series of catches contain information on both fishing effort and stock biomass. This assumption will only hold for a complete catch time series that includes data from the start of exploitation, and throughout the developing, maturity and senescent phases of the fishery. This method only applies if this development of the fishery evolved in the absence of effective management. A reliable record of total removals is essential.

Applications and reviews:

- Vasconcellos and Cochrane (2005) applied this method to historical catch time series for two data-rich stocks, Atlantic yellowfin tuna and Namibian hake, for the periods when these fisheries were unregulated. They compared posterior distributions with the "true" parameter values (obtained from full stock assessments) for both the linear and logistic effort models. In the case of yellowfin tuna, the logistic effort model gave a worse fit to the catch data, but resulted in better parameter estimates. In contrast, the simpler linear model gave better parameter estimates than the logistic model for Namibian hake. In both cases, their model had a tendency to over-estimate both r and K. Based on their study, Vasconcellos and Cochrane warn that catch data can provide meaningful results only when combined with prior information about the dynamics of similar species/stocks.

- Rosenberg *et al.* (2014) used a Bayesian algorithm, Sampling Importance Resampling (SIR), to obtain posterior parameter distributions for the catch-only model (COM-SIR). They simulation tested performance by categorising stocks in terms of four resilience groups: very low, low, medium and high resilience and assigning prior distributions to r and K. Their analysis confirms that provisional estimates of stock status can be obtained from catch data in combination with supporting information on the dynamics of the fishery and productivity of

the stock: more informative priors for r and K would result in better estimates. Harvest dynamics was the main variable that effected performance, emphasising the importance of establishing an accurate catch time series that incorporates discards.

2.4.4   State-Space Catch-only Model (SSCOM)

Developed by Thorson *et al.* (2013), SSCOM combines population biomass and effort dynamics models in a coupled system similar to the COM-SIR model of Vasconcellos and Cochrane (2005) described above. Stochasticity is incorporated by adding random process error to the biomass and effort dynamics. In addition, process error is added to the model-predicted catches to allow for time-varying catchability. A state-space estimation procedure is employed to integrate over these random effects thereby reducing the number of estimable parameters. A Bayesian approach is adopted where posterior probability distributions for model parameters are generated using Markov Chain Monte Carlo (MCMC). The model assumes that a complete time series of catches are available from the start of the fishery when the stock biomass was at the pre-exploitation equilibrium biomass and that fishing mortality followed predictable dynamics over time.

Model:

The population dynamics is assumed to be described by a Schaefer[8] surplus production model:

$$B_{y+1} = \left[B_y + rB_y \left(1 - \frac{B_y}{K} \right) - C_y \right] \exp(\varepsilon_y)$$

(2.44)

where r is the intrinsic growth rate, K is the pre-exploitation biomass (or carrying capacity), B_y and C_y are the predicted biomass and observed catch, respectively ,for year y , and $\varepsilon_y \sim N(0, \sigma_\varepsilon^2)$ reflect the fluctuations about the model-predicted biomass. The biomass is assumed to be at the deterministic equilibrium at the start of the assessment period so that $B_0 = K$.

Let B_{BE} denote the equilibrium biomass below which an increase in fishing effort will result in a loss of profit (the bionomic equilibrium):

$$B_{BE} = aK / 2$$

(2.45)

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[8] Other forms of the production function, such as a Fox or Pella-Tomlinson, may be substituted if a skew production function is desired.

where $K/2$ corresponds to the biomass at which the sustainable yield is maximised according to equation (2.44), i.e. MSYL, and a is the fraction of MSYL at which the bionomic equilibrium occurs for the fishery.

The effort dynamics (the change in fishing mortality as a function of biomass) is assumed to be described by the two-parameter function[9]:

$$E_{y+1} = E_y \left(\frac{B_y}{aK/2} \right)^x \exp(\tau_y) \tag{2.46}$$

where E_y is the estimated fishing effort for year y, x denotes the rate at which effort enters and exits the fishery, and $\tau_y \sim N(0, \sigma_\tau^2)$ denotes the associated process error.

The expected catch, $\widehat{C}_y$, in any given year is assumed to be directly proportional to the population biomass and fishing effort (equations (2.44) and (2.46)):

$$\widehat{C}_y = qE_yB_y \exp(\omega_y) \tag{2.47}$$

where q is the constant of proportionality, or catchability coefficient, and $\omega_y \sim N(0, \sigma_\omega^2)$ reflect the annual fluctuations in catchability. Note that q is set equal to be 1 as it is confounded with the scale of E_y.

All process error terms (ε_y, τ_y and ω_y) are assumed to be independently and normally distributed about the logarithms of the predicted population biomass, effort and catch for each year. For simplicity, it is further assumed that all error terms have the same variance such that $\sigma_\varepsilon = \sigma_\tau = \sigma_\omega$.

Prior distributions for the model parameters are updated by computing the associated likelihood:

$$L = \frac{1}{\sqrt{2\pi\sigma_\omega^2}} \exp\left[\frac{(\ln C_y - \ln \widehat{C}_y)^2}{2\sigma_\omega^2} \right] \tag{2.48}$$

where L denotes the likelihood and C_y and $\widehat{C}_y$ are the observed and predicted catch, respectively, for year y.

---

[9] Other models to describe the effort dynamics, such as those proposed in Section 2.4.3, can also be used.

Input: A complete catch time series, C_y, in addition to prior information on r, K, a, x and E_1.

Assumptions: The population biomass is assumed to be at carrying capacity at the start of the assessment period. Fishing effort is assumed to follow predictable dynamics. The catch time series is assumed to equal total removals, including bycatch. Catchability is assumed to vary randomly with time, i.e. without any systematic increase in q associated with advancements in technology.

Advantages: Random fluctuations in catchability are incorporated in this model. Unlike DB-SRA, no prior distribution is required for final depletion.

Disadvantages: This is the most complex of the models listed in this section and requires a high level of statistical expertise to understand and apply. A complete time series of catches, with adequate contrast, is required: developing fisheries with increasing catch time series cannot provide information about relative biomass or MSY. Incorrectly specified priors will result in poor estimates of population biomass. This biomass-effort model is not applicable to (non-target) bycatch species (fishing effort is a function of the bioeconomic equilibrium of the target species).

Reviews:

- Thorson *et al.* (2013) demonstrate how this method could be used for data-poor stock assessment by applying SSCOM to catch data for eight groundfish stocks from the West Coast of the US. They show how meta-analyses of assessed (data-rich) stocks can generate priors for the effort dynamics parameters, a and x. Results (in terms of coupled stock status and effort trajectories) are compared to DB-SRA estimates when a prior for current depletion is specified. Their results show that a prior on final depletion is required to improve performance when confronted with high levels of process error. SSCOM was able to construct strong posterior probability distributions from weak prior distributions for the biological parameters, r and K, and hence for MSY. However, the catch data were not able to update the prior distributions for the effort model parameters further, as these were already highly informed via meta-analysis. They list several reasons where SSCOM failed to reconstruct biomass trajectories accurately: e.g. not sufficient contrast in the catch data (e.g. an increasing time-series), or when the catch data violate the biomass and/or effort model assumptions (e.g. bycatch species).
- Rosenberg *et al.* (2014) conducted a simulation study to compare the performances of different catch-only models, including SSCOM, in a consistent manner across a range of scenarios. They show that much simpler methods such as Catch-MSY (Section 2.4.2) perform

better than SSCOM when confronted with short catch time series. The study emphasises the need for accurate information on fishing effort and total removals.

2.4.5 Depletion-Based Stock Reduction Analysis (DB-SRA)

Developed by Dick and MaCall (2011), this method generates probability distributions for sustainable yield and biomass management reference points for data-poor fisheries. It is a combination of Depletion-Corrected Average Catch (DCAC) and stochastic Stock-Reduction Analysis (SRA, Kimura *et al.* 1984, Walters *et al.* 2006).

The model:

This model incorporates a Pella-Tomlinson production function which allows for the maximum of the sustainable yield curve to occur anywhere between zero and the pre-exploitation biomass, B_0. Production is assumed to be lagged by a time equal to the age-at-maturity. A knife-edged function (by age) is assumed for maturity and recruitment to the fishery.

The depletion-based SRA is based on a delay-difference model of the form:

$$B_{y+1} = B_y + P(B_{y-t_m}) - C_y \tag{2.49}$$

where B_y is the biomass at the start of year, y, t_m is the age-at-maturity, C_y is the total catch (including discards), assumed to be taken by a single fishery during year y, and P is the latent annual production based on the mature biomass in year $y - t_m$, adapted from the generalized production model proposed by Fletcher (1978):

$$P(B_{y-t_m}) = g \times MSY \left(\frac{B_{y-t_m}}{K} \right) \left[1 - \left(\frac{B_{y-t_m}}{K} \right)^{n-1} \right] \tag{2.50}$$

where K is the pre-exploitation biomass (or carrying capacity), MSY is the maximum sustainable yield, $n > 0$ determines the shape of the production curve, and $g = \dfrac{n^{n/(n-1)}}{n-1}$ is a numerical quantity dependent on n.

In term of the general Pella-Tomlinson-Fletcher production function, the maximum, *MSYL*, is located at:

$$MSYL = n^{\frac{1}{n-1}}$$

Special cases are:

$$n = 1: \quad MSYL = e^{-1} = 0.37$$

$$n = 2: \quad MSYL = n^{\frac{1}{n-1}} = 0.5$$

corresponding to the Fox and Schaefer forms of the production function respectively.

To avoid the occurrence of unrealistically high productivity at low biomass levels, Dick and MacCall (2011) developed a hybrid model in which the generalised production model described by equation (2.50) is used when the biomass is above a join-point, B_{join}. Below this point, a Schaefer surplus production model applies:

$$P(B_{y-t_m} < B_{join}) = B_{y-t_m} \left[\frac{P(B_{join})}{B_{join}} + c(B_{y-t_m} - B_{join}) \right] \tag{2.51}$$

where c is the production-to-biomass ratio at the join-point, given by:

$$c = (1-n)g \times MSY \times B_{join}^{n-2} K^{-n} \tag{2.52}$$

and B_{join} is given by:

$$B_{join} / K = \begin{cases} 0.5MSYL & \text{for} & MSYL < 0.3 \\ 0.75MSYL - 0.075 & \text{for} & 0.3 < MSYL < 0.5 \\ MSYL & \text{for} & MSYL > 0.5 \end{cases} \tag{2.53}$$

Given an estimate for F_{MSY}, the maximum sustainable yield can be estimated:

$$MSY = (1 - \exp(-Z_{MSY})) \frac{F_{MSY}}{Z_{MSY}} MSYL \times K \tag{2.54}$$

where $Z_{MSY} = M + F_{MSY}$ is the total mortality rate when fishing at MSY, and

K is the pre-exploitation biomass that would lead to a current depletion of $1 - \Delta$.

Input:

The data requirements of this method are a complete time series of annual catches from the beginning of the exploitation period, C_y, and estimates/distributions for age-at-maturity, t_m, the F_{MSY}/M ratio, the maximum sustainable yield level, $MSYL$, the natural mortality rate, M, as well as the current depletion, specified in terms of $(1 - \Delta)$.

Advantages:

Apart from a reliable catch time series, this method requires no additional data (such as an index of abundance) other than the specification of probability distributions of life-history parameters and current depletion. This method outputs posterior distributions for sustainable yield and MSY which can serve as the basis for on-going catch recommendations: the lower percentiles (rather than medians) could well be used to provide precautionary management advice for data-poor stocks.

Disadvantages:

This method is not suitable for short-lived species that are prone to large recruitment fluctuations. This method relies on a complete and reliable catch time series - this can be a major disadvantage: catches at the beginning of the fishery are often poorly documented. The definition of plausible prior distributions for model parameters can be tricky, especially for current depletion which is difficult to estimate reliably, even for data-rich stocks. The comparative complexity of this method renders it less intuitive than the simpler catch-only methods described in the preceding sections.

Applications and reviews:

- This method was evaluated a Review Panel in 2011 organised by the National Marine Fisheries Services (NMFS 2011). The Panel agreed that application of a hybrid productive function, described by equations (2.51) to (2.53), adequately deals with the undesirable high productivity at low biomass levels associated with the Pella-Tomlinson function. However, the Panel suggested that other functional forms need to be investigated, particularly for highly depleted stocks that would be sensitive to changes in the model dynamics at low biomass levels. The sustainable yield estimates obtained by this method were generally less than the "true" MSY. This method proved to be robust across a wide range of scenarios and biological parameter choices. However, the simulation study conducted by Wenzel and Punt (2011) showed that DB-SRA estimates are highly sensitive to the prior distribution assumed for final depletion (expressed in terms of $1 - \Delta$): a positively-biased estimate of depletion (such that the actual resource biomass is lower than that assumed in the model), may cause the estimates of MSY to exceed the "true" values. NMFS (2011) suggested that a Productivity and Susceptibility Assessment (PSA) be performed to assist in developing prior distributions for current depletion – this has recently been conducted by Cope *et al.* (In press). The Panel advised that further investigation is required regarding the bias correction necessary to render this method risk-neutral.

- Dick and MacCall (2011) compared the DB-SRA outputs with estimates from data-rich assessments for groundfish stocks on the west coast of the United States. Given a reliable catch time series, they found that useful information can be gained despite little knowledge of current biomass: the progressive reduction in abundance allows for the separation of yield that

the stock can sustain indefinitely and the non-sustainable "windfall" portion. Unlike other catch-only assessment methods such as SS-COM, Dick and MacCall showed that DB-SRA worked well in situations where the stock biomass has declined almost monotonically.

- Carruthers *et al.* (2014) evaluated the performance of DB-SRA by means of simulation testing. Compared to other catch-only methods tested, DB-SRA led to the best performance given a good estimate of depletion, which is unlikely to be available for data-poor stocks. Performance was affected by bias in the input for current depletion.

2.4.6 Catch-curve stock-reduction analysis (CC-SRA)

Developed by Thorson and Cope (2014), this approach is based on stock reduction analysis (SRA) and incorporates age-composition data from the most recent year(s) to allow for the estimation of a catch-curve and an associated fishing mortality rate(s). The advantage of this method over other stock-reduction approaches, such as DB-SRA, is that no prior assumptions regarding final depletion are required.

Using age-structured population dynamics, the numbers-at-age, $N_{a,y}$, for age a and year y are given by:

$$N_{a,y} = \begin{cases} R_y & \text{if } a = 0 \\ N_{a-1,y-1} \exp(-(Z_{a,y-1})) & \text{if } a > 0 \end{cases} \tag{2.55}$$

where R_y are the number of recruits for year y and $Z_{a,y} = M + S_a F_y$ denotes the total mortality rate, where M is the natural mortality rate, S_a is the age-specific fishing selectivity (approximated by a logistic function with maximum of 1.0), and F_y is the fishing mortality rate at the age of maximum selectivity.

The spawning biomass in year y is given by:

$$B_y^{sp} = \sum_{a=0}^{a_{\max}} w_a m_a N_{a,y} \tag{2.56}$$

where w_a denotes the weight-at-age and m_a the maturity-at-age.

The total number of fish caught of age a in year y is approximated by the Baranov equation:

$$C_{a,y} = N_{a,y} \frac{S_a F_y}{Z_{a,y}} (1 - \exp(-Z_{a,y})) \tag{2.57}$$

Assuming a Beverton-Holt stock recruitment relationship with a lognormal error distribution, the number of recruits at the start of year y is given by:

$$\ln R_y \sim N\left(\ln \frac{4hR_0 B_y^{sp}}{B_0^{sp}(1-h) + B_y^{sp}(5h-1)} - \frac{\sigma_R^2}{2}, \sigma_R^2 \right) \tag{2.58}$$

where h denotes the steepness of the stock-recruitment relationship (the degree of compensation) and σ_R is the standard deviation of the log-residuals, assumed known.

The numbers-at-age at the beginning of the assessment period are assumed to lognormally distributed about the unfished numbers:

$$N_{a,1} \sim N(\ln(R_0 \exp(-aM)) - \sigma_R^2 / 2, \sigma_R^2) \tag{2.59}$$

Lastly, a multinomial distribution is assumed for the age-composition data:

$$A_y \sim Multinomial(C_{a,y}, n_{comp}) \tag{2.60}$$

where n_{comp} denotes the number of age-composition samples.

The model parameters, R_y, h, M, F_y and the fishing selectivity parameters are estimated using maximum penalized likelihood.

Input: A complete catch time series, C_y, and age-composition data for the final year(s). In addition, prior information about the steepness parameter, h, and natural mortality, M.

Assumptions: The abundance-at-age at the beginning of the assessment period is assumed to be approximately the same as in the unfished state. Population weight-at-age, w_a, and maturity-at-age m_a are assumed to be known without error. Fishing selectivity is assumed to be asymptotic and natural mortality is assumed to be constant over all ages and years.

Advantages: This method offers a data-poor assessment technique that combines compositional and catch time series data. It allows for time-varying fishing mortality. No assumption regarding final biomass is required. CC-SRA allows for rapid data collection of compositional data, without requiring data collection from historical periods, allowing fishery managers to prioritize which stocks to assess, and then collect necessary data (unlike index-based methods, which generally require continuous data records from historical periods).

Disadvantages: CC-SRA requires the assumption that selectivity is asymptotic, and offers no obvious way to diagnose whether this assumption is correct. The model has not been tested on real-world assessment data, and its performance in these cases is unknown. Compositional data is often more ambiguous to interpret than index data, due to difficulties when standardizing or estimating its effective sample size. This may mean that CC-SRA is more dependent upon modeller assumptions than index-based data-poor methods.

Applications and reviews:

- Thorson and Cope (2014) show that CC-SRA gives unbiased estimates of fishing mortality when recruitment variability is low or moderate. They recommend CC-SRA as a data-poor assessment method that incorporates age-composition data in recent years.

- It is currently being explored using real-world data by Cope and Thorson (unpublished results).

2.4.7   Catch-based Harvest Control Rules (C-HCRs)

Both methods that follow rely on estimates (distributions) of stock status to parameterise the control rule. Wetzel and Punt (2011) point out that choosing a distribution for (relative) depletion is a major drawback of these methods: if sufficient data were available to estimate the level of depletion, then the stock would not be considered data-poor. In the absence of regular updates of stock assessments to provide estimates of stock depletion, the catch-based HCRs that follow are effectively constant catch rules. With no feedback mechanism, this type of HCR requires thorough simulation testing to tune control parameters to ensure adequately risk-averse performance under high levels of uncertainty about stock status.

2.4.7.1   Depletion Adjusted Catch Scalar (DACS) HCR

This simple approach provides an estimate of sustainable catch when only catch data are available. It is based on the average historical catch during a time period during which the stock is believed to have been stable, i.e. a period over which there is no evidence of a declining biomass trend. The target catch for the next year is given by (Berkson *et al.* 2011):

$$DACS = s / (y_2 - y_1 + 1) \sum_{y=y_1}^{y_2} C_y \qquad (2.61)$$

where y_1 and y_2 are the years that span a period of stable historical catches during which the stock is considered to have been near a sustainable equilibrium, and s is the scalar multiplier that reflects the perceived level of stock depletion, e.g., $s \propto B / B_{MSY}$. For data-poor stocks lacking a complete catch time series dating back to the start of the fishery, the target catch is based on a recent average catch.

Input:

The catch time series, C_y , and information (expert judgement) about stock status.

Assumptions:

The main assumption is that the average historic catch is a true reflection of the sustainable yield of the stock. This assumption holds only if the period of stable catches coincided with stable fishing

effort and stock biomass. Furthermore, the method relies on the assumption that stock status can be inferred reliably from qualitative information and/or expert judgement.

Advantages: This method is simple, intuitive, and easy to understand and implement. It is suitable for the provision of short-term (stop-gap) catch advice.

Disadvantages:

Catch data from all developmental stages of the fishery are required to be able to distinguish a period when the stock was stable and catches were sustainable. Judging stock-status is difficult, particularly when data are limited. The suggested scalar multipliers are somewhat arbitrary and conservative (to account for high levels of uncertainty) and could lead to substantial underutilisation of a stock. There is no feed-back control feature embedded in this rule to self-correct if the choice of control parameters was wrong. This method does not present a long-term solution for stock management.

Reviews and applications:

- This method was proposed by Restrepo *et al.* (1998) to advise catch targets and limits for US fisheries given in the National Standard 1 of the MSA for those stocks that lacked sufficient data to enable quantitative assessments to be conducted. Three scalar multipliers were proposed in accordance to the perceived status of the stock: 0.25 if the stock is believed to be depleted below the minimum stock size threshold, 0.75 if the stock was believed to above MSY level, and 0.5 between the two thresholds. Based on simulation studies, the default acceptable biological catch (ABC) for data-poor stocks was set to 0.75 of the recent average catch by the North Pacific Fishery Management Council (PFMC) (see Appendix A.1).

- Berkson *et al.* (2011) reviewed the Restrepo approach for stocks for which the reliable catch data only (ORCS) method is used. They noted that the method would not be suitable for lightly fished stocks as the control rule excludes the possibility of future catches exceeding those taken in the past. They suggest that fewer data and shorter catch time series would necessitate a reduction in the scalar multiplier to account for increased levels of uncertainty. Furthermore, a Bayesian approach is recommended that incorporates prior knowledge on stock status in a statistically defensible manner. The ORCS Working Group emphasise that this method is intended as a "sort-term fix" until additional data are collected.

- New Zealand (NZHSS 2011) applies a similar method to estimate maximum constant yield (MCY[10]) for data-poor stocks, but here the scalar multiplier is based on natural mortality: $s = 1$ when the natural mortality rate of the stock is believed to be very low ($M < 0.05$),

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[10] Maximum Constant Yield (MCY) "is the maximum sustainable yield that can be produced over a long term by taking the same catch year after year, with little risk of stock collapse" (NZHSS 2011). In New Zealand, MCY is used as a proxy for static MSY when accounting for the dynamic effects of the stock.

decreasing to $s = 0.6$ as M increases to 0.35 or above. The scalar multiplier is a measure of the natural variability of the stock biomass: the greater the variability of stock biomass, the lower the value of s needs to be.

- Carruthers *et al.* (2014) evaluated the performances of DACS and compared its performance with other data-poor methods within a Management Strategy Evaluation (MSE) framework. With no feedback control mechanism, this average catch method performed the worst of all the methods which they simulation tested. According to their simulation results, this type of HCR led to a high probability stock over-exploitation and was shown to be unsuitable for stock-rebuilding purposes.

2.4.7.2 Shepherd's Hang Over TAC (SHOT) HCR

Termed Shepherd's Hang Over TAC (SHOT), Shepherd (1984) developed this simple method to generate catch advice when only annual catches are available. Assuming that fishing mortality remains constant over the projection period, the status quo catch can be approximated by the weighted average of the previous year's catch and the production due to new recruits:

$$C_{SQ} = (1 - \tilde{F})C_y + \tilde{F}P_y \qquad (2.62)$$

where C_{SQ} is the status quo catch, C_y is the total catch taken in year y, P_y is the stock production from new recruits in year y, and $\tilde{F}$ denotes the catch/biomass ratio.

If only a catch time series is available, and assuming constant recruitment, the status quo catch, C_{SQ}, can be expressed as a weighted average of the previous year's catch and the historic average (Shepherd 1984):

$$C_{SQ} = (1 - \tilde{F})C_y + \tilde{F} \ \overline{C} \qquad (2.63)$$

where $\overline{C}$ is the average historic catch taken over n years. When assuming near constant fishing mortality, $\tilde{F}$ can be estimated by regression of C_{y+1} on C_y. Applied over a sufficiently long time-period, the status quo catch will eventually converge to the average catch.

Input: A catch time series, C_y.

Assumptions: Recruitment is assumed to be near constant and the future fishing mortality is assumed to remain unchanged (i.e. status quo is maintained).

Advantages: SHOT is a simple method for estimating a status quo catch when only catch data are available.

Disadvantages: The catch-only application of the SHOT method is not applicable to declining stocks or stocks with high recruitment fluctuations.

Applications and Reviews:
- The ICES Working Group on Methods of Fish Assessments ICES (1984) compared the performance of the SHOT with the more complex DROP and DOPE methods, developed by Deriso (1980), Roff (1983) and Pope (1984), on three simulated stocks:
  - Stock 1 with high recruitment and low fishing effort variations,
  - Stock 2 with moderate recruitment and low fishing effort variations, and
  - Stock 3 with low recruitment and high fishing effort variations.

  SHOP, DROP and DOPE were also tested on data from two real stocks: Georges Bank scallop and Baltic herring. Based on these simulation studies, the simple SHOT method performed best when recruitment variability was low, while the more complex DROP and DOPE methods are preferred when confronted with high levels of recruitment variability. However, when fluctuations in effort dominated the population dynamics, the SHOT method performed best. The Working Group (ICES 1984) concluded that this shortcut method may be useful to estimate status quo catches when more complex methods cannot be applied due to sparse data; while they may be useful for short-term forecasting, they cannot be used to evaluate the long-term management consequences.

2.4.7.3 Depletion-Corrected Average Catch (DCAC) HCR

Developed by MacCall (2009) for application to data-poor stocks, this method is derived from the potential yield formula and provides a moderately high yield estimate that is likely to be sustainable (though is typically less than MSY). This method is applicable to long-lived species with natural mortality rates less than 0.2yr^{-1}.

Unlike the average catch method which requires catch data from a period when the stock was stable, this method incorporates the catch time series (which need not go back as far as the start of the

fishery) and accounts for the change in stock biomass over this time period. The method involves dividing the catch series into a sustainable yield component and an unsustainable "windfall" component corresponding to the initial reduction in stock biomass, expressed as a "windfall ratio". The DCAC is calculated as the cumulative catches divided by the number of years in the time series and this "windfall ration". The resultant estimate for sustainable yield should be less than MSY.

Specifically, the depletion-corrected average catch is given by:

$$DCAC = \frac{\sum C_y}{n + W/Y_{pot}} \qquad (2.64)$$

where W is the change in biomass from the first year (B_{FYR}) to the most recent year (B_{LYR}) in the catch time series denoted by $\Delta B_0 = (B_{FYR} - B_{LYR})$, and Y_{pot} is the potential sustainable yield. The "windfall ratio", W/Y_{pot} is then given by:

$$\frac{\Delta B_0}{MSYL \times c \times M \times B_0} \qquad (2.65)$$

where B_0 is the pre-exploitation (unfished) biomass, $MSYL$ is the biomass level (relative to B_0) corresponding to MSY, and $c = F_{MSY}/M$ is a tuning parameter that links the natural mortality, M, and the fishing mortality rate associated with MSY.

After elimination of the unknown quantity, B_0, and substitution into equation (2.64), the estimate of sustainable yield is given by:

$$DCAC = \frac{\sum C_y}{n + \Delta / (MSYL \times c \times M)} \qquad (2.66)$$

While an estimate of the DCAC can readily be obtained given point estimates for each of the parameters, a Monte-Carlo approach is required to account for uncertainty: posterior probability distributions are generated by randomly sampling parameter values from pre-specified prior distributions. For this extension of the method, prior distributions must be specified for Δ, c, $MSYL$ and M.

For the case where stock status has remained unchanged, Δ is zero and the sustainable yield is equal to the historic average catch. However, if there has been a decrease in biomass, Δ will be positive and the estimate for sustainable yield will be less than the historic average catch.

Input:

Input data include a time series of total annual removals (landings plus discards) over an extended period (typically in excess of ten years) and estimates for the life-history parameters such as natural mortality rate, *M*, maximum sustainable yield level, MSYL, relative stock status, Δ, and an estimate of F_{MSY} (for the data-poor situation, the latter can be estimated by performing a per-recruit analysis).

