Assessment of Indian Ocean kawakawa (*Euthynnus affinis*) using data-limited methods

30th June 2023

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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 kawakawa (*Euthynnus affinis*) from 2013 to 2015, and again in 2020 using data-limited methods (Zhou & Sharma, 2013, 2014; Martin & Sharma, 2015, Fu 2020). In 2020 the C-MSY method (Froese et al. 2016) was used to assess the status of *E. affinis* (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 *E. affinis*.

2. Basic Biology

The Eastern little tuna or kawakawa, *Euthynnus affinis* (Cantor 1849), is a medium-sized epipelagic, migratory neritic tuna is widely distributed across the Indo-West Pacific region in open waters close to the shore. It has a maximum fork length of 100 cm (Froese & Pauly 2015) and generally forms multispecies schools by size with other scombrid species comprising 100 – 5,000 individuals or more (Collette & Nauen 1983). It is a highly opportunistic predator feeding indiscriminately on small fishes, including clupeoids and atherinids as well as squids, crustaceans, molluscs and zooplankton (Collette 2001; Gupta et al. 2014). The species supports substantial commercial and artisanal fisheries in many countries bordering the Indian Ocean, including Indonesia, India, Iran, Pakistan and Sri Lanka (IOTC 2023). Most research 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. Studies on the growth of E. affinis indicate that it is a fast growing species, attaining a fork length of 30-49 cm in the first year (IOTC-2015).

3. Catch, CPUE and Fishery trends

Nominal catch data were extracted from the IOTC Secretariat database for the period 1950-2021, given that records for 2021 were still incomplete at the time of writing. Gillnet fleets are responsible for the majority of reported catches of kawakawa, followed by purse seine gear and lines, with the majority of catches taken by coastal country fleets (Figure 1). **Error! Reference source not found.** shows the increase in total catches since 1950, at an increasing rate in recent years, reaching approximately 160,000 t across the entire Indian Ocean region in 2013 (**Error! Reference source not found.**). The catches have since then fluctuated considerably but remained at historically high levels. Some revisions have been made to the nominal catch series since the assessment that took place in 2015, including the revisions of Pakistani gillnet catches (IOTC 2019), which appears to have a minor effect on the kawakawa catch series since 1990 (Figure 3).

Fu et al. (2019) developed standardised CPUE indices for several neritic tuna species including kawakawa 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 kawakawa showed some discontinuity in both 2010 and 2012 (Figure 4), indicating potential catchability changes. Thus, only the indices from 2012 to 2017 (annualised by taking the average of the quarterly indices) are included in the Bayesian Schaefer production model (see Section 4.2).

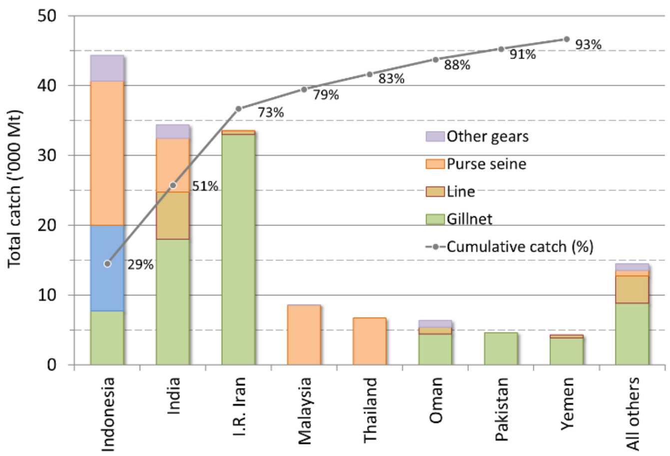

Figure 1: Average catches in the Indian Ocean over the period 2012-2021, by country. The red line indicates the (cumulative) proportion of catches of kawakawa by country.

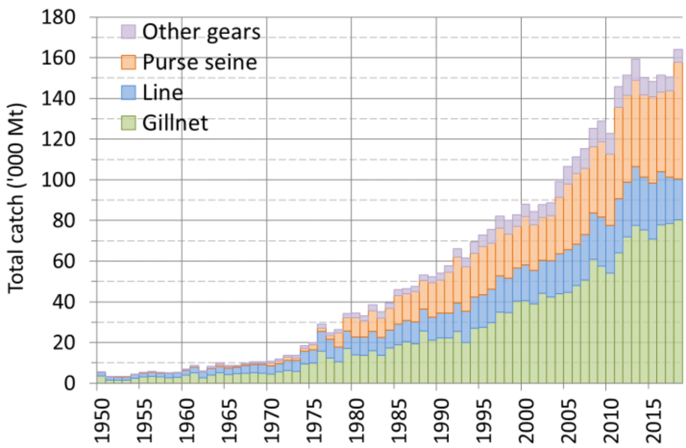

Figure 2: Annual catches of kawakawa by gear, 1950 – 2021 (IOTC database).

