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Review of data-poor assessment methods for New Zealand fisheries

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EXECUTIVE SUMMARY

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There is growing interest from MPI and other fisheries stakeholders in methods to assess New Zealand fish stocks with low levels of data. While some preliminary work has been done in New Zealand, there has been no recent overview of available methods or practices internationally. This qualitative review gives an overview of data-poor methods in use internationally, drawing in particular on those presented at the world conference on stock assessments methods (WCSAM) held in Boston MA, USA, in July 2013. Reference is also made to interesting presentations from the Knowledge Based Bio-Economy (KBBE) workshop in Hobart TAS, Australia, in November 2013. I have noted the types of data required for each method, summarised the assumptions required, and, where appropriate, linked to examples of their use. In addition, I have further commented on the potential utility of each method in New Zealand.

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1. Introduction

1.1. Definition of data-poor fisheries

Fisheries have been defined as data-poor if information is insufficient to produce a defensible quantitative stock assessment (Dowling et al., 2011), meaning that the best scientific information available is inadequate for determining meaningful reference points or current stock status relative to such reference points. This is consistent with the FAO definition that data-limited fisheries are considered to be fisheries lacking sufficient biological information to infer the exploitation status of the targeted stocks. It is often difficult therefore to bring data-poor fisheries into alignment with legislative requirements concerning estimation of reference points and relative stock status. In the United States for example, the Magnuson-Stevens Act requires fisheries to be managed on the basis of MSY, and a similar situation exists in New Zealand (Sections 1.2 and 1.3). Shortcomings in data provide an incentive for the development of assessment methods that have lower data requirements than those currently in use.

Data-poor stocks are therefore usually those with limited data or limited information content in the data that have been collected. Within the concept of data poor it is possible to further distinguish fisheries that are not necessarily data limited, but limited by technical capacity (i.e. the scientific capacity to carry out a stock assessment is not available). These situations could be classified as capacity-poor. However, using the above definitions they are often grouped together with strictly data-poor fisheries, since they are all similarly deficient in a quantitative assessment.

A lack of informative data and technical capacity are often concurrent characteristics for economic reasons. Data-poor fisheries are often characterised as such because they are of low value and have prohibitive costs of data collection, which similarly implies a lack of support for technical analysis (Dowling et al., 2011). In New Zealand specifically, the costs of data collection are offset by cost-recovery and therefore the quantity of data collected tends to be related to economic value of the fishery.

1.2. Legislative background in New Zealand

A literal interpretation of the New Zealand Fisheries Act 1996 is that it requires estimates of both the current biomass and the biomass needed to produce the maximum sustainable yield (B_{MSY}). This applies to all fisheries within the Quota Management System (QMS). In a subsequent 2008 amendment it states that all QMS fisheries must have a Total Allowable Catch (TAC) defined that is "not inconsistent with the objective of maintaining the stock at or above, or moving the stock towards or above, a level that can produce the maximum sustainable yield." This is interpreted by the 2008 Harvest Strategy Standard (HSS) and associated Operational Guidelines as meaning "MSY-compatible reference points or better" (Ministry of Fisheries, 2008, 2011). The HSS further promotes use of a *harvest strategy*, which it defines loosely as the management actions required for a particular stock to both reach (i.e. fluctuate around) its target reference points and avoid limit reference points. The target reference points can be formulated in terms of biomass or fishing mortality, or proxies for these.

The Fisheries Assessment Working Groups convened by the Ministry for Primary Industries (MPI) therefore have terms of reference that include a requirement "to assess, based on scientific information, the status of fisheries and fish stocks relative to MSY-compatible reference points and other relevant indicators of stock status" (Ministry for Primary Industries, 2014). Furthermore they may be required to define the projected consequences of different TAC implementations, thereby providing guidance for management. As part of this process assessments are characterised according to the following Levels of complexity (Ministry for Primary Industries, 2014):

1. Full Quantitative Stock assessment: There is a reliable index of abundance and an assessment indicating status in relation to targets and limits.

2. Partial Quantitative Stock Assessment: An evaluation of agreed abundance indices (e.g. standardised CPUE) or other appropriate fishery indicators that have not been used in a full quantitative stock assessment to estimate stock or fishery status in relation to reference points.

3. Qualitative Evaluation: A fishery characterisation with evaluation of fishery trends (e.g. catch, effort, unstandardised CPUE, or length-frequency information) has been conducted but there is no agreed index of abundance.

4. Low information evaluation: There are only data on catch with no other fishery indicators.

These are differentiated largely on the basis of a) whether or not a reliable abundance index is available; and b) whether the resource is valuable enough to spend time conducting an assessment. Only for Level 1 assessments are both of these criteria true, making it possible to deliver estimates of biomass or fishing mortality relative to established reference points. For Level 2 assessments, predominantly the less valuable stocks, only an evaluation of appropriate abundance indices is usually reported by the working groups. For Level 3 and 4 assessments, an abundance index is not available and scientific recommendations have to be made based on a qualitative evaluation of the available indicators and the catch time series.

In New Zealand therefore, data-poor fisheries can be classified as those belonging to assessment Levels 2-4, for which developing MSY-compatible reference points and etimates of stock status within a quantitative framework has not been attempted. These stocks represent about 80% of all fisheries in New Zealand (by number; Bentley & Stokes, 2009) and therefore constitute a considerable challenge to implementation of the HSS. The Operational Guidelines do however recognise that the requirements of the Fisheries Act "need to be applied in different ways for different fisheries depending on the available data." They further define analytical and conceptual proxy reference points that can be used in lieu of an analytical assessment (Ministry of Fisheries, 2011, pp. 3–8). As an example, an historic abundance index may be used as a management target if an estimate of B_{MSY} is not available. In practice the MSY itself is often equated to the Maximum Constant Yield (MCY), which is "the maximum constant catch that is estimated to be sustainable" (Ministry for Primary Industries, 2014, p. 26), and in the context of data-poor fisheries can be set using an historic period of catches (Section 2.1).

