Assessment of Indian Ocean longtail tuna (*Thunnus tonggol*) using data-limited methods

30th June 2020

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1. Introduction

Assessing the status of the stocks of neritic tuna species in the Indian Ocean is challenging due to the paucity of data. There is lack of reliable information on stock structure, abundance and biological parameters. Stock assessments have been conducted annually for Longtail tuna (*Thunnus tonggol*) from 2013 to 2017 using data-limited methods (Zhou and Sharma, 2013; Zhou and Sharma, 2014; Martin and Sharma, 2015; Martin and Robinson, 2016, Fu & Martin, 2017). In 2017, three data-limited methods were explored to assess the status of *T. tonggol*: (i) a C-MSY method (Froese et al. 2016), (ii) an Optimised Catch-Only Method, or OCOM (Zhou et al., 2013), and (iii) a stochastic SRA (Carruthers et.al. 2014). This paper provides an update to the C-MSY assessment based on the most recent catch information. In addition, a Bayesian biomass dynamic model was also implemented to include the recently available CPUE indices of the longtail tuna developed from the Iranian gillnet fishery.

2. Basic Biology

Longtail tuna (*Thunnus tonggol*) is an epipelagic species inhabiting tropical to temperate provinces of the Indo-Pacific, found almost exclusively in the neritic waters close to the shore, avoiding estuaries, turbid wasters and open ocean (Froese & Pauly 2015). It is one of the smallest species of the genus *Thunnus*, but relatively large compared with other neritic species with a maximum length of 145cm. Longtail tuna in the Indian Ocean is primarily caught by gillnet fleets operating in coastal waters with the highest reported catches from Iran, followed by Indonesia, India, Pakistan, Oman, Malaysia, Thailand and others (Geehan et al. 2016). Most research on Indian Ocean longtail tuna has been focussed in these areas where there are important fisheries for the species, with the most common methods used to estimate growth being through length-frequency studies. These studies have provided varied estimates of growth, with the majority of estimates of von Bertalanffy k values ranging from 0.18 (Ghosh et al. 2010) – 0.55 (Yesaki, 1989) with some more extreme values; 1.5 (Itoh et al. 1999). Some of these differences may be due to the different estimation techniques, due to regional differences in the maximum size of fish in the areas and due to differences in the size selectivity of the different fish sampling methods (IOTC, 2015).

3. Catch, CPUE and Fishery trends

Nominal catch data were extracted from the IOTC Secretariat database for the period 1950–2018, given that records for 2019 were still incomplete at the time of writing. Gillnet fleets are responsible for the vast majority of reported catches of longtail with a much smaller proportion caught by purse seine and line gear, with the majority of catches taken by coastal country fleets, namely I.R. Iran, Indonesia, Pakistan, India, and Oman (Figure 1).

Figure 2 shows the increase in total catches since 1950, highlighting a particularly rapid increase between 2004 and 2012, when catches reached a maximum of 176,551 t. This has since been followed by a decline to the current estimated total catches of 135, 282t in 2018 (Table 1). In 2019, IOTC endorsed the revisions of Pakistani gillnet catches that introduce some changes in the catches of tropical tuna, billfish, as well as some neritic tuna species since 1987 (IOTC–WPDCS15 2019). However, the revision appears to have very minor effects on the longtail nominal catch series since the last assessment (Figure 3).

There is a relatively high uncertainty associated with the catch data for neritic tunas due to the difficulties in differentiating amongst the different species resulting in highly aggregated reported data, often as 'seerfishes' or other groupings. Therefore, the IOTC Secretariat uses various methods of estimating the disaggregated catches by species for assessment purposes. Fu & Martin (2017) showed there are close correlations between the catches over time of each of the six neritic tunas. The high level of correlation amongst these species is likely to be because they are often caught together, due to difficulty with species identification and also because of the estimation procedures used to assign proportions of catch amongst the various species. Species-specific reporting has improved over time, leading to a lower level of correlation in more recent years.

Fu et al. (2019) developed standardised CPUE indices for several neritic tuna species including longtail tuna from the Iranian coastal gillnet fishery using the catch effort data collected from the port-sampling program. That analysis represented an effort to estimate a relative abundance index for neritic tuna stocks for potential use in stock assessments. The quarterly indices (2008–2017) for the longtail tuna showed a large decline since 2012 (Figure 4). The annualised indices (by taking the average of the quarterly indices) are included in the assessment method based on Bayesian Schaefer production model (see Section 4.2).

