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The good practices of practicable alchemy in the stock assessment continuum: Fundamentals and principles of analytical methods to support science-based fisheries management under data and resource limitations

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ABSTRACT

It is the exceptionally rare case one can directly and with little uncertainty measure fish absolute abundance through many stock generations in all areas of a stock's range. Instead, we often seek "gold standard" stock assessments—models that use catch, abundance indices and biological compositions to produce precise and unbiased indicators of stock status for management use. Unfortunately, data and resource limitations affect our ability to collect all the desired information and apply methods with low uncertainty in the results. To confront this challenge of poorly informative data and low resource situations, a host of analytical approaches have been developed to engage the power of fisheries science to inform management decisions despite limitations. These methods are numerous and often challenging to understand and navigate, despite being simplified (though not simple) approaches. It is important to understand where these methods come from, how they can be used, and how to evaluate them. Often they are presented as alchemically providing golden outputs despite heavy assumptions and impure inputs. Here I aim to provide both scientific context of and guidance in organizing and applying so-called data and resource limited stock assessments. I offer a list of best practices by presenting fundamental principles of modelling and highlighting leading edge tools for organizing and conducting analyses under a variety of constraining conditions, offering a conceptualization of stock assessment expressing the interconnectedness of each method and how those can be largely unified under a common modeling framework. The concept of a stock assessment continuum is described, along with discrete examples in the form of a decision tree outlining the major modelling groups for a large variety of data availability scenarios. The basic approach to applied fisheries science and management is presented as interpreting uncertain model outputs (i.e, indicators) using reference points that can then be linked to management decisions via control rules that should express risk tolerance to meeting management objectives in light of uncertain outcomes. The role of simulation testing of management procedures is highlighted in order to evaluate robustness to uncertainty. While more and better data should be a focus of any management system, there is no excuse to wait for golden outputs. We have the tools and theory ready to help direct management of data and resource limited stocks now.

1. Introduction

The ability to assess the status of a fish population (i.e., a fish stock) is foundational to a science-based fisheries management process (Carvalho et al., 2021a) and one of the three pillars of a harvest strategy (the others being data collection and management measures; Dowling et al., 2015a; Dowling et al., 2023; Fig. 1A). The application of well-articulated harvest strategies connected to management objectives through control rules have been shown to improve fisheries management across a wide-range of fishery types as part of adaptable feedback systems (Fig. 1A; Dowling et al., 2016; Dowling et al., 2023; Melnychuk et al., 2021). Assessment methods figure so prominently because they hold the potential to use the available data (pillar 1) and produce meaningful indicators of stock status (pillar 2) that inform management measures and subsequent implementation benchmarks (pillar 3).

This desirable framework has several points of potential instability as weakness in any of these pillars can destabilize the entire management loop (Fig. 1B). One of the most common scenarios is the lack of data and resources that exert limitations on what analyses can be done to provide estimates of stock status. The term "data-limited" or "data-poor" stock assessment is widely used and relatable, though exceptionally broad in its definition and application (Chrysafi and Kaparinen, 2016; Cope et al.,

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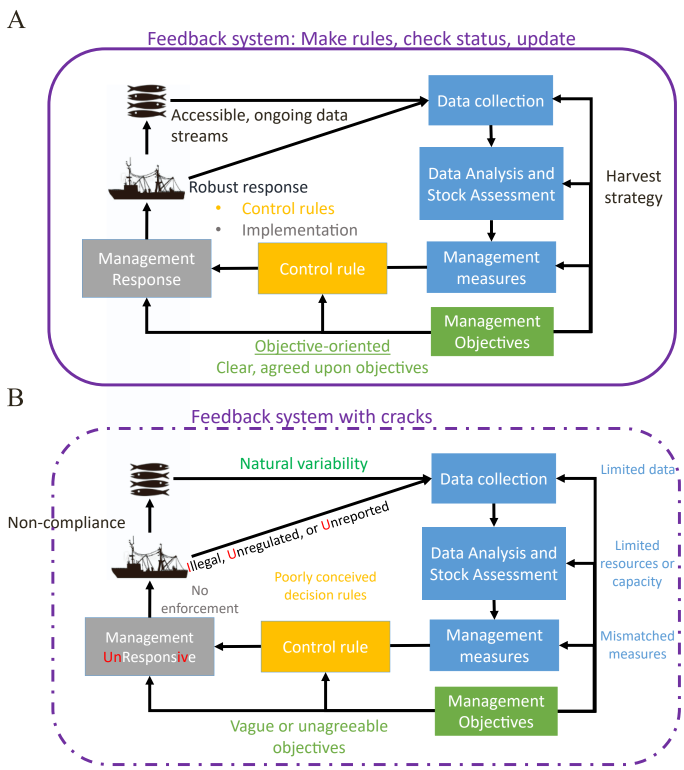

Fig. 1. A) The closed loop management system with clear objectives, adaptive feedback and fully realized components. Data collection, data analysis and stock assessment, and management measures collectively make up the harvest strategy. The stock assessment, management measures and control rules combine to form the management procedure. Management objectives define the targets of the harvest strategy and response components. B) The broken loop management system highlighting areas where and reasons why the system can break down.

2023). More accurately, we should speaking directly about the information content in data (i.e., its quality to contain a signal) rather than just the amount collected, as large amounts of data may contain no useable signal. But more pointedly, it has led to the common tact of either avoiding science-based management "until there is enough data" or attempting vast and rapid applications of "simple" approaches (e.g., model-free empirical methods, simplified model-based methods) to expedite the assessment of stocks without consideration of the specific fishery interaction (i.e., selectivity) and or key biological details of each stock. Additionally, simple measures may have been established and applied at some point, but then never revisited or revised because they provide the minimum requirement to meet policy mandates, yet have become critically outdated or unnecessarily static.

The "gold standard" for stock assessments has long been associated with multiple data sources integrated into a statistical model (e.g., statistical catch-at-age or length models) that combines a variety of data types (e.g., catches, indices of abundance, biological compositions) to produce one population signal, with the moniker "data-moderate" or even "data-limited" often reserved for production models, which is still a relatively data-intensive approach (Hilborn and Walters, 2013). In recognition of the global need for available methods under a variety of data constraints and resource scenarios (Cope et al., 2023), there has been an acceleration in development of "data-limited" methods over the past 15 years, tilting the balance to the side of doing something rather than nothing.

The search to provide "gold standard" outputs and advice from data-limited methods is akin to alchemy— the practice of using impure base metals and, through a process of refinement and purification, turning them into more desirable gold. Unfortunately, the application of data-limited methods can also claim the alchemical promise of providing unbiased and/or precise (e.g., "golden") measures of key stock assessment outputs such as catch limits or relative stock status with very poor (i.e., highly impure) or limited information. Simulation testing of the methods seem to initially back up such claims, but inevitably reveal performance deterioration upon further scrutiny (Chong et al., 2020; Free et al., 2020; Ovando et al., 2022; Pons et al., 2020).

The reality is we face enormous challenges managing natural marine resources under significant data and resource constraints that are unlikely to disappear, and yet there are options and tools to support science-based fisheries management under these conditions. We can do something better than nothing– we just need to understand how best to determine and apply those solutions. Here I offer best practice guidance on how to most appropriately apply a suite of stock assessment tools despite data and resource limitations (Table 1). These best practices are rooted in principles of life history theory, modeling protocols, uncertainty characterization, and risk analysis. While not a promise of pure gold, we can still produce practicable, valuable outputs to drive science-based decision-making.

2. Identifying good practices for stock assessments in data and resource limited (DRL) situations

2.1. Understanding modeling fundamental principles and context

We begin these best practices of alchemical modeling by outlining fundamental modeling principles that provide essential context for understanding analytical methods and outputs. The word "model" hereafter is used for any method used to produce metrics for interpretation to support fisheries management, not just those that use data and have a formal quantitative structure. The following principles are key to the critical eye needed to evaluate the application of any stock assessment approach, and are particularly handy when confronted with the many flavors of DRL methods.

2.1.1. Models are abstractions of reality

Let us start with the noted aphorism by G.E.P. Box that "all models are wrong, but some are useful". This aphorism is an amalgamation of several publications, the first being Box (1976) where he elevates the scientific method as a refiners tool for wrong models. The concept is that models are, by necessity and definition, simplifications of complex systems. This, he argues, supports the ideas of parsimony (i.e., do not overcomplicate your models) and "worrying selectively" (i.e., identifying the "importantly wrong" aspects of any model). He distilled these ideas into another succinct statement: "Remember that all models are wrong; the practical question is how wrong do they have to be to not be useful." (Box and Draper, 1987). Here he elevates the use of models upon the back of the scientific method (i.e., hypothesis testing), and emphasizes the need for additional experimentation and feedback analysis. In order to experiment, the user must have in mind objectives to optimize, which naturally leads to performance measures to indicate how well those objectives are being met. We will return to these concepts when we discuss sensitivity analysis (Section 2.2.5) and simulation testing (Section 2.2.7) as further good practices. The key concept to recognize is that analysis of stock condition and health should be treated as a science (i.e., fisheries science) and that management objectives should be articulated and understood at the very beginning of the stock assessment process. This leads into the next critical principle of model building and hypothesis testing: the tug of war between data and assumptions (Fig. 2).

2.1.2. Model building is a trade-off between data and assumptions

"Model specification" describes how a model is put together: which parameters and functional forms are used to simplify complex processes into abstract models (i.e., a population sub-model). Data can then be

Table 1
Good practices when conducting DRL stock assessments. The term "stock assessment" is used broadly to refer to any analysis that provides an indicator used to interpret population status and/or define a management metric.

