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Using data-limited approaches to assess data-rich Indian Ocean bigeye tuna: Data quantity evaluation and critical information for management implications

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Abstract

The majority of fishery stocks in the world are data limited, which limits formal stock assessments. Identifying the impacts of input data on stock assessment is critical for improving stock assessment and developing precautionary management strategies. We compare catch advice obtained from applications of various data-limited methods (DLMs) with forecasted catch advice from existing data-rich stock assessment models for the Indian Ocean bigeye tuna (*Thunnus obesus*). Our goal was to evaluate the consistency of catch advice derived from data-rich methods and data-limited approaches when only a subset of data is available. The Stock Synthesis (SS) results were treated as benchmarks for comparison because they reflect the most comprehensive and best possible scientific information of the stock. This study indicated that although the DLMs examined appeared robust for the Indian Ocean bigeye tuna, the implied catch advice differed between data-limited approaches and the current assessment, due to different data inputs and model assumptions. Most DLMs tended to provide more optimistic catch advice compared with the SS, which was mostly influenced by historical catches, current abundance and depletion estimates, and natural mortality, but was less sensitive to life-history parameters (particularly those related to growth). This study highlights the utility of DLMs and their implications on catch advice for the management of tuna stocks.

Key words: stock assessment, bigeye tuna, data-limited, fisheries management, Indian Ocean

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1 Introduction

Fisheries stock assessment provides critical information necessary for the conservation and management of fish stocks. Stock assessment models estimate fish stock parameters, determine stock status, and provide management advice on optimal fishing levels (Hilborn and Walters, 1992). The evolvement of stock assessment methods and the advancement of computing power enabled sophisticated stock assessment models to be built that make use of multiple datasets to inform a wide range of population and fishing processes. Both the richness of data and the complexity of assessment models have increased overtime (Maunder and Punt, 2013). Assessment models range from very simple models that utilize only a single data source (e.g., catch-only method) to highly integrated analysis, which is capable of simultaneously analyzing a large number of data inputs including environmental and ecosystem drivers.

Integrated analysis methods have become the preferred approach for conducting stock assessments since the publication of a seminal paper by Fournier and Archibald in 1982 (Fournier and Archibald, 1982; Fournier et al., 1998; Bull et al., 2012; Methot and Wetzel, 2013; Doonan et al., 2016; Punt et al., 2020). Integrated analyses, such as Stock Synthesis (SS) (Methot and Wetzel, 2013), are commonly employed because they are able to integrate multiple data sources, simultaneously model various processes, and are flexible in terms of model configuration (Cope, 2013; Methot and Wetzel, 2013). Integrated models are based on a coherent mathematical and statistical framework, which governs the population and fishing processes, and links the system dynamics to observational data (Maunder and Piner, 2017). Integrated analysis typically requires more data in order to support the modelling of population dynamics at a finer scale. However, for many stocks, data collected from different sources may have conflicting signals, often due to inadequate sampling processes, resulting in poor model fits. In some instances, conflicts among data sets can be caused by model misspecification as some population processes are not well understood (Maunder et al., 2017; Sagarese et al., 2019). Data conflict can introduce significant bias and uncertainty to the estimates of essential parameters and derived quantities which are difficult to quantify, and potentially result in inadequate management recommendations (Maunder et al., 2017; Griffiths and Fay, 2015; Van Beveren et al., 2017; Zhu and Kitakado, 2019).

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Comparing different modelling approaches helps us better understand population dynamics, allows us to evaluate the influence of crucial data inputs that on the assessment, and to identify appropriate data-limited approaches for coping with data limitations (Arnold and Heppell, 2015; Sagarese et al., 2019; Zhu and Kitakado, 2019). As data-limited methods (DLMs) was often used as interim solutions to allow time for data collection (e.g., Berkson and Thorson, 2015; Newman et al., 2015), understanding the impact of data quantity on stock assessment is important for improving stock assessment and developing precautionary management strategies (Cummings et al., 2014; Sagarese et al., 2019).

Tuna are among the world's most commercially valuable species, and are exploited by fleets from more than 70 countries. The most important species for commercial and recreational tuna fisheries are yellowfin (*Thunnus albacares*), bigeye (*Thunnus obesus*), bluefin (*Thunnus thynnus*), albacore (*Thunnus alalunga*), and skipjack (*Katsuwonus pelamis*) (ISSF, 2018). Assessing and managing these highly migratory species has been the focus of regional tuna fisheries management organizations (tRFMO). Integrated models such as MULTIFAN-CL and SS are commonly used by most tRFMOs to assess tuna stock status and provide management advice (ISSF, 2018). These integrated models are known to be able to capture well a range of uncertainty, including input uncertainty (uncertainty about input data or the quality of the information), statistical uncertainty (parameter estimation), and structural uncertainty (uncertainty associated model configurations or assumptions) (ISSF, 2018). One, or a combination of these uncertainties, is usually considered when determining stock status for providing management advice.

The Indian Ocean bigeye tuna (BET) is a large epi- and mesopelagic species distributed in the tropical and sub-tropical waters of the Indian Ocean. BET is a high-value species caught in large volumes by industrial fleets, subject to intense data collection. Thus, there is relatively more information collected on this species that allows the undertaking of fully quantitative stock assessments. Indian Ocean BET has been subject to stock assessment using SS3 (Fu, 2019), on the weight-of-evidence available in 2019, the BET stock is determined to be not overfished but subject to overfishing (IOTC Secretariat, 2020). The assessment has particularly highlighted the input uncertainty with respect to data quality and quantity (Fu, 2019). The research effort to evaluate and reduce the input uncertainty for improving management advice has been recommended by the IOTC Scientific Committee (ISSF, 2018).

In this study, we applied the DLMs to the Indian Ocean BET stock, and quantitatively compare the input data sets to identify their impacts on the stock assessment and the formulation of management strategies. Incorporating multiple sources of input uncertainty in a stock assessment can better account for the risks associated with proposed management options and promote decisions that are more robust to such uncertainties. The results are also relevant to many other commercial target and bycatch species under the IOTC mandate (e.g., neritic tuna, billfish, and shark), with most of these species lacking sufficient biological or exploitation information to produce a defensible quantitative stock assessment, as their data collection and reporting mechanisms are limited to the artisanal and semi-industrial fleets. Thus, another objective of this study is to evaluate if it is possible to use DLMs to provide fisheries management advice for data-limited stocks.

2 Materials and methods

2.1 *Data-rich model: SS*

SS (version v.3.30.15; Methot et al., 2020) is an age- and size-structured assessment model in the class of models termed integrated analysis models. The SS model has a population sub-model that simulates a stock's growth, maturity, fecundity, recruitment, movement, and mortality processes, an observation sub-model estimates expected values for various observed data, a statistical sub-model characterizes the data's goodness of fit and obtains best-fitting parameters with associated variance, and forecast sub-model projects need management quantities (Methot, 2009; Cope, 2013; Methot et al., 2020). The SS model outputs the quantities with confidence intervals required to implement risk-averse fishery control rules. SS has been applied in a wide variety of fishery assessments globally (Methot et al., 2020). The latest stock assessment for Indian Ocean BET was conducted using SS3 in 2019 (Fu, 2019). The SS3 assessment implements an age- and spatially structured model that reflected the population and fishery dynamics of the species. The assessment model covers the period 1975–2018 with the inclusion of composite longline CPUE indices, length compositions, and tag release/recovery data. To date model development has focused on accounting for the differences in regional exploitation patterns, resolving data conflicts, and exploring seasonal movement patterns.