Advantages:

The method is applicable in circumstances when a comprehensive time series of catch data are lacking. The DCAC is relatively robust to the misspecification of M and F_{MSY}/M .Uncertainty regarding model parameters can be incorporated explicitly by the definition prior distributions.

Disadvantages:

This method is not recommended for highly productive stocks with natural mortality rates exceeding about 0.2yr$^{-1:}$ the windfall ratio becomes negligible and the DCAC approaches the average catch with increasing *M*. MacCall (2009) warns that DCAC gives an estimate of yield that is likely to be sustainable only if the stock is maintained near levels of abundance experienced during the time period for which catch data are available. However, there are conditions under which the estimated yield may not be sustainable: for stocks that have experienced a large reduction in biomass in recent years, the estimated yield, while being sustainable over the historic period, will not be sustainable at low biomass levels. Therefore, DCAC is not suitable for generating catch advice for heavily depleted stocks that require rebuilding to previously productive levels.

Applications and reviews:

- Following a formal review of a variety of data-poor methods initiated by the National Marine Fisheries Services (NMFS 2011) in the US, the review panel found the performance of DCAC to be robust across a wide range of scenarios. Simulation testing showed that estimates were generally negatively biased in comparison to the true OFL (generally equivalent to the current yield when fishing at F_{MSY}). However, the DCAC estimates were found to be sensitive to the assumptions regarding Δ. In particular, if the estimate for Δ is below the true value, the DCAC is positively biased (larger than the true OFL). As such, the parameters estimates (distribution) that are used to compute the "windfall ratio" need careful consideration. Furthermore, if the stock biomass has declined after the period for which data are available, the estimate DCAC may no longer be sustainable. While it is not necessary to update the DCAC as it provides a one-time estimate of sustainable catch, effort should be directed to

updating and improving the catch time series and reviewing the prior distributions to accurately reflect the uncertainty about the input parameters.

- Wetzel and Punt (2011) conducted simulation studies to evaluate the performance of DCAC compared to DB-SRA and a data-poor application of Stock Synthesis (SS) (Cope 2013) based on catch data for US west coast flatfish and rockfish. In their study, DCAC resulted in harvest estimates that were lower than the true OFLs for flatfish and rockfish, even when life-history parameters were misspecified. However, while DCAC is fairly robust to misspecification of distributions for M and c, it was found to be highly sensitive to the assumed distribution for Δ. However, they suggest that prior information might be incorporated from assessed stocks with similar life-history traits to allow for inferences to be made about depletion. Their analysis also highlights the importance of performing multiple runs to examine the impact of different assumptions regarding prior distributions to determine the potential range of harvest levels under a variety of conditions.

- This method is applied to ICES Category 4 stocks (stocks with reliable catch time series) to determine suitable exploitation rates. Catch advice is derived by applying a 20% uncertainty cap to the DCAC (ICES 2012).

- Carruthers *et al.* (2014) evaluated this method for setting catch limits in data-poor fisheries and found that it performed well for long-lived species. However, because the DCAC is a proxy for MSY, this method is not suitable for stock rebuilding purposes (MacCall 2009) - the method therefore performed poorly when the initial stock size was low.

Catch-based methods	
Assumptions	The simplest catch-based methods assume that the trend in catch is proportional to the trend in biomass, with no effort restrictions or increase in fishing efficiency. The catch time series is generally assumed to be complete and representative of all the development stages of the fishery. The majority of the catch-based assessment methods rely on the assumption that current depletion is known.
Advantages	Catch time-series data are widely available for most fisheries. Assessment methods such as Catch-MSY, COM and SSCOM present flexible frameworks into which additional data, such as an index of relative abundance, can be incorporated, thereby facilitating the transition from data-poor to data-sufficient and to data-rich. The associated harvest control rules are simple and easy to understand, but, in the absence of supporting assessments, they are effectively constant-catch strategies.
Disadvantages	The catch time-series is basically not of itself informative about stock productivity and size. For data-poor fisheries, the total removals are not well known. Total catches are affected by changes in effort regulations, market demands and catchability, not only by abundance. These models are generally suitable only for long-lived low-productivity data-poor stocks for which biomass levels are driven by the production function rather than by recruitment variability. Harvest control rules incorporate no feedback about trends in biomass, and these rules need to be very conservative to satisfy biological risk criteria. Catch-only methods are suitable for short-term (interim) TAC advice only; longer periods require additional data (e.g. a reliable biomass index) becoming available. Comprehensive Management Strategy Evaluation (MSE) – a time-intensive overhead – should be implemented to demonstrate robustness of these simple catch-based assessment methods and control rules prior to their application.

Table 4: Summary of general assumptions and advantages/disadvantages associated with catch-based methods.

2.5 Index-type methods

More typically associated with data-moderate and data-rich stocks, index-based methods for generating catch advice require a reliable index of abundance to track trends in stock biomass, for example Namibian hake (Butterworth and Geromont 2001) and ICES Category 3 stocks (ICES 2012b). However, these methods can sometimes be applied to stocks that are considered data-poor, for example when confronted with a short survey or CPUE time series, or an indirect index of abundance as provided by the mean length data (see length-based methods).

2.5.1 An Index Method (AIM)

Developed by Rago (2008), this method fits a relationship between the index of abundance and the catch time series to estimate the catchability coefficient, q. It is based on a linear model of population growth to characterize the population response to varying levels of fishing mortality. Given an estimate for the catchability coefficient, the relative fishing mortality rate at which the population is likely to be stable can be approximated.

Model:
The current and lagged relative fishing mortality is given by:

$$relF_y^C = \frac{C_y}{(I_{y-1} + I_y + I_{y+1})/3}$$

and

$$relF_y^L = \frac{C_y}{(I_{y-2} + I_{y-1} + I_y)/3}$$

respectively, where C_y is the catch and I_y is the index of abundance for year y.

Assuming that the index of abundance is directly proportional to the stock biomass, so that $I_y = qB_y$ where q is the catchability coefficient, then the replacement ratio can be approximated by:

$$\Psi_y = \frac{I_y}{1/A \sum_{j=1}^{A} I_{y-j}}$$

When the replacement ratio is greater than one, the population is growing and vice versa.

The software is available from the NOAA Fisheries Toolbox [nft.nefsc.noaa.gov/AIM.html]

Input: Time series for the catch, C_y, and index of abundance, I_y.

Assumptions: The main assumptions are that the time series is a reliable index of stock biomass and represent current and future conditions and that the linear model describes the population dynamics.

Advantages: Given reliable time series with sufficient contrast and information content, this method can track biomass trends and is useful to construct reference points based on relative abundance indices and catches.

Disadvantages: This method does not give reliable estimates of stock status when confronted with poor data (short, or noisy, time series).

Applications and reviews:

- Miller *et al*. (2009) reviewed assessments of five data-poor stocks or stock complexes: the skate complex, deepsea red crab, Atlantic wolfish, scup and black seabass. These stocks either lack data or the data did not contain sufficient contrast or information. While AIM was able to tracks biomass trends, it could not reliably estimate stock status.

2.5.2 Surplus production models

These biomass dynamics models are the simplest and most widely used assessment models. The production function can take many forms of which the Schaefer (1954) model is the best known and most commonly applied. Given sufficient contrast in the catch and abundance index data, these assessment models can reliably estimate stock status and related management quantities such as MSY.

Method:

Under the assumption of deterministic dynamics, the resource biomass is modeled by:

$$B_{y+1} = B_y + f(B_y) - C_y \tag{2.67}$$

where B_y is the biomass for year y, C_y is the total catch for year y and $f(B_y)$ is the net growth function. A flexible form of the production function, developed by Pella and Tomlinson (1969), is assumed:

$$f(B_y) = rB_y \left[1 - \left(\frac{B_y}{K} \right)^\mu \right] \tag{2.68}$$

where r is the intrinsic growth rate, K is the pre-exploitation equilibrium biomass (or carrying capacity), and μ determines the shape of the production function: the Schaefer form of the growth function is obtained by setting $\mu = 1$ in equation (2.68), while the Fox form is obtained as $\mu \to 0$. Note that for the data-poor scenario, the shape parameter μ is unlikely to be estimable – rather, it is fixed, generally to some value between zero and one, depending on the value assumed for MSYL.

The catch is defined by:

$$C_y = qB_y E_y \tag{2.69}$$

where q is the catchability coefficient (effectively the multiplicative bias if the index reflects abundance in absolute terms), and E is the fishing effort for year y.

Assuming that the CPUE provides an index of abundance which is proportional to resource biomass, then:

$$I_y = C_y / E_y = qB_y \tag{2.70}$$

allows for the estimation of model the parameters r and K by fitting the model-predicted biomass to the index of abundance. Assuming a log-normal error distribution for that relationship, the negative of the log-likelihood (-ln L) is:

$$-\ln L = \sum_y \left[\ln \sigma + (\ln I_y - \ln(\hat{q}\hat{B}_y))^2 / 2\sigma^2 \right] \tag{2.71}$$

where the biomass is given by equation (2.67).

A Bayesian approach is recommended in situations where data are sparse, or the quality of the data is poor. For such cases, the specification of prior distributions for the model parameters r, K (or final depletion), q and σ is recommended.

Input: A catch time series, C_y, and a relative index of abundance, I_y, and, depending on the quality of the data, prior distributions for r, K (or final depletion), q and σ.

Assumptions: The main assumption is that the index of abundance is proportional to stock biomass and that the catchability coefficient is time-invariant. The initial biomass is generally assumed to be equal to the pre-exploitation biomass so that $K = B_0$ (Punt 1990).

Advantages: The Schaefer model is one of the simplest and most commonly used age-aggregated assessment models and has a proven track record. Given time series with sufficient contrast and information content, this method is able to reliably estimate stock-status and related management quantities, such as MSY (Ludwig and Walters 1985, Hilborn and Walters 1992).

Disadvantages: The reliability of the parameter estimates is dependent on the information content of the data. If there is limited contrast in the time series, then the model cannot distinguish between high r - low K, and low r - high K scenarios. The index (for example CPUE) may not be proportional to the biomass due, for example, to an undetected increase in the catchability coefficient.

Reviews and applications:

- These models have been widely used for the provision of management advice for data-rich stocks, for example Atlantic tuna stocks under ICCAT management.
- Ludwig and Walters (1985) showed that, given adequate data, biomass dynamics models outperform more complex models and generally gave good estimates of management parameters.
- Hilborn and Walters (1992) reviewed biomass dynamics models and warned that adequate contrast is required in the data to estimate stock status reliably.

2.5.3 Replacement Yield (RY) method

Developed by Brandão and Butterworth (2008), this model is a simplified form of the surplus production model described above and provides a one-time estimate of replacement yield which can be used as a basis for catch advice.

The dynamics of the stock is modelled by:

$$B_{y+1} = B_y + RY - C_y \tag{2.72}$$

where B_y is the biomass for year y, C_y is the total catch for year y and RY is the replacement yield (assumed to be constant over the period under consideration).

An estimate of RY is obtained by fitting the model to a survey or CPUE index of abundance. The likelihood is calculated assuming that the observed index values are log-normally distributed about their expected values. Contributions to the negative of the log-likelihood are given by equation (2.71) above.

Input: A catch time series, C_y, and an index of abundance, I_y. For a Bayesian analysis, prior distributions for B_1 and RY must be specified.

Assumptions: The index of abundance is assumed to be directly proportional to the biomass.

Advantages: This model generates a distribution for replacement yield that serves as a basis for catch advice. This simplified version of the surplus production model requires fewer assumptions to be made about r, K and μ.

Disadvantages: Unlike the surplus production models, this simplification does not provide estimates for management quantities such as *r*, *K* and MSY.

Reviews and applications:

Brandão and Butterworth (2013) applied this RY model to total annual catches and survey abundance estimates for the South African kingklip resource. Posterior distributions for replacement yield for both South and West coast stocks were generated. The medians of these distributions provided upper bounds for the catch limit recommendations. It was recommended that the catch limits be set at the 25th percentile of the posterior RY distribution to achieve the desired population growth.

2.5.4 Index-type Harvest Control Rules (I-HCRs)

For this type of rule, it is assumed that there is at least some index of abundance (I) available, be it a CPUE series which is reasonably comparable over time, or a survey series. It is further assumed that these data have reasonable information content and that the observation error is not too large. Based on these premises it can be assumed that any trend in the index of abundance is a fairly reliable indicator of trend in resource abundance. The idea underlying these empirical HCRs is that the catch advice each year is adjusted up or down from the previous year's catch depending on either the rate of increase or decrease in size of the resource as indicated by the index of abundance (e.g. CPUE), or the extent to which this index is above or below target level. The success of these rules depend on how much information relative to noise due to observation error, the data series contains, i.e. whether the HCRs are reacting to real trends in abundance or simply following noise. A few examples of index-based HCRs that have been simulation tested and/or applied are given below.

2.5.4.1 Index-adjusted status-quo HCR

ICES (2012b) propose this rule for Category 3 stocks when a reliable abundance index is available. Catch advice is based on a control rule that compares the most recent average of index values with the average of the preceding years. The catch for the next year is computed by adjusting the current catch with this ratio:

$$C_{y+1} = C_{y-1} \left(\frac{1/x \sum_{i=y-x}^{y-1} I_i}{1/(z-x) \sum_{y=y-z}^{y-x-1} I_i} \right) \tag{2.73}$$

where I_i is the index of abundance value for year i, x and $z > x$ are the number of years over which the recent and preceding survey values are respectively averaged, and C_{y-1} is an average recent catch.

The number of years over which the average is computed should take account of the expected interannual variability in the index. ICES (2012b) suggest values of 2 and 5 for x and z respectively; the average catch is computed over the most recent three years although a longer period may be required for long-lived species.

In addition, a 20% change limit (the catch advice is constrained to change by no more than 20%) and, if appropriate, a precautionary buffer (a multiplier of 0.8 on top of the change limit) is applied to the catch advice. The precautionary buffer is not applied when expert judgement determines that the stock is not reproductively impaired, and where there is evidence that the stock size is increasing or that the

level of exploitation has been substantially reduced (e.g. reduction in fishing effort in the main fishery where the stock is taken as a bycatch; ICES 2012b).

Input: A direct index of abundance, I_y, such as provided by CPUE or survey.

Advantages: This HCR generates stable catch advice and is suitable for stocks that are fully exploited.

Disadvantages: The HCR is not suitable for application to depleted stocks as the rule is not able to rebuild biomass levels satisfactorily.

Reviews and applications:
- ICES (2013) simulation tested this HCR (including variants that incorporated the variance of the surveys and smoothing) within a MSE framework and found that this HCR (and its variants) led to increased biological risk over time, and although it stabilises spawning stock biomass in the short-term (~5 years), it would not be considered precautionary in the medium- to long-term. They concluded that the main reason for this behaviour was the lack of a target in the rule.

2.5.4.2 Slope-type HCR

This HCR is similar to the one implemented for the data-rich Namibian hake fishery (Butterworth and Geromont 2001). The catch advice for the next year is given by:

$$C_{y+1} = C_y(1 + \lambda s_y) \tag{2.74}$$

where C_y is the observed catch for year y, λ is a control parameter that reflects how strongly the catch advice is adjusted in response to the perceived trend in resource biomass, and s_y is a measure of the trend in the survey abundance index given by the slope of the linear regression of $\ln I_{y'}$ against y' for years $y' = y - p + 1, y - p + 2, ..., y$ for abundance index I, and p is the number of years over which the slope is calculated. Note that if p is too small the trend estimates would fluctuate too much (tracking noise), but if p is too large, the HCR would not be able to react sufficiently rapidly to recent trends in resource abundance.

For the first year of the projection period an appropriate "starting level", C^*, must be chosen (not necessarily equal to the actual catch that year). The choice of this starting level is important for the performance of the HCR because one that is too low will result in an unrealistically large drop in TAC advice in the first year of management, while one that is too high may necessitate subsequent severe cuts in the catch.

Input: A direct index of abundance, I_y, such as provided by CPUE or survey.

Advantages: This is a very simple and intuitive rule that moves the catch up or down in relation to the trend in the recent survey data. This rule can be tuned to give the desired level of stability in catch advice: fluctuations in catch advice are dampened by reducing λ and choosing a longer period over which the slope is calculated.

Disadvantages: In the absence of a target (see target-type HCR discussed below), this rule cannot rebuild stock biomass adequately from low depletion levels. Given a data-poor scenario, associated with lack of information about stock status and noisy data, it would be difficult tune this rule react quickly to a decreasing trend in index of abundance while at the same time ignoring situations where such a trend reflects only noise.

Reviews and applications:
- Butterworth and Geromont (2001) developed this HCR for the management of the data-rich hake stock in Namibia. A slope type-rule was chosen to distinguish between two possible stock status scenarios: a depleted stock requiring future TAC advice to adjust catches downward, or a healthy stock which could support higher future catches. The feedback provided in terms of the slope of the most recent abundance estimates would determine if catches were to be adjusted up or down. This MP was implemented successfully for three years, also providing a basis to distinguish the two scenarios.
- Catch advice for Tier 4 (data-poor) stocks in Australia was initially based on a slope-type rule (Wayte 2009). However, this rule has since been replaced with a target-type HCR.
- Geromont and Butterworth (2014a) evaluated this rule for "severely depleted" data-poor stocks, typically associated with high levels of uncertainty, and found the performance satisfactory given appropriate risk-averse tuning with a low starting level, C^*.

2.5.4.3 Target-type HCR

This type of HCR is based on moving resource abundance to a chosen target level in terms of some abundance index I_y. The annual catch is adjusted up or down depending on whether the most recent abundance index is above or below the target level.

$$C_{y+1} = \begin{cases} C^{t\arg et} \left[w + (1-w) \dfrac{I_y^{recent} - I^0}{I^{t\arg et} - I^0} \right] & \text{if } I^{recent} \geq I^0 \\[2em] w C^{t\arg et} \left[\dfrac{I_y^{recent}}{I^0} \right]^2 & \text{if } I^{recent} < I^0 \end{cases} \qquad (2.75)$$

where $0 \leq w \leq 1$ is a smoothing parameter, I^{target} is the desired target value for the index of abundance (chosen at some percentage above an historical average when the fishery was stable), C^{target} is a target catch associated with the target index (chosen as an average over a predefined historical period of stable catches), I_y^{recent} is the average survey or CPUE index of abundance over the most recent (e.g. two to three) years, and $I^0 < I^{target}$ is the limit index below which future TACs are reduced quadratically rather than linearly with I.

A simplified form of equation (2.75), with $w=0$, is used to compute the recommended biological catch for Tier 4 stocks in Australia (Wayte 2009, Little *et al.* 2011):

$$C_{y+1} = \min \left[C_{\max}, C^{t\arg et} \max \left(0, \frac{I_y^{recent} - I^0}{I^{t\arg et} - I^0} \right) \right] \qquad (2.76)$$

where $C_{\max}$ is the maximum level of catch allowed. Here, the TAC is set to zero if the abundance index falls below the lower limit I^0.

The formulation given by equation (2.75) allows for a non-zero TAC of $w C^{t\arg et}$ when $I^{recent} = I^0$, which has the effect of dampening the inter-annual variation in catches, thereby stabilizing the output from the HCR. Setting $w = 0$ would necessitate a steeper slope of the linear relationship given by equation (2.76), leading to more variability in future catches. On the other hand, setting $w = 1$ would result in no inter-annual fluctuations in catch, but also no adjustment of catch in response to changes in survey abundance indices.
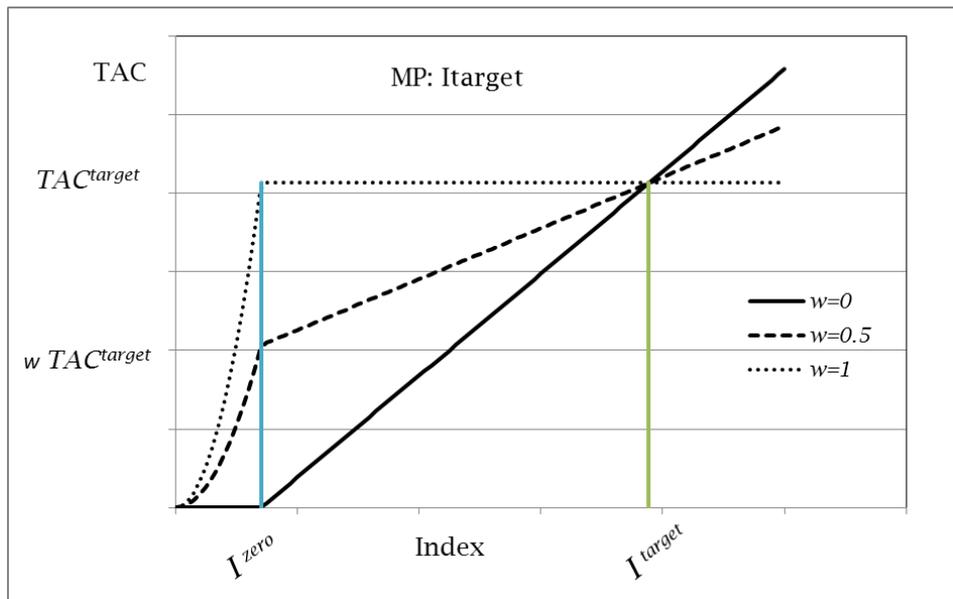
Figure 11: Different target-type rules for alternative values of the control parameter *w*: the dashed lines correspond to intermediate smoothing ($w = 0.5$), while the solid black lines reflect the rule without smoothing. The vertical lines indicate the zero and target survey values, while the horizontal dotted line corresponds to a simple constant catch rule when *w=1*.

Input: A direct index of abundance, I_y, such as provided by CPUE or survey.

Advantages: Management reference points (targets and limits) are incorporated in the rule explicitly. The rule is intuitive: the catch is adjusted up or down to move the resource biomass towards a target while avoiding the limit.

Disadvantages: Choosing the target reference points for the control rule can be tricky when confronted with a short time-series that does not correspond to a period of stable biomass and fishing mortality: the average historical index of abundance and catch are then probably far below the desired target value. In this case, alternative targets are best explored through simulation testing.

Reviews and applications:

- Wayte (2009) performed simulation studies to evaluate the performance of the target rule (with $w = 0$) for Tier 4 Southern and Eastern Scalefish and Shark Fishery (SESSF) stocks in Australia using management strategy evaluation (MSE). The biological component of the operating model was conditioned on flathead or school whiting. Different depletion levels at the start of the projection periods were considered (low, target and high: 35%, 48%, 60% of

K respectively). Their simulation studies show that the success of this rule depends on well-chosen target values for the abundance index and the future catch. In the absence of an assessment to provide an estimate of K, the target should be based on a period of time during which the fishery was economically and biologically stable.

- Little *et al.* (2011) report that the target-type rule, adopted for setting the recommended biological catch (RBC) for the Southern and Eastern Scalefish and Shark Fishery of Australia, is able to guide a stock to the desired state from different initial levels of depletion. They warn that the selection of appropriate control parameter values for the rule is critical to its performance; better performance is achieved if the catch target is defined in terms of the average catch over a preselected historical reference period, rather than a recent average. They conclude that the target-based rule is a valuable tool when data are scarce.

- Geromont and Butterworth (2014a) evaluated the target rule for application to a generic group of severely depleted (spawning biomass between 10% and 30% of K) data-poor stocks of medium productivity ($0.2 < M < 0.4$), for which the South African horse mackerel is an example. Different values for the index and catch targets were simulation tested: the target index ranged from multiples of 1.5 to 2.5 of the historical average, while the catch target was chosen as the average historical catch, or 70% thereof. A smoothing parameter of $w = 0.5$ was applied to avoid large inter-annual fluctuations in TAC. Based on simulation trials, this target rule performed slightly better than the slope-type rule discussed above, giving more catch in median terms over the projection period for the same level of risk (a 90% probability that the biomass would be above $0.2K$, the limit reference point).

- Geromont and Butterworth (2014b) simulation tested target- and slope-type rules and compared their performance to assessment-based management in a retrospective study of four North Atlantic data-rich stocks: North Sea sole and plaice, and New England with flounder and plaice. Choices for the index and catch targets were based on simulation testing and tuning of the control rule to achieve the target biomass at the end of the projection period. Based on this retrospective study, the slope and target rules achieved comparable average catch over the projection period to what was achieved in reality (based on VPA assessments) without an increase in resource risk, but with far less interannual variability in catch advice.

2.5.4.4 Index distribution HCR

This HCR, developed by Jardim *et al.* (2015a), is based on the position of the latest data point in the biomass time-series distribution about the mean value. This HCR adjusts the status quo catch up or

down if the most recent survey value falls outside some confidence interval about the mean. The catch advice for the next year is given by:

$$C_{y+1} = C_{y-1}\alpha \qquad (2.77)$$

where C_{y-1} is the total catch in the previous year, α is catch multiplier given by:

$$\alpha = \begin{cases} \alpha_l & \text{if} & I_{y-1} < \mu_I + z_{low}\dfrac{\sigma_I}{\sqrt{n_I}} \\[2ex] 1 & \text{if} & \mu_I + z_{low}\dfrac{\sigma_I}{\sqrt{n_I}} \leq I_{y-1} \leq \mu_I + z_{upp}\dfrac{\sigma_I}{\sqrt{n_I}} \\[2ex] \alpha_u & \text{if} & I_{y-1} > \mu_I + z_{upp}\dfrac{\sigma_I}{\sqrt{n_I}} \end{cases} \qquad (2.78)$$

where α_l and α_u are pre-specified catch multipliers, I_{y-1} is the index of abundance value (survey estimate) for previous year, μ_I denotes the mean in the abundance index, σ_I is the corresponding standard deviation, n_I is the length of the index time-series, and z_{low} and z_{upp} define the confidence interval limits (which may be non-symmetrical).

The precision with which the mean and standard deviation is estimated will likely increase with the length of the index (larger n_I), leading to narrower confidence intervals and more reliable adjustments to catch advice as more data becomes available.

Input: A direct index of abundance, I_y, such as provided by CPUE or survey.

Advantages: The length of the time-series and distribution of data points about the survey mean are explicitly incorporated into this HCR, thereby avoiding unnecessary annual changes in TAC in response to noise in the data.

Disadvantages: This rule needs to be tuned within a MSE framework to determine appropriate values for the control parameters z_{upp}, z_{low}, α_l and α_u to be able to achieve adequate risk-averse performance. While comprehensive tuning of HCRs is standard practice for data-rich stocks, this may not be a viable option for data-poor stocks especially when they are low-value and low-expertise.

Reviews and applications:
Jardim *et al.* (2015a in press) compared the performance of this HCR with the index-adjusted "status quo" and length–based "reference point" HCRs (described earlier) and found it to be the best

performer overall. To ensure adequately risk-averse, asymmetrical confidence intervals were applied ($z_{low} = -0.33$ and $z_{upp} = 1.96$) as well as asymmetrical catch multipliers ($\alpha_l = 0.75$ and $\alpha_u = 1.05$).

Index-type methods	
Assumptions	The main assumption is that the index of abundance is a reliable indicator of trend in biomass. Catchability is assumed to be constant.
Advantages	Biomass dynamic models generally provide reliable estimates of stock status and management quantities. Index-based methods have been used extensively for assessment and management purposes, and have a good track record. Index-based harvest control rules can track trends in biomass effectively. These simple rules have been demonstrated by simulation to be robust to the high levels of uncertainty typically associated with data-poor stocks. CPUE-based rules are easily understood by all stakeholders and serve as an incentive for industry to fish towards biomass levels that yield a higher CPUE.
Disadvantages	Noisy data can obscure trends in biomass. Assessment methods need good contrast in the data to be able to estimate model parameters reliably.