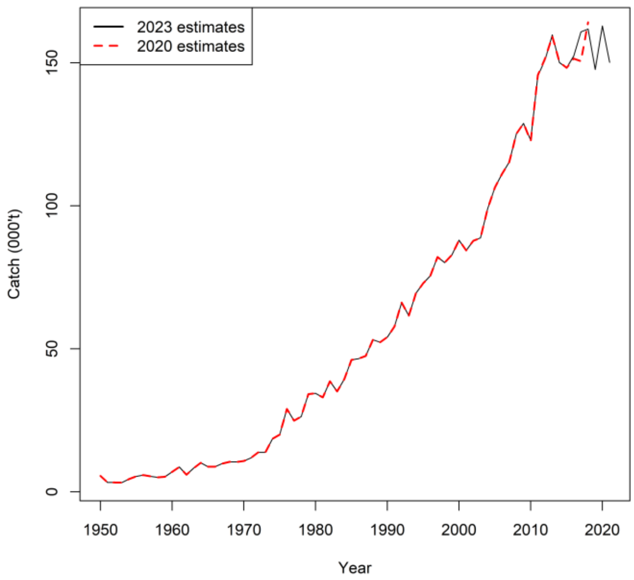

Figure 3: Revisions to IOTC nominal catch data for kawakawa (datasets used for the 2015 and 2021 assessments).

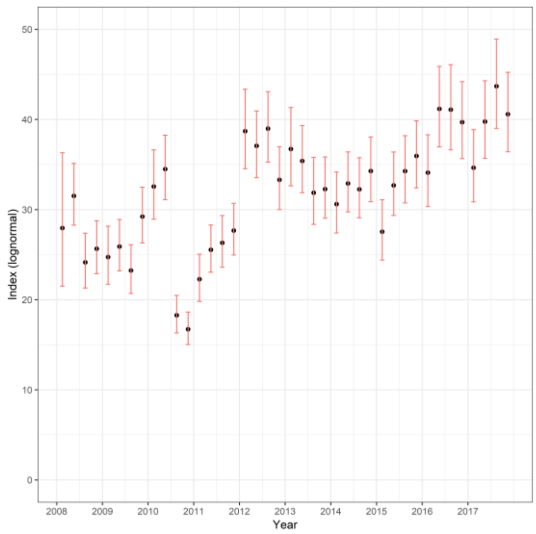

Figure 4: Standardised CPUE indices (year-quarter) for kawakawa 2008–2018 from the GLM lognormal model. See Fu et al. (2019) for details.

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

Year	Catch (t)	Year	Catch (t)
1950	5 570	1986	46 524
1951	3 249	1987	47 479
1952	3 281	1988	53 183
1953	3 238	1989	52 304
1954	4 491	1990	54 077
1955	5 377	1991	57 788
1956	5 859	1992	66 162
1957	5 394	1993	61 589
1958	5 071	1994	69 463
1959	5 272	1995	72 867
1960	6 974	1996	75 481
1961	8 682	1997	82 087
1962	5 991	1998	80 126
1963	8 265	1999	82 804
1964	10 153	2000	87 966
1965	8 776	2001	84 391
1966	8 822	2002	87 745
1967	9 877	2003	88 769
1968	10 493	2004	98 990
1969	10 451	2005	106 399
1970	10 789	2006	111 173
1971	11 861	2007	115 261
1972	13 763	2008	125 187
1973	13 815	2009	128 774
1974	18 556	2010	122 939
1975	20 004	2011	145 495
1976	28 953	2012	150 935
1977	24 880	2013	159 761
1978	26 286	2014	150 050
1979	34 149	2015	148 247
1980	34 435	2016	152 355
1981	33 034	2017	160 786
1982	38 629	2018	161 785
1983	35 092	2019	147 645
1984	39 368	2020	162 887
1985	46 105	2021	150 170

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 kawakawa. 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 *E. affinis* (including growth, natural morality, maturity, and length-weight relationship) are based on values collated and recommended by IOTC (2015), which was estimated to have a credible range of approximated 0.4–1.6. 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, *E. affinis* has a high level of resilience (Froese and Pauly 2015), which overlaps with what was estimated by the LHM method. For this analysis, the prior range of r was set to 0.6 – 1.5.