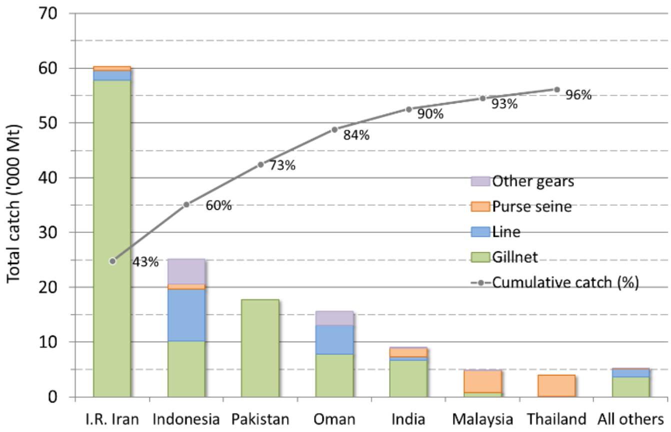

Figure 1: Average catches in the Indian Ocean over the period 2012-2018, by country. The red line indicates the (cumulative) proportion of catches of longtail by country.

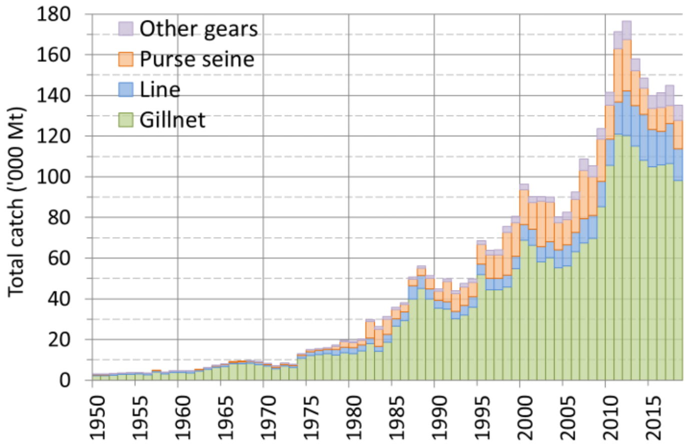

Figure 2: Annual catches of longtail tuna by gear, 1950 – 2018 (IOTC database).

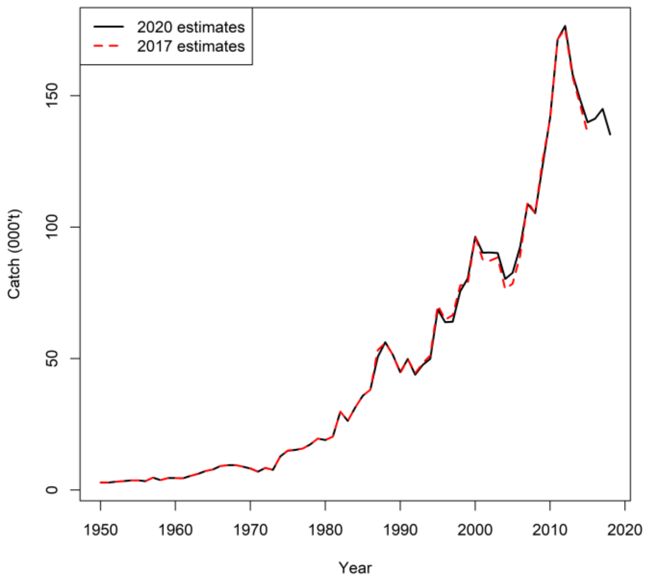

Figure 3: Revisions to IOTC nominal catch data for longtail tuna (datasets used for the 2017 and 2020 assessments).

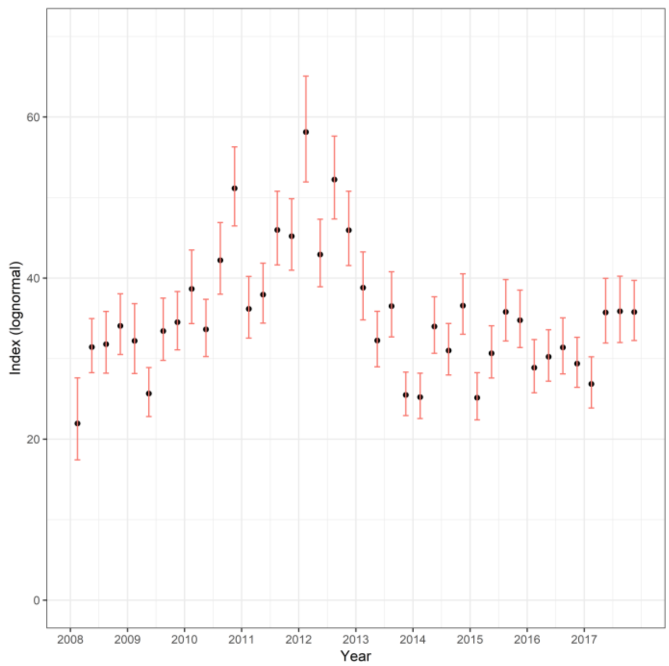

Figure 4: Standardised CPUE indices (year-quarter) for longtail tuna 2008–2017 from the GLM lognormal model . See Fu et al. (2019) for details.