1. Define your constraints in terms of data and resources. The details matter (Cope et al., 2023)!
2. Define management objectives and have them pre-agreed upon; note trade-offs (Dowling et al., 2023)
3. Understand inputs and assumptions to find the right-fit model(s) (Dowling et al., 2023). Beware of rapid and broad application of the same assessment method.
4. Understand and track all assumptions and use those to build multiple model specifications (hypotheses;Box and Draper, 1987;Chamberlin, 1965)
5. Characterizing uncertainty (Francis and Shotton, 1997) is paramount and should be in terms of bias (among model/hypothesis) and imprecision (within model)
   a. Data representativeness must be considered as it can be a major source of bias (Cope et al., 2023)
   b. Spend time understanding and tracking uncertainty in life history values being used
   c. Always know the assumed or estimated selectivity being used and ensure it makes sense before moving ahead (Cope and Punt, 2009; Sampson, 2014)
   d. Use Monte Carlo, likelihood or Bayesian methods to estimate within model uncertainty (Fournier and Archibald, 1982; Punt and Hilborn, 1997; Methot and Wetzel, 2013)
   e. Use sensitivity analysis and likelihood profiling to characterize among model uncertainty (Tagliarolo et al., 2021; Pantazi et al., 2020)
   f. Building ensemble models (i.e., combining common outputs among models) can be a complex process, but worth consideration when attempting to incorporate multiple model results (Jardim et al., 2021; Stewart and Hicks, 2018; Stewart and Martell, 2015)
   g. Bookending the variances across sensitivity runs is another option for estimating broad uncertainty with limited model applications
6. Stock assessments can be interpreted in three dimensions: Scale, Status, and Productivity.
   a. Can be used to determine what assessment method will yield what indicators and reference points
   b. Can be used to explain why results change over different modeling scenarios or previous assessments (Cope and Gertseva, 2020)
7. There are eight major assessment method groupings that can be broken into two indicator (i.e., model output) types: Status-only and Scale-based:
   a Risk assessments are best used to group priorities for assessment and management and target data collection (Patrick et al., 2009; Zhou et al., 2019)
   b Index-only (see Harford et al., 2021 for good practices). An "index" is any metric of management interest. This usually refers to a direct observations (e.g., effort) or analytically-derived metric (e.g., catch-per-unit-effort, species composition) that bypasses a formal population model (i.e., model-free empirical methods).
   c Length/age-based (Froese et al., 2018; Hordyk et al., 2015, 2016): often an entry point method; use compositional data over summarized statistics if possible; make sure to evaluate fit to the data and understand selectivity.
   d Mulitple indicators: A combination, whether sequential or simultaneous, of the indicators in (b) and (c). See Harford et al., 2022 for good practices in developing multiple indicators.
   e Catch estimators (Cope, 2013; Dick and MacCall, 2011; Froese et al., 2012; Ovando et al., 2022): use only to explore sustainable catch levels, not for stock status (which is an input). Beware the sensitivity to the assumption of stock status and productivity (Wetzel and Punt, 2011).
   f-h Integrated models: A combination of catch plus any indices of abundance or biological compositions (e.g., catch + length; production models). These can demonstrate a continuum of data availability and quality (e.g., catch and 1 year of length vs catch and all years having length and age compositions), and thus contain varying degrees of model output uncertainty.
8. Stock assessments methods can be viewed as being on a continuum (Cope, 2013;Methot and Wetzel, 2013;Rudd et al., 2021); building familiarity with a complex modeling framework and using it to do a range of methods, from simple and building toward complex, may be a good investment when resources are limited. It can also avoid the need to learn different frameworks once more or different data types are collected, but may need ongoing support to understand how to grow into complex modelling with more data.
   a. Use nested methods (based on different data applications) when building up to a "gold standard" assessment for better understanding (Rudd et al., 2021)
9. Use decision support tools to help identify and understand the assumptions of the most appropriate assessment method(s) for the specific situation (Dowling et al., 2016, 2023)
10. Link assessments to management procedures (a control rule based on the model indicator relative to the reference point) that operationalize assessment results.
    a. Control rules should allow for the expression of risk tolerance (Privitera-Johnson and Punt, 2020)
    b. Management objectives and control rules need to be pre-agreed upon (Dowling et al., 2023)
11. Simulation testing is a powerful tool to test assessment methods and management procedures (Punt et al., 2016)
    a. There is no one assessment approach or management procedure that works in all cases; testing is needed in each situation (Dowling et al., 2019).
    b. Performance metrics should be specified to express all management objectives (Punt et al., 2016)
    c. Management procedure evaluations (MPEs) take high analytical capacity to administer and interpret, so may be limited in accessibility (Carruthers et al., 2023)
    d. Reducing the data of "gold standard" models can also be used to test assessment methods and management procedures and should be considered complementary to simulation testing approaches (Cope et al., 2015; Rudd et al., 2021)
12. Capacity building is needed to meet stock assessment needs (Dowling et al., 2019;Dowling et al., 2023):
    a. Avoid the "fly in, fly out" engagements– it does not build capacity, only dependence
    b. Need to maintain relationships outside of trainings workshops
    c. Building a network of practitioners that can support each other is the ultimate goal

added to estimate those parameter values (i.e., an observation sub-model), and statistical frameworks can be applied to determine how well the data are incorporated into the model specification (i.e., statistical sub-models). Most of our "gold standard" stock assessments are integrated analyses (Fournier and Archibald, 1982; Maunder and Punt, 2013) that attempt to use flexible and complex model specification to balance the signals of multiple data types into a cohesive picture of some metric of the stock (e.g., the stock size or status). When we are blessed with extensive data sets, we are able to let the data dictate parameter values and model results and use model diagnostics to evaluate model fit to data (Maunder and Punt, 2013; Carvalho et al., 2021a). Doing this over time leads to formulating prior belief on the parameters based on old data or knowledge that are updated with new data (Punt and Hilborn, 1997). When there is less informative or even no data, we cannot estimate parameters, and instead need to pre-specify (i.e., "fix") parameter values based on other sources (see Section 2.2.1 for more information). This sets up the tug of war between data and assumptions (Fig. 2). In general, the weaker (i.e, poorer information content) the data, the stronger the assumptions need to be and vice versa. Assumptions thus need to be understood and tracked when using models as abstractions of reality. This becomes an especially good practice for DRL approaches that often rely more heavily on strong assumptions. The base assumptions of the DRL approach being used are largely defined by the initial specification. Model specification then becomes an important area of exploration, forming additional hypotheses to consider.

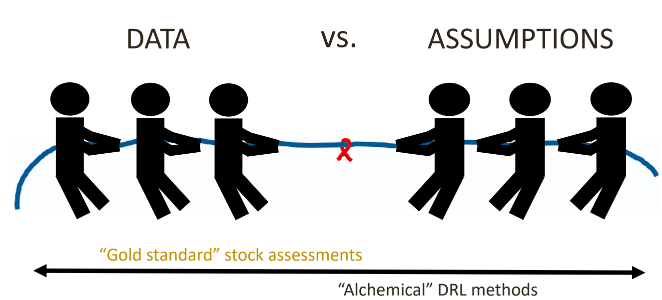

Fig. 2. The tug of war between data and assumptions. A model has to rely less on pre-specified parameters and strict model specification (i.e, stronger assumptions) when there is more informative data (i.e., more model realism vs more model abstraction). Less informative data leads to stronger assumptions and more alternative model specifications (i.e., hypotheses), and thus greater need to explore sensitivity of models to assumptions (i.e., characterizing uncertainty).

2.1.3. Each model is a testable hypothesis

It is good practice to view each of these modeling specifications–alternative choices of parameter estimation and assessment type– as different hypotheses for consideration and testing (Millar et al., 2015). These specifications are testable experimental treatments, and help confront the issues of parsimony, identifying the importantly wrong aspects of a model, and model usefulness highlighted by Box. It also will help us avoid "falling in love" with a model (Box, 1976) or "avoid[ing] parental affection for a favorite" model (Chamberlin, 1965), insisting there is gold where there is none. Understanding the assumptions and simplifications that make each model an abstraction of reality supports defining and testing multiple hypotheses, and leads to the next essential concept for good practices in any stock assessment: quantifying uncertainty.

2.1.4. Uncertainty must be characterized

The concept of uncertainty can be considered in several ways. Firstly, uncertainty acknowledges that some things are unknown. Secondly, those unknowns can cause a situation to be unpredictable. Lastly, unpredictable scenarios can lead to a heightened risk of bad outcomes. Francis and Shotton (1997) outlined four common sources of modelling uncertainty relevant to the data vs assumptions trade-off: a) "Observation (or measurement) uncertainty" describes uncertainty coming from the nature of the data and its collection; b) "process uncertainty" is natural process variability (e.g., recruitment variability or variance of size at age); c) "model uncertainty" is our previously identified model specification uncertainty (e.g., model abstraction); and d) "estimation uncertainty" is the previously noted uncertainty in parameter and subsequent model output values (Thorson et al., 2023). This can either be pre-specifying a parameter at a wrong value or poorly estimating its value. These sources of uncertainty collectively make up the total model uncertainty that can be expressed in two major ways: 1) bias, or a systemic misrepresentation of a true value (Magnusson and Hilborn, 2007; Yin and Sampson, 2004) and 2) imprecision, or how close repeated measures of a value are to each other (Yin and Sampson, 2004). Variance is one common expression of imprecision, while a central tendency value (e.g., mean or median) different from the true value would indicate bias. While we may be able to calculate imprecision, we usually do not know the true values (if we did, we would not need a model), thus the level of bias will need exploration and extra consideration.

Improved data collection can reduce measurement errors (i.e., data impurities) and improve our understanding of structural uncertainty of modeled natural processes and parameter estimation. But even under conditions of strong data collection, natural variability that may change over time is still present, thus uncertainty remains a modelling issue. With special consideration to data-limited situations, both measurement error and natural sources of uncertainty will largely be present, underscoring the essential practice of characterizing uncertainty (i.e., recognizing the impurities) however and wherever it may present itself (e.g., any place an assumption is made).

It is strongly recommended that as models are specified and parameters values identified, the analyst documents every place where uncertainty may occur (whether these prove important to model results (Box's "worrying selectivity") is explored in sensitivity analyses (see Section 2.2.5)). Each of these will then help structure how the overall uncertainty will be quantified. Consider this challenge— the job of the stock assessor is not to provide point estimates of desired stock metrics, but rather to characterize the uncertainty (e.g., the variance or probability statement) of desired stock metrics (see Section 2.2.6 to see what fisheries managers should do with that uncertainty). This is particularly important when data and model structural limitations increase the reliance on assumptions over data. Identifying sources and quantifying uncertainty allows decision makers the most complete view of stock understanding from which risk tolerance (i.e., for fisheries management, how willing are you to be wrong and not meet management objectives? What are the consequences of being wrong?) can be applied to management decisions. Section 2.2.5 offers specific good practices on how to identify and quantify uncertainty and evaluate robustness to uncertain model inputs. Next we consider the necessary qualities of useful data that goes beyond just quantity.

