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ORIGINAL RESEARCH

The stock assessment theory of relativity: deconstructing the term "data-limited" fisheries into components and guiding principles to support the science of fisheries management

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Abstract The term "data-limited fisheries" is a catch-all to generally describe situations lacking data to support a fully integrated stock assessment model. Data conditions range from data-void fisheries to those that reliably produce quantitative assessments. However, successful fishery assessment can also be limited by resources (e.g., time, money, capacity). The term "data-limited fisheries" is therefore too vague and incomplete to describe such wide-ranging conditions, and subsequent needs for management vary greatly according to each fishery's context. Here, we acknowledge this relativity and identify a range of factors that can constrain the ability of analyses to inform management, by instead defining the state of being "data-limited" as a continuum along axes of data (e.g., type, quality, and quantity) and resources (e.g., time, funding, capacity). We introduce a tool

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(the DLMapper) to apply this approach and define where a fishery lies on this relativity spectrum of limitations (i.e. from no data and no resources to no constraints on data and resources). We also provide a ranking of guiding principles, as a function of the limiting conditions. This high-level guidance is meant to identify current actions to consider for overcoming issues associated with data and resource constraints given a specific "data-limited" condition. We apply this method to 20 different fisheries to demonstrate the approach. By more explicitly outlining the various conditions that create "data-limited situations" and linking these to broad guidance, we aim to contextualize and improve the communication of conditions, and identify effective opportunities to continue to develop and progress the science of "limited" stock assessment in support of fisheries management.

Keywords Stock assessment · Fisheries management · Data-limited · Resources · Capacity

Introduction

Fisheries management has shown great power to achieve the goal of natural resource sustainability (e.g., Hilborn and Ovando 2014; Hilborn et al. 2020). If one were to construct an unrealistic, yet ideal situation for fisheries management, it would include the following elements: (i) Fully articulated management objectives including stakeholder participation and buy-in , (ii) A complete understanding of biological and systems processes, (iii) Multiple types of fully representative data and uncompromised resources to support precise and unbiased stock assessments conducted by fully trained analysts with no competing duties or time constraints, (iv) Model outputs that inform tractable management measures (v) Full compliance or absolute ability to implement regulations, and (vi) Seamless integration of all these synergistic components into a responsive and adaptable management system. That ideal checklist is obviously never fully realized, and fisheries must instead reconcile with limitations in most, if not all, parts of this system (Pilling et al. 2008; Honey et al. 2010; Dowling et al. 2015a,b; Blasco et al. 2020).

In particular, deficiencies in the application of analytical methods to derive stock status information (i.e., traditional stock assessment methods such as statistical catch-at-age models; Methot and Wetzel, 2013) and/or to set and adjust particular management measures (e.g., size or catch limits; Liu et al. 2016) have been the focus of concern in fisheries management. These analytical methods provide the most direct means of making scientifically-informed, evidence-based decisions, and each has explicit data requirements. We hereafter refer to the collection of analytical methods to support management decisions generally as "stock assessments".

The ability to perform traditional stock assessment methods is often constrained by limitations in the amount, quality and types of available data (Smith et al. 2009; Carruthers et al. 2014; Omori et al. 2016; Dowling et al. 2019). Catch time-series, indices of abundance, length and age composition, along with life history parameters and an understanding of the technical interaction with the fishery(ies), are the core inputs of quantitative stock assessments, and deficiencies in these inputs restrict the application of historically acceptable stock assessment models (Legault et al. 2023). Limitations in resources enabling formal assessments to be undertaken, regardless of the amount and quality of available data, or unfamiliarity with methods that could possibly use all available data, can also restrict analysis and lead to a fishery being classified as "data-limited" (Dowling et al. 2008, 2015a,b, 2019).

Lack of or problems with data have affected fisheries throughout the history of management efforts (e.g., Eichenberg and Shapson 2004; Garibaldi and Caddy 2004), and recognition of this problem has grown over recent decades. The terms "data-limited",

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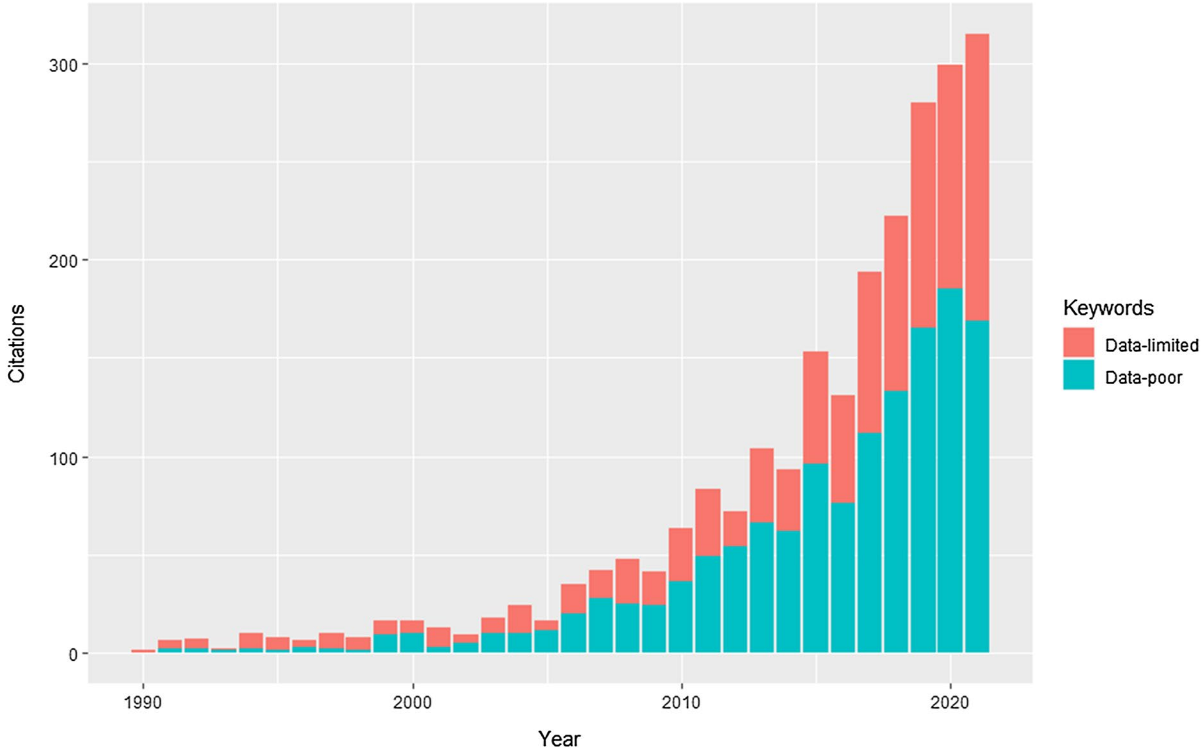

Fig. 1 The use of the keywords "data-limited" and "data-poor" in Fisheries-themed journals from 1990-2021. Source: Web of Science

"data-poor", and "data-less" are increasingly being used (e.g., Dowling et al. 2008, 2015a, b, 2019) as shorthand to signal situations under which some levels of data constraints are compromising fisheries management. The use of those terms in the scientific literature has increased exponentially over the past 30 years, with particular expansion since around 2010 (Fig. 1). The increase in attention to these challenges facing fisheries assessment and management is welcome, with an ever-expanding array of methods and tools developed to tackle them (e.g., Carruthers et al. 2014; Geromont and Butterworth 2015; Pantazi et al. 2020). But with increased appreciation for this "data" dilemma, it is also apparent the terms "data-limited", "data-poor", and "data-less" do not adequately capture important differences among diverse and complex situations.

The term "data-limited" (hereafter used to include "data-poor" and "data-less") is also insufficient as data quality and quantity are not the only obstacles to undertaking a stock assessment. Resource limitations, such as analytical technical capacity (e.g., number and relative expertise of trained analysts), number of stocks needing management relative to those assessing stocks, time available to conduct stock assessments, financial support for data collection and stock assessment reviews, and other required commitments supporting science-driven management may constrain the type and interpretation of stock assessment conducted, or indeed, whether a formal stock assessment is conducted at all. Consequently, the confluence of data and resource constraints result in the majority of global fish stocks remaining unassessed (Costello et al. 2012; Blasco et al. 2020). These issues can also drive strategic decisions to do less data-intensive stock assessments and/or reduce data collection for some stocks to allow more resources for other stocks (Zimmermann and Enberg 2017; Rudd et al. 2021; Tribuzio et al. 2021), despite many issues associated with the assumptions and potential reliability of data-limited stock assessment methods (Wetzel and Punt 2011; Dowling et al. 2019; Chong et al. 2019; Free et al. 2020, Ovando et al. 2021). In other cases, stock assessments are strategically limited to a

Fig. 2 Comparing "data-limited" situations can sometimes feel like the scar comparison scene from the movie *Jaws* (Spielberg 1975), with each scar origin story escalating the intensity of the experience, not unlike what can happen when comparing the relative "data-limitedness" among management scenarios. While Dr. Hooper (middle) thought his scars were the worst (i.e., the most data-limited), Captain Quint (left) ultimately makes it very clear his scars are *much* worse (i.e., more data-limited). Chief Brody (right) is undeniably data-rich in this scene

few key "indicator" stocks, as the primary basis for assessing the biological sustainability of an entire fishery complex (e.g., Newman et al. 2018), or traditional assessment models are sometimes applied to combined data for multiple species (Ralston and Polovina 1982; Mueter and Megrey 2006). Thus, both data and resource constraints contribute to limitations in applying stock assessment methods.