2.2 *Data-limited methods*

The Data-Limited Methods Toolkit (DLMtool, version 5.4.5; Carruthers and Hordyk, 2018, 2020) is a software library for evaluating the performance of data-limited MPs. The DLMtool R package offers a robust, transparent approach for comparing, selecting, and applying various data-limited management methods. DLMtool utilizes parallel computing to make powerful diagnostics accessible (Punt et al., 2016; Carruthers and Hordyk, 2020). The DLM tool has two distinct components, a management strategy evaluation (MSE) simulation module and an application module which estimates the target catch using available data input. We used the application portion of DLMtool (and not the MSE), which has a wide range of built-in methods of varying complexity, but also allows users to specify their own options or to modify the existing methods. In this study, various DLMs were applied in setting target catches to the Indian Ocean BET stock, and these results were compared with those obtained with the SS3 assessment model. The data inputs for the SS3 assessment were extracted from IOTC Working Party on Tropical Tuna Meeting Website (https://iotc.org/WPTT/21/Data/14-SA-BET). Specific details on the data sources required for the DLMs are provided in Table 1.

We categorized the DLMs into five categories: catch-based methods, abundance-based methods, index-based methods, length-based methods, and age-based methods. A summary of these methods was highlighted and is presented in Table 2. Catch-based methods have generally been employed where insufficient data exist for determining an overfishing limit (*OFL*) using more sophisticated methods (Carruthers et al., 2014). Several catch-based methods have been adopted for the neritic and tuna assessments in the past several years and were deemed the best choice for the available data in the IOTC (Zhou et al., 2019). As an alternative to DLMs that rely solely or primarily on catch data and/or depletion estimates, there are also abundance-based and index-based methods. We tested a class of methods relying on estimates of current abundance and the fishing mortality rate at maximum sustainable yield (*FMSY*). We also explored length-based methods and age-based methods, as length and age composition data are the second-most abundant information held by the IOTC Secretariat, which potentially provides information on

Table 1. Data extracted from the 2019 Indian Ocean BET SS assessment model file for DLMs

Input	Description	Data	
		Value	Coefficient of variation (*CV*)
Year	years corresponding to data	1975–2018	–
t/a	number of years	44	–
Units	metric tonnes	–	–
Life history			
MaxAge/a	maximum age	11	–
Mort/a^{-1}	natural mortality rate	0.29	0.20
steep	steepness of the Beverton Holt stock-recruitment relationship	0.8	0.20
vbLinf/cm	Von Bertalanffy *Linf* parameter	150.91	0.10
vbK	Von Bertalanffy *K* parameter	0.11	0.10
vbt0	Von Bertalanffy t_0 parameter	−1.16	0.10
wla	weight-length parameter alpha	2.22×10^{-05}	0.10
wlb	weight-length parameter beta	3.01	0.10
L50/cm	length at 50 percent maturity	44.25	0.10
L95/cm	length increment from 50 percent to 95 percent maturity	52.64	0.10
Fishery			
Cat	annual sum of total catch (1975–2018)	40 020–93 515	0.10
AvC	average catch (*Cat*) over period with depletion estimates (1975–2018)	960 008.67	0.20
LFC	length at first capture	13.35	0.20
LFS	shortest length fully vulnerable to fishing	30.94	0.20
Cref	reference or target catch set to *MSY*	86 235.60	0.20
Bref	reference or target biomass set to spawning biomass at *MSY*	555 249	0.20
Abundance			
Ind	relative total abundance index (1975–2018)	Longline CPUE indices: 1.50–0.51	0.20
Dt	depletion over time *t* $SSB_{\text{now}}/SSB_{\text{now-}t+1}$	0.34	0.25
Dep	stock depletion $SSB_{\text{current}}/SSB_{\text{unfished}}$	0.31	0.25
Abun	current abundance (2018) (spawning biomass)	688 529	0.25
Composition			
CAA	catch-at-age data (1975–2018)	44 a×11 ages	–
CAL	catch-at-length data (1975–2018)	44 a× 95 length bins	–
CAL_bins	the values delimiting the length bins for the catch-at-length data	10–200 cm, 2 cm bins	–
ML	mean length time series (1975–2018)	121.46–71.90 cm	–
Reference (2019 SS assessment)			
BMSY_B0	the most productive stock size relative to unfished	0.25	0.045
FMSY_M	an assumed ratio of *FMSY* to *M*	0.90	0.25
Ref	reference *OFL*(a reference quota level)	61 931.40	–

Note: – represents no data.

fishery status we note that we focus only the DLMs that can be applied to the bigeye tuna fishery and not all the DLMs in the toolkit were tested.

2.3 *Species information and data*

The data used in the bigeye tuna assessment consist of catch and length composition data, longline CPUE indices, and tag release-recapture data. Figure 1 shows the stock trajectory from stock assessments of bigeye tuna in the Indian Ocean (1975–2020). The age-frequency and length-frequency distributions for bigeye tuna are shown in Figs 2 and 3 (every five years). The *Dep*, *Mort*, *BMSY_B0*, *FMSY_M*, *vbK*, *vbLinf* distributions from stock assessments of bigeye tuna in the Indian Ocean are shown in Fig. 4.

2.4 *Sensitivity to data inputs*

A sensitivity analysis was conducted for all DLMs to explore which data inputs most affect catch advice (Carruthers and Hordyk, 2020). Sensitivity analysis is a method in DLMtool that determines the inputs for a given DLM of class output and then analyse the sensitivity of catch advice estimates to marginal differences in each input (Carruthers and Hordyk, 2020). The variation assigned to each input determines the range of values over which the sensitivity is evaluated. In this way, the sensitivity test is standardized to be commensurate with the uncertainty ascribed to each parameter. The input data explored included bigeye tuna life history data, fishery data, abundance data, composition data and reference data depending on the different DLMs.

2.5 *Comparison of catch advice from data-rich and data-limited assessments*

Data-limited catch advice was produced for the years following the terminal year of data and was held constant between assessments. The SS catch advice equivalent to the overfishing limit was determined by the prescribed optimal target reference point and current stock status and was extracted from SS projections (via the forecast submodel) three years after the terminal assessment year (Table 1). To enable comparisons of catch advice from DLMs with SS-derived catch advice, 34 DLMs were used to produce catch advice.

