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

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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 for Longtail tuna (*Thunnus tonggol*) from 2013 through 2017 utilising a variety of data-limited methods (Zhou & Sharma 2013, 2014; Martin & Sharma, 2015; Martin & Robinson, 2016, Fu & Martin, 2017). In 2020 the C-MSY method (Froese et al. 2016) was used to assess the status of *T.tonggol* (Fu 2020) using historical catches. This paper provides an update to the C-MSY assessment based on the most recent catch information. This assessment also explored several alternative methods including the Optimised Catch-Only method (Zhou et al., 2013), the JABBA model (Winker et.al. 2014), and the length-based spawning potential ratio model (Hordyk et al. 2014). In addition to examining various population dynamic assumptions, these models allow for the evaluation of the usefulness of alternative data in determining the status of T. *tonggol*.

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 waters 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 (IOTC 2023). 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 (IOTC 2015). These studies have provided varied estimates of growth, with most estimates of von Bertalanffy k values ranging 0.18–0.55 with some more extreme values. 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). A more complete biological study on longtail tuna in Australia (Griffiths et al., 2010) have provided the required information to estimate age and growth, maturity, and natural mortality parameters. Using those information, Griffiths 2010 undertake an assessment of the current fishing mortality of longtail tuna in Australian waters using a yield per recruitment analysis.

3. Catch, CPUE and Fishery trends

Nominal catch data were extracted from the IOTC Secretariat database for the period 1950–2021 (records for 2022 were still incomplete at the time of the assessment). 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 estimated total catches of 113,022 t in 2019 (Table 1). The catches in 2020 and 2021 were 137 194 t and 134 171 t, respectively. 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 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 the JABBA model (see Section 4.3).

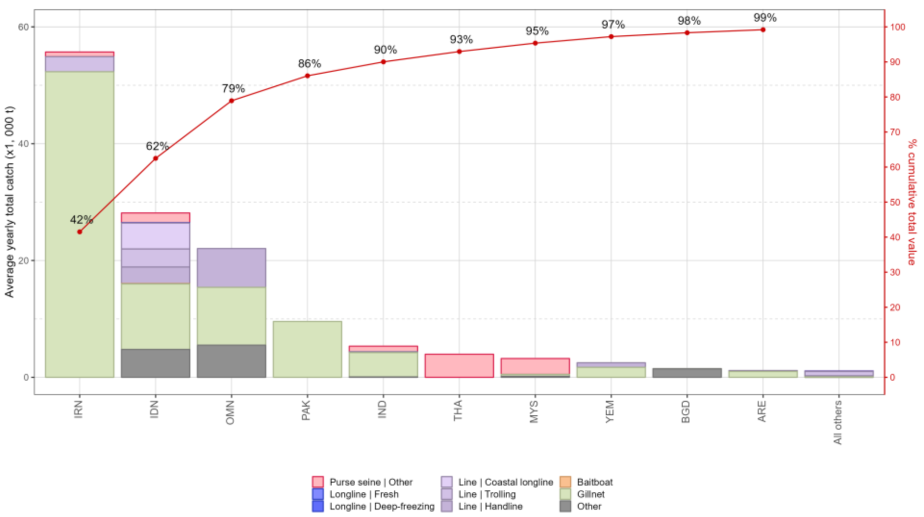

Figure 1: Average catches in the Indian Ocean over the period 2012-2021, by country. The red line indicates the (cumulative) proportion of catches of longtail by country.

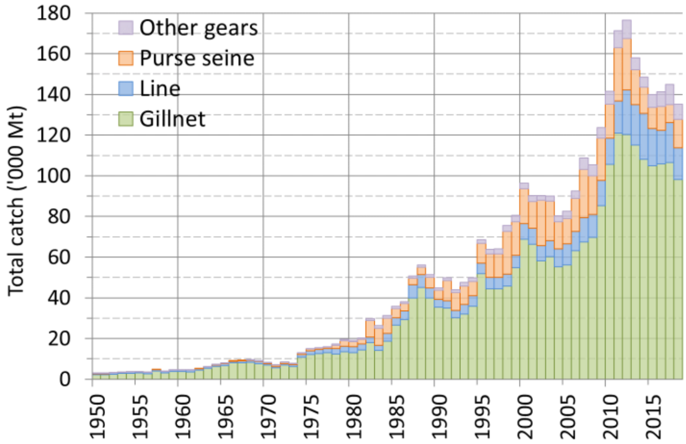

Figure 2: Annual catches of longtail tuna by gear, 1950 – 2021 (IOTC database).

