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Generic solutions for data-limited fishery assessments are not so simple

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Abstract

The majority of the world's fisheries, by number, are data-poor/limited, and there is a growing body of literature pertaining to approaches to estimate data-limited stock status. There are at least two drivers for assessing of the status of data-limited fisheries. The first is to try to understand and report on the global or regional status of fisheries across many stocks. The second is to attempt to assess individual data-limited stocks, for status reporting and/or guiding management decisions. These drivers have led to attempts to find simple, generic, low-cost solutions, including broad application of generically parameterised models, and the blanket application of a single, or limited number of possible, analytical approach(es). It is unclear that generic methods function as intended, especially when taken out of their original design context or used without care. If the intention is to resolve individual stock status for the purposes of management, there is concern with the indiscriminate application of a single method to a suite of stocks irrespective of the particular circumstances of each. We examine why caution needs to be exercised, and provide guidance on the appropriate application of data-limited assessment methods (DLMs). We recommend: i) obtaining better data, ii) using care in acknowledging and interpreting uncertainties in the results of DLMs, iii) embedding DLMs in harvest strategies that are robust to the higher levels of uncertainty in the output of DLMs by including precautionary management measures or buffers, and iv) selecting and applying DLMs appropriate to specific species' and fisheries' data and context.

Keywords: data-poor, data-limited stock assessment, stock status

Introduction

The majority of the world's fisheries, by number, are data-limited (Costello et al. 2012). That is, they have insufficient data (e.g., type, amount, and/or quality of) and/or capacity (e.g., research, institutional, or funding) to enable undertaking a quantitative, model-based stock assessment to estimate time series of biomass and fishing mortality relative to their reference points. There is a growing body of literature aimed at developing approaches to estimate the status of data-limited stocks (e.g. Anderson et al. 2017; Dowling et al. 2008; Dichmont and Brown 2010; Plaganyi et al. 2015; Wayte and Klaer 2010; Dowling et al. 2014; Dowling et al. 2016; Pilling et al. 2008), and increasing use of these data-limited assessment methods (DLMs) for management purposes (Bentley 2015; Carruthers et al., 2012, 2014, 2016; Dichmont et al. 2017; Geromont and Butterworth 2015a,b). Several of the classical, average-length-based methods developed in the 1950s by

Beverton and Holt, Gulland, Ricker and other early quantitative fishery scientists are data-limited assessment methods, many of which are being revisited and re-emphasised (eg., Gedamke and Hoenig 2006; Prince et al. 2014; Then et al. 2016). DLMs range from empirical methods, in which performance indicators are based on directly-measured properties, to model-based approaches, where performance indicators are model outputs. **Table 1** provides a summary of types of DLMs, including empirical assessments.

There are at least two contexts for undertaking an assessment of the status of data-limited fisheries. The first is to try to understand and report on the global or regional status of fisheries across many stocks. This typically involves application of a single DLM to a large number of stocks (e.g. Rosenberg et al. 2017; Zeller et al. 2016; Costello et al. 2012; Froese et al. 2012; Thorson et al. 2012; FAO 1995), to gain an understanding of the general health of fisheries for the purpose of motivating funding, research and reform. The second is to assess the status of individual data-limited stocks, for status reporting or guiding management decisions, the latter typically within a harvest, or management, strategy (e.g., Sainsbury et al. 2000; Butterworth and Punt 2003, and Fish. Res. Special Issue 94(3) 2008) (Figure 1).

DLM approaches are also increasingly being used in formal harvest strategies (e.g. Dichmont and Brown 2010; Klaer et al. 2012). The main distinction being highlighted within this paper is the use of assessments for stock status determination, compared to connecting a control rule to the assessment output in order to provide a direct link to a pre-specified management action , as per a formal harvest strategy (e.g., Sainsbury et al. 2000; Butterworth and Punt 2003) (Figure 1). We discuss more fully the stock assessments whose outputs are embedded within harvest strategies below.

There are good reasons for management agencies, national governments and international organisations such as the Food and Agricultural Organisation to report on the status of individual stocks. Over the last 20 years, fisheries policy has increasingly required the maintenance of stocks at or around biomass-based target reference points, and the avoidance of biomass-based limit reference points (Oremus et al. 2014; FAO 2016). The stock status reporting requirement associated with managing around target and limit reference points imposes a daunting task for fishery management agencies, leading in many cases to a substantial number of stocks being classified as "uncertain", and many others being designated as "not overfished" or "overfished", but with a high risk of misclassification (e.g., Flood et al. 2016; NRC 2012).

At the same time, there is, understandably, pressure to resolve the status of "uncertain" stocks (e.g., Flood et al. 2016) to increase the number of species assessed and decrease the number of species whose status is designated as "uncertain". While the initial focus of national level stock status reports (e.g., in Australia or the USA) has been on data-rich stocks, there is interest to report on the large number of stocks which are currently listed as uncertain, and to use DLMs to do so. For example, the Status of Australian Fish Stocks (SAFS), the nationally standardised approach to assessing stock status, aims to increase the number of included species from 83 to 200, and to reduce the number of species classified as "undefined" from the current approximately 30%, to less than 10% (Flood et al. 2016). In the United States, there is a legal requirement to assess and set Acceptable Catch Levels for all species, per the 2006 amendment to the Magnuson–-Stevens Act (Newman et al. 2015). The interest in resolving stock status extends to developing nations whose legislative requirements are also becoming more stringent, demanding the use of standard target and limit reference points to set management regulations (e.g., Chile, Wiff et al. 2016).