Table 2. Description of DLMs applied and model inputs

Type	Method abbreviation	Description	Input	Reference
Catch-based	AvC	average catch over entire time series	*Cat*	Newman et al. (2014); Carruthers and Hordyk (2020)
	CC1	recent mean catch (last 5 a) Constant catch linked to average catches (TAC = C_{average}).	*Cat*	Geromont and Butterworth (2015b); Carruthers et al. (2016); Carruthers and Hordyk (2020)
	DCAC	depletion-corrected average catch Depletion is estimated each management interval and used to update the catch limit recommendation based on the historical catch.	*AvC, BMSY_B0, Dt, FMSY_M, Mort*	MacCall (2009); Harford and Carruthers (2017); Carruthers and Hordyk (2020)
	DCAC_40	DCAC is assuming current stock biomass to be exactly at 40 percent of unfished levels.	*AvC, BMSY_B0, FMSY_M, Mort*	MacCall (2009); Harford and Carruthers (2017); Carruthers and Hordyk (2020)
	DCAC4010	The dynamic DCAC is paired with the 40-10 rule that throttles back the *OFL* to zero at 10 percent of unfished stock size.	*AvC, BMSY_B0, Dt, FMSY_M, Mort*	MacCall (2009); Harford and Carruthers (2017); Carruthers and Hordyk (2020)
	DBSRA	depletion-based stock reduction analysis	*BMSY_B0, Cat, Dep, FMSY_M, L50, vbK, vbLinf, vbt0*	Dick and MacCall (2010, 2011); Carruthers and Hordyk (2020)
	DBSRA_40	DBSRA assuming stock depletion is 40% of unfished levels (B_{current}/B_0= 0.4).	*BMSY_B0, Cat, FMSY_M, L50, vbK, vbLinf, vbt0*	Dick and MacCall (2010, 2011); Carruthers and Hordyk (2020)
	DBSRA4010	DBSRA with a 40-10 harvest control rule	*BMSY_B0, Cat, Dep, FMSY_M, L50, vbK, vbLinf, vbt0*	Dick and MacCall (2010, 2011); Carruthers and Hordyk (2020)
	DD	Delay-Difference Stock Assessment	*Cat, Ind, L50, MaxAge, Mort, vbK, vbLinf, vbt0, wla, wlb*	Hilborn and Walters (1992); Carruthers et al. (2012); Carruthers and Hordyk (2020)
	DD4010	Delay-Difference Stock Assessment with a 40-10 harvest control rule	*Cat, Ind, L50, MaxAge, Mort, vbK, vbLinf, vbt0, wla, wlb*	Hilborn and Walters (1992); Carruthers et al. (2012); Carruthers and Hordyk (2020)
	SPMSY	catch trend surplus production MSY method	*Cat, L50, MaxAge, vbK, vbLinf, vbt0*	Martell and Froese (2013); Carruthers and Hordyk (2020)
Index-based	Islope1	Index Slope Tracking method CPUE slope (Adjust catch advice based on slope in CPUE for last 5 a or 10 a.)	*Cat, Ind*	Geromont and Butterworth (2015a); Carruthers et al. (2016); Carruthers and Hordyk (2020)
	Itarget1	CPUE target (Adjust catch advice to achieve a target CPUE, where target=1.5×mean CPUE during reference period.)	*Cat, Ind*	Geromont and Butterworth (2015a); Carruthers et al. (2016); Carruthers and Hordyk (2020)
	IT5	Iterative Index Target method. Maximum annual changes in TAC are 5 percent.	*Ind, Iref*	Carruthers and Hordyk (2020)
	Iratio	Mean Index Ratio	*Cat, Ind*	Jardim et al. (2015); ICES (2012)
	SBT1	Make incremental adjustments to TAC recommendations based on index levels relative to target levels (B_{MSY}/B_0) and catch levels relative to target levels (*MSY*).	*Cat, Ind*	Li (2011); Carruthers and Hordyk (2020)
	SPmod	surplus production based catch-limit modifier	*Cat, Ind*	Carruthers et al. (2016); Carruthers and Hordyk (2020)
	GB_slope	Geromont and Butterworth index slope Harvest Control Rule	*Cat, Ind*	Carruthers and Hordyk (2020); Geromont and Butterworth (2015b)
Abundance-based	SPslope	catch trend surplus production *MSY*	*Abun, Cat, Ind*	Carruthers et al. (2016); Carruthers and Hordyk (2020)
	Fratio	*FMSY/M* ratio method Requires an estimate of current abundance.	*Abun, FMSY_M, Mort*	Gulland (1971); Walters and Martell (2002); Martell and Froese (2013); Carruthers and Hordyk (2020)
	DepF	Depletion Corrected Fratio	*Abun, Dep, FMSY_M, Mort*	Gulland (1971); Walters and Martell (2002); Martell and Froese (2013); Carruthers and Hordyk (2020)
	DynF	Dynamic Fratio MP	*Abun, Cat, FMSY_M, Ind, Mort*	Carruthers and Hordyk (2020)
	Fadapt	Adaptive Fratio	*Abun, Cat, FMSY_M, Ind, Mort*	Carruthers et al. (2016); Maunder (2014)
	Fratio4010	Paired with the 40-10 rule that throttles back the *OFL* to zero at 10 percent of unfished biomass.	*Abun, Dep, FMSY_M, Mort*	Gulland (1971); Walters and Martell (2002); Martell and Froese (2013); Carruthers and Hordyk (2020)
	BK	Beddington and Kirkwood life history method	*Abun, LFC, vbK, vbLinf*	Beddington and Kirkwood (2005); Carruthers and Hordyk (2020)

to be continued

Continued from Table 2

Type	Method abbreviation	Description	Input	Reference
Length-based	LstepCC1	step-wise constant catch using mean length (Catch adjusted based on ratio of recent to reference mean length.)	*Cat, ML*	Geromont and Butterworth (2015a); Carruthers et al. (2016); Carruthers and Hordyk (2020)
	Ltarget1	length target (Adjust catch advice to achieve a target mean length, where target=1.05×mean length during reference period.)	*Cat, ML*	Geromont and Butterworth (2015a); Carruthers et al. (2016); Carruthers and Hordyk (2020)
	Lratio_BHI	mean length-based indicator MP Assumes *M/K*=1.5 and *FMSY/M*=1.	*CAL, CAL_bins, Cat, LFS, vbLinf*	Jardim et al. (2015)
	Lratio_BHI2	More general version that calculates the reference mean length as a function of *M, K,* and presumed *FMSY/M.*	*CAL, CAL_bins, Cat, FMSY_M, LFS, Mort, vbK, vbLinf*	Jardim et al.(2015)
	Lratio_BHI3	A modified version of Lratio_BHI2 where mean length is calculated for lengths>modal length (*Lc*).	*CAL, CAL_bins, Cat, FMSY_M, LFS, Mort, vbK, vbLinf*	Jardim et al.(2015)
	DCAC_ML	Depletion-Corrected Average Catch that uses a mean length estimator for current depletion.	*AvC, CAL, Cat, Lbar, Lc, Mort, vbK, vbLinf*	Gedamke and Hoenig (2006); MacCall (2009); Carruthers and Hordyk (2020)
Age-based	Fratio_CC	Current abundance is estimated using average catch and estimate of fishing mortality from an age-based catch curve.	*CAA, Cat, FMSY_M, Mort*	Gulland (1971); Walters and Martell (2002); Martell and Froese (2013); Carruthers and Hordyk (2020)
	BK_CC	Beddington and Kirkwood life history method that uses Catch Curve to estimate current abundance based on catches and recent fishing mortality.	*CAA, Cat, LFC, vbK, vbLinf*	Beddington and Kirkwood (2005); Carruthers and Hordyk (2020)
	YPR_CC	Yield per recruit analysis that uses a Catch Curve to estimate recent abundance.	*CAA, Cat, LFS, MaxAge, vbK, vbLinf, vbt0*	Beverton and Holt (1993)
Integrated analysis	SS	Stock Synthesis statistical age-structured population model	–	Methot (2009); Methot and Wetzel (2013); Methot et al. (2020);Fu (2019)

Note: – represents no data.