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.

The medium range (0.2 – 0.6) assumption was adopted for the final depletion level in the 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 kawakawa 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	106 – 1055

4.2. OCOM model

Similar to the C-MSY approach, the Optimised Catch-Only approach (Zhou et al. 2013 & 2016) uses the biomass dynamic model (i.e., Schafer 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, (Zhou et al., 2021), 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) model. 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 (0.6–1.5) and on S (0.2–0.6) as those used in the C-MSY models to allow easier comparison with the C-MSY model.

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 F40%, 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 E. affinis are obtained from IOTC (2015).

The length data (IOTC-2023-WPNT13-DATA09-SFdata) used includes length samples by fleet, gear, year, month, and region. The majority of the Kawakawa samples come from the Iranian/Pakistani gillnet fishery from 2009 to 2021 (earlier samples are also available, although there is more variation in sample size and quality). The length distribution of samples from the line fisheries is comparable to that of the gillnet fishery. We used the approach on both sets of data.

5. Results

5.1. C-MSY method

Figure 5 shows the results of the 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 347 000 – 686 000 (mean of 488 000). 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 kawakawa 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 154 000 t. The KOBE plot indicates that based on the C-MSY model results, kawakawa mackerel is currently not overfished (B2021/BMSY=1.00) but is not subject to overfishing (F2021/FMSY = 0.98). The catches over the last five years are higher than the estimated MSY.

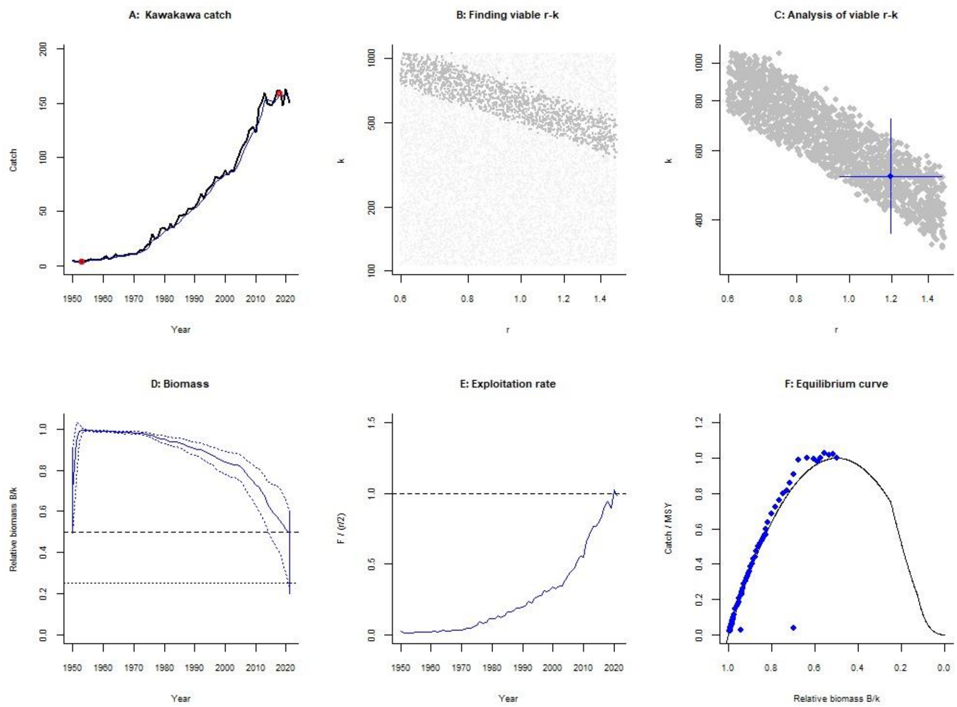

Figure 5. Results of CMSY reference model for kawakawa.