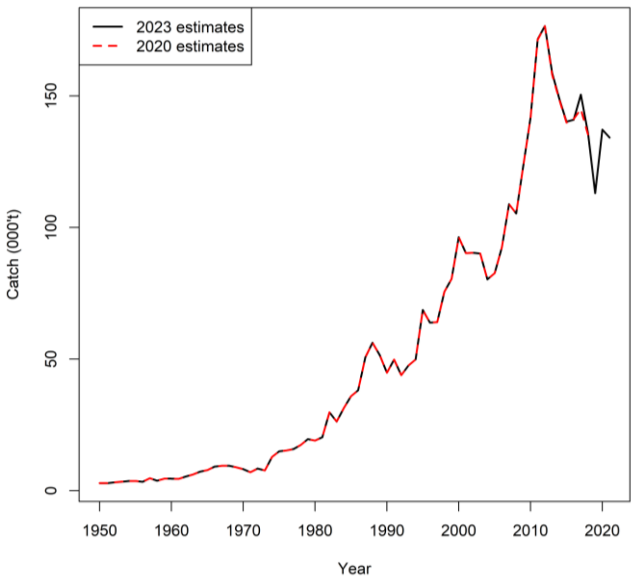

Figure 3: Revisions to IOTC nominal catch data for longtail tuna (datasets used for the 2020 and 2023 assessments).

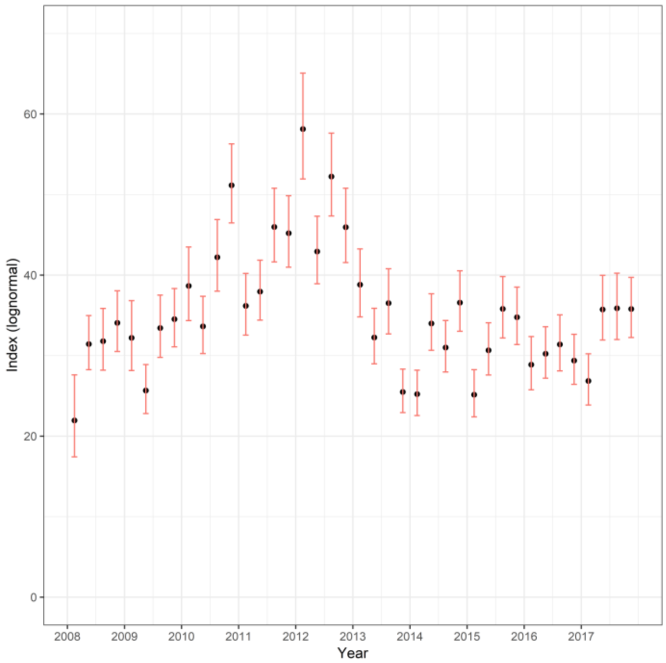

Figure 4: Standardised CPUE indices (year-quarter) for longtail tuna 2008–2017 from the GLM lognormal model. See Fu et al. (2019) for details.

Table 1. Catch data for *T. tonggol* in the Indian Ocean, 1950-2021 (source IOTC Database)

Year	Catch (t)	Year	Catch (t)
1950	2 840	1986	38 147
1951	2 816	1987	50 624
1952	3 093	1988	56 190
1953	3 360	1989	51 478
1954	3 603	1990	44 802
1955	3 638	1991	49 825
1956	3 317	1992	43 854
1957	4 695	1993	47 556
1958	3 740	1994	49 874
1959	4 521	1995	68 655
1960	4 535	1996	63 850
1961	4 449	1997	64 015
1962	5 332	1998	75 618
1963	6 127	1999	80 477
1964	7 190	2000	96 344
1965	7 772	2001	90 253
1966	9 113	2002	90 357
1967	9 426	2003	90 104
1968	9 463	2004	80 269
1969	8 876	2005	82 631
1970	8 162	2006	92 483
1971	6 977	2007	108 844
1972	8 363	2008	105 307
1973	7 644	2009	123 694
1974	12 804	2010	141 772
1975	14 937	2011	171 583
1976	15 256	2012	176 592
1977	15 782	2013	158 700
1978	17 346	2014	148 940
1979	19 541	2015	140 194
1980	19 010	2016	140 980
1981	20 274	2017	150 523
1982	29 798	2018	135 944
1983	26 251	2019	113 022
1984	31 386	2020	137 194
1985	35 850	2021	134 171

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.

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

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

The prior range for *r* was estimated using the life history module (LHM) developed by Edwards (2016). The model implements Monte Carlo sampling of life history parameter distributions, with iterated solving of the Euler-Lotka equation (McAllister et al. 2001). The population parameters of *T. tonggol (*including growth, natural morality, maturity, and length-weight relationship) are based on values collated by Griffiths (2011). The estimated distribution of r suggested a credible range of 0.2 – 0.9 for *T. tonggol*. Martell and Froese (2012) proposed a classification of the stock resilience levels 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 (0.6 – 1.5) (Froese and Pauly 2015). For this analysis, the LHM estimate of 0.2 – 0.9 was used a reference case as they are based on existing parameters and the FishBase resilience estimate of 0.6–1.5 was used as a sensitivity.