The above drivers have led to attempts to find simple, generic, low-cost solutions to assess fishery status. Such solutions include "silver bullet", or one-size-fits-all approaches, that are simple to implement without much scientific expertise. It is unclear that these generic methods function as intended, especially when taken out of their original design context or used without care.

For example, the abovementioned Australian SAFS process has, as an initial step, focused on building capacity around a small number of possible quantitative methods (3) to assess a large number of species, while acknowledging the challenge of appropriate application and interpretation (Haddon et al. in prep). In a developing nation context, the authors have consulted in countries where an outside expert has proposed a method for one species or fishery, and subsequently a blanket application of that approach to other species has occurred, without due critical appraisal of the appropriateness of the method or its assumptions.

While all of the above motivations are legitimate, the approach to undertaking an assessment of stock status needs to be appropriate to the objective. If the intention is to resolve individual stock status for the purposes of managing the stock, particularly within a management or harvest strategy, the concern is with the indiscriminate application of a single method to a suite of stocks irrespective of the particular circumstances of each.

In this paper, we examine why caution needs to be exercised when using generic approaches to data-limited stock assessment, and provide guidance on the appropriate application of DLMs.

What do we mean by "generic assessment approaches"?

Generic approaches to stock assessments include two important potentially undesirable applications: i) species-unspecific parameterised models, and ii) blanket application of a single or very few analytical approach(es) to many stocks that do not discriminate among the different circumstances and requirements of each stock. **Table 2** provides a review of regional or global assessment applications, with examples of one-size fits-all approaches, and the rationale or impetus for each. Note that the methods here summarised are not intended as examples of incorrect application; the point is that such approaches exist, and along with them exists the possibility of misapplication or misinterpretation.

Generic assessment approaches may include methods that have been tested using data-rich stocks, and are then applied in the same manner to data-limited stocks. We emphasise that we are not against generic approaches *per se*, if they are tuned intelligently and used with care to the specific application, such as with, Froese et al.'s 2017 application of a catch-MSY assessment to a range of data-limited fisheries.

i) Broad application of generically parameterised, or data-aggregated, models

Generically-applied DLMs may be appropriate (and thus the value of individually-tailored DLMs diminished) if their purpose is not to examine individual stock status, but rather, to undertake a broader (regional, or global) "health check" of overall sustainability (examples include Rosenberg et al. (2017), Costello et al. (2012, 2016), Kleisner et al. (2013), and Thorson et al. (2012)– see **Table 2** for details). Despite the concern of compounding sources of uncertainty, at such scales, it could be argued that the inaccuracy of DLMs due to lack of data/information may be absorbed, rather than compounded by, the lack of accuracy caused by generic parameterization of DLM. That is, if the uncertainty about key input parameters is large (with wide associated prior distributions) then potentially a number of stocks could be included within the range of uncertainty allowed for that particular stock, and the accuracy or lack thereof would be the same whether or not the DLM is generically parameterised. If the assumptions of the method hold for all species to which it is being applied, then this argument may have some validity.

Yet there remain examples of misapplication of empirical DLMs – specifically, the use of aggregated time series of catch or catch-per-unit-effort - in the context of obtaining a regional or global estimate of sustainability. Edgar et al.'s (2018) use of aggregated catch time series across over 200 Australian fisheries, each normalised to its maximum value, to infer that Australian fisheries are in decline, acknowledges but fails to account for management intervention and large-scale environmental changes, fails to weight each time series according to (for example) relative biomass, and fails to acknowledge the lack of desirability of maximum catch as a reference point. The now-classic Myers and Worm (2003) claim of rapid worldwide depletion of predatory fish communities, based on analysis of nominal catch-per-unit-effort data combined globally, was rebutted by Hampton et al. (2005), Maunder et al. (2006), and Polacheck (2006).

A preferable approach to identifying regional stock status might be to undertake an in-depth analysis of a sample of stocks from the region, rather than attempting to estimate the status of many stocks using a one-size fits all approach. More broadly, if DLMs are to be applied for purposes of fishery-specific management, then generic parameterisation is inadvisable.

ii) Blanket application of a single, or limited number of possible, analytical approach(es)

Some regional, and, especially, global analyses have applied a single DLM to all stocks (including regression models from data-rich stocks to make predictions for data-poor stocks (Costello et al. 2012)), irrespective of whether better information or assessments are available for some. Blanket application of DLMs may be problematic or inappropriate due to a lack of data, problems with data quality, a lack of required inputs, or the violation of assumptions. However, this has typically been done as a practical approach to provide global assessments of stock status or to assess groups of stocks in the face of limited time and resources, and balanced against the relatively low value of some data-limited stocks. We caution that this may not yield meaningful results for individual stocks, but the outcome is preferable to no assessment and no management.

