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Stock Assessment of Indian Ocean Longtail Tuna (*Thunnus tonggol*) using data-limited methods

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1. EXECUTIVE SUMMARY

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 and Sharma, 2013; Zhou and Sharma, 2014; Zhou, 2020; Fu, 2023). In 2023 the CMSY method (Froese et al. 2016) was used to assess the status of *T.tonggol* using historical catches. This paper provides an update to the CMSY assessment based on the most recent catch information. This assessment also explored alternative methods including the Just Another Bayesian Biomass Assessment model (JABBA, (Winker, Carvalho and Kapur, 2018)), and the length-based spawning potential ratio model (LBSPR, (Hordyk *et al.*, 2015)). 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 LOT.

The assessment uses catch data from 1950 to 2024 and a standardised gillnet CPUE index from 2008-2017.

Estimates from the CMSY++ BSM model suggests that currently the stock of Longtail tuna in the Indian Ocean is **overfished** ($B_{2024} > B_{MSY}$) and **is subject to overfishing** ($F_{2024} > F_{MSY}$). The estimates produced by the JABBA method, suggest that the stock is **not overfished** ($B_{2024} < B_{MSY}$) but **is subject to overfishing** ($F_{2024} < F_{MSY}$).

The CMSY++ model estimated an average MSY of ~ 123 000 t which is lower than that estimated by JABBA (135 000 t). The 2024 catch (148 572 t) is above to that of MSY (from both models) and has been higher than estimated MSY for ~ 20 years.

Estimates of stock status from the LBSPR method cannot be directly comparable to the catch-only models as they have made very different assumptions about target reference points. Nonetheless, the SPR estimated by the LBSPR method was below the SPR40% for gillnet fisheries, while fishing mortality is estimated to be much higher than F_{MSY}.

Estimated spawning potential ratio throughout the time series is well below 0.4, indicating that the stock is depleted in relation to the risk-averse target (the SPR of 0.4 is often considered as a risk-averse target; see Hordyk et al. 2014a), and has decreased throughout the time period of the fishery.

Based on a weight-of-evidence approach, it is likely that Longtail tuna is, in 2024, **overfished** and **subject to overfishing** in the Indian Ocean. However, there are several caveats to this, stated below:

a) The trend in reported nominal catch of longtail tuna over time in the Indian Ocean has been continuing to increase and has been above or in the higher ranges of estimated MSY for nearly 20 years. High catches, in combination with less biological resilience to fishing, is resulting in a higher impact of fishing on stock levels.
b) Length-based analyses suggest that the stock is likely to be overfished, however the length data are unlikely to be representative of the entire Indian Ocean stock(s), based on recent biological studies (Griffiths *et al.*, 2020).
c) Recent work suggests there are likely several stocks of longtail tuna (Griffiths *et al.*, 2020), however catch, and length data are not reported at a fine-enough scale to capture individual

stock dynamics. Additionally, representative abundance indices should be developed on a similar spatial scale to putative stocks..

2. 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 and Sharma, 2013; Zhou and Sharma, 2014; Zhou, 2020; Fu, 2023).

In 2023 the CMSY method (Froese et al. 2016) was used to assess the status of *T.tonggol* using historical catches. This paper provides an update to the CMSY assessment based on the most recent catch information. This assessment also explored alternative methods including the Just Another Bayesian Biomass Assessment model (JABBA, (Winker, Carvalho and Kapur, 2018)), and the length-based spawning potential ratio model (LBSPR, (Hordyk *et al.*, 2015)). 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 LOT.

In this assessment, we have implemented the updated CMSY method (CMSY++; (Froese *et al.*, 2023)) that implements both CMSY and a Bayesian Schaefer Model (BSM) separately, allowing for abundance indices to be incorporated if available, similar to CMSY, but including the ability to introduce gear creep. The results were compared to an implementation of the CMSY method and were consistent, so we recommend using the CMSY++ method for following assessments.

We also implemented the JABBA model, although the model had difficulty fitting to the one abundance index available (a standardised gillnet CPUE index based on data from the Islamic Republic of Iran (I.R. Iran); Fu (2019)), possibly due to the short nature of the index compared to the catch data series, and the lack of representativeness of the index for the whole Indian Ocean population of longtail tuna.

We did not implement the Optimised Catch-Only method but did implement one length-based method: the length-based spawning potential ratio model (LBSPR, (Hordyk *et al.*, 2015)). A separate analysis was completed to test a new Bayesian-based length-based model fishblicc [Fu, 2026; github.com/paulhmedley/fishblicc]. Both length-based methods provide a useful monitoring tool for the stock in the final year of the assessment, rather than a time-series of stock status.

The assessment uses catch data from 1950 to 2024 and a standardised gillnet CPUE index from 2008-2017.

2.1. Species 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 and Pauly, no date). 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 2026). 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 Secretariat, 2022). 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 Secretariat, 2022). More complete biological studies on longtail tuna in Australia, and the Indian Ocean (Griffiths, 2010; Griffiths *et al.*, 2020) have provided the required information to estimate age and growth, maturity, and natural mortality parameters.

A recent review of longtail tuna (Griffiths *et al.*, 2020) suggests that there are likely four putative stocks of longtail tuna in the Indian Ocean: in the western, northern, south east Asian, and Oceania regions of the Indian Ocean (see paper for more details, and putative stock boundaries). Additionally, the paper describes that size increases with latitude, and there are possible nursery grounds in the northern areas of the Indian Ocean, with a wide range in maximum size reported (from L_{max} = 58 cm in south east Asia, to 120 cm in the Gulf of Oman / Persian Gulf, and South East Australia). These results suggest that the biology and ecology of longtail tuna in the Indian Ocean is far from well-known, and potentially has significant implications for the assessment, as spatial and temporal affects of sampling need to be incorporated into length-based assessment methods (and currently we do not have sufficient data to do this).

2.2. Fishery information

Disaggregated nominal catch data were extracted from the IOTC database for the period 1950–2024. Gillnet fleets are responsible for most of the reported catches of longtail tuna followed by line and purse seine gear, with most of the catch taken by coastal country fleets (Figure 1).

Indonesia, India and I.R. Iran together account for 69 % of catches in 2024. Figure 2 shows the total catch of Longtail tuna since 1950, which increased to a peak of 174,055 t in 2012, then declined to 112,148 t in 2019, rising again to a peak in 2024 (148,572 t; Table 1). In 2019, IOTC endorsed the revisions of gillnet catch from Pakistan that introduced some changes in the catches of tropical tuna, billfish, as well as some neritic tuna species from 1987 (IOTC 2019). The Pakistani revision appears to have very minor effects on the longtail tuna nominal catch series since the last assessment (Figure 3).

Additionally, endorsed revisions of Indonesia's catches for all historical data, are minimal for longtail tuna (Figure 3), unlike other neritic species.

Fu et al. (2019) developed standardised CPUE indices for several neritic tuna species including longtail tuna from the I.R. Iran 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 longtail tuna show an increasing trend over time since 2011/12 (Figure 4), with a strong seasonal pattern driven mostly by the productivity cycle in the southern Gulf as well as market conditions (Fu et al. 2019). The annualised indices (by taking the average of the quarterly indices) were tested in the CMSY++ model but ultimately excluded from the reference model. The indices were included in the JABBA model (see Section 4.2).

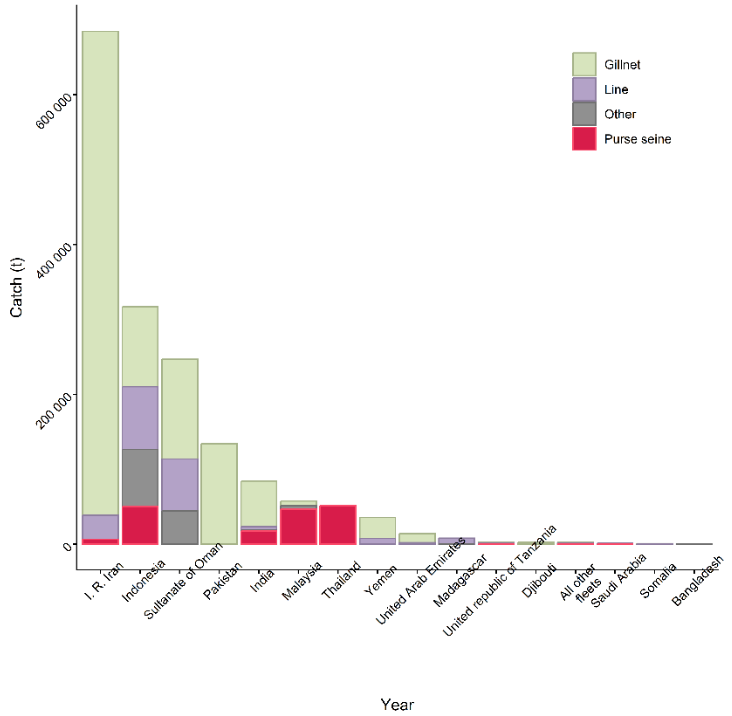

Figure 1: Average catches of Longtail tuna (*Thunnus tonggol*) in the Indian Ocean over the period 2012-2024, by country, and gear grouping.