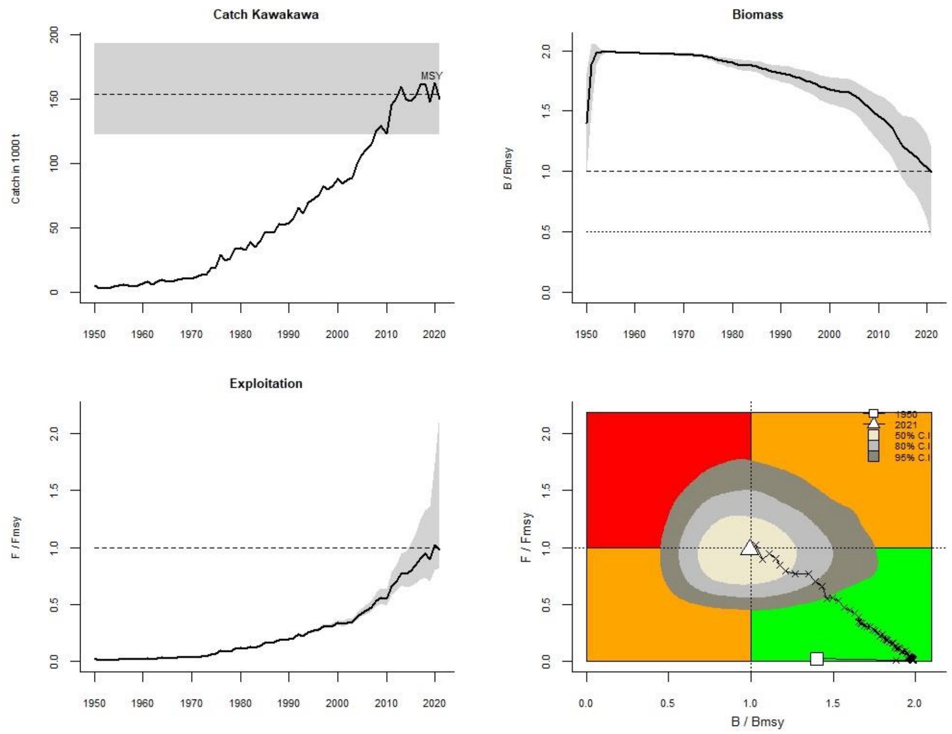

Figure 6. Graphical output of the CMSY reference model of kawakawa for management purposes.

Table 3. Key management quantities from the Catch MSY assessment for Indian Ocean kawakawa 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)	164,133 t (2018)	150 170 (2021)
Mean catch – most recent 5 years[2]	152 919 t (2014 – 2018)	156 655 (2017 – 2021)
MSY (95% CI)	145 000 (114 000 – 185 000)	154 000 (122 000 – 193 000)
Data period used in assessment	1950 – 2018	1950 – 2021
F_{MSY} (95% CI)	0.60 (0.48 - 0.74)	0.60 (0.48 – 0.74)
B_{MSY} (95% CI)	244 000 (173 000 – 343 000)	258 000 (185 – 359)
$F_{current}/F_{MSY}$ (95% CI)	1.16 (0.95 – 2.59)	0.98 (0.82 – 2.20)
$B_{current}/B_{MSY}$ (95% CI)	0.97 (0.44 – 1.19)	1.00 (0.45 – 1.20)
$B_{current}/B_0$ (95% CI)	0.49 (0.22 – 0.60)	0.50 (0.22 – 0.60)

[2] Data at time of assessment

5.2. OCOM

Figure 7 shows the strong correlation of *r* and *K* parameter values retained by the biomass dynamics model. 80% posterior range of r is 0.70 – 1.32, are mostly overlap with the prior. Esimated K ranges from 420 000 to 714 000. 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.

Base case model results indicate that the biomass was approximately 550 000 t in 1950 and declined to approximately 217 000 t by 2021 (Figure 7). The estimated MSY associated with this projection is 145 000 t and ranges from approximately 135 000 t to 151 000 t based on the assumed depletion level (Figure 7). The model estimated that the stock is currently overfished (B2021/BMSY=0.80) and is subject to overfishing (F2021/FMSY = 1.28). The estimated stock status of the OCOM model is more pessimistic than the C-MSY model, despite 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.