It is clear from the literature that, while the application of DLMs may be simple, these methods are very context-specific and each has its own assumptions and caveats, requiring expert guidance and/or local knowledge (Geromont and Butterworth 2015a,b; Dowling et al. 2014; Carruthers et al. 2014; Pilling et al. 2008). Blind application of generic assessment packages, be these data-rich or data-limited, may inadvertently result in erroneous assessment outputs and misinformed guidance because of assumption violations and method outputs not fitting management objectives. An example of potential blanket application of a single, or limited number of analytical approaches includes the aforementioned Australian SAFS approach of, as an initial step, advocating a limited number of assessment methods to resolve status for 200 species (Haddon et al. in prep). In developing nations, authors have observed, during capacity building exercises, the misapplication of assessments recommended for a particular species, to others for which it is not appropriate, or where assumptions are violated.

The misapplication of any assessment method, be it data-rich or data-limited, can lead to erroneous results and interpretation. This is more likely to be a problem for DLMs, however, since their information requirements are fewer, and, as such, they can be more readily applied. More generally, blanket application of the same models to a suite of species, or species complexes, may result in varying levels of certainty in parameter estimation, according to the amount and quality of data available (Bentley 2015).

Why do we need to be so careful about the generic application of DLMs?

While generic methods may be quicker and easier to implement, their broad or blanket application increases the likelihood of violating assumptions, and of not paying due attention to issues of data quality (errors, gaps, bias) or representativeness (of the stock, of the fishery, and in terms of whether data is temporally or spatially consistent) (**Table 3** provides a summary list of typical assumptions, required inputs, and assumed knowledge associated with DLMs). This compromises the reliability of generic methods.

The application of traditional model-based assessment to data-limited fisheries is often further limited (Dowling et al. 2007, 2008a, 2008b) because many such fisheries also have other complicating features, such as high variability in productivity (e.g., squid and scallops), spatial heterogeneities (e.g., sedentary or low-mobility species) or large numbers of interacting species and gears (e.g., tropical multi-species fisheries).

For both developed and developing nations, there is the need to counter a legacy from a “quick-and-dirty”-methods era, when stock assessment tools were made readily available with little training support and little awareness of their limitations. This frequently results in the misapplication of DLMs, whereby assumptions are violated, or the input data are uninformative. For example, yield-per-recruit models are widely available in a variety of user-friendly applications that also promote simple reference points (e.g., F=M). This user friendliness allows access to the method, but is sometimes not flexible enough to include important aspects of a fishery. If selectivity is rigidly assumed to be asymptotic, but true selectivity is dome-shaped (often the case in fisheries that fish shallow, but ontogenetic shifts result in larger individuals in deeper water), the interpretation of the fishing rate at maximum yield (F_{max}) will be incorrect. Increased training and bottom-up engagement and support should help overcome the misapplication of DLMs, and enable the results of user-friendly applications to be correctly interpreted.

Although many DLMs are computationally simple to undertake (e.g., via the use of packages (e.g., Carruthers and Hordyk 2018; Cope 2018)), caution needs to be applied to interpretation and use of their outcomes, because of the inherent propensity of DLMs to yield highly uncertain results. Moreover, the application of DLMs and interpretation of their output are less simple when the assumptions of the DLM are not respected. In addition, many DLMs can still be resource-demanding - even, at times, approaching the requirements of a data-rich approach. As such, there is a costbenefit balance between their generic application versus devoting resources to ensuring the most appropriate method is applied. However, the latter is readily facilitated using decision support tools (e.g. FishPath (Dowling et al. 2016)) to guide the choice of appropriate methods.

<u>DLMs have an inherent propensity of to yield highly uncertain results</u>

Even if a DLM is appropriate for a fishery or stock, in general, data-limited stock assessments have a higher degree of uncertainty and potential bias in their estimates of stock status than data-rich approaches (Fulton et al. 2016). The extent of this uncertainty is highly case specific. It follows that generic application of DLMs further compounds this uncertainty.

All stock assessment methods result in some level of uncertainty in status determination: uncertainty in priors and measurement error in the data, and naturally occurring variability in biology result in a lack of certainty in output. Data rich methods usually deal with this uncertainty explicitly –e.g. they can estimate and report the "probability that the stock is below a limit reference point" or undertake sensitivity tests that can be well defined. By contrast, the uncertainty involved in stock assessments conducted using DLMs is rarely estimated or reported (Dichmont et al. 2017 is an exception). However, to adequately define and calculate the uncertainties associated with DLM methods requires only an awareness of the assumptions of the DLM and unknown parameter inputs. In the USA, the Pacific Fishery Management Council has set the uncertainty around a data-limited assessment to be a coefficient of variation of 1.44 (Ralston et al. 2011. This uncertainty is used to describe the distribution around a catch limit derived from a data-limited method. The risk tolerance is then defined as a certain percentile of the distribution, this determining the reduction from the median. A catch-limit based on a data-limited method, therefore, has a larger reduction in catch than other, less data-limited methods (Ralston et al. 2011).