Table 5: Summary of general assumptions and advantages/disadvantages associated with Index-type methods.

2.6   MPA-based Harvest Control Rules (MPS-HCRs)

No-take marine protected areas have great potential to provide improved management for data-poor stocks by comparing harvested stocks with populations inside MPAs. The methods generally rely on the assumption that the no-take areas provide a good proxy for the unfished population and are therefore suitable only if certain conditions are satisfied. These include good monitoring of well-established MPAs to ensure equilibrium conditions, and sufficiently large MPAs to limit overspill of species into the surrounding fishing grounds.

2.6.1   Density-ratio control rule (DRCR)

McGillard *et al.* (2011) developed a survey-based control rule to generate total annual effort (TAE) advice based on the annual density ratio of a fish species outside an MPA to that inside. The density ratio can be used as an indicator of stock status if the density inside the reserve represents unfished conditions.

The DRCR adjusts the effort for the next year up/down according to the value of the density ratio in the current year y:

$$E_{y+1} = E_y + \text{slope}(\tilde{\rho}_y - x_{\text{intercept}})\qquad(2.79)$$

where the slope controls the magnitude of change in TAE, and the *x*-intercept is the target density ratio corresponding to zero change in effort. The density ratio in year y is given by:

$$\tilde{\rho}_y = \frac{\tilde{D}_{\text{out}}}{\tilde{D}_{\text{in}}} = \left(\frac{\tilde{N}_{\text{near}} + \tilde{N}_{\text{far}}}{n_{\text{near}} + n_{\text{far}}}\right) \Big/ \left(\frac{\tilde{N}_{\text{in}}}{n_{\text{in}}}\right)\qquad(2.80)$$

where $\tilde{N}$ are the sampled number of fish in each stratum and n is the number of cells open to fishing near, far and in the MPA.
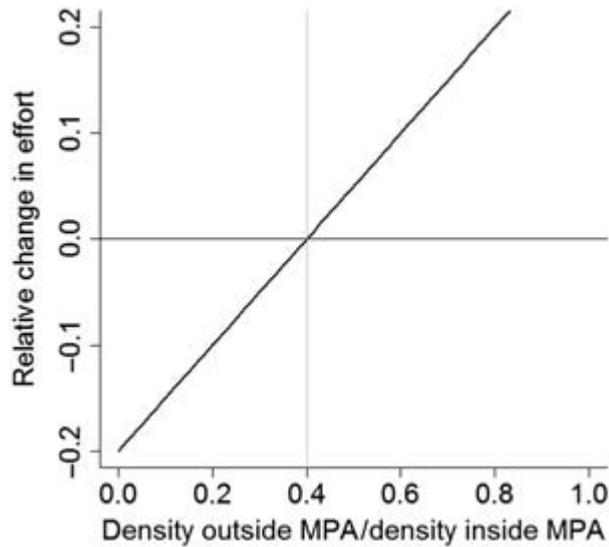
Figure 12: This plot (taken from McGilliard *et al.* 2011.) shows how annual TAE advice is adjusted according to the ratio of the density outside the reserve to that inside.

Babcock and MacCall (2011) evaluated a similar metric for multi-species fisheries. The HCR reduces the catch if the density ratio between the outside and inside the reserve fall below a certain level. The density ratio for each species is given by the average number of fish seen per transect outside the reserve divided by the average number inside the reserve:

$$D_{sp} = \frac{\sum \tilde{N}_{sp,out} / n_{out}}{\sum \tilde{N}_{sp,in} / n_{in}}$$ (2.81)

where $\tilde{N}$ is the number of fish seen and n is the number of transects in fished areas or in the marine reserve. Multispecies density ratios are approximated by the mean of the density ratios for each species. To avoid unwanted fluctuations in catch advice due to recruitment variability and low sample sizes in the monitoring program, the rule can be stabilised by applying a multi-year density ratio.

Input: The number of fish seen outside and inside the marine reserve during surveys.

Assumptions: The main assumptions relate to adult fish movement which is taken to be relatively slow.

Advantages: This approach is suitable for managing data-poor stocks as it requires no historical catch data and no size or age composition data. The density inside an MPA, used as a proxy for the unfished population, is subject to the same environmental conditions as the fished portion of the stock. The multi-species approach is simple and integrates over many species to provide a community metric.

Disadvantages: It is difficult to obtain unbiased density estimates from fisheries-dependent sampling programs. The approach is not effective when an MPA is new, and the density ratio will not serve as a reliable indicator of stock status.

Applications and reviews:

- Wilson *et al.* (2010) developed an MPA-based decision tree for data-poor sedentary nearshore species based on indicators sampled from inside and outside MPAs, but here in combination with a MPA-based reference point. The rule was simulation tested using MSE to demonstrate robustness to process, observation and model uncertainty. The HCR consistently improved yields while maintaining biomass and SPR levels. They advise that this approach is suitable for species with small home ranges relative to the size of the MPA so that limited spill-over occurs, e.g. California's nearshore rocky reef species such as sea urchins, abalone, crabs and lobsters.

- McGilliard *et al.* (2011) used management strategy evaluation (MSE) to evaluate the performance of DRCR for a range of movement rates of larvae and adults (and other biological scenarios) to find the tuning parameters that maximised the cumulative catch. The performance of the rule was insensitive to the value chosen for the slope parameter, but highly sensitive to the x-intercept. The optimal value for the x-intercept increased with increasing variability in the survey data. An x-intercept of 0.4 to 0.5 produced 75% or more of the cumulative catch produced by the optimal constant effort rule for a range of operating model scenarios. The optimal DRCR produced 90% of the cumulative catch obtained from an optimal constant effort rule. This simulation study showed that the DRCR was most sensitive to the movement patterns of larvae and adults and survey variability.

- Based on the simulation study by Babcock and MacCall (2011), a target density ratio of 60% of mature fish, or 80% of all fish performed best for a wide range of fish life history characteristic. Multi-year density ratios were required to dampen variability. They emphasize the need to monitor indicators that the HCR may no longer be valid, for example a sudden drop in density inside the reserve, or a substantial change in relative density of species.

- This HCR was evaluated at the CGFI Data-limited Assessment Workshop held in 2013. The Workshop noted that the monitoring program should provide adequate density information. Precaution is recommended when applying this rule to compensate for the lag needed for the reserve to take effect (Cummings *et al.* 2014).

MPA-based methods	
Assumptions	MPA methods rely on the assumption that the reserves are well-enforced so that the conditions inside the reserve mimic unfished population dynamics. The size of the reserve is assumed to be sufficiently large to offset the effect of fish movement.
Advantages	No historical data are required. The TAC or TAE for outside the MPA is adjusted in an intuitive manner that is easily understood by stakeholders. MPAs allow for simple multi-species assessments of relative abundance amongst species.
Disadvantages	These methods provide advantages only to near-sedentary species. It may be difficult to obtain unbiased density estimates. The MPA must be well-monitored and long-established to provide resource benefits.

Table 6: Summary of general assumptions and advantages/disadvantages associated with MPA-based methods.

2.7   Current scientific collaborations

A number of initiatives that focus on the assessment and management of data-poor stocks/fisheries have been established to consolidate the vast array of research performed world-wide. Short descriptions of some of these initiatives follow.

2.7.1   Strategic Initiative on Stock Assessment Methods (SISAM)

This ICES initiative entailed the classification of stock assessment methods according to the amounts and/or types of data required. The goal of this classification is to guide fisheries scientists in the selection of the most appropriate stock assessment methods given the data available (SISAM 2012). However, as methods are likely to evolve and improve in response to lessons learned from their application, the process was seen to be iterative, consisting of a number of steps:

1. Identification of the current set of methods available.
2. Guidance to select the most appropriate method according to the application and data availability.
3. Education and access to expert information regarding these methods.
4. Encouragement to develop and test assessment methods in support of management requirements.

SISAM endeavoured to contribute directly to steps 1 and 2 while serving as a catalyst for steps 3 and 4. A range of assessment approaches was evaluated, from simple quantitative procedures suitable for data-poor stocks, to statistical assessments for data-rich stocks, as well as advanced multi-species and environmentally-linked models. To review these and other stock assessment issues, ICES organised a World Conference on Stock Assessment Methods for Sustainable Fisheries (WCSAM 2013) in Boston in July 2013 with an aim to explore the merits and performance of the assessment methods currently available for providing fisheries management advice, so as to highlight typical problem areas and to initiate the development of the next generation of state-of-the-science assessment models.

2.7.2   Workshop on the Development of Assessments based on LIFE history traits and Exploitation Characteristics (WKLIFE)

This ICES initiative is focussed on developing a methodological framework for providing assessments and advice on data-poor and method-poor stocks. Stocks are classified into categories according to the type and quality of the data and methods available. In addition, target categories are

identified for all stocks with the aim to move data- and method-poor stocks into higher categories over time. (ICES 2012a,b).

The objectives are:

a) Identify F_{MSY} proxies for stocks without quantitative forecasts, based on life-history traits and exploitation characteristics.

b) Identify methods for estimating current exploitation when data such as catch and survey data, are limited.

c) Identify data-poor stocks for application of these methods.

d) Identify the data that need to be collected to be able to implement points a) and b).

e) Identify and evaluate multi-annual harvest control rules for application to stocks for which the approach suggested under a) and b) fail due to lack of data.

Six categories were identified to classify stocks from data-rich to data-poor (ICES 2012b):

Category 1. Data-rich stocks with accepted quantitative assessments.

Category 2. Stocks with analytical assessments and forecasts that are treated qualitatively only.

Category 3. Stocks for which survey-based assessments indicate trends.

Category 4. Stocks for which reliable catch data are available.

Category 5. Data-poor stocks.

Category 6. Stocks for which landings are negligible and stocks from which bycatches are taken in minor amounts.

2.7.3   Assessment for All (A4A)

The Assessment for All (a4a) initiative of the European Commission Joint Research Centre (JRC) aims at increasing the number of stocks with analytical assessments, while simultaneously promoting a risk-based type of analysis, so that scientific advice provides policy and decision makers with a clearer perspective of the uncertainty existing on stock assessments and its propagation into advice (Jardim *et al.* In press).

The approach developed to achieve this objective is to identify the major sources of uncertainty and to implement a framework that allows the analyst to incorporate these in an efficient and coherent way. One can make the analogy with building with Lego, where for each layer the builder may use the pieces provided by a particular boxset of his/her choice. In this manner, observation, process and model error (e.g. uncertainty about growth, reproduction, natural mortality, fishing selectivity and catchability) can be taken into account and their uncertainty propagated through the estimation of

population abundance and fishing mortality by the stock assessment model. Rather than selecting a single 'best' stock assessment model, this initiative suggests combining the final outcomes from a range of stock assessment models using model averaging (Millar *et al.* In press), although other solutions, such as scenario analysis, may also be implemented.

The methodologies being developed are made available through a R/FLR package, FLa4a, published in the FLR repository (http://flr-project.org).

The a4a objectives are:
1. to develop a stock assessment approach for stocks with limited biological information and moderately long exploitation and abundance time series data,
2. to encourage discussions about problems associated with performing stock assessments for a large number of stocks, and
3. to build capacity for stock assessments.

The main focus is on securing the robustness of management advice. The stocks assessment models and MSE tools are distributed as FLR packages (Kell *et al.* 2007).

2.7.4   Data-Limited Fisheries Toolkit

The Data-Limited Fisheries Toolkit was developed by Carruthers (2014) of the University of British Columbia Fisheries Centre as part of the Data-Limited Methods Workshop convened by the Natural Resources Defence Council (NRDC) in early 2014. The purpose of the Toolkit is to provide a transparent, reproducible mechanism for simulation testing different data-limited methods for generating catch advice and to evaluate their comparative performance. As of September 2014, the Toolkit featured closed-loop management strategy evaluation, over 40 data-limited methods, and various diagnostic tools such as sensitivity analysis and automated functions for determining which methods are available to apply given specific data limitations, and what additional information is needed for to be able to apply methods for which there is insufficient data. The Tookit developers are collaborating with various fishery management bodies on its application, including: the National Marine Fisheries Service Southeast and Northeast Science Centers, the Mid-Atlantic Fishery Management Council, and the Inter-American Tropical Tuna Commission. The Toolkit is freely available from the CRAN-R repository (http://cran.r-project.org/web/packages/DLMtool/index.html) and instructions for downloading the software, as well as a complete tutorial, are available at www.datalimitedtoolkit.com.

Potential benefits of the Toolkit include (Newman *et al.* 2014):

- Powerful diagnostic tools for testing methods to generate catch advice.
- Improved efficiency of stock assessment throughput (requires a day or two to complete analyses that would normally take weeks).
- Free access to many data-limited methods.
- Pre-tested computer code (avoids duplicative effort writing code).
- Enhanced reliability (avoids review time wasted on bugs).
- User-friendly graphical output.
- Rapid execution and reduced computational workload for data-limited assessments.
- Open access facilitates rapid incorporation and dissemination of new methods.
- Facilitated simulation testing and direct comparison of methods.

2.7.5   Environmental Defence Fund (EDF): catch share design manual

The EDF is a non-profit environmental group based in the US dedicated *inter alia* to restoring fisheries by using catch shares. As part of this approach, Apel *et al.* (2013) developed a structured and integrated framework to produce adaptive and precautionary management guidance on the utilisation of data-poor assessment methods. This six-step framework consists of the following:

Step 1:   Assess the ecosystem status and impacts of fishing.

Step 2:   Assess the vulnerability of stocks to fishing pressure by conducting a Productivity and Susceptibility Analysis (PSA).

Step 3:   Estimate the level of stock depletion using methods such as the MPA density ratio, length-based indicators and the SPR-based decision tree.

Step 4:   Prioritise stocks for further assessment and precautionary management according to vulnerability and depletion levels.

Step 5:   Assess priority stocks to set catch limits or fishing mortality controls using data-poor assessment methods such as catch-MSY, DCAC and DB-SRA.

Step 6:   Collect additional data to improve future stock assessments to move data-poor stocks towards data-sufficient.

2.7.6 Science for Nature and People (SNAP): Managing Data-Limited Fisheries for Economic and Biological Objectives

This working group was constituted in 2014 to develop novel assessment and management solutions for data-poor fisheries. The particular focus of SNAP is to bridge the current gap between the scientific assessments and their effective implementation. The objectives of SNAP (2014) are as follows:

1. Develop a comprehensive assessment and management framework for data-poor fisheries:

   a. Compile a data-base of the data-poor assessment methodologies currently available.

   b. Review social, economic and biological metrics that can be used as performance indicators.

   c. Categorise fishery archetypes in terms of life-history parameters, spatial scale, etc.

   d. Compare and contrast existing data-poor assessment methods using MSE.

   e. Develop a comprehensive framework to assess and manage data-poor fisheries and to provide guidance regarding the most suitable method according to fishery archetype and data availability.

2. Evaluate the costs/benefits of additional data:

   a. Quantify the costs of collecting and analysing additional data for different fisheries archetypes.

   b. Evaluate the socio-economic and biological benefits of extra data to reduce uncertainty/risk.

   c. Design adaptive management guidelines for fishers.

   d. Provide guidance to maximise economic benefits resulting from monitoring, data collection and alternative assessment approaches.

3. Implement assessment and management framework for depleted data-poor fisheries:

   a. Identify the data-poor fisheries for the case study.

   b. Train fishers to use the assessment and management framework.

   c. Organise the data.

   d. Design adaptive management and monitoring protocols.

   e. Organise workshops to discuss engaging local fishers in data collection, analysis, application and enforcement of management framework.

2.7.7   Technical experts overseeing third country expertise (TXOTX):

This EU project was initiated in 2008 to coordinate the analysis of data and methods applied in regional assessment and management procedures for fish resources in the third country waters where the EU has important development goals, and where often the fisheries under harvest are data-poor. The aim of the project was to build a scientific network and identify opportunities for greater research coordination between these strategic regions and the EU. This research program was concluded in 2011 (www.txotx.net).

2.7.8   Developing probability model applications in data-poor fisheries (POORFISH)

This EU initiative was established in 2005 to improve the quality of scientific advice relating to data-poor fisheries by formulating harvest strategies to ensure sustainable use of marine ecosystems and provide better security to fishers and, in turn, promote greater stability in communities dependent on fisheries. POORFISH was concluded in 2008.

Objectives included:

1. To review potential assessment and management approaches for data-poor fisheries.
2. To improve the structure and reliability of assessment models.
3. To apply the model to case studies.
4. To produce assessment and management guidelines for data-poor situations.

2.7.9   The Marine Stewardship Council (MSC)

While not a new initiative (originally started in 1997), this has gained momentum in establishing itself as the most recognisable global eco-label in the market place. The objective of this international fish produce ecolabelling and certification program is to contribute to the health of global fish stocks by transforming global seafood markets to stock seafood from sustainable sources, and influencing buyers to make informed choices when buying seafood. The MSC is currently addressing issues of certification of small-scale and developing-country fisheries. There are currently over 30 small scale and developing country fisheries in the MSC programme. The low level of participation is partly due to the lack of adequate data to evaluate sustainability, the high certification cost (cost of auditing and cost of implementing improvements to the fishery to meet requirements of the standard), limited availability of local auditing capacity, and lack of formal management measures and infrastructure often encountered in developing countries. To facilitate that more developing countries and small-

scale fisheries participate in, and benefit from, certification, the FAO has developed and adopted international ecolabelling guidelines in 2005. These guidelines provide a global framework to ensure that ecolabelling programmes are implemented in a manner that is not detrimental to fisheries in developing countries and ensures that concerns raised by developing countries are addressed. For situations when data are limited, the FAO guidelines recommend the adoption of assessment methods appropriate to the fishery and that application of less elaborate assessment methods should not preclude certification. With this in mind, the MSC has commenced work to develop a risk-based assessment approach for data-poor fisheries. The LB-SPR approach (Section 2.3), funded by the Packard Foundation to the MSC, is an initiative to link the MSC's standards for risk-based assessment with stock assessment models.

2.8   Discussion

The methods described in the sections above have been categorised according to method types and data requirements. However, there is much overlap between methods and data requirements as would be expected. Furthermore, these methods are generally not suitable for application in isolation, but better applied in combination, or in support of each other. This is particularly important for data-poor stocks which typically lack estimates of stock status. Therefore, before a suitable method is selected for purposes of generating management advice, some preliminary assessment(s) is/are recommended. These might include performing a PSA (Section 2.2) to rank the resource according to vulnerability to overfishing, followed by per-recruit analysis (Section 2.3) to compute appropriate management reference points. Length-based methods (Section 2.3) present cost-effective management options in the absence of time series data. Size-based methods such as LB-SPR (Section 2.3) could provide selectivity-based management to promote sustainable (albeit not economically optimal) harvesting of the resource until a direct index of abundance (survey) becomes available. A variety of methods for generating annual catch advice are summarised in Sections 2.4 to 2.6. Catch-only methods (Section 2.4) are frequently applied to assess data-poor stocks, however these methods are notoriously unreliable in the absence of additional supporting biological (life-history) information and reliable estimate/distribution for current depletion. Index-type methods (Section 2.5) are typically preferred for management purposes and generating catch advice when a reliable index of abundance for the stock is available; however reliable survey or CPUE data are rarely available for data-poor fisheries. There are therefore no hard and fast rules when selecting the method (or suite of methods) that is/are most suitable to assess and manage a stock. To assist with selection, Table 7 gives a summary of methods, the data requirements, and the main advantages and disadvantages.

Model	Method	Input data	Advantages	Disadvantages	Reference
Qualitative and semi-Quantitative	Fishers Knowledge (FK)	Very few: data are reconstructed from FK	FK essential to reconstruct catch time series and to construct priors for model parameters	FK prone to bias. No estimates of stock status.	Orensanz *et al.* (2013)
	Productivity and Susceptibility Analyses (PSA)	Some knowledge of life-history parameters and fishery attributes	Prioritise stocks in terms of their productivity and susceptibility.	Does not output quantitative management measures. No estimates of stock status	Patrick *et al.* (2009)
	Length-based decision trees	Rapid visual assessment (RVA)	Local fishers take part in data-collection, assessment and management of resource.	This method is only suitable for sedentary nearshore species	Prince (2010)
	Traffic-light framework	Limit reference points based on life-history parameters or input from assessments	Intuitive management approach	quantitative	Caddy (1999,2002)
Per-Recruit and Length-based	Beverton-Holt	Life-history parameters	Simple to implement, few data required and widely used.	Equilibrium model assumptions may not hold. No estimates of stock status.	Beverton and Holt (1957)
	Length-Based Spawning Potential ratio (LB-SPR)	Life-history parameters and length composition data	Cost effective length-based method for possible use in HCRs. No time-series data required.	Equilibrium model assumptions may not hold.	Hordyk *et al.* (2014a)
	Length-based per-recruit	Life-history parameters and mean length data	Provide estimate of M from length data. Change in F allowed.	Knife-edged/constant selectivity.	Gedamke and Honig (2006)
	P_{mat}, P_{opt}, P_{mega}	Length composition data	Intuitive indicators for possible use in HCRs.	Not yet simulation tested.	Cope and Punt (2009)
	Bayesian length-based indicators	Life history parameters and length data	Incorporates uncertainty.	Equilibrium conditions unlikely to hold.	Daan *et al.* (2005)
	Harvest Control Rules (HCRs)	Mean length data	Simple empirical rules provide intuitive management. Have been simulation tested.	Lag time in response of HCR to changes in biomass.	Geromont and Butterworth (2014a)
Catch-based	SHOT	Catch time series	Simple empirical methods to estimate status quo catch for forecasting.	Reliability of the status quo catch is highly dependent on the reliability of the time series data	Shepherd (1984)
	Depletion-Corrected Average catch (DCAC)	Catch time-series and prior distributions for M, $MSYL$, F_{MSY} and stock status.	Incorporates uncertainty and outputs distribution for the DCAC.	Not applicable to severely depleted or highly productive stocks. Relies on estimates of depletion.	MacCall (2009)

	Catch Only Model (COM)	Catch time-series and prior distributions for r, K and x.	Combines effort and biomass dynamics in one model.	A complete (unregulated) catch time series is required.	Vasconcellos and Cochrane (2005)
	State-Space catch-Only Model (SSCOM)	Catch time-series and prior distributions for r, K, x, a and E_1.	Incorporates fluctuations in catchability. Flexible model framework to progress from data-poor to data-sufficient	Complexity of model makes it less intuitive. Definition of prior distributions may be tricky.	Thorson *et al.* (2013)
	Depletion-Based Stock Reduction Analysis (DB-SRA)	Catch time-series and prior distributions for M, $MSYL$, F_{MSY}/M and stock status.	Outputs posterior distributions for sustainable yield and MSY. Medians and lower %-iles could be used in HCRs	A complete catch time-series is required. Not suitable of short-lived species with large recruitment fluctuations. Relies on estimates of depletion.	Dick and MacCall (2011)
Index-based	Harvest Control Rules (HCRs)	Reliable index of abundance	Only the most recent period of the index is required.	Not applicable if the data is not a reliable index of biomass	Wayte (2009) Prince *et al.* (2011) Geromont and Butterworth (2014a,b)
	An Index Method (AIM)	Catch and abundance time series	Can track biomass reliably. Outputs management reference points.	Reliability depends heavily on the data quality (short, or noisy, time series)	Rago (2008)
	Surplus Production models	Catch and abundance time series	Gives estimates of stock status and other management quantities.	Need contrast in the time series.	Prager (1992, 1994) McAllister and Babcock (2006)
MPAs	MPA Density ratio model	Number of fish seen outside and inside the MPA	Simple HCR that can be applied to stock complexes.	Difficult to obtain unbiased density estimates.	McGilliard *et al.* (2011), Babcock and MacCall (2011), Wilson *et al.* (2010)

Table 7: A summary of data-poor assessment methods summarising the key advantages and disadvantages of each method.

Part 3 Simulations

The majority of data-poor methods described in this document fall in the category of empirical harvest control rules, rather than statistical stock assessments that provide estimates (with distributions) of stock status and productivity. Moreover, with limited or poor data to inform these simple models, estimates of management quantities (such a MSY) can lead to unreliable or biased management advice. It is therefore imperative that these simple methods be simulation tested to evaluate their robustness to a full range of uncertainty associated with data-poor stocks/fisheries before they are applied to serve as a basis for management advice in particular cases.

Management Strategy Evaluation (MSE) provides a scientifically defensible framework to simulation test alternative methods across a range of operating (population) models that represent different plausible realities. The performances of the different methods are then compared to ascertain which method is more likely to realise the management objectives for the stock under consideration, while taking full account of different sources of uncertainty (Punt *et al.* In press).

Different implementations of MSE have been applied globally to evaluate the comparative performance of simple harvest control rules to set annual TACs. In Australia, alternative harvest control rules for data-poor stocks (Tier 4) have been simulation tested within an MSE framework to select the best performing rule when data are limited (Wayne 2009, Prince 2010). In Europe, the ICES WKLIFE Working Group (ICES 2012b, ICES 2013e) has evaluated different empirical control rules with the aim to generate annual catch advice for ICES stocks that lack sufficient data for formal stock assessments (Categories 3 - 6). Geromont and Butterworth (2014a) simulation tested a number of simple generic control rules on generic Bayesian-type operating models that integrated over key uncertainties: model uncertainty, process error, observation error, and finally, implementation error. More recently, Carruthers (2014) developed a Data-Limited Methods toolkit (DLMtool) that allows for rapid testing of control rules on simulated stocks (Newman *et al.* 2014).

Part 3 of this report compares the performance of a selection of empirical methods to generate TAC advice for two "real" data-poor stocks, South African panga and Jamaican queen conch.

3.1   The Management Procedure (MP) Approach

The MP approach, known as Management Strategy Evaluation (MSE) in Australia, is a system that encompasses all aspects of fisheries management, from defining the management objectives for

fisheries, to data collection and analysis, the development of harvest control rules that can be shown to be robust to key uncertainties via simulation testing, and monitoring (Punt 2006). Furthermore, the most compelling reason to use the MP approach is to take formal account of uncertainties as required by the Precautionary Approach and in line with the FAO Technical Guidelines for Responsible Fisheries (FAO 1996), as described below.

In practice, the application of a MP approach comprises of a number of equally important steps as elaborated in Punt and Donovan (2007) and De Oliveira *et al.* (2008). These can be summarised as (see Figure 13):

1) Specify strategic objectives: All stakeholders (industry, fishery regulatory bodies and scientists) take part in discussions to prioritise the most important biological, economic and social objectives. The management objectives for the fishery need to be identified upfront, and defined explicitly with the full support of all stakeholders, to ensure subsequent buy-in and compliance.

2) Decide on performance measures: Quantify the qualitative management objectives defined in step 1. It is important to realize that it will not be possible to achieve every objective as there will be conflicts, e.g. between maximizing longer-term catches and minimizing risk to the resource. An iterative process may be required here, as stakeholders become better able to fully grasp what ranges of trade-off choices are possible only as computations proceed.

3) Develop a set of operating models (OMs): These OMs must best represent the dynamics of the resource and fishery while also incorporating the key uncertainties. A Bayes-like approach is desirable for data-poor stocks for which data and knowledge regarding stock structure and productivity is limited; this approach provides one way to account for this by admitting the use of "prior" distributions for parameters based on information obtained from data-rich stocks. Stakeholders should take part in discussions to identify areas of concern and to delineate different plausible hypotheses, as well as to specify further plausible "prior" distributions by drawing on collective knowledge of the fishery.