This review is focused on methods that could be used to better define proxy reference points, that are compatible with the HSS, and can be applied to estimate the status of stocks currently subjected to Level 2–4 assessements. This includes methods that are quick to apply (for application to Level 2 stocks), as well as those that do not require an index of abundance to provide management advice (Levels 3 and 4).

1.3. Legislative requirements in Australia and the United States of America

To identify data-poor methods that could be used in New Zealand, it is helpful to locate jurisdictions with similar legislative requirements, under which such methods are most likely to have been developed and applied. The 2007 Harvest Strategy Policy (HSP) in Australia was introduced to eliminate overfishing and rebuild overfished stocks (Department of Agriculture, Fisheries and Forestry, 2007), and is also underpinned by target and limit reference points. In this case the target is B_{MEY}: the biomass at Maximum Economic Yield (MEY); or a proxy, equivalent to $1.2B_{MSY}$. Similar to policy in New Zealand, a harvest strategy refers to the management actions necessary to achieve defined resource objectives in a given fishery. However the definition in Australia is more precise, specifically including a process for monitoring and conducting assessments of the fishery as well as *decision rules* that control the intensity of fishing activity. Harvest strategies consistent with the HSP needed to be implemented in all Commonwealth fisheries by 1st January 2008, and this has driven widespread development and application of data-poor methods.

The information needed to apply control rules is best derived from quantitative stock assessment models, but in a manner similar to New Zealand it is recognized that information about many stocks is limited and that it may not be possible to make direct use of the target and limit reference points described in the HSP (Department of Agriculture, Fisheries and Forestry, 2007). Each stock is classified according to one of four Tiers depending on the amount and type of information available to assess status - where Tier 1 represents the highest quality of information available (i.e. a robust quantitative stock assessment) and Tier 4 the lowest - but even for higher tiered stocks scientifically defensible proxies for reference points and corresponding control rules need to be specified (e.g. Smith & Smith, 2005; Smith et al., 2008). Underpinned by stronger requirements the HSP advocates three important approaches that distinguish if from the HSS as currently applied in New Zealand. First, it requires decision rules to be made explicit. This has provided focus for a great deal of analytical work and led to the development of simple empirical decision rules that can be applied even when stock status is highly uncertain (e.g. Prince et al., 2011; Little et al., 2011; Wayte & Klaer, 2010; Klaer et al., 2012). These provide a recommended biological catch (RBC), which is used to determine a TAC. Second, the HSP promotes the use of a risk management approach whereby exploitation levels decrease as uncertainty around stock status increases. Thus although the harvest control rules use similar reference points there is a discount factor applied to the RBC for higher tier levels so that similar levels of risk operate across all tiers (Smith et al., 2009). Third, decision rules have been developed to prompt the collection of additional data and perform associated analyses if or when the fishery expands, so that uncertainty is reduced as pressure on the resource grows (Dowling et al., 2008; Smith et al., 2009).

Legislation and policy in New Zealand and Australia share many similarities with that of the United States, described by the Magnuson-Stevens Fishery Conservation and Management Act and associated guidelines (Restrepo et al., 1998). This Act, reauthorised in 2006, requires regional Fishery Management Councils to develop Fishery Management Plans (FMPs) to set annual catch limits (ACLs) for all federal stocks, with the specific objective of reaching an MSY-related target reference point. The guidelines do however acknowledge the difficulties associated with estimating MSY for even the most well studied fisheries, and propose suitable proxy reference points (Restrepo et al., 1998).

Setting ACLs is a three-step process that begins by identifying an overfishing limit (OFL). The OFL is the annual catch when fishing the current stock abundance at the maximum sustainable fishing mortality rate (F_{MSY}). A harvest control rule is then used to determine the acceptable biological catch (ABC). The ABC is a catch level equal to or less than the OFL that accounts for the scientific uncertainty in the estimate of the OFL. Finally, fisheries managers use the ABC to set an ACL, equal to or below the ABC, that accounts for ecological, social and economic factors in addition to uncertainty in management controls. Tiered approaches have been developed by Fisheries Science Centres in both Alaska (Reuter et al., 2010) and New England (Brodziak et al., 2008), which scale the OFL by varying degrees to produce the ABC according to the degree of uncertainty associated with that tier, in a manner similar to that applied in Australia (Smith et al., 2009).