Table 1. Catch data for *T. tonggol* in the Indian Ocean, 1950-2018 (source IOTC Database)

Year	Catch (t)	Year	Catch (t)
1950	2 841	1985	35 850
1951	2 817	1986	38 147
1952	3 095	1987	50 624
1953	3 362	1988	56 190
1954	3 604	1989	51 478
1955	3 640	1990	44 802
1956	3 318	1991	49 825
1957	4 696	1992	43 854
1958	3 742	1993	47 556
1959	4 523	1994	49 874
1960	4 536	1995	68 655
1961	4 451	1996	63 848
1962	5 333	1997	64 015
1963	6 128	1998	75 614
1964	7 192	1999	80 473
1965	7 773	2000	96 343
1966	9 115	2001	90 250
1967	9 428	2002	90 357
1968	9 465	2003	90 104
1969	8 877	2004	80 269
1970	8 162	2005	82 631
1971	6 977	2006	92 483
1972	8 363	2007	108 844
1973	7 644	2008	105 307
1974	12 804	2009	123 696
1975	14 937	2010	141 618
1976	15 256	2011	171 396
1977	15 782	2012	176 551
1978	17 346	2013	158 058
1979	19 541	2014	148 577
1980	19 010	2015	139 899
1981	20 274	2016	141 256
1982	29 798	2017	144 968
1983	26 257	2018	135 282
1984	31 386		

4. Methods

4.1. C-MSY method

The C-MSY method of Froese et al. (2016) was applied to estimate reference points from catch, resilience and qualitative stock status information for the longtail tuna. The C-MSY method represents a further development of the Catch-MSY method of Martell and Froese (2012), with a number of improvements to reduce potential bias. Like the Catch-MSY method, The C-MSY relies on only a catch time series dataset, which was available from 1950 – 2018, prior ranges of *r* and *K*, and possible ranges of stock sizes in the first and final years of the time series.

The Graham-Shaefer surplus production model (Shaefer 1954) is used (equation 1), but it is combined with a simple recruitment model to account for the reduced recruitment at severely depleted stock sizes (equation 2), where B_t is the biomass in time step *t*, *r* is the population growth rate, B_0 is the virgin biomass equal to carrying capacity, *K*, and C_t is the known catch at time *t*. Annual biomass quantities can then be calculated for every year based on a given set of *r* and *K* parameters.

$$B_{t+1} = \left[B + r\left(1 - \frac{B_t}{K}\right)B_t - C_t \right] \qquad \text{if } \frac{B_t}{K} > 0.25 \qquad (1)$$

$$B_{t+1} = \left[B + 4\frac{B_t}{K}r\left(1 - \frac{B_t}{K}\right)B_t - C_t \right] \qquad \text{if } \frac{B_t}{K} \le 0.25 \qquad (2)$$

There are no known prior distributions of the parameters *r* and *K*, so a uniform distribution was used from which values were randomly drawn. A reasonably wide prior range was set for *r* based on the known level of resilience of the stock as proposed by Martell and Froese (2012) where stocks with a very low resiliency are allocated an r value from 0.05 – 0.5, medium resiliency 0.2 – 1 and high resiliency 0.6 – 1.5. Based on the FishBase classification, *Thunnus tonggol* has a high level of resilience and a range of 0.6 – 1.5 was used (Froese and Pauly 2015). The prior range of K was determined as

$$k_{low} = \frac{\max(C_t)}{r_{high}}, k_{high} = \frac{4\max(C_t)}{r_{low}} \qquad (3)$$

Where k_{low} and k_{high} are the lower and upper lower bound of the range of *k*, max(C) is the maximum catch in the time series, and r_{low} and r_{high} are lower and upper bound of the range of r values.

The ranges for starting and final depletion levels were assumed to be based on one of possible three biomass ranges: 0.01–0.4 (low), 0.2–0.6 (medium), and high (0.4–0.8), using a set of rules based on the trend of the catch series (see Froese et al. (2016) for details). The prior range for the depletion level can also be assumed optionally for an intermediate year, but this option was not explored in this report. With this approach, the prior range for the depletion level in 2018 was determined to be high, which stands in sharp contrast with the low deletion for year 2015 assumed in the previous assessment. It was therefore decided to adopt the medium range (0.2 – 0.6) assumption for the final depletion level in the reference model, considering the recent reduction in total catches. This assumption is supported by the estimated depletion level the BDM model (see section 5.2). The high range (0.4–0.8) was explored in a sensitivity model. The prior ranges used for key parameters are specified in Table 2.