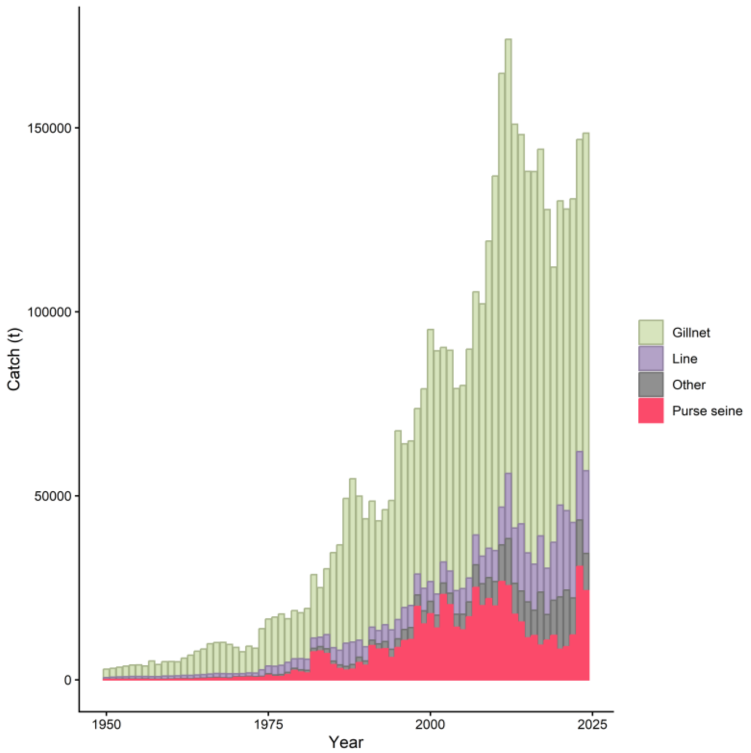

Figure 2: Total nominal catch of Longtail tuna by gear grouping, 1950 – 2024 (IOTC database).

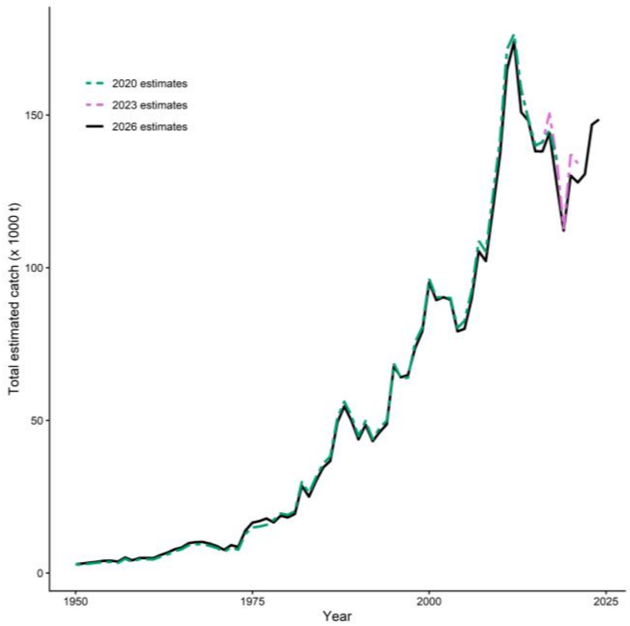

Figure 3: Revisions to IOTC nominal catch data for longtail tuna (datasets used for the 2020, 2023, and 2026 assessments, using data up to 2019, 2021, and 2024 respectively).

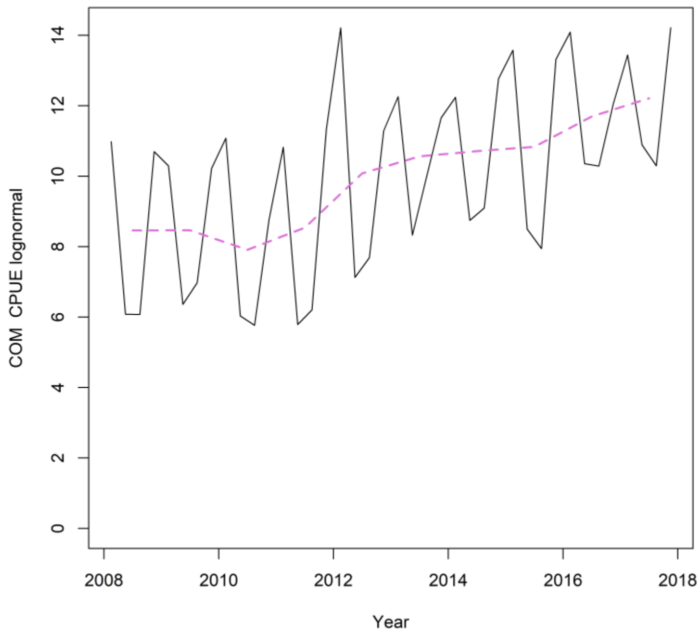

Figure 4: Standardised CPUE indices (year-quarter) for Longtail tuna 2008–2017 from the GLM lognormal model. See Fu et al. (2019) for details. Purple dashed line represents the mean annual index.

Table 1. Catch data for Longtail tuna (*Thunnus tonggol*) in the Indian Ocean, 1950-2024 (source IOTC Database)

Year	Catch (t)	Year	Catch (t)
1950	2,892	**1988**	54,630
1951	3,121	**1989**	49,925
1952	3,425	**1990**	43,765
1953	3,697	**1991**	48,567
1954	4,019	**1992**	43,207
1955	4,054	**1993**	46,217
1956	3,759	**1994**	48,723
1957	5,117	**1995**	67,678
1958	4,162	**1996**	64,117
1959	4,942	**1997**	64,882
1960	4,951	**1998**	73,725
1961	4,896	**1999**	79,067
1962	5,885	**2000**	95,207
1963	6,691	**2001**	89,391
1964	7,765	**2002**	90,329
1965	8,377	**2003**	89,548
1966	9,814	**2004**	79,158
1967	10,139	**2005**	80,003
1968	10,175	**2006**	89,860
1969	9,613	**2007**	105,409
1970	8,809	**2008**	102,158
1971	7,605	**2009**	119,229
1972	9,145	**2010**	136,909
1973	8,565	**2011**	164,792
1974	13,887	**2012**	174,055
1975	16,524	**2013**	150,945
1976	17,026	**2014**	148,138
1977	17,875	**2015**	138,142
1978	16,591	**2016**	138,101
1979	18,790	**2017**	144,175
1980	18,213	**2018**	127,773
1981	19,388	**2019**	112,148
1982	28,588	**2020**	130,159
1983	25,035	**2021**	127,930
1984	30,160	**2022**	130,696
1985	34,578	**2023**	146,819
1986	36,682	**2024**	148,572
1987	49,299		

3. METHODS

3.1. CMSY

The CMSY method (Froese Rainer *et al.*, 2016) was applied to estimated reference points from catch, resilience and qualitative stock status information for Longtail tuna (*Thunnus tonggol*, hereafter Spanish mackerel, github.com/SISTA16/cmsy; version CMSY_2019_9f.R). The CMSY method represents a further development of the Catch-MSY method (Martell and Froese, 2013), with several improvements to reduce potential bias. Like the Catch-MSY method, The CMSY relies on only a catch time series dataset, which was available from 1950 – 2024, prior ranges of r and k, and possible ranges of stock sizes in the first and final years of the time series. The model does allow the addition of a biomass index, if one is available.

A modified Schaefer surplus production model (Schaefer, 1954) is used (Equation 1). This model combines the classic Schaefer surplus production model with a simple recruitment model to account for reduced recruitment at severely depleted stock sizes (Equation 2; Figure 5), where B_t is the biomass in time step t, ***r*** is the population growth rate, B_0 is the virgin (unexploited) 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.

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

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

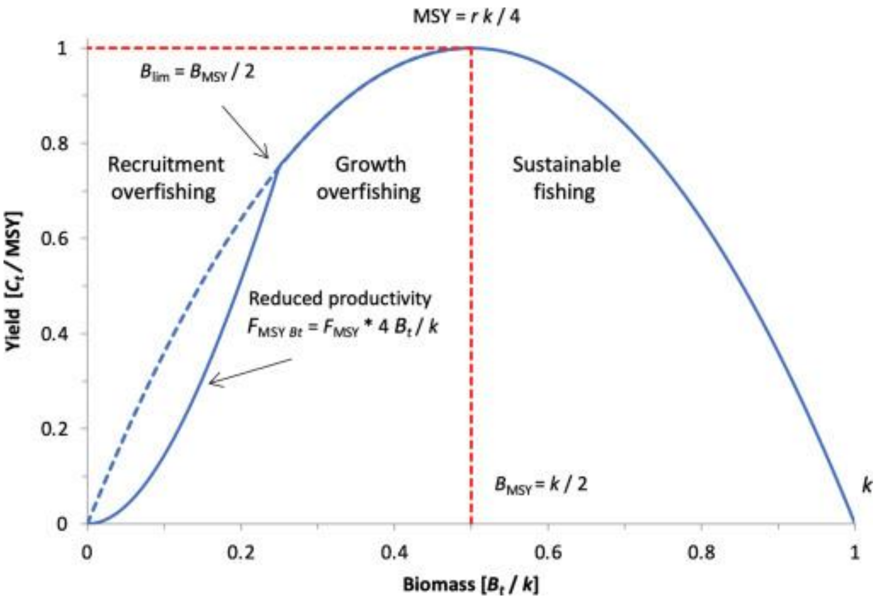

Figure 5: A schematic representation of the modified Schaefer surplus production model used by CMSY (Figure 2 from Froese et al., 2023), that highlights the reduced productivity of a stock under recruitment overfishing where F_{MSY} reduces linearly with a decline in biomass.