Where uncertainty has been reported, data-limited assessments have been often imprecise for status determination of specific stocks. This has been demonstrated by Dichmont et al. (2017), and by studies (e.g., Klaer et al. 2012; Plaganyi et al. 2013; Dichmont et al. 2017) resulting from the Australian government-funded initiative to explore and understand DLM methods through the "Reducing Uncertainty in Stock Status" program (Larcombe et al. 2015). Although it is difficult to generalise because performance is highly species-specific, the comprehensive management strategy evaluation of Dichmont et al. (2017), that considered assessments embracing fully quantitative model-based assessments, catch curves, empirical analysis of average catch-per-unit-effort CPUE relative to target and limit CPUE reference points (Wayte and Klaer 2010), length-based yield-per-recruit (Haddon et al. 2015), SAFE (Zhou et al. 2011), an empirical catch-based trigger system, and an empirical multi-indicator trigger system (Dowling et al. 2008), showed that, given the same inputs and data, stock-specific data-limited assessments generally tended to be highly uncertain and biased towards overestimating population size. In consequence, more precautionary management is required to achieve the same risk outcomes when using data-limited assessment methods, including generic application of outcomes from data-rich situations (Fulton et al. 2016; Dichmont et al. 2017).

As such, care needs to be exercised to ensure that the estimates produced by DLMs are appropriately robust given the circumstances. More thought is also required than is usually given to adequately represent the uncertainties in all status determinations given what one knows about the approach and the unknowns due to lack of information. For example, catch-only assessment methods are known to perform poorly or well in different circumstances especially depending on available knowledge of key inputs such as natural mortality (Wetzel and Punt 2011; Caruthers 2014; Arnold and Heppell 2014).

<u>Embedding DLMs within harvest strategies</u>

Harvest strategies are formal frameworks for managing exploitation of fisheries, usually applied to the target species (e.g., Sainsbury et al. 2000; Butterworth and Punt 2003, and Fish. Res. Special Issue 94(3) 2008) (Figure 1).They comprise a fully-specified set of rules for making tactical management decisions, including specifications for (i) a monitoring program, (ii) the indicators to be calculated from monitoring data (usually via a stock assessment) and (iii) the use of those indicators and their associated reference points to adjust harvest controls (e.g., total allowable catches) through application of harvest control rules (HCRs, Sainsbury et al. 2000; Butterworth and Punt 2003; Punt et al. 2002; Rayns 2007; Butterworth 2007). The motivations for using DLMs in a harvest strategy context are usually resource limitations (e.g., sparse or uninformative data, funding limitations, or a lack of scientific capability). Commonly there is limited time or resources to apply the best (tailor-made) assessment for each, often relatively low-value, stock (Bentley 2015).

We encourage the use of harvest strategies in many data limited management contexts. DLMs can be embedded within a harvest strategy with control rules that explicitly link the assessment to a specific management action. Moreover, control rules within a harvest strategy can be designed to be conservative and compensate to some extent for imprecision in the assessment. Simulation and real-life experience have shown DLMs to be biased and have higher variance than data-rich assessments (Dichmont et al. 2016), yet can perform adequately in a precautionary HCR setting (Fulton et al. 2016). DLMs linked to precautionary HCRs within a harvest strategy can therefore perform adequately in avoiding overfishing at the expense of less yield, to compensate for poor estimates of stock status by DLMs.

DLMs can still be resource-demanding

Ironically, some of the more data-limited assessment options (e.g., ratios of fish density inside compared to outside marine protected areas (Babcock and MacCall 2011; McGilliard et al. 2011), hierarchal decision trees based on combinations of multiple empirical indicators (Prince et al. 2011)) are labour intensive, and hence quite costly. Undertaking even the more empirical assessments requires investment of a base level of resources and may also require new data to be collected if stock status is determined to be below target levels, demanding a more rigourous assessment (often, “trigger based” empirical assessment frameworks demand that a more quantitative assessment is undertaken, if a trigger is reached that suggests the stock is below target levels (Dowling et al. 2008)). We reiterate the need to balance the costs of generically applying DLMs, and those of ensuring the most appropriate method is applied.

Stock-specific knowledge and solutions are required to guide decision making

While there are no simple generic solutions to resolve stock status when data are limited, there are simple stock-specific solutions to manage fisheries in data-limited situations. We would argue that the preferred approach, for the purposes of sustainable management using harvest strategies, is to tailor DLMs to individual stocks or fisheries. Overall management success is strongly dependent on the reliability of the stock status estimate (especially when this is not associated with precautionary HCRs), which we argue can be compromised by the application of generic approaches. Tailored application of DLMs is made more feasible by decision support tools that help users easily select the DLM(s) that are most appropriate for their circumstances (Dowling et al. 2016, Carruthers et al. 2012, 2014).

A fishery’s specific data collection protocols and operational characteristics, the life history characteristics of the species of interest, and the management objectives and capacity all should be explicitly considered in the application of any assessment. It is these aspects of a stock and its fishery that help match appropriate methods and assumptions to inform management. For instance, knowing not just whether data can be collected or are available for a particular method (e.g., a catch-only method) but whether that method performs well for a given life history (e.g., some are better for faster than slower life history types; Wetzel and Punt 2015) and whether the management system can manage the output of that method, are all fundamental to determining the case-specific appropriateness of any given method. Practitioners should apply a DLM that is appropriate to their data and fishery context (in terms of life history and operational characteristics) (Carruthers et al. 2012, 2014, 2016; Dowling et al. 2016).

What is the way forward for the application of data-limited assessments?