2. Data-poor assessment methods

2.1. Catch-only methods

Rather than inferring stock status, catch only methods (Zhou, 2013a) are typically concerned with estimating a sustainable catch based on the logic that historic catches reflect a level of exploitation the stock can sustain, provided the stock itself is still considered to be in a reasonable state. Thus a simple average catch taken from a period of assumed stability is probably sustainable. This approach stems from the work of Mace (1988) and has a long history of application in New Zealand, where in the absence of a stock assessment the MCY is set as:

$$MCY = c.\bar{Y}$$

where $\bar{Y}$ is the average yield over a reference period and c provides a way of incorporating the natural variability of a stock's biomass into the calculation of MCY (Ministry for Primary Industries, 2014, p. 31). For example, some unassessed New Zealand barracouta and jack mackerel stocks have an MCY set using $c = 0.7$ and $c = 0.8$ respectively (Ministry for Primary Industries, 2014, pp. 76 and 457). Typically, the higher the assumed natural mortality, the lower the value of c, which has a range of 0.6-1.0 (Ministry for Primary Industries, 2014, p. 29). This approach is similar to that advocated more recently by Patrick et al. (2011), who describe a Productivity-Susceptibility Analysis that derives an appropriate scalar for catches based on a subjective evaluation of stock vulnerability. They are appropriately known as *scalar* methods of setting catch limits and although justified differently have direct analogy with scalar methods that are based on perceived depletion. These are referred to as Depletion Adjusted Catch Scalar (DACS) methods. They are implemented in the United States, where Restrepo et al. (1998) specifically advocates use of a downward adjustment of 0.25-0.75 to average catches to account for the perceived stock status (Restrepo et al., 1998, p. 36):

$$ABC = \begin{cases} 0.25(\bar{Y}) & \text{if } B < B_{MSY} \\ 0.50(\bar{Y}) & \text{if } B \approx B_{MSY} \\ 0.75(\bar{Y}) & \text{if } B > B_{MSY} \end{cases}$$

This range of values was selected based on an observation that conservative catch limits can yield disproportionately large increases in stock biomass (Mace, 1994; Restrepo et al., 1998). They are further discussed by Berkson et al. (2011), who give an extensive review of procedures in the United States for setting catch limits when only catch data are available.

The use of methods that set catch limits according to a recent catch history is widespread in the United States (Berkson & Barbieri, 2013). MacCall (2009) extended the underlying concept to situations where the abundance is assumed to have changed, proposing a method to calculate the Depletion

Corrected Average Catch (DCAC). This adjusts recent catches according to an assumed level of depletion, by dividing the historic fisheries yield into a sustainable component and an unsustainable "windfall" that was responsible for the reduction in stock biomass. The DCAC limit is calculated as:

$$OFL = \frac{\sum_n Y}{n + \delta \left[P_{MSY} . \left(\frac{F_{MSY}}{M}\right) .M\right]^{-1}}$$

where n is the length of the historic catch time series in years, δ is the expected proportional change in stock biomass from the first year of the catch series to the end year. For example if the catch series begins at the start of the fishery then $\delta = 1 - B_y/K$ is the current relative stock status. Importantly however, there is no requirement that the time period being evaluated begin with an unfished population, and the change in stock status can reflect population growth ($\delta < 0$) or depletion ($\delta > 0$). P_{MSY} is the depletion at MSY (B_{MSY}/K) and is a measure of productivity, M is the instantaneous rate of natural mortality, and F_{MSY}/M is the ratio between the fishing mortality rate that corresponds to P_{MSY} and M. Distributions of all of these inputs must be assumed and a Monte Carlo approach is then used to reconstruct a distribution of DCAC values (MacCall, 2009), which represents the "sustainable catch". In the United States, OFL values are often taken as the median of this distribution, and then multiplied by a scalar to derive the ABC.

An alternative approach that uses a similar set of input assumptions, is Depletion Based Stock Reduction Analysis (DB-SRA; Dick & MacCall, 2011). Interpretation of δ can differ depending on whether the fishing is assumed to start at unexploited equilibrium. In the form most usually applied (e.g. Dick & MacCall, 2010), it is assumed that the time series of catch begins from an unfished population. In this context, δ is the proportional reduction in biomass relative to K. For example, if a stock is expected to be at 40% of unfished biomass in the target year, $\delta = 0.6$.

DB-SRA incorporates concepts from stock reduction analysis (SRA, Kimura et al., 1984), and from later work that implemented SRA within a stochastic framework (Walters et al., 2006). Similar to DCAC, Monte Carlo draws from the four parameter distributions (δ, P_{MSY} , F_{MSY}/M, and M) are used to generate probability distributions for current stock status and management reference points. DB-SRA implements a delay-difference production model (requiring a fixed age at maturity parameter input that is equal to the age of selectivity), the application of which is described in detail by Dick & MacCall (2011). For each Monte Carlo sample, a value for K is estimated that is compatible with the current depletion value, also providing a value for the current biomass B. This gives a catch limit of:

$$OFL = (1 - \exp(-M - F_{MSY})) . \left(\frac{F_{MSY}}{M + F_{MSY}}\right) .B$$

and an associated MSY at $B_{MSY} = P_{MSY}.K$.

These methods have now been extensively tested (Wilberg et al., 2011; Wetzel & Punt, 2011; Carruthers et al., 2013, 2014) and found to have obvious shortcomings. Both DCAC and DB-SRA have been shown to be highly sensitive to the assumed current status of the stock δ, and can easily produce overestimates of the OFL if an optimistic distribution for δ is assumed. This is a major shortcoming, since if depletion of the stock is known already, then it is unlikely to be considered data-poor. Consequently it is difficult to conclude that these methods are an improvement on the scalar methods already in use. Indeed it appears from recent simulation studies that DACS methods produce comparable results (Carruthers et al., 2014).

Nevertheless, through necessity this approach continues to attract attention. In a recent study by Martell & Froese (2013), assumptions made by the DB-SRA approach have been relaxed. Their

Table 1: Uniform input distributions assumed by the Catch-MSY method of Martell & Froese (2013): a) depletion assumed in first and final years according to catch statistics; b) assumed range of productivity (r) values based on perceived resilience of stock.