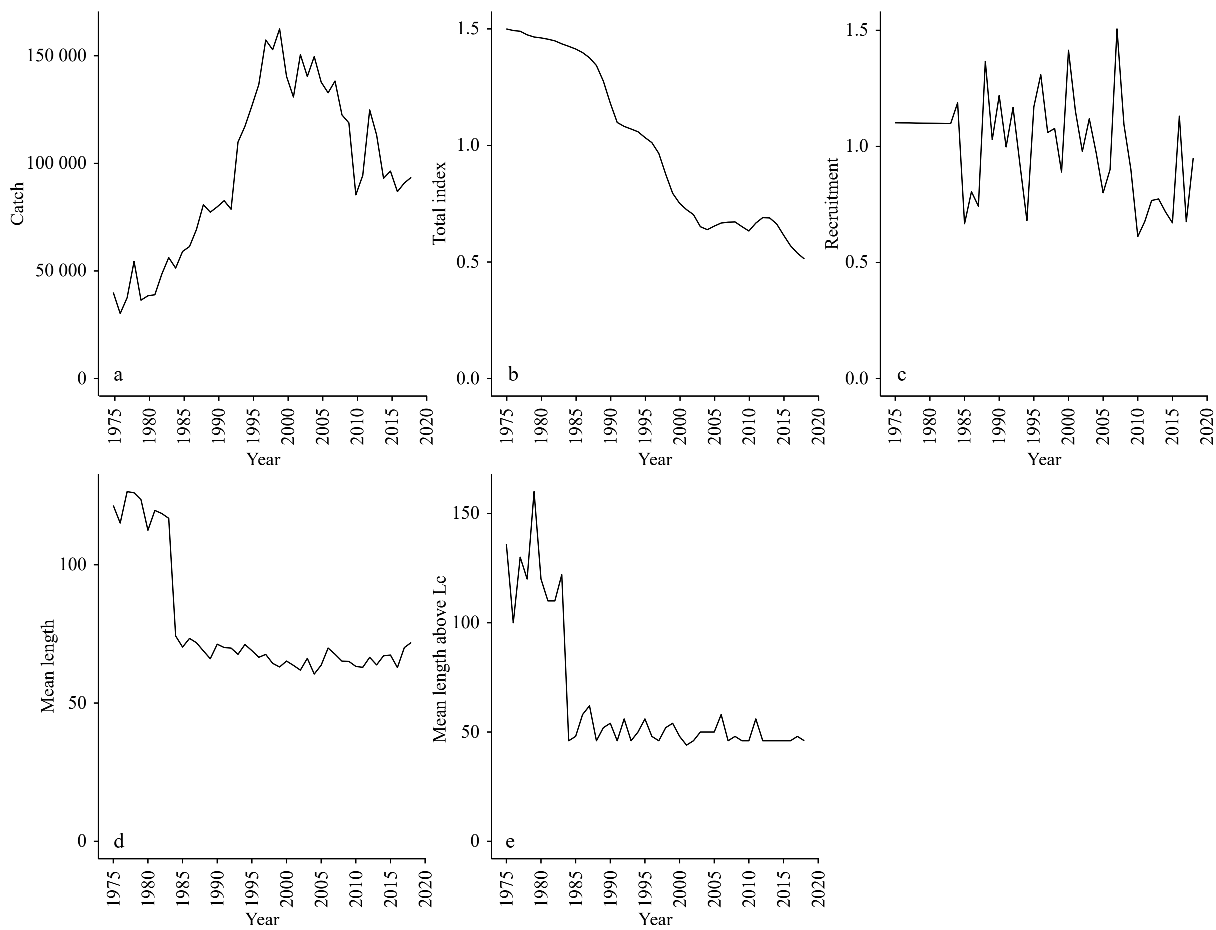

Fig. 1. The stock trajectory from the stock assessments of BET in the Indian Ocean (1975–2018).

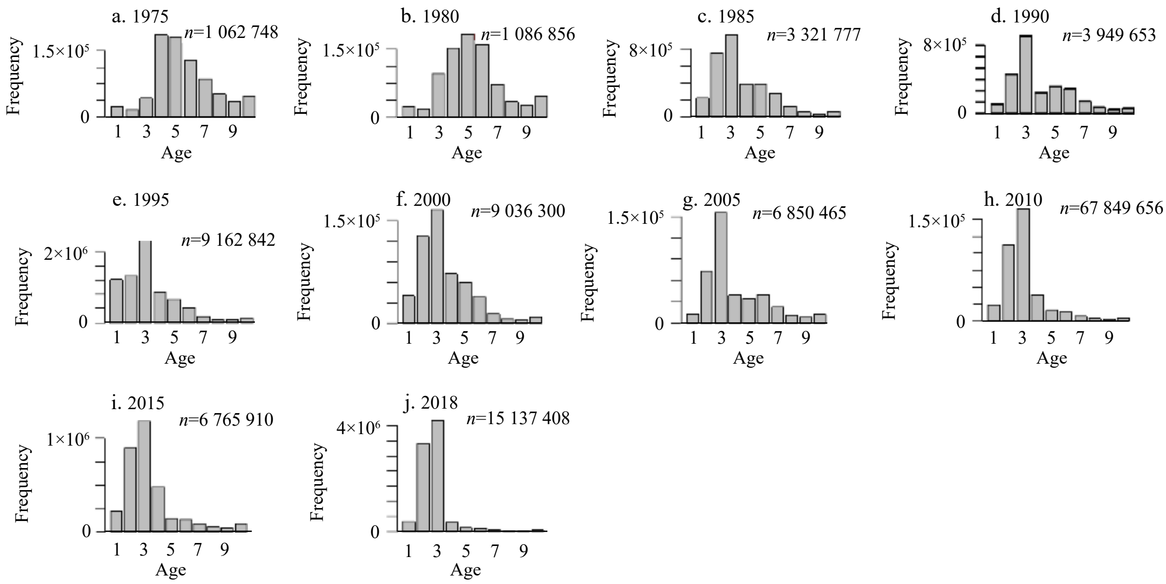

Fig. 2. Age-frequency distributions form stock assessments of BET in the Indian Ocean (1975–2018).

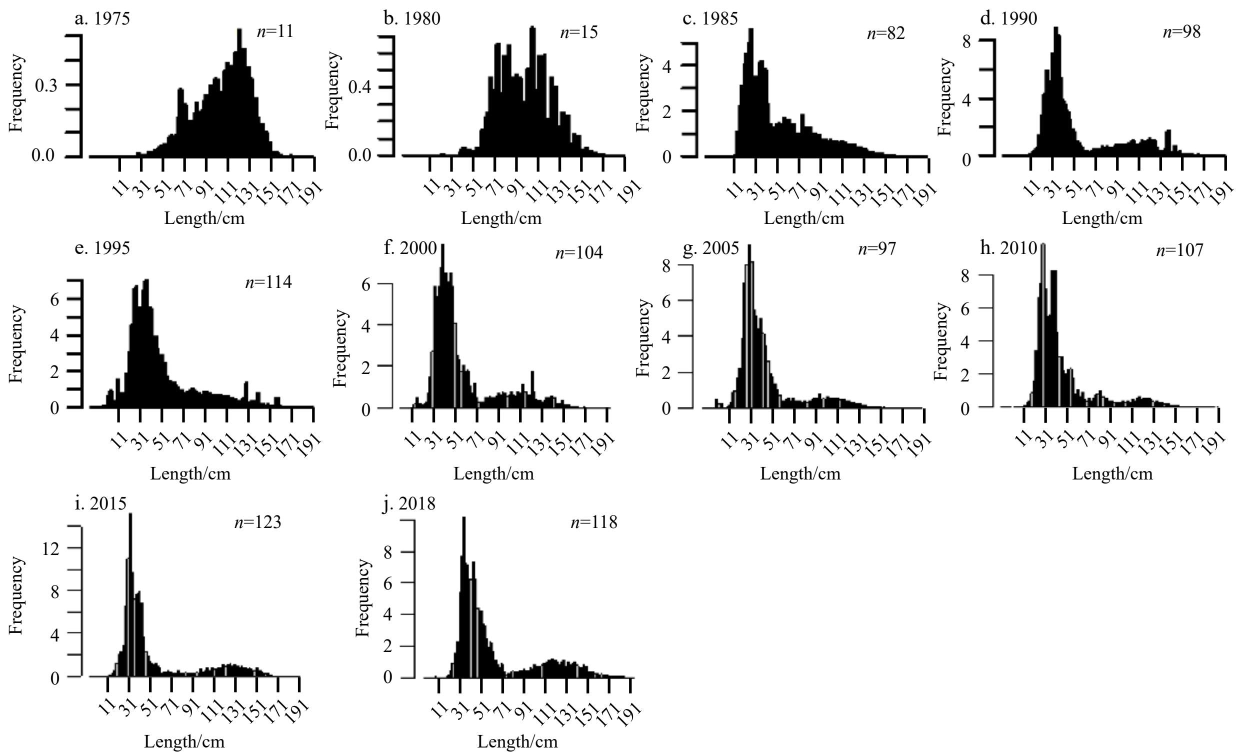

Fig. 3. Length-frequency distributions form stock assessments of BET in the Indian Ocean (1975–2018).