The prior range for ***r*** was estimated using the life-history module (github.com/cttedwards/lhm) developed by C.T.T. Edwards. The model implements Monte Carlo Markov Chain (MCMC) sampling of life history parameter distributions, with iterated solving of the Euler-Lotka equation (McAllister, Pikitch and Babcock, 2001). The population parameters of longtail tuna (including growth, natural morality, maturity, and length-weight relationship) are based on values collated and recommended by the IOTC (2015).

Froese (Froese *et al.*, 2023) proposes a classification of the stock resilience levels (SEE TABLE X) where stocks with a very low resiliency are allocated an r value of 0.05 – 0.5; medium resiliency r = 0.2 – 1 and high resiliency r = 0.6 – 1.5. Based on the FishBase classification (Froese and Pauly, 2025), Spanish mackerel has a high level of resilience, and so the r prior was set to 0.6–1.5. The LHM method produced similar values for ***r***, and therefore for the CMSY / CMSY++ analyses, the prior range of ***r*** was set to 0.6 – 1.5.

The prior range of *k* was determined using the following (Equation 3):

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

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 initial, intermediate, 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. (2023) for details). For the current assessment, it was decided to adopt the medium range of biomass (0.2 – 0.6) assumption for the final depletion level (e.g. lower depletion) in the reference model, considering the decline in recent years in total catches. The same level of biomass was assumed in the intermediate year, and the intermediate year was set to 2012, as this is the year the highest catches were observed, before a general decline in catches. This may signal a fundamental change in the fishery.

A sensitivity run was conducted using the previous model's use of 0.2-0.6 (medium biomass) for the final depletion level, along with alternative values for the intermediate years, as misspecification of this parameter can result in erroneous stock status (Froese *et al.*, 2023). The prior ranges used for key parameters are specified in Table 2.

CMSY estimates biomass, exploitation rate, maximum sustainable yield (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 Markov Chain (MCMC) 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, depending on biomass, and 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 estimates fall within the assumed depletion range. All ***r-k*** combinations for each starting biomass which were considered feasible were retained for further analyses. The search for viable ***r-k*** pairs is terminated once more than 1000 pairs are found.

The CMSY package was implemented in R (version 4.5.2 (2025-10-31 ucrt) -- "[Not] Part in a Rumble") using RStudio (2026.01.1 Build 403 "Apple Blossom" Release (0e924abb, 2026-02-04) for Windows). Code to run the models can be provided by the IOTC Secretariat on request.

3.2. CMSY++

The CMSY++ approach was applied to the *S. commerson* data. CMSY++ [github.com/SISTA16/cmsyPlusPlus; Froese et al., (2023)] represents an update of the CMSY method above, using an advanced state-space Bayesian method for stock assessment, using the same modified Schaefer surplus production model as used in CMSY. An Artificial Neural Network (ANN) is used to select objective priors for relative stock size, based on patterns from 400 catch time series used to train the model. The main differences between CMSY++ and CMSY are documented in the paper by Froese et al., (2023) but briefly, are: (i) the use of a full Bayesian approach with MCMC modelling for the CMSY analysis; (ii) the use of the ANN to predict default biomass priors from catch; and (iii) the introduction of multivariate lognormal priors for r and k, replacing the uniform distributions in CMSY. Additionally, gear creep can also be included in the parameters, as implemented in (Palomares and Pauly, 2019).

Additionally, the CMSY++ package allows for the running of retrospectives, where sequential years of data are removed from the analysis, to understand the impact of the final years of catch data on the stock status. This analysis was completed for Longtail tuna. Both a catch-only model was developed, and a model incorporating the CPUE index. Management quantities were taken from the Bayesian Schaefer Model (BSM) as is default in CMSY++.

The CMSY++ package was implemented in R (version 4.5.2 (2025-10-31 ucrt) -- "[Not] Part in a Rumble") using RStudio (2026.01.1 Build 403 "Apple Blossom" Release (0e924abb, 2026-02-04) for Windows). Code to run the models can be provided by the IOTC Secretariat on request.

Table 1: Parameters used for Longtail tuna in the setup of CMSY and CMSY++ reference model

	Initial rel. biomass	**Intermediate rel. biomass**	**Final rel. biomass**	***r***	**Resilience**
Year	1950	2016	2024		
Value	0.5 – 0.9	0.2 – 0.6	0.2 – 0.6	0.2 – 0.9	Medium

3.3. JABBA

Both CMSY (and CMSY++) models impose strong assumptions on the stock abundance trend. Although the estimates of MSY from catch-only models are generally robust, estimates of other management quantities can be sensitive to the assumed level of stock depletion, although running sensitivities on this did not result in significant deviations in management quantities.

We explored the use of JABBA (Winker, Carvalho and Kapur, 2018) which also incorporates 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 allows for both observation and process errors (see (Winker, Carvalho and Kapur, 2018) for details). The prior range for ***r*** and ***k*** used for the Bayesian estimation were the same as in CMSY++ (see Table 2). A lognormal likelihood with a CV of 0.2 was assumed for the CPUE index, however this was reduced to 0.1 in the final reference model to improve the fits to the index. 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.

3.4. LBSPR

The LBSPR method (Hordyk *et al.*, 2015) 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.*, 2015) 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 or precautionary for many species.

The LBSPR method 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.*, 2015). 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 *T. thonggul* were obtained from previously used figures (IOTC (2015)).

The length frequency data (IOTC-DATASETS-SF-LOT-1987-2024-WIDE-FORMAT) used includes length samples by fleet, gear, year, month, and region. The majority of the longtail tuna samples come from the Iranian/Pakistani gillnet fishery from 2009 to 2024 (earlier samples are also available, although there is more variation in sample size and quality). The length distribution of samples from the gillnet fisheries (Figure 6) is comparable to that of the line fishery (Figure 7). We used the approach on both sets of data.

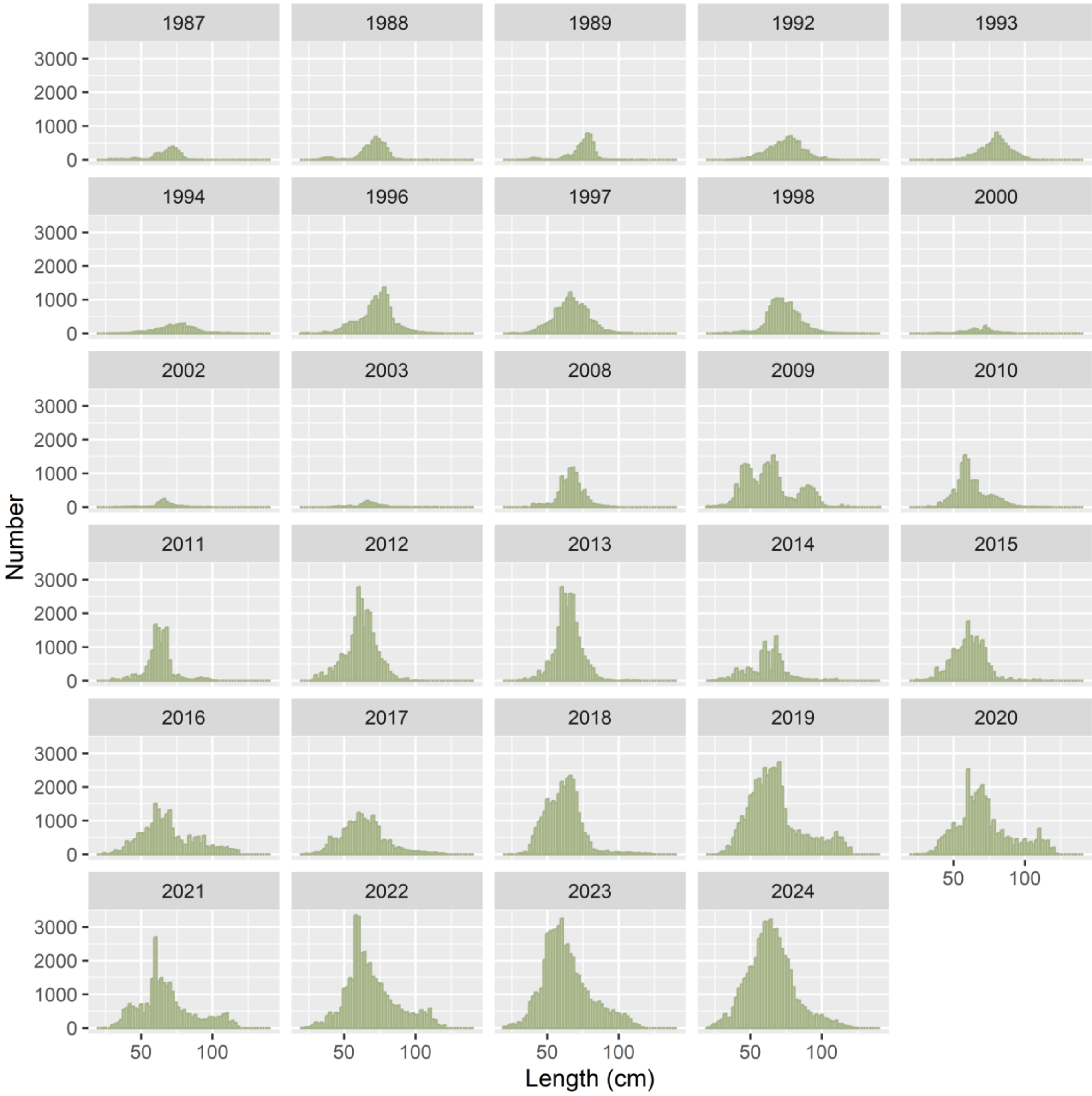

Figure 6: Length frequency data for longtail tuna available in 2026 for the assessment (data up to 2024) from gillnet fisheries in the Indian Ocean. Data are aggregated to a "fishery grouping" level and represent data reported to the IOTC from several fisheries across the Indian Ocean, however most data are from gillnet fisheries in I.R. Iran. Data were used from 1992 to 2024 in the LBSPR analyses.