(a)

	Catch/max(Catch)	B/K
First year	<0.5	0.5–0.9
	≥ 0.5	0.3–0.6
Final year	>0.5	0.3–0.7
	≤ 0.5	0.01–0.4

(b)

Resilience	High	Medium	Low	Very low
r (per year)	0.6–1.5	0.2–1.0	0.05–0.5	0.015–0.1

Catch-MSY method implements a production model and estimates a value for K using an assumed depletion and productivity in a manner similar to DB-SRA. It is then possible to derive the MSY from well know characteristics of the model (in this case a logistic model is used, implying $MSY = rK/4$; Schaefer, 1954). However, in comparison to DB-SRA the Catch-MSY method requires as input only fairly wide ranges of potential productivity, which may be derived from perceived resilience. It compensates by requiring both initial and final depletion values, which may be derived from initial and final catches relative to the maximum catch in the time series (Table 1).

Although the Catch-MSY method retains many of the shortcomings associated with DCAC and DB-SRA, it is simpler to implement, is compatible with a production modelling approach (Section 2.5), and may represent an appropriate starting point for stocks with known catch but limited abundance data. Furthermore, when considering their utility it is worthwhile noting the philosophical stance represented by these catch-only methods. They are centrally based on prior assumptions regarding the state of the fishery (specifically the depletion), which is a departure from previous conceptions of prior information that typically refer directly to parameter values within a particular model specification. Including this type of "soft" information could allow more "sporadic, qualitative or subjective" data to partake in the estimation process (Bentley, 2015), and the methods described by MacCall (2009), Dick & MacCall (2011) and Martell & Froese (2013), represent an important step in that direction.

2.2. Length-based methods

One of the simplest indicators of stock status is the average length of fish in the catch. Assessments based on the average length can be used for data-poor stocks if some basic biological information is also available. This type of approach was first proposed by Beverton & Holt (1956) who described a method for estimating the total mortality Z using the average length and von Bertalanffy growth parameters (L_∞ and k). It has since been extended by Powel (1979) and Wetherall et al. (1987). If a value of M can be guessed, the fishing mortality can then be calculated from $F = Z - M$. Beddington & Kirkwood (2005) suggested that this estimate could be compared to the reference point F_{MAX}, the fishing mortality rate associated with maximum yield, also calculated from easily obtained length frequency data. Typically these methods assume that the current population is in equilibrium (but see Gedamke & Hoenig, 2006), which is unrealistic but allows them to be applied with only a single year of data. A more recent method developed by Klaer et al. (2012) estimates the current fishing mortality directly from average length data, again assuming equilibrium and some knowledge of the von Bertalanffy growth parameters, in addition to the natural mortality and length at (knife-edge) selectivity.

These length-based methods can therefore give an indication of the total mortality Z, which combined with an additional assumption of M yields the fishing mortality F, and tracking these estimates over time can be useful for detecting trends in the level of exploitation. However they do not provide any indication of the biomass status. The use of length frequency data to obtain information on biomass depletion has recently been proposed by Hordyk & Prince (2013) and Hordyk et al. (2015a,b). Specifically, they describe a method for calculating the Spawning Potential Ratio (SPR), which is the ratio of the total egg production (or spawning biomass) in fished and unfished (equilibrium) states, using length frequency data only. The method is based on the theoretical observation that shape of the von Bertalanffy growth curve is completely determined by the ratio M/k (Hordyk et al., 2015a), which subsequently dictates the expected length-frequency distribution. A review of empirical data by Prince et al. (2015) records values of $0 < M/k < 4$ which correspond to a broad range of expected equilibrium length-frequency distributions (Prince et al., 2015; Hordyk et al., 2015a).

By re-paramaterising the von Bertalanffy growth equation through the origin, Hordyk et al. (2015a) show how the ratio Z/k can be estimated from length frequency data. Alternatively F/M can be estimated if M/k is assumed. Using a standardised measure of length at age $\tilde{L}_x = L_x/L_\infty$, the SPR in terms of M/k and F/M can be given as:

$$SPR = \frac{\sum(1-\tilde{L}_x)^{Z/k}\tilde{L}_x^3}{\sum(1-\tilde{L}_x)^{M/k}\tilde{L}_x^3}$$

with summations over ages $x_m \leq x \leq 1$, where the starndardised age at maturity x_m is equivalent to the standardised length at maturity $L_m/L_\infty = 3/(3+M/k)$ derived from Beverton (1992). Further modifications allow knife-edge selectivity at length (Hordyk et al., 2015a), yielding an estimation equation equivalent to that of Wetherall et al. (1987).

Using length-frequency data and prior information on L_∞ and M/k, possibly from meta-analysis (Prince et al., 2015), it is therefore possible to estimate F/M and the SPR. Simulation evaluation has demonstrated that it is sensitive to the input values, particularly the selectivity pattern. Specifically the model underestimates SPR if provided with length data from a fishery with dome-shaped selectivity (Hordyk et al., 2015b). As with most length-based methods accuracy is also undermined by stochastic recruitment. However the most important criticism is that these methods are incompatible with density dependent growth, which may maintain the length-frequency distribution of a stock as it is being depleted. In such cases, the size of fish is an insensitive measure of stock status, and a dependent assessment would yield an overly-optimistic result. Application of these methods will therefore depend to a large extent on perceived plasticity of the growth rate, which in data-poor situations can be assumed unknown. For this reason, and pending further testing by proponents of these approaches, they are not considered suitable for immediate application in New Zealand.