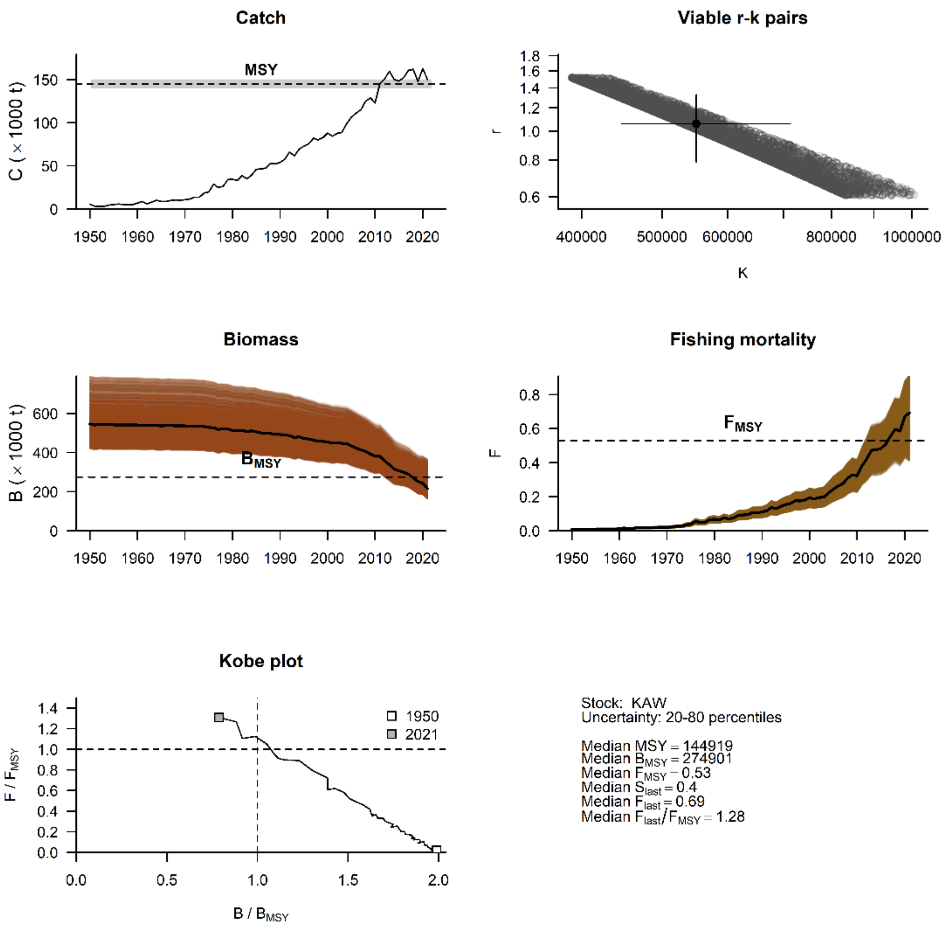

Figure 7: Graphical output of management quantities from the OCOM reference model of kawaka

5.3. JABBA model

The abundance estimates were exceedingly uncertain with a very wide posterior range (upper range of K surpassed 3 000 000 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. However, this model did not explain well the pattern in CPUE, which predicted a considerable increase in abundance starting in 2016 (Figure 9).

Estimates of management quantities from model 2 are shown in Figure 10. The estimated stock status is slightly more optimistic to the CMSY model (apparently driven by the CPUE index). The MSY varies between 130 000 and 319 000 t, with an average of 157 000 t. According to estimates, the biomass of the spawning stock in 2021 is 4 % higher compared to the BMSY, and the fishing mortality is roughly about 9% lower than the FMSY (B/BMSY = 1.04, F/FMSY = 0.91). 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 consistency between the CPUE and catch series.

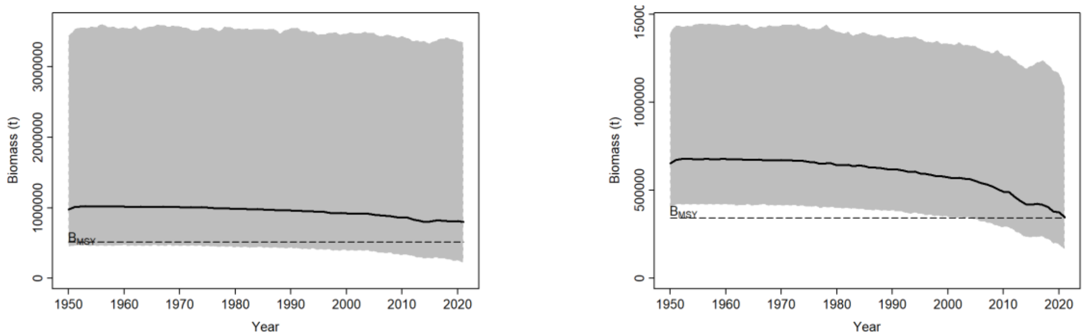

Figure 8: Biomass estimates (median and 95% CI) from JABBA model 1 (left, no prior on final depletion), and model 2 (right, a normal prior on final depletion with mean of 0.4 and CV of 25%, corresponding to an approximate range 0.2 – 0.6). Dashed line indicates median BMSY.