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). For the current assessment, it was decided to adopt the medium range (0.2 – 0.6) assumption for the final depletion level in the reference model, considering the long exploitation history of the fishery and the recent reduction in total catches. The prior ranges used for key parameters for the reference model 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	0.2–0.9	188 – 3377

4.2. OCOM model

Similar to the C-MSY approach, the Optimised Catch-Only model (Zhou et al. 2013 & 2016) uses the Schafer biomass dynamic model to describe population dynamics and seeks to determine the most probable r and K combination that maintains a viable population throughout time. By excluding the unlikely parameter values from a large number of simulations, this method generates estimations of biological reference points and stock status. Since r and K are negatively correlated, the initial version of this approach employed unconstrained priors on both parameters (for example, the maximum K is bound by r = 0 and the maximum r is constrained by the minimum viable K) (Zhou et al. 2013). In subsequent development, the population growth rate r can be constructed using a Bayesian error-in-variable model based on life-history parameters (particularly natural mortality and/or maximum age) and the prior for the final depletion S using a Boosted Regression trees (BRT) (Zhou et al., 2020). Additionally, the model contains a setting that enables the user-specified priors for r and S to be provided. We run the OCOM model with the same priors on r (0.2-0.9 and 0.6-1.5) and on S (0.2-0.6) as those used in the C-MSY model to facilitate comparison.

4.3. JABBA model

Both C-MSY and OCOM models 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 JABBA (Winker et al. 2014) which utilised the available CPUE indices. The JABBA model 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 Winker et al. 2018 for details). The prior range for *r* and *K* was translated into priors for the Bayesian estimation (see Table 2). 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. The reference model made no assumption on the depletion level. To explore the effect of the depletion constraint on model results, an additional model was conducted which penalise the final depletion outside the range of 0.2–0.6. 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.

4.4. LBSPR method

The LBSPR method (Hordyk et al. 2014) estimates the Spawning Potential Ratio (SPR) of a stock directly from the size composition of the catch. The SPR of a stock is defined as the proportion of the unfished reproductive potential (often approximated by spawning biomass) left at any given level of fishing pressure (Hordyk et al. 2014) and is commonly used to set target and limit reference points for fisheries. The $F_{40\%}$, i.e., the fishing mortality rate that results in SPR at 40% of unfished level, is considered risk adverse for many species. The LBSPR establish that how length compositions and spawning ratios are determined by fishing mortality and life history ratio, which are known to be less variant across species. The LBSPR uses maximum likelihood methods to estimate relative fishing mortality (F/M) and selectivity-at-length that minimize the difference between the observed and the expected length composition of the catch and calculates the SPR (Hordyk et al. 2014). The LBSPR model requires the following parameters: an estimate of the ratio M/k (i.e., the individual values of the M and k parameters may be unknown), L^{∞} (and associated variance), and maturity-at-size. These parameters for *Thunnus tonggol* are obtained from Griffiths (2010).

The length data used (IOTC-2023-WPNT13-DATA09-SFdata) contains length samples by gear, fleet, year, month, and spatial area. For longtail tuna, most samples are from the Iranian/Pakistan gillnet fishery from 1992 to 2021. There are some samples from the line and purse seine fisheries, but they mostly contain younger fish less than 50 cm (the LB-SPR model should be applied to data from the fleet that target the adult portion of the stock). Therefore, we applied the method to only the length data from the gillnet fishery.

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 0.43–0.88 (mean of 0.61) while probable K values ranged from 544 000 – 1380 000 (mean of 867 000). 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 133 000 t. The KOBE plot indicates that based on the C-MSY model results, longtail is currently overfished (B2021/BMSY=0.96) and is subject to overfishing (F2018/FMSY = 1.05). The average catch over the last five years is slightly higher than the estimated MSY (Table 3).

The estimated stock state is similar to the previous assessment but slightly pessimistic (in relation to MSY-based reference points). However, due to the use of a r prior (0.2 - 0.9) that suggested a less intrinsically productive stock, abundance estimates are significantly higher in absolute terms (e.g., BMSY is about twice that of the previous estimates). The sensitivity model using a prior range of 0.6 - 1.5 gives very similar estimates of absolute abundance to the previous assessment. The high correlation between r and K means there change of r prior has relatively little impact on the MSY estimation. The assumed stock depletion range in the final year (i.e., 0.2–0.6) has a significant impact on estimation of stock status.