2.3. Non-parametric and time-series models

Stock assessment modelling typically involves the parmaterisation of process based models using input data and statistical assumptions regarding how the data were generated. Usually the structure of the model is underpinned by a mechanistic understanding of reality. Recently a contrasting group of models has emerged that are data-driven, with weaker assumptions concerning the underlying process. Although they still assume a parametric distribution for the data, they are referred to as *non-parametric* models to distinguish them from the process-driven approach typically applied in fisheries. This class of model has been most frequently applied to estimation of the stock-recruitment relationship (e.g. Munch et al., 2005; Hillary, 2012; Cadigan, 2013), but Hillary (2012) also showed that they can be used to reproduce a time series of relative biomass values from catch and abundance data. Philosophically similar data-driven approaches have been proposed that use an auto-regressive component to track a relative abundance index (Trenkel, 2008; Spencer et al., 2013). Broadly speaking, their intention is to extract a trend signal from noisy data, potentially integrating over more than one index. Assuming a linear relationship between abundance and biomass, this in turn yields an index of depletion relative to the first data point (Hillary, 2012).

Importantly, these methods are not dependent on catch data being available. However more advanced methods are starting to be developed that do include (possibly uncertain) catch information. For example, the particular approach of Thompson (2013) combines catches and abundance in a bivariate, auto-regressive time series, and provides an estimate of the exploitation rate and associated U_{MSY} reference point. Neither the state transition nor U_{MSY} depend on a mechanistic description of the system, conforming to the non-parametric modelling approach.

A key benefit of the data-driven approach is that it requires minimal assumptions regarding the process being modelled. In a data-poor setting this distinguishes it from other approaches, which often compensate for a lack of data by making strong assumptions (e.g. an equilibirum size structure or deterministic recruitment), which will in turn influence the assessment of relative status. Unfortunately they have not been fully developed or tested in a data-poor setting. Although promising results have been presented by Thompson (2013) and Spencer et al. (2013), their utility is still unclear.

2.4. Swept area methods

These approaches are based on a simple assumption that the species in question is distributed homogeneously and fished at random in only part of its spatial range. In the most simple weighted swept-area approach, local exploitation rate u is considered proportional to the fraction of the inhabited area swept by fishing gear (Daan, 1991). It therefore requires survey data on spatial distribution but is otherwise undemanding. By assuming a catchability q equal to the proportion of the total area A swept by one unit of fishing effort (a/A), multiplied by an efficiency term π (Paloheimo & Dickie, 1964), and that tows are random with respect to the local population, the annual local exploitation rate for region r is simply the product of catchability and total effort $U_r = q.E_r$, where $q = \pi.a/A$. Using survey data to provide information on both the density and the total area occupied by the population, the total exploitation rate for the overall stock can then be obtained as a weighted mean of U_r with weightings equal to the relative abundance per region, which gives:

$$U = \sum_r w_r.U_r; \qquad w_r = \frac{A_r.I_r}{\sum_r A_r.I_r}$$

where I is the abundance per unit area swept by the survey (Pope, 2000). The key assumption is that fishing is spatially random with respect to the species of interest. If $\pi = 1$ it further assumes that all individuals in the path of the gear are caught. The assumption of random encounter is more likely to approximate reality for non-target species, making this approach more suitable for by-catch species.

An useful method was proposed by Zhou & Griffiths (2007) to better quantify the spatial distribution of by-catch species. They used a probabilistic model of spatially disaggregated presence-absence survey data to estimate total abundance in numbers N across the surveyed area. This allowed a better representation of the population proportion that was being exposed to fishing. The approach assumes an homogenous (uniform) distribution across space, which has proved to be a necessary simplification in some data-poor situations (Zhou et al., 2012). Using estimates of abundance in fished (r_1) and unfished (r_0) regions the exploitation rate is estimated as:

$$U = \frac{(1-\gamma)\sum_{r_1} q_r.E_r.N_r}{\sum_{r_1} N_r + \sum_{r_0} N_r}$$

which includes an extra γ term that can represent escapement or post-capture survival (Zhou & Griffiths, 2008; Zhou et al., 2009, 2012). An appropriate value for q is calculated from assumptions about efficiency and effective area covered by the fishing gear. This approach has been widely applied to data-poor by-catch fisheries in Australia (e.g. Zhou et al., 2007), with estimates of U typically compared to fishing mortality based reference points (F_{REF}) using the assumption that $U_{REF} = 1 - e^{-F_{REF}}$ (Zhou & Griffiths, 2008; Zhou et al., 2009, 2012).

More recently a similar method for estimating F directly has also been proposed (Zhou et al., 2011; Zhou, 2013b; Zhou et al., 2013), the derivation of which assumes a continuous (rather than instantaneous) fishing process:

$$F = \frac{a.\pi.(1-\gamma)\sum_r d_r.E_r}{\sum_r d_r.A_r}$$

where A is the total area, d is the average density, and E is the total fishing effort; all of which are specific to region r. The swept area per unit effort a and efficiency π are assumed constant across regions. This approach is referred to here as a *sustainability assessment*, to distinguish it from the swept-area methods for estimating U.

A major advantage of these approaches is that they require neither an accurate record of commercial catch, nor any time series data. An estimate of exploitation (U or F) can be obtained from a single year of survey data and fishing effort records only. However they are based on strong assumptions, particularly regarding spatial distribution of the stock, the efficiency π and swept area of the fishing method being considered. Recent advances have focused on estimates of F and sought to address some of these shortcomings: by estimating π from contrasting catch rates of the survey and other fishing methods; and by using statistical models to predict heterogeneous spatial distributions of the density d (Zhou, 2013b; Zhou et al., 2013, 2014).