2.1.5. Data representativeness must be considered

Data, or lack thereof, largely drives what analyses can be done and the ultimate form of the stock assessment. Above we note measurement error as a key source of uncertainty. While this can simply be due to sample size issues (leading to imprecision), a more insidious factor, data representativeness, is an essential consideration to evaluate the information content of data (Cope et al., 2023). "Representative data" means data that match the level and characteristics at which the stock is being considered. If data are not representative of the unit stock of interest, then major biases can be introduced.

Some of the most common deficiencies causing unrepresentative data are:

a. Short time series. A restricted data time series may have limited contrast or a hard to interpret and possibly shifting baseline from which to determine stock status (Alexander et al., 2011; Ommer and Perry, 2022; Pauly, 1995; Simard et al., 2021).
b. Limited area coverage. It is dubious and potentially a source of major bias to assessment output to apply DRL methods to a larger stock area with data collected from a restricted range of a stock's distribution (Goethel et al., 2023; Cope and Punt, 2011; Field et al., 2006). Data should match the scale of the population in question.
c. Fleet or métier representation. Having a complete (or mostly complete) recording of removal (i.e., landings plus dead discards) sources is critical to estimate total fishing mortality, and knowing total mortality is often a key metric of stock status. If removal sources are missing or not being monitored, results of assessments could be biased or misleading.
d. Species identification. If species differ in life history or other significant ways, data should be resolved enough to identify species. If not, data of mixed life histories may not represent any given species or species complex and introduce biases.
e. Sex-specific information. Similar to species identification, if there are notable sex-specific differences in life history, data should be recorded by sex. If not, biases may be introduced when interpreting/applying the data.
f. Stock identification. Similar to species identification, there may be important intraspecific differences among populations within a species. Such considerations as genetic differentiation, life history differences (see more below), exploitation histories, habitat availability, and environmental conditions can all drive localized dynamics. Overlooking this finer resolution of population dynamics may miss localized stock depletion and lead to bias in the understanding of stock status (Cope and Punt, 2009, 2011).
g. Management changes. Changes in management could require changes in sampling for proper monitoring or alternative treatment of the data (e.g., selectivity changes). Ignoring these changes can bias model specification and derived outputs.

A good practice is to consider these and any other sources of unrepresentativeness when evaluating the data. Any areas where representativeness is a concern should be noted and considered a source of uncertainty for further exploration (see Section 2.2.5). It may ultimately be determined that the lack representativeness is so great the data are not currently useful (i.e, too impure with no amount of purification sufficient to fix it), and uncertainty exploration is not sufficient to deal with data deficiencies. No one should feel forced to use highly impure data. In these circumstances, best practices are to re-evaluate stock assessment options removing those highly impure data types, but also triggering data collection systems that can confront the deficiencies in current data streams (Cope et al., 2023; see Section 2.2.4.5 and the use of decision support tools to select stock assessment options suitable for viable data streams and identify data collection methods to improve data representativeness) to support and grow future stock assessment opportunities.

2.2. DRL modeling options and practices

Once (circa early 1900s) it was generally accepted that fish stocks were indeed both variable and exhaustible (Sims and Southward, 2006), the attempt to measure population condition and ongoing stock status took on a diversity of evolving forms. Collecting lengths proved some of the earliest and easiest direct measures of populations, revealing meaningful population structure (Schwach, 2014). Data on individual lengths and even ages led to both characterizing population life history (mortality, growth, reproduction) and estimation of abundance through tagging and population surveys. Once data and patterns started to emerge, models to describe both life history and population dynamic processes were developed. Foremost in these were life tables, growth curves, catch equations to separate mortality due to fishing from natural causes, and biomass dynamics models (Kingsland, 1995). Ricker (1940, 1944) and Beverton and Holt (1957) synthesized much of this knowledge and developed age and size structured population models that included dynamic processes such as recruitment. While the various biomass and biologically structured models continued to develop, the next great advance introduced the ability to integrate multiple data types using a statistical framework of likelihood components (Fournier and Archibald, 1982; Methot and Wetzel, 2013). With advances in computing, the accessibility of Bayesian approaches (Punt and Hilborn, 1997; Magnusson et al., 2013) and more complex modeling specifications emerged, particularly incorporating spatio-temporal dynamics and multi-species and ecosystem considerations (Cadrin et al., 2023; Fulton, 2010; Fulton et al., 2011; Goethel et al., 2023; Hollowed et al., 2011; Pauly et al., 2000; Plagányi et al., 2014; Spence et al., 2021).

Despite these major advances, most stocks affected by fishing do not have the data or resources to meet the requirements of advanced methods. Additionally, most data collection systems are fighting entropy, and must continue to collect information or suffer from lapsed time series and degraded stock status signals. This can occur due to base funding, changes in funding prioritization (Freire et al., 2021), or management measures that reduce chances to collect data (Wetzel et al., 2018), among other things. Additionally, there may be an abundance of data, but the lack of adequately trained analysts and/or the time needed to conduct complex or "gold standard" stock assessments for each stock may constrain model complexity (Cope et al., 2023). There are a multitude of reasons why any particular fishery may be DRL or enter a state of DRL. The ongoing need for options when data and resources are limited is therefore unlikely to go away. The following good practices highlight how to think about the interrelatedness of DRL stock assessment options as a system of models, to understand and interpret them, and to link them to control rules and test their effectiveness to meet management objectives. Let the alchemy begin!

2.2.1. Life history underpins the interpretation of all models

Life history refers to the population expression of how individuals grow, reproduce and die (Ebert, 1999; Roff, 2001; Stearns, 1992). It describes the essence of the stock and contextualizes its ability to withstand fishing (i.e., its vulnerability to being overfished). In population models, these are expressed in the age-structured concepts of individual growth (e.g., von Bertalanffy growth functions), length-weight relationships, size and/or age at maturity, fecundity at size and/or age, longevity, and mortality (both natural and fishing). In production models, they are captured in the synthetic term r, or intrinsic population growth (or expressed as λ, the finite rate of increase, in matrix models; Caswell, 2006), that combines growth, mortality and reproduction into one inclusive parameter describing population increase.

Life history is present in every approach used to analyze stock status (if it is not, then the model is too abstract!). A basic understanding of life history parameters is therefore essential to any stock assessment. Life history also collectively defines the productivity of the stock and, in conjunction with fishery selectivity, subsequent biological reference points (i.e., sustainable fishing rates or biomass that supports sustainable catch levels; Clark, 2002; Cordue, 2012; Mace, 1994; Williams and Shertzer, 2003; Zhou et al., 2012). Uncertainty in life history parameters often greatly influences stock assessment results (Hordyk et al., 2019; Punt et al., 2021). You cannot apply the data and interpret a stock assessment without establishing the life history. A good practice for every stock assessment is to have a strong understanding of either the life history parameters of the stock or the assumptions and uncertainty in those parameters. DRL assessments often rely heavily on assumed life history parameters, so this is typically a major source of uncertainty.

Life history theory reveals patterns in life history parameters across species, and can be a guide to defining or estimating life history values when direct measures are unavailable. Beverton and Holt (1959) prominently presented these then emerging life history relationships in three instructive ways. The first described life's "endpoints" (L_∞/T_{max}), and compared the maximum age T_{max} (e.g., average longevity in the population) to the average maximum size (L_∞ in the von Bertalanffy growth function), finding that within taxa, stocks that grew to larger sizes tended to also live longer. The next pattern described the "course of events" (M/k), wherein the individual growth (as measured by k in the von Bertalanffy growth function) was related to natural mortality (M). This relationship described the overall pace of life, with individuals in general growing slower also living longer. Thirdly, they described "reproductive drain" ($(L_{mat}/L_\infty)/T_{max}$), or the timing of reproduction to life's endpoints. Generally within taxa, it was found that individuals who mature later also grow slower, reach larger sizes and live to older ages, and this logically results in lower population natural mortality.

These relationships have been developed more formally throughout the years, and have taken on descriptors such as "r-K selection" (Adams, 1980) to more detailed "life history assemblage rules" (Beverton, 1992; Charnov et al., 2013; Charnov and Berrigan, 1991), and have been used to develop general management frameworks (King and McFarlane, 2003). They have also resulted in what were once considered "invariant" relationships (Charnov and Berrigan, 1990), but more appropriately deemed "dimensionless" ratios (Mangel, 2005; Nee et al., 2005). Some of the relationships have specifically allowed the development of more data-restricted stock assessment approaches (Dick and MacCall, 2011; Froese et al., 2018; Prince et al., 2015).

These relationships also provide means to estimate some harder to measure life history parameters from those parameters that are easier to measure (Binohlan and Froese, 2009; Dureuil and Froese, 2021; Froese, 2000; Froese and Binohlan, 2000). Natural mortality is one of the most influential life history parameters in any stock assessment model, yet one of the hardest to directly measure (Lee et al., 2011; Maunder et al., 2023). Leveraging life history patterns to estimate natural mortality from other life history parameters is common practice, and tools are accessible to get these and other life history values when none are directly available (Cope and Hamel, 2022; Hamel and Cope, 2022; Thorson, 2020; Thorson et al., 2017; Thorson et al., 2023). Further best practices on the treatment of natural mortality in stock assessments are found in Maunder et al., 2023.

It is therefore good practice to understand these general life history patterns, as they will become important building blocks for any assessment method used. Time should be invested in understanding the basic life history values (natural mortality, growth and reproduction) and how they relate. Getting specific life history values may be difficult in data-limited situations, or values may be from very old sources. Pulling parameters from databases or using life history relationships may be considerations, but caution should always be applied (Patrick et al., 2014; Thorson et al., 2013). One should apply reality checks that may rely on expert opinion or common sense to any life history values obtained. For instance, any L_∞ value that is greater than the observed maximum size should immediately be flagged as suspicious. If L_∞ is wrong, k will also be wrong, and any subsequent analyses using those values will suffer. Likewise, natural mortality values should be checked against reasonable longevity (i.e., maximum age) estimates if at all possible (Dureuil and Froese, 2021; though an already exploited stock may not have older individuals from which to obtain a reasonable estimate of longevity (Cope and Hamel, 2022)). And much more important than point estimates, one should apply the good practice of characterizing uncertainty to define distributions or bounds of uncertainty for each life history parameter. Uncertainty exploration in life history values should be a regular feature of any stock assessment, and even more so for those methods that assume pre-specified values rather than estimating them from data.