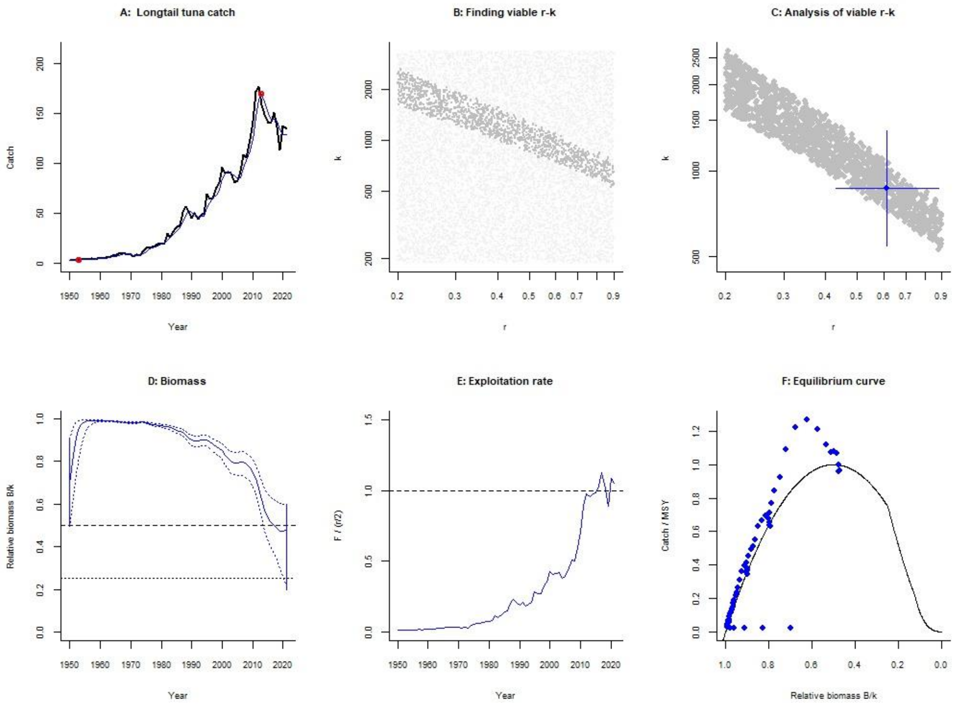

Figure 5. Results of CMSY reference model for longtail tuna.

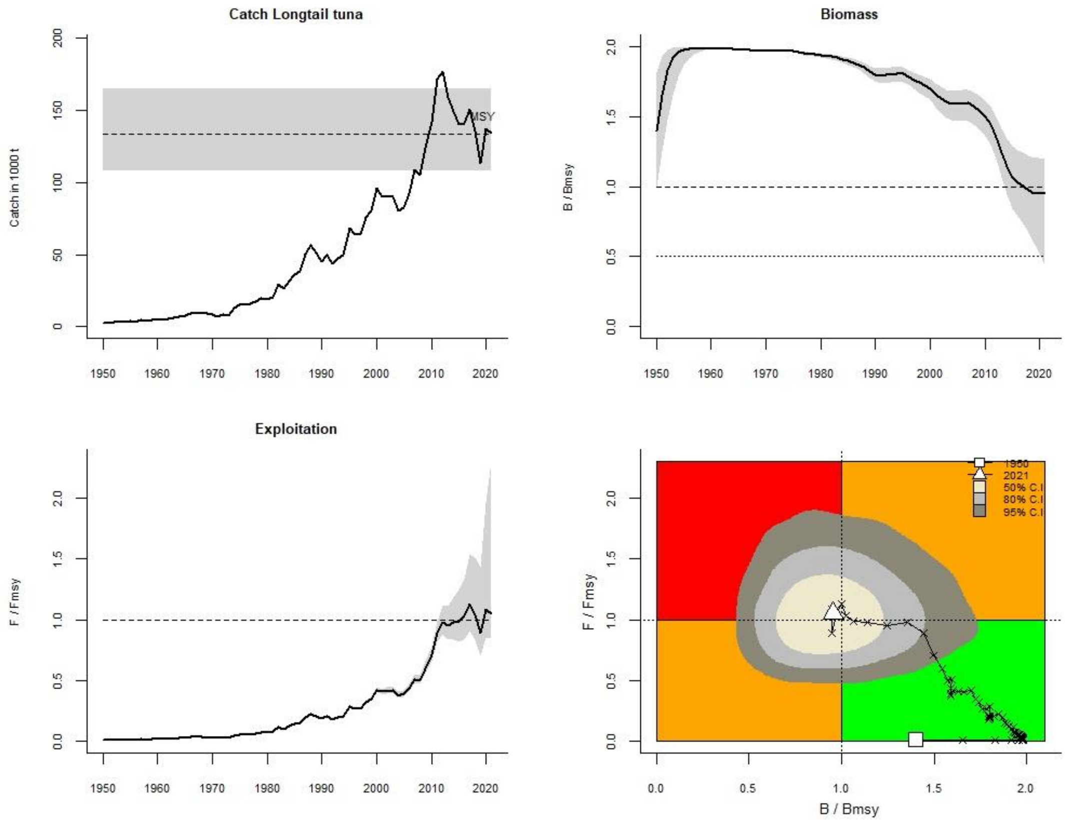

Figure 6. Graphical output of management quantities from the CMSY reference model of longtail tuna.