C-MSY estimates biomass, exploitation rate, MSY and related fisheries reference points from catch data and resilience of the species. Probable ranges for r and k are filtered with a Monte Carlo approach to detect 'viable' r-k pairs. The model worked sequentially through the range of initial biomass depletion level and random pairs of *r* and *K* were drawn based on the uniform distribution for the specified ranges. Equation 1 or 2 is used to calculate the predicted biomass in subsequent years, each *r-k* pair at each given starting biomass level is considered variable if the stock has never collapsed or exceeded carrying capacity and that the final biomass estimate which falls within the assumed depletion range. All *r-k* combinations for each starting biomass which were considered feasible were retained for further analysis. The search for viable r-k pairs is terminated once more than 1000 pairs are found.

The most probable r-k pair were determined using the method described by Ferose et.al (2016). All viable r-values are assigned to 25–100 bins of equal width in log space. The 75th percentile of the mid-values of occupied bins is taken as the most probable estimate of r. Approximate 95% confidence limits of the most probable *r* are obtained as 51.25th and 98.75th percentiles of the mid-values of occupied bins, respectively. The most probable value of k is determined from a linear regression fitted to *log(k)* as a function of log(r), for r-k pairs where r is larger than median of mid-values of occupied bins. MSY are obtained as geometric mean of the MSY values calculated for each of the r-k pairs where r is larger than the median. Viable biomass trajectories were restricted to those associated with an r-k pair that fell within the confidence limits of the C-MSY estimates of r and k.

Table 2: Prior ranges used for the longtail tuna in the C-MSY analysis reference model

Species	Initial B/K	Final B/K	*r*	*K (1000 t)*
Reference model	0.5–0.9	0.2–0.6	0.6–1.5	112 – 1124

4.2. Bayesian Schaefer production model (BSM)

C-MSY imposed strong assumptions on the stock abundance trend. Although the estimate of MSY is generally robust, estimates of other management quantities are very sensitive to the assumed level of stock depletion. Thus, we explored the use of a Schaefer production model (BSM) which utilised the newly available standardised CPUE indices. The BSM was implemented as a Bayesian state-space estimation model that was fitted to catch and CPUE. The model allowed for both observation and process errors (see Froese et al. 2016 for details). The prior range for *r* and *K* was translated into lognormal priors for the Bayesian estimation, with the mean and standard deviation derived from the range values specified in **Error! Reference source not found.**. A lognormal likelihood with a CV of 0.1 was assumed for the CPUE indices. The prior range for the initial and final depletion can be applied optionally and are implemented as a penalty on the objective function rather than hard constraints. The reference model made no assumption on the depletion level. To explore the effect of the depletion constraint on model results, two additional exploratory models were conducted which penalise the final depletion outside the range of (1) 0.2–0.6, and (2) 0.4–0.8, respectively. The model also estimates the catchability scalar which relates the abundance index and estimated biomass trajectory and is calculated as a set of most likely values relative to the values of other parameters, assuming a uniform prior.

5. Results

5.1. C-MSY method

Figure 5 shows the results of the reference model from the CMSY analysis. Panel A shows the time series of catches in black and the three-years moving average in blue with indication of highest and lowest catch. The use of a moving average is to reduce the influence of extreme catches.

Panel B shows the explored r-k values in log space and the r-k pairs found to be compatible with the catches and the prior information. Panel C shows the most probable r-k pair and its approximate 95% confidence limits. The probable r values did not span through the full prior range, instead ranging from 0.96–1.48 (mean of 1.19) while probable K values ranged from 353 000 – 681 000 (mean of 491 000). Given that r and K are confounded, a higher K generally gives a lower r value. CMSY searches for the most probable r in the upper region of the triangle, which serves to reduce the bias caused by the triangular shape of the cloud of viable r-k pairs (Ferose et al. 2016).

Panel D shows the estimated biomass trajectory with 95% confidence intervals (Vertical lines indicate the prior ranges of initial and final biomass). The method is highly robust to the initial level of biomass assumed (mainly due to the very low catches for the early part of series), while the final depletion range has a determinative effect on the final stock status. The biomass trajectory closely mirrors the catch curve with a rapid decline since the late 2000s.

Panel E shows in the corresponding harvest rate from CMSY. Panel F shows the Schaefer equilibrium curve of catch/MSY relative to B/k. However, we caution that the fishery was unlikely to be in an equilibrium state in any given year.

Figure 6 shows the estimated management quantities. The upper left panel shows catches relative to the estimate of MSY (with indication of 95% confidence limits). The upper right panel shows the total biomass relative to Bmsy, and the lower left graph shows exploitation rate F relative to Fmsy. The lower-right panel shows the development of relative stock size (B/Bmsy) over relative exploitation (F/Fmsy).

The IOTC target and limit reference points for longtail tuna have not yet been defined, so the values applicable for other IOTC species are used. Management quantities (estimated means and 95% confidence ranges) are provided in Table 3, which shows an average MSY of about 146 000 t. The KOBE plot indicates that based on the C-MSY model results, longtail is currently overfished (B2018/BMSY=0.96) but is not subject to overfishing (F2018/FMSY = 0.94). The average catch over the last five years is lower than the estimated MSY. The results are very similar to the previous assessment.