We therefore recognize that the term "data-limited" encompasses a range of both data and resource constraints that form a multidimensional spectrum, embracing a range of fisheries, and is therefore relative by nature. Similarly, use of the term "data rich" would imply relatively no or less constraints for both data and resources. Thus "data-limited", "data-rich" and anything in between are part of a continuum of data and resource scenarios. The relativity of these scenarios is important to understand and communicate, and is defined by the situational details. When these details are not recognized, practitioners may feel isolated, unrepresented, and/or in much more dire, unique or unrelatable circumstances than other so-called "data-limited" fisheries (Fig. 2). Understanding, therefore, where within the spectrum any given stock finds itself and what features of the system are contributing to that position can better articulate what "data-limited" truly means, and may help broadly diagnose better solutions specific to a stock's context and identify next steps for improvement in any given situation.

This paper deconstructs the term "data-limited" into its components. An approach applicable to any stock/fishery is then presented to help practitioners understand where along the data and resource condition spectrum any stock/fishery may reside, identify what factors lead to limitations in effective management, and then provide general guiding principles to highlight priority areas to address those limitations. We consider a variety of nominally "data-limited" examples to demonstrate the usefulness of this approach. These examples range from single stock to groups of species to demonstrate flexibility in application to specifically diagnose limiting conditions. The proposed approach here is meant to improve relatability and communication of limiting conditions, and encouragingly lead to targeted approaches to improve the science behind fisheries management options despite limiting factors.

Methods

Data and resource limitations are first organized into component attributes to provide space to identify main constraints. Within the data category we recognize six main attributes contributing to data limitations (defined Table 1). These attributes within the data category cover the types, quality (precision, bias, and species identification), and coverage (both temporal and spatial) of data. Under the resource category there are four attributes that address time (i.e., time available to collect data and/or do stock

Table 1 Definitions of data and resource attributes that can be constraining or limiting. Some general guidance on scoring is also provided. CV = coefficient of variation

Attribute	Definition	
Data-limitations	# Types	Different types of data available (e.g., catch, indices of abundance, and/or biological data). Having all of the above data types would give a score of 0; having none would give a score of 3.
	Precision	Level of imprecision based on low sample size, high measurement error, or other causes of high variance or low signal power. Very high (CV <5%) precision would give a score of 0; very low precision (CV >50%) would give a score of 3.
	Bias	Bias due to general representativeness issues, poorly met assumptions, or other issues. Near zero bias would give a score of 0;
	Species ID	Data not collected at the species-specific level. Perfect species identification would give a score of 0; no species identification (i.e., only a broad species category is reported) would give a score of 3.
	Spatial	Spatial limitations in the data (e.g., some areas are better sampled than others). Full spatial coverage of whatever data types are available gives a score of 0; Very little spatial coverage compared to fishery extent is a score of 3.
	Temporal	Temporal or time series issues in the data (e.g., data snapshots or large data gaps in important years). All years reported in whatever data types are available is a score of 0; no data would be near a score of 3.
Resource-limitations	Time	Major time constraints in performing data analysis and stock assessment. Such a constraint or limit the number and types of assessments that can be done. Unconstrained time for performing stock assessments would be a score of 0; almost no time for performing stock assessments is a score of 3.
	Funding	Major funding constraints that limit the collection of data or ability to support the stock assessment process would be a score of 3. A score of zero would reflect unlimited funding for data and stock assessments.
	Capacity	Technical capacity constraints to conduct stock assessment of varying complexity. Highly trained analysts that can perform complex stock assessments would be a score of 0. No technically trained analysts would be a score of 3.
	Analysts : Stocks	Ratio of the number of stock assessment analysts to the number of stocks needing to be assessed. At least one assessor for each stock being managed would be a score of 0; having 1 assessor per many (e.g., 10) stocks would be near a score of 3.

assessments), funding (i.e., institutional resources put towards data collection and stock assessment), technical capacity (i.e., the technical ability of available analysts) and the ratio of available analysts to stocks needing assessment (Table 1). Constraints in each of these attributes are then scored on a continuous scale from 0 to 3, with 0 being that there is no constraint imposed by that attribute, and 3 being that the attribute fully constrains the ability to undertake an assessment. For instance, if many data types are available, but the sampling design of each leads to high imprecision and bias, data types would be scored with low constraint, but bias and imprecision would be given a high constraint score. There is no exact score mapping to any given situation, and thus scoring remains subjective, though some general guidance is offered in Table 1. Knowing the bookends (e.g., having many years of data vs 0 years), it is left up to the user to evaluate where they think they are relative to the worst and ideal condition based on each category.

We began with descriptions of 20 case studies provided by the panelists, presenters, and attendees of the data-limited stock assessment session of the 2021 World Fisheries Congress (held in September of 2021). The scoring of the attributes for 20 case studies involved an iterative process with our co-authors to ensure all limitations were sufficiently captured and appropriately scored. Examples of fishery descriptions and the scoring derived from those descriptions can be found in Table 2. Plots of individual fishery attribute scores show the pattern of constraints. Each combination of attribute scores leads to a unique signature of constraints for each stock or fishery, and thus a specific description of what "data-limited"

Table 2 Attribute limitation scores and associated guiding principle scores for fishery examples.

		Type of Constraints:	Fishery examples							
			Cameroon Kadey River		SESSF Eastern Gemfish		Western Australia (WA) Non-indicator fishes		SESSF Tiger Flathead	
			Data and Resource		Data		Resource w/ medium Data		No Constraints	
Attribute limitations	*Data-limitations*	# Types	Extremely limited; no data on key species harvested, total catches, # of fishers, gears used, etc. **	3	Data before prohibited targeting in the early 2000s included: CPUE, catch, discard, length, and age data. No fishery indep data.	1	Commercial catch/ effort data from 1975. Limited recreational catch/ effort and age and length data.	1.5	Fishery dependent catch, CPUE, discard, length and age data; 2 fishery independent surveys available	0
		Precision	--	3	No accurate index of abundance available (due to prohibited targeting).	2	No reliable abundance indices. Recreational catch uncertain for some stocks, notably for early years.	2	Considered data rich for the fishery with a relatively complete data set.	0
		Bias	--	3	CPUE violates assumptions due to altered targeting practices from management changes	3	Abundance indices unreliable due to issues with targeting in multi-species fisheries. Length age data not fully representative for some stocks.	2	Data are considered to be of a high quality with no known violations of assumptions.	0
		Species ID	--	3	Managed as single species and stock.	0	Some species id issues, notably in earlier years.	1.5	NA	0
		Spatial	--	3	Limitations in age and length data due to limited spatial sampling with low catches.	2	Full spatial coverage for commercial catch/ effort. Course resolution for early years and recreational survey ests.	1.5	Some spatial aggregation of discard, length and age data, with limited samples collected from fishery, but overall good coverage.	1

Table 2 (continued)

	Type of Constraints:	Fishery examples							
		Cameroon Kadey River		SESSF Eastern Gemfish		Western Australia (WA) Non-indicator fishes		SESSF Tiger Flathead	
		Data and Resource		Data		Resource w/ medium Data		No Constraints	
	Temporal	--	3	Adequate catch and length time series; limited temporal coverage of discard, age and length data since prohibited targeting.	2	Adequate commercial catch. Age and length data available ~one or a few years. Most recreational catch data only for recent years.	2.5	Full time series available.	0
Resource-limitations	Time		0	Adequate time to complete assessment if data were available.	0	Challenging given large no. of sp. and focus on higher level assessments	2	Adequate time to compete assessment.	0
	Funding	Extremely limiting (no $$ for any data collection or other resources)	3	Adequate resources to complete assessment if data were available. Previously assessed at highest tier level due to fishery value.	0	Challenging given large no. of sp. and remoteness of areas.	2.5	Adequate resources	0
	Capacity	Almost non-existent	3	High technical capacity	0	Relatively high technical capacity	1	High technical capacity	0
	Analysts : Stocks	Only a handful of fishery scientists in the country to cover large spatial scale.	3	Multiple assessors available to complete assessment if representative data were available.	0	Very few highly-trained analysts for many stocks.	3	High	0
Guiding Principles	Data training	3.0		1.4		1.7		0.1	
	Improve data	3.0		1.7		1.8		0.2	
	Local input	3.0		0.8		2.0		0.1	
	Analytical training	3.0		0.6		1.8		0.1	
	Simple methods	2.4		0.2		2.0		0.0	
	Complex methods	0.0		2.2		1.0		2.9	