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	2020	2023
Most recent catch estimate (year)	135282 t (2018)	134171(2021)
Mean catch – most recent 5 years[2]	141 996 t (2014 – 2018)	134170 (2017 – 2021)
MSY (95% CI)	146 000 (118 100 – 181 000)	133 000 (108 –165)
Data period used in assessment	1950 – 2018	1950 – 2021
F_{MSY} (95% CI)	0.60 (0.48 - 0.74)	0.31 (0.22 – 0.44)
B_{MSY} (95% CI)	245 000 (177 000 – 341 000)	433 000(272000 – 690000)
$F_{current}/F_{MSY}$ (95% CI)	0.97 (0.78 – 2.12)	1.05 (0.84 – 2.31)
$B_{current}/B_{MSY}$ (95% CI)	0.96 (0.44 – 1.19)	0.96 (0.44 – 1.19)
$B_{current}/B_0$ (95% CI)	0.48 (0.22 – 0.60)	0.48 (0.22 – 0.60)

[2] Data at time of assessment

5.2. OCOM model

Figure **7** shows the strong correlation of *r* and *K* parameter values retained by the biomass dynamics model. 80% posterior range of r is 0.27 – 0.84, and is mostly overlap with the prior. Estimated K ranges from 647 000 to 1 605 000 t. The range of values was dependent on the level of stock depletion assumed for the final year, with *r*, *K* and *MSY* all positively correlated with the depletion level.

Reference model (*r* prior range 0.2 – 0.9) indicate that the biomass was approximately 910 000 t in 1950 and declined to approximately 364 000 t by 2021 (

Figure **7**). The estimated MSY associated with this projection is 128 000 t and ranges from approximately 107 000 t to 138 000 t. The model estimated that the stock is currently overfished (B2021/BMSY=0.80) and is subject to overfishing (F2021/FMSY = 1.35). The estimated stock status of the OCOM model is more pessimistic than the C-MSY model, de3pite the same prior assumptions (the result showed a larger probability that the stock is in the Kobe red quadrat). This is most likely because the C-MSY method chose higher r values—located in the top 75% quantile of the posterior probability range—as the most viable values. Similar to the C-MSY model, the estimates of stock status changed very little under the the alternative prior range for r (0.6–1.5).