The CMSY produced much more optimistic results under the alternative final depletion range of 0.4 – 0.8, with B2018 estimated to be 1.44 of BMSY, and F2018 estimated 50% of FMSY. This demonstrated that to a very large extent the estimates of management quantities of the CMSY analysis are largely driven by the assumed level of stock depletion (particularly the final depletion).

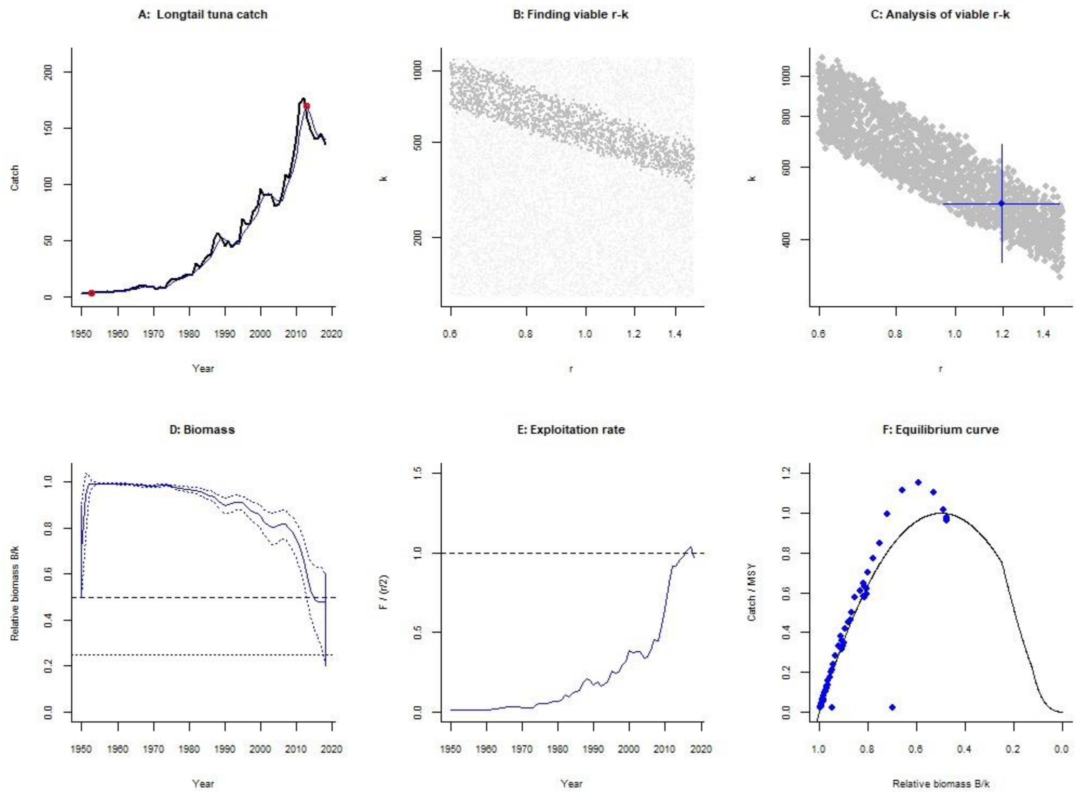

Figure 5. Results of CMSY reference model for longtail tuna.