2.5. Process-based models

Data-poor stocks are defined as those stocks for which a quantitative assessment is not available, either through a lack of informative data or the capacity to analyse them, or both. The application of simple yet representative models has the potential to alieviate capacity constraints if they can be rapidly applied and their characteristics explored. The surplus production models of Schaefer (1954) and Pella & Tomlinson (1969), and associated reparameterisations by Fox (1970) and Fletcher (1978), have the potential to achieve this, and are justified by a long history of application in fisheries. Their commonly applied discrete forms can be written generically as:

$$B_t = B_{t-1} + g(B_{t-1}) - C_{t-1}$$

where $g(.)$ is a production function representing the combined effects of somatic growth, recruitment and natural mortality, and C is the catch.

Delay-difference models (Deriso, 1980) are an alternative to production models that provide a useful way of integrating over a variety of life-history and abundance information:

$$B_t = g(B_{t-1}) + h(B_{t-a}) - C_{t-1}$$

In this case recruitment $h(.)$ is represented seperately to other growth components of the model, and may easily include a lag term (a) representing the age at recruitment. Because of this they are particularly useful for modelling highly variable, recruitment driven abundance data (e.g. Smith & Hubley, 2014). Important to the legislative context in New Zealand, both these classes of model have well defined reference points and the potential to estimate stock status relative to them.

If limited by the information content of the data, parameterisation of surplus production models can be augmented by a Bayesian approach with informative priors (e.g. McAllister et al., 2000; Stanley et al., 2009; Edwards, 2013). Priors are most easily constructed for rate (rather than scale) parameters by sharing life-history information across related stocks. Specifically in the case of production models, a prior for the intrinsic rate of increase r can be constructed using assumed distributions of the parameters that describe growth, maturity, natural mortality and recruitment (McAllister et al., 2001). Most of this information can be obtained from life-history correlations if distributions for M/k and M are assumed, using the approach described in Section 3.

Interestingly, production models may still be informative even if an abundance index is completely absent. If we know that $B > 0$ for all years (i.e. the stock has not been fished to extinction) then this places a lower limit on the unfished biomass K conditional on the productivity (Bentley, 2013). Similarly it could be argued that the stock size has not increased above K, or that catch is always less than B. Sharma & Zhou (2013) for example applied this logic to data-poor tuna stocks that do not have a useable abundance index. Assuming a Schaefer production model and enforcing initial and final biomass depletion values of $0.5-0.9K$ and $0.3-0.7K$ respectively, they were able to identify a range of plausible values for r and K and an estimate for MSY. This approach is analogous to that of Martell & Froese (2013), who were able to estimate MSY for 146 stocks using broadly defined priors on r and depletion. Their catch-only estimates corresponded well with those from the associated, fully quantitative stock assessments.

The concept of selecting trajectories that match certain prior assumptions has been extended by Bentley & Langley (2012) to include a wide variety of empirical data and information types, which they use to select *feasible stock trajectories* compatible with a range of *ad hoc* information. Bentley (2013) suggests that this approach could be usefully applied in data-poor situations, which may be characterised by sporadic and inconsistent data.

3. Effective use of prior information

Many data-poor methods depend on the availability of some prior information on life-history parameters, particularly natural mortality and somatic growth, and even the simplest catch-only methods can accept information on the likely productivity (Section 2.1). Natural mortality and growth are essential to fully describe the population dynamics of any stock, but appropriate data for estimation are often lacking even in data-rich settings. As a result a great deal of research has been invested into methods that can provide values for key life history parameters. One of the most useful is the identification of correlations in the available empirical data. For example, natural mortality has a strong inverse correlation with the maximum age a_{MAX} (Then et al., 2013), so that approximate values of M can be obtained from $M = -ln(0.015)/a_{MAX}$ (Hoenig, 1983; Hewitt & Hoenig, 2005).

A benefit of this approach is that it allows information to be shared across stocks (Edwards et al., 2012). A value for a_{MAX} for example is usually taken as the maximum age observed, but if no ageing data are available then meta-analysis could be used to give an approximation. A strong argument has been

Table 2: Outputs and example applications of data-poor methods included in this review.

Method	Output	Example applications
DACS	Catch-limit	Berkson et al. (2011)
DCAC	Catch-limit	Dick & MacCall (2010)
DB-SRA	Catch-limit and MSY	Dick & MacCall (2010)
Catch-MSY	Catch-limit and MSY	Martell & Froese (2013)
Average-length	Fishing mortality (F)	Kell et al. (2013a,b)
Length-based SPR	Spawning potential ratio	Hordyk et al. (2015b)
Swept area	Exploitation rate (U)	Zhou & Griffiths (2008); Zhou et al. (2009, 2012)
Sustainability assessment	Fishing mortality (F)	Zhou et al. (2011, 2013)
Non-parametric models	Trend	Hillary (2012)
Time-series models	Trend	Spencer et al. (2013); Thompson (2013)
Production models	Depletion and MSY	McAllister et al. (2000); Stanley et al. (2009)
Delay-difference models	Depletion and MSY	Bentley & Langley (2012); Smith & Hubley (2014)

made that the sharing of information across stocks is best achieved via the dimensionless numbers known as *life history invariants*. Three that are commonly invoked are $M_\alpha/k \approx 1.5$, $L_\alpha/L_\infty \approx 2/3$ and $M_\alpha.\alpha \approx 2$, where α is the age at maturity (Charnov, 1993; Jensen, 1996). These are notably less variable than their component parameters and therefore more justifiably shared between groups of species. Furthermore, a number of useful relationships have been proposed between M_α/k and L_α/L_∞ (Charnov, 1993), the most recent being $M_\alpha/k = (L_\alpha/L_\infty)^{-1.5}$ (Charnov et al., 2013).