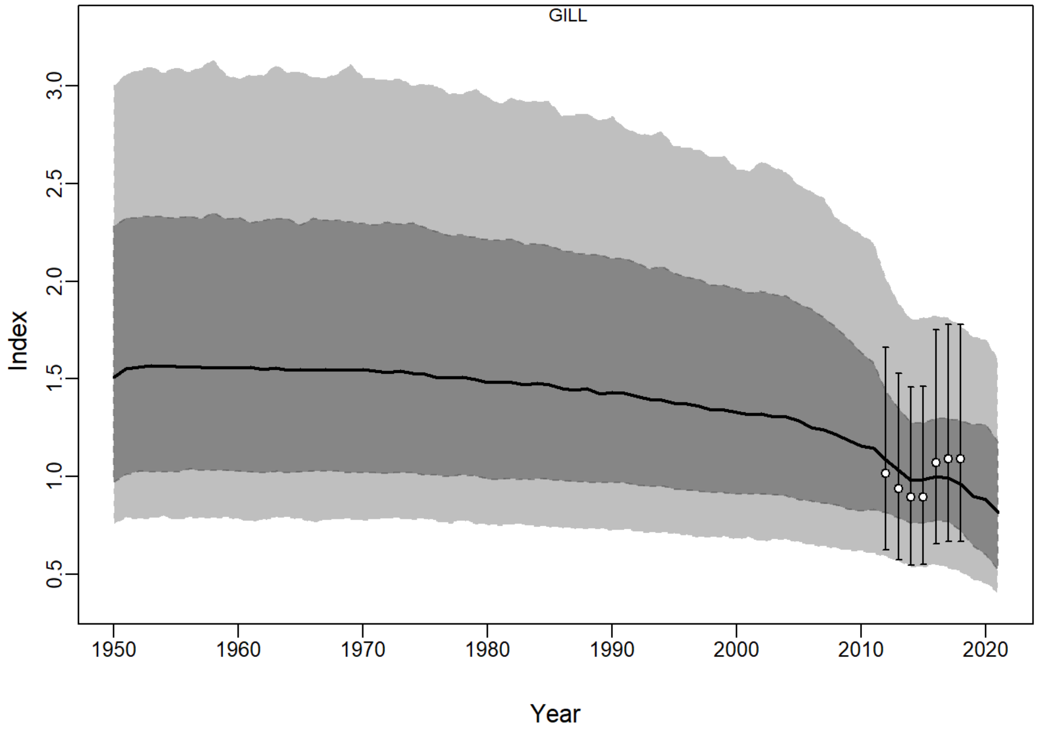

Figure 9: Fits to CPUE indices 2008–2017 form JABBA model 2. Shaded areas indicates 50% and 95% CI, vertical lines indicates observation errors.

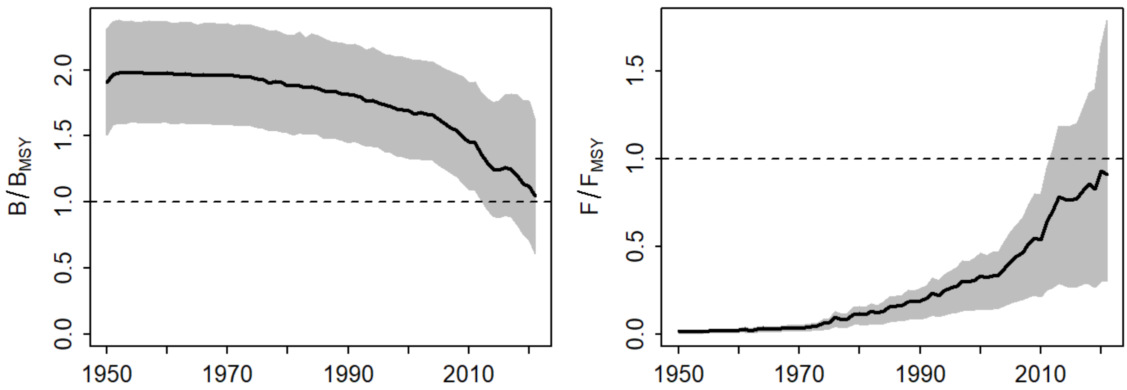

Figure 10: Estimates of management quantities of the JBBBA model 2 (B/BMSY and F/FMSY).