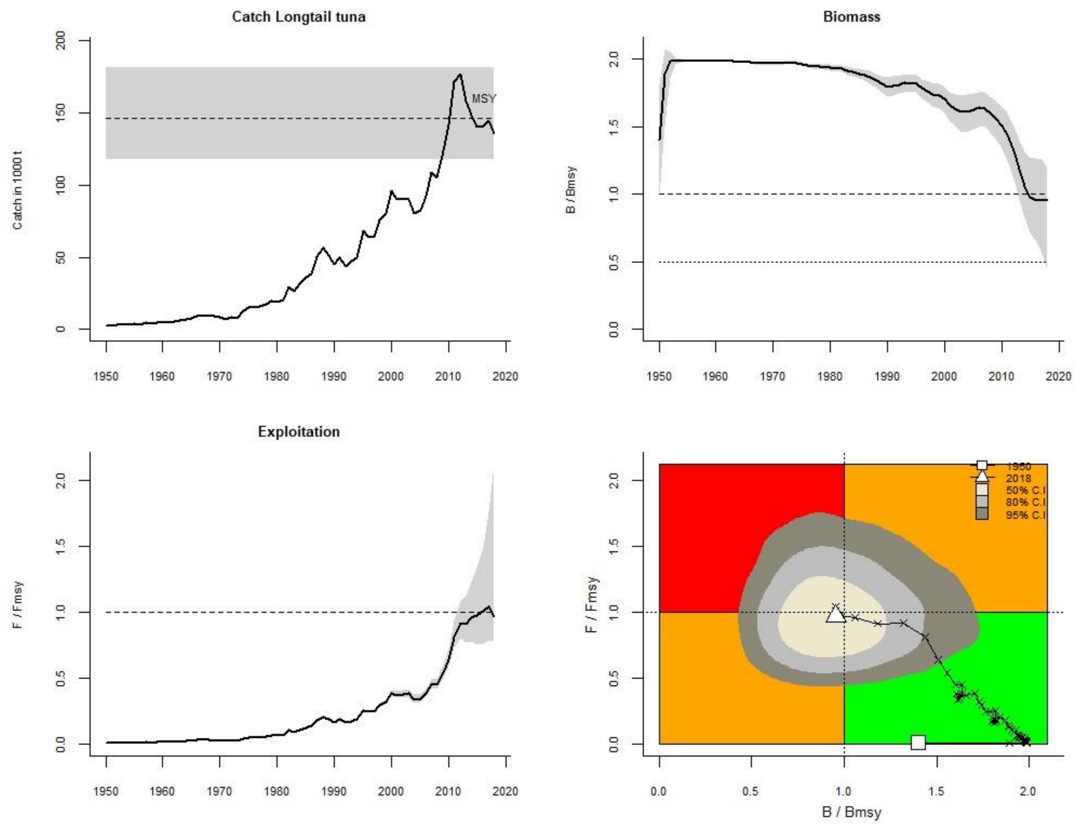

Figure 6. Graphical output of the CMSY reference model of longtail tuna for management purposes.

Table 3. Key management quantities from the Catch MSY assessment for Indian Ocean longtail tuna. Geometric means (and plausible ranges across all feasible model runs). n.a. = not available. Previous assessment results are provided for comparison.

Management Quantity	2017	2020
Most recent catch estimate (year)	132 723 t (2015)	135282 t (2018)
Mean catch – most recent 5 years[2]	150 208 t (2011 – 2015)	141 996 t (2014 – 2018)
MSY (95% CI)	144 000 (105 000 –198 000)	146 000 (118 100 – 181 000)
Data period used in assessment	1950 – 2015	1950 – 2018
F_{MSY} (95% CI)	0.60 (0.48 - 0.74)	0.60 (0.48 - 0.74)
B_{MSY} (95% CI)	242 000 (166 000 – 354 000)	245 000 (177 000 – 341 000)
$F_{current}/F_{MSY}$ (95% CI)	1.00 (0.79 – 2.19)	0.97 (0.78 – 2.12)
$B_{current}/B_{MSY}$ (95% CI)	0.94 (0.43 – 1.19)	0.96 (0.44 – 1.19)
$B_{current}/B_0$ (95% CI)	0.47 (0.22 - 0.60)	0.48 (0.22 – 0.60)

[2] Data at time of assessment

5.2. Bayesian Schaefer production model (BSM)

The estimated posterior distributions of r-k from the BSM are located in the tip region of the viable r-k triangle from the CMSY analysis, with a credible interval similar to the most probable r-k range from the CMSY analysis (**Figure 7**–left). The estimated biomass trend is generally consistent with the decline in the observed CPUE since 2011 but did not capture the increase in the CPUE prior to 2011 (**Figure 7**–right).

Estimates of management quantities are shown in Table 4. These estimates are broadly similar to the reference CMSY analysis assuming the medium final depletion. MSY is estimated to range from 127 010 to 156 000 t with an average 141 000 t. The catch in 2018 is about 4% lower than the mean MSY but is well within the estimated range. Spawning stock biomass in 2018 is estimated to be 10% lower than BMSY and the current fishing mortality is about 8% higher than the FMSY. These estimates suggest that the stock is overfished, and overfishing has occurred. Most estimates have narrower confidence bound than the CMSY analysis (

Figure **8**).

Further model runs by placing penalty on the final depletion level did not appear to have an appreciable impact on model results: assuming a median depletion of 0.2–0.6, B2018/BMSY estimated to be 0.91 and F2018/FMSY estimated to be 1.06; assuming a high depletion 0.4–0.8, B2018/BMSY estimated to be 1.04 and F2018/FMSY estimated to be 0.95. The indicated that with the incorporation of CPUE indices to provide information on relative abundance changes, the BSM model is not relying on the depletion assumptions to estimate stock trend.