Rather than only seeking simple, generic solutions, we recommend dedicating effort to: i) obtaining better (less measurement error, more spatially and temporally continuous and representative, or additional) data, ii) using care in acknowledging and interpreting the uncertainties in the results of DLMs, iii) embedding DLMs in harvest strategies that are robust to the higher levels of uncertainty in the output of DLMs (both stock status and reference points), by including precautionary management measures (e.g., setting size limits that prevent or limit exploitation until after the size at first or second spawning), or precautionary buffers that set more conservative measures to account for assessment uncertainty, and iv) selecting and applying DLMs appropriate to specific species' and fisheries' data and context.

i) There is no substitute for better data

There is no replacement for data quantity and quality, particularly time series data, to enable reliable assessment of stock status (Bentley 2015). In the absence of a time series of data and/or current (research, or funding) capacity to conduct assessments, it is important to make a commitment to improve the amount and quality of data informing any assessment, for example, by archiving time series of fishery or biological data for later analysis (Dowling et al. 2008).

Improved data can be obtained in cost-effective ways (Dowling et al. 2016). These include market, port or processor monitoring programs, interviews (Moore et al. 2010), voluntary logbooks (Breckwoldt and Seidel 2010), participatory community data collection and assessments (Schroeter et al. 2009; Kittinger 2013), and eliciting local ecological knowledge; (Beaudreau and Levin 2014). These nonetheless require some minimum, ongoing financial and capacity commitment.

ii) Acknowledge uncertainties and assumptions

DLMs should not be applied as a routine, low-risk or technically trivial exercise. The process, uncertainties and outcomes must be critically confronted. Practitioners should be aware of and report on the limitations of the available data inputs, such as their representativeness, uncertainty (in terms of measurement error and reliability), level of contrast (i.e., that a time series of abundance or proxy abundance data embraces both periods of highs and lows), or spatial/temporal continuity.

It is good practice to apply more than one DLM method (and this will usually be technically possible) in order to assess consistency of results (e.g., Fitzgerald et al. 2018). The assumptions and limitations of the chosen DLM(s) should be clearly understood and reported. Where appropriate, uncertainties in inputs (prior ranges for parameters) should be considered via Monte Carlo approaches and sensitivity analyses (e.g., Prince et al. 2011).

It follows that care should be taken in interpreting the outcomes of DLMs. The uncertainties in the results should be made explicit. For example, typical DLM problems include the inability of sparse/poor data to update priors to give meaningful posteriors, and difficulty estimating MSY. Effort should be dedicated to considering the implications of this uncertainty as it affects management decision efficacy and future monitoring requirements (e.g. Dowling 2011). HCRs should be adequately precautionary (conservative) given the risk associated with the strength of the data (relative to data-rich stocks) and perceived robustness of the DLM. Such measures may provide incentives to resolve uncertainties identified through sensitivity analysis (sensitivities to assumed model inputs and priors).

The legislative, policy and/or commercial (through seafood certification requirements) pressures to evaluate stock status of data-limited fisheries, together with a view that inexpensive, generic approaches are available, begs the question: what level of certainty do agencies or organisations regard as acceptable in moving a species from an “uncertain” stock status to a reportable status designation? It may be misleading to assume that a highly uncertain, yet designated stock status category is preferable over an honest categorization of "uncertain". However, this policy question is rarely addressed. The recent SAFS discussion (Flood et al. 2016) and reconsideration of the Australian Fisheries Management Authority (AFMA) tiers (Dichmont et al. 2017; 2016), the Alaskan tier system (North Pacific Fishery Management Council (NPFMC) 2014), and the U.S. Pacific Fishery Management Council stock assessment categories (Ralston et al. 2011) are exceptions. Demanding that data-limited fisheries meet the same precision and accuracy as data rich fisheries is unrealistic. However, data limited methods have value in identifying species at risk of being overfished, even if the assessment is not "certain" enough to, for example, set catch or effort limits as in a data rich fishery. Generic application of outcomes from data-rich situations may also be appropriate in guiding, for example, the setting of broader control rules such as size limits or gear restrictions. Another valid application of DLMs is via the “Robin Hood” approach of Punt et al. (2011) that uses insights from data-rich assessments to inform data-poor assessments.

iii) Embed DLMs in harvest strategies

We recommend embedding DLMs within data-limited harvest strategies: precautionary HCRs can compensate for poor estimates of stock status by DLMs. At the same time, we caution that this is not a trivial undertaking: data-limited harvest strategies demand expertise and can sometimes be as time consuming to develop as data-rich ones (Dowling et al. 2016; Plaganyi et al. 2013; Dowling et al.