4) Specify a set of MPs: Identify a range of candidate MPs together with associated historical and future data required by each MP. An MP is essentially a formula for which the input is a pre-agreed set of resource monitoring data, and which outputs a regulatory measure such as a TAC or TAE value. For data-poor stocks, candidate MPs are typically very simple empirical harvest control rules that are easily understood by all stakeholders, and that rely on the regular availability of relatively few data only.

5) Simulation test each MP over the range of OMs: This entails examining the candidates from step 4 in terms of the OMs developed in step 3 to determine which MP would best satisfy the management objectives defined in step 1, regardless of which OM might actually best

describe the true underlying dynamics. These tests for robustness of performance involve forward projection of the resource dynamics under each OM with catches set by the candidate MP, where these catches are based on simulated data which incorporate observation error. Such tests are the foundation of the MP development process. The future success of the end-product relies on this step.

6) Evaluate performance statistics: During the simulation testing of each candidate MP, the summary statistics defined in step 2 are output for inspection, comparison, MP tuning (adjusting the values of the control parameters of the MP to achieve particular objectives) and candidate MP rejection purposes.

7) Select MP for implementation: Based on the performance statistics output for each candidate MP in the previous step, choose the MP that performs best in terms of the objectives specified in step 1. All stakeholders should take part in the MP selection process to ensure that their pre-defined objectives are met to the extent possible in relation to trade-offs which are acceptable, so as to promote understanding and collaboration between the different interest groups. Once selected, the MP runs as if on autopilot for typically 4 to 5 years.

The choice of a range of OMs, similar to a suite of traditional stock assessment models, depends largely on the data available. For data-poor stocks where no or limited reliable data are available to include in a likelihood function for conditioning (fitting) the OM to available information, a Bayes-like approach which relies on qualitative information for some parameter values is appropriately adopted, as is the case here.
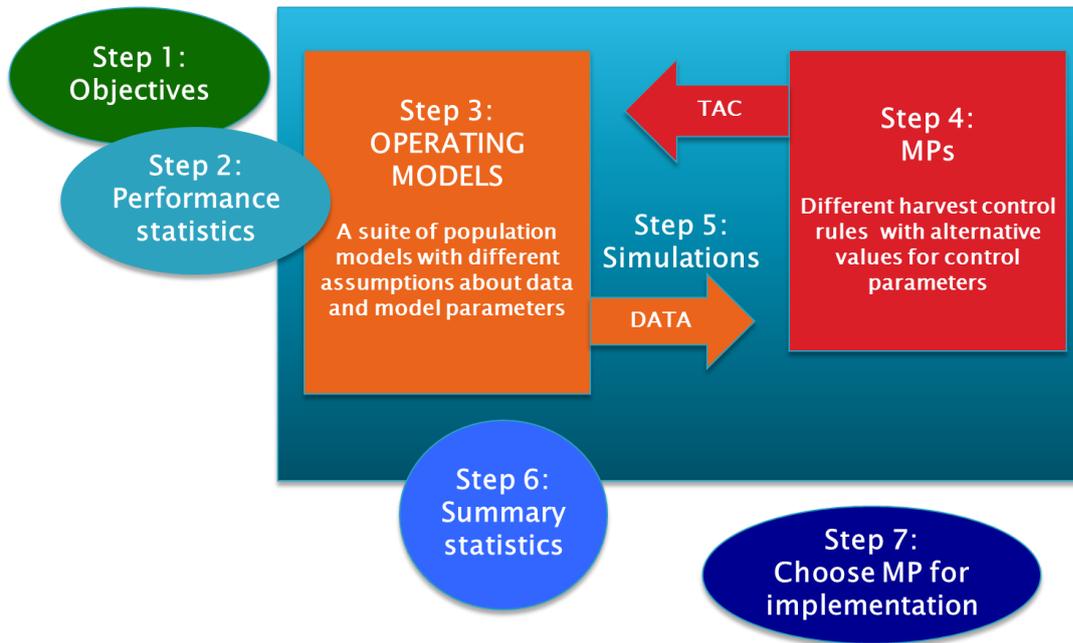
Figure 13: A formal management procedure (MP) approach consists of seven main steps.

3.2 Operating models

A Bayes-like approach has been adopted to evaluate a selection of simple candidate harvest control rules. The operating models (OMs) that form the basis of this comparative study are age-structured production models (ASPM). They include:

- Model uncertainty, by effectively integrating over the ranges specified for model parameter values.

- Observation error, taken into account by including stochastic components when generating future abundance index and length data.

- Process error, by incorporating past and future recruitment and fishing selectivity fluctuations for each simulation.

- Implementation error, by incorporating fluctuations about the historical catch time series and projected TAC advice.

These sources of uncertainty are incorporated explicitly into the MP approach adopted here: simulated trajectories are generated by sampling from pre-specified distributions for key model variables such as the current depletion B_n^{sp} / K^{sp} (from which the pre-exploitation equilibrium spawning biomass, K^{sp}, is back-calculated), the "steepness" of the stock-recruit relationship h, natural mortality rate M_a, the growth parameters, as well as for selectivity, stock-recruit and catch residuals. The distributions chosen are intended to reflect some of the qualitative and quantitative information available for the two data-poor stocks under consideration, while still allowing for the extent of model uncertainty to be expected in reality. A large set of biomass trajectories is generated by sampling from these distributions. Each population biomass trajectory, or simulation, corresponding to a plausible reality was then projected forward for twenty years under alternative MPs (or harvest control strategies). In order to ensure comprehensive sampling from these distributions, 1000 simulations were generated. Technical specifications of the OMs are detailed in Appendix B.

3.3   Candidate harvest control rules

A number of empirical MPs (harvest control rules) for application to data-poor stocks are evaluated below. These simple MPs have been developed and applied for generating catch advice in different parts of the world in situations with limited data. The five candidate rules considered for simulation testing are summarised in
Table 8. Detailed descriptions of these methods are given in Part 2 of this Report.

The main advantage of empirical techniques lies in their simplicity, which makes them easy to understand and implement. A more intuitive rule that is well understood by all stakeholders encourages buy-in by industry and is more likely to lead to better compliance to management regulations. By contrast, statistical stock assessments are generally fully grasped only by a handful of scientists, and these complex models are therefore not really comprehended by the fishing community and/or the management agencies. This is particularly important in developing countries where numerical expertise is fairly limited. Furthermore, the high levels of uncertainty associated with data-poor stocks may render fine-tuning of statistical assessments to update annual management advice counter-productive, and a more broad-brush (and precautionary) approach has been indicated to be more effective (Geromont and Butterworth 2014).

Both constant catch and feedback strategies are evaluated to contrast the potential gain associated with the improved monitoring and data collection which the latter can take into account.

Summary of candidate MPs:	
Depletion Adjusted Catch Scalar (DACS): Catch time series over a stable period and estimate of current depletion	$DACS = s / (y2 - y1 + 1) \sum_{y=y1}^{y2} C_y$ where $s = 1 - (0.5 - B_n^{sp} / K)$.
Depletion Corrected Average Catch (DCAC): Catch time series and estimates of relative depletion, F_{MSY}/M, $MSYL$	$DCAC = \dfrac{\sum C_y}{n + \Delta / (MSYL \times c \times M)}$ where Δ is an estimate for relative depletion, $MSYL$ is level of biomass at which MSY is achieved, M is the estimate for natural mortality, and $c = F_{MSY} / M$ assumed to be equal to 1 for data-poor stocks.
Index ratio: Mean length or survey/CPUE time series.	$TAC_{y+1} = TAC_{y-1} \dfrac{1/3 \sum_{y-1}^{y-3} I_y}{1/5 \sum_{y-4}^{y-8} I_y}$ where I_y is the index of abundance.
Index slope: Mean length or survey/CPUE time series.	$TAC_{y+1} = TAC_y (1 + \lambda s_y)$ where $\lambda = 0.4$ and s_y is the slope of the CPUE over the last 5 years.
Target MP (Itarget): Mean length or survey/CPUE time series, guess of B_n / B_{MSY} to set the target.	$TAC_{y+1} = 0.5 TAC^* [1 + (\dfrac{I_y^{recent} - I^0}{I^{target} - I^0})]$ if $I_y^{recent} \geq I^0$, or $TAC_{y+1} = 0.5 TAC^* \left[\dfrac{I_y^{recent}}{I^0} \right]^2$ if $I_y^{recent} < I^0$, where $I^{target} = \bar{I} \times B_n / B_{MSY}$, $\bar{I} = 1/n \sum I_y$ $I^0 = I^{target} / 2$, and $TAC^* = DACS$ or $DCAC$.

Table 8: The five types of control rules considered here to provide catch advice for data-poor stocks. Detailed descriptions of these "off-the-shelf" rules can be found in Part 2 of this Report.

3.4 Management performance statistics

For these simulations, performance is evaluated over a projection period of 20 years, from year 2014 to 2033 for South African panga and from 2013 to 2032 for Jamaican conch. Four statistics are used to compare performance by the various MPs considered in the main text.

- B^{sp}_{final} / K^{sp}, the final biomass depletion where B^{sp}_{final} is the spawning biomass for the last year of the projection period as given by equation (B.7) in Appendix B.

- $B^{sp}_{final} / B^{sp}_{msy}$, the spawning biomass at the end of the projection period, as a fraction of B^{sp}_{msy}, the deterministic equilibrium spawning biomass at which maximum sustainable yield is achieved, given by:

$$B^{sp}_{msy} = R \sum_{a=a_{min}}^{m} f_a w_a N^{eq}_a$$

where N^{eq}_a are the equilibrium population numbers-at-age corresponding to F_{msy} (the fishing mortality at which the maximum yield is obtained) for $S_{n,a}$ (the fishing selectivity vector at the end of the pre-management period) and M (the natural mortality), with R the number of recruits which is given by:

$R = (\alpha - \beta / SPR)$

where SPR is the equilibrium spawning biomass per recruit at F_{msy} and α and β are the Beverton-Holt stock-recruit parameters. Note that a different B^{sp}_{msy} is computed for each simulation, corresponding to the different values for M and $S_{n,a}$ (which are re-sampled per simulation) as well as the stock-recruit parameters α and β (which are re-computed for different values of K^{sp} and h).

- $\overline{TAC}_{future}$, the average future annual TAC, given by:

$$\overline{TAC}_{future} = 1/20 \sum_{y=n+1}^{n+20} TAC_y$$

- AAV, the average inter-annual variation in future TAC given by:

$$AAV = 1/20 \sum_{y=n+1}^{n+20} \frac{\left| TAC_y - TAC_{y-1} \right|}{TAC_{y-1}}$$

- $\overline{C}_{future}$, the average future annual total catch, accounting for implementation error (which is not included in the TAC), given by:

$$\overline{C}_{future} = 1/20 \sum_{y=n+1}^{n+20} C_y$$

Target and limit reference points were chosen as 20% above and 50% of B_{MSY}, respectively. Expressed in terms of the pre-exploitation biomass, K, and assuming that maximum sustainable yield is achieved at $MSYL = 0.4K^{sp}$, the proxy target and limit reference points are approximately 50% and 20% of the pre-exploitation spawning biomass.

3.5   Application to example stocks

3.5.1   South African panga

The South African panga stock (*Pterogymnus lanniarius*) provides a minor by-catch in the valuable demersal trawl fishery for hake and is also caught by the commercial linefishery. Though not currently regulated, control could be effected in a manner similar to some other species which are by-caught in the hake trawl fishery that are subject to precautionary upper catch limits (PUCLs). The stock is considered data poor as the trawl catch time series available does not reflect the total annual removals. For the data considered here, the total annual landings from the trawl fishery have been inflated by 30% to approximately reflect catches from the linefishery. Regular surveys for the data-rich high-value target stock (hake) provide a survey index of abundance for panga (Tracey Fairweather pers. comm.).

Nearly twenty years ago, a stock assessment was performed by Booth and Punt (1998) by fitting an age-structured production model to biomass indices derived from the trawl surveys. These results showed that the panga population had recovered from low levels in the mid-1970s and that higher levels of fishing mortality would likely be sustainable. Annual catches have subsequently increased substantially, although no further stock assessments have been performed for almost two decades. There is thus a pressing need to ascertain whether current fishing mortality is sustainable.

3.5.1.1   Operating model parameters

The operating model (OM), described in Appendix B, is conditioned on fishery and biological parameter ranges which are based on estimates from Booth and Buxton (1997a and b).
Table 9 summarizes the "prior" distributions and fixed parameter choices assumed for the operating model. To account for high levels of uncertainty typical for data-poor stocks and associated parameter estimates, fairly wide parameter distributions have been adopted to condition the operating model. Note that the distribution selected for current depletion is much lower than the point estimate for 1995 due to subsequent continued high catches.

Parameter	Point estimate (from literature)	Distribution assumed for base case simulations
Minimum age	0 years	
Maximum age	20 years	
Age-at-maturity	4 years (204mm)	
Age at first capture	5 years (232mm)	
Von Bertalanffy growth:	$l_{\infty} = 379.4$ mm	$N(379.4, 0.1^2)$
	$\kappa = 0.13\,\mathrm{yr}^{-1}$	$N(0.13, 0.1^2)$
	$t_0 = -1.78$ years	$N(-1.78, 0.1^2)$
	$\alpha = 0.00002$ g mm$^{-3.013}$	$N(0.00002, 0.1^2)$
	$\beta = 3.013$	$N(3.013, 0.1^2)$
Natural mortality rate: M	0.28 yr^{-1}	$U[0.2, 0.4]$
Selectivity: a_{50}	5.5 years	Log-normal error distribution of residuals $\chi_{y,a} \sim N(0, 0.4^2)$
Selectivity: δ	0.6 yr^{-1}	
Stock-recruitment	Beverton-Holt	Log-normal error distribution of residuals $\zeta_y \sim N(0, 0.5^2)$
Steepness h	0.59	$U[0.5, 0.7]$
B^{sp}/K	0.67	$U[0.1, 0.3]$

Table 9: Parameter estimates taken from Booth and Buxton (1997a, 1997b) – the estimate for the steepness parameter, h, and spawning biomass depletion in 1995 is from Booth and Punt (1998) for an estimate for M of 0.28 yr^{-1}. Appendix B provides parameter definitions.

Age	0	1	2	3	4	5	6	7	8	9+
S_a^{com}	0	0	0.01	0.03	0.16	0.5	0.84	0.97	0.99	1
S_a^{survey}	0	0	0	0	0	1	1	1	1	1

Table 10: Logistic fishing selectivity-at-age vector for panga for the commercial fleet and the survey vessel (Booth and Punt 1998).

3.5.1.2 Data

Year	Landings	Survey	Mean length (mm)
1983	41.06		
1984	336.64		
1985	652.50		
1986	762.07		
1987	1011.01		
1988	884.82	50.62	255
1989	666.44	58.97	268
1990	591.20	57.24	267
1991	578.55	88.75	
1992	717.83	56.19	263
1993	905.69	89.82	250
1994	675.01	68.74	267
1995	845.51	103.13	264
1996	784.30	88.60	228
1997	977.24	105.51	254
1998	940.37		
1999	1061.05	129.15	249
2000	1044.26	80.12	277
2001	1325.47		
2002	1501.61		
2003	1748.56	91.25	267
2004	1629.13	85.01	277
2005	1303.69	59.58	261
2006	1132.07	108.51	280
2007	1142.88	38.51	282
2008	1341.67	63.55	241
2009	1812.84	62.66	237
2010	1871.75	42.88	278
2011	1422.16	71.74	278
2012	1068.13		
2013	951.33		

Table 11: Time series data for the panga bycatch in the demersal trawl fishery (courtesy of Tracey Fairweather, DAFF). The landings have been inflated by 30% to account for landings by the commercial linefishery. The survey and length indices are from data collected by the autumn demersal trawl surveys.
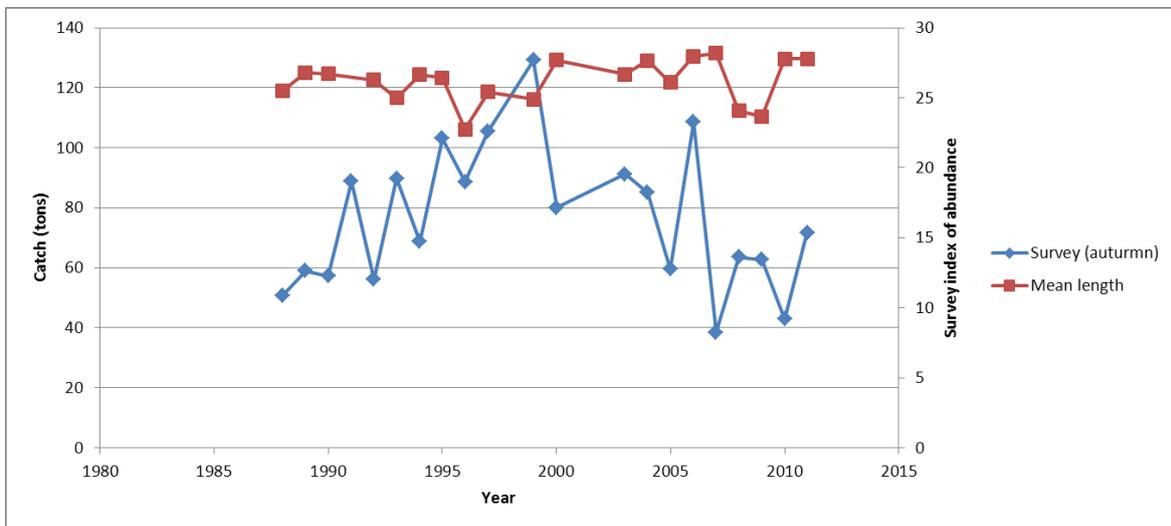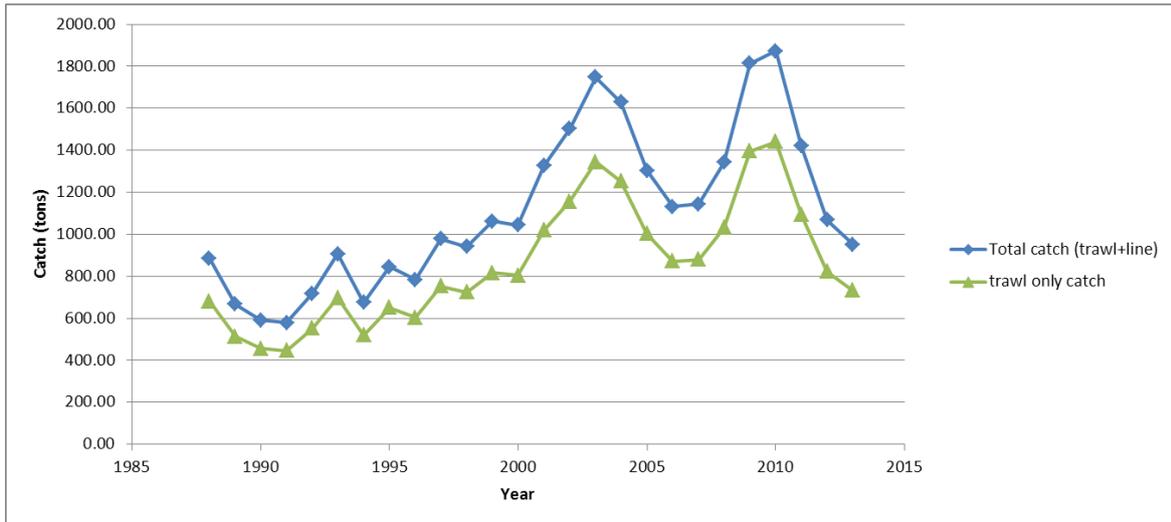
Figure 14: Top plot: Annual landings of panga by the demersal hake-directed trawl fishery are indicated by the green triangles. In the absence of landings data from the commercial line fishery, it is assumed that the line fishery catch is about 30% of the trawl bycatch. The total annual panga catch from both fisheries is approximated by simply inflating the trawl bycatch by 30% (indicated by the blue diamonds). Bottom plot: The blue diamonds correspond to the index of abundance provided by the demersal trawl surveys. The red squares correspond to the annual mean length in the survey catch. Panga landings and survey data from the demersal trawl fishery were obtained from Tracey Fairweather, DAFF (pers. comm.).

3.5.1.3   Results

Table 12 gives the TAC for the next year (2014) when applying the six "off the shelf" MPs, summarized in
Table 8, to the historical data in Table 11. The TAC advice for 2014 ranges between 524 to 983 tons, depending on which harvest control rule is applied, compared to a total catch of 951 tons assumed to have been taken in 2013. For the constant catch strategies (DACS and DCAC), depletion was assumed to be 0.3 for calculating the TAC.

Table 13 shows medians and 90% probability intervals for pertinent management quantities when projecting forward for twenty years under catch advice generated by these control rules. These stochastic projections include model uncertainty (by integrating over the wide ranges assumed for model parameters), process error (by allowing for fluctuations about fishing selectivity and the stock-recruitment function), observation error (by incorporating stochastic effects in the future data generated by the operating model) and implementation error (by adding bias and random variations to historical catch data as well as projected TAC advice). Given the extent of uncertainty, none of the candidate MPs, except Itarget, satisfies the risk criterion by ensuring that the spawning biomass at the end of the projection period exceeds the limit reference point of $0.2K$ at the lower percentile (second row of results in Table 13).

Figure 15 shows a subset of biomass, TAC and catch trajectories under alternative harvest control rules. While the TAC trajectories differ markedly from one strategy to another, the "true" total catch distributions are difficult to distinguish once implementation error is added. In the absence of annual assessments to inform the DCAC, this rule is essentially constant catch rule which cannot adjust TAC downwards when biomass levels are low (top row of plots). While incorporating feedback from the data to some extent, the TAC advice generated by the Ltarget and Islope rules is not adequately conservative to ensure subsequent increases in spawning biomass (second and fourth row of plots). The Iratio and Itarget rules are more conservative and take less catch initially, thereby ensuring faster spawning biomass recovery (third and last row of plots).

Pertinent performance statistics are compared for the different harvesting strategies in Figure 16. The top plot shows the distribution for spawning biomass depletion at the end of the 20-year projection period. The second plot shows the same, but here in terms of B_{MSY} rather than the pre-exploitation biomass, K. The target and limit reference points are indicated by the solid and dotted horizontal lines respectively. The third plot shows 90% probability intervals for the average TAC achieved by the alternative rules over the projection period, followed by a plot comparing the average inter-annual

variation in TAC for each of the rules. Note that the inter-annual variation in the TAC was restricted to a maximum of 15% for all candidates other than the constant catch type rules. The bottom plot compares the median and 90% probability intervals for "true" average catch under the different catch strategies when allowing for implementation error and bias. It is clear from the top two plots that the DACS, DCAC and Ltarget rules are not sufficiently precautionary, with the distributions for the final spawning stock biomass extending well below the limit reference points of $0.2K$ and $0.5B_{MSY}$ respectively at the lower percentiles. With no, or very little, feedback, these rules are associated with zero, or very low, inter-annual changes in TAC advice. However, if very little is known about stock-status, feedback and corresponding adjustments to TAC advice become that much more important in order to move/maintain the stock to/at safe levels. Of the feedback strategies that rely on a survey data, Islope is not sufficiently reactive and fails to recover the stock to the target biomass level in median terms over the 20-year projection period. The Iratio rule fares somewhat better, but only Itarget is able to ensure adequate recovery from low biomass levels (0.1 to $0.3K$) to the target spawning biomass of $0.5K$.

The trade-offs between potential yield and associated biological risk the candidate HRCs are compared in Figure 17. The best performing rules would lie towards the top right of these plots, i.e. the highest median yield and the largest stock size in terms of the pre-exploitation level. While better performance can undoubtedly be obtained for these strategies by tuning the control parameters to obtain better yield-risk performance, the objective here was to see how well these "off-the-shelf" type rules would perform when the data are limited and noisy. The dashed lines indicate different risk levels associated when projecting under alternative constant catches, ranging from 300 to 1000 tons. This provides a baseline with which to compare feedback strategies.

As expected, the DACS and DCAC strategies (which incorporate no index of abundance and therefore have no feed-back mechanism) perform the worst, lying on the yield-risk baseline. The rules that incorporate a direct index of abundance as provided by the survey data outperform the length-based rule (dark dot, top plot) that relies on information in the mean length time-series. This poor performance is due to the lack of trend information in the mean length time-series (see Figure 14). This is most likely due to the lag in feedback to be expected from the mean length index in response to a change in stock biomass. The three survey-based MPs (Itarget, Iratio and Islope) all lie well above and to the right of the baseline, providing better yield-risk performance. Of these feedback strategies, the Itarget (that relies on a survey time-series) is the most risk-averse, succeeding to maintain the spawning biomass above the limit reference point of 20% of the pre-exploitation level.

3.5.1.4 Discussion and conclusions

While the South African panga stock might be considered as "data-rich" thanks to regular demersal trawl surveys, it suffers from poor quality of data due to the high levels of uncertainty regarding total removals by different fleets. In particular, no catch or CPUE data could be obtained from the commercial line-fishery, rendering the status of this stock highly uncertain. The extent to which uncertainty has been incorporated in the operating model, in particular uncertainty regarding total removals and the full extent of implementation error, has resulted in obscuring management effects under the candidate harvest control rules investigated. Once noise and bias are added to the TAC advice, the subsequent effect on the stock biomass is "diluted", but some effect does still remain. This uncertainty- and noise-rich environment will be an unavoidable reality for most data-poor stocks. An additional disadvantage for low-value data-poor stocks is the cost of tuning stock-specific control rules: in the vast majority of cases, "off-the-shelf" rules will have to suffice.

Given the high levels of uncertainty about the stock dynamics and fishery data some broad conclusions can nevertheless be drawn: of the off-the-shelf control rules evaluated, the target-based rule that relies on a survey index is the most risk averse. At the other extreme, the constant catch-strategies exhibit the worst performance from a risk point of view. With no feedback, such strategies need to be rather conservative and take less catch on average. This is best illustrated by examination of the yield-risk results in Figure 17. To exceed the risk limit reference point of $0.2K$ at the 5%-ile, the Itarget rule (blue diamond) achieves an average future catch of over 600 tons compared to a constant catch (dashed line) of just over 400 tons (see grey arrow in top plot). Conversely, for the same average future catch of 600 tons, the constant catch strategy (as provided under the DACS rule) results in double the risk of resource depletion compared to the Itarget strategy (see grey arrow in bottom plot).

Figure 17 clearly illustrates the value of a survey index for management purposes. From these initial results, the potential gain in terms of average yield provided by the survey index of abundance is approximately 200 tons (50% increase in average catch at the limit reference point) while maintaining the same biological risk.