A specific good practice should be highlighted here for the input M/k that features in some methods (Froese et al., 2018; Hordyk et al., 2015, 2016; Prince et al., 2015; see Section 2.2.4). It has often been assumed this ratio has a value of 1.5, but it instead ranges widely, commonly between 0.5 and 2.5 (Beverton, 1992; Prince et al., 2015; Prince et al., 2023). This variability can cause great sensitivity to model results. Only use $M/k = 1.5$ as a point estimate or even median value with careful consideration, which presumes you do have some knowledge of what the M/k value should be. Otherwise, it is good practice to spend time building the M/k relationship from each individual parameter and exploring uncertainty (both bias and imprecision) in it.

Process variability is linked directly to life history parameters and productivity, often formulated as a stock-recruit relationship. There are many forms of a stock-recruit relationship, with the Beverton-Holt very commonly encountered or presumed across many fish stocks (Punt and Cope, 2019). One can also assume no relationship between stock and recruitment, thus a small stock may still be able to produce a large recruitment. Having a firm understanding of what is being assumed regarding the reproductive compensatory capacity of a stock will dictate its productivity and any subsequent reference points. The Beverton-Holt steepness parameter is a prominent measure of stock productivity, yet like natural mortality, difficult to directly measure and a source of major uncertainty in stock assessments (Mangel et al., 2013; Miller and Brooks, 2021; Thorson et al., 2019). A good practice regarding process variability is understanding the assumptions of the applied relationship and prioritizing exploration of its uncertainty.

Stressing the importance of obtaining life history values should include a focus on conducting and/or maintaining future basic biological research. If these life history values are being derived or borrowed from other sources, it is good practice to prioritize future resources toward collecting data to support estimation of these parameters. Age and growth and maturity studies are cost-effective ways to build a strong foundation for any future stock assessment.

2.2.2. A generalized concept of stock assessment

In the most generalized form of a stock assessment, data and life history parameters combine to go into an analysis (i.e., "stock assessment") to produce an indicator (i.e., an output of choice; Fig. 3) that provides a population metric used to interpret population status and/or define a management metric. The indicator can then combine with a reference point and control rule to dictate management measures that influence either input or output controls on the fishery(ies) (see Section 2.2.6). This general system includes the "gold standard" stock assessment when all data types are included, as well as the DRL approaches that depend on the combination of available data and parameters. Using this generalized approach highlights how interconnected stock assessment types are, and that they form more of a continuum of model abstractions rather than discrete approaches (Cope et al., 2023). Notice each of the arrows in the flowing diagram have a haze of uncertainty around them to underscore the good practice of identifying uncertainty at every level and connection of the diagram. This means all sources of uncertainty should be accumulated along the way.

Consider first the data inputs. The main data types in most single species stock assessments are removal histories, indices of abundance, and biological compositions, mainly length and/or age compositions. A variety of other data types can also be considered (e.g., weights, tagging data, environmental indices), but most common are the three types stated above. The data can also, and ideally, inform life history parameters (whether estimated external or internal to the model). As we remove data types, we will reveal different analytical methods to use instead of the "gold standard" stock assessment– these will make up the multitude of alchemical (i.e. assumption-laden) DRL approaches for consideration under different data scenarios.

The forms, sources and values of common model parameters also dictate what can be done, and Section 2.2.1 offers insights into good practices to obtain, interpret and characterize the uncertainty in life history parameters. An additional key functional form added here is the

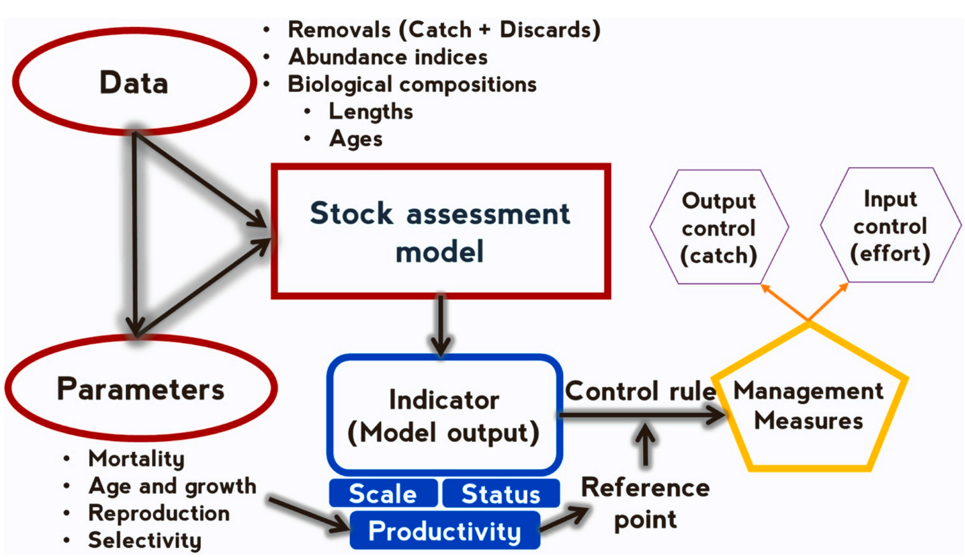

Fig. 3. The generalized form of a stock assessment model. It features data inputs and parameters that combine to work in a stock assessment model. The model produces an indicator (i.e., model output) that can be interpreted in one or all of the following ways: Stock scale, relative stock status, and/or stock productivity. These features can also describe the expectation of any DRL method applied, and thus the nature of the resultant indicator. For management purposes, an indicator can then be compared to a reference point and combined into a control rule, then translated through management measures to determine input or output management controls.

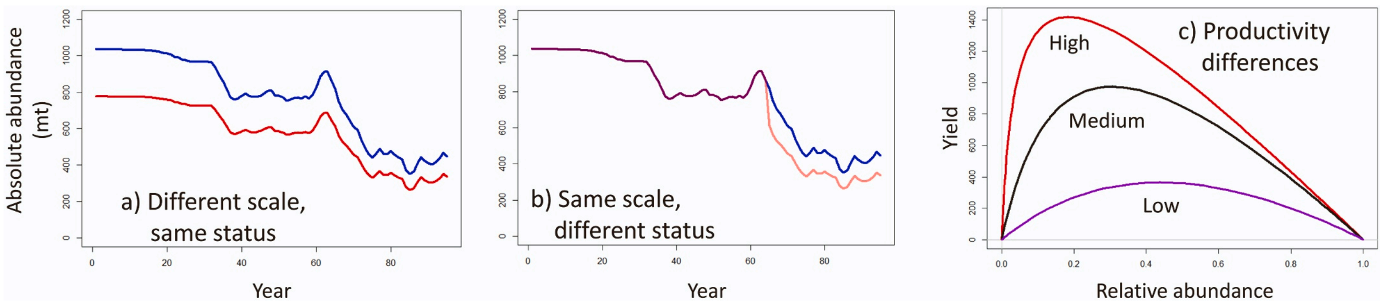

Fig. 4. Illustration of the concepts of scale, status and productivity used to interpret stock assessment output and DRL assessment options. In figures (a) and (b), productivity is held constant. In (c), the equilibrium curves show higher catch at higher productivity.

technical interaction of the stock with the fishery. This is most commonly referred to as population selectivity and is an expression of how the fishery removes individuals permanently from the population (Sampson, 2014). It is usually expressed as the vulnerability of fish to capture (e.g., What proportion of sizes can be caught by the gear?; Vasilakopoulos et al., 2020; Sampson, 2014). Just as stock assessments are ultimately uninterpretable without life history parameters, removal histories and/or fishing mortality are uninterpretable without understanding selectivity. A key good practice in regard to selectivity is to always recognize how it is being included in any method applied and the assumed functional form. It is very common to assume knife-edged asymptotic (S-shaped) selectivity, but this may be an important simplification that could bias stock assessment results. It is also important to distinguish retention (i.e., all individuals kept) from selectivity (i.e., all individuals caught). If only landed individuals are considered when defining selectivity, and the proportion of released individuals is significant and leads to high death rates, true total selectivity is hidden, and the subsequent interpretation of selectivity (impure from the assumption of total selectivity) is unrepresentative and will lead to bias. Therefore, it is best practice to define selectivity as the form applied to the proportion of the population that leads to individual death.

2.2.3. *Interpreting stock assessment models: scale, status and productivity*

Alchemists recognized the importance of three key elements (*Tria Prima*, or three primes) to their work: salt, sulfur, and mercury (Nicholson, 1808). These three elements represented the major dimensions of matter (body, mind and spirit, respectively) from which one could understand all other elements and materials. For our stock assessment purposes, an additional preparatory step before addressing analytical options is to understand three key dimensions of model output that allow for the interpretation of any stock assessment, as well as understanding what DRL methods will provide. These key three dimensions (the stock assessment *Tria Prima*) are 1) stock scale (i.e., the absolute abundance of a stock), 2) the relative stock status (e.g., the abundance relative to a reference value, such as unfished or target size), and 3) productivity, or the rate of new numbers or biomass into the population (Fig. 4; Cope and Gertseva, 2020). Understanding the scale of the stock allows for the specification of abundance-based management measures such as catch limits. Understanding the relative stock abundance helps determine stock status relative to management objectives. Finally, productivity (i.e., a reflection of life history) sets the ability for a population to recover from being reduced in size by fishing and other mortality events.

For a better understanding of these concepts, consider two stocks under the same fishing selectivity. When the relative stock status and productivity are held constant, more yield can be realized from the stock with a higher scale (Fig. 4a). For two stocks with the same productivity and start at the same scale, more yield is possible from the stock with a higher relative stock status given more individuals are available (Fig. 4b). And for two stocks with the same scale and same stock status, the one with more productivity will allow for higher yield because it produces more recruits to the population (Fig. 4c). Note that the maximum theoretical yield for the more productive stocks happens at lower relative stock sizes. This will be the basis from which reference points based on maximizing sustainable yield are devised (see Section 2.2.6).