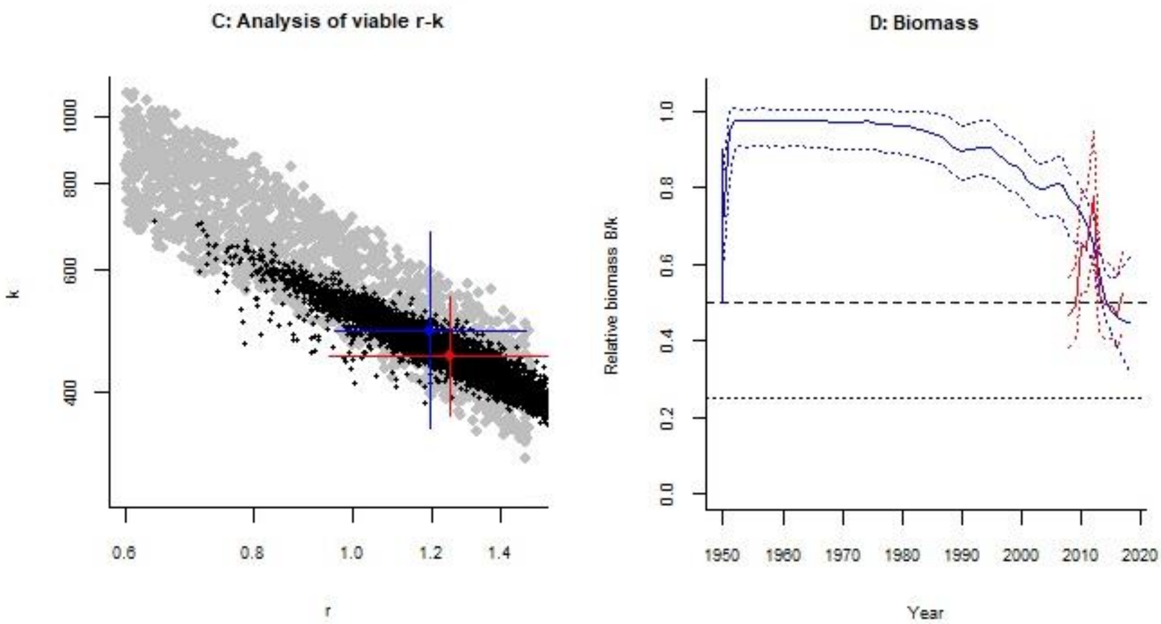

Figure 7: Results of BDM reference model for longtail tuna: left–posterior estimates of *r* and *K* (black dots) and the 95% CI (the red cross), overlaid with the viable r-k pairs as well as the probable range from the CMSY analysis (grey dots and the blue cross); right – median and 95% CI of the posterior estimates of biomass, overlaid with the standardised CPUE indices 2008–2017 with observation errors (red).