Table 2 (continued)

Type of Constraints:	Fishery examples			
	Cameroon Kadey River	SESSF Eastern Gemfish	Western Australia (WA) Non-indicator fishes	SESSF Tiger Flathead
	Data and Resource	Data	Resource w/ medium Data	No Constraints
Improve Mod. Specs.	0.0	2.2	1.0	2.9
Static MMs	3.0	1.7	2.1	0.2
Dynamic CRs	0.0	2.3	1.3	2.9
Improve governance	3.0	0.2	1.7	0.0

** No data are available, thus, the remaining data-limitation attributes scored 3s.

(or in some cases "data-rich") actually means in the context of a specific fishery, and in relation to other fisheries using comparison plots. This approach covers the continuum of constrained situations from fully constrained to situations without any substantial constraints.

A set of guiding principle scores (i.e. recommendations to overcome certain constraints) is then produced given the unique signature of constraints. Ten guiding principles are recognized in three general groups: addressing data needs, analytical approaches, and management approaches. Values for each are calculated as functions of the constraint scores (Table 3 which also provides detailed descriptions of each guiding principle). These conditionally-based principles range from improving data, capacity training, and governance, potentially applying simple (or simpler) assessment methods (Carruthers et al. 2014; Chrysafi and Kuparinen 2016), and/or static management measures (Carruthers et al. 2016), up to using complex, integrated population dynamics models (Maunder and Punt 2013) and, where appropriate given economic, social and other factors, using dynamic management measures (Anderson et al. 2019; Table 3). As there is no exact quantitative link between constraining attributes (the factors describing why a given fishery is data-limited) and guiding principles (the steps needed to resolve constraints), the subsequent equations for each guiding principle (as a function of the constraining attributes) are inherently subjective, but based on the authors collective experience and opinion, and therefore a practical interpretation of needs from constraints. Similar to the iterative process we used to generate the list of limiting attributes, the guiding principles were carefully selected to identify areas where analysts and managers can focus their attention (while noting the principles do not prescribe specific solutions). The formulation of the conditionally-based guiding principles were developed by the authors and discussed at length to determine which limiting attributes best contribute to the guiding principle. The formulations were iteratively tested and tuned to four hypothetical extreme-case scenarios (see below) and verified using the 20 case studies. The guiding principles are designed to be high-level from which a more comprehensive decision support tool (i.e., FishPath (Dowling et al. 2016; Dowling et al. *in review*)) can provide more customized, detailed and explicit advice, as

Table 3 Glossary and formulas for the guiding principles. Each guiding principle is derived from the scores from the limiting attributes described in Table 1. ***Data*** indicates all data-limitations (i.e., # Types, Precision, Bias, Species ID, Spatial, Temporal). ***Resource*** indicates all resource-limitations (i.e., Time, Funding, Capacity, Analysts:Stocks)

Guiding Principle	Description	Formula
Data training	Train on the collection and preparation of data for use in stock assessment.	$\mathrm{avg}(\boldsymbol{Data})\begin{cases} = 3 & \rightarrow 3 \\ < 3 & \rightarrow \mathrm{avg}(\boldsymbol{Data}, \mathit{Capacity}) \end{cases}$
Improve data	Improve the quality and/or quantity of data, to overcome one or more data limitation attributes (i.e., types, imprecision, bias, species-specific, spatial and temporal limitations).	$\mathrm{avg}(\boldsymbol{Data})$
Local input	Consider including local knowledge for basic biological understanding and model specifications.	$\mathrm{avg}(\boldsymbol{Data})\begin{cases} = 3 & \rightarrow 3 \\ < 3 & \rightarrow \mathrm{avg}(\mathrm{avg}(\boldsymbol{Data}), \mathrm{avg}(\boldsymbol{Resources})) \end{cases}$
Analytical training	Increase the analytical capacity to undertake quantitative stock assessment through technical training.	$\mathrm{avg}(\mathit{Capacity}, \mathrm{avg}(\boldsymbol{Data}), \mathrm{avg}(\mathit{Time}, \mathit{Funding}, \mathit{Analysts} : \mathit{Stocks}))$
Simple methods	Consider applying simple analytical methods for producing quantitative stock status information (as an introductory assessment approach).	$\mathrm{avg}(\#\mathit{Types}, \boldsymbol{Resource})\begin{cases} = 3 & \rightarrow 0 \\ < 3 & \rightarrow \mathrm{avg}(\#\mathit{Types}, \boldsymbol{Resource}) \end{cases}$
Complex methods	Consider the use of more complex modelling options.	$\mathrm{avg}(\boldsymbol{Data})\begin{cases} = 3 & \rightarrow 0 \\ < 3 & \rightarrow \mathrm{avg}(3 - \mathrm{avg}(\boldsymbol{Data}), 3 - \mathrm{avg}(\boldsymbol{Resource})) \end{cases}$
Improve Mod. Specs.	Consider focusing on increasing the sophistication of analyses to improve data treatment and assessment model specification.	$\begin{matrix}\mathrm{avg}(\boldsymbol{Data})\mathrm{or} \\ \mathrm{avg}(\boldsymbol{Resource})\end{matrix}\begin{cases} = 3 & \rightarrow 0 \\ < 3 & \rightarrow \mathrm{avg}(3 - \mathrm{avg}(\boldsymbol{Data}), 3 - \mathrm{avg}(\boldsymbol{Resource})) \end{cases}$
Static MMs	Consider using static management measures as an introductory management approach.	$\max(\mathrm{avg}(\boldsymbol{Data}), \mathrm{avg}(\boldsymbol{Resource}))$
Dynamic CRs	Consider using dynamic control rules updated by stock assessments instead of static management measures.	$\mathrm{avg}(3 - \#\mathit{Types}, 3 - \mathrm{avg}(\mathit{Spatial}, \boldsymbol{Resource})$
Improve governance	Improve the governance and policy around the data, assessment, and management measures.	$\mathrm{avg}(\mathit{Time}, \mathit{Funding}, \mathit{Capacity})$ $\begin{cases} = 3 & \rightarrow 3 \\ < 3 & \rightarrow \mathrm{avg}(\#\mathit{Types}, \mathit{SpeciesID}, \mathit{Time}, \mathit{Funding}, \mathit{Capacity}) \end{cases}$

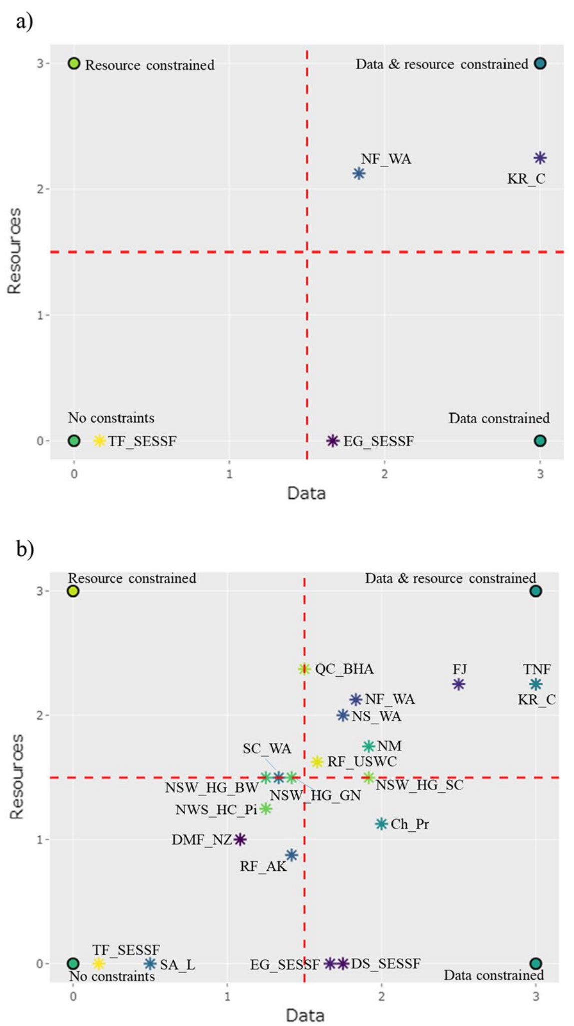

Fig. 3 Average data and resource constraint scores, ranging from 0 (no concern or constraint) to 3 (high concern or constraint), for **a** 4 featured applied fisheries (EG_SESSF, KR_C, NF_WA, TF_SESSF), and **b** all 20 applied fisheries along the spectrums of data and resources. The four hypothetical extremes (circles) of data and resource constraints are also provided. Constraint scores for different fishery attributes associated with data availability and resourcing Legend: NM, North of Madang; FJ, Fiji; DMF_NZ, data moderate fisheries, New Zealand; KR_C, Kadey River, Cameroon; SA_L, South Australian lobster, SC_WA, Sea Cucumber, Western Australia; NS_WA, Non-indicator sharks, Western Australia; NF_WA, Non-indicator fish, Western Australia, RF_AK, Alaskan rockfish; NSW_HG, New South Wales Hand-Gathering Estuary General Fishery (BW, Beachworm; Pi, Pipi; SC, Sydney Cockle; GN, Ghost Nipper); EG_SESSF, Eastern Gemfish, south-east Australia; TNF, Tropical nearshore fisheries; RF_WCUS, rockfish, West Coast United States; DS_SESSF, Deepwater sharks, south-east Australia; TF_SESSF, Tiger Flathead, south-east Australia