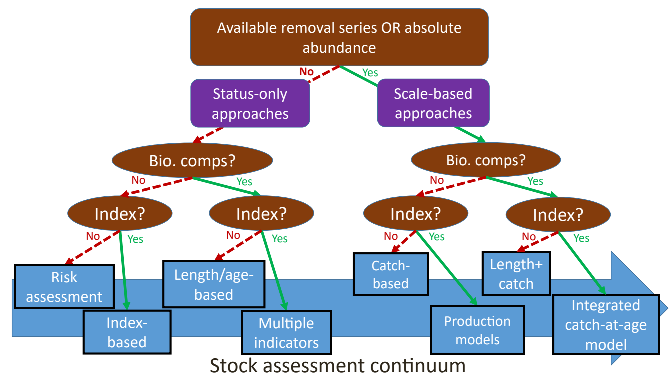

Fig. 5. Decision tree for DRL assessment options based on data availability. Two main groupings are approaches that inform status-only (left side) and those that can inform scale (right side). Status-only approaches can be used to manage fishing rates, while scale-based methods can be used to set catch limits.

The concepts of scale, status, and productivity can also be linked back to the data and parameters– the inputs into stock assessments (Fig. 3). The main data types that inform scale are removal histories and absolute indices of abundance. The main data types that inform status are relative indices of abundance and biological compositions. Productivity has already been shown to derive from life history parameters. Thus, one can already reverse engineer what indicators will be expected from what stock assessment methods given what inputs are used (see more in Section 2.2.4). In addition, we can anticipate that changes in any life history parameter while keeping other inputs constant can lead to changes in any of the dimensions of scale, status and productivity (see Section 2.2.5). These simple concepts of scale, status and productivity are collectively an exegesis of stock assessment, allowing one to both interpret changes in stock assessment results (either from model specification changes or from year to year applications) and anticipate what a DRL method can and cannot offer (given the available data) as an indicator.

2.2.4. *DRL options*

Stock assessments are conceptually a continuum of methods (Fig. 5). They comprise a set of data and parameters combined into a model that produce an indicator (i.e., output). As such, all of the above good practices are just as relevant to the "gold standard" stock assessments as it is to their more alchemical DRL relatives. The main difference comes back to the trade-off between data and assumptions (Fig. 2), with DRL approaches taking on stronger assumptions than assessments driven by more comprehensive data. The DRL approaches thus necessitate intensive focus on uncertainty characterization (Section 2.2.5). There are also differences in the data used and the type of indicators produced by each method. Fig. 5 presents a single-species stock assessment decision tree rooted on data availability that outlines the eight main stock assessment categories. These cover qualitative to semi-quantitative measures (risk analysis) and model-free (index-based) approaches all the way up to fully integrated "gold standard" stock assessment models (here noted as integrated catch-at-age models or ICA). This section outlines the traits of these broad groups rather than listing the numerous ways in which they can be and have been conducted (e.g., all the variations on the theme of length-based models). Notably, these methods largely recapitulate the development of analytical assessment methods as outlined in Section 2.2 (as DRL approaches were the first to be developed and applied), but now take new forms based on a history of fisheries science theory, creativity and advanced computing (the alchemist's furnace of fisheries science; Fig. 6).

2.2.4.1. Status indicators. The first step in the decision tree is to determine whether catch or absolute abundance indices are available (Fig. 5). If not (a common condition; Blasco et al., 2020), what remains are methods that will provide a measure of status (i.e., relative stock size, fishing rate, or general stock health), but not scale (i.e., absolute stock size or absolute catch). Each of these methods require expressions of productivity via life history parameters and some understanding of selectivity.

Risk assessment: Some of the simplest methods are risk assessments (Fletcher, 2015), and they require none of the big three data types (Fig. 5). That does not mean they require or contain no information. Inputs can simply be expert opinion used to make judgment on stock health to semi-quantitative methods that incorporate measures of stock productivity (i.e., life history) and susceptibility (i.e., interactions with fisheries) into indicators of overfishing (Beauchard et al., 2021; Hobday et al., 2011; Patrick et al., 2009; Stobutzki et al., 2001; Zhou et al., 2019, 2016; Zhou and Griffiths, 2008). As an example, the Productivity-Susceptibility Analysis (Cope et al., 2011; Patrick et al., 2010) uses a binned-scoring method to produce a value of stock productivity (based on life history parameters) and susceptibility (based on gear selectivity and current management actions) to interpret stock vulnerability to overfishing. Under certain assumptions it can also be used to indicate stock status (Cope et al., 2015). Scoring bins can also be modified to create more resolution in the scoring of vulnerability (Field et al. 2010), but it is recommended to also do the standard version for comparison across studies. Uncertainty should still be considered and explored in the attribute scoring or data quality of the attributes (Patrick et al., 2010). If data on gear efficiency is available (a more data-informed risk assessment), rough estimates of fishing mortality can be compared to a reference point to measure overfishing (Zhou et al., 2019).

These approaches are most useful when applied across many species to help prioritize where focused management attention, data collection, and analytical resources may be best allocated. Good practices for these methods are to use them as a strategic planning tool to highlight the most vulnerable species of a group, trigger management attention for them, then move toward data collection for more data-driven methods.

Index-based methods: : Index-based (or indicator) methods use an index or measure of something, not including a removal times series or biological data that are considered in other methods (Fig. 5). The term "index" can be broadly applied to mean any metric that indicates stock status. This usually refers to a direct observation or analytically-derived metric that bypasses a formal model (model-free empirical methods; Dowling et al., 2015a). The most data-rich version of this would be a complete census of the stock (in which case you do not need a model estimate of the biomass), but the DRL examples emphasized here are instead relative signals of abundance or fishing intensity such as catch-per-unit effort, species composition, changes in fishing effort or a variety of other direct measures that reflect a quantity of interest. Harford et al. (2022) review good practices for using indicator approaches, which includes choosing an interpretable indicator, defining the reference point that helps interpret the indicator, and quantifying its associated uncertainty. Indices require multiple years of sampling in order to conduct trend-based analyses (Legault et al., 2022), and short time series and/or potential shifting baselines make establishing a reference level for the indicator (e.g., a target level you want to achieve, minimum value you do not want to go below or maximum value you do not want to exceed) critical. But if an interpretable indicator and reference level can be devised, it may provide a way to bypass formal modeling (i.e., skip the "stock assessment model" box in Fig. 3 and go straight from data to the indicator) and focus more attention on indicator measurement and interpretation.

One model-based index-only approach is AMSY (Froese et al., 2020), which uses a Schaefer surplus-production model and its associated assumptions with life history included in the form of r and stock status in some year as inputs (we will see the use of what is typically model output (e.g., stock status) as method input again in the catch estimator approaches, Section 2.2.4.2). The approach has several filters used to reject certain model results and retain others. Ultimately it is doing what other index methods are doing– interpreting stock status based on the provided index– but with more structural assumptions based on a specific model type (i.e., the Schaefer model), and using stock status in some year as a way to establish a reference level. To emphasize again, good practices for index-based methods are to identify an interpretable index with a reference level, while noting all assumptions that will drive uncertainty analysis.

Length/age-based methods: While biological data can be included in the index-based approach above, they also present a special group of methods that have been given significant attention and development over time, and so are presented as a separate group here. "Length-based" or "length-only" methods generally require a sample of lengths from a fished population and life history information (Fig. 5), as lengths are often easier to obtain than ages in resource limited situations. The lengths can be summarized into a metric (e.g., mean length, length at optimal yield, mean length of largest 5%; Ault et al., 2008, 2019; Froese, 2004; Gedamke and Hoenig, 2006; Kell et al., 2022; Miethe et al., 2019) or used as frequencies by length bin (i.e., compositions). The length compositions can then be evaluated by individual time step (Froese

Fig. 6. Alchemist with furnace. Fresco, Padua c. 1380. Looks strikingly similar to a latter-day fisheries scientist at their computer.
Source: https://www.alchemywebsite.com/painting_laboratory_fresco.html.

et al., 2018; Hordyk et al., 2016; O'Farrell and Botsford, 2005) or as a time series in a population dynamic models (Rudd and Thorson, 2017; Thorson and Cope, 2015). Along with life history parameters (and especially asymptotic length), selectivity is key to interpreting any length-based metric (Cope and Punt, 2009). The resultant metric is some measure of relative stock status (e.g., relative fishing intensity, spawning potential or abundance), then interpreted using a reference level (e.g., SPR40%, FMSY). Length-based approaches are attractive DRL methods because lengths are often one of the easiest data to collect when there is no current data available, and even one year can be used to estimate stock status under strong assumptions.

Admittedly, lengths are used in these situations as proxies for ages that are less easy to obtain, but ages could also be used to interpret stock status as outlined above (e.g., per-recruit reference points (Chen, 1997); catch curve analyses (Nelson, 2019; Smith et al., 2012) or age-only stock status calculations (Thorson and Cope, 2015)), and are typically preferred over lengths, as they offer more resolution in estimating key life history parameters (e.g., natural mortality and growth) and recruitment.

Because of the nature of age and length relationships, lengths lose fidelity to age as they approach L_∞. Thus length-based methods are highly sensitive to the life history parameter being used (in particular, to L_∞) and bin sizes of the composition, so careful exploration of those sources of uncertainty is an essential good practice (Hordyk et al., 2016; Huynh et al., 2018). Recall that the life history parameters not only affect the model being used, but also define the reference levels to interpret the length-based indicator. A good practice to explore uncertainty in life history parameters is to use resampling to capture variability in life history values and quantify the uncertainty in stock status coming from lengths or ages. Length/age-based approaches are also subject to major assumptions about selectivity and recruitment that need serious consideration (Hommik et al., 2020; Hordyk et al., 2015, 2016; Rudd and Thorson, 2017). One important trait of length/age-based approaches using biological composition data is that data are fit, thus an essential practice is to evaluate the fit to the data (e.g., residual patterns, likelihood values).

Multi-indicator approaches: At this point, we have established the use of different types of individual indicators, with a special emphasis on either index-based or length/age-based indicators. The multi-indicator approach (Fig. 5) allows for the combining of any indicators into a hierarchical or sequential system of interpreting each indicator. The same good principles for devising individual indicators remain, along with the added need to consider how to assemble them (see Harford et al., 2021). "Traffic lights" (Caddy, 2004, 2002), sequential trigger systems (Dowling et al., 2008), or hierarchical decision trees (Dowling et al., 2015b; Harford et al., 2019; Prince et al., 2011; Wilson et al., 2010) are the most common approaches, and differ in the interpretation approach (e.g., course interpretations ("red", "yellow", or "green") vs more formalized and resolved decision rules) and structure (simultaneous vs. hierarchical consideration of indicators). This is a way to use multiple data types to make a synthetic decision on stock status, yet does not apply formal statistical integration of the data types. An important consideration of the multiple indicator approach is how one takes different output metrics of status (e.g., relative stock size vs relative fishing intensity) and assembles them. Good principles favor the most informative indicators higher up in an hierarchical approach, using indicators that give common metrics of status, careful selection of reference points for each indicator, and the incorporation of uncertainty into any decision rules (Harford et al., 2021). Another good practice is to allow this to be an interactive, adaptive process (Fig. 1), updatable as one learns more about the information content of each indicator (Harford et al., 2016).