A meta-analysis of M/k suggests that it is a highly informative measure of species biology (Hordyk & Prince, 2013; Prince & Hordyk, 2013; Prince et al., 2015), and could be usefully shared between species groups. Combined with an assumed value of M and an empirical relationship $k \propto L_\infty^{-0.6}$ (Gislason et al., 2008), it should be possible to estimate a realistic value for L_∞, fully parameterising a von Bertalanffy growth curve through the origin. A similarly interesting study is that of He et al. (2006), who used decision theory to identify plausible values for steepness (h) based on M and recruitment variability. This is particularly important since the stock recruitment relationship defined by h largely determines the biomass depletion at MSY, an important reference point for management (Mangel et al., 2013). An approach whereby information is shared accross stocks and potentially augmented by proposed relationships between life-history parameters has a great deal of promise. Furthermore this promise has begun to be realised through development of the **R** package `fishnets`, the logic of which is informally discribed by Bentley (2015).

Alternative types of prior worthy of attention are the "soft" priors referred to in discussions on catch-only methods (Section 2.1). Specifically, DCAC, DB-SRA and the Catch-MSY method of Martell & Froese (2013) use an assumed depletion to inform the assessment. Although there is circularity to the argument that assessments should be informed by our preconceptions of resource status, this is nevertheless often implicit in the review process, and formal inclusion of these types of assumptions could improve transparency. Other soft inputs could include priors on "smoothness" or direction of trend over time (e.g. Trenkel & Rochet, 2010). These are particularly useful for data-driven approaches (Section 2.3), which are arguably focused on detecting a trend signal indicative of depletion. Both Hillary (2012) and Spencer et al. (2013) for example employ hierachical methods to identify an appropriate level of smoothing, which is central to their extraction of a signal from noisy data.

Table 3: Summary of data requirements for each method: a) Meta-data that is assumed known from other sources; b) Empirical data. Shaded cells marked with an '**X**' indicate required data inputs. Lighter shaded cells marked with an 'O' indicate data that could be accommodated if available.

(a)

Method	Life-history				Fishery			Status	
	Mortality	Growth	Maturity	Productivity	Selectivity	Catchability	Area	Depletion	Trajectory
DACS				O				X	
DCAC	X			X				X	
DB-SRA	X			X				X	
Catch-MSY				X				X	
Average-length	X	X			X				
Length-based SPR	X	X	X		X				
Swept area						X	X		
Sustainability assessment						O	X		
Non-parametric models									O
Time-series models									O
Production models				X		O		O	O
Delay-difference models	O	O	O	X	O	O		O	O

(b)

Method	Time-series data		Current data		
	Catch	Abundance	Length	Survey	Effort
DACS	X				
DCAC	X				
DB-SRA	X				
Catch-MSY	X	O			
Average-length			X		
Length-based SPR			X		
Swept area				X	X
Sustainability assessment				X	X
Non-parametric models	O	X			
Time-series models	O	X			
Production models	X	X			
Delay-difference models	X	X			

Table 4: Potential applications to New Zealand species of data-poor methods included in this review.

Method	Potential applications
Production modelling approaches	Barracouta; Blue mackerel; Jack mackerels; Kingfish; Southern blue whiting; School shark; Rig; Elephant fish.
Swept area methods	Ghost sharks; Skates; Dogfish.

4. Conclusions

Even for data-rich assessments, MSY-based reference are often unknown or poorly estimated. In order to meet legislative requirements in New Zealand, proxy MSY-based reference points for Level 1-4 assessments are usually represented by a reference period of catch or abundance (Ministry for Primary Industries, 2014). For example, a reference catch rate can be used as a proxy target for B_{MSY}. Similarly, scalar estimates of MCY are based on the presumption that the reference catch is a suitable proxy for MSY (Section 2.1). Despite the established practical utility of these approaches it would be advantageous for any data-poor method to include a more well defined assessment of status. A variety of approaches were presented at WCSAM 2013 (and the KBBE 2013 workshop) that could fulfill this role, and are listed with examples in Table 2. Species to which these methods could be applied within a local context are listed in Table 4. Of course the appropriate method will depend on the quality and type of data available for the particular situation (Table 3), but it is useful nevertheless to summarise common themes in the methods currently being developed globally and address their likely relevance to local fisheries.

4.1. Potential applications of data-poor stock assessment methods to fisheries in New Zealand

The two most fundamental types of fisheries data are catches and abundance indices, and data-poor methods can be categorised according to the relative uncertainty associated with each, and in particular the length and integrity of the time series.

Assuming that reasonably accurate catch data are available for the duration of exploitation, process-based models can yield an estimate of reference points and stock status, even if abundance data are completely lacking (Dick & MacCall, 2011; Martell & Froese, 2013). However this requires strong prior assumptions regarding productivity and depletion, which are often poorly justified. If the time series of catches is incomplete, then scalar methods may be more appropriate. Simulation based studies have concluded that neither scalar nor model-based catch-only methods are reliable (Wetzel & Punt, 2011; Carruthers et al., 2014; Arnold & Heppell, 2015) but they are still widely used, particularly in the United States (Berkson & Thorson, 2015), and are active area of research (e.g. Sharma & Zhou, 2013; Zhou, 2013b; Owashi & Sampson, 2013).