well as explicit planned pathways for jurisdictions to evolve their capacities. The guiding principle scores, where a high score indicates higher priority for that principle, are also plotted both individually, and in comparison to other fisheries, to help evaluation.

A Shiny (Chang et al. 2021) based application (the DLMapper[1]) was developed for users to enter attribute scores, obtain attribute and guidance profiles, and save outputs and figures. Multiple stocks and fisheries can be scored in the tool, offering the opportunity to compare across situations. In addition to the fishery-specific plots, there are two types of comparison plots. The first is a biplot of the average data (x-axis) and resources (y-axis) limitation scores. The four extreme cases of fully constrained, data fully constrained but resources unconstrained, data unconstrained but resources fully constrained and no constraints make up the four corners of the plot and frame the spectrum. The biplot offers a summary glimpse at the contributions of data and resources to overall limitations, providing a convenient way to compare across stocks or fisheries. The second figure type provides attribute- and guidance-level comparisons. This visualization helps identify groupings and commonalities among situations.

Our diagnostic tool was applied to 20 case study fisheries that span 10 countries and 16 jurisdictions that represent a variety of data and resource limitations, to characterize each fishery, illustrate the benefits of comparing situations, and help articulate the nature of the constraints in the system, while offering ranked guidance on how available resources could be prioritized for the system. All detailed descriptions and subsequent attribute scoring of the fisheries are provided in Supplementary Information Table 1.

Results

Hypothetical cases of extreme data and resource availability

To ground truth our approach, we first considered the four most extreme cases possible for varying data and resource availability (Fig. 3a): (1) A fishery with the

[1] This tool can be accessed at https://connect.fisheries.noaa.gov/DLMapper/; tool development code can be found at https://github.com/shcaba/DL-Mapper.

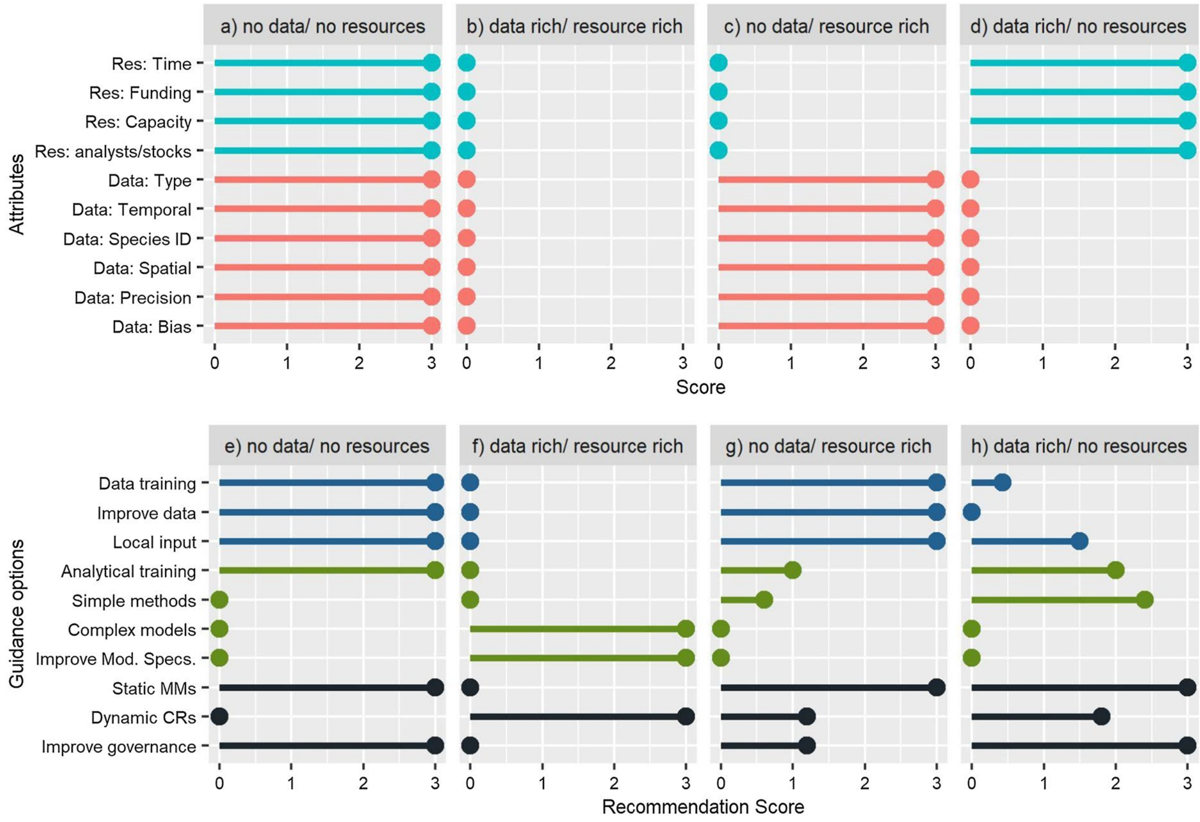

Fig. 4 Constraint scores for fishery attributes associated with data availability and resourcing (top row) and associated recommendation scores for alternative fishery guidance options (bottom row). The constraint scores, ranging from 0 (no concern or constraint) to 3 (high concern or constraint), are used to illustrate differences among (hypothetical) extreme cases, i.e., fisheries with, **a** no data or resources, **b** data and resource rich, **c** no data and resource rich, and **d** data rich and no resources. recommendation scores, ranging from 0 (no focus) to 3 (high focus), for the guidance options associated with data, assessment and governance, availability, and resourcing, for the (hypothetical) extreme cases of **e** no data or resources, **f** data and resource rich, **g** no data and resource rich, and **h** data rich and no resources

highest possible average data and resource constraint scores (x=3, y=3), 2) a fishery with no constraints in data or resources (x= 0, y=0), 3) a fishery with the no data constraints (x=0) but highest resources constraints (y=3), and 4) one that has the highest data constraints (x=3), but no resource constraints (y=0).

In the extreme case of a fishery fully constrained by data and resources, each of the six data and four resource attributes receive a score of 3 (Fig. 4a). In contrast, all data and resource attributes receive a score of 0 for a fishery with no constraints on data and resources (Fig. 4b). For those fisheries with full data constraints, but no resource constraints, all scores for data are 3 and all for resources are 0 (Fig. 4c). The opposite scores are attributed to a fishery that has no data constraints (all data attribute scores = 0), but resources are fully constrained (all resource attribute scores = 3; Fig. 4d).