For each data-limited approach, a probability density function of catch advice was derived using 10 000 random draws from parameter distributions defined by the input mean and *CV* (Table 1). The median of the probability density function was used for the purpose of comparison (Carruthers et al., 2016). The distribution of the catch recommendation from SS was assumed to be normal and was obtained using a maximum likelihood approach. Because catch advice was set for a number of years in advance (to account for time lags caused by data collation and assessment implementation), assumed catches are fixed at predetermined quota levels for the first two years of the projection in SS. Thus, the third year of the projection represents the first year of catch advice; therefore, the forecasted catch (extracted as a point estimate with standard deviation) was used for comparison. Although the years being compared are not identical (e.g., terminal year of data, 2018; data-limited catch advice, 2019; SS catch advice, 2021), the approach to developing catch advice is similar (i.e., produce catch advice for the next possible year).

To quantitatively compare catch advice from each DLMs to the data-rich SS model (i.e., data-rich projection from current stock assessment model; *OFL* assessment), we calculated the relative absolute error (*RAE*) for the *OFL* (Dick and MacCall, 2011)

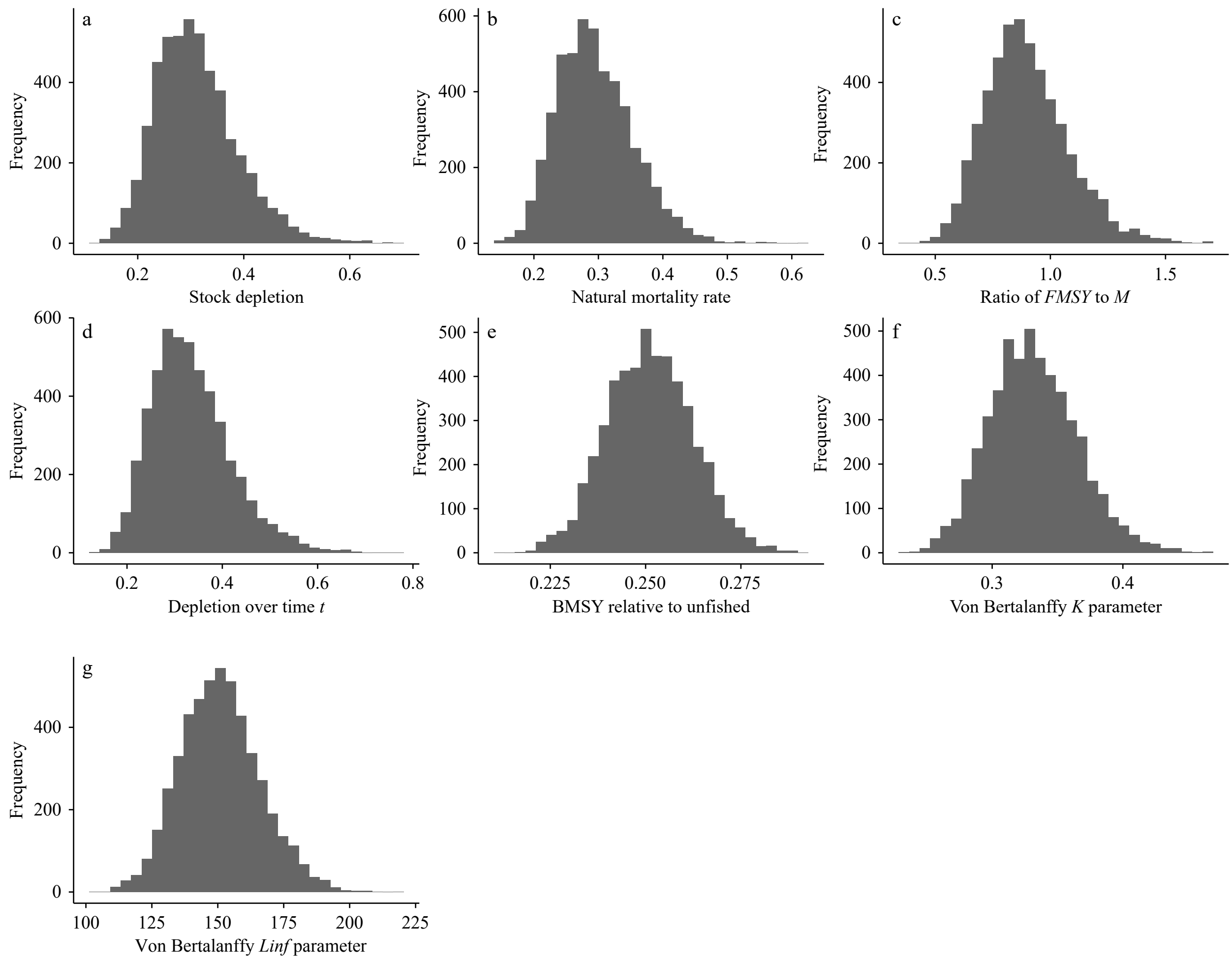

Fig. 4. Parameter distributions form stock assessments of BET in the Indian Ocean (1975–2018).

with the following equation:

$$RAE = \frac{|DLM - OFL_{\text{assessment}}|}{OFL_{\text{assessment}}}, \tag{1}$$

where $OFL_{\text{assessment}}$ was extracted from projections using the base SS assessment model as discussed above. The median of the probability density function was used for the purpose of comparison (Carruthers et al., 2016). Data-limited catch advice was produced for the year following the terminal year of data and was held constant between assessments. Larger *RAE* values indicate higher data-limited catch advice compared with SS catch advice, whereas smaller *RAE* values suggest similar catch advice between methods (close to zero). Inherently we assume that derived products and parameters from SS reflect the "known truth" for the purpose of addressing whether simpler models can produce similar results, an assumption that may not be accurate.

3 Results

3.1 *Sensitivity of performance to inputs and value of information*

Sensitivity analyses revealed that input data tended to affect the catch advice for all methods included in this study, and detailed information on the input data is provided in Table 1. For almost all DLMs catch advice was sensitive to catch data (*Cat, AvC*) (Table 3). The majority of DLMs requiring an estimate of *Mort* in the input, catch advice was particularly sensitive. Other inputs such as depletion estimates, abundance, *BMSY_B0* and *FMSY_M* were also influential in deriving catch advice (Table 3). In instances in which catch data was required as data inputs, these recommendations were seldom sensitive to life-history parameters related to growth such as *wla* and *wlb*, and the theoretical age at length zero (*vbt0*).