2008), and they are frequently difficult to implement and to simulation test (e.g., Carruthers et al. 2016; Dowling et al. 2016). Additionally, it is often difficult to provide defendable indicators and reference points for management frameworks based on empirical assessments. For example, what level of catch or catch rate, at what geographical scale, is considered 'good' and can be related to an overall objective, such as optimising human benefits and avoiding recruitment overfishing? Or, in multispecies fisheries, which species should be considered, what is the basis of the proxy reference points for them, and how should the status of many species be reconciled to yield an overall status for a stock complex, or to determine management advice for the fishery? Despite these challenges, DLMs have been successfully embedded within harvest strategies (Dowling et al. 2008; Fulton et al. 2016), and we believe that the use of harvest strategies provides the best outcomes for sustainable fisheries management. A process of bottom-up engagement, facilitated by a decision support tool such as FishPath (Dowling et al. 2016), may best enable the design of effective harvest strategies.

iv) Context and consequence matter

There is a difference between attempts to assess the status of stocks for situations in which dynamic (based feedback from a stock assessment) management protocols exist - typically, developed countries that set total allowable catches (TACs), and situations in which static ("set and forget") management protocols, such as closed seasons, exist. Many fisheries, especially (but not exclusively) small-scale fisheries from developing nations, remain unassessed and largely unmanaged. In those cases, the imperative to estimate stock status is usually less important than establishing some form of management even in the absence of formal stock assessments and harvest control rules (Mahon 1997). Ultimately, the resolution of stock status by an appropriately-selected DLM is still paramount, but the introduction of a formal harvest strategy is certainly not essential, at least initially. The immediate priority is to establish interim management controls identified as feasible and affordable within the social-economic and governance contexts and constraints impacting the fishery. Any required reduction in fishing effort, for example, may have to be achieved as a longer-term goal.

More broadly, context and consequence must be considered: the same reasons that resulted in the fishery being data-limited may also cause restrictions on assessment and management options. This is typically the case for small-scale coastal fisheries where data limitations go hand in hand with difficulties in enforcement and management more generally as a result of the fishery being quite complex (e.g., multispecies, multisector, spatially dispersed), which preclude certain forms of harvest controls (Parma et al. 2003; Garcia et al. 2008).

A common issue is that of migratory, shared and high seas stocks where there is a contrast in information quality from different regions. Practitioners can either agree to using the best available data, regardless of its place of origin, as being representative to inform an assessment, or "manage their own backyard" to the extent that this is possible, given the extent of site fidelity of fish and the available local data. The Australian Eastern Tuna and Billfish Fishery makes local management decisions informed by a hierarchical decision tree based on combinations of empirical indicators (Prince et al. 2011), which draws more broadly from the regional (South Pacific Commission) stock estimates.

<ins>Conclusion</ins>

Costs and associated resources for fisheries management are substantial. Management requires a consistent investment and commitment to research, monitoring, assessment and enforcement, and to the collection of data to inform these. Fisheries need to be managed in a demonstrably sustainable manner in the face of limited resources. Even if generic approaches are used, there is a minimum cost associated with stock status resolution for data-limited fisheries. Recognising that there are no cheap, simple, generic, solutions to evaluating stock status for data-limited fisheries does not preclude agencies and other fisheries stakeholders from implementing pragmatic fisheries management. This should involve commitments to cost-effective data collection programs, careful selection of DLMs based on available data, critical evaluation of their results and their associated uncertainties, and embedding DLMs within appropriate harvest strategies to formalise specific management actions.

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Table 1: Overview of data-limited assessment methods, from empirical (in which performance indicators are based on directly-measured properties) to model-based (where performance indicators are model outputs).