The subsequent guidance principles prioritization scores are directly linked to current resource and data conditions to address the most pressing issues (Fig. 4, row 2). For instance, a fishery in the extreme situation of no data and no resources (Fig. 4e) will indicate attention to data as the greatest need and highlight data collection training and/or improvement while leaning on local expert knowledge (e.g., Johannes 1998; Berkström et al. 2019; Sjostrom et al. 2021). Additionally, analytical capacity training, and two of the three governance-related options (using static management and improving governance) are all highly ranked. The remaining guidance options score zero (i.e., no focus on any assessment modeling and

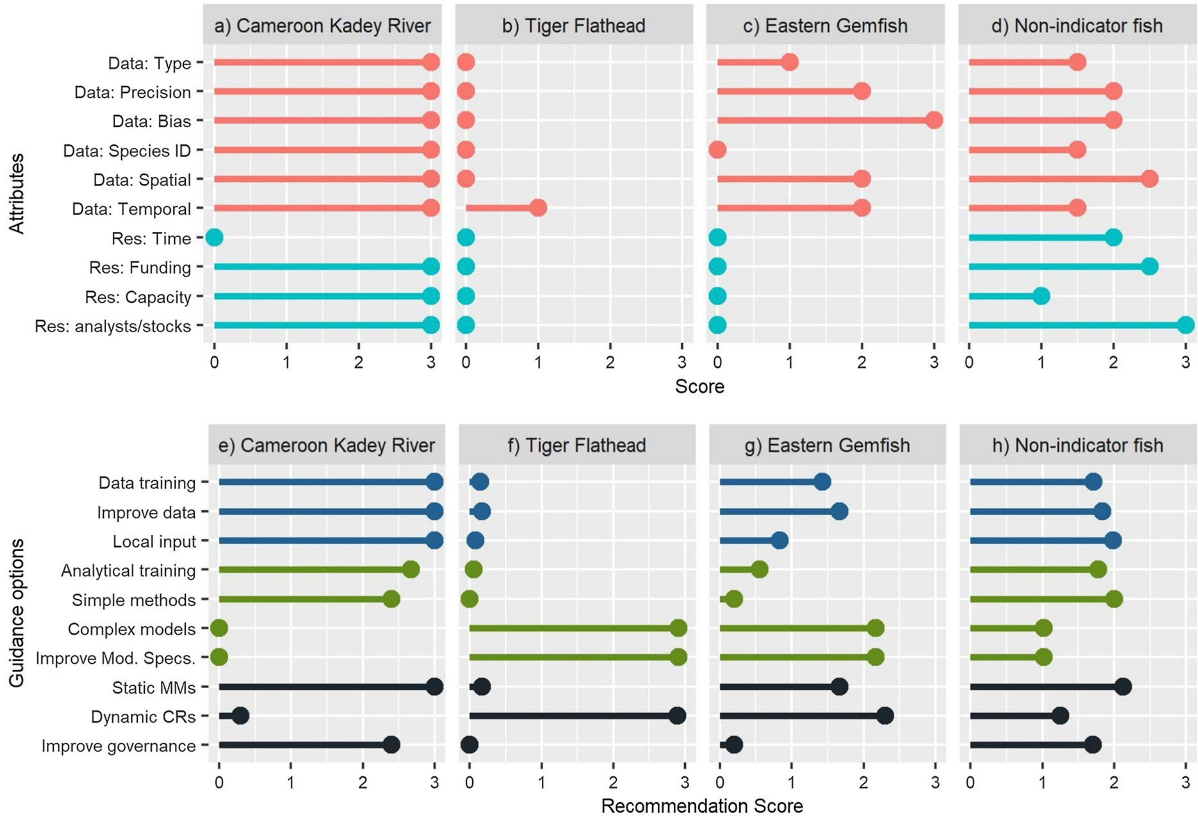

Fig. 5 Constraint scores for fishery data and resource attributes (top row) and associated recommendation scores for alternative fishery guidance options (bottom row), produced for fisheries identified as having high data and resource constraints (Cameroon Kadey River fisheries; **a**,**e**), few limited data and resource constraints (SESSF Tiger Flathead; **b**, **f**), high data but few resource constraints (Eastern Gemfish, SESSF; **c**, **g**), and high resource with moderate data constraints (WA non-indicator fish, WA **d**, **h**)

no application of dynamic control rules that would require modeling outputs due to the initial need to build data and establish simple management rules). The guidance option scores calculated for the unconstrained data and resource situation are the opposite of those just described and highlight the need for complex (from more quantitative up to fully integrated) models, focus on model specification issues (to improve the performance of the models) and the application of dynamic management measures informed by stock assessments (Fig. 4f).

For fisheries fully constrained by data but not by resources, the three guidance options associated with data are highly prioritized, as is implementing static management measures (Fig. 4g). Scores for guidance options associated with stock assessment are all low given the data constraints, as are dynamic control rules and improving governance, but they are not at 0 (as they are when both data and resources are fully constrained or absent), indicating that once the data condition is improved, more advanced options may potentially rapidly become available because resources are not constrained. By contrast, for the no data constraints /high resource constraints scenario (Fig. 4h), the highest ranked guidance options are two stock assessment options (analytical training and using simple methods), and two governance options (using static management and improving governance).

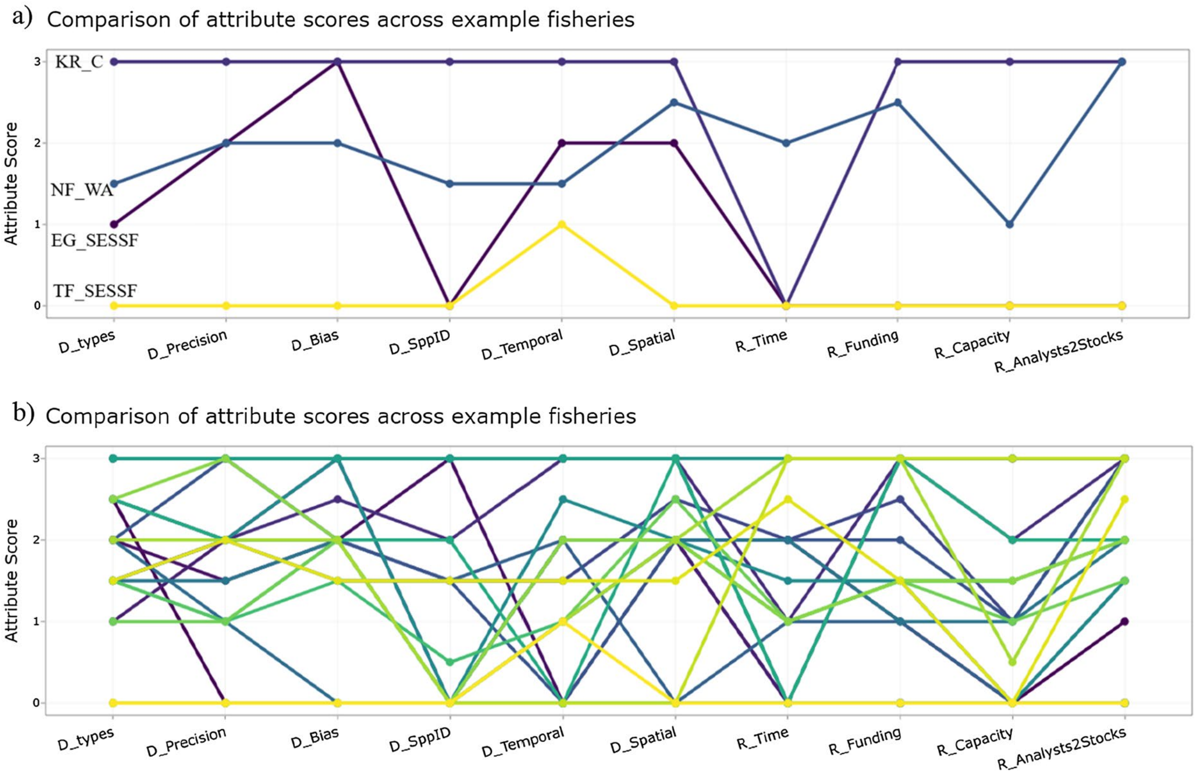

Fig. 6 Fishery attribute constraint scores associated with data and resource limitations, ranging from 0 (no concern or constraint) to 3 (high concern or constraint), for **a** four featured applied fisheries (EG_SESSF, KR_C, NF_WA, TF_SESSF), and **b** 20 applied fisheries along the spectrums of data and resourcing

Applied case studies with differing extremes of data and resource limitations

Of the 20 example fisheries, several have very strong data and resource constraints (Figure 3b). Here we highlight the four most extreme (Table 2; Figures 3a and 5). The attribute constraint scores for the Cameroon Kadey River fishery are the same as the above hypothetical extreme case of full data and resource constraints, except the time available to analysts to undertake an assessment is not a constraint (Fig. 5a). The guidance scores for this fishery are thus very similar to the extreme limitations hypothetical example (Fig. 5e, row 2, column 1). Conversely, the Southern and Eastern Scalefish and Shark Fishery (SESSF) Tiger Flathead fishery in Australia resembles the hypothetical extreme of no data or resource constraints, except that the spatial data constraint attribute score is 1 (some constraints), rather than 0 (Day, 2019; Fig. 5b). Consequently, the corresponding guidance scores are also very similar to those for the hypothetical extreme data- and resource-rich fishery (Figure 5f).