2.2.4.2. Scale indicators. The previous section covered approaches that included two (i.e., indices of abundance and biological composition) of the big three data types used in stock assessments, and that resulted only in indicators of relative stock status. The inclusion of removal data or absolute abundance estimates now offers the opportunity to estimate scale (i.e., absolute abundance), as long as both life history values and estimates of status are available to scale the absolute biomass to the reported removals (Fig. 5). It is commonly observed that uncertainty in estimating scale in a "gold standard" stock assessment exceeds the uncertainty estimating stock status (Yin and Sampson, 2004). This is due to the fact that uncertainty in scale is determined not just by the sources of direct scale measurement (e.g, uncertainty in removal history and the selectivity applied in each fisheries; absolute abundance indices variance), but also from the uncertainty in stock productivity (i.e., the life history parameters that dictates relative fishing intensity status) and the relative stock size. Thus, scale-based indicators include all of the uncertainty sources inherent in stock status and productivity as well as the measure of scale. It therefore becomes crucial in scale-based indicators for the analyst to understand where the information on productivity and stock status is being produced— in addition to removal histories and/or absolute abundance measures— as they comprise major sources of uncertainty in interpreting scale (Magnusson and Hilborn, 2007).

Catch estimators: One of the most popular DRL method groups developed over the last few years are catch estimators (Fig. 5). Setting catches as a management metric is very prominent worldwide, yet takes high levels of information to do so properly (Macpherson et al., 2022). In order to meet catch setting mandates, a variety of catch estimators were devised (Berkson and Thorson, 2015). These methods use different types of analytical forms:

- model-less catch scalar approach (Berkson et al., 2011; Free et al., 2017),
- catch ratios (Froese and Kesner-Reyes, 2002; Anderson et al. 2012),
- simplified analytical equations (MacCall, 2009),
- one lump production models (Martell and Froese, 2013; Froese et al., 2023),
- two lumps delay-difference models (Dick and MacCall, 2011),
- many lumps age-structured models (Cope, 2013),

All but the scalar approaches essentially do the same thing– use a resampling approach to draw a value for the initial scale of the stock, productivity of the stock, and an estimate of stock status, and apply then them to the given catch history, filtering out what are considered unreasonable results (e.g., populations that go extinct), in order to define sustainable catch limits. It is extremely important to recognize that the alchemical magic in these approaches is the use of what is typically an output of a "gold standard" stock assessment— relative stock abundance (i.e., stock status)— as an input. Putting what is essentially believed to be gold into the reaction unsurprisingly yields gold back. The calculation is now based on one degree of freedom– if you know both the productivity (and therefore the reference points) and status of the stock (and the relationship to the reference points) and have total removals, then you can solve for the stock size and the sustainable catch, no matter how simple or complex the underlying population dynamics model becomes. Expectedly, these methods are highly sensitive to productivity and stock status inputs (Carruthers et al., 2014), and it is a common criticism of these method to question how one would know the stock status in order to use it as an input. Good practices for catch estimators includes explicitly stating assumptions for all inputs, and uncertainty explorations that do not just apply distributions to each parameter, but vary the central tendency of those inputs as well as exploring uncertainty in the removal time series. While using less informed priors (e.g., wide uniform priors) is one way to explore a broader range of possible input values, it typically only rules out one end of the distribution via filtering results. It is also a good practice to put efforts into historical catch reconstructions in order to explore uncertainty in the scale input (Blasco et al., 2020; Ralston et al., 2010). These reconstructions may be highly uncertain, but still offer a starting point for use in catch estimators and other models that use removal time series. The key is to include all sources of removals, as not including sources or years of significant removals can bias results (See Section 2.1.5 on data representativeness).

Subsequent use of the catch estimator models have often drifted away from the initial intent of providing estimates of sustainable catches, and instead are often applied to report relative stock abundance almost exclusively (Costello et al., 2012; Froese et al., 2017; Rosenberg, 2014). There remains significant questions as to the quality and information content of catch data alone to inform stock status (Anderson et al., 2012; Branch et al., 2011; Carruthers et al., 2012; Froese et al., 2012) while also using stock status as an input to return stock status as an output, even if the prior distribution is considered broad (Bouch et al., 2020; Chrysafi and Cope, 2019; Cope, 2013; Dick and MacCall, 2011; Free et al., 2020; Kell et al., 2022; Ovando et al., 2022; Cope et al., 2015). While some methods have attempted to use patterns in catch and stock status from global stock assessment databases to better define priors on stock status for use in catch estimator approaches (Froese et al., 2023; Kleisner et al. 2013; Zhou et al. 2017, 2018), the relationship remains unsurprisingly highly variable. While other methods have also attempted to provide additional means by which to develop informative stock status priors (Chrysafi et al. 2019; Chrysafi and Cope, 2019; Cope et al. 2015), the fact remains that most of the catch estimator methods ultimately rely on stock status as an input to define the stock status as an output, regardless as to how the prior is developed. A good practice is not to develop stock status priors quickly across many species (e.g., do not just accept default priors), but thoughtfully on a case-by-case basis (Froese et al., 2023). A better practice is to use catch estimators with their original intention of providing sustainable catch levels conditioned on stock status, not as estimators of stock status. Exceptions to this could be when stock status is specified in some past year (e.g., 20 years before the current year), and letting the remaining years of removals update current stock status from the specified year. But even under that example, it should be made clear that the resultant current stock status is still conditioned on an assumption of stock status, and thus not an independent measure of status. The circularity here is that it takes a stock assessment output (i.e., stock status) to get a stock assessment output (i.e., stock status). To quote Bernard of Trevisan, the Italian alchemist, on his deathbed, "To make gold, one must start with gold" (Jaffe, 1957). Let us not wait that long to recognize the best practice of being very careful with reporting stock status from catch estimator approaches.

Integrated stock assessments: Given life history traits define productivity, that relative stock status may be informed from indices of abundance and/or length composition data, and scale is derived from catches and selectivity, we can now begin to build on the combinations of the three main data types to produce more recognizable stock assessments (Fig. 5, inclusive of depletion (Babcock et al., 2015) and production (Winker et al., 2018), length + catch (Rudd et al., 2021) and integrated catch-at-age (Methot and Wetzel, 2013) models) that inform scale, status, and productivity from data, what we generally call integrative analysis using statistical frameworks. These types of data combinations and modeling good practices are covered in detail elsewhere (Dichmont et al., 2016; Hilborn and Walters, 2013; Quinn and Deriso, 1999; Rudd et al., 2021), including good practices throughout this special volume of Fisheries Research. Like the catch estimator methods, integrated models can also have different population dynamic resolutions, from the many forms of the 1-lump production models (Winker et al., 2018; Winker et al., 2020), to the two lump delay-difference models (Quinn and Deriso, 1999), less lumpier stage structured models (Caswell, 2006), to the many lumps of age or size-structured models (Punt, 2003; Methot and Wetzel, 2013; White et al., 2016). What carat gold they yield will depend on the ongoing impurities in the data and parameter inputs (Kell et al., 2021).

Statistically fitting to different data types and combining them into a single signal (Punt, 2017; Thorson et al., 2023) is a problem akin to the multi-indicator approach resolving how to treat multiple indicators, though the diagnostics are more sophisticated in statistically-integrated models (Carvalho et al., 2021a, 2017). The integration of different data combinations and underlying population models will also offer different ways to characterize uncertainty. The general good practice is to track all assumptions being made for a given model (especially selectivity; Winker et al., 2020), understand the sources and uncertainties that inform scale, status (some integrated models still use stock status priors; Cope et al., 2015; Wetzel and Punt, 2011; Winker et al., 2018) and productivity, diagnose model fits, and spend time characterizing uncertainty (Section 2.2.5).

2.2.4.3. Using complex frameworks to do simpler methods. Fig. 5 outlines a network of interconnected stock assessment methods by data type. I have noted that stock assessment methods are part of a continuum that can be interpreted as a trade-off between data and assumptions (Section 2.1.2). From that point one can conceive of a complex and flexible stock assessment framework that consists of all pre-specified parameters and no data. One can then start to introduce data of different types and quality while starting to better inform or even estimate parameters and provide a loosening of structural assumptions (e.g., estimating selectivity or recruitment). This evolves towards a model (still an abstraction of reality to some degree) driven mostly by a long time series of representative data with good sampling, contrast, and signal providing direct estimation of parameters and derived model outputs (i.e., indicators) and their uncertainty. On this continuum, we find most of the eight model groups in Fig. 5.

While each one of the eight nodes has numerous methods associated with them, seven of the eight nodes are theoretically possible within the nested framework of integrated models. As an example, the surplus production modeling framework has been used for index-only (Froese et al., 2020), length-based (Froese et al., 2018), catch estimator (Froese et al., 2017), and surplus production approaches (Winker et al., 2018). The Stock Synthesis framework, a statistically-integrated catch-at-age model (Methot and Wetzel, 2013), produces, in addition to the fully integrated age-structured model, catch and length models (Rudd et al., 2021), age-structured production models (Carvalho et al., 2017; Maunder and Piner, 2014; Minte-Vera et al., 2021), catch estimators (Cope, 2013; Punt and Cope, 2019), and length-only models (with the indicator and multi-indicator approach in development). This makes the inclusion of new data and data types convenient, and avoids the need to have to move to a new modeling platform once new data types are obtained, thus reducing the need to learn different inputting formats and modeling operations, and instead focus on the modeling itself. Using a complex modeling structure such as an age-structured model is also beneficial in it forces the user to confront their assumptions rather than having them hidden or unappreciated in simpler modeling formulations. While entry into a more complex system may seem daunting, take more time to set up than other simpler modelling approaches, and need ongoing support as more data leads to more complex modelling, the investment and advantage of becoming familiar with an inclusive modelling framework provides a continuous system to work in future data sources; and the additional time it takes to set up a complex modelling framework illuminates the explicit interaction of parameters and uncertainties with more transparent assumptions.