Input-based category	Data-limited assessment	References
Expert Judgement	Move directly to harvest control measures	Dowling et al. (2014)
	Discourse/expert judgement	Dowling et al. (2008a)
	Data exploration via plotting and descriptive statistics	Dowling et al. (2008a)
	Analysis of changes in the spatial distribution of fishing effort	Dowling et al. (2008a)
	Analysis of changes in the spatial distribution of catch	Dowling et al. (2008a)
	Analysis of changes in gear type or manner of deployment	Dowling et al. (2008a)
Empirical Reference Points	Size-based sequential trigger system	Dowling et al. (2008a)
	Sequential effort triggers	Dowling et al. (2008a)
	Sequential catch triggers	Dowling et al. (2008a)
Risk Analysis/Vulnerability	Comprehensive assessment of risk to ecosystems (CARE)	Battista et al. (2017); Fujita et al. (2014)
	Ecosystem threshold analysis	McClanahan et al. (2011)
	RAPFISH (Multi-dimensional scaling)	Pitcher and Preikshot (2001); Pitcher et al. (2013)
	Productivity and Susceptibility Analysis (PSA) to estimate risk of overfishing	Patrick et al. (2010)
	Ecological Risk Assessment for the Effects of Fishing (ERAEF)	Hobday et al. (2007, 2011a,b)
	Sustainability Assessment for Fishing Effects (SAFE)	Zhou et al. (2016a); Zhou et al. (2011); Zhou and Griffiths (2008, 2009)
Abundance Indicators	Analysis of changes in species-composition	Dowling et al. (2008a)
	Use of biomass surveys to inform management	Dowling et al. (2008a); Parma et al. (2003)
	Single-indicator analysis using standardized CPUE	Hinton and Maunder (2004); Maunder and Punt (2004)
	Linear regression to recent time series of CPUE	Haddon (2010); Maunder and Punt (2004); Dichmont and Brown (2010)
MPA	Analysis of ratio of density inside and outside marine protected areas (MPAs)	Babcock and MacCall (2011); McGilliard et al. (2011)
	Analysis of length/size-specific catch-rate indicators for fish sampled inside and outside of marine protected areas (MPAs), and per-recruit	Wilson et al. (2010)
Catch Only	Optimized catch-only method (OCOM)	Zhou et al. (2016b)
	Boosted Regression Tree (BRT) model for stock depletion using catch data	Zhou et al. (2017)
	Only Reliable Catch Series (ORCS)	Berkson et al. (2011); Free et al. (2017)
	Depletion-Corrected Average Catch (DCAC)	MacCall (2009)
	Depletion-Based Stock Reduction Analysis (DB-SRA)	Dick and MacCall (2011)
	Simple Stock Synthesis (SSS)	Cope (2013)
	Stochastic Stock Reduction Analysis (stochastic SRA)	Lombardi and Walters (2011); Walters et al. (2006)
	Catch-MSY/CMSY (MSY = maximum sustainable yield)	Froese et al. (2017); Martell and Froese (2013)
	Feasible stock trajectories	Bentley and Langley (2012)
Population Dynamics Model	Depletion analysis	Hilborn and Walters (1992)
	Production model	Fox (1970); Hilborn and Walters (1992); Haddon (2010); Schaefer (1954, 1957)
	Statistical catch-at-age (SCAA)	Hilborn and Walters (1992); Quinn and Deriso (1999)
	qR Method	McGarvey and Matthews (2001); McGarvey et al. (1997); McGarvey et al. (2005)
Size/Age-Based	Analysis of size relative to size at maturity	Basson and Dowling (2008)
	Analysis of changes in mean length/weight or length/weight percentiles	Dowling et al. (2014); Quinn and Deriso (1999)
	Analysis of sustainability indicators based on length-based reference points (LBRP)	Cope and Punt (2009)
	Catch curve analysis	Chapman and Robson (1960); Dunn et al. (2002); Gulland (1971); Smith et al. (2012)
	Length-based Spawning Potential Ratio (LB-SPR)	Hordyk et al. (2015a, b)
	Mortality estimates from length data in non-equilibrium situations	Gedamke and Hoenig (2006)
	Length-based Integrated Mixed Effects (LIME)	Rudd and Thorson (in press)
Multiple Indicators	Hierachical decision trees	Dowling et al. (2014); Prince et al. (2011)
	Traffic lights	Caddy (2004, 2009); Caddy et al. (2005); Halliday et al. (2001)
	Cumulative Sum (CUSUM) Control Charts	Mesnil and Petitgas (2009); Scandol (2003, 2005)
	Sequential trigger framework involving catch and/or effort, catch-per-unit-effort (CPUE), size, sex ratio etc.	Dowling et al. (2008a)

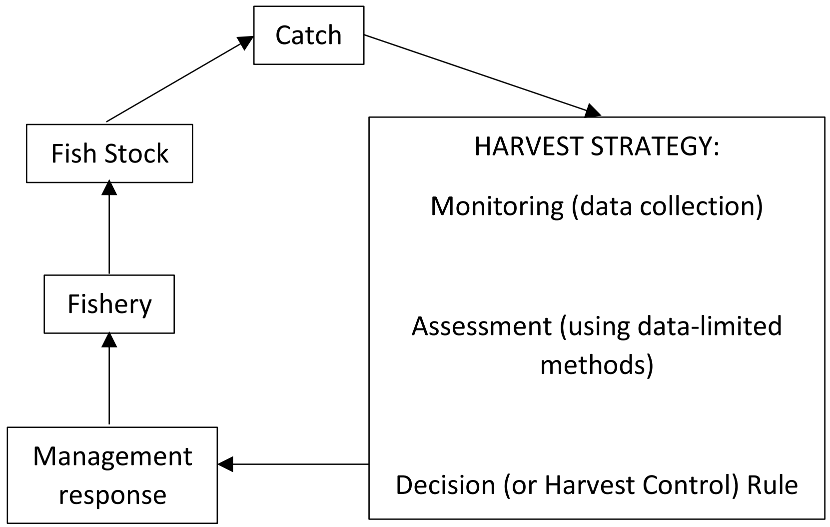
Table 2: Review of regional or global assessment applications, with examples of one-size fits-all approaches and the rationale or impetus for each. Note that the methods here summarised are not intended as examples of incorrect application.