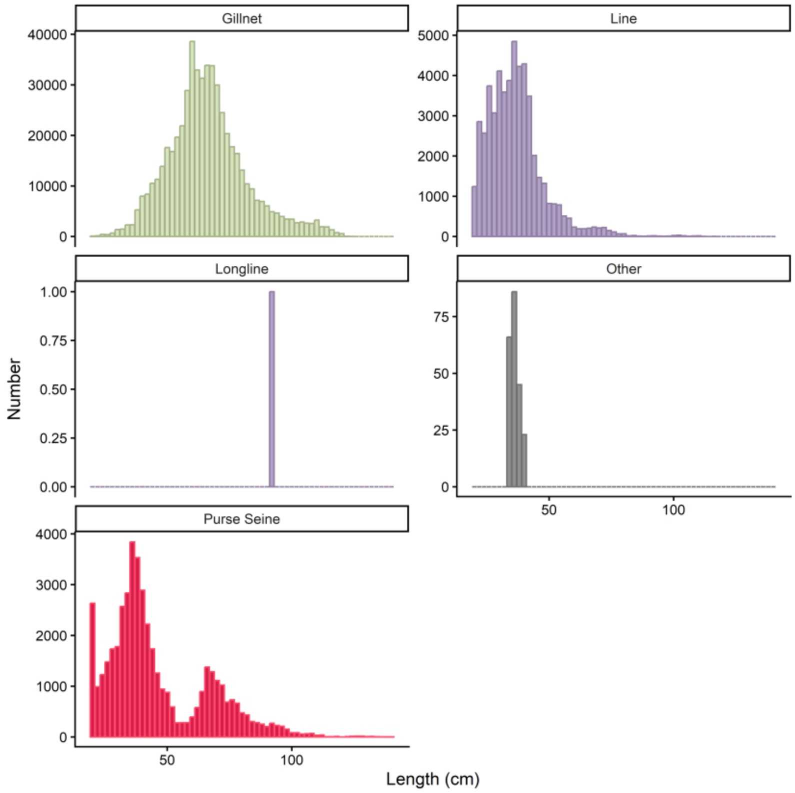

Figure 7: Length frequency data for longtail tuna available in 2026 for the assessment (data up to 2024) from all fisheries in the Indian Ocean. Data are aggregated to a gear grouping level and represent data reported to the IOTC from several fisheries across the Indian Ocean. Data were used from 2010 to 2024 in the LBSPR analyses. Note the varying y axes.

4. RESULTS

4.1. CMSY

Both the CMSY and CMSY++ models were fitted to the available catch data for Longtail tuna. As the models produced very similar outputs, and the CMSY++ model represents an improvement in methodology, this was taken forward in the analyses. For a comparison of the model outputs from the reference model using CMSY and CMSY++, see Figure 1 in the Appendix.

The reference model for Longtail tuna did not include the CPUE index, as this did not provide any meaningful information to the model, and the model was unable to fit to the index satisfactorily. The following results are from the Bayesian Shaefer Model component of CMSY++ as the default setting in the package. The reference model used 2016 as the intermediate year as this is the final year of highest mean catches prior to the terminal year of the assessment. As such this represents a change in the fishery dynamics, from a fishery that is undergoing consistent increases in catches, to one where the maximum sustainable yield may have been caught (noting the final year of catch data are substantially higher than all previous years).

Figure 8 shows the results of the CMSY++ analysis – there are six panels in the figure, providing different outputs.

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 lognormal 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 were narrower than the full prior range (0.2 – 0.9), ranging from 0.19 – 0.44 (mean = 0.33) while probable ***k*** values ranged from 1 131 000 – 2 281 000 t (mean = 1 509 000 t). Given that ***r*** and ***k*** are confounded, a higher ***k*** generally gives a lower ***r*** value. CMSY++ implementation allows for viable ***r-k*** pairs to be estimated from information from 400 stocks (Froese *et al.*, 2023).

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 2012, due to several years of catch close to or above estimated MSY.

Panel E shows the corresponding exploitation (harvest) rate from CMSY++ (F/FMSY) showing that exploitation rates are increasing, and currently they are likely to be above that of FMSY.

Panel F shows the modified Schaefer equilibrium curve of catch/MSY relative to relative biomass (B/k). However, we caution that the fishery was unlikely to be in an equilibrium state in any given year.

Figure 9 shows the estimated management quantities from the BSM model. The upper left panel shows catches relative to the estimate of MSY (with indication of 95% confidence limits), suggesting that catches have increased over time, above the plausible range of CMSY with the final three years showing increasing catches in the upper end of MSY estimates. The upper right panel shows the total stock size (biomass) relative to B_{MSY}, suggesting a decreasing stock size, to below that of B/B_{MSY}. The lower left panel shows the exploitation rate F in relation to F_{MSY}. The lower-right panel shows the trajectory of the stock in relation to the relative stock size (B/B_{MSY}) and relative exploitation (F/F_{MSY}).

Figure 10 is a retrospective analysis of the reference CMSY++ BSM model, that suggests that removing sequential years of catch data (left-hand panel) does not overly influence the trend in stock status (B/B_{MSY}, right-hand panel).

The IOTC target and limit reference points for Longtail tuna have not yet been defined, so values applicable for other IOTC species are used. Management quantities (estimated means and 95% confidence ranges) are provided in Table 3, which show an estimated MSY of **123,000** t.

The KOBE plot (**Figure 11**) and management values indicate that based on the CMSY++ model results, longtail tuna is currently **overfished** (B_{2024}/B_{MSY} = 0.88) and **is subject to overfishing** (F_{2024}/F_{MSY} = 1.44). The average catch over the last five years is higher than the estimated MSY (136,853 t). These results are more pessimistic than the last assessment (which suggested the stock was in the centre of the KOBE plot).

The deterioration in stock status in 2026 is likely influenced by the following:

a) The trend in reported nominal catch of longtail tuna over time in the Indian Ocean has been continuing to increase and has been above or in the higher ranges of estimated MSY for nearly 20 years. High catches, in combination with less biological resilience to fishing, is resulting in a higher impact of fishing on stock levels.
b) The previous model (2023) fixed the 'intermediate' year as the final year, which has significant implications on the final status. The 'intermediate' year should be set as the year that there has been a substantial change in the fishery dynamics. This could be due to the introduction of new gear, significant spatial fishing changes (fleet dynamics), or after the peak in catches (which would usually signal that CMSY has been hit). If the final year is fixed to 2024, the assessment produces a less pessimistic outlook (which is unlikely to be more accurate).

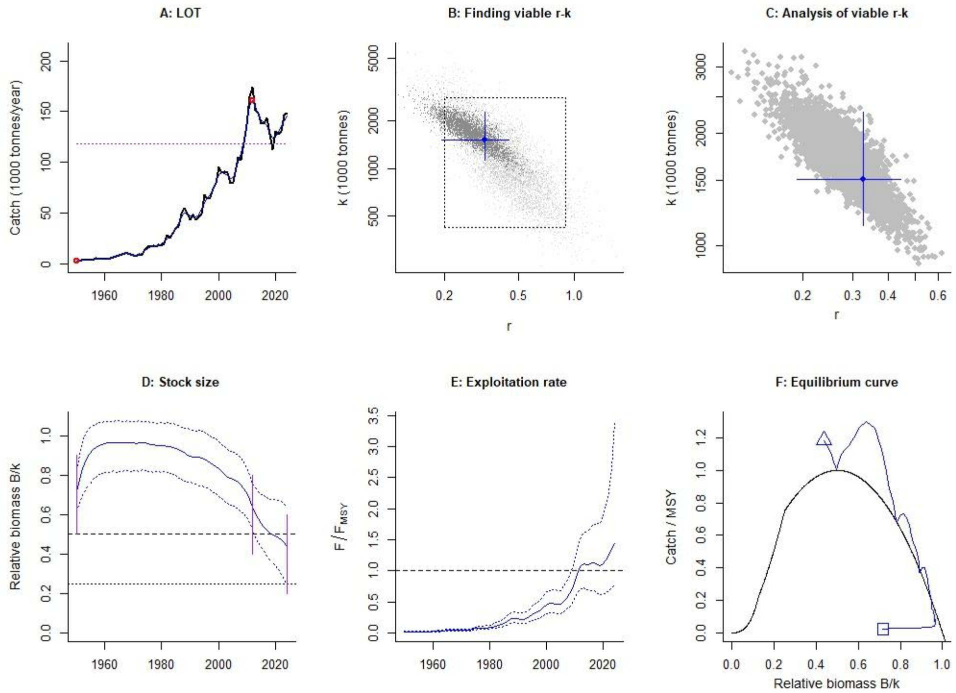

Figure 8. Results of CMSY model for longtail tuna. Each lettered panel represents a different output from the CMSY++ model. The red dot in panel A and the furthest left vertical line in panel D represent the intermediate year for the assessment (2016), chosen as this may represent a significant change in the fishery as it is the final year of high catches before a dip (barring the increase in catch in the final year of data).