The Stock Assessment Continuum tool (formerly the SS-DL tool; https://github.com/shcaba/SS-DL-tool) is an application that allows available data to determine the proper configuration for Stock Synthesis into the most suitable model type. It then leverages the advanced diagnostics, visualization tools, and modeling techniques (e.g., likelihood profiling, retrospective analysis) in Stock Synthesis for model investigation and interpretation (Carvalho et al., 2021b; Taylor et al., 2021), while also making a convenient way to move from simple to more complex models with the addition of more and different data. This approach is technically achievable in other age-structured modeling frameworks, and is a recommended feature in the development of future flexible modeling frameworks (Punt et al., 2020). A good practice would be to consider using a more complex framework that can be reduced to match the available data (i.e., finding the right-sized model for the data), while checking those results against non-continuum methods (i.e., methods built specifically for one type of application) to gain further understanding of the assumptions and results. This avoids forcing data to conform to a specific model specification, and instead leverages the content of all available information.

The ability to move back and forth between different data usages is convenient beyond just making more complex models. It also provides a way to diagnose more complex models for misspecification (Carvalho et al., 2017; Kell et al., 2021; Maunder and Piner, 2014). It is therefore a good practice to use DRL formulations to break down complex models in order to understand data influence and possible model misspecification.

2.2.4.4. Using decision support systems to select stock assessment options. DLR methods are numerous and the options in any given situation may be confusing, as one needs to follow the inputs needed, the resources available (Cope et al., 2023), and track the assumptions inherent in each method. While using a common modeling framework can reduce this complexity (see Section 2.2.4.4), there is room for guidance for most practitioners on what methods could be considered. A good practice is to use decision support tools to determine a method or methods appropriate for a given situation. This can help avoid using assessment methods not appropriate for the available data or using only what is familiar or convenient to the practitioner— as there are no generic solutions to DRL stock assessment (or management; Dowling et al., 2019)— and instead reveal options that may be better suited for specific situations.

One example of a decision support tool that helps develop harvest strategies is FishPath (https://www.fishpath.org; Dowling et al., 2016; Dowling et al., 2023). In addition to data collection and management modules, FishPath contains a stock assessment module meant to match stock assessment options against prevailing conditions. The matchmaking is done via a questionnaire that asks questions regarding life history, data availability and quality, operational characteristics of the fishery(ies), and governance. Matches are expressed based on data criteria of each method, the quality of the criteria matches, and the assumptions for each assessment option based on inherent method structure (static caveats) and questionnaire answers (question-based caveats). This approach also highlights the important distinction between being technically able to do a method and deciding to do it when weighed against data quality, assumptions and resource constraints. The tool transparently lays out each option, and guides the user through the process of identifying a short list of what the user deems the most viable options. This process can also be undertaken with any number of stakeholders or rightsholders in order to raise transparency and encourage dialogue in the process.

Given the complex nature of many DRL situations, it is good practice to use such decision support tools to justify and document the best way forward in order to find the right-fit model for the situation. These tools can also be used strategically to identify what is needed to improve data and advance analysis to more data-driven models (Cope et al., 2023; Dowling et al., 2023).

2.2.5. Methods for quantifying uncertainty

One recurring good practice across all stock assessment methods (regardless of data availability and content quality) is the characterization of uncertainty in the assessment indicator(s). There are several common ways this can be approached for DRL methods, but it is helpful to first understand that model uncertainty is composed of within and among model specifications. Within model specification uncertainty describes the resultant uncertainty from using specified functional forms with either pre-specified or estimated parameters, as well as the uncertainty in the population signals from the data. Estimated parameters have pre-specified distributions that capture the prior belief in potential parameter values. In DRL methods that do not have or have limited data to estimate parameters, Monte Carlo resampling is commonly used to generate many draws of model parameter inputs and subsequent model results that are combined (e.g., taking the median across all model runs) in order to characterize uncertainty in indicators and/or management metrics (Cope, 2013). If models are fit to data to estimate parameters, maximum likelihood-based (MacCall, 2013; Methot and Wetzel, 2013) or Bayesian (Punt and Hilborn, 1997) methods can be used to estimate within model indicator uncertainty. These are estimates of indicator imprecision specific to the current model specification.

Within model uncertainty does not include all sources of bias from a single model's structural and parameter uncertainty. Given most DRL methods are heavily dependent on assumptions and uncertain parameter values, it is important to address bias by exploring changes in model specifications (i.e., alternative hypotheses). Sensitivity analysis is an approach for re-running models by changing any aspect of the model specification (e.g., different pre-specified values, input distributions, functional forms and/or data treatments) or model itself (e.g., using a different type of length-based model or underlying population dynamics formulation) and quantifying how much model indicators change (Cope and Gertseva, 2020). Sensitivity analysis can be a direct expression of setting up multiple model hypotheses (e.g., different life history assumptions (Pantazi et al., 2020), exploring data representativeness) and is the most direct way to get at bias uncertainty, while also including the imprecision of each model specification explored. It can demonstrate model robustness to certain changes (i.e., alternative hypotheses do not result in significantly different model outputs) and indicate where the model is most sensitive to structural or input uncertainty. Sensitivity analysis is a good practice for any stock assessment, and should be a routine part of reporting model outcomes.

For models that need to pre-specify some parameters, likelihood profiles (Tagliarolo et al., 2021) are another type of sensitivity analysis that looks across pre-specified values of one or more parameters to see how model fits (i.e., likelihood values) change. This highlights both the sensitivity of the model fit and indicator values to parameter changes. Likelihood profiling can therefore provide support for multiple realizations of models that contain similar model support (i.e., statistically similar total likelihood values), but may result in different indicator values.

If one is to move beyond the use of a single reference model with exploratory sensitivity modeling, ensemble modeling is one way to combine the outputs of multiple models (Jardim et al., 2021; Stewart and Hicks, 2018; Stewart and Martell, 2015). The combination of multiple model hypotheses (whether model specifications or across model types) into a composite model requires the assigning of weights to each hypothesis. While the use of model inference is common (Dormann et al., 2018; Millar et al., 2015), there is no single way to do this (Rudd et al., 2019), and DRL models often lack data to have informed model fits, or the change in data treatment renders different models incomparable. Expert opinion therefore becomes an important consideration on how to combine models (Millar et al., 2015). The idea of ensemble models is alluring, though the time and technical skill needed to cover the extent of model specification uncertainty is not trivial, as is the potential complication in communicating the results of multiple models. Jardim et al. (2021) give a useful overview of these and other aspects when considering how to make ensemble models practicable.

When it comes to good practice for characterizing uncertainty in DRL models, it is essential to explore within model uncertainty estimation along with exploring multiple model specifications via sensitivity analyses. How to then use and communicate all of those results (e.g., bookended variances from alternative models around a reference model vs ensemble models) will require further consideration. Incorporating uncertainty into the reporting and interpretation of stock status to inform management decisions is the focus of the next section on control rules and risk tolerance.

2.2.6. Building control rules for model outputs to meet objectives

To this point we have focused on obtaining an indicator of stock status from data and parameters using a "stock assessment" method (Fig. 3). Obtaining that indicator is a big step, but it is not the final one for fisheries management. One needs to now interpret the indicator and decide what to do with that interpretation. This is the realm of management objectives, reference points, control rules, and ultimately management measures (Fig. 1; Dowling et al., 2015b).

The combination of an indicator compared to a reference point linked to a control rule is a management procedure (De Oliveira and Butterworth, 2004; Fischer et al., 2022; Geromont and Butterworth, 2015; Punt and Donovan, 2007). The indicator is the product of the stock assessment method, the reference point is typically reflective of the life history and any other considerations (e.g., socio-economic, ecosystem-based) that reflect the management objectives of the fishery, and the control rule operationalizes stock assessment outputs relative to the reference points, and reflects the intent to meet management objectives with respect to uncertainty and risk tolerance in the system (Fig. 3). These components combine to reflect a management action ultimately manifested through management measures (Fig. 3).

A generic equation to operationalize indicators (Jardim et al., 2015) can be expressed as.

$$MM_{y+x} = MM_y{}^*\Omega$$

where *MM* is a management metric (e.g., catch, effort, fishing intensity, number of licenses, etc.), *y* is a given year, *x* is a number of time steps after the reference year (e.g., ≥ 1), and *Ω* is a modifier. The modifier is the control rule (CR), and is the action dependent on the indicator (I) relative to the reference point (RP). Thus the control rule is a function of the I-RP relationship: *f*(I,RP) = CR. These can be very simple ($MM_{y+x} = MM_y{}^*$I/RP; Jardim et al., 2015) or more complex to include uncertainty, different response surfaces or capture more features of the system that managers should consider (Geromont and Butterworth, 2015; A. R. Hordyk et al., 2015; Jardim et al., 2015). They can also be used with multiple indicators/reference points (Harford et al., 2021). Good practices for all practitioners doing any stock assessment method is to 1) identify your indicator(s), 2) understand management objects and identify your reference point(s), and 3) use control rules that include considerations of uncertainty (Dowling et al., 2015a). This can sometimes be tricky in DRL methods, but is essential to comprehend and explain how each component connects (or which are missing). Removing any of the components short circuits the interpretability and practicability of assessment outputs and is not good practice.

Stock assessment analysts deliver the science to apply to control rules, and that science should be rooted strongly in determining uncertainty (Section 2.1.4) to support managers in risk-based decision-making (Fischer et al., 2023; Privitera-Johnson and Punt, 2020). Risk tolerance is the expression of the willingness to meet or not meet management objectives, and in fisheries has generally weighted toward avoiding outcomes (risk aversion) that may lower population status below target levels (i.e., the precautionary approach; Caddy, 1999; Cadrin and Pastoors, 2008). Risk tolerance in control rules is often expressed via buffers on management metrics based on uncertainty in indicators that protect against violation of target and/or reference points (Privitera-Johnson and Punt, 2020; Ralston et al., 2011; Shertzer et al., 2008; Wetzel and Hamel, 2023). It is therefore expected that indicators derived from DRL methods will have higher uncertainty than more data-informed applications, and thus have higher risk aversion and subsequent buffers away from target values (Privitera-Johnson and Punt, 2020). A good practice in developing risk tolerance in a control rule system is to ensure these rules are pre-agreed and understood by managers, stakeholders, and rightsholders (Dowling et al., 2008, 2016, 2019, 2023; Miller et al., 2019; Smith, 1994). Without agreement on design and implementation, the system becomes unsteady, may change over time without heed to management objectives, and lose tractability to risk tolerance.