Reference	Method	Rationale/what is estimated	Limitation
Costello et al. 2012	Multivariate regression to identify predictors of stock status from assessed fisheries and use these models to estimate status of unassessed fisheries	Estimates the status of collections (including the global status) of previously unassessed stocks	Per authors, this approach does not produce precise estimates for individual fisheries and therefore is not a substitute for formal assessment.
Costello et al. 2016	Global regression analysis merged with Catch-MSY used to estimate instrinsic populatiog growth rate (r), carrying capacity (K), maximum sustainable yield (MSY), and merged with a microlovel structural bioeconomic model based on global regresssion analysis	Global MSY and individual stock status based on 4713 fisheries in RAM (Dr. Ransom A. Myers) Legacy and FAO marine capture databases	Emphasis was on investigating alternative approaches to recovering depleted fisheries. Fisheries that failed to meet minimum criteria excluded
Froese et al. 2012	Comparison of maximum catch with MSY and of catch-based analysis with biomass-based analysis.	Evaluates whether maximum catch is correlated with MSY, and whether temporal trends in catch data are consistent with trends in biomass.	Limited to FAO (Food and Agriculture Organization of the United Nationa) catch database. Not aiming to resolve stock status for intent of formal management.
Rosenberg et al. 2017	Four catch-only methods were applied, and estimates from these were combined using a superensemble. The 4 catch-only methods included one empirical model (panel regression approach (PRM) developed by Costello et al. (2012)), and three mechanistic models (catch-MSY; catch-only model with sampling-importance resampling (COMSIR), and state-space catch-only model (SSCOM).	Quantitative estimates of exploitation status for 785 FAO fish stocks.	Estimates of stock status were global and within each FAO statistical region. Per authors, there are still many limitations to using this information for stock-specific or even regional advice. These include the high variability of the estimates, the need for longer time series of data, limited life history information for many stocks, and the difficulties of assigning prior distributions.
Branch et al. 2011	Analysed i) simulated random catch data with no trend; ii) stocks classified as collapsed on the basis of catch data to determine whether these stocks actually were collapsed; iii) stock assessments to compare stock status derived from catch data with status derived from biomass data.	How use of catch data affects assessment of fisheries stock status.	Limited to FAO catch database, and stock assessments in RAM Legacy database. Not aiming to resolve stock status for intent of formal management.
Thorson et al. 2012	This model uses logistic regression to extrapolate from assessment results to available landings, life history, and location data. The model classifies stocks into different prediction bins and estimates the probability of collapse in each using cross-validation.	Assesses whether globally available landings, life history, and location information are sufficiently informative to allow model-based predictions regarding stocks for which single-species assessments are not available. An extrapolation model uses stock assessment results to estimate parameters for a model that predicts the probability of collapse.	Estimates probability of collapse. Is a "global extrapolation model" which uses the opportunistic data that are available on a global scale for evaluating fishery questions.
Kleisner et al. 2013	Reviews stock status plots as means to provide a robust overview of fisheries and of the major trends besetting them	Considers challenges, improvements, and uses of stock status plots, and examines their expected performance under alternate scenarios	Uses global catch data; provides broad and indirect overview of stock status. Not intended to guide management of individual stocks. Acknowledges that catch statistics are not a silver bullet when it comes to evaluating stock status, but points out that they are the only means to obtain a global picture of stock status, when analysed with an understanding of the scenarios which may cause misinterpretations.

Table 3: A list of common assumptions, required inputs and assumed knowledge associated with data-limited assessments, with some examples of assessments to which these apply. Acronyms and abbreviations are as defined in Table 1.

Assumption	Example assessments
The approach assumes the population is currently in equilibrium (with constant recruitment)	Catch curves; LB-SPR
The approach requires that unexploited, or theoretical equilibrium, biomass (B0) is stationary (i.e. meaningful regardless of time)	Many
Selectivity needs to be at least able to be inferred	Most
Selectivity has not changed over time	Most
Asymptotic fishing selectivity	Catch curves; LB-SPR
There have been no major temporal changes in sampling patterns, fishing operational characteristics, management, markets or the environment	Most
Species is actively and consistently targeted	Many
Sampling is representative of the stock	Most
Sampling is representative of the spatial extent of the fleet(s)	Most
Required inputs	
Estimate of the ratio of fishing mortality at maximum sustainable yield (FMSY) relative to natural mortality (M) (FMSY/M)	DCAC; DB-SRA; SSS
Estimate of FMSY	Stochastic SRA;
Estimates of von Bertalanffy growth parameters	LBRP; Size-specific catch rate indicators for fish sampled inside and outside of MPAs, and per-recuit; LB-SPR; SSS; Stochastic SRA; Feasible stock trajectories; Mortality estimates from length data in nonequilibrium situations; SCAA; qR method; LIME
Estimate of steepness	SSS; Feasible stock trajectories; SCAA, qR method; LIME
Estimate of natural mortality	Size-specific catch rate indicators for fish sampled inside and outside of MPAs, and per-recuit; Catch curves; SAFE; DCAC; DB-SRA; SSS; Stochastic SRA; Feasible stock trajectories; Mortality estimates from length data in nonequilibrium situations; SCAA; qR method; LIME; OCOM
Estimate of length-fecundity relationship	SCAA
Estimate of size at maturity	Hierarchical decision trees; LBRP; DB-SRA; LB-SPR; SSS; Stochastic SRA; Feasible stock trajectories; SCAA; LIME
Estimate of life-history ratio M/k	LB-SPR
Estimate of length-weight relationship	SSS; Feasible stock trajectories; SCAA
Prior estimate for stock status (depletion)	RAPFISH; BRT model for stock-depletion using catch data; ORCS; DCAC; DB-SRA; SSS; Catch-MSY; Feasible stock trajectories
Assumed knowledge	
Some notion of spatial distribution	SAFE
The number of times mortality is thought to change, and initial guesses of the years during which mortality is thought to change	Mortality estimates from length data in nonequilibrium situations

Figure 1: The fisheries adaptive management cycle, underpinned by a harvest strategy


Catch
Fish Stock
Fishery
Management response
HARVEST STRATEGY:
Monitoring (data collection)
Assessment (using data-limited methods)
Decision (or Harvest Control) Rule