TAC advice for 2014	Harvest control rules and choice of control parameters
Depletion Adjusted Catch Scalar (DACS): DACS=610 tons (assume current depletion is 0.3)	$$DACS = s/(y2-y1+1)\sum_{y=y1}^{y2} C_y$$ where $s = 1-(0.5-B/K) = 0.8$, and $y_1 = 1988$ and $y_2 = 1997$.
Depletion Corrected Average Catch (DCAC): DCAC=861 tons (assume current depletion is 0.3)	$$DCAC = \frac{\sum_{1983}^{2013} C_y}{n + \Delta/(MSYL \times c \times M)}$$ where $\Delta = 1-B/K = 0.7$ $n = 31$, $MSYL = 0.4$, $M = 0.3$, and $c = 1$.
Length target (Ltarget): Ltarget=884 tons	$$TAC_{2014} = 0.5TAC^*[1+(\frac{L_y^{recent}-L^0}{L^{target}-L})]$$ where L^{recent} is average index over the most recent 3 years, $L^{target} = L_{F=M} = 0.75L_c + 0.25L_\infty = 269\text{mm}$, $I^0 = I^{target}/2$, and $TAC^* = DCAC$
Index ratio (Iratio): Iratio=791 tons	$$TAC_{2014} = TAC_{2013}\frac{1/3\sum_{2009}^{2011} I_y}{1/5\sum_{2004}^{2008} I_y}$$
Index slope (Islope) Islope=983 tons	$$TAC_{2014} = TAC_{2013}(1+\lambda s_y)$$ where $\lambda = 0.4$ and s_y is the slope of the CPUE over the last 5 years.
Index target (Itarget): Itarget=524 tons	$$TAC_{2014} = 0.5TAC^*[1+(\frac{I_y^{recent}-I^0}{I^{target}-I^0})]$$ where I^{recent} is average index over the most recent 5 years. $I^{target} = 0.4 \times \bar{I}/0.3 = 92$, $\bar{I} = 1/n\sum I_y$, $I^0 = I^{target}/2$, and $TAC^* = DCAC$.

Table 12: MP generated TAC advice when applying the six "off-the-shelf" control rules to the panga data.

	DACS	DCAC	Ltarget	Iratio	Islope	Itarget
B^{sp}_{2013} / K^{sp}	0.23 (0.12, 0.29)	0.23 (0.12, 0.29)	0.23 (0.12, 0.29)	0.23 (0.12, 0.29)	0.23 (0.12, 0.29)	0.23 (0.12, 0.29)
B^{sp}_{2033} / K^{sp}	0.49 (0.10, 0.68)	0.31 (0.07, 0.57)	0.37 (0.08, 0.62)	0.42 (0.16, 0.62)	0.32 (0.10, 0.51)	0.49 (0.22, 0.64)
$B^{sp}_{2013} / B^{sp}_{MSY}$	0.69 (0.36, 0.90)	0.69 (0.36, 0.90)	0.69 (0.36, 0.91)	0.69 (0.36, 0.90)	0.69 (0.36, 0.90)	0.69 (0.36, 0.91)
$B^{sp}_{2033} / B^{sp}_{MSY}$	1.45 (0.30, 2.11)	0.91 (0.21, 1.75)	1.09 (0.23, 1.89)	1.25 (0.46, 1.90)	0.95 (0.29, 1.56)	1.44 (0.64, 1.97)
$\overline{TAC}_{future}$	624 (624, 624)	861 (861, 861)	767 (653, 888)	690 (472, 957)	847 (644, 975)	619 (406, 781)
AAV	0.02 (0.02, 0.02)	0.00 (0.00, 0.00)	0.03 (0.03, 0.05)	0.13 (0.11, 0.15)	0.05 (0.03, 0.07)	0.12 (0.09, 0.15)
$\overline{C}_{future}$ (implementation error)	651 (535, 795)	900 (727, 1092)	798 (627, 1025)	718 (486, 1013)	872 (667, 1093)	644 (425, 847)

Table 13: Medians (with 5% and 95%-iles in parenthesis) of summary performance statistics are shown for the six candidate "off the shelf" rules (i.e. no tuning of MP control parameters to improve performance). The parameter distributions for the operating model are summarized in Table 12. A total of 1000 simulations were performed. Units, where pertinent, are tons. The inter-annual fluctuations in TAC were restricted to 15% for all feedback MPs.
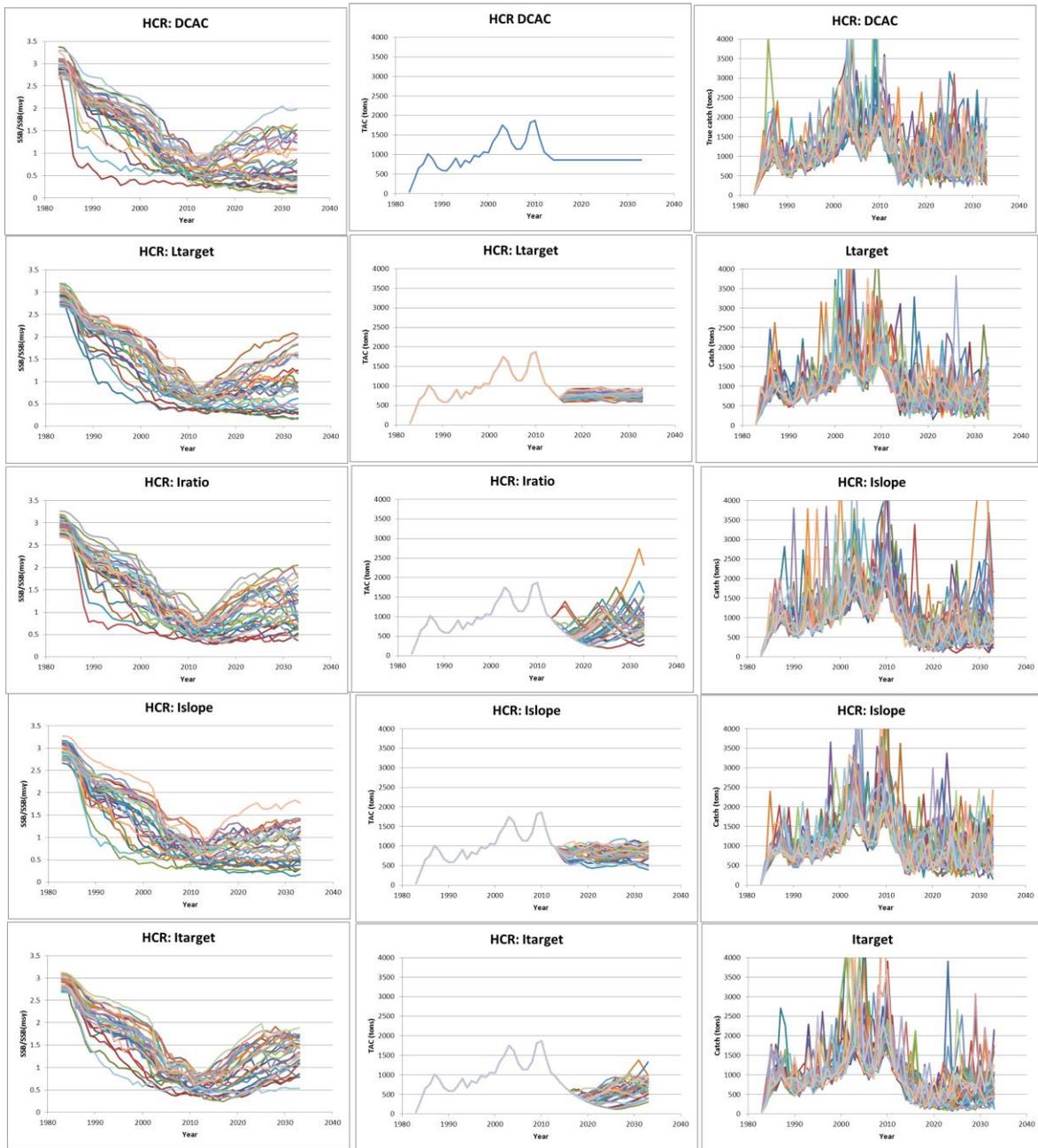
Figure 15: Plots of the projections under alternative harvesting strategies. The left-hand column of plots show spawning biomass as a fraction of B_{MSY}, the middle column shows the projected TACs under different harvesting strategies, while the right-hand column represents the "true" past and projected catches when incorporating implementation error. The trajectories correspond to the first thirty simulations of the one thousand performed.
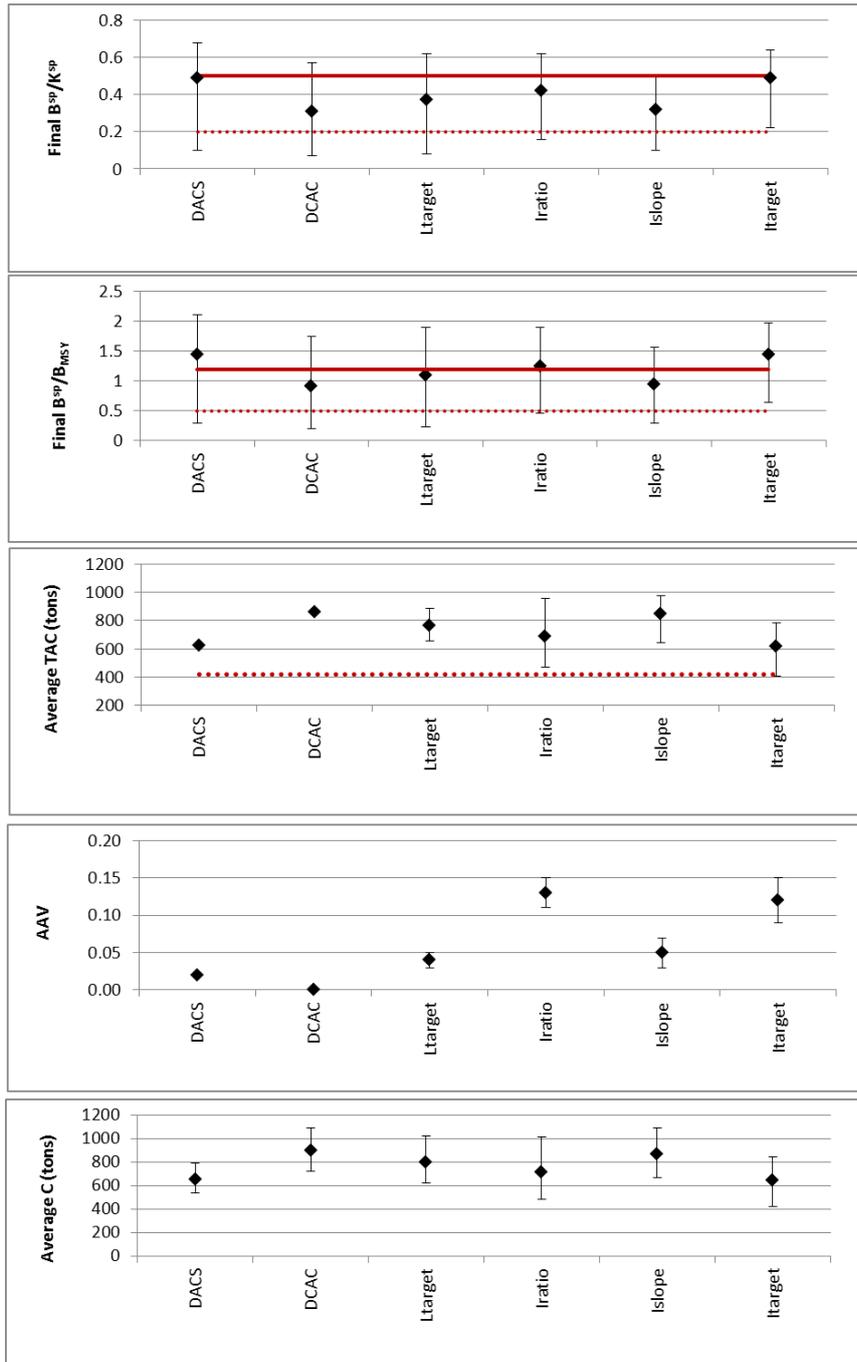
Figure 16: Comparison of management statistics for the six harvest control rules. The top two plots compare spawning biomass distributions for the final year of the projection period, i.e. 2033. The inter-annual variation in TAC was restricted to a maximum of 15% for all candidate rules (excluding the constant catch rules), although this constraint came to be applied for the Iratio and Itarget rules only.
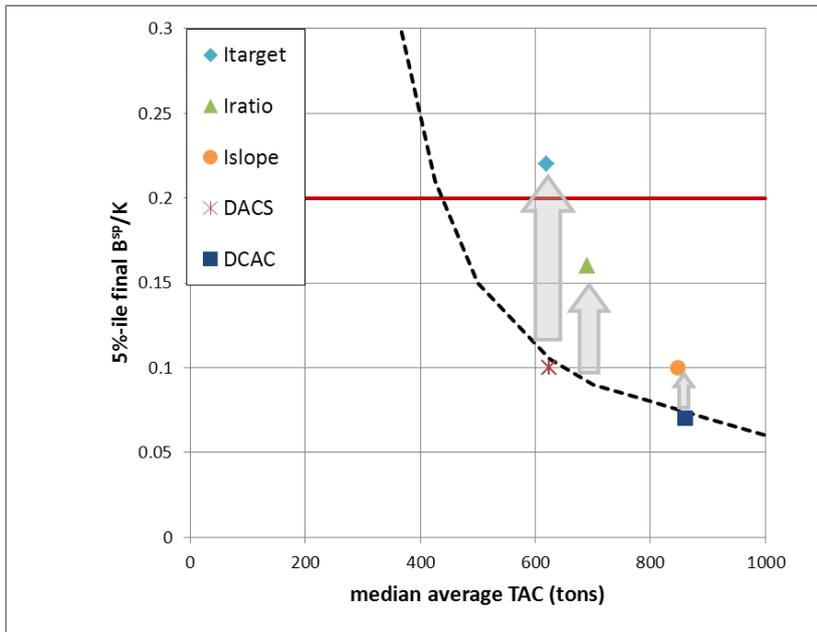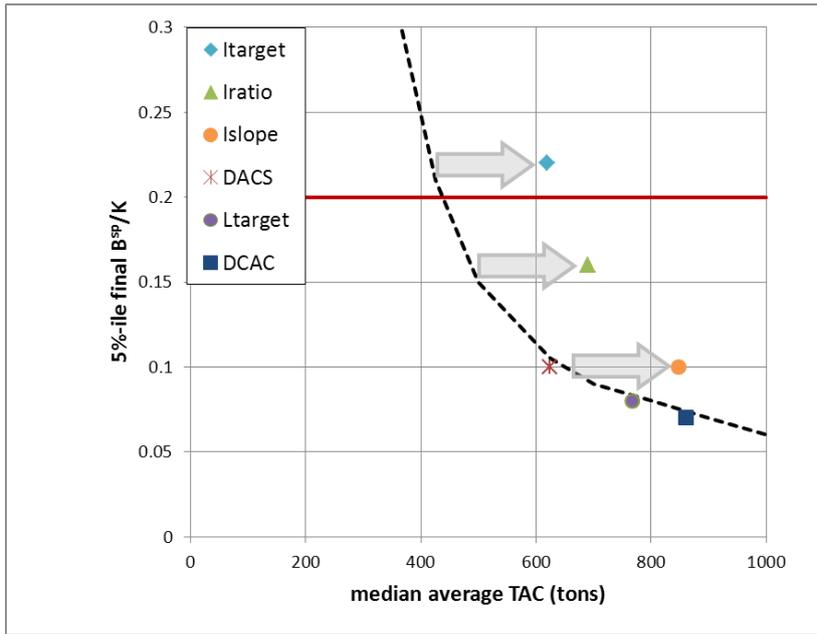
Figure 17: Risk versus yield achieved by the "off-the-shelf" MPs. The solid horizontal lines indicate the biological limit reference point (0.2K). The dashed lines correspond to increasing biological risk associated with alternative constant catch strategies ranging from 300 to 1000 tons. The grey arrows indicate the difference in potential yield under constant catch and feedback strategies (top plot) and the increased risk associated with non-feedback strategies for the same average yield (bottom plot).

3.5.2 Jamaican queen conch

Queen conch (*strombus gigas*) is Jamaica's most valuable fishery, mainly geared for the export market. The fishery developed rapidly in 1990's with the main harvest coming from the Pedro Bank where most large adult conch are found. With the aim to monitor and control the conch fishery to achieve optimum sustainable yields, a Queen Conch Fishery Management Plan was introduced in 1994 to set guidelines for the quota management system and an annual National Total Allowable Catch (NTAC) based on the best available scientific data (FAO Western Central Atlantic Fishery Commission 2013). Even though the stock is under formal management by both national and international institutional arrangements, with a CITES Appendix II listing in 1992, Aiken *et al* (2006) warn of the possibility of continued high levels of poaching and under-reporting of catches.

A Schaefer model has been applied to assess the stock in the past, and resulted in estimates of MSY of 715 (corresponding to a high intrinsic growth rate of 0.5) and 1297 tons (corresponding to a low intrinsic growth rate of 0.24) (CFMC/CFRAMP 1999). This divergence in results underscores the high level of uncertainty regarding the dynamics of the stock and what would constitute sustainable levels of harvest. Aiken *et al.* (2006) estimated the stock abundance to be stable in 2002. Healthy stock densities in all surveys have been reported since 1994, although the most recent 2007 estimate is somewhat lower than before. A preliminary Schaefer assessment by FAO conducted this year estimates biomass to be well above MSY level. However, the Schaefer model biomass estimates do not follow the recent downward trend in the survey index (Marcelo Vasconcellos, FAO pers. comm.). With this current uncertainty about stock status, a reliable target for the NTAC is required to ensure sustainable use of the stock.

3.5.2.1 Operating model parameters

Based on current estimates of spawning biomass depletion from Schaefer assessments (Marcelo Vasconcellos, FAO pers. comm.), a depletion range from 0.3 to $0.5K$ was assumed for the base case OM.

Growth of conch is modeled in two stages: growth in juvenile conch is measured in shell length, while that of adults is measured in lip thickness, with each stage modeled by a separate von Bertalanffy function. However, for simplicity here a combined model for growth, developed by Appeldoorn (2005), has been used for this study (see Figure 18).

The natural mortality rate for conch is assumed to be constant over all ages for the base case simulations. However, a natural mortality function which decreases with age and has the form $M_a = -0.242 + 4.33/a$ (Table 14) was suggested at the queen conch stock assessment and management workshop held in Belize City in 1999 (CFMC/CFRAMP 1999, SEDAR 2007, McCarthy 2008). These function parameter values result in negative mortality rates at older ages and the workshop recommended that mortality rates be restricted to a minimum of $0.1 yr^{-1}$ for older conch. This restricted function was adopted for some robustness tests to eliminate implausible values for natural mortality rate when sampling parameter values from distributions (see Table 15 for parameter ranges).

To account for possible under-reporting of catches and poaching (Aiken *et al.* 2006), implementation error has been incorporated in this analysis. The historical catches are assumed to be negatively biased, and in addition some random fluctuations about reported total landings are assumed (see Appendix B).

Age	0	1	2	3	4	5	6	7	8	9	10	11	12+
M_a	4.09	1.92	1.20	0.84	0.62	0.48	0.38	0.30	0.24	0.19	0.15	0.12	0.1
S_a^{com}	0	0	0.5	0.8	1	1	1	1	1	1	1	1	1
S_a^{survey}	0	0	1	1	1	1	1	1	1	1	1	1	1

Table 14: Age-dependent natural mortality and commercial fishing selectivity values assumed for calculations. Fully selected selectivity from age 1 is assumed for the surveys (McCarthy 2008, Morris 2013, Marcelo Vasconcellos, FAO pers. comm.).

Parameter	Point Estimate	Distribution assumed for base case simulations
Minimum age	0 years	
Maximum age	30 years	
Age-at-maturity	3.2-6 years	$U[3,6]$
Growth:	$w_a = \alpha \exp(l_\infty (1 - \exp(-\kappa a)))$	
	$l_\infty = 20.12\,\text{cm}$	$N(20.12, 0.1^2)$
	$\kappa = 1.275$	$N(1.275, 0.1^2)$
	$\alpha = 4.394 \times 10^{-7}$	$N(4.394 \times 10^{-7}, 0.1^2)$
Natural mortality rate	Base case: age-independent	$U[0.05, 0.3]$
	Age-dependent: $M_a = \alpha + (\beta / a)$ (with min $M_a = 0.1$)	
	$\alpha = -0.242$	$U[-0.3, -0.2]$
	$\beta = 4.33$	$U[3.0, 5.0]$
Commercial selectivity	Log-normal error distribution of residuals	$\chi_{y,a} \sim N(0, 0.4^2)$
Steepness h	High density dependence	$U[0.5, 0.7]$
Current depletion	B_n^{sp} / K	$U[0.3, 0.5]$
Implementation error	Log-normal error distribution of residuals	$\varepsilon_y \sim N(\mu_C, 0.2^2)$ $\mu_C \sim U[0, 0.1]$

Table 15: Parameter estimates and ranges based on Appeldoorn (2005a, b). The range assumed for the steepness parameter, *h*, is based on density-dependence estimates reported in Stoner and Ray-Culp (2000). The age-dependent natural mortality function parameterisation is based on that reported in McCarthy (2008), but here excluding negative M_a at old ages. To account for the high levels of uncertainty typical for data-poor stocks and associated parameter estimates, fairly wide parameter distributions have been adopted to condition the operating model. Details regarding parameter specifications can be found in Appendix B.
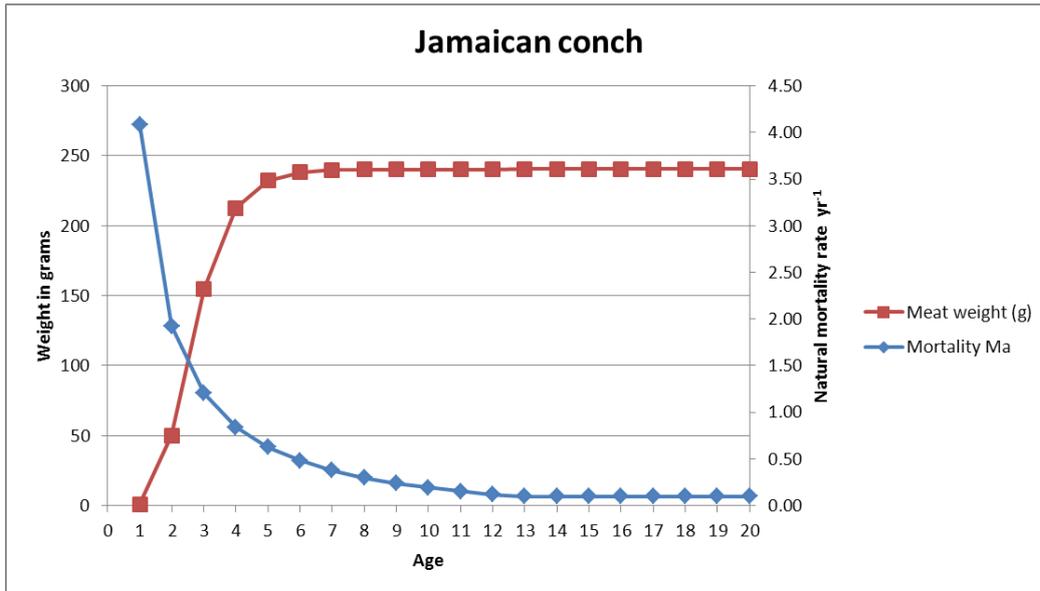
Figure 18: The squares represent the growth curve for conch for 50% cleaned meat weight-at-age in grams (Appeldoorn 2005b). The age-dependent natural mortality rate (CFMC/CFRAMP 1999) is indicated by the diamonds. Note, however, that M is assumed to be age-independent for the base case operating model.

3.5.2.2   Data

Catch data reported to FAO are given in Table 16 and plotted in Figure 19. The first column corresponds to annual catches in tons of live weight. Prior to 1988, the fishery was artisanal and annual catches were comparatively small with exports less than 50 tons per annum. To convert these catches to 50% cleaned (the way conch is exported from Jamaica) a conversion factor of 7.5 was applied to correspond to the National Total Allowable catch (NTAC) (Marcelo Vasconcellos, FAO. pers. comm.). Due to prolonged legal battles the Jamaican conch fishing season was closed during the 2000/2001 season (Aiken *et al.* 2006).

Multi-annual visual surveys are conducted on the Pedro Bank by commercial and scientific divers. These surveys assess three depth strata (0 to 10m, 10 to 20m and 20 to 30m). The first three surveys (1994, 1997 and 2002) showed an increase in density with depth. The survey performed in 2007 indicated a low density of conch at depths deeper than 10 meters, with most conch located in the artisanal (0-10m) stratum, and with a 50% decrease in associated biomass estimate from the previous survey estimate. However, the most recent survey conducted in 2011 indicated higher density estimates at depths deeper than 10m, comparable to the pre-2007 estimates (Morris 2013).

Year	Catch: live weight	Catch: (7.5 conversion) 50% cleaned meat	NTAC (tons) 50% cleaned meat	Survey biomass estimates
1988	4500.00	600		
1989	5250.00	700		
1990	6000.00	800		
1991	7500.00	1000		
1992	11250.00	1500		
1993	15000.00	2000		
1994	17250.00	2300	3000	13325.48
1995	15998.00	2133	2000	
1996	10740.00	1432	1900	
1997	13658.00	1821	1800	12203.27
1998	12750.00	1700	1700	
1999	10245.00	1366	1366	
2000				
2001	9120.00	1216	1216	
2002	7095.00	946	946	15305.85
2003	3780.00	504	950	
2004	4125.00	550	550	
2005	4800.00	640	640	
2006	4875.00	650	690	
2007	4800.00	640	650	7421.78
2008	3000.00	400	400	
2009	3000.00	400	400	
2010	3300.00	440	400	
2011	3000.00	400	400	12213.98
2012	3000.00	400		

Table 16: Total annual catches for the Jamaican queen conch stock in tons in terms of live meat weight (column 1) and "50% cleaned" weight using a 7.5 conversion factor (column 2). The National Total Allowable Catch (NTAC), expressed in terms of "50% cleaned" weight, is given in column 3. Survey biomass estimates in tons are given in column 4. Units are tons. Catch data are from FAO FishStat; NTACs and survey biomass estimates are from Morris (2013).
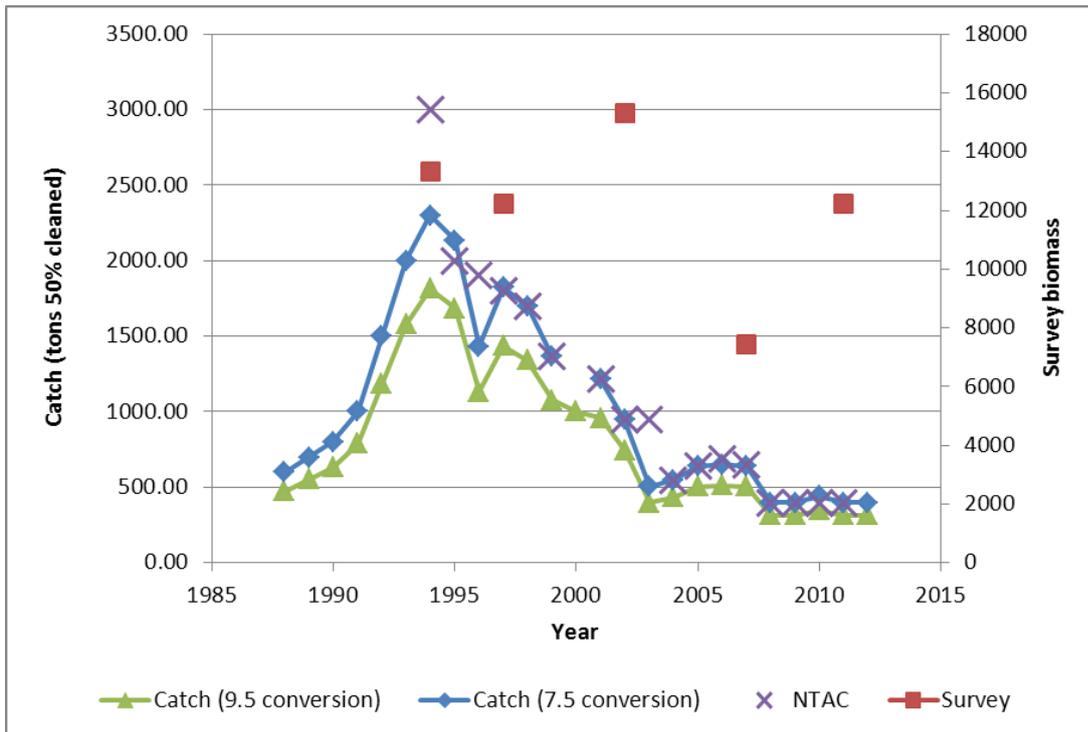
Figure 19: The national total allowable catches (NTACs) for Jamaican conch are indicated by the crosses. The blue and green triangles correspond to FAO estimates of 50% cleaned meat weight in tons when applying a conversion factors of7.5. Survey estimates for the years 1994, 1997, 2002, 2007 and 2011 are indicated by the red squares (Morris 2013).