5.4. LB-SPR model

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). The SPR was estimated to be declining overtime and was 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.

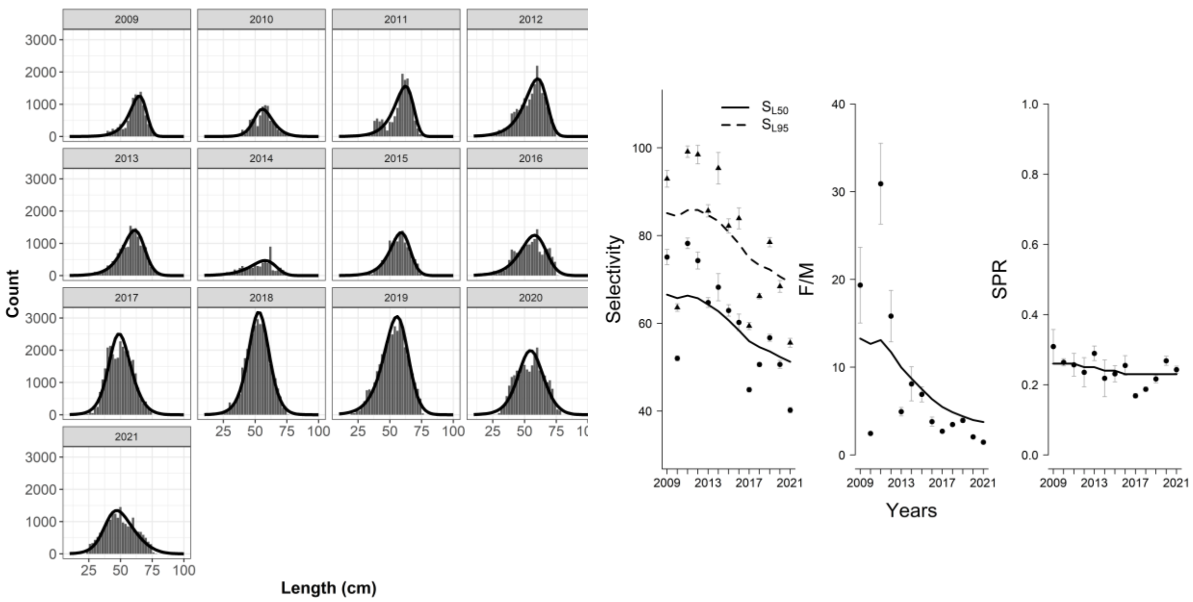

Figure 11: Results of LB-SPR method applied to the length samples from the gillnet fishery for longtail tuna: Fits to the length frequency in 2009–2021 (black dots); right – estimates (with 95% CI) of annual logistic selectivity parameters (a50 and a95), F/M, and Spawning Potential Ratio over time.

6. Discussion

In this report we have explored several data-limited methods in assessing the status of Indian Ocean longtail tuna: C-MSY, OCOM, JABBA, and LB-SPR methods. Both C-MSY and OCOM methods are based on based on an aggregated biomass dynamic model and require only the catch series as model input and uses simulations to locate feasible historical biomass that support the catch history. The JABBA has incorporated time series of relative abundance indices, and estimated model parameters and management quantities in a Bayesian framework. Estimates from the C-MSY and JABBA model suggested that currently the stock of kawaka in the Indian Ocean is not overfished (B2012 > BMSY) and is not subject to overfishing (F2021 < FMSY). The estimates produced by the OCOM method is more pessimistic, suggesting that the stock is overfished and is subject to overfishing. However, it has been demonstrated in many occasions that the estimates of management quantities of the CMSY analysis are sensitive to assumption of the final stock depletion.

The JABBA 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. However, for kawakawa, there appears to be inconsistency between the CPUE index and the catch history. Furthermore, it remains to be seen whether CPUE indicators obtained from Iranian coastal gillnet fishing fleets can index abundance of kawakawa 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.

Estimates of stock status from the LB-SPR method cannot be directly comparable to the catch-only models as they have made very different assumptions about target reference points. The LB-SPR 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; see Hordyk et al. (2014a) for more information). 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 kawakawa.

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