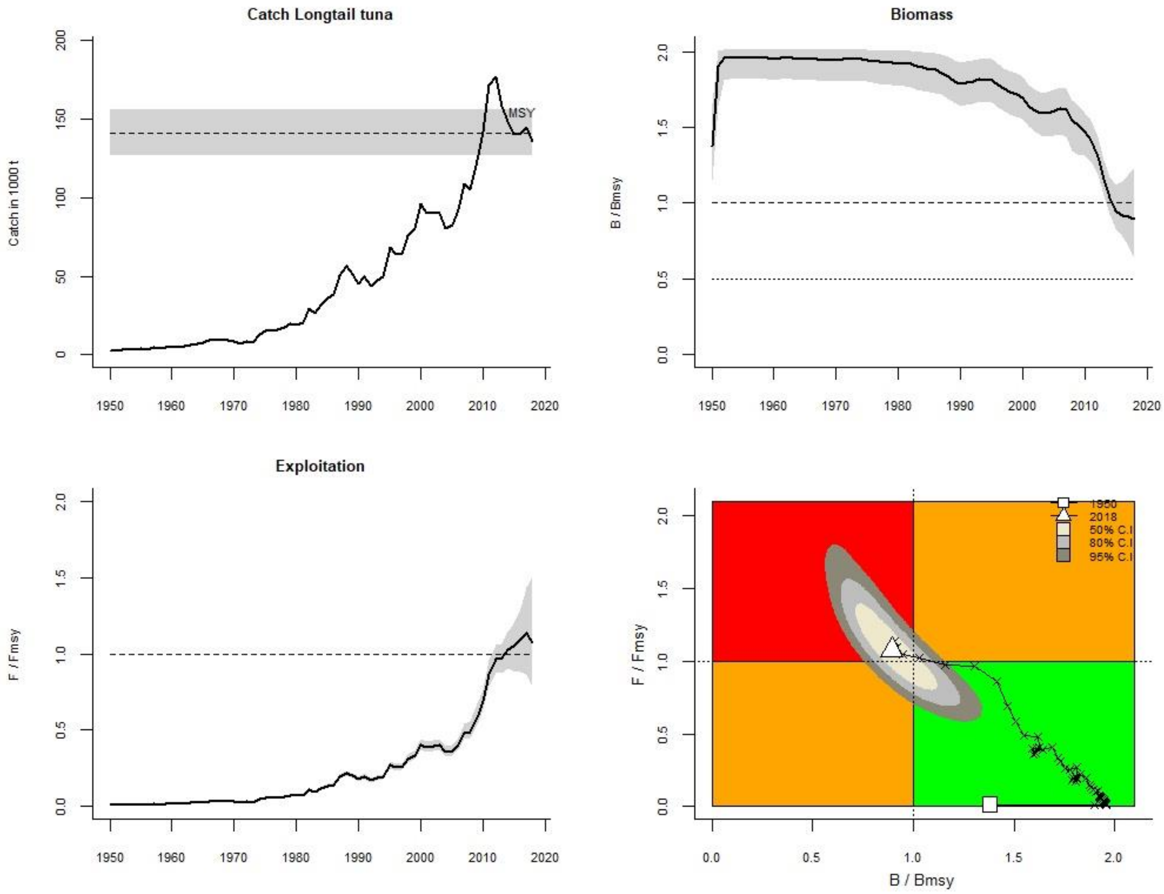

Figure 8: Management quantities of the BDM reference model.

Table 4: Management quantities from the Bayesian Schaefer production model (BSM) – reference model for Indian Ocean longtail tuna, means and 95% confidence interval.

Management Quantity	2019
MSY (95% CI)	141 000 t (127 010 – 156 000)
Data period used in assessment	1950 – 2018
F_{MSY} (95% CI)	0.62 (0.48 – 0.82)
B_{MSY} (95% CI)	226 000 t (185 000– 275 000)
$F_{current}/F_{MSY}$ (95% CI)	1.08 (0.78 – 1.51)
$B_{current}/B_{MSY}$ (95% CI)	0.90 (0.64 – 1.23)
$B_{current}/B_0$ (95% CI)	0.45 (0.32 – 0.62)

6. Discussion

In this report we have explored two data-limited methods in assessing the status of Indian Ocean longtail tuna: C-MSY and Bayesian Schaefer production model (BSM), both of which are based on an aggregated biomass dynamic model. The C-MSY requires only the catch series as model input and uses simulations to locate feasible historical biomass that support the catch history. The BSM has incorporated time series of relative abundance indices, and estimated model parameters and management quantities in a Bayesian framework. The BSM model yielded broadly similar but slightly more pessimistic results to the C-MSY reference model that assumed a medium depletion range in the final year (0.2 – 0.6). Estimates from the C-MSY model suggested that currently the stock of longtail tuna in the Indian Ocean is overfished (B2018 < BMSY) but is not subject to overfishing (F2018 < FMSY). The estimates produced by the BSM method suggested that the stock is overfished (B2018 < BMSY) and is also subject to overfishing (F2018 > FMSY).

The estimated MSY is similar between the two models. The C-MSY estimated a mean MSY of approx. 146 000 t with a relatively wider range. The BSM estimated a mean MSY of approx. 141 000 t with a much narrower confidence bound. Reported catches of longtail tuna in the Indian Ocean has declined considerably from its peak in 2012, with recent catches ranging between 131000 and 148000. The catch in 2018 was below the estimated MSY. However, both models appear to suggest that the exploitation rate (F/FMSY) has been increasing over the last few years, as a result of the declining abundance. Despite the substantial uncertainties described throughout this paper, this suggests that the stock is very close to being fished at MSY levels and that higher catches may not be sustained. A precautionary approach to management is recommended.

The C-MSY assessment is based primarily on the catch data and an underlying Schaefer model. Production models often provide robust or stable estimates regardless of uncertainties in basic biological characteristics (IOTC 2019). In general, simple model cannot represent important dynamics and thus is more likely to yield biased results. The consistent estimates amongst C-MSY simulations are largely attributed to the strong assumptions imposed on the population dynamics and stock productivity, including the intrinsic growth rate and carrying capacity parameters. The assumption made on the terminal depletion level is subjective but is highly influential on estimates of stock status.

The BDM model utilised the standardised CPUE indices to provide information on abundance trend, and as such, the model is less reliant on some of the subjective assumptions (particularly those relating to the depletion levels, which are imperative in the stock reduction analysis). The Bayesian paradigm also provides a more robust statistical estimation framework, allowing key parameters and management quantities to be estimated with better precisions. It remains a question whether the CPUE indices derived from the Iranian coastal gillnet fleets can index the abundance trend of longtail tuna stock in the Indian Ocean (the CPUE has various caveats even as a local index for the Iranian coastal waters, see Fu et al. (2019)). Nevertheless, the availability of the standardised CPUE as a potential abundance index and its incorporation in the assessment represents a marked improvement in the development of more robust methods to assess IOTC neritic tuna species in the context of data deficiency. Future assessments could consider develop more realistic population models, including age structured models that could utilise more biological and fishery data beyond simple catch series.

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