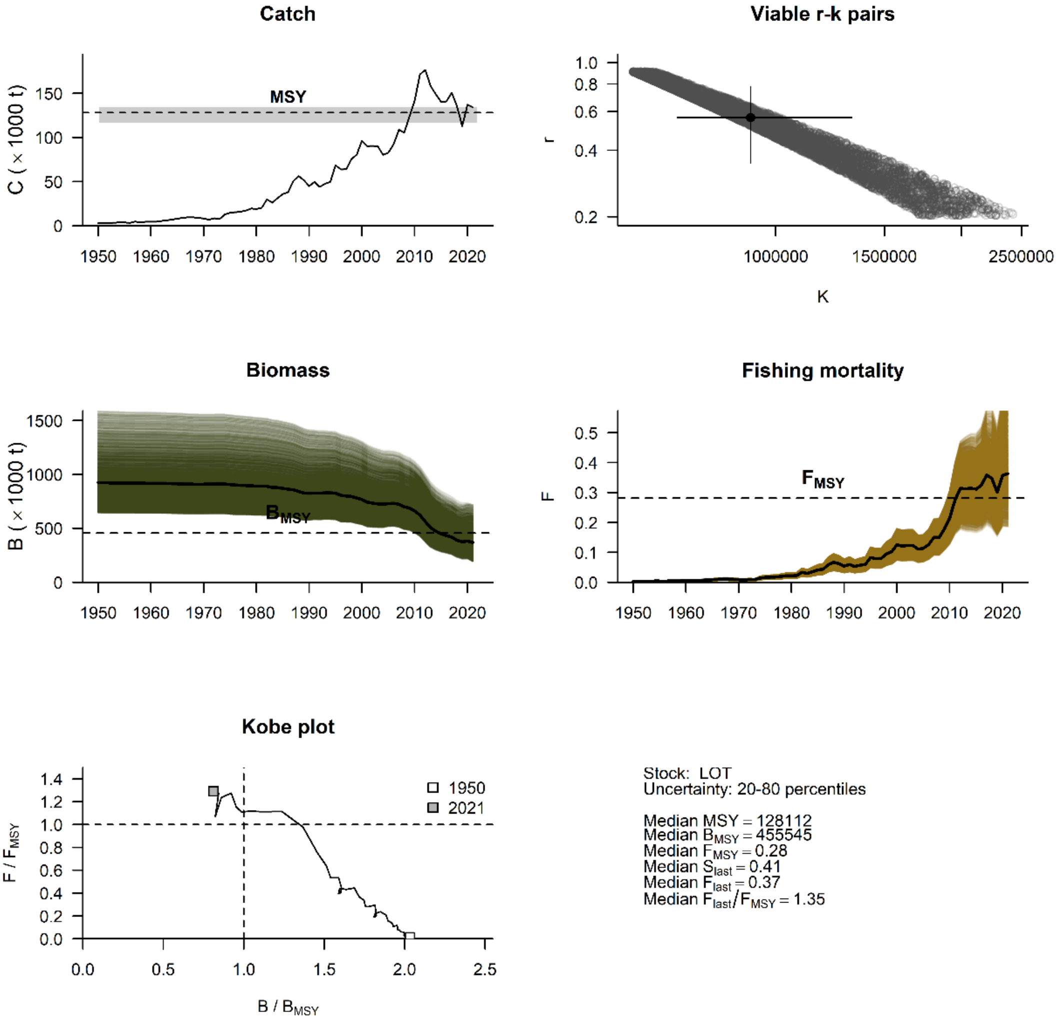

Figure 7: Graphical output of management quantities from the OCOM reference model of longtail tuna

5.3. JABBA model

The abundance estimates were exceedingly uncertain with a very wide posterior range (upper range of K surpassed 6 000 000 t, see Figure 8) when the stock depletion in the terminal year was unconstrained (model 1). This shows that the very short CPUE and increasing catch trend give very little information on absolute abundance and relative depletion. In this condition, there is a wide range of potential abundance levels that could support the catch and explain the observed CPUE.

However, penalizing the final depletion outside the range of 0.2–0.6 (model 2) lowered the uncertainty of abundance estimations and resulted in a somewhat more plausible pattern in stock depletion. The projected biomass trend in this model is broadly consistent with the observed reduction in CPUE since 2011, but it did not capture well the increase in CPUE before 2011 (Figure 9). Prior to 2011, the CPUE increased, but this increase cannot be attributed to catches; rather, it was explained by to process errors that were allowed in the stock dynamics.

Estimates of management quantities from model 2 are shown in Figure 10. The estimated stock status is comparable (but slightly more optimistic) to the CMSY model. The MSY varies between 94 000 and 338 000 t, with an average of 137 000 t. According to estimates, the biomass of the spawning stock in 2021 is 2% higher compared to the BMSY, and the fishing mortality is roughly about 4% lower than the FMSY (B/BMSY = 1.02, F/FMSY = 0.96). Compared to the CMSY analysis, the confidence bounds for most estimations are wider. Despite the addition of CPUE indices to provide information on relative abundance changes, the information is limited due to the relatively short time series and lack of contrast between the CPUE and catch time.

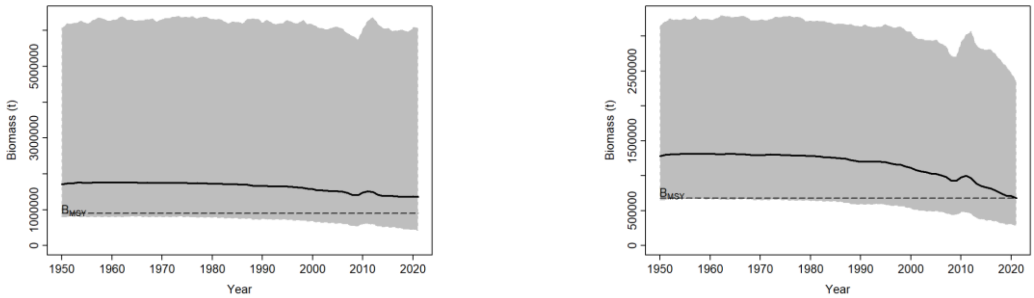

Figure 8: Biomass estimates (median and 95% CI) from JABBA model 1 (left, no prior on final depletion), and model 2 (right, a normal prior on final depletion with mean of 0.4 and CV of 25%, corresponding to an approximate range 0.2 – 0.6). Dashed line indicates median BMSY.

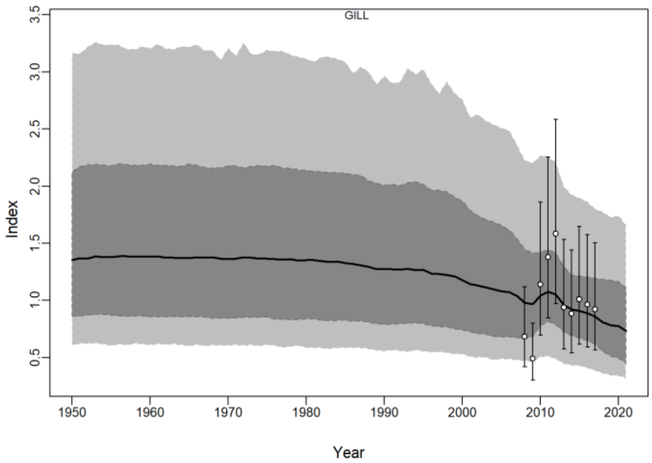

Figure 9– Posterior fits to CPUE indices 2008–2017 from JABBA model 2. Shaded areas indicates 50% and 95% CI, vertical lines indicate observation errors.