For bigeye tuna life-history data (Table 1), except for *Mort*, the historical life history data of bigeye tuna was not sensitive to catch advice using catch-based methods (Table 3). This result indicated that for most catch-based methods, the bigeye tuna fishery life-history data had little influence on catch advice. However, for Delay-Difference Stock Assessment (DD and DD4010), the sensitivity analysis results showed that the catch advice was more sensitive to the current level of *Dep* and the shortest length at full selection (*LFS*), where catch advice was positively correlated to *Dep* and negatively correlated to *LFS* (Table 3). For the abundance-based method, the catch advice of Beddington and Kirkwood life history method (BK) was sensitive to life-history parameters *vbLinf* and *vbK*, and we also found that catch advice from BK was fairly linearly related to the level of *vbLinf* and *vbK* over which sensitivity was tested. Lratio_BHI, Lratio_BHI2, Lratio_BHI3 and age-based (BK_CC) methods have similar results (Table 3).

However, for composition data (Table 1), the sensitivity analysis results of age-based methods showed that age composition

Table 3. Sensitivity analysis (SA) of input data needed for DLMs

Method	Input data																						
	Life history									Fishery						Abundance				Com*		Ref*	
	MaxAge	*Mort*	*vbLinf*	*vbK*	*vbt0*	*wla*	*wlb*	*L50*	*L95*	*Cat*	*AvC*	*LFC*	*LFS*	*Cref*	*Bref*	*Ind*	*Dt*	*Dep*	*Abun*	*CAA*	*CAL*	*BMSY_B0*	*FMSY_M*
Catch-based																							
AvC	–	–	–	–	–	–	–	–	–	**SA**	–	–	–	–	–	–	–	–	–	–	–	–	–
CC1	–	–	–	–	–	–	–	–	–	**SA**	–	–	–	–	–	–	–	–	–	–	–	–	–
DCAC	–	**SA**	–	–	–	–	–	–	–	–	**SA**	–	–	–	–	–	**SA**	–	–	–	–	**SA**	**SA**
DCAC_40	–	**SA**	–	–	–	–	–	–	–	–	**SA**	–	–	–	–	–	–	–	–	–	–	**SA**	**SA**
DCAC4010	–	**SA**	–	–	–	–	–	–	–	–	**SA**	–	–	–	–	–	**SA**	–	–	–	–	**SA**	**SA**
DBSRA	–	–	SA	SA	SA	–	–	SA	–	**SA**	–	–	–	–	–	–	–	**SA**	–	–	–	**SA**	**SA**
DBSRA_40	–	–	SA	SA	SA	–	–	SA	–	**SA**	–	–	–	–	–	–	–	–	–	–	–	**SA**	**SA**
DBSRA4010	–	–	SA	SA	SA	–	–	SA	–	**SA**	–	–	–	–	–	–	–	**SA**	–	–	–	**SA**	**SA**
DD	SA	**SA**	SA	SA	SA	SA	SA	**SA**	–	**SA**	–	–	–	–	–	SA	–	–	–	–	–	–	–
DD4010	SA	**SA**	SA	SA	SA	SA	SA	**SA**	–	**SA**	–	–	–	–	–	SA	–	–	–	–	–	–	–
SPMSY	SA	–	SA	SA	AS	–	–	SA	–	**SA**	–	–	–	–	–	–	–	–	–	–	–	–	–
Index-based	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Islope1	–	–	–	–	–	–	–	–	–	**SA**	–	–	–	–	–	**SA**	–	–	–	–	–	–	–
Itarget1	–	–	–	–	–	–	–	–	–	**SA**	–	–	–	–	–	**SA**	–	–	–	–	–	–	–
IT5	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	**SA**	–	–	–	–	–	–	–
Iratio	–	–	–	–	–	–	–	–	–	**SA**	–	–	–	–	–	**SA**	–	–	–	–	–	–	–
SBT1	–	–	–	–	–	–	–	–	–	**SA**	–	–	–	–	–	**SA**	–	–	–	–	–	–	–
SPmod	–	–	–	–	–	–	–	–	–	**SA**	–	–	–	–	–	**SA**	–	–	–	–	–	–	–
GB_slope	–	–	–	–	–	–	–	–	–	**SA**	–	–	–	–	–	**SA**	–	–	–	–	–	–	–
Abundance-based																							
SPslope	–	–	–	–	–	–	–	–	–	**SA**	–	–	–	–	–	SA	–	–	**SA**	–	–	–	–
Fratio	–	**SA**	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	**SA**	–	–	–	**SA**
DepF	–	**SA**	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	**SA**	**SA**	–	–	–	**SA**
DynF	–	**SA**	–	–	–	–	–	–	–	**SA**	–	–	–	–	–	**SA**	–	–	**SA**	–	–	–	**SA**
Fadapt	–	**SA**	–	–	–	–	–	–	–	**SA**	–	–	–	–	–	SA	–	–	**SA**	–	–	–	**SA**
Fratio4010	–	**SA**	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	**SA**	**SA**	–	–	–	**SA**
BK	–	–	**SA**	**SA**	–	–	–	–	–	–	–	**SA**	–	–	–	–	–	–	**SA**	–	–	–	–
Length-based																							
LstepCC1	–	–	–	–	–	–	–	–	–	**SA**	–	–	–	–	–	–	–	–	–	–	–	–	–
Ltarget1	–	–	–	–	–	–	–	–	–	**SA**	–	–	–	–	–	–	–	–	–	–	–	–	–
Lratio_BHI	–	–	**SA**	–	–	–	–	–	–	**SA**	–	–	**SA**	–	–	–	–	–	–	–	SA	–	–
Lratio_BHI2	–	**SA**	**SA**	**SA**	–	–	–	–	–	**SA**	–	–	**SA**	–	–	–	–	–	–	–	SA	–	**SA**
Lratio_BHI3	–	**SA**	**SA**	**SA**	–	–	–	–	–	**SA**	–	–	**SA**	–	–	–	–	–	–	–	SA	–	**SA**
DCAC_ML	–	**SA**	SA	SA	–	–	–	–	–	**SA**	**SA**	–	–	–	–	–	–	–	–	–	SA	–	–
Age-based	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Fratio_CC	–	**SA**	–	–	–	–	–	–	–	**SA**	–	–	–	–	–	–	–	–	–	SA	–	–	**SA**
BK_CC	–	–	**SA**	**SA**	–	–	–	–	–	**SA**	–	**SA**	–	–	–	–	–	–	–	SA	–	–	–
YPR_CC	SA	–	SA	**SA**	SA	–	–	–	–	**SA**	–	–	**SA**	–	–	–	–	–	–	SA	–	–	–

Note: The criteria for sensitive and not sensitive, the range of values over which the sensitivity is evaluated in DLMs; deep color, sensitive; light color, not sensitive; Com*, Composition; Ref*, Reference (2019 SS assessment); –, no data.

data were not sensitive to catch advice (Table 3). For *BMSY_B0* and *FMSY_M*, all methods that require these two parts of the data were sensitive, especially for catch-based and abundance-based methods. The catch advice was positively correlated to *FMSY_M*, and negatively correlated with *BMSY_B0*.

3.2 *Comparison of catch advice between DLMs and SS*

Catch advice derived from data-limited approaches for bigeye tuna in the Indian Ocean was shown in Table 4. We found that catch advice for data-limited approaches was highly variable and uncertain, with standard deviations greatest for BK_CC (244 970 t) and smallest for DynF (60 t). Among the five categories of DLMs, the age-based method has a larger standard deviations than the other four categories, and the corresponding *CV* was also the largest (Table 4). Among the 34 DLMs, the catch advice varies so much between the different methods, BK (227 622 t) has the highest catch advice and Itarget1 (54 681 t) has the lowest catch advice. The index-based and length-based methods had lower catch advice than the other three categories of methods (Table 4).