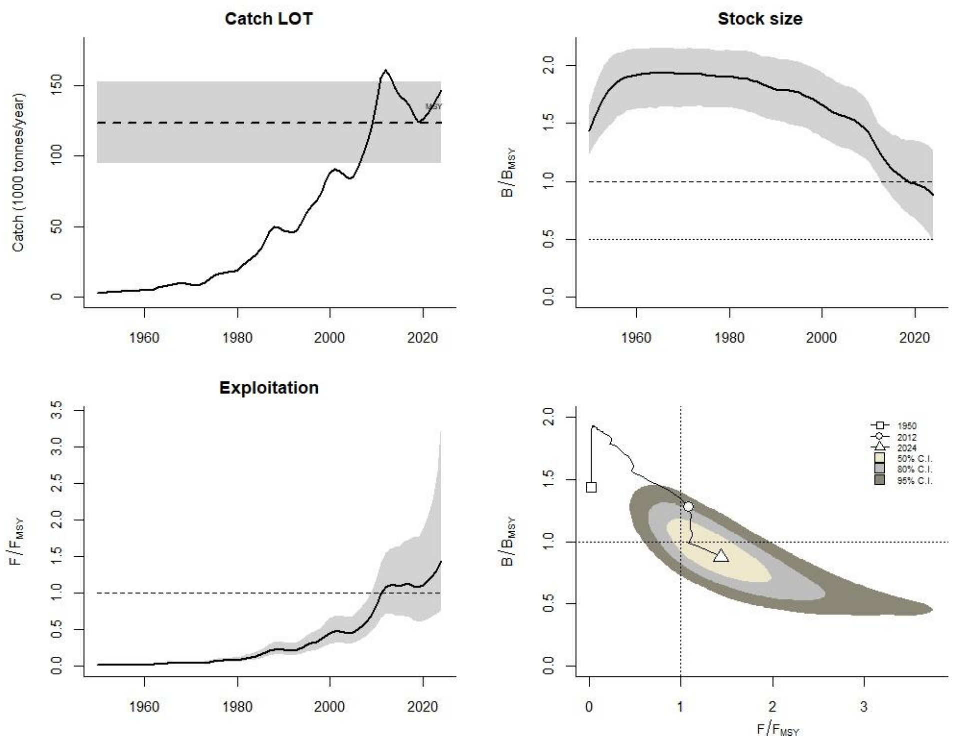

Figure 9. Management quantities from the CMSY++ model of longtail tuna.

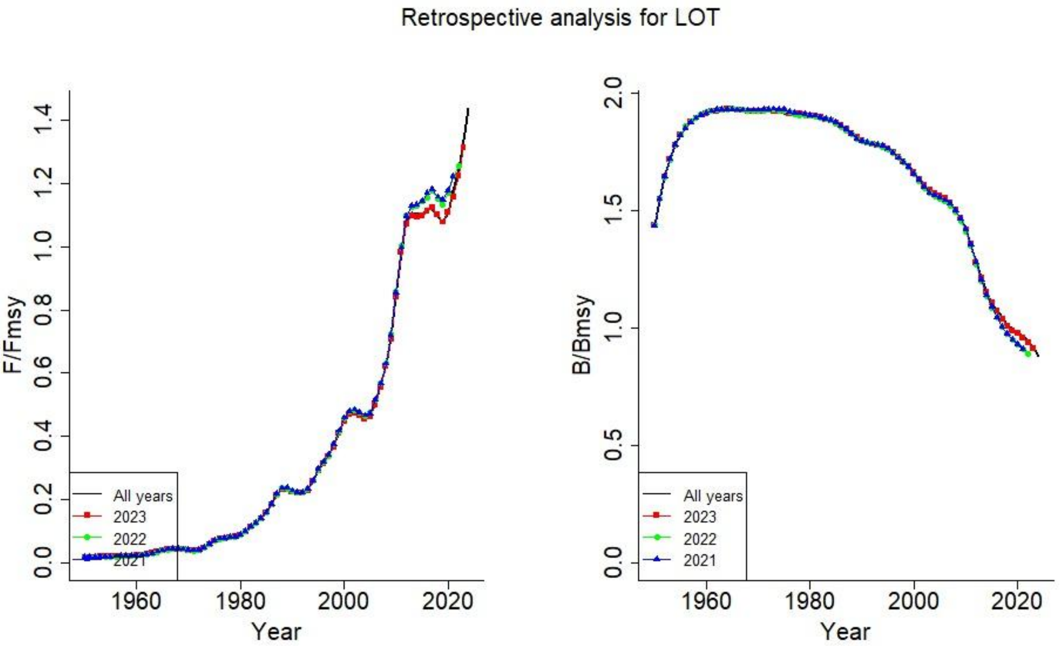

Figure 10. Retrospective analysis for the reference model for longtail tuna using CMSY++. Individual years of catch data are sequentially removed from the model. If the catch data in a specific year were significantly influencing the analysis, this analysis would reveal changes to the trajectory or trends in F/F_{MSY} and B/B_{MSY}.

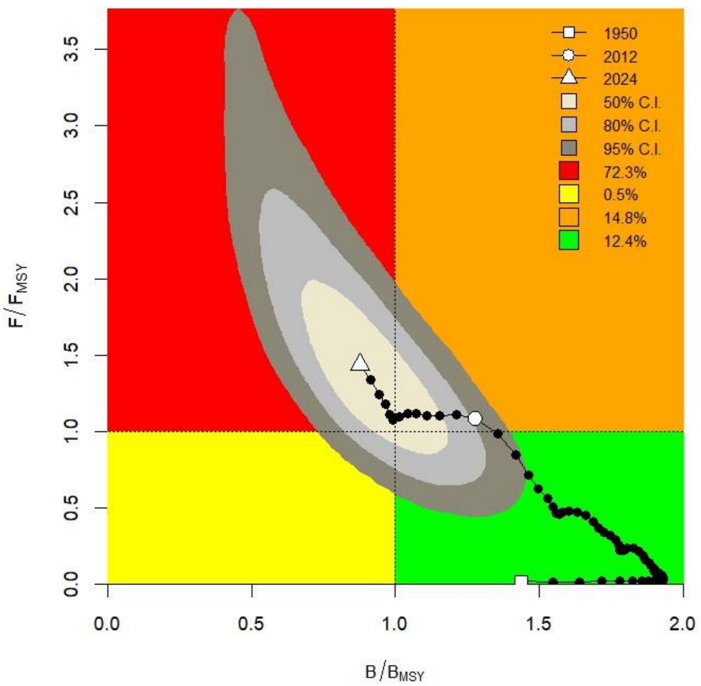

Figure 11: KOBE plot for Longtail tuna from the output of the CMSY++ reference model.

Table 3. Key management quantities from the CMSY++ stock assessment for Indian Ocean Longtail tuna. Geometric means (and plausible ranges across all feasible model runs). Previous assessment results are provided for comparison, but note that between models, significant revisions in catch data mean that results are unlikely to be comparable between assessments (see Figure 3).

Management Quantity	**2020**	**2023**	**2026**
Most recent catch estimate (year)	135 282 (2018)	134 171 (2021)	148 572 (2024)
Mean catch (t) – most recent 5 years[3]	141 996 (2014 – 2018)	134 170 (2017 – 2021)	136 853 (2020 – 2024)
MSY (t) (95% CI)	146 000 (118 100 – 181 000)	133 000 (108 000 –165 000)	123 000 (94 000 - 152 000)
Data period used in assessment	**1950 – 2018**	**1950 – 2021**	**1950 - 2024**
F_{MSY} (95% CI)	0.60 (0.48 - 0.74)	0.31 (0.22 – 0.44)	0.16 (0.10 - 0.22)
B_{MSY} (95% CI)	245 000 (177 000 – 341 000)	433 000(272 000 – 690 000)	75 000 (266 000 – 518 000)
$F_{current}/F_{MSY}$ (95% CI)	0.97 (0.78 – 2.12)	1.05 (0.84 – 2.31)	0.16 (0.10 - 0.22)
$B_{current}/B_{MSY}$ (95% CI)	0.96 (0.44 – 1.19)	0.96 (0.44 – 1.19)	0.88 (0.47 - 1.27)
$B_{current}/B_0$ (95% CI)	0.48 (0.22 – 0.60)	0.48 (0.22 – 0.60)	0.33 (0.19 – 0.44)

[3] Data at time of assessment

4.2. JABBA

The model was fitted to the short CPUE index from I.R. Iran, and catch data, however the initial model struggled to fit to the CPUE index. The initial abundance estimates were quite uncertain, (see **Figure 12**). Estimates were uncertain, and higher than those from CMSY++. The posterior estimates for ***k*** did not resolve into a single peak initially, suggesting the model had difficulty in estimating a carrying capacity, or initial biomass, given the data informing the model. As the catch data do plateau, and then decrease, there is likely sufficient contrast in the trends, however the CPUE index is short in comparison, and is unlikely to be representative of the abundance in the Indian Ocean (as it comes from one fishery, in one region of the Indian Ocean. Additionally, the 'intermediate' year is not estimated well (the outputs estimate the intermediate year as 2002, however catches were still increasing at this time point, and the CPUE index had not started), and a more appropriate year would be 2012. Misspecification of this year is likely to cause issues with model fitting, and therefore the usability of the outputs and/or predictive power of the model.