The attribute scores for Eastern Gemfish in the SESSF most closely resemble the extreme hypothetical data constrained scenario (Little and Rowling, 2010; Fig. 5c). While the resource attribute constraint scores for both SESSF fisheries are all 0, four of the data attribute scores (dealing with data quality issues) are 2 or above (i.e., highly constrained; compare to almost all 0s for Tiger Flathead; Fig. 5b) despite the availability of multiple data types, leading to a moderate-high average data constraint score. However, while the resulting guidance scores for Eastern Gemfish place moderate focus on improving some data aspects (i.e. improving data and data training, both scores ~ 1.5), they place a moderate-high emphasis on several aspects of stock assessment (use more complex models, improve model specification, score

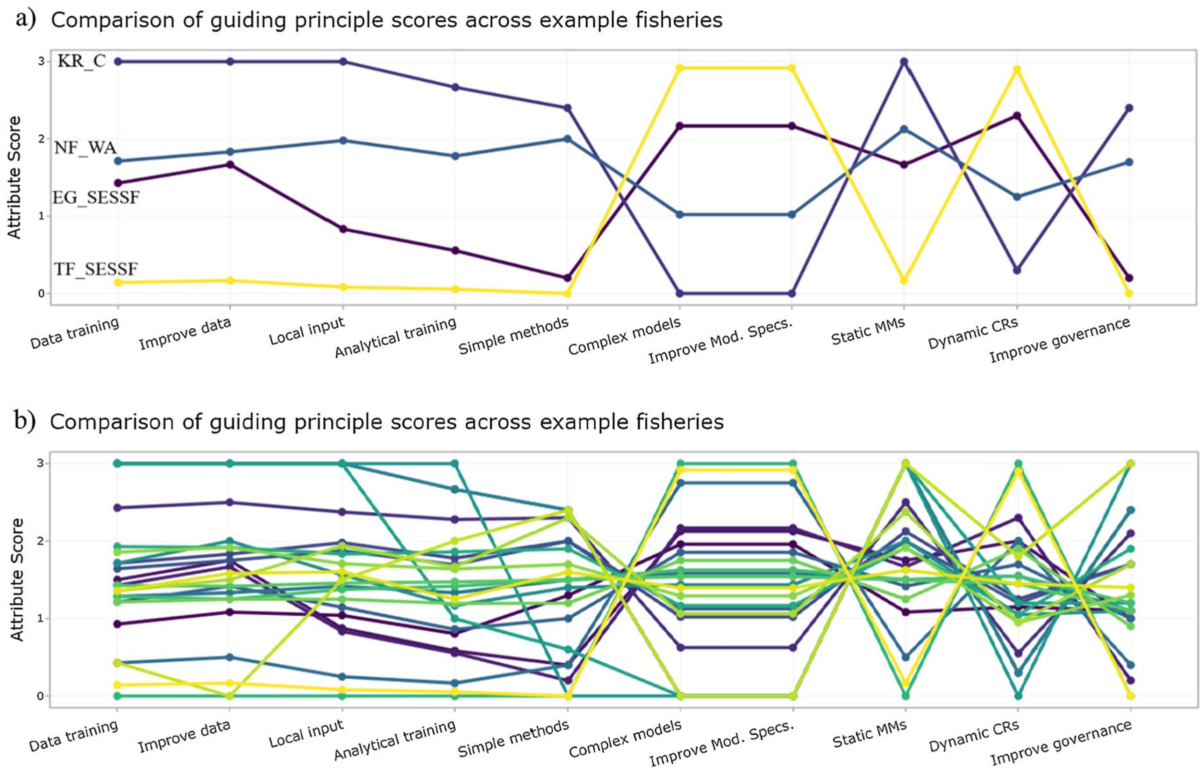

Fig. 7 Recommendation scores for alternative fishery guidance options produced for **a** four featured applied fisheries (EG_SESSF, KR_C, NF_WA, TF_SESSF), and **b** 20 applied fisheries along the spectrums of data and resourcing

> 2), and adopting dynamic control rules (score > 2; Figure 5g).

None of the 20 fishery examples closely resemble the extreme hypothetical resource constrained, but data unconstrained scenario. The situation in Western Australia for non-indicator fish species, however, exhibits some degree of resemblance to this situation (Fig. 5d). The fisheries for these species score as one of the most resource-constrained fisheries of the 20 examples (resource constraint scores typically >2), with only low-medium constraints on data (for 5 of 6 data attributes; Table 2). This yields a mix of guidance recommendations, with the highest being improving data, using local knowledge, applying simple analytical methods and implementing static management measures (Fig. 5h).

Moving from the individual to comparison plots, the average attribute constraint scores for these four fisheries (Cameroon Kadey River fishery, SESSF Tiger Flathead, SESSF Eastern Gemfish and WA non-indicator fishes) result in these fisheries occupying very different positions (Fig. 3a). They also highlight similarities to hypothetically extreme scenarios. Further comparisons of the individual attributes (Fig. 6a) and guiding principles (Fig. 7a) among the four fisheries highlight the specific differences that exist for these fisheries. The key recommended improvements for the Cameroon Kadey River fishery (limited data/resources) pertain to data (increase data training, improve data, use local input), providing analytical training to conduct simple assessments, and using static management measures. In contrast, none of these aspects are identified as key priorities for the SESSF Tiger Flathead fishery (low data and resource constraints), with the guidance pointing to use of more realistic assessment models, improving model specifications and dynamic control rules as priorities. The guidance options that score highest for the SESSF Eastern Gemfish fishery (moderate-high data constraints/no resource constraints) are the same as for the SESSF Tiger Flathead fishery, but the overall scores are less, and guidance also includes improving data training, improving data as well as an elevated consideration for static management measures. The scores for WA non-indicator fishes (greater resource than data constraints) are more even across alternative guidance options, with improving data, application of simple assessment methods and static management measures scoring highest (Fig. 7a). Overall guidance from these case studies was evaluated by the case study expert and found to be either consistent with their expectations or revealing additionally useful suggestions. The ability to both ground truth expectations and offer new insights (especially by comparing multiple fisheries) is a design feature of this approach and tool.

Further comparisons of fisheries with varying data and resources constraints

Most of the 20 applied fisheries occupy either the lower left or upper right quadrants of the data/resource constraint biplot (Fig. 3b). Four fisheries (South Australian Lobster, SESSF Eastern Gemfish, SESSF Deepwater Sharks and SESSF Tiger Flathead) lay low on the biplot (indicating limited or no resource constraints), all with low-moderate data constraints and no resource constraints. Six fisheries are relatively high on the plot (= resource constraint score 2 or above), four of which have moderate-high data constraints (North of Madang and Fiji fisheries, Cameroon Kadey River and Tropical nearshore fisheries). Several fisheries lay toward the center of the plot, reflecting both moderate data and resource constraints, though in different ways (Fig. 3b). Collectively, there is a pattern of a positive linear correlation between data and resource limitations.

Comparison plots of the individual data and resource attribute constraint scores for the 20 example fisheries highlights the diversity in fishery attribute constraints that exist in these fisheries (Fig. 6b). Despite similar average data and resource attribute scores, fisheries may have very different combinations of specific data and resource limitations. For example, the Western Australia non-indicator sharks (NS_WA) and non-indicator fishes (NF_WA) occupy very similar positions on the biplot, but NS_WA is constrained more by imprecision of data while NF_WA is more constrained by temporal data availability. The differences are even larger between the New Zealand (DMF_NZ) and New South Wales (eastern Australian) Hand Gathering Pipi Fishery (NSW_HG_PI) that occupy similar biplot positions. The New Zealand example is highly constrained by the number of data types and spatial and temporal data availability, but unconstrained by data bias and species identification in the fishery; the NSW Pipi fishery is primarily constrained by data bias and temporal limitations. Resource constraints also show differences: the New Zealand fishery is more constrained by time available for doing assessments, while the Australian fishery is constrained by the ratio of trained analysts to stocks needing stock assessments. These examples show how even fisheries with apparent broad similarity along the axes of data and resource limitations have unique prevailing conditions that necessitate different solutions.

As with the parallel plot for fishery attribute constraints, the corresponding plot for guiding principle scores across all the fisheries shows the diversity and unique rankings with respect to identified areas of focus for fishery improvement (Figure 7b). These could subsequently be used to group fisheries with similar improvement signatures for either comparison, discussion, or more efficient implementation of improvement options.

Discussion

Overview of approach

This paper strives to acknowledge how the term “data-limited” often fails to capture the important aspects of a given fishery management situation. To confront this challenge, we provide a conceptual framework and tool to better characterize fisheries, articulate the main constraints practitioners are facing while also offering practical guidance for moving forward. This need became clear as we assimilated the messages and lessons arising from the 2021 World Fisheries Congress data-limited fisheries sessions’ presentations and lively panel discussions. We focused on outlining the conditions that create “data-limited situations”, acknowledging the difference between, for example, the large number of data-less fisheries that are effectively “starting from scratch”, and fisheries that are largely constrained in attempts to best use limited data, with both situations dealing with degrees of resource limitations that may or may not call for similar solutions. As recently highlighted by Dowling et al. (2019), each "data-limited" case is uniquely facing its own challenges, and there is not a single solution or generic best practice across all such fisheries. The diversity of issues raised in the conference session highlighted long-held concerns regarding the lack of recognition of the sources of data- and resource-constrained fisheries, and motivated us to consider and confront the interpretation and meaning of "data-limited" fisheries to improve situational communication.