3.5.2.3 Results

Table 17 gives the TAC for the next year (2013) when applying the five candidate MPs, or harvest control rules, to the historical data in Table 16. According to these "off-the-shelf" rules, the TAC advice for 2013 ranges from 289 to as high as 899 tons in terms of 50% cleaned wet meat weight, compared to a "50% cleaned" catch of 400 tons reported for 2012. In order to apply the constant catch strategies (DACS and DCAC), an initial guess for current depletion is required – a value of 0.4, which corresponds to the midpoint of the depletion range assumed by the base case operating model, was assumed.

Table 18 shows medians and 90% probability intervals for the base case OM when projection forward for 20 years under five alternative control rules: two constant catch-type strategies and three feed-back rules based on the multi-annual survey biomass estimates. The feedback strategies (Iratio, Islope and Itarget) rely on new survey biomass estimate to become available every four years to adjust the TAC. For the intervening years, the TAC is simply left unchanged. Of the candidate rules, all strategies except DCAC are able to satisfy the risk criteria by ensuring (at the 5%-ile level) a stock depletion above 20% at the end of the twenty-year projection period. The DCAC of 899 tons has a high probability of resulting in a large decrease in spawning biomass over the projection period and is therefore not a viable option.

Figure 20 shows worm plots for the first 30 simulations of a 1000 performed under alternative MPs for the base case OM. Spawning biomass is plotted as a fraction of virgin biomass in the first column of these plots; the second column shows TAC advice generated by the different strategies; the third column depicts the "true" catches when accounting for implementation error. It is clear from the left-hand plots that application of all candidate rules lead to continued stock rebuilding, with the exception of DCAC for which catches are clearly not sustainable given the underlying assumptions for the base case OM. Initial inspection of the right-hand column of plots seem to indicate that the benefits of the multi-annual adjustments to TAC advice generated by the feed-back strategies are lost once implementation error is incorporated. However, MPs that use information in the survey data to adjust TAC advice up or down are able to self-correct and adapt to low biomass levels thereby avoiding further (unchecked) stock depletion, as is evident from Table 25 and Figure 24. While the feedback strategies (Iratio, Islope and Itarget) often lead to elevated inter-annual fluctuations in TAC advice, this disadvantage is eliminated here thanks to the multi-annual availability of survey estimates – the TAC advice is adjusted only once a new survey estimate becomes available.

Table 19 to Table 24 compare medians and 90% probability intervals for average future catch and final depletion for six robustness tests:

- Table 19 evaluates the effect on management statistics when assuming that natural mortality is age-dependent rather than constant for all ages. For this robustness test, the natural mortality rate for young conch is well above 1, decreasing to $0.1yr^{-1}$ at older ages (see Table 14 and Figure 18). While the final depletions are somewhat lower for this robustness test, all MPs (except DCAC) nevertheless satisfy the minimum risk criterion of maintaining the spawning biomass above 20% of virgin levels at the 5%-ile.

- Table 20 shows results when assuming that the conch stock is more depleted (10-30% of K) than assumed for the base case OM (30-50% of K). If the "true" depletion is indeed lower than expected, both constant catch rules, and indeed the Itarget rule which is partly based on DACS, lead to even further stock depletion. Only the Iratio and Islope feedback strategies are able to self-correct and result in stock recovery, even at the lower percentile.

- Table 21 shows projection results when assuming higher levels of under-reporting, poaching and/or implementation error (and/or error in the conversion factor when calculating the 50% cleaned weight catch from total weight). Not surprisingly, an increase in implementation error leads to slightly lower biomass levels. However, all the MPs except DCAC demonstrate adequate robustness.

- Table 22 shows yield/risk results when basing management advice on a survey index that is less reliable. While not effecting final depletion, the increase in noise about the data leads to slightly less yield in terms of the median average catch for some of the feedback strategies.

- Table 23 compares results when increasing the frequency of the multi-annual surveys. The increase in data improves performance to some extent, but by less than would be hoped. This is likely mainly due to the choice of control parameters adopted for these "off-the-shelf" rules, combined with multi-annual TACs and the initial assumption for stock size: the base case OM assumes biomass to be close to MSY level; under this assumption, the survey data generated are unlikely to exhibit any discernable increasing or decreasing trend biomass, but rather reflect noise. If annual survey estimates were to become available in future, these "off-the-shelf" rules would desirably be adjusted and tuned to be able to respond to possible decreasing trends in the biomass quickly with annual adjustments to TAC.

- Table 24 shows projection results when combining robustness tests 2, 3 and 4 (depleted stock with high levels of implementation error and noisy data). This final test demonstrates the danger of implementing a constant catch strategy. Both DACS and DCAC fail to maintain biomass levels at the lower percentile. The Itarget rule also leads to severe biomass depletion, indicating that the performance of this rule is very sensitive to the choice of index and catch target. On the other hand, the two other feedback strategies (Iratio and Islope) lead to an increase in biomass from current low levels (10 to 30% of K) to approximately 25% to 90%

of virgin spawning biomass at the end of the projection period. This comes at the cost of less catch on average in median terms: 339 and 384 tons compared to the NTAC of 400 tons.

- Table 25 is the same as Table 24, except that biomass surveys are assumed to be conducted every year with TAC advice adjusted accordingly, i.e. annually. These results indicate that, for a very depleted stock, additional (annual) biomass estimates can potentially lead to improved performance in terms of both yield and risk: note, for example, that the Itarget rule shows an increase in mean average catch and lower percentile final depletion from 476 to 504 tons and 0.01 to 0.18, respectively.

Figure 22 compares yield-risk statistics for the base case operating model and the robustness tests. The solid horizontal line indicates the 20% depletion level that acts as the risk limit reference point for this study. It is clear that the DCAC strategy (square) fails consistently to reach the biomass limit reference point. Three of the five candidates fail to satisfy the risk criterion for robustness test 2: here, spawning biomass is much lower than assumed for the base case when applying the DACS, DCAC and Itarget rules. However, the two feedback strategies, Iratio and Islope, are able to rebuild spawning biomass to reasonably high levels even at this lower percentile.

Error! Reference source not found. plots yield-risk results for the combined robustness test. learly, the constant catch and Itarget rules fail to maintain or rebuild biomass and are therefore not viable candidates to provide TAC advice. Of the feedback strategies, the more conservative Iratio and Islope rules demonstrate adequate robustness throughout the simulation trials, with the Islope rule giving the the greatest median yield (384 tons 50% cleaned meat) while still satisfying the risk criterion. The advantage of conducting annual biomass surveys is clearly visible in Figure 24: for the same biological risk the feedback strategies achieve much higher yields than the constant catch strategies indicated by the dashed lines.

3.5.2.4   Discussion and conclusions

The range of uncertainty incorporated in these simulations makes it more difficult to evaluate and compare the merits of the different candidate MPs. The challenge is to be able to react to trend information while at the same time ignoring the high levels of noise typically associated with the biomass index. Once implementation error (both past and future) is incorporated, the effect of the control rule is partially obscured. Nevertheless, these initial results show that constant catch type rules (DACS and DCAC) are not robust as they cannot self-adjust to signals in the data as the stock becomes increasingly depleted. Of the feedback strategies, the Islope and Iratio rules performed best, providing measured adjustments to TAC advice in response to signals in the data. The Itarget rule did

not perform well given its "off-the-shelf" parameterization. The poor performance is a consequence of the construction of the control rules and the choice of control parameters. However, this evaluation is preliminary and current projections have been conducted with "off-the-shelf" MPs. Future work would entail tuning these control rules to achieve improved yield-risk performance for different data availability scenarios.

Based on these preliminary results, the overriding concern is to be able to categorise the stock according to the appropriate depletion level. The less information regarding stock status there is, the more conservative the rule needs to be: of the five candidates considered, only the most conservative rules, Islope and Iratio, were able to rebuild the stock from low biomass levels. Increasing the frequency of the surveys did not lead to much improvement in performance when the current stock biomass is assumed to be close to MSY level. The value of annual surveys became more evident when stock size is very low: for the depleted scenario, the performance of the Itarget rule improved greatly with the addition of annual biomass estimates. As evident from Figure 24, for the same level of risk, the Itarget MP achieved an average future catch of about 500 tons in median terms compared to a constant catch (dashed line) of just over 350 tons (grey arrow in top plot). Conversely, for the same median average future catch of approximately 500 tons, the constant catch strategy DACS rule led to unacceptably low biomass depletion at the 5%-ile of 0.1 compared to 0.18 achieved by the Itarget rule (grey arrow bottom plot). Similarly, the more conservative Islope MP halved the biological risk for a median average catch of 400 tons, compared to the constant catch equivalent.

TAC calculation using actual data	
Depletion Adjusted Catch Scalar (DACS): DACS= 488 tons (assume current depletion is 0.4)	$DACS = s / (y2 - y1 + 1) \sum_{y=y1}^{y2} C_y$ where $s = (1 - (0.5 - B/K)) = 0.9$, $B/K = 0.4$, and $y_1 = 2003$ and $y_2 = 2012$.
Depletion Corrected Average Catch (DCAC): DCAC=899 tons (assume current depletion is 0.4)	$DCAC = \dfrac{\sum_{1988}^{2012} C_y}{n + \Delta / (MSYL \times c \times M)}$ where $n = 25, \Delta = 1 - B/K = 0.6, MSYL = 0.4$, $\bar{M} = 0.4$, and $c = 1$
Index ratio (Iratio): Iratio= 289 tons	$TAC_{2013} = TAC_{2011} \dfrac{1/2 \sum_{2007}^{2011} I_y}{1/3 \sum_{1994}^{2002} I_y}$
Index slope (Islope) Islope=397 tons	$TAC_{y+1} = TAC_y (1 + \lambda s_y)$ where $\lambda = 0.4$ and s_y is the slope over the most recent four CPUE values.
Target MP (Itarget): Itarget= 490 tons	$TAC_{2013} = 0.5 TAC^* \left(1 + \dfrac{I_y^{recent}}{I^{target}} \right)$ where $TAC^* = DACS$, I^{recent} is the most recent index value, $I^{target} = 12094$ is the historical average.

Table 17: MP generated TAC for 2013 when applying the five candidate "off-the-shelf" MPs to Jamaican conch data.

	DACS	DCAC	Iratio	Islope	Itarget
B_n^{sp} / K^{sp}	0.4 (0.31, 0.49)	0.4 (0.31, 0.49)	0.4 (0.31, 0.49)	0.4 (0.31, 0.49)	0.4 (0.31, 0.49)
B_{final}^{sp} / K^{sp}	0.63 (0.40, 0.97)	0.36 (0.01, 0.76)	0.69 (0.46, 1.0)	0.67 (0.46, 0.99)	0.60 (0.34, 0.96)
B_n^{sp} / B_{MSY}^{sp}	1.25 (0.94, 1.60)	1.25 (0.94, 1.60)	1.25 (0.94, 1.60)	1.25 (0.94, 1.60)	1.25 (0.94, 1.60)
$B_{final}^{sp} / B_{MSY}^{sp}$	1.95 (1.21, 3.04)	1.13 (0.04, 2.34)	2.12 (1.39, 3.19)	2.08 (1.39, 3.11)	1.87 (1.06, 2.97)
$\overline{TAC}_{future}$	488	899	373 (294, 458)	403 (366, 443)	526 (430, 646)
AAV	0.01 (0.01, 0.01)	0.06 (0.06, 0.06)	0.04 (0.03, 0.04)	0.01 (0.01, 0.02)	0.03 (0.02, 0.04)
$\overline{C}_{future}$ (implementation error)	513 (469, 558)	943 (863, 1027)	387 (304, 487)	423 (371, 480)	552 (443, 697)

Table 18: Medians (with 5% and 95%-iles in parenthesis) are shown for performance statistics for the five "off the shelf" MPs applied over a 20-year period. A CV of 20% is assumed for the survey index. A thousand simulations were performed to ensure adequate coverage over multiple model parameter ranges. Units, where pertinent, are tons. The shaded rows correspond to medians and distributions at the start of the projection period.

Robustness test 1: Sharply decreasing M_a: $M_a = -\alpha + \beta / a$	DACS:	DCAC:	Iratio	Islope	Itarget
B_n^{sp} / K^{sp}	0.4 (0.31, 0.49)	0.4 (0.31, 0.49)	0.4 (0.31, 0.49)	0.4 (0.31, 0.49)	0.4 (0.31, 0.49)
B_{final}^{sp} / K^{sp}	0.57 (0.23, 0.94)	0.33 (0.03, 0.76)	0.63 (0.29, 1.02)	0.62 (0.29, 1.0)	0.55 (0.19, 0.95)
$\overline{TAC}_{future}$	488	899	360 (270, 477)	397 (358, 441)	503 (414, 620)
$\overline{C}_{future}$ (implementation error)	513 (469, 560)	944 (864, 1030)	374 (281, 496)	418 (362, 475)	528 (425, 658)

Table 19 : Comparison of performance of MPs to age-dependent natural mortality.

Robustness test 2: Low depletion: $B / K \sim U[0.1, 0.3]$	DACS:	DCAC:	Iratio	Islope	Itarget
B_n^{sp} / K^{sp}	0.2 (0.11, 0.29)	0.2 (0.11, 0.29)	0.2 (0.11, 0.29)	0.2 (0.11, 0.29)	0.2 (0.11, 0.29)
B_{final}^{sp} / K^{sp}	0.46 (0.01, 0.86)	0.01 (0.0, 0.51)	0.59 (0.31, 0.94)	0.54 (0.26, 0.90)	0.46 (0.01, 0.87)
$\overline{TAC}_{future}$	488	899	351 (258, 423)	390 (333, 438)	498 (344, 651)
$\overline{C}_{future}$ (implementation error)	513 (469, 558)	943 (863, 1027)	365 (266, 450)	409 (343, 475)	507 (412, 641)

Table 20: Comparison of performance of MPs to the misspecification of current depletion. For these simulations the "true" current depletion is lower than assumed for the base case and falls in the range 0.1 to 0.3 of the pre-exploitation biomass.

Robustness test 3: Increased under-reporting: $\mu_C \sim U[0, 0.2]$	DACS:	DCAC:	Iratio	Islope	Itarget
B_n^{sp} / K^{sp}	0.4 (0.31, 0.49)	0.4 (0.31, 0.49)	0.4 (0.31, 0.49)	0.4 (0.31, 0.49)	0.4 (0.31, 0.49)
B_{final}^{sp} / K^{sp}	0.62 (0.39, 0.96)	0.35 (0.01, 0.74)	0.68 (0.46, 1.0)	0.67 (0.46, 0.99)	0.60 (0.34, 0.95)
$\overline{TAC}_{future}$	488	899	373 (293, 459)	403 (366, 443)	525 (430, 646)
$\overline{C}_{future}$ (implementation error)	539 (477, 606)	992 (877, 1115)	409 (317, 514)	445 (381, 521)	579 (462, 749)

Table 21: Comparison of performance of MPs to increased levels of under-reporting of catches.

Robustness test 4: Noisy survey: CV=0.4	DACS:	DCAC:	Iratio	Islope	Itarget
B_n^{sp} / K^{sp}	0.4 (0.31, 0.49)	0.4 (0.31, 0.49)	0.4 (0.31, 0.49)	0.4 (0.31, 0.49)	0.4 (0.31, 0.49)
B_{final}^{sp} / K^{sp}	0.63 (0.40, 0.97)	0.36 (0.01, 0.76)	0.69 (0.46, 1.0)	0.67 (0.46, 1.0)	0.61 (0.36, 0.97)
$\overline{TAC}_{future}$	488	899	363 (271, 483)	400 (353, 444)	505 (412, 641)
$\overline{C}_{future}$ (implementation error)	513 (469, 558)	943 (863, 1027)	377 (282, 502)	418 (360, 482)	528 (426, 679)

Table 22: Comparison of performance of MPs to increased levels of noise in the survey biomass index.

Robustness test 5: More data: Annual survey	DACS:	DCAC:	Iratio	Islope	Itarget
B_n^{sp} / K^{sp}	0.4 (0.31, 0.49)	0.4 (0.31, 0.49)	0.4 (0.31, 0.49)	0.4 (0.31, 0.49)	0.4 (0.31, 0.49)
B_{final}^{sp} / K^{sp}	0.63 (0.40, 0.97)	0.36 (0.01, 0.76)	0.68 (0.46, 1.0)	0.67 (0.45, 1.0)	0.60 (0.39, 0.92)
$\overline{TAC}_{future}$	488	899	376 (291, 517)	417 (384, 452)	533 (464, 632)
$\overline{C}_{future}$ (implementation error)	513 (469, 558)	943 (863, 1027)	400 (299, 542)	438 (388, 494)	562 (475, 678)

Table 23: Comparison of performance of MPs to an increased frequency of surveys. While the survey biomass index is updated every year, the TAC advice is changed every four years.

Combined robustness tests 2+3+4:	DACS:	DCAC:	Iratio	Islope	Itarget
B_n^{sp} / K^{sp}	0.2 (0.11, 0.29)	0.2 (0.11, 0.29)	0.2 (0.11, 0.29)	0.2 (0.11, 0.29)	0.2 (0.11, 0.29)
B_{final}^{sp} / K^{sp}	0.45 (0.01, 0.86)	0.01 (0.0, 0.5)	0.59 (0.29 0.94)	0.54 (0.25, 0.91)	0.47 (0.01, 0.88)
$\overline{TAC}_{future}$	488	899	339 (258, 441)	384 (324, 437)	476 (348, 624)
$\overline{C}_{future}$ (implementation error)	539 (477, 606)	992 (877, 1115)	371 (271, 488)	423 (346, 510)	520 (378, 706)

Table 24: Comparison of performance of MPs for a combination of robustness tests: the OM assumes that the "true" depletion falls within in a range of 0.1 to 0.3 of virgin spawning biomass. In addition, the under-reporting/poaching and non-compliance is more severe than assumed in the base case OM with the "true" catches now higher than before. Lastly, future survey biomass estimates are less reliable (more noisy) than for the base case simulations.

Combined robustness tests 2+3+4+5:	DACS:	DCAC:	Iratio	Islope	Itarget
B_n^{sp} / K^{sp}	0.2 (0.11, 0.29)	0.2 (0.11, 0.29)	0.2 (0.11, 0.29)	0.2 (0.11, 0.29)	0.2 (0.11, 0.29)
B_{final}^{sp} / K^{sp}	0.45 (0.01, 0.86)	0.01 (0.0, 0.5)	0.52 (0.28, 0.83)	0.52 (0.27, 0.86)	0.43 (0.18, 0.75)
$\overline{TAC}_{future}$	488	899	371 (196, 721)	410 (321, 505)	504 (375, 691)
AAV	0.01	0.06	0.13 (0.11, 0.14)	0.06 (0.04, 0.08)	0.07 (0.04, 0.09)
$\overline{C}_{future}$ (implementation error)	539 (477, 606)	992 (877, 1115)	411 (215, 810)	450 (348, 579)	558 (409, 795)

Table 25: Results for circumstances as described for Table 24, except, that in addition future survey biomass estimates become available annually and TAC advice is provided at this same shorter interval.