The reliability of simple process model-based approaches is often dependent on the availability of prior information, and this is true for the catch-only methods such as Catch-MSY and DB-SRA, as well as the more standard approches discussed in Section 2.5. Regardless of whether an abundance index is available, prior information will improve their performance. In particular, life-history information can be used to derive a prior on productivity (McAllister et al., 2000; Stanley et al., 2009). Bentley (2015) proposed that statistical models of the relationship between abiotic factors and density could be used to generate priors for the unexploited equilibrium biomass, and a simple version of this approach has recently been developed for data-poor orange roughy stocks in New

Zealand (Clark et al., 2014). Nevertheless, the availability of a time series of abundance data will substantially improve the prospects for a reliable stock assessment, and unless progress is made towards the development of informative priors for both productivity and initial biomass, model-based catch-only methods are of limited use.

In summary, the application of process-based models can only be seriously attempted if an abundance index is available. However they still require some contrast in the time series (i.e. if the catch has changed over time then the abundance index must have also changed). This can be a fundamental limitation. If the abundance time series is unresponsive to, or inconsistent with, the catch then either: i) catches are very small relative to absolute biomass; ii) indices are not tracking abundance; or, iii) abundance is being driven by other unknown factors (McAllister & Edwards, 2014). In these instances a process-based modelling approach will likely fail. Non-parametric approaches may however still be useful (Section 2.3). At the very least these may be able to extract a signal from the data to determine whether abundance is increasing or decreasing. This class of models is less reliant on accurate catch data (e.g. Trenkel, 2008), and even if they are not able to estimate status, an indication of trend may still be useful for management (particularly if it is placed within the context of a feedback control rule - Section 4.2). Of the data-driven methods discussed, those of Hillary (2012) and Thompson (2013) hold the most promise, but have yet to be fully established or tested.

When time series data are not available, the sustainability assessment approach represents a well developed alternative method that has been applied to a variety of Australian fisheries (e.g. Zhou et al., 2013). It is particularly suited to the study of non-target by-catch species, which are recorded in surveys but do not have a reliable catch history. Although more complicated to apply, it is preferrable to the swept-area methods discussed, since it is able to estimate the fishing mortality directly (rather than an exploitation rate). Assessments of elasmobranch by-catch species could benefit from this type of approach, and work in this area has already been initiated (e.g. Trenkel et al., 2014). The current focus of research around this approach concerns the estimation of catchability and the inclusion of an heterogeneous species distribution (Zhou, 2013b). However these methods are complex and will require a substantial investment to develop the technical capacity necessary for application in New Zealand.

4.2. Stock assessment and feedback control

The discussion so far has dealt with the application of methods that could potentially increase the number of New Zealand stocks subjected to a quantitative assessment of status. However an assessment of status relative to management objectives, while necessary, does not immediately determine what the management action should be. Conversion of status information into a TAC can be formalised by a decision rule, and the construction of such rules can form an important component of successful management. In the United States, this decision rule is often a simple adjustment to the OFL ouput from the assessment. However, it may also be quite independent of the assessment. In Australia for example, decision rules have been developed for data-poor fisheries that convert empirical observations directly into management advice (Dowling et al., 2008; Dichmont et al., 2011), and simulation testing shows that they can perform well even when stock status is poorly quantified (e.g. Prince et al., 2011). A scientific emphasis on the decision making process, rather than on estimates of status, is a distinctive feature of fisheries management in Australia (Dowling et al., 2011; Dichmont et al., 2011), with similar ideas being promoted in the United States (Berkson & Thorson, 2015).

Simulation testing of decision rules requires a realistic representation of the resource (an *operating* *model*) that is difficult to develop in a data-poor setting. However it can be facilitated through recognition of the fact that an operating model should first represent the dynamics of the resource, followed by the scale (e.g. Plagányi et al., 2011; Plagányi, 2013; Prince et al., 2011), noting also that prior information on productivity parameters is more likely to be available. Attempts are also being made to identify generic control rules with desirable properties that could be applied over a wide range of resources with uncertain status (Froese et al., 2011; Geromont & Butterworth, 2015b).

Progressive parmeterisation of the operating model can be facilitated by sequential stock assessments as further data are collected. Indeed, it is not unusual for the assessment model to be used as an operating model for testing of a decision rule. This situation is exemplified by rock lobster management frameworks in New Zealand and elsewhere (Edwards & Rademeyer, 2013), which combine a highly parameterised assessment model with simple empirical decision rules to convert commercial catch rates into a TAC or TACC.

Annual calculation of the TAC using a decision rule, with less frequent stock assessments that provide both an operating model and a best estimate of resource status, is an assessment and management paradigm that is gaining traction globally (Geromont & Butterworth, 2013, 2015a; Bentley, 2015; Berkson & Thorson, 2015). In a data-poor setting it is equally valid, and should allow scientifically justified management despite the large uncertainties that exist.

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Appendix: Glossary of abbreviations and acronyms

DCAC	Depletion-corrected average catch
DB-SRA	Depletion-based stock reduction analysis
DACS	Depletion-adjusted catch scalar
OFL	Over-fishing limit
ABC	Acceptable biological catch
ACL	Annual catch limit
FMP	Fishery management plan
RBC	Recommended biological catch
HSP	Harvest strategy policy
HSS	Harvest strategy standard
MSY	Maximum sustainable yield
MCY	Maximum constant yield
MEY	Maximum economic yield
QMS	Quota management system
TAC	Total allowable catch
TACC	Total allowable commercial catch
F	Instantaneous fishing mortality rate
M	Instantaneous natural mortality rate
Z	Instantaneous total mortality rate (F+M)
Y	Yield (total catch)
U	Exploitation rate
B	Stock biomass
K	Equilibrium stock biomass