The term "data-limited" has too long been used as a catch-all for fisheries that lack the ability to conduct a fully integrated stock assessment. Lumping an extensive range of fisheries, with equally vast ranges of unique conditions, under one term typically has led to dissonant or disappointing comparisons that have not constructively supported or improved the management of these fisheries. Much like other types of spectra or continua (e.g., light, autism, space-time), it is not serviceable to report important relative differences among fisheries with one vague term. We instead need to acknowledge that, while there is a common set of identifiable attributes that may contribute to rendering the management of a fishery "limited", these attributes are not just based on data, and vary in relative strength and presence for each individual fishery. As the majority of the world's fisheries by number and catch volume are broadly "data-limited" (e.g., Costello et al. 2012; Geremont and Butterworth 2015), it is beneficial to explicitly acknowledge that such fisheries reflect this theory of relativity (i.e., comprise a spectrum of conditions) as applied to stock assessment, and subsequently, management needs. As such, guiding principles for formal science-based management are dictated by those specific combinations and strengths of attributes, and will have different emphases according to where on the spectrum the fishery lies. This provides the template to go from articulating fishery constraints to prioritizing recommendations to improve technical advice and management of those fisheries.

The interactive DLMapper tool helps illustrate where on the constraints spectrum a fishery resides, and provides a ranking of broad guiding principles likely needed to improve the ability to assess and manage a particular stock or fishery. This approach bypasses the question of minimum standards for "good enough" stock assessment or management performance: we feel there is greater value in using the relative attribute constraints to determine a profile of guiding principles that prioritize where future emphases should lie. The tool provides a platform to compare multiple fisheries and highlight similarities and dissimilarities in order to identify other fisheries with comparable conditions and constraints. Our comparative tool recognizes the uniqueness of any given fishery and allows for the specificities to be described, but also reveals the relative nature of the comparisons to find fisheries with common conditions, highlighting opportunities for collaborative work toward common solutions. In this way, practitioners working on fisheries with similar profiles may seek each other out and find value in learning from each other's experiences and proposed ways forward.

One emergent pattern applying this approach to 20 fisheries is the relationship of data and resource constraints where more data constraints often meant more resource constraints. This is consistent with the conclusions of Bentley (2015) that "data poverty is usually associated with time-poverty". Though this trend is visible and not entirely unexpected, the underlying attributes driving the relationship between data and resource constraint scores are not always the same. There are also important exceptions to this trend where data constraints existed despite adequate resources. There were no examples within our sample of case studies with low data constraints and high resource constraints. The DLMapper tool will facilitate further exploration from a wider inclusion of experts and cases to see how well this initial relationship holds and determine where the largest density of examples reside on the constraints spectrum.

In order to maintain a digestible amount of detail, the tool only broadly characterizes a fishery's condition, and provides only a high-level profile of guidance, so important details remain to be determined. For example, bias in data can derive from an array of sources (Francis and Shotton 1997) and "improving data" can take on a variety of specific forms (Fischer and Quist, 2014). To illustrate this point, consider the NSW Hand Gathering Pipi Fishery example that was scored as being strongly constrained by temporal data issues. The temporal issue is not strictly from a short time series or sporadic records as is often the case, but instead due to management regulations causing discontinuities in what otherwise appears to be a continuous time series. Futhermore, when considering the three general management-based guidance principles (static management measures, dynamic control rules and improving governance), specific thought is needed to recognize any obstacles (compliance, enforcement, emergent challenges) to implementation (Liu et al. 2016).

As such, the DLMapper tool is meant to help articulate the "data-limited" conditions, identify the big issues, and provide general guidance on next steps. More specific, detailed and tailored advice for data collection, stock assessment and management is the domain of decision support tools (e.g., FishPath provides tailored harvest strategy options given fishery circumstances; see also FISHE (http://fishe.edf.org/) and AFAM (McDonald et al. 2018)). Those tools can provide further insights on data and resource conditions (with associated caveats) supporting detailed decision making that is both transparent and tractable. Thus, the approach illustrated in this work should not replace a careful analysis and examination of case-specific data. Rather, it allows for rapid initial assessment of a fishery situation to provide a broad overview of constraints that exist, identifies commonalities between fishery constraint profiles, provides general guidance on alternative options for fishery improvement, and enables better communication on the extent of constraints in the fishery. This all leads to a more informed way to talk about one's situation and find others in similar circumstances.

It should be noted that we did not include "maintaining data collection", "characterize uncertainty", "determine management objectives", and "develop harvest strategies" as guiding principles. Maintaining any current data collections is a given, as reducing data would create additional complications (Wetzel et al. 2018), and quantifying uncertainty should be standard for any treatment of data and specification of stock assessment (Hordyk et al. 2019; Magnusson et al. 2013; Mildenberger et al. 2022). Determining management objectives and developing harvest strategies to achieve the objectives should also be a constant priority for all fisheries regardless of their condition. There is ample evidence and methodology in the literature arguing for the veracity of harvest strategy development even for so-called "data-limited" fisheries (e.g., Dowling et al. 2008, 2015a,b, 2019). It is recognised, however, that effective development and evaluation of harvest strategies remains a key challenge, particularly for "data-limited" fisheries (Dowling et al. 2015a,b), and that valuable work is occurring in this area (e.g., Plagányi et al. 2020; Loneragan et al. 2021; Dowling et al. 2023). Finally, partnerships with other agencies, non-governmental organizations, stakeholders, and other consultants should be an ongoing consideration to share resource load and build collaborative and cost effective relationships.

Application of approach and limitations

The choice of attributes and guiding principles, and, particularly, the relative strength of the latter as a function of the strength and combinations of the former, were derived via expert opinion and strongly influenced by the WFC panel discussion. For example, as raised in this panel discussion, consistent with the conclusions of Bentley (2015), "data-poor" fisheries will generally also have "time-poor" scientists, and thus highly sophisticated methods of stock assessment are not always suited to this situation. Yet, because many may have a diverse range of data, there remains scope for developing analytical approaches that can make best use of all available data despite resource limitations. For the fully constrained fishery, the importance of clearly identifying first steps, rather than focusing on complex solutions and tools that cannot be applied locally for these fisheries, is emphasized. Essentially, the view was that the focus for these fisheries should be on "getting something started" rather than aiming straight for a complex integrated stock assessment model (Prince 2003; Prince and Hordyk 2019). Alternatively, if the lead time between starting to collect data and produce assessments is measured in decades, a sophisticated method that could cut that time to only a fraction of a decade would be extremely valuable. Another key point was that the quality of community-gathered data is often unstructured and opportunistic. Even if these data are not directly usable in a stock assessment model, incorporating local expert knowledge can help specify stock assessment models, provide valuable complementary information for fisheries management (e.g., see Berkström et al. 2019), inform monitoring program design and help emphasize community involvement in sustainable management (e.g., size at maturity vs what is caught). Likewise, the use of local expert knowledge provides a way to establish relationships between communities and scientists as well as facilitate bottom-up empowerment.

In data-less fisheries, very simple numbers and management can be important, whereas in more data endowed situations, it is unacceptable not to show quantitative assessment outcomes complete with estimates of uncertainty. Additionally, where folks have collected data, they are often proud of them and want to share and use them. To devalue the usefulness of such data can be demoralizing. But, when the currently available data in a fishery are idiosyncratic, patchy and heterogeneous, more complex statistical tools may be needed to properly reveal the signals they contain, so there is an important role for skilled quantitative stock assessment scientists to assist developing countries. The spirit of these points is captured in the inclusion and functional form of the guidance principle related to incorporating local knowledge versus those of utilizing complex models and improving model specification. For more fisheries with moderate constraints, the point was made that there should be an increased focus on developing approaches to get the most out of existing data, which is reflected in the guiding principles around implementing simple or complex assessment methods, as well as analytical training.