Figure 20: Plots of the projections under alternative MPs for the base case OM. The left-hand column of plots show spawning biomass depletion, the middle column shows the projected TACs under different harvesting strategies, while the right-hand column shows the "true" past and projected catches when incorporating implementation error. The trajectories correspond to the first thirty simulations of the one thousand performed.
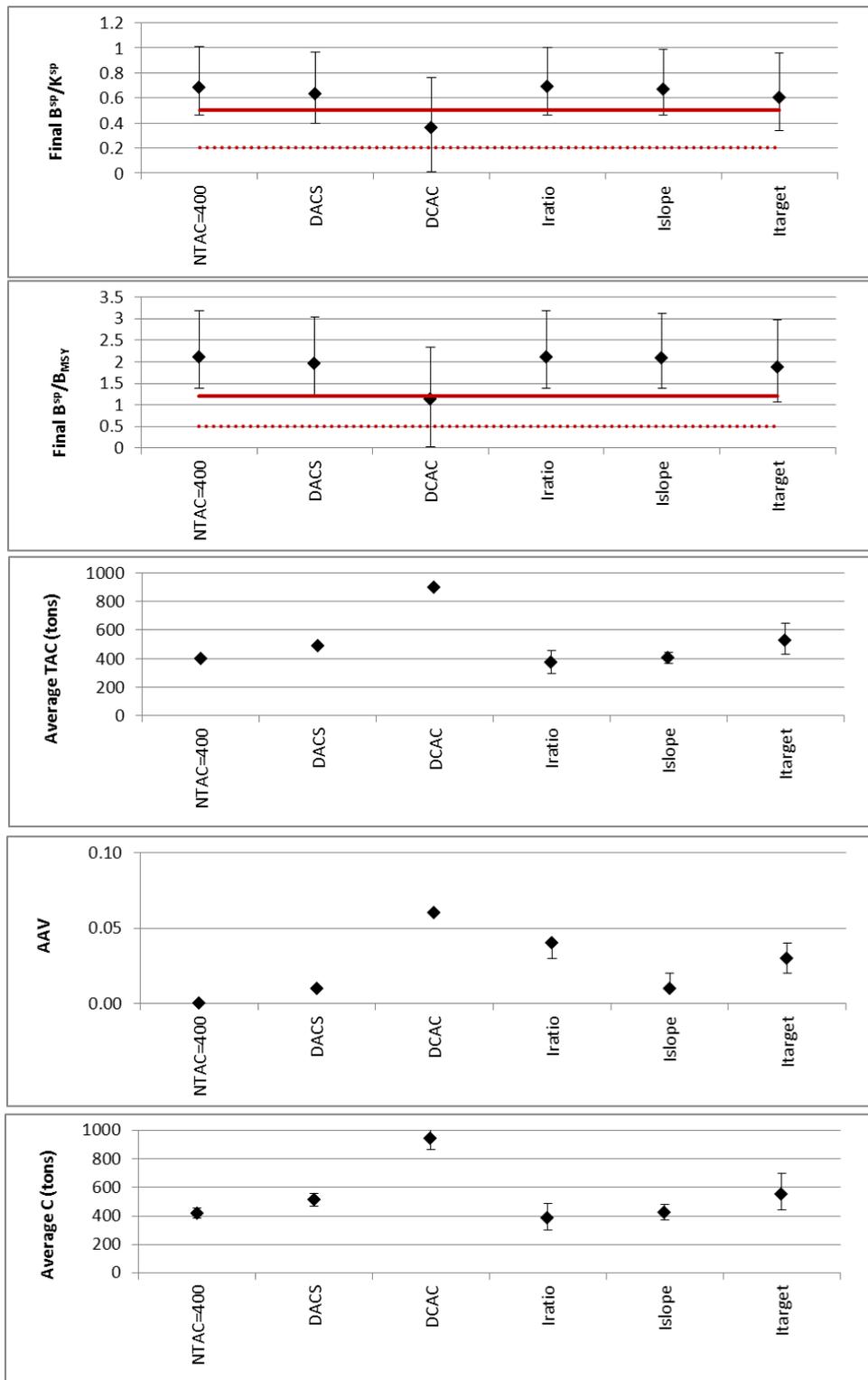
Figure 21: Comparison of management statistics under alternative MPs for the base case OM. The top two plots compare spawning biomass distributions for the final year of the projection period, i.e. 2032 when projecting under alternative MPs. The inter-annual variation in TAC was restricted to a maximum of 15% for the three feedback rules.
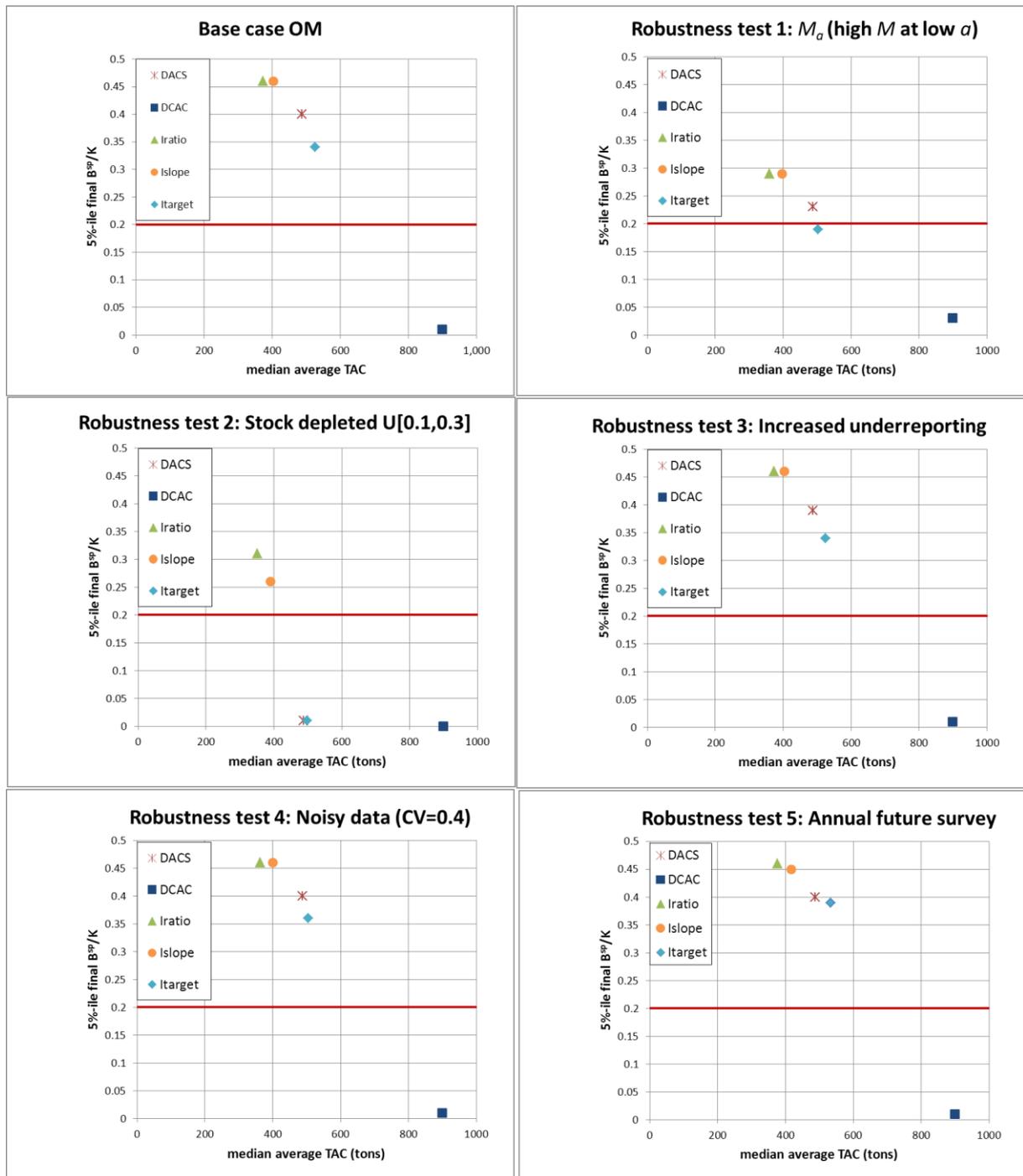
Figure 22: Median average yield over the 20-year projection period versus risk of stock depletion (at the 5%-ile) under alternative MPs for the base case OM (top left) and various robustness tests.
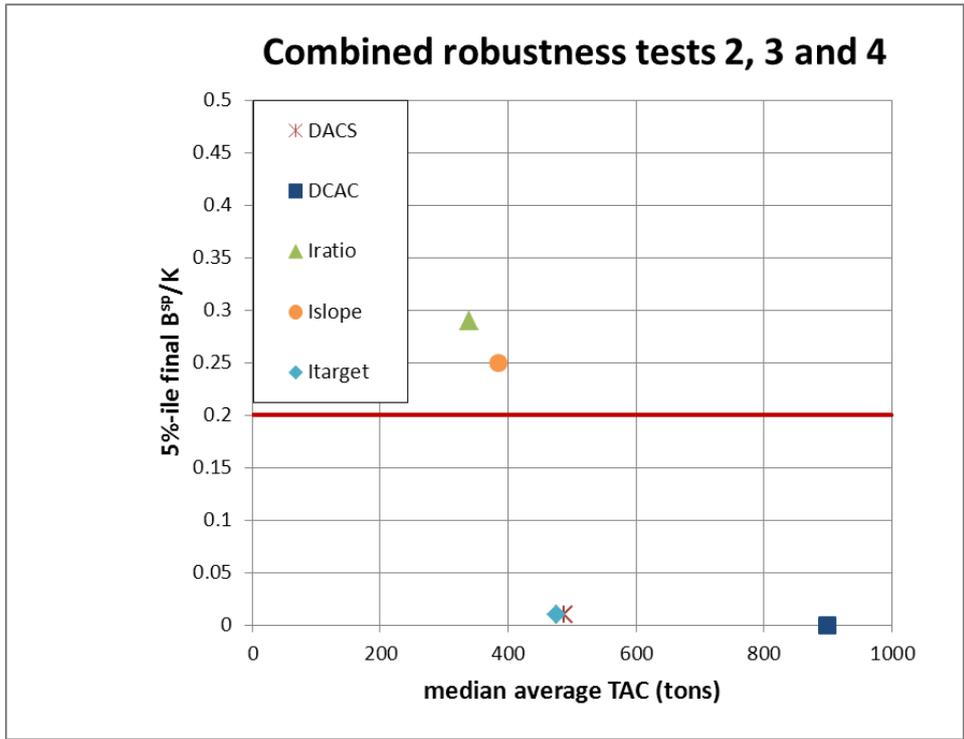
Figure 23: The same as Figure 22, but here comparing yield-risk trade-offs under alternative MPs for the combined robustness test.
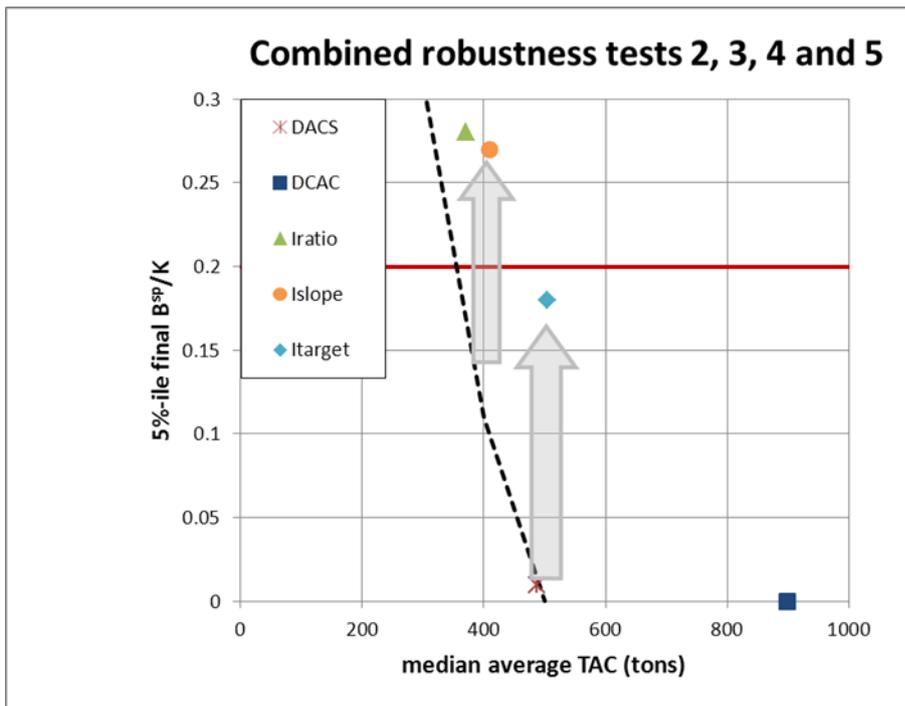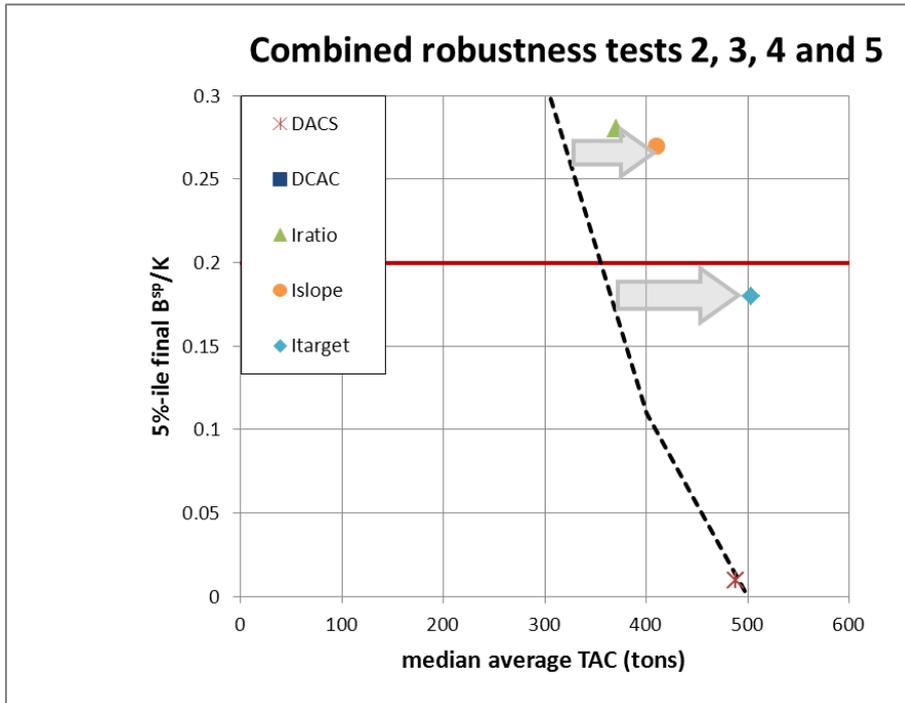
Figure 24: The same as for Figure 23, but here assuming that biomass surveys will be conducted every year in future, with annual adjustments to TAC advice. The dashed lines correspond to increasing biological risk associated with alternative constant catch strategies ranging from 300 to 500 tons. The grey arrows indicate the difference in potential yield under the constant catch and feedback MPs (top plot) and the increased risk associated with the non-feedback MPs for the same average yield (bottom plot).

Acronyms

ABC	Acceptable Biological Catch
ACL	Annual Catch Limit
ADAPT-VPA	Adaptive framework - Virtual Population Analysis
ADMB	Automatic Differentiation Model Builder
AFMA	Australian Fisheries Management Agency
AIM	An Index Method
ALK	Age-Length Key
ASPM	Age-Structured Production Model
BSAI	Bering Sea and Aleutian Islands
BSP	Bayesian Surplus Production
ASPIC	A Surplus-Production model Incorporating Covariates
CASAL	C++ Algorithmic Stock Assessment Laboratory
CAY	Current Annual Yield
CCAMLR	Commission for the Conservation of Antarctic Marine Living Resources
CCSBT	Commission for the Conservation of Southern Bluefin Tuna
CPUE	Catch Per Unit Effort
CSA	Collie-Sissenwine Analysis
DB-SRA	Depletion-Based Stock Reduction Analysis
DCAC	Depletion Corrected Average Catch
EEZ	Exclusive Economic Zone
ETBF	Eastern Tuna and Billfish Fishery
FAO	Fisheries and Agriculture Organisation of the United Nations
FMA	Fishery Management Areas
FMP	Fisheries Management Plan
HCR	Harvest Control Rule
HSP	Harvest Strategy Policy
ICCAT	International Commission for the Conservation of Atlantic Tuna.
ICES	International Council for the Exploration of the Sea
IWC	International Whaling Commission
LRSG	Lagged Recruitment, Survival and Growth
LRP	Limit Reference Point
MCY	Maximum Constant Yield
MEY	Maximum Economic Yield
MSA	Magnuson-Stevens Fishery Conservation and Management Act
MSRA	Magnuson-Stevens Reauthorisation Act
MP	Management Procedure

MSE	Management Strategy Evaluation
MSY	Maximum Sustainable Yield
NOAA	National Oceanic and Atmospheric Administration (USA)
NPFMC	North Pacific Fisheries Management Council
OFL	OverFishing Limit
PFMC	Pacific Fisheries Management Council
PSA	Productivity and Susceptibility Analysis
QMA	Quota Management Area
QMS	Quota Management System
RBC	Recommended Biological Catch
RVA	Rapid Visual Assessment
SAM	State-Space Assessment Model
SCAA	Statistical Catch At Age
SESSF	Southern and Eastern Scalefish and Shark Fishery
SIR	Sampling Importance Resampling
SISAM	Strategic Initiative on Stock Assessment Methods
SS	Stock Synthesis
SSC	Scientific and Statistical Committee
TAC	Total Allowable Catch
TACC	Total Allowable Commercial Catch
TAE	Total Annual Effort
TRC	Target Reference Point
UNCLOS	United Nations Convention on the Law of the Sea
VPA	Virtual population Analysis
WSSD	World Summit on Sustainable Development
XSA	Extended Survivor Analysis

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Appendix A: Categorisation of stocks

A.1   United States of America

In 1976, the Magnuson-Stevens Fishery Conservation and Management Act (MSA) created eight regional fisheries management councils to address overfishing of marine stocks in the various regions comprising the EEZ of the USA. The 2006 Magnuson-Stevens Reauthorisation Act (MSRA) gave a mandate to regional councils to, *inter alia*, develop research priorities in conjunction with a Scientific and Statistical Committee (SSC) to set annual catch limits (ACLs) for all stocks or stock complexes based on the best available science and to develop and implement rebuilding plans, with an increased emphasis on data-poor stocks (Seagraves and Collins 2012).

In the bid to promote sustainable harvesting of exploited stocks, a more structured approach to management has been adopted by some regional Councils: fish stocks are categorised into categories, or tiers, according to their information type and availability, from data-rich to data-poor. Catch advice is then based on harvest control rules (HCRs) that are defined for each category, or tier, with HCRs becoming increasingly precautionary with increasing tier level.

Management advice takes the form of Annual catch Limits (ACLs) that are more precautionary/conservative as data and knowledge decrease from one category, or tier, to the other, thereby preventing overfishing and assisting stock recovery as required by the statutory requirements established under the MSRA of 2006. While the MSRA does not define ACLs, the relationship between ACLs, Overfishing Limits (OFLs) and Acceptable Biological Catch (ABCs) are such that OFL$\geq$ABC$\geq$ACL. Therefore, in order to determine the ACL, the first step is to determine the OFL, after which the OFL is adjusted downwards to obtain an ABC to account for scientific uncertainty, which then acts an upper bound for the ACL (Dick and MacCall 2010).

A.1.1 The North Pacific Fishery Management Council (NPFMC)

The North Pacific Fishery Management Council (NPFMC) is one of eight regional fisheries councils in the USA. The Council has primary responsibility for the management of Gulf of Alaska and Bering Sea/Aleutian Island groundfish and Bering Sea/Aleutian Island crab stocks.

Stocks, or stock complexes, are assigned to tiers according to the type and amount of information available. Catch advice is based on tier-based harvest control rules (HCRs) that incorporate MSY reference points and/or proxies and buffers to account for scientific uncertainty. Target and limit

reference points are defined in terms of an acceptable biological catch (ABC) and an overfishing limit (OFL) with a buffer between two to make allowance for scientific uncertainty (see Figure 4). For stocks estimated to be at, or above, B_{MSY} the overfishing limit is set equal to F_{MSY} (or its proxy $F_{35\%}$). When the stock biomass is below B_{MSY}, the overfishing limit decreases from F_{MSY} (or proxy value) to zero as a function of the level of depletion. The acceptable biological catch (ABC) is defined in terms of a more conservation reference point at some percentage below F_{MSY} (or the proxy $F_{40\%}$ for Tier 2 and 3 rules).

A precautionary approach is followed in which the annual catch limit (ACL) for each stock is taken to be equal to the ABC. The total allowable catch (TAC) is set at, or below, the ABC to take various sources of uncertainty into account. As a consequence of the long-term application of conservative annual catch limits (ACLs), none of the stocks in the Bering Sea and Aleutian Islands (BSAI) is estimated to be overfished or subject to overfishing (DiCosimo *et al.* 2010).

HCRs corresponding to the top three tiers are based on the most recent biomass estimates provided by quantitative assessments to determine the ABC and OFL. In terms of the HCR, the fishing mortality rate is maintained at a constant level when the stock is estimated to be above the target biomass. Once stock biomass drops below the target reference point, fishing mortality is decreased linearly. If the stock is depleted beyond some threshold level (expressed as a percentage of the target biomass), the fishing mortality is set to zero. Biological reference points cannot be calculated for higher tier (data-poor) stocks. In the absence of quantitative information to indicate otherwise, the HCR therefore maintains fishing mortality at some conservative level (Grabacki 2008).

The NPFMC introduced a tier system in 1999 to categorise North Pacific groundfish into six tiers (NPFMC 2014).

Tier 1. Stocks with quantitative assessments and estimates (with distributions) of MSY reference points:
Reserved for data-rich stocks with sufficient data from which to estimate the pre-exploitation biomass and obtain reliable estimates of B_{MSY} and F_{MSY} reference points and distributions to reflect uncertainty.

Tier 2. Stocks with quantitative assessments and estimates of MSY reference points:
This category includes data-rich stocks with reliable estimates of biomass, B, and management reference points, B_{MSY} and F_{MSY}, but no probability density function for F_{MSY}. Instead, the OFL and ABC are defined in terms of proxy values $F_{35\%}$ and $F_{40\%}$.

Tier 3.   Stocks with quantitative assessments and proxy MSY reference points:
             Stocks in this category lack adequate information to obtain reliable estimates of MSY
             related management quantities due to uncertainty regarding the spawner-recruitment
             relationship. Instead, proxy values are used: the OFL and ABC are based on $F_{35\%}$ and
             $F_{40\%}$ respectively and a proxy value, $B_{40\%}$, is used instead of B_{MSY} .

Tier 4.   Stocks with biomass estimates but lacking growth/fecundity data:
             This tier is reserved for stocks for which recruitment cannot be estimated. A simple
             HCR based on proxy reference points, $F_{35\%}$ and $F_{40\%}$ is implemented.

Tier 5.   Data-poor stocks without estimates of stock status:
             This tier corresponds to stocks for which the pre-exploitation biomass cannot be
             estimated. In the absence more appropriate fishing mortality reference points, F_{OFL} is
             set equal to the natural mortality rate, with the F_{ABC} 25% below the overfishing rate,
             or lower.

Tier 6.   Data-poor or catch-only stocks:
             This tier is reserved for stocks with a reliable catch time-series only. In the absence of
             biomass and reference points estimates, the OFL is set equal to the average historic
             catch, with the ABC 25% below that, or lower. Alternative approaches are suggested
             for stocks for which the catch is not a reliable indicator of sustainable yield.

Crab stocks are categorised into five tiers.

Tier 1.   Stocks with quantitative assessments and a reliable stock-recruitment relationship and
             estimates of B_{MSY} and F_{MSY} .

Tier 2.   Similar to tier 1 but allowing for more uncertainty about estimates.

Tier 3.   Stocks with life history information and quantitative assessments but no MSY
             estimates.

Tier 4.   Stocks with estimates of biomass but limited life history data.

Tier 5.   Stocks with reliable catch data but lacking a biomass estimate.

A.1.2 The Pacific Fishery Management Council (PFMC)

The Pacific Fisheries Management Council's (PFMC's) Groundfish Management Plan (FMP) includes more than 90 species that are organised into three main categories: data-rich, data-moderate and data-poor according to the data available. The categories are divided into subcategories based on the methods used to estimate the OFLs. These categories and subcategories reflect the extent of scientific uncertainty in terms of data availability, suitable methods of analysis and robustness of assessment results. The extent of uncertainty is reflected in the size of the uncertainty buffer between the ABCs and the OFLs (see Figure A.1.1 and Figure A.1.2 below).

The ABCs for stocks managed under the Coastal Pelagic Species and Groundfish FMPs are defined in terms of two parameters: σ that characterises the level of scientific uncertainty as evaluated by the Scientific and Statistical Committee (SSC), and P^*, the level of risk as evaluated by the Management Council. The application of arbitrary uncertainty buffers between the OFL and the ABC, such as ABC=0.75*OFL, are thereby avoided. Increasing values of σ are assigned to data-poor stocks characterised by greater uncertainty. To improve specification of scientific uncertainty, the SSC is considering setting stock-specific σ s for data-rich stocks and using an MP approach (or MSE) to evaluate σ for data-poor groundfish stocks (Seagraves and Collins 2012). In addition, the long-term trade-offs corresponding to different values of P^*, the probability that overfishing, need to be investigated.

Particular attention is given to data-poor stocks: estimates of sustainable yield have been obtained for 50 data-poor stocks in the Pacific Coast Groundfish Management Plan (Dick and MacCall 2010).

Species are categorised according to the amount of data informing the HCR. Three categories are specified:

    Category 1. Data-rich:

        The OFL is based on F_{MSY} (or proxy) estimated by an age- or length based assessment model.

        The ABC is based on the P* buffer.

        1a) An age/length based model fitted to reliable age/length composition data and fishery-dependent trend data.

        1b) Same as 1a, and survey trend data.

        1c) An age/length based model with reliable estimation of the stock-recruitment relationship.
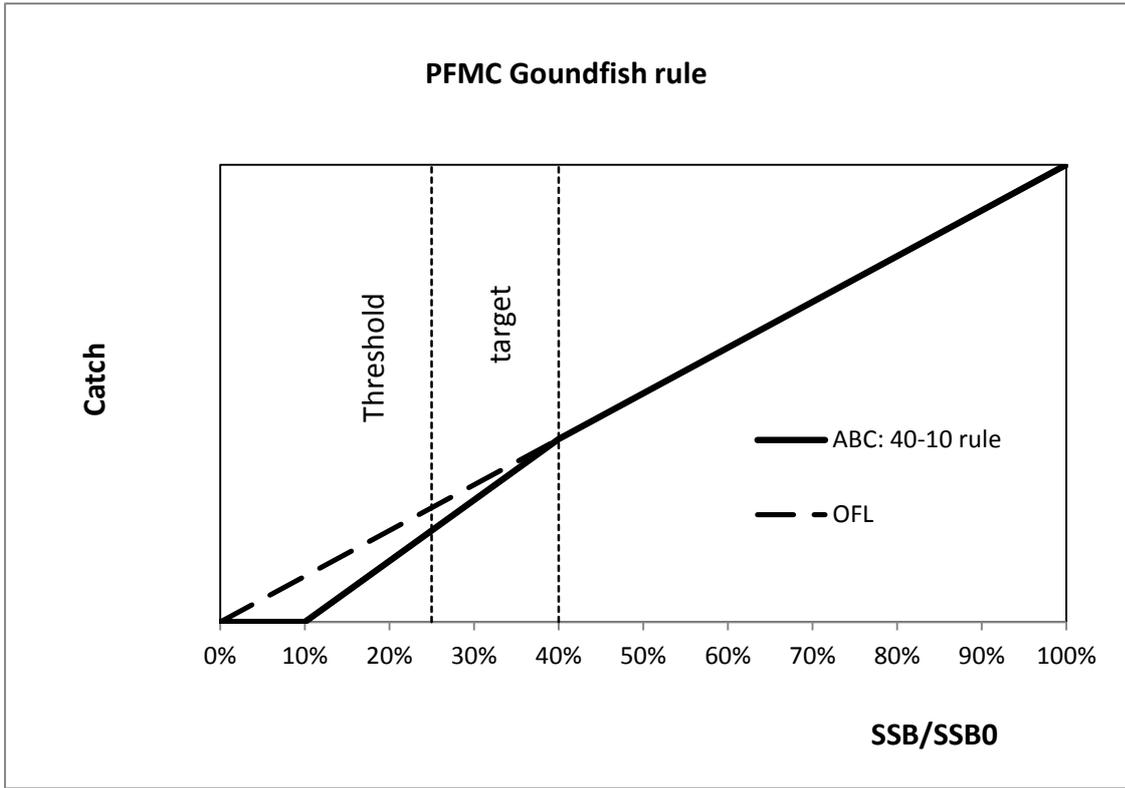
Figure A.1.1: The Pacific Fishery management Council (PFMC) 40-10 harvest control rule for groundfish.
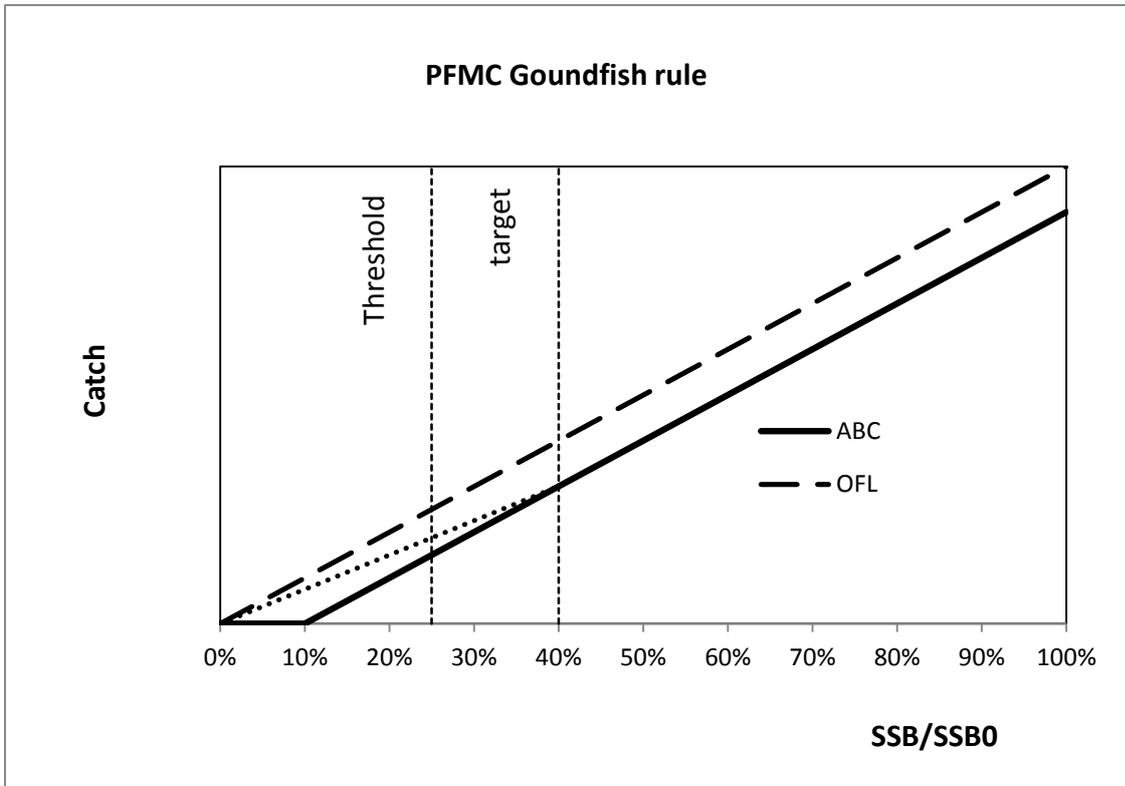
Figure A.1.2: The revised control rule to establish a buffer between the OFL and ABC (Carmichael and Fenske 2011).

Category 2. Data-moderate:

The OFL is derived from model output or natural mortality. ABCs are derived from OFLs by applying a buffer of 0.25 and assuming a value for σ of 0.72.

2a) Natural mortality and a survey biomass estimate.

2b) An age-aggregate population model based on historical catches and fishery trend information.

2c) An age-aggregate population model fitted to historical catches and survey trend information.

2d) A full age-structured assessment, with high uncertainty (e.g. assessment results are highly sensitive to model and data assumptions).

Category 3. Data-poor:

OFLs are derived from historical catch time series. ABCs are derived from OFLs by applying a buffer of 0.5 and assuming a value for σ of 1.44.

3a) No reliable catch data and no basis for estimating OFL.

3b) Reliable catch time-series over recent years. OFL is set equal to an average catch.

3c) Reliable catch time-series during the period of fishery development, as well as some information on natural mortality. A catch-only method, Depletion-Corrected Average Catch (DCAC), is used to obtain OFLs.

3d) Reliable catch time-series and qualitative information of biological parameters such as natural mortality rate and maturity. The default method is Depletion-Based Stock Reduction Analysis (DB-SRA).

A.2   Europe (ICES)

ICES recognise six main categories according to the availability of biological and fishery data and whether stocks are (have been) regularly assessed quantitatively and estimates of biomass, fishing effort and/or management reference points are available to serve as basis for catch advice (ICES 2013b). Stocks with a full complement of data with which to conduct age/length based assessments are termed data-rich and fall in category 1. The stocks that fall in the remaining five categories are considered data-limited (at least to some extent) and do not benefit from regular quantitative assessments. However, most data-limited stocks have at least some information available in addition to the historical catch series. To aid decision making, these data-limited stocks are grouped according

to the methods that can be applied to the data that are available, with stock uncertainty increasing with category number.

The current ICES approach to fisheries management is anchored on the concept of achieving maximum sustainable yield. However, the EU's implementation of the WSSD (UN 2002) call for the recovery of depleted stocks to levels that produce MSY by 2015 has differed slightly from approaches followed in other parts of the world. Based on the assumption that stock recovery must theoretically occur at a fishing mortality of F_{MSY}, ICES adopted a MSY framework in 2010 to reduce of fishing mortality to F_{MSY} by 2015 where possible (ICES 2013b). The delay in achieving the WSSD objective is partly due to the European Commission who requested a gradual reduction of fishing effort to levels corresponding to F_{MSY} (EC 2006) for socio-economic reasons.