Following methods in the previous assessment that improved the model, the final depletion was penalised outside the range of 0.2 to 0.6 (model 2), which then slightly lowered the uncertainty of abundance estimations, and the model fitted better to the CPUE index. The stock depletion pattern in this model is more plausible than the initial model 1. The model fitted better to CPUE index by assuming a much lower observation error for the index (reducing from 0.25 to 0.1, models 3-8; **Figure 13**), however, this is achieved by generating a somewhat increasing patterns in the process errors. Additionally, the ***k*** prior range was set to be narrow – forcing the model to have an estimated carrying capacity of ~ 1,500,000 t (similar estimate to CMSY++, model 4). Several iterations of ranges for the ***k*** prior were tested, and narrowing the range removed the multiple peaks in the posterior distribution. This also meant the model fitted well to the CPUE index and provided some realistic trends in the stock trajectory. However, the realism of the estimate of the initial carrying capacity requires further research.

Estimates of management quantities from model 8 (reference model) are shown in **Figure 14**. The estimated stock status is more optimistic than the CMSY++ model (apparently driven by the CPUE index). The MSY varies between 95,000 and 230,000 t, with an average of 135,000 t which is higher than the estimates from CMSY++ (123,000 t). According to the JABBA estimates, the biomass of the spawning stock in 2024 is 1.8 % higher than B_{MSY}, while the fishing mortality (F2024) is 9 % higher than the F_{MSY} (B/B_{MSY} = 1.02 (0.62 – 1.53), F/F_{MSY} = 1.09 (0.44 – 2.28).

The stock trajectory (**Figure 15**) and KOBE plot from the reference model (model 8; **Figure 16**) are shown and provide reasonable results, based on the information available at the time of the assessment. The stock is following the surplus production model in a reasonable way, considering the data available.

The JABBA model results suggest that the stock is **not overfished** but **is subject to overfishing** in 2024.

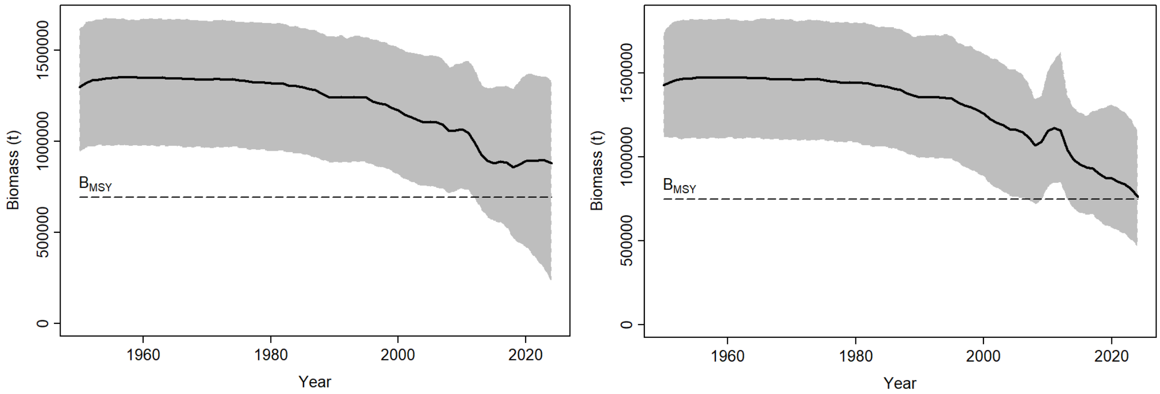

Figure 12: Biomass estimates (median and 95% CI) from JABBA model 1 (left, no prior on final depletion), and the reference model, model 8 (right, a normal prior on final depletion with mean of 0.4 and CV of 10%, corresponding to an approximate range 0.2 – 0.6). Dashed line indicates median B_{MSY}.

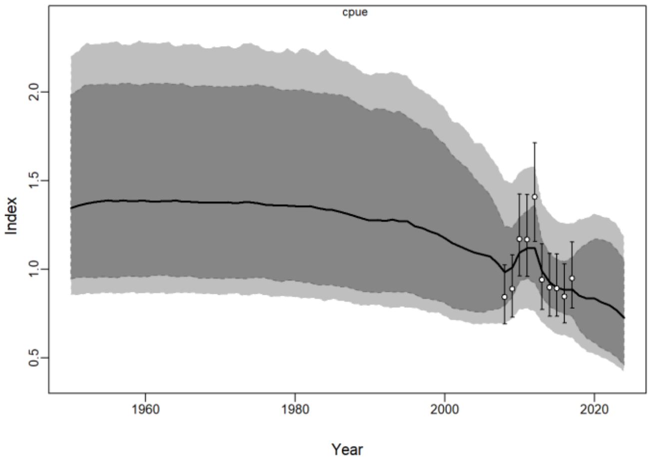

Figure 13: Fits to CPUE indices 2008–2017 from the JABBA reference model. Shaded areas indicate 50% and 95% CI, vertical lines indicate observation errors.

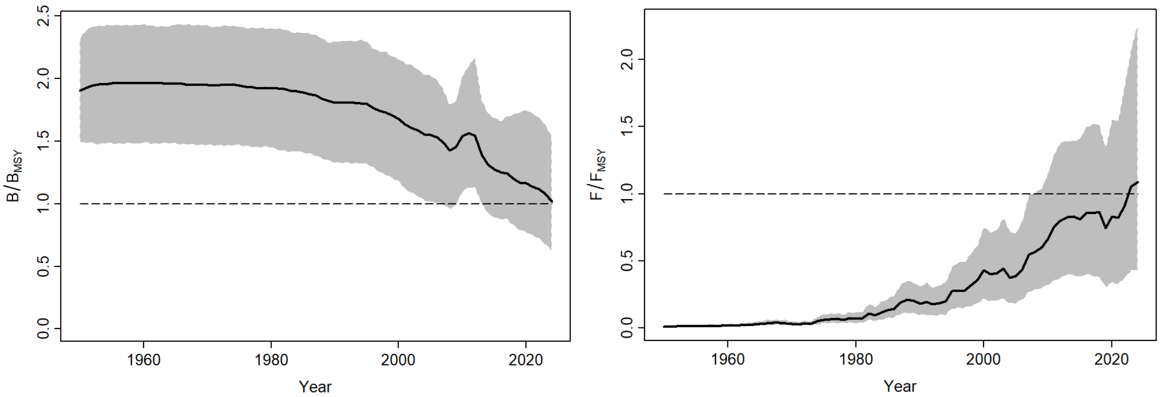

Figure 14: Estimates of management quantities from the JABBA reference model (B/B_{MSY} and F/F_{MSY}).

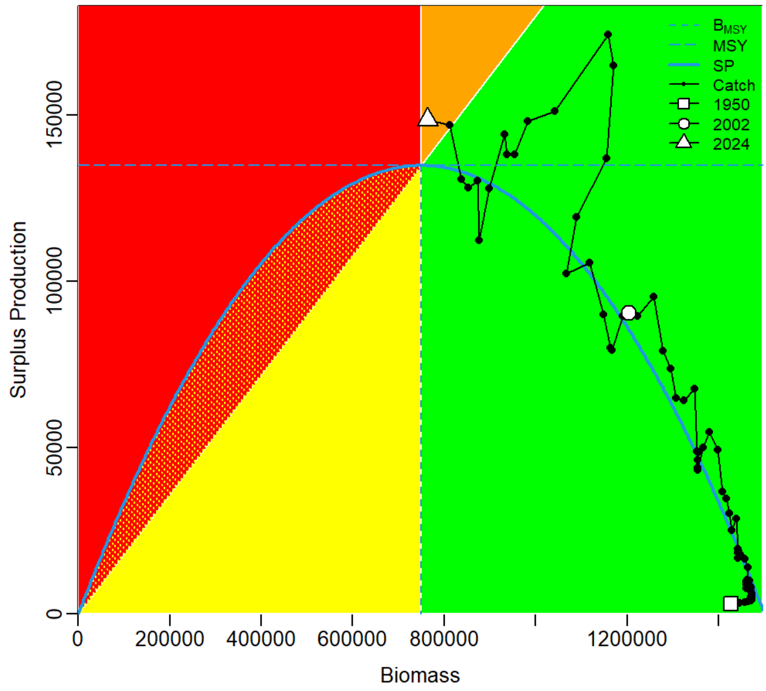

Figure 15: Trajectory of the stock against the Schaefer surplus production model from 1950 to 2024. The intermediate year (2002) has been estimated by the JABBA model.