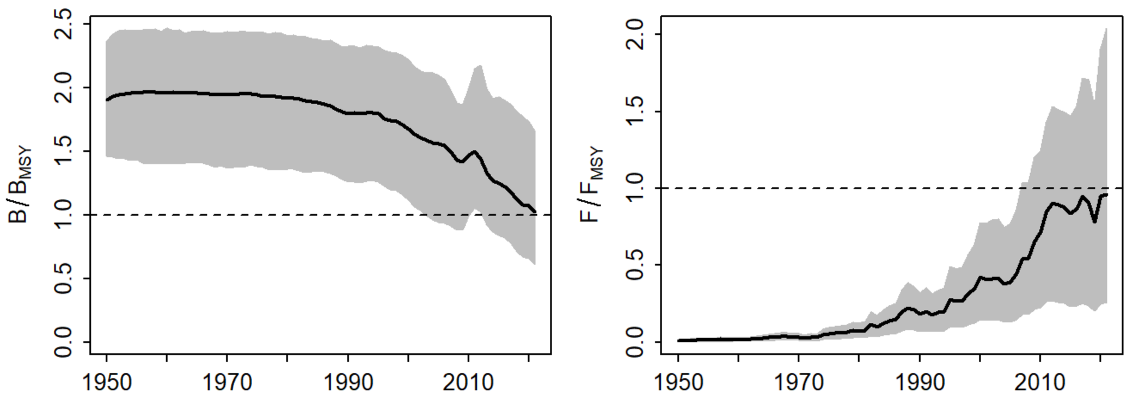

Figure 10: Estimated time series of B/BMSY and F/FMSY from JBBBA model 2.

5.4. LBSPR method

The length distribution from 1992 to 2021 can be reasonably fit by the LB-SPR (Figure 11). According to the model, there has been a significant shift in the gillnet fishery toward the selection of younger fish (Figure 11), but fishing mortality has decreased over time (Figure 11), even though it is still significantly higher than the potential FMSY (0.87M was thought to be a reasonable approximation of FMSY for teleost; see Zhou et al., 2012). Throughout most of the time series, the SPR was estimated to be around 0.2; even though it seems to have increased in recent years, it is still significantly below 0.4 (the SPR of 0.4 is frequently thought of as a risk-averse target, see Hordyk et al. 2014), suggesting the stock is still depleted in relation to the risk-averse target.

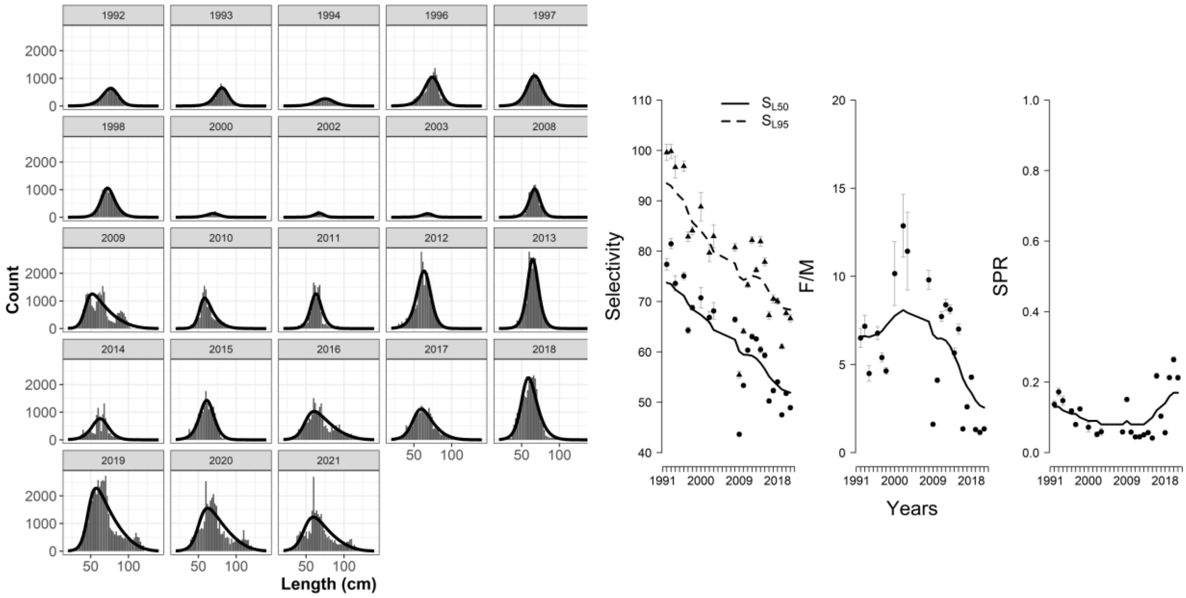

Figure 11: Results of LB-SPR method applied to the length samples from the gillnet fishery for longtail tuna: fits to the length frequency 1992–2020 (black dots); right – estimates (with 95% CI) of logistic selectivity parameters (a50 and a95), F/M, and SPR.