For data-rich stocks that undergo regular assessments (category 1 stocks), ICES calculates the TAC to achieve the desired fishing mortality rate of F_{MSY}, as per the HCR implemented for the stock. The MSY management approach is also based on a biomass reference point: $B_{TRIGGER}$ is a lower bound for spawning biomass below which fishing mortality must be reduced to allow the stock to recover to a level of abundance which would maximise the sustainable yield (see Figure 6). In cases where a range of estimates of stock size associated MSY is not available to yield a plausible lower bound, the lower bound under the precautionary approach, B_{PA}, is used in lieu of $B_{TRIGGER}$. For fish stocks that are not considered data-rich (i.e. stock that fall into categories 2 to 6), an increasingly precautionary margin is applied with decreasing knowledge about stock status, with fishing mortality rates set well below F_{MSY}. When stock status is unknown, a precautionary buffer of a 20% reduction is applied, unless expert judgement shows that there is evidence of stock recovery and no sign of recruitment overfishing.

Category 1: Data-rich stocks with quantitative assessments

> This category includes all stocks that undergo full quantitative assessments with forecasts. ICES define two sub-categories: one for longer-lived species with several year classes contributing to the fishery and the other for short-lived species. Catch advice is based on estimates of current biomass in relation to the level that produces maximum sustainable yield (MSY), obtained via full quantitative assessments of the stock – see sections 1.4.5 to 1.4.8 for different age and length models typically applied to data-rich stocks. A precautionary approach is followed by incorporating PA limit reference points.

Category 2: Stocks with quantitative assessments, used qualitatively

This category includes stocks for which quantitative assessments are available. However, assessments are considered as indicative of trends in fishing mortality, recruitment, biomass and future catches.

Category 3: Stocks with reliable time-series data

This category includes stocks for which one or more relative index of abundance is available to track trends in stock metrics such as recruitment and biomass (see time-series methods in section 1.4.2). Such a time-series can be either a direct or indirect index of abundance, e.g. from survey, CPUE or mean length of catch. Catch advice is typically based on a harvest control rule (HCR) that adjusts the status quo catch up or down if the average of the most recent index values is above or below some historical average.

Category 4: Stocks with reliable catch data

This category includes stocks for which an adequate catch time-series is available. Assuming that the historic catch series is an indicator of trend in biomass, the depletion corrected average catch (DCAC – see catch-only methods in section 1.4.1) is computed to serve as a basis for catch advice.

Category 5: Data-poor stocks with landings data only

A Productivity and Susceptibility Analysis (PSA) risk assessment is currently being developed by ICES to manage data-limited stocks. In the absence of a PSA, ICES propose some rudimentary set of rules on which to base catch advice (e.g. applying the Precautionary Buffer to the previous year's catch).

Category 6: Stocks with negligible landings data

This category includes extremely data-limited stocks for which landings are negligible. Reasons for negligible landings data may be include low stock abundance, discarding of species due to low economic value, or incidental catches (bycatch) in fisheries that target

other species. For category 6 stocks, for which little information is available, catch advice is based on the same criteria as apply to category 5 stocks.

A.3 Australia

To manage the Australian Commonwealth fisheries sustainably and economically, and rebuild depleted fish stocks, a formal harvest strategy policy (HSP) was adopted in 2007 (DAFF 2007). It is based on the harvest strategy framework developed for Southern and Eastern Scalefish and Shark Fishery (SESSF) which was introduced in 2005 with the aim to generate precautionary management advice for stocks based on a set of tier-based HCRs.

The SESSF is a multi-species fishery comprising over 30 commercial stocks that fall under the quota management system of the Australian Fisheries Management Authority (AFMA). To ensure the success of this management framework, a partnership approach was adopted involving key stakeholders (fishers, non-governmental organisations, scientists and managers) in the management process (Smith *et al.* 2008). This framework includes an agreed process for fishery monitoring, stock assessment, and decision rules for translating stock assessment outputs into clear advice on the Recommended Biological Catch (RBC) for each stock managed under the Quota Management System. A tier system of assessment methods and associated control rules is used with the highest tiers corresponding to detailed integrated assessments for data-rich stocks, whereas the lowest tiers correspond to harvest control rules based on limited data. A management strategy evaluation (MSE) approach was used to evaluate the performance of the SESSF harvest strategy framework, with HCRs within each tier simulation tested to demonstrate robustness (Wayte 2009).

The policy is defined in terms of MSY reference points: a target of maximum sustainable yield and a limit of half the biomass that would produce MSY is incorporated explicitly. In addition, acceptable risk levels are defined for stocks that fall below their limit reference point (Smith *et al.* 2013).

A precautionary approach to management is incorporated by specifying target and limit reference points: overfishing is defined in terms of a maximum fishing mortality rate, F_{LIM}, while optimum fishing pressure is defined in terms of a target fishing mortality rate, F_{TARG}. Target fishing mortality rates decrease with increasing Tier levels, in the light of the increasing uncertainty (Smith *et al.* 2008).

In terms of this framework, a conservative biomass target is chosen which is based on maximum economic yield, which is assumed to lie 20% above the biomass that would support maximum sustainable yield ($B_{MEY} = 1.2B_{MSY}$), with an associated limit reference point set at half that biomass ($B_{LIM} = 0.5B_{MSY}$). A maximum sustainable yield proxy is defined for B_{MSY}, assumed to occur at 40% of the unexploited spawning biomass (termed $B_{40} = B_{MSY}$), with associated proxy values for the target and limit reference points are given by $B_{48} = B_{MEY}$ and $B_{20} = B_{LIM}$ respectively. Once the stock biomass is estimated to fall below B_{20}, the HCR sets the targeted catch to zero (see

Figure 5). Using the same terminology, the limit, MSY and target fishing mortality reference points correspond to F_{20}, F_{40} and F_{48} respectively, where F_{40} is the fishing mortality rate that would maintain the stock biomass at MSY level, or B_{40} (Smith *et al.* 2013).

Each stock is assigned to one of four Tier levels depending on the amount and quality of data available to assess the stock. Stocks that fall into Tier 1 undergo robust quantitative stock assessments, while Tier 2 stocks also undergo full assessments, but with increased levels of uncertainty. Management advice for Tier 3 stocks is based on catch curve analysis, while Tier 4 advice is based on trends in catch rates (CPUE). A summary of the 2009 SESSF harvest strategy framework from AFMA (2009) is given below.

Tier 1 and 2: Stocks with robust quantitative assessments

> Typically reserved for data-rich stocks where all available data are used in an integrated assessment (see section 1.4.8) to provide estimates of current relative and absolute biomass. These biomass estimates are used in the HCR to calculate the target fishing mortality from which the RBC is calculated. Also termed as the 20:35:F48 rule, the target fishing mortality is calculated as (see Figure A.3.1 below):

$$F_{TARG} = 0 \qquad\qquad \text{if } B_{CUR} < B_{20}$$

$$F_{TARG} = F_{48}\left(\frac{B_{CUR} - B_{20}}{B_{35} - B_{20}}\right) \qquad\qquad \text{if } B_{20} \leq B_{CUR} \leq B_{35}$$

$$F_{TARG} = F_{48} \qquad\qquad \text{if } B_{CUR} > B_{35}$$

> The RBC for Tier 1 stocks is calculated by applying the target fishing mortality, F_{TARG}, to the current biomass to calculate the catch (including discards) for the next year, using the agreed base case assessment model.
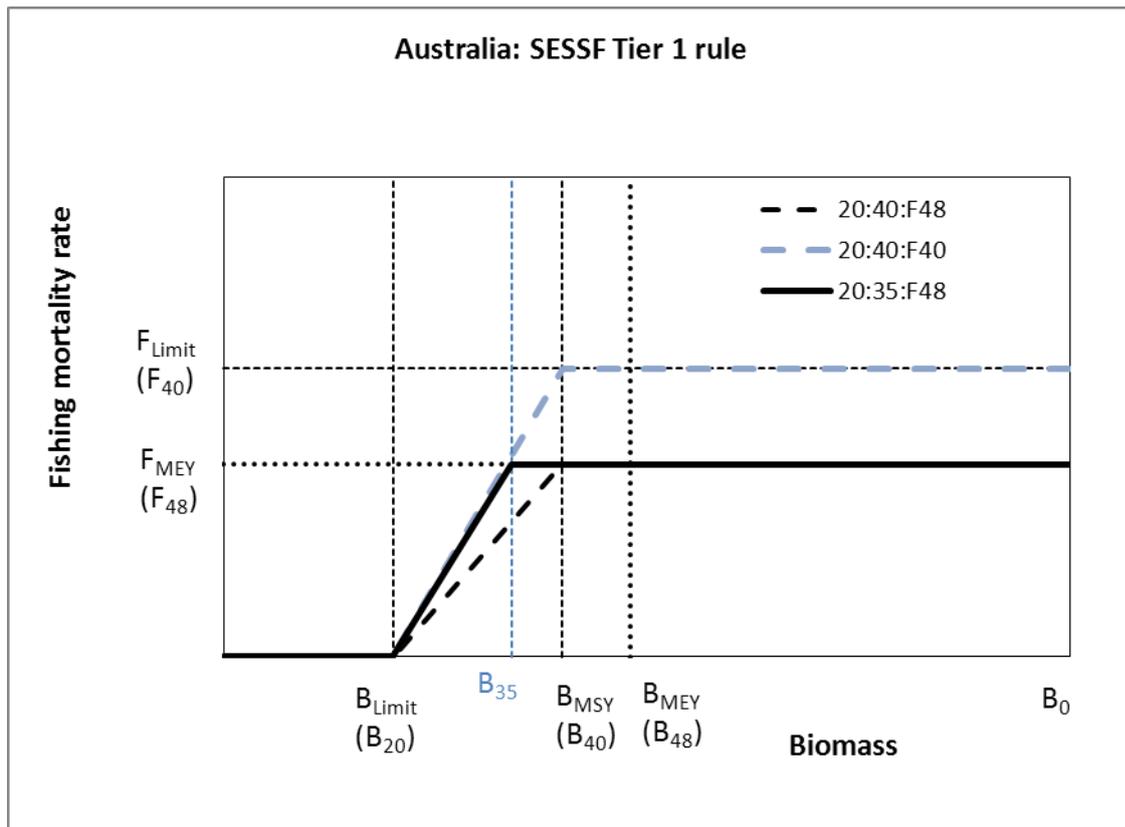
Figure A.3.1: The current SESSF Tier 1 harvest strategy is indicated by the solid black line. The biomass limit, inflection and target reference points for this Tier are B20, B35 and B48. The dashed lines correspond to alternative Tier 1 rules used earlier by the SESSF. The current 20:35:F48 rule is derived from these earlier rules (Haddon 2012).

Tier 2: Stocks with less robust quantitative assessments

This tier includes stocks with less robust quantitative assessments and more uncertainty about biomass estimates. Reference points for Tier 2 stocks are currently the same as for Tier 1. Increased uncertainty levels could be taken into account by discounting of the RBC. However, at present there are no stocks falling into this Tier and this rule is therefore not currently applied.

Tier 3: Stocks with no quantitative assessment but with estimates of fishing mortality.

The Tier 3 HCR applies to stocks with robust estimates of natural mortality rate, M, and fishing mortality, F, but no estimates of current biomass. Catch/length composition data are used in a yield-per-recruit analysis to determine the fishing mortality rates that will reduce the stock biomass to 20%, 40% and 48% of the pre-exploitation level.

The fishing mortality corresponding to the RBC, F_{RBC}, is given by the current fishing mortality in relation to the F_{40} and F_{20} reference points:

$$F_{RBC} = 0 \qquad\qquad\qquad\qquad \text{if } F_{CUR} > F_{20}$$

$$F_{RBC} = F_{48}\left(\frac{F_{20} - F_{CUR}}{F_{20} - F_{40}}\right) \qquad\qquad \text{if } F_{40} \leq F_{CUR} \leq F_{20}$$

$$F_{RBC} = F_{48} \qquad\qquad\qquad\qquad \text{if } F_{CUR} < F_{40}$$

The RBC adjusts the current catch (C_{CUR}) up or down according to the ratio of the intended and current exploitation rates:

$$RBC = \frac{1 - e^{-F_{RBC}}}{1 - e^{-F_{CUR}}} C_{CUR}$$
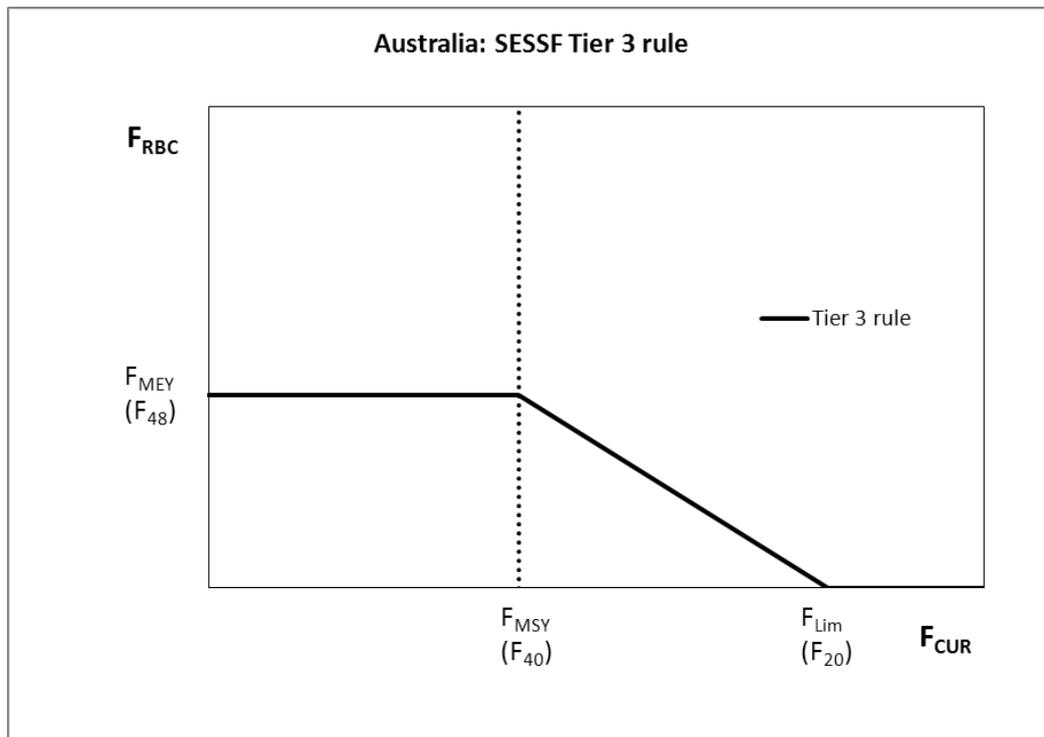
Figure A.3.2: The SESSF Tier 3 rule applied to assessments for which an estimate of current fishing mortality, F_{CUR}, is available. The fishing mortality limit, MSY and target reference points for this Tier are F20, F40 and B48.

Tier 4: Stocks with no quantitative assessments but with reliable catch rate data

The Tier 4 HCR applies to stocks with the least amount of information about stock status. This rule is used when no reliable information on current biomass or fishing mortality rate is available, but information about current catch levels and catch rates. No formal assessments are conducted and catch-per-unit-effort (CPUE) data are used directly in an empirical HCR. CPUE reference points are used as proxies for limit and target reference points, B_{LIM} and B_{TARG}. The RBC is given by:

$$RBC = \min\left[C_{\max}, C^* \max\left(0, \frac{\overline{CPUE} - CPUE_{LIM}}{CPUE_{TARG} - CPUE_{LIM}}\right)\right]$$

where

$C_{\max}$ is the maximum allowable catch,

C^* is the target catch derived from the historical period,

$\overline{CPUE}$ is a recent average CPUE,

$CPUE_{LIM}$ is the limit reference point, CPUE$_{20}$, below which the recommended catch is zero, and

$CPUE_{TARG}$ is the target reference point, CPUE$_{48}$, above which the recommended catch is set to $C_{\max}$.

The SESSF framework is precautionary between tiers: the increase in uncertainty about stock status that is associated with a lower Tier level would correspond to a decrease in RBC to reflect the level of uncertainty. The discount factor for Tier 3 and 4 stocks are 5% and 15%:

Tier 3: $RBC_{DISC} = 0.95 \times RBC$

Tier 4: $RBC_{DISC} = 0.85 \times RBC$

The HCRs for all tiers are also subject to TAC change limiting rules: the "small change limiting rule" requires that the TAC for the next fishing year is left unchanged if the recommended TAC is within 10% (or 50 tons) of the TAC for the previous fishing season. The corresponding "large change limiting rule" puts a limit of 50% inter-annual change in TAC between fishing seasons, unless there is significant risk of resource depletion.

Appendix B: Operating model

An age-structured production model (ASPM) is used to model the resource dynamics of the populations considered in the paper. Fishing is assumed to be continuous throughout the year, so that the population dynamics are described by the equations:

$$N_{y+1,a\min} = R_{y+1} \tag{B.1}$$

$$N_{y+1,a+1} = N_{y,a}e^{-(M_a + S_{y,a}F_y)} = N_{y,a}e^{-Z_{y,a}} \qquad \text{for } a_{\min} \le a < m-2 \tag{B.2}$$

$$N_{y+1,m} = N_{y,m-1}e^{-(M_{m-1} + S_{y,m-1}F_y)} + N_{y,m}e^{-(M_m + S_{y,m}F_y)} \tag{B.3}$$

where

$N_{y,a}$ is the number of fish of age a at the start of year y,

M_a denotes the natural mortality rate for fish of age a (for the analyses of this paper age-independence is assumed),

$S_{y,a}$ is the age-specific selectivity for year y and set to 1 for the age at which there is full selectivity,

F_y is the fishing mortality for year y,

m is the maximum age considered (taken to be a plus-group),

$a_{\min}$ is the minimum age considered, and

y denotes the year, with the first year considered being $y = 1$.

The total number of fish caught of age a in year y is given by the Baranov equation:

$$C_{y,a} = N_{y,a}\frac{S_{y,a}F_y}{Z_{y,a}}(1 - e^{-Z_{y,a}}) \tag{B.4}$$

where $Z_{y,a} = M_a + S_{y,a}F_y$ is the total mortality for fish of age a in year y.

The corresponding total catch by mass for each year is given by:

$$C_y = \sum_{a=a_{\min}}^{m} w_{y,a+1/2} C_{y,a} \tag{B.5}$$

where $w_{y,a+1/2}$ denote the mid-year weights-at-age of fish caught in year y.

Stock-recruitment relationship:

The number of recruits at the start of year y (for $y>1$) is related to the spawning stock size by a Beverton-Holt stock-recruitment relationship:

$$R_y = \frac{\alpha \, B_{y-a\min}^{sp}}{\beta + B_{y-a\min}^{sp}} e^{\varsigma_y - \sigma_R^2/2} \tag{B.6}$$

where

α and β are spawning biomass-recruitment parameters,

$\varsigma_y \sim N(0, \sigma_R^2)$ reflect fluctuations about the expected recruitment for year y,

σ_R is the standard deviation of the log-residuals about the stock-recruitment relationship, and

$B_{y-a\min}^{sp}$ is the spawning biomass at the start of year $y - a_{\min}$, given that:

$$B_y^{sp} = \sum_{a=a\min}^{m} f_a w_a N_{y,a} \tag{B.7}$$

where w_a is the begin-year mass of fish of age a (spawning is assumed to take place at the start of the year) and f_a is the proportion of fish of age a that are mature.

In order to work with estimable parameters that are more meaningful biologically, the stock-recruitment relationship is re-parameterised in terms of the pre-exploitation equilibrium spawning biomass, K^{sp}, and the "steepness" of the stock-recruitment relationship, h (recruitment at $B^{sp} = 0.2K^{sp}$ as a fraction of recruitment at $B^{sp} = K^{sp}$):

$$\alpha = \frac{4hR_K}{5h-1} \tag{B.8}$$

and

$$\beta = \frac{K^{sp}(1-h)}{5h-1} \tag{B.9}$$

where the pristine equilibrium recruitment R_K is given by

$$R_K = K^{sp} / [\, f_0 w_0 + \sum_{a=a\min+1}^{m-1} f_a w_a e^{-(\sum_{a'=a\min}^{a-1} M_{a'})} + f_m w_m \frac{e^{-(\sum_{a'=a\min}^{m-1} M_{a'})}}{1-e^{-M_m}} \,] \tag{B.10}$$

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Biomass:

The model estimate of the exploitable ("available" to the fishing fleet) component of biomass is given by:

$$B_y^{\exp} = \sum_{a=a\min}^{m} w_{y,a} S_{y,a} N_{y,a} \qquad \text{for begin-year biomass, and} \qquad (B.11)$$

$$B_{y+1/2}^{\exp} = \sum_{a=a\min}^{m} w_{y,a+1/2} S_{y,a} N_{y,a} e^{-Z_{y,a}/2} \qquad \text{for mid-year biomass} \qquad (B.12)$$

where $w_{y,a}$ denote the begin-year weights-at-age of fish caught in year y, and $w_{y,a+1/2}$ are the mid-year weights-at-age.

The model estimate of the survey biomass is given by

$$B_y^i = \sum_{a=a\min}^{m} w_{y,a} S_a^i N_{y,a} \qquad (B.13)$$

where $w_{y,a}$ denote the population weights-at-age for each year, and

S_a^i is the fishing selectivity corresponding to survey index i.

It is usual to assume that the resource is at the deterministic equilibrium that corresponds to an absence of harvesting at the start of the initial year ($B_1^{sp} = K^{sp}$). The age-structure of B_1^{sp} is taken here to be that corresponding to the equilibrium with no fishing mortality.

B.1 Model parameters

B.1.1 Natural mortality rate:

A general natural mortality function is adopted to allow for decreasing *M* as age increases, viz.:

$$M_a = \alpha + \beta / a$$

The base case operating model for both South African panga and Jamaican conch assumes a constant mortality rate over all ages (i.e. $\beta = 0$). However, a decreasing natural mortality function with high

mortality rates typically associated with juvenile fish is adopted for some robustness trials for Jamaican conch (i.e. $\beta > 0$).

B.1.2 Fishing selectivity:

The expectation for fishing selectivity is assumed to be time-invariant with a logistic form:

$$S_a = \frac{1}{1+\exp(-(a-a_{50})/\delta)}$$

Log-normally distributed variability about these values is taken to be correlated across both ages and years, such that:

$$S_{y,a} = S_a e^{\tau_{y,a}-\sigma_\tau^2/2} \tag{B.14}$$

where

$\tau_{1,a_{min}} \sim N(0,\sigma_\tau^{\,2})$ is the log-residual for the first year and minimum age,

$\tau_{y,a} = \rho\tau_{y,a-1} + \sqrt{1-\rho^2}\,\chi_{y,a}$ is the log-residual for year y and year a, which is generated for ages $a=a_{min}+1$ to m and years y,

$\tau_{y,a_{min}} = \rho\tau_{y-1,a_{min}} + \sqrt{1-\rho^2}\,\chi_{y,a_{min}}$ is the residual for the minimum age a_{min} and year y,

$\chi_{y,a} \sim N(0,\sigma_\tau^2)$,

σ_τ is the standard deviation of the log-residuals ($\sigma_\chi = 0.4$ is used here), and

ρ is the serial correlation coefficient ($\rho = 0.5$ is assumed for these calculations).

B.1.3 Weight-at-age:

For the South African panga stock, the length (l) and mass (w) of a fish at age (a) is assumed to be related to a von Bertalanffy growth equation:

$$l_a = l_\infty (1-\exp(-\kappa(a-t_0)))$$
$$w_a = \alpha\,[l_a\,]^\beta \tag{B.15}$$

Growth parameter from Booth and Buxton (1997a and 1997b) were adopted. These are summarized in Table 10. For Jamaican conch, separate von Bertalanffy growth curves apply to juveniles and adults. Growth curves for adults are based on lip thickness, while those for juveniles are based on shell

length. For simplicity, a combined growth curve for both adults and juveniles, developed by Appeldoorn (2005b), has been used in this study. The mass of meat at age a is given by:

$$w_a = \alpha \exp(l_\infty (1 - \exp(-\kappa a))) \tag{B.16}$$

where w_a corresponds to the 50% cleaned wet meat weight in grams (Table 14).

B.2 Data generated by operating model for use in MPs

B.2.1 Mean length data

For South African panga, the annual mean length of the catch, when allowing for observation error, is given by:

$$\hat{l}_y = \sum_{a=a\min}^{m} \hat{P}_{y,a} \; l_a \tag{B.17}$$

where

l_a is the length of fish of age a as per the von Bertalanffy growth curve given by equation (S.15), and

$\hat{P}_{y,a} = P_{y,a} \; e^{\varphi_{y,a} - \sigma_l^2/(2P_{y,a})}$ is the model-generated proportion of fish caught of age a in year y which is renormalized such that $\sum_{a=a\min}^{m} \hat{P}_{y,a} = 1$.

In the above formulation $P_{y,a}$ denotes the proportion of fish of age a caught in year y of the simulation, given by:

$$P_{y,a} = \frac{C_{y,a}}{\sum_{a'=a\min}^{m} C_{y,a'}}$$

where $C_{y,a}$ is the total number of fish caught of age a in year y, given by equation (B.4), and

$\varphi_{y,a} \sim N(0, \sigma_l^2 / P_{y,a})$ reflect the variability for which the variance is assumed to be greater for those ages where sample sizes are smaller, with σ_l being a parameter related to the coefficient of variation

(CV) associated with the mean length data. A value of $\sigma_l = 0.4$ is assumed which is consistent with fisheries such as that for South African hake. This "Punt-Kennedy" distribution form assumption for composition data is as advocated by Maunder (2011) in his comparative review of a number of such approaches.

B.2.2 Index of abundance

The CPUE/survey data are generated assuming that the abundance index is log-normally distributed about its expected value such that:

$$I_y = \hat{I}_y e^{\varepsilon_y} \tag{B.18}$$

where

I_y is the abundance index generated for year y,

$\hat{I}_y = \hat{q}\,\hat{B}_y$ is the corresponding model value, where $\hat{B}$ is the model value for exploitable or survey biomass, given by equations (B.11) , (B.12) and (B.13),

$\hat{q}$ is the constant of proportionality for the abundance series (effectively the multiplicative bias if the series reflects abundance in absolute terms), and

$\varepsilon_y \sim N(0, \sigma_I^2)$ where σ_I is the coefficient of variation (CV) associated with the resource abundance index. A value of $\sigma_I = 0.4$ was assumed for the South African panga stock, consistent with what might typically be expected from a demersal trawl survey bycatch index. A value of $\sigma_I = 0.2$ was assumed for survey estimates for the Jamaican conch stock.

B.2.3 Annual catches

A key uncertainty when dealing with a data-poor resource is associated with the reliability of a limited set of data, in particular the historical catch series. Rather that assume that the historical catches are known without error, simulated catch data are generated assuming that total removals are log-normally distributed about the reported historical catches, i.e.:

$$C_y = \hat{C}_y e^{\varepsilon_y^C - \sigma_C^2/2} \tag{B.19}$$

where

C_y is the true catch in year y,

$\hat{C}_y$ is the reported catch for year y, which is input, and

$\varepsilon_y^C \sim N(\mu_C, \sigma_C^2)$ where $\sigma_C = 0.2$ is the standard deviation of the log-residuals, and $\mu_C \sim U[0,0.1]$ is the mean which is sampled from a uniform distribution to account for the possibility of negative bias (under-reporting).

Bias and noise are taken forward and incorporated in future catches in the same manner:

$$C_y = TAC_y e^{|\varepsilon_y^C| - \sigma_C^2/2} \tag{B.20}$$

where TAC_y is the TAC generated by the harvest control rule for year y.