Our attempts to define attributes, guiding principles, and the relationship between them, based on collective expertise, are nonetheless decisions of judgment, and we openly acknowledge their subjectivity. The choice of attributes within the two big categories of Data and Resources were based on the authors' experiences and the reoccurring issues that were raised in the sessions when describing the biggest challenges to conducting stock assessments. We attempted to balance the need to define informative multiple attributes without being overly detailed, while also limiting the overlap in each attribute. We present these as a parsimonious accounting of the major attributes, but realize that emergent issues may bring other attributes to the forefront in the future. The tool offers a flexible framework for bringing in other attributes. Understandably, the attribute scoring is subjective to the analyst's perception of the fishery; however, the goal of the scoring process is to identify those attributes that are perceived to be most limiting. Experts from each of the case studies explicitly verified the attribute limitation and resultant guiding principles scores. In providing the detailed descriptions and subsequent scoring of the 20 fisheries used here, we hope to allow for calibration of user scores.

As the tool is applied to more case studies, the formulation of the guiding principles can be adapted to reflect updated issues and future concerns. The iterative process by which we worked through the 20 case studies with our co-authors, yielded feedback that the tool's output reflected the state of the fishery, and that the profile of guiding principles compared well with practitioner's own perceived recommendations. This argues well for the approach's general application and continued evaluation.

Lessons learned from case studies with differing extremes of data and resource limitation

Of the 20 fisheries considered, several were highly constrained. As would be expected for those highly constrained by both data and resources, the associated guiding principles suggested the need for a strong focus towards improving data, using local knowledge, and increasing resources for stock assessment and governance, but little or no focus on the immediate use of stock assessment models and dynamic harvest control rules. It is logical that data are needed before a model can be applied, and a degree of analytical training is needed to empower local jurisdictions/communities to be able to assess stocks. The starting point for these highly constrained fisheries typically begins with initial assistance involving external expertise, but there can be several pathways forward to lead to the ultimate goal of providing effective management advice. For example, reef fisheries north of Madang (Papua New Guinea) lacked catch or biological data until external expertise provided basic training to collect and interpret species-specific fish measurements. The training invested in the local community enabled them to determine sizes of maturity and breeding seasons, and catalyzed their concern for food security into simple adaptive village-based management systems. Another example of high data and resource constraints is the Kadey River artisanal fishery in Cameroon, where external expert analysts are reconstructing catch histories based on local fisher's recall and attempting to improve options for future stock assessment. These examples are meant to illustrate the general nature of our guiding principles and their prioritization as they do not fully reflect all possible options for a given situation, leaving it to the experts to pursue those details.

Of the 20 example fisheries, the SESSF Tiger Flathead fishery has the fewest data and capacity constraints. A range of “good quality” data types are available for this fishery, including relatively complete, informative species-specific data series for catches (and on discards), fishery-independent CPUE indices, and length and age composition data, all typical of the relatively “data-rich” end of the spectrum. As there are no (perceived) constraints on resources (including technical capacity), integrated age-structured assessment models are possible. The guidance recommendation scores reflect this by prioritizing improving model specifications (i.e., optimizing application of integrated stock assessment models), encouraging application of dynamic control rules, while deprioritizing improving data, simple assessment models and governance improvement. While relatively unconstrained by data quality and resources, the South Australian Rock Lobster fishery was constrained in terms of the number of types of data. In this case, the guidance scores emphasized improving model specification or complexity. The veracity of this (broad) advice is borne out, for example, by the development of the qR approach (McGarvey et al. 1997, 2005; McGarvey and Matthews 2001) to fit to catch data recorded in numbers, rather than weight, which resulted in improved stock estimates.

The differing data constraint scores for Tiger flathead versus Eastern Gemfish, both species within the SESSF, highlight that data (and/or resource) constraints can vary markedly for different stocks within a given fishery. Despite multiple sources of data and resource availability for both Eastern Gemfish and Tiger Flathead, there are multiple data quality issues for the former. Eastern Gemfish has been assessed as heavily depleted since the early 2000s (Little and Rowling, 2010; Emery et al. 2021) with consequential management action taken to cease targeted fishing in order to rebuild the stock. This management action has meant that high quality, spatially representative fishery dependent and independent data are now unavailable. As such, a once- data-rich fishery now has data constraints, impacting the ability to undertake robust assessments (Wetzel et al. 2018). However, our associated guidance placed priority on applying complex models, improving model specification and adopting dynamic control rules, and lower focus on improving data. While such guidance broadly follows given the attribute scores, this is one example where it fails to acknowledge a fishery’s specific nuance: although capacity might exist and various data types might currently be available, the recent quality of the data is such that it is likely futile to attempt more complex models or improve model specification in the future, although there may be merit in applying the expertise of highly-trained analysts to determine whether models can be modified to reduce the impact of data-limitation on assessment reliability. One would also expect a re-scoring of the data attributes if they deteriorate over time, pointing to new guidance.

The relatively high resource constraints and lower data constraint scores for Western Australian non-indicator fish species largely reflect the situation-specific circumstances associated with monitoring and assessing finfish fisheries in a region of low ecosystem productivity and high species diversity (e.g., Lenanton et al. 1991; Molony et al. 2011; Newman et al. 2018). As it is not logistically and economically possible to monitor and assess the status of all species, a fish species indicator approach was adopted in 1993 to assess sustainability of “like” species, for optimal use of available jurisdictional resources (e.g., Newman et al. 2018). Monitoring of the indicator species has, however, resulted in increased collection of data (e.g., species composition and abundance) for some additional fish species. In recent years, there has been increased demand for quantitative stock assessments for increased numbers of species to meet national reporting requirements (Status of Australian Fish Stocks Reports (SAFS), used to inform Australia’s progress against UN Sustainable Development Goal 14.4.1), on the proportion of fish stocks within biological sustainable levels. A key constraint for these fisheries is lack of analysts with high technical expertise, with the few available required to focus much of their attention on higher value stocks. Unsurprisingly, the priority guidance options were improving data, application of simple assessment methods and static management, with the latter two options reflecting the fact that complex models and dynamic management are not likely to be possible (or practical) with few analysts for so many species over an extremely large region with some very remote areas.

Common attributes among fisheries, such as low species-specific data quality, does not necessarily result in similar scores or managerial outcomes. The

West Coast United States rockfish and Alaskan rockfish fisheries scored similarly in most data-limitation attributes as the Western Australian non-indicator fish species, and face the similar challenge of managing a large number of species, but scored differently on resource limitations. As a result, a different emphasis is placed on stock assessment model type (simpler versus more complex) and management measure guidance options. Additionally, the management approach for each of these fisheries is distinct. In contrast to managing based on indicator species, most of the Alaskan rockfish are assessed and managed as a single unit (i.e., stock complex) by aggregating the biomass for the multiple species in the assessment and providing a single harvest limit for the unit (Tribuzio et al. 2021). Conversely, the West Coast United States rockfishes example manages some species within stock complexes with an overall harvest limit, and others individually with individual harvest limits (PFMC 2020). Thus, despite similarities in attributes and situations (e.g., poor species-specific data), analytical and managerial approaches are case-specific and depend on many factors.

Conclusion

The data-limited session and panel discussion at the 2021 World Fisheries Congress generated a diverse, fruitful conversation illuminating different limitations to fisheries that posed challenges when considering possible common avenues forward to support science-based fisheries management. We emphasize that the term "data-limited" covers a broad spectrum of conditions that not only include data constraints, but resource limitations as well. Our tool provides an accessible way for scientists and managers to identify where on the "spectrum" of data and resource availability their fishery lies, and provides a ranking of guiding principles, as functions of these attributes, that are likely needed to improve the ability to assess and manage a particular species fishery. As more fisheries engage with the tool, common patterns are likely to emerge, facilitating the global connection of scientists and managers of similar fisheries to share ideas and develop more targeted solutions with the aid of other tools (e.g., FishPath). We maintain that there is no "gold standard approach" for fisheries management; we should instead make management goals attainable and pragmatic while balancing economics with biological fishery sustainability and culture sustainability. By acknowledging the "Stock Assessment Theory of Relativity" and deconstructing the term "data-limited" into its proper components, we can talk more precisely about what challenges we are experiencing. And with that understanding, we can gain insight into the spectrum of conditions and offer appropriate guiding principles to better communicate and support the science of fisheries management.

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Author contributions JM. Cope was a co-lead developer of the paper concept, provided lead writing of the Introduction and Methods sections, produced several figures, edited the final version of the manuscript and developed the software application DLMapper. NA. Dowling, SA. Hesp, and KL. Omori were co-lead developers of the paper concept, providing lead writing of the results and discussion sections, produced figures and tables, provided major editing of the manuscript, and provided significant feedback on the DLMapper application. The remaining authors provided fishery examples to use in the paper and/or editorial assistance with the paper along with review of the DLMapper application.

Data availability The datasets generated during and/or analyzed during the current study are available at the following repository: https://github.com/shcaba/DL-Mapper

Declarations

Conflict of Interest The authors have no relevant financial or non-financial interests to disclose. The authors have no competing interests to declare that are relevant to the content of this article. All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript. The authors have no financial or proprietary interests in any material discussed in this article.

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