6. Discussion

The C-MSY, OCOM, JABBA, and LB-SPR methodologies have all been investigated in this report to evaluate the state of Indian Ocean longtail tuna. Only the catch series is needed as input for the C-MSY and OCOM methods, which both rely on an aggregated biomass dynamic model and use simulations to find historical biomass that is plausible and supports the known catch history. Time series of relative abundance indices have been included into the JABBA model, together with model parameters and management quantities estimated in a Bayesian framework. The estimates of key quantities produced by the three methods are largely comparable in this case, but overall, the results of OCOM model are more pessimistic and the JABBA model is more optimistic. Estimates from the C-MSY and OCOM model suggested that currently the stock of longtail tuna in the Indian Ocean is overfished (B20121< BMSY) and is subject to overfishing (F2021> FMSY). The estimates produced by the JABBA method suggested that the stock is not (B2021 < BMSY) and is not subject to overfishing (F2021 > FMSY).

The C-MSY estimated an average MSY of about 133,000 tons and had a relatively wide range. Reported long-tail tuna catches in the Indian Ocean have declined significantly since peaking in 2012, with recent catches ranging from 131,000 to 148,000. The 2021 catch was very close to the estimated MSY. Decreases in abundance appear to have been offset by declining catches, resulting in a relatively flat trend in exploitation rates over the past decade. Despite the significant uncertainties outlined in this paper, this suggests that stocks are approaching being fished at MSY levels and that higher catches may not be sustainable. A precautionary approach to management is recommended.

Catch-only assessments are primarily based on catch data and the underlying Schaefer model. Production models often provide robust or stable estimates independent of uncertainties in underlying biological properties. In general, simple models cannot represent important dynamics and are more likely to produce biased results. Consistent estimates in catch-only model simulations are largely due to assumptions made about population dynamics and stock productivity, including the intrinsic growth rate, and carrying capacity parameters. Assumptions about the extent of final depletion are often subjective, but have a large impact on estimates of stock status.

The JABBA model used the standardized CPUE index to provide information on abundance trends. Ideally, this makes the model less dependent on several subjective assumptions, especially those related to depletion levels that are essential for stock reduction analysis. The Bayesian paradigm also provides a more robust statistical estimation framework that allows more accurate estimation of key parameters and control variables. However, the available CPUE for longtail tuna is relatively short and overall does not respond consistently to the pattern observed in catch removes. It is therefore not indicative of stock productivity and depletion in this case. Furthermore, it remains to be seen whether CPUE indicators obtained from Iranian coastal gillnet fishing fleets can index abundance of long-tail tuna stock in the Indian Ocean, in addition to the various caveats even as a local indicator (see Fu et al 2019). Nevertheless, the availability of a standardized CPUE as a potential abundance index and its inclusion in the assessment would be a useful step forward in the context of assessing data deficient neritic tuna stocks. The CPUE should be regularly updated to a monitoring tool, potentially providing longer and more informative time series. Standardised indices should also be developed for other fisheries/regions to ensure better spatial coverage of stock populations.

Stock status estimates using the LB-SPR method are not directly comparable to catch-only models as they use very different target reference points. Nevertheless, the SPR estimated by the LB-SPR method is well below the target of 40%, fishing mortality is estimated to be much higher than FMSY. It thus supports the C-MSY conclusion that fish is subject to overfishing. However, one major concern is that the LB-SPR model assumes asymptotic selectivity, and results have been shown to be sensitive to this assumption (the model is highly sensitive to the absence of large individuals in the size structure, see Hordyk et al. 2014). In the analysis, the LB-SPR was applied to the length samples from the gillnet fishery. Gillnets typically exhibit domed selectivity, which can be problematic for long-tailed tuna. First, longtails are usually larger in body size ($L^{\infty} \approx 145cm$). Griffiths (2010) showed that Taiwanese gillnet fisheries across northern Australia between 1979 and 1986 were significantly domed compared to sport fisheries that caught larger longtail. Secondly, Hordyk et al. (2014) found that species with high M/K ratios are less susceptible to doming because fewer individuals live longer to reach asymptotic size, thus affecting a smaller fraction of the dome population. However, Griffiths 2010 suggested that the life history of long-tail tuna is relatively slow-growing and long-lived, similar to what has been observed for large *Thunnus* species, such as bigeye tuna. Ideally, LB-SPR should be applied to fisheries targeting larger adult long-tail tuna.

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