We also compared the distributions of relative absolute errors between SS and DLMs for Indian Ocean BET (Fig. 5). The majority of catch-based, index-based, and length-based tested (excluding DBSRA, SPMSY) resulted in *RAE*s less than 1 (Fig. 5). Most abundance-based and age-based methods resulted in *RAE*s greater than 1 (Fig. 5). Only Itarget1, DCAC4010, Islope1 and IT5 produced an *RAE* below 0.1, and relatively similar *OFL* distributions compared to SS (Figs 5 and 6). The median catch advice of

Table 4. Catch advice (unit, t) derived from data-limited approaches for BET in the Indian Ocean

Method	Percentile					Mean value	*SD*	*CV*
	0%	25%	50%	75%	95%			
AvC	42 982	83 732	95 695	109 422	132 435	97 557	19 542	0.20
CC1	77 643	89 424	92 103	94 884	99 042	92 174	4 089	0.04
DCAC	51 772	74 312	77 754	80 632	84 277	77 326	4 647	0.06
DCAC_40	58 180	76 301	79 037	81 491	84 667	78 720	3 955	0.05
DCAC4010	7 347	44 053	57 887	73 636	83 281	57 759	17 522	0.30
DBSRA	24 674	100 709	125 733	156 165	212 521	131 782	43 585	0.33
DBSRA_40	142 250	172 261	178 896	185 519	195 422	179 044	9 894	0.06
DBSRA4010	0	52 125	86 420	135 382	211 378	98 773	60 128	0.61
DD	77 715	100 266	106 888	113 756	124 094	107 241	9 832	0.09
DD4010	72 611	100 597	106 856	113 722	124 024	107 350	9 732	0.09
SPMSY	58 118	109 687	137 981	157 536	169 613	132 010	29 725	0.23
Islope1	59 962	60 259	60 321	60 384	60 473	60 322	92	0.00
Itarget1	45 508	53 019	54 681	56 334	58 776	54 709	2 454	0.04
IT5	28 308	55 590	63 426	72 829	88 320	64 857	13 033	0.20
Iratio	34 344	68 736	79 084	91 321	110 840	80 894	16 897	0.21
SBT1	60 541	84 898	90 803	97 226	107 028	91 316	9 129	0.10
SPmod	1 778	73 427	84 251	93 839	105 964	83 035	15 509	0.19
GB_slope	74 811	81 136	86 904	93 106	103 026	87 610	8 453	0.10
SPslope	76 927	88 790	91 864	94 984	99 445	91 918	4 544	0.05
Fratio	41 906	132 359	169 883	219 604	315 231	182 374	69 922	0.38
DepF	28 688	107 361	140 791	183 081	269 037	151 165	61 636	0.41
DynF	92 711	92 711	92 711	92 711	92 711	92 712	60	0.00
Fadapt	109 321	115 927	117 695	119 498	122 239	117 776	2 656	0.02
Fratio4010	0	78 253	114 160	159 439	245 602	125 180	65 050	0.52
BK	78 369	189 727	227 622	272 895	356 358	236 085	64 401	0.27
LstepCC1	77 680	89 370	92 078	95 021	99 270	92 207	4 176	0.05
Ltarget1	71 799	82 385	84 864	87 460	91 442	84 983	3 812	0.04
Lratio_BHI	57 360	96 251	106 083	117 023	134 707	107 186	15 659	0.15
Lratio_BHI2	46 075	75 779	84 593	94 851	111 461	85 977	14 375	0.17
Lratio_BHI3	47 747	76 026	84 869	94 684	111 086	85 959	14 020	0.16
DCAC_ML	80 079	88 373	89 603	90 663	91 889	89 410	1 751	0.02
Fratio_CC	25 896	88 877	127 001	199 889	532 951	191 280	216 492	1.13
BK_CC	49 377	119 849	162 504	251 020	644 250	238 947	244 970	1.03
YPR_CC	36 783	92 241	126 980	196 721	537 264	191 021	212 107	1.11

Note: *SD*, standard deviation; *CV*, coefficient of variation.

these four DLMs was within 10% of the *OFL* of SS, and *OFL* distribution peaked near the *OFL* distribution of SS (Fig. 6).

The comparison of the *OFL* estimated by the SS model and DLMs for Indian Ocean BET was showed in Fig. 6. Most methods resulted in wider *OFL* distributions (median range: 54 681 (Itarget1)–227 622 t (BK)) compared to SS (61 931 t) (Table 4). This indicated a substantial amount of uncertainty when compared to the *OFL* distribution produced by the data-rich SS model. For catch-based methods, except DBSRA4010, DCAC4010, CC1, SPMSY, the *OFL* distributions of the other seven methods were relatively narrow (Fig. 6a). For index-based methods, only Itarget1 *OFL* distribution was relatively close, and the catch advice was smaller than SS (Fig. 6b, Table 4). The *OFL* distribution of IT5 was similar to SS; *OFL* distribution peaked near the *OFL* distribution of SS (Fig. 6b). For the abundance-based methods, Fratio, DepF and Fratio4010 result in high and relatively wide *OFL* distributions (Fig. 6c). This showed that these three methods have higher uncertainty. The *OFL* distribution of the Length-based method was more uniform and narrower than the other four types of DLMs methods (Fig. 6d). The *OFL* distribution of the three age-based methods was wider, and the catch advice was much higher than the catch advice based on SS (Fig. 6e, Table 4).

4 Discussion

Identifying the impacts of input data quality and quantity was critical for improving stock assessment and developing precautionary management strategies. This analysis aimed to investigate whether similar assessment results could be achieved with DLMs as opposed to more complex conventional stock assessment methods for Indian Ocean BET. We applied a DLM sensitivity analysis to explore which input data most affect catch advice. Catch-based, index-based, and length-based DLMs tended to produce similar results across life-history stages, other methods included abundance-based and age-based DLMs also produced viable results for Indian Ocean BET. This analysis focused on the range of DLMs commonly applied to date. While most methods examined in the study were feasible for bigeye tuna based on available data inputs, the resulting *OFL* distributions were not necessarily accurate or robust to uncertainty. Many DLMs produced relatively wide *OFL* distributions, suggesting a substantial amount of uncertainty. For almost all applicable DLMs, catch advice was particularly sensitive to *Cat*, *Mort*, *Abun*, *Dep*, and

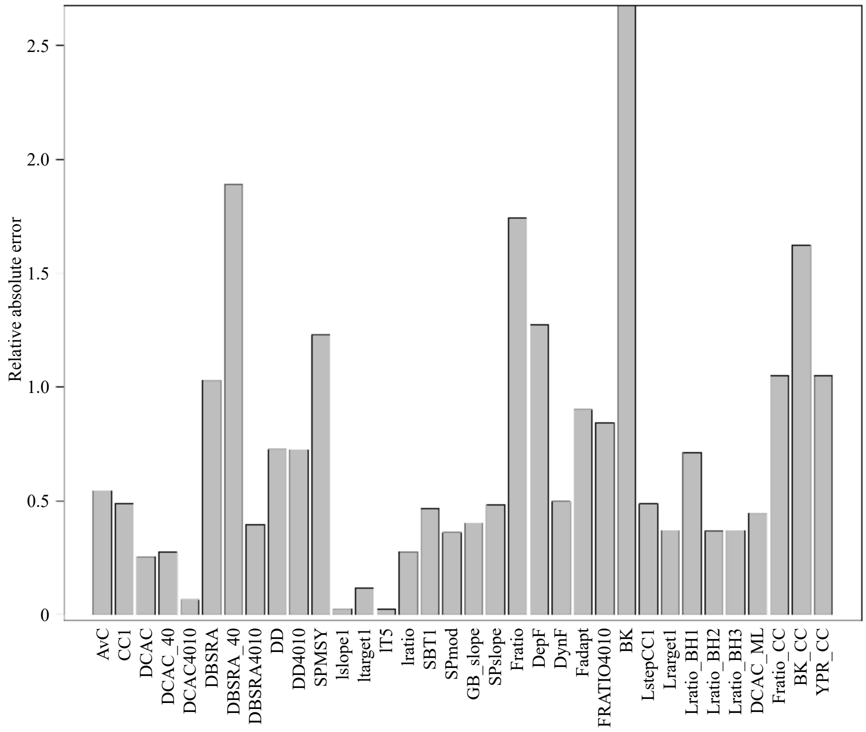

Fig. 5. Comparison of relative absolute error of DLMs for Indian Ocean BET.