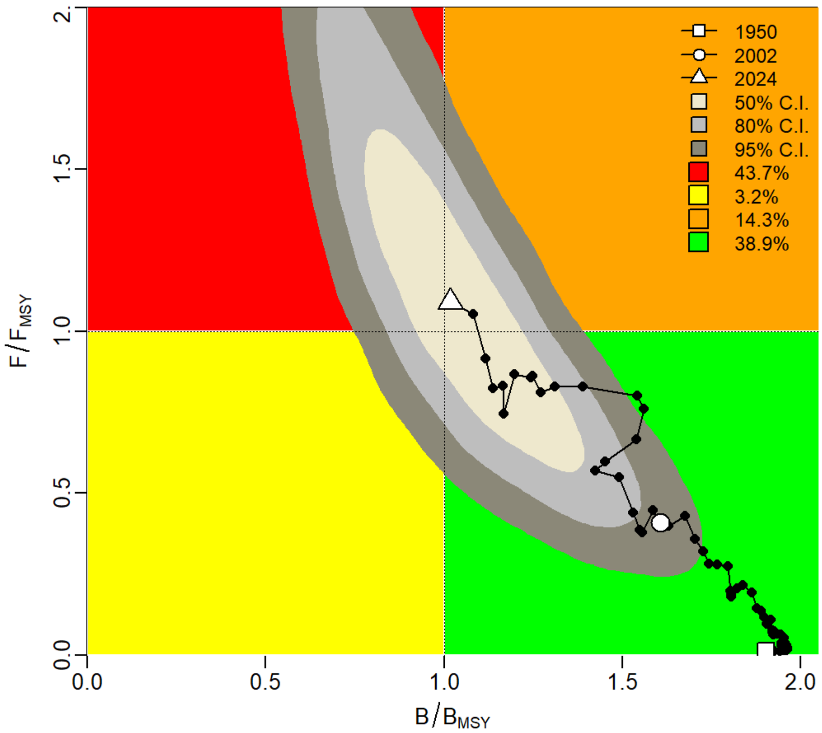

Figure 16: KOBE plot from the JABBA reference model, showing the stock trajectory. The stock is found within the orange quadrant of the KOBE plot, which represents a fishery that is not overfished, but is subject to overfishing.

4.3. LBSPR

The length distributions from the gillnet fishery are well fitted (**Figure 17**).

4.3.1. Gillnet

Selectivity trends have significantly decreased throughout the fishery, suggesting a shift towards smaller fish sizes over time (**Figure 17**). The fishing mortality is estimated to have decreased (**Figure 17**), after high effort in the early 2000s, but throughout the fishery it has been well above the potential F_{MSY} (0.87 M was regarded a realistic approximation of F_{MSY} for teleosts, see (Zhou, Smith and Fuller, 2011)). Estimated spawning potential ratio throughout the time series is well below 0.4, indicating that the stock is depleted in relation to the risk-averse target (the SPR of 0.4 is often considered as a risk-averse target; see (Hordyk *et al.*, 2015)), although the SPR has increased in later years, moving towards a value of 0.4.

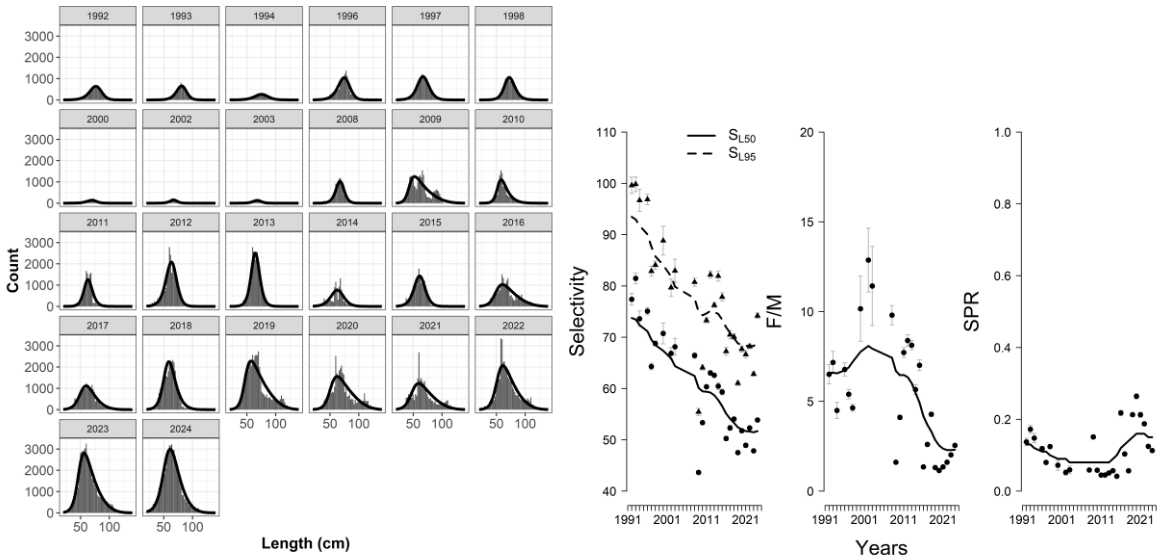

Figure 17: Results of LBSPR method applied to the length samples from the gillnet fishery for longtail tuna: Fits to the length frequency in 1992–2024 (black dots) right – estimates (with 95% CI) of annual logistic selectivity parameters (L50 and L95), F/M, and spawning potential ratio (SPR) over time.

5. DISCUSSION

The CMSY++, JABBA, and LBSPR methods have all been investigated in this report to evaluate the status of Indian Ocean Longtail tuna. Only the catch series is needed as input for the CMSY++ method, which relies on an aggregated biomass dynamic model and uses simulations to find historical biomass that is plausible and supports the known catch history. Although there was the option to include a CPUE index, and indeed gear creep, this was trialled, but not included in the final model, as the model was unable to fit well to the CPUE index.

A time series of relative abundance (gillnet standardised CPUE index) was included into the JABBA model, together with model parameters and management quantities estimated in a Bayesian framework.

5.1. CMSY++ and JABBA

Estimates from the CMSY++ BSM model suggests that currently the stock of Longtail tuna in the Indian Ocean is **overfished** ($B_{2024} < B_{MSY}$) and **is subject to overfishing** ($F_{2024} > F_{MSY}$). The estimates produced by the JABBA method, suggest that the stock is **not overfished** ($B_{2024} > B_{MSY}$) but **is subject to overfishing** ($F_{2024} < F_{MSY}$).

The CMSY++ model estimated an average MSY of ~ 123 000 t which is lower than that estimated by JABBA (135 000 t). The 2024 catch (148 572 t) is above to that of MSY (from both models) and has been higher than estimated MSY for ~ 20 years.

The CPUE data suggest increasing biomass, as the index is increasing, while over the same time, catches are remaining constant (and high). This is likely why the JABBA model estimates a higher MSY than CMSY++ as more data are available, and the CPUE suggests the stock can sustain higher exploitation, as biomass is increasing (the model assumes the CPUE is an abundance index). As the previous assessment stated, it is likely that the stock is being fished above MSY levels and has been for several years. These high catches are unlikely to be sustainable. A precautionary approach to management is recommended, particularly with only one standardised index of abundance, that does not represent the entire Indian Ocean.

The JABBA model utilised the standardised CPUE index to provide information on abundance trend, and as such, the model is less reliant on some of the subjective assumptions relating to k and r. However, for longtail tuna, there appears to be inconsistency between the CPUE indices, and the catch history, and productivity assumptions of the species. The increasing CPUE can be attributed to other (unknown) random variations in the population (e.g., process error) but there is a risk of overparameterizing the model (such that it has little predictive power). Furthermore, it remains to be seen whether CPUE indicators obtained from the Islamic Republic of Iran's coastal gillnet fishing fleets can index the abundance of longtail tuna stocks in the Indian Ocean, in addition to the various caveats even as a local indicator (see Fu et al 2019). Nevertheless, the availability of updated standardised CPUE indices as potential abundance indices and their inclusion in following assessments will be a useful step forward in the context of assessing data deficient neritic tuna stocks. CPUE indices should be regularly updated to be a reliable monitoring tool, potentially providing a longer and more informative time series. Standardised indices should also be developed for other fisheries/regions to ensure better spatial coverage of stock populations.

5.2. LBSPR

Estimates of stock status from the LBSPR method cannot be directly comparable to the catch-only models as they have made very different assumptions about target reference points. Nonetheless, the SPR estimated by the LBSPR method was **below** the $SPR_{40\%}$ for gillnet fisheries, while fishing mortality is estimated to be much higher than F_{MSY}, in contrast to the result of the CMSY++ models.

Estimated spawning potential ratio throughout the time series is well below 0.4, indicating that the stock is depleted in relation to the risk-averse target (the SPR of 0.4 is often considered as a risk-averse target; see Hordyk et al. 2014a), and although the SPR increased 2009, mirroring the upward trend in the CPUE in the same time period, there has been a decrease in SPR from 2017 to 2024. The LBSPR model assumes asymptotic selectivity, and it has been demonstrated that the results are sensitive to this assumption (the model interprets the absence of the large individuals from the size structure as evidence for a high level of exploitation).

Additionally, the high variation in SPR around the mean line suggests that there are biases in the length frequency data (e.g. they do not necessarily represent a true sample of all fish sizes selected by fishing gear in the Indian Ocean). The spatial and temporal stratification of length frequency data for neritic species in the Indian Ocean should be well investigated to ensure that these biases are not unduly impacting stock assessment results.

6. CONCLUSIONS

Based on a weight-of-evidence approach, it is likely that Longtail tuna is, in 2024, **overfished** and **subject to overfishing** in the Indian Ocean. However, there are several caveats to this, stated below:

a) The trend in reported nominal catch of longtail tuna over time in the Indian Ocean has been continuing to increase and has been above or in the higher ranges of estimated MSY for nearly 20 years. High catches, in combination with less biological resilience to fishing, is resulting in a higher impact of fishing on stock levels.
b) Length-based analyses suggest that the stock is likely to be overfished, however the length data are unlikely to be representative of the entire Indian Ocean stock(s), based on recent biological studies (Griffiths *et al.*, 2020).
c) Recent work suggests there are likely several stocks of longtail tuna (Griffiths *et al.*, 2020), however catch, and length data are not reported at a fine-enough scale to capture individual stock dynamics. Additionally, representative abundance indices should be developed on a similar spatial scale to putative stocks.