One difficult attribute of many DRL situations is the stock may already be in a non-desirable condition given no prior assessment and low priority in data collection. Communicating bad news can be a common occurrence for DRL stock assessments, which can also create the perception that DRL methods are biased towards reporting low stock status. This is another reason why it is important to separate out expectations based on initial conditions (e.g., a long time series of fishing with no management attention) from the method output (indicator) from the reference point of the indicator from the control rule that incorporates the elevated risk of higher uncertainty with strong assumptions/lower data availability. It also emphasizes why it may be an expected practice to have higher risk aversion when DRL stock assessments are applied for the first time.

2.2.7. Simulation testing DRL methods via management procedures

The theoretical framework for control rules was outlined in the previous section, but understanding how they perform relies on further exploration. One main attribute of a well-designed control rule is that it may rescue a highly uncertain (whether bias or imprecise) or assumption laden DRL indicator (Fischer et al., 2021). In order to understand the performance of a control rule using a given indicator and reference point, simulation testing is commonly used (Peck, 2004; Winsberg, 2008). Simulation testing is a way to experiment on complex systems by setting up an "operating model" (OM) or relatively complex representation of the system in order to test the performance of something on that system (Punt et al., 2016). In this case that something can be DRL methods or management procedures (Carruthers et al., 2016; Kell et al., 2007). The experimenter can now control the specification of the operating model and challenge the DRL methods and management procedures under a variety of scenarios. It is akin to sensitivity analysis (Section 2.2.5) in changing OM specifications to create new scenarios, and both bias and imprecision can be explored (Punt, 2017).

In order to understand control rule performance, performance metrics are chosen that reflect management objectives (e.g., fishing intensity, relative stock size, or yield relative to reference points). The idea is that if one knows the real answer (from the OM) and applies a DRL method or management procedure, then compares the DRL outputs to the OM outputs for the identified performance metric, one can quantify performance. And if this is done many times using process variability and under different model specifications and even projected over a number of years, one can ultimately describe what conditions (if any) these management procedures hold up and meet management objectives despite the limitations of the data, inputs and method used.

Simulation testing has become standard practice to demonstrate the utility of a DRL method (Anderson et al., 2017; Dick and MacCall, 2011; Free et al., 2020; Froese et al., 2017, 2018, Hordyk et al., 2015, 2016; Ovando et al., 2022; Rosenberg, 2014), and is generally considered a good practice tool. Management procedure (or strategy) evaluation (MPE or MSE) is becoming increasingly applied to explore how DRL methods interact with control rules as management procedures (Carruthers et al., 2016, 2014; Punt et al., 2016 for general good practices on MSE). Accessibility to these advanced experimental methods has increased with tools such as the DLMtoolkit (Carruthers and Hordyk, 2018), MERA (https://www.merafish.org/), and FLR (Kell et al., 2007) that allows any user open source access to this arena of research and apply it to their own specific situations. One may envision that instead of using an individual stock assessment method to get tactical advice, one instead can specify a suite of DRL management procedures (or have a readymade set of them) and via MPE see which meet management objectives the best (Anderson et al., 2017; DFO, 2021; Huynh et al., 2020; Carruthers et al., 2023).

While the benefits of simulation testing are demonstrable, significant challenges remain in their everyday, tactical application. As there is no one DRL method or management procedure that fits all situations (Dowling et al., 2019), there remains the need to run simulations to test

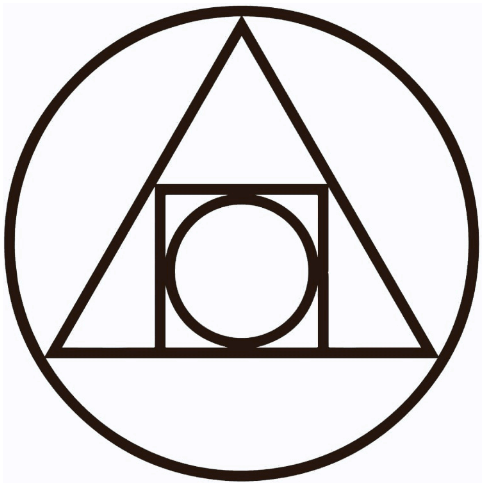

Fig. 7. The alchemist symbol of squaring the circle, also known as the philosophers' stone. The philosophers' stone was a sought after but never found substance that would turn base metals into gold. For stock assessment alchemy, it serves as a warning that DRL methods are full of assumptions, there is no one method right for all situations, and rapid application of stock assessments under information constraints may not lead to golden results. It is also a reminder that much has been learned about how to provide science-based guidance from the application of a variety of DRL analytical methods.

candidate management procedures for any given situation. This takes high level technical capacity (which is part of the resource limitation issue in DRL). It is well known that performance of methods varies across life history types (Wetzel and Punt, 2015; Wiedenmann et al., 2013), so life history parameters, and the associated errors in their estimation, will continue to be an important consideration. This raises the issue of how best to specify operating models and the higher level model specification needed to explore a variety of OMs in addition to the bias and imprecision within any given OM specification. This is typically beyond the capacity and time constraints of even well-trained assessment analysts. Even assuming a high level of capacity to perform MPEs, presenting and digesting the voluminous results across many performance metrics and scenarios is a real challenge for those receiving results. It can be difficult to communicate results of a single-species stock assessment with multiple explorations of uncertainty; summarizing MPEs significantly increases that challenge.

A simpler, alternative way to look at DRL method and management procedure performance leverages the nested modeling framework, uses "gold standard" stock assessment output as the operating model "truth", then peels away layers of data to compare indicators and management metrics (Cope et al., 2015; Sagarese et al., 2015; Sagarese et al., 2019). This is the reverse tactic of building up to more complex models, and allows scenarios of data quality and model specification issues that may be hard to replicate in simulated data. It essentially asks the question "how wrong would we have been if we had not used or had all of the data?" and thus allows a reverse engineering of measuring DRL method and/or management procedure performance. Rudd et al. (2021) used both simulation testing and the data reduction approach to test a data-moderate catch and length method in Stock Synthesis. Both approaches contributed important and unique understanding of the DRL method being tested. It is good practice to consider using the data reduction approach when exploring the performance of DRL methods and management procedures, as well as using this method to build up to "gold standard" assessments to observe the influence of each data set and model assumption (Carvalho et al., 2021b; Maunder and Piner, 2017; Minte-Vera et al., 2021).

3. Conclusions and general recommendations

3.1. Squaring the circle

A longstanding challenge in the discipline of geometry has been to create a square the same area as a perfect circle using only a compass and straightedge. This challenge is called "squaring the circle", and it was ultimately deemed an impossible task. It also became a key part of the symbol for alchemy (another impossible task), but also represents the ability to see in four directions at once (up, down, in and out) — vision complete and unrestrained (Fig. 7).

The alchemical search for DRL methods that can reveal precise and unbiased stock status and other sustainability measures with little to no data has met a similar fate as squaring the circle. But in trying all of these different "compasses and straightedges", we have learned many things and seen in many directions (Table 1). The capacity to apply abstractions usefully by identifying and respecting the amount of uncertainty inherent in the task is a major step forward toward providing science-based management decisions under a variety of constraints. Moving away from point estimation and into probabilistic space allows management objectives to be evaluated against risk tolerance. Recognizing that stronger assumptions and less data increases uncertainty helps frame our task ahead. We value representative data and should prioritize that quality. We understand that life history is a fundamental aspect of a stock that needs to be understood before we can assess the stock. This elemental truth argues for a renewed value placed on the funding and dissemination of basic biological studies, not just borrowing values (Patrick et al., 2014; Punt et al., 2011; Thorson et al., 2013).

We can observe that assessing stock status can be placed within a generalized framework that allows for model building forward and backward, and that there is a lot to learn from doing both. We can also use three key concepts (scale, status and productivity) to help create and see the relatedness of DRL methods, and interpret stock assessments in general. Using these three concepts coupled with a continuum approach to understanding method connectivity often unearths assumptions and issues with the data and inputs that can be overlooked when going straight for the "gold standard" or stopping short and viewing any method as only a discrete entity.

Rising computing power has opened up powerful tools to investigate the complex situations under which DRL methods are needed (Fig. 6). Simulation experimentation can reveal situations where certain methods may or may not perform well, discover management procedures that can save poorly performing DRL methods or maximize the performance of good ones, and ways to explore and eventually combine multiple hypotheses into one composite model with more inclusive measures of bias and imprecision. It can also demonstrate the power of data collection while emphasizing that something can still be done under data and resource limitations.

Despite the challenges of setting up and testing DRL management procedures stated above, it should not be overlooked that model free (i.e., indicator approaches) management procedures may still be the most cost effective and best performing (i.e., meets mangement objectives) option for a given situation.

3.2. Simplified but not simple

DRL methods may be simplified from the "gold standard" stock assessments, but they are not necessarily simple. The details of each situation are critical to recognize and to develop case specific solutions. This takes time and attention. The prospect of doing rapid assessments of stock status (outside of risk assessment methods that are built for such a purpose) that do not take the time to consider major issues of information content, data representativeness or bias, and imprecision in dubious model inputs are highly susceptible to poor behavior and questionable results (Kell et al., 2022). It is very common to refine an stock assessment by doing an initial run of an assessment, ponder over the results, discover an issue with the inputs, revise the inputs, then come back and try the model again. This iterative application of stock assessment purification is commonplace across the continuum of model options and should be normalized.

If stock management is the priority and there are many stocks to assess, it may be better to choose a stock as a representative of other stocks (possibly identified via a risk assessment) and take the care needed to evaluate data and parameter quality, as well as the right fit assessment method. This can also trigger data collection and adaptive management and outline the needs for evolving assessment capacity in order to meet the demands of the management objectives.

3.3. *Avoiding fool's gold*

DRL methods are not gold, but they are elemental to fisheries management, and will be for the foreseeable future. Most stock assessments will never get to gold, but can still be used to support science-based fisheries management. The good practices shared throughout the paper (Table 1) are instructions for establishing context, outlining discerning principles, and offering practicable guidance for DRL method application and interpretation. While valuing and collecting data should remain a high priority, levaraging life history theory, applying technical and analytical advances, and coupling uncertainty characterization with risk tolerance have taken the place of excuses to "wait for all the data" before managing marine resources.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

No data was used for the research described in the article.

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