FMSY_M with higher data inputs corresponding to higher quotas (positive correlation). In some instances, catch advice was also sensitive to life-history parameters relating to growth (*vbLinf*, *vbK*) and *BMSY_B0*.

In recent years, the IOTC explored various DLMs for some small tuna species, including application of catch-based methods and length-based methods (Dick and McCall, 2011; Martell and Froese, 2013; Cope, 2013; Hordyk et al., 2015; Hordyk, 2019; Froese et al., 2017, 2018; Rudd, 2018; Rudd and Thorson, 2018). There was generally substantial uncertainty in the estimation of stock status, and the results were susceptible to input parameters. The examination of data-rich assessment management frameworks using DLMs has revealed common patterns and highlighted potential challenges in developing catch advice for data-poor stocks. The catch-based, index-based, or length-based methods showed considerable promise. Index-based methods and length-based methods in particular often outperformed other DLMs in reproducing the *OFL* that is consistent with the SS model. Yet, additional testing using a management strategy evaluation framework is required to adequately evaluate the performance of both methods based on representative stock life histories and fleet characteristics. The closed-loop simulation studies such as MSE should be considered most appropriate to determine the most feasible management strategy. Data-limited applications can provide much-needed insight into stock dynamics within data-poor stocks (such as small tuna or like-species tuna) until data collection improves, time series of abundance lengthen, and/or analytical resources expand.

In this study, the output from SS was taken as the “truth” or more realistic reflection of “true” fisheries dynamics, an approach which sought to determine whether simple models could obtain similar results to a more complex model. Neither the aforementioned assumption nor the statistical procedures necessarily imply that any of the models were correct. In the practice of setting harvest recommendations, complex models were often regarded as more reputable sources. However, for data-poor stocks, complex models may also be biased due to violation of assumptions (e.g., constant fishing efficiency) or model misspecification, and some key parameters (e.g., steepness, natural mortality, etc.) are often inestimable (Carruthers et al., 2014). Therefore, we recommend that more DLMs be explored for data-poor stocks using data-limited assessment methods and MSE.

For data-poor species, the lack of consistent and long-term fishery-independent surveys exacerbates uncertainty in assessing stock dynamics (Cummings et al., 2014). Simple management procedures based on an index of abundance and length have gained momentum in recent years (Geromont and Butterworth, 2015a, b). They thus warrant additional efforts to quantify the relative abundance. For length-based methods, mean length information was relatively easy to obtain even in data-poor fisheries. Closed-loop simulation studies such as management strategy evaluation should be considered to determine the most feasible management. DLMs to bigeye tuna can serve as a learning experience for managing data-limited stocks in the Indian Ocean. With their sensitivity to data inputs in the analyses of results, DLMs can provide much-needed insight into the stock dynamics of data-poor stocks (such as small tuna or like-species tuna) until data collection, time series of abundance length and/or analytical resources expand.

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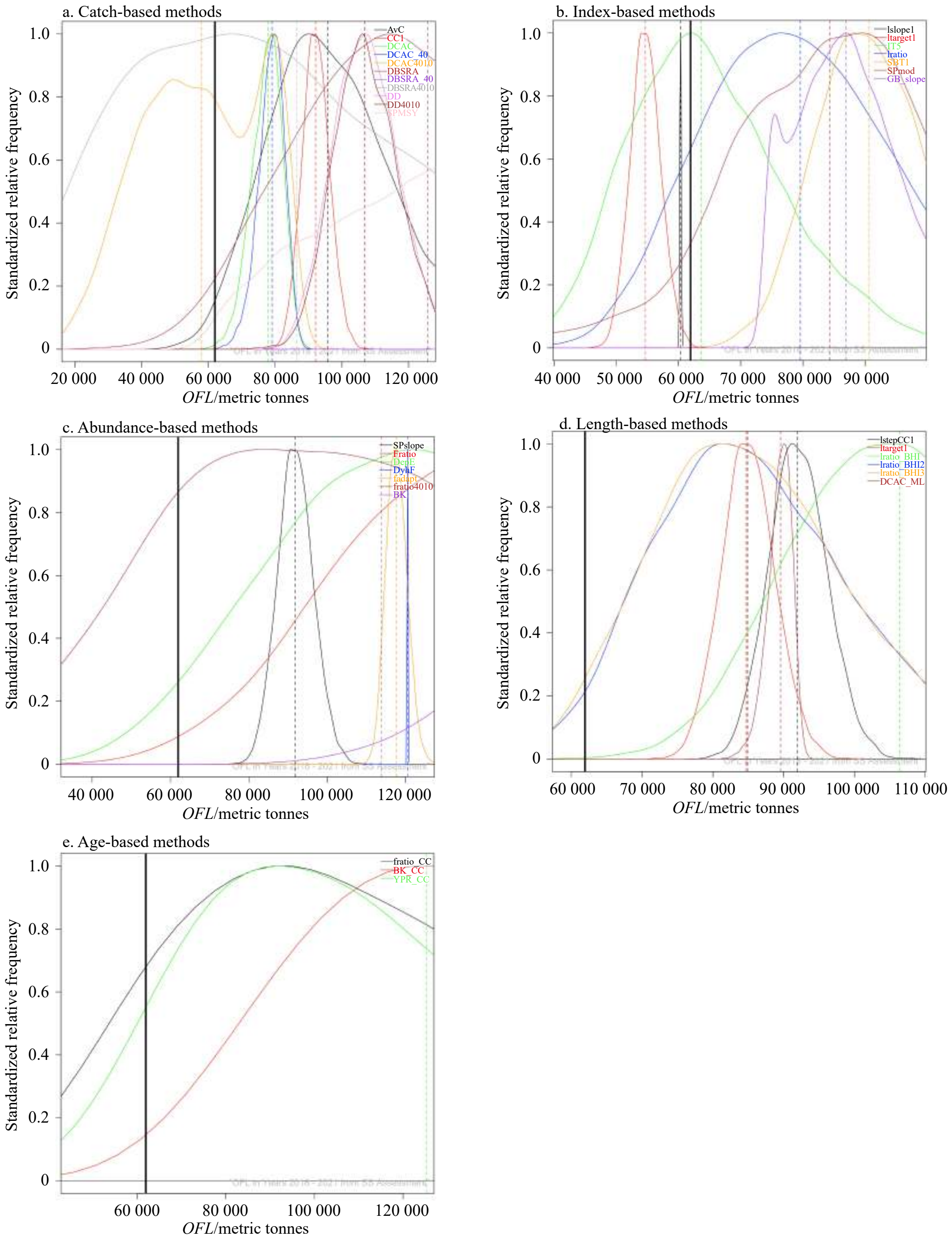

Fig. 6. Comparison of the overfishing limits (*OFL*) estimated by the data-rich SS.

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