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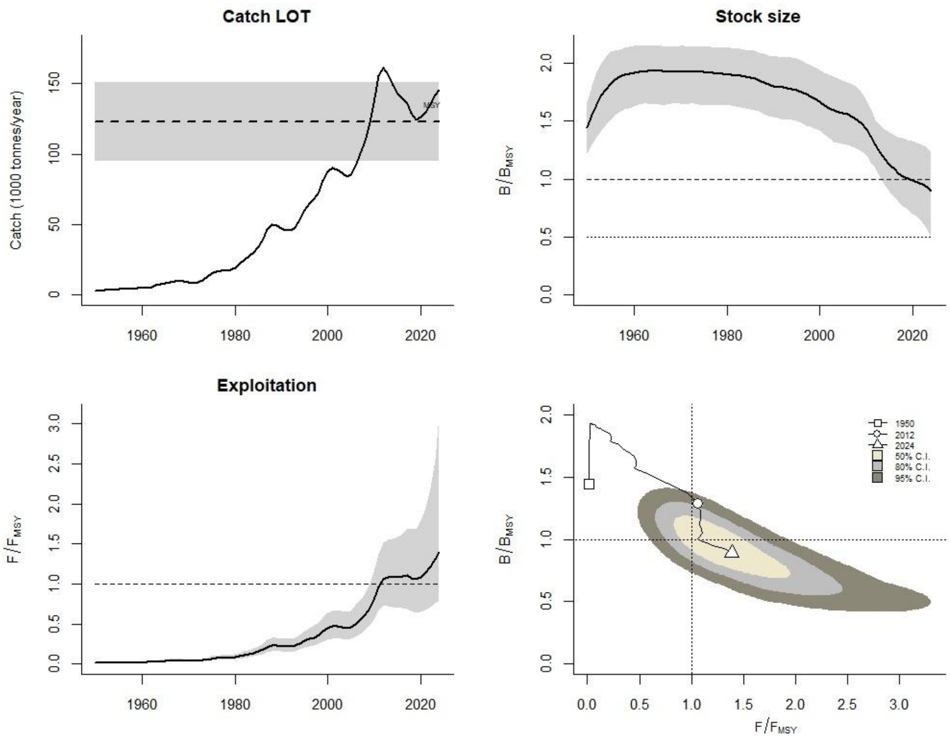
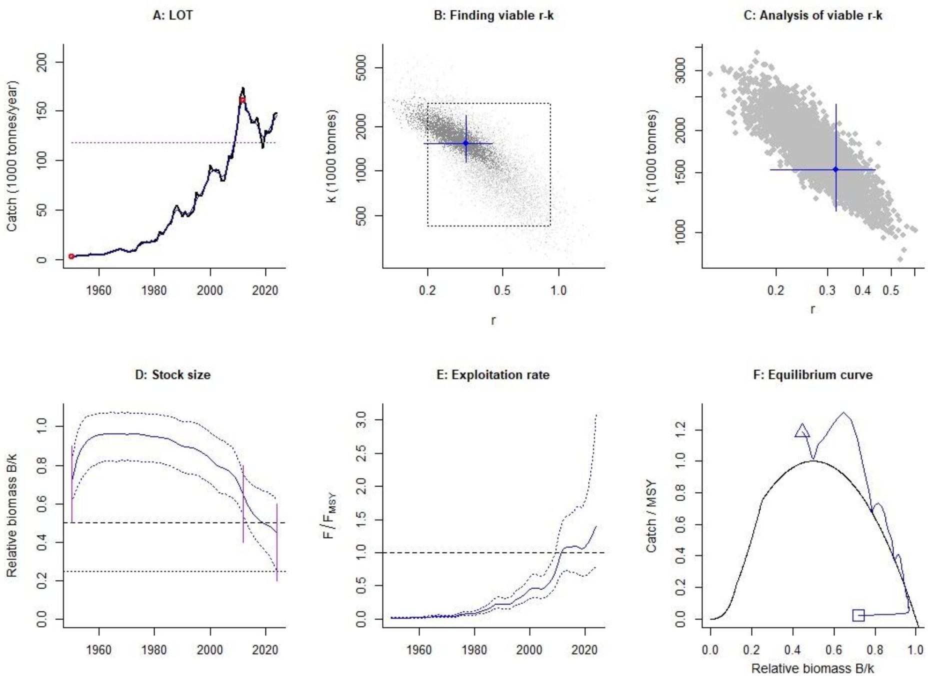
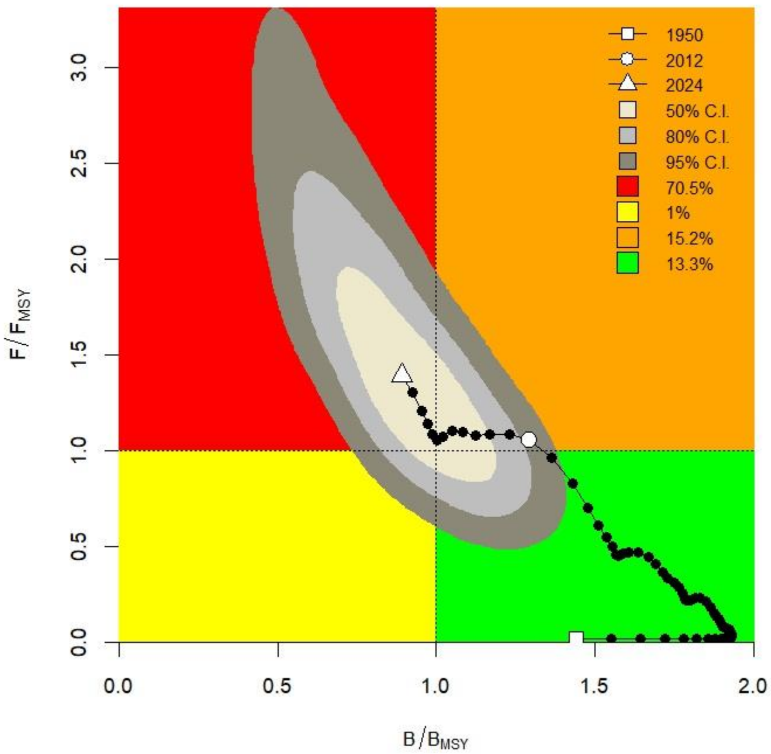
8. APPENDIX

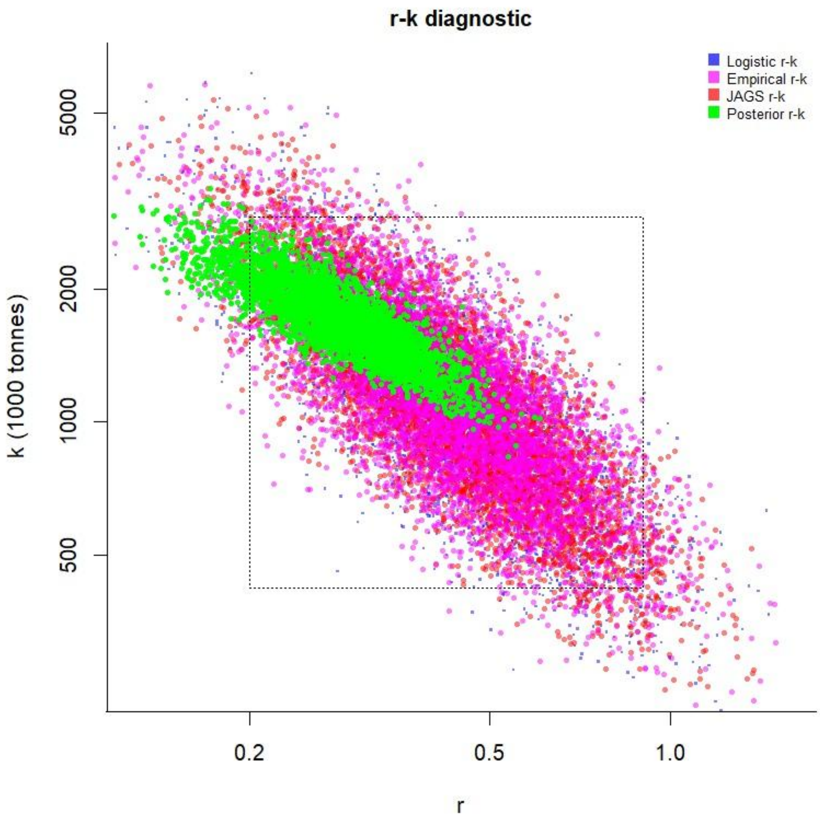
8.1. Comparison of outputs from CMSY++ and CMSY for the reference model

1) Outputs from CMSY++






1950
2012
2024
50% C.I.
80% C.I.
95% C.I.
70.5%
1%
15.2%
13.3%
F/F_MSY
0.0
0.5
1.0
1.5
2.0
2.5
3.0
0.0
0.5
1.0
1.5
2.0
B/B_MSY


r-k diagnostic
Logistic r-k
Empirical r-k
JAGS r-k
Posterior r-k
k (1000 tonnes)
500
1000
2000
5000
0.2
0.5
1.0
r

2) Outputs from CMSY (v9f)