

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

30th June 2020

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1. Introduction.....	2
2. Basic Biology.....	2
3. Catch, CPUE and Fishery trends.....	2
4. Methods.....	6
4.1. C-MSY method.....	6
4.2. Bayesian Schaefer production model (BSM).....	7
5. Results.....	8
5.1. C-MSY method.....	8
5.2. Bayesian Schaefer production model (BSM).....	11
6. Discussion.....	Error! Bookmark not defined.
References.....	18

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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 using data-limited methods (Zhou and Sharma, 2013; Zhou and Sharma, 2014; Martin and Sharma, 2015). This paper provides an update to these assessments based on the most recent catch information report to the IOTC, using two methods to assess the status of *E. affinis*: (i) an updated Catch-MSY method (Kimura and Tagart 1982; Walters et al. 2006; Martell and Froese 2012; Froese et al. 2016) and (ii) a Bayesian biomass dynamic model, BSM (Froese et al. 2016), which utilised the recently available CPUE indices of the kawakawa developed from the Iranian gillnet fishery.

2. Basic Biology

The Eastern little tuna or kawakawa, *Euthynnus affinis* (Cantor 1849), is a medium-sized epipelagic, migratory neritic tuna 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 (Pierre et al. 2014). 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-WPTN05-DATA12).

3. Catch, CPUE and Fishery trends

Nominal catch data were extracted from the IOTC Secretariat database for the period 1950–2018, given that records for 2019 were still incomplete at the time of writing. Gillnet fleets are responsible for the 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, currently reaching approximately 160,000 t across the entire Indian Ocean region (**Error! Reference source not found.**). 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–WPDCS15 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).

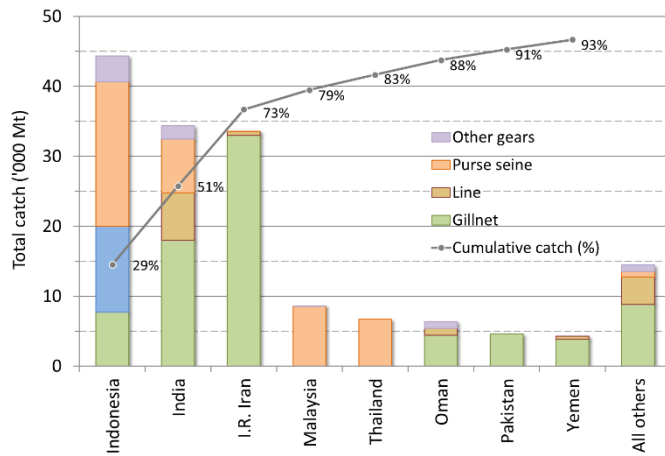


Figure 1: Average catches in the Indian Ocean over the period 2012-2018, by country. The red line indicates the (cumulative) proportion of catches of kawakawa by country.

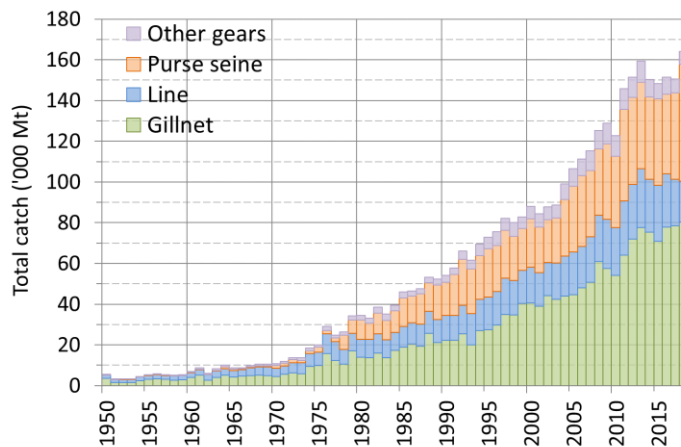


Figure 2: Annual catches of kawakawa by gear, 1950 – 2018 (IOTC database).

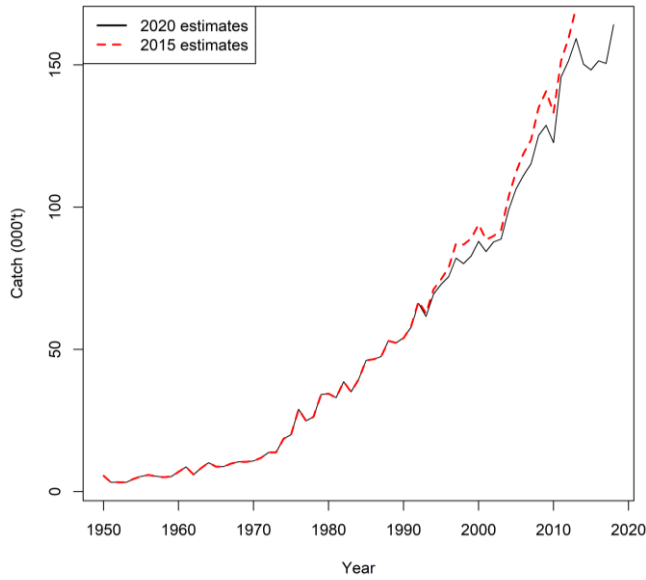


Figure 3: Revisions to IOTC nominal catch data for kawakawa (datasets used for the 2015 and 2020 assessments).

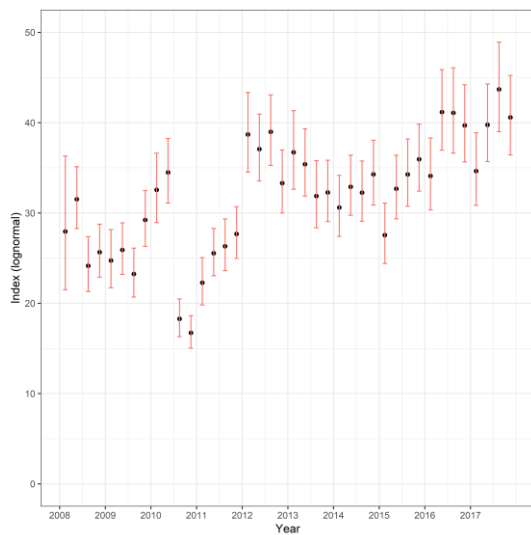


Figure 4: Standardised CPUE indices (year-quarter) for kawakawa 2008–2017 from the GLM lognormal model. See Fu et al. (2019) for details.

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

Year	Catch (t)	Year	Catch (t)
1950	5 569	1985	46 105
1951	3 248	1986	46 524
1952	3 280	1987	47 479
1953	3 237	1988	53 183
1954	4 489	1989	52 304
1955	5 375	1990	54 077
1956	5 858	1991	57 788
1957	5 393	1992	66 162
1958	5 070	1993	61 589
1959	5 271	1994	69 463
1960	6 973	1995	72 867
1961	8 681	1996	75 483
1962	5 990	1997	82 087
1963	8 264	1998	80 130
1964	10 152	1999	82 807
1965	8 775	2000	87 967
1966	8 821	2001	84 395
1967	9 876	2002	87 745
1968	10 491	2003	88 769
1969	10 450	2004	98 990
1970	10 789	2005	106 399
1971	11 861	2006	111 173
1972	13 763	2007	115 261
1973	13 815	2008	125 187
1974	18 556	2009	128 774
1975	20 004	2010	122 675
1976	28 953	2011	145 699
1977	24 880	2012	151 449
1978	26 286	2013	159 264
1979	34 149	2014	150 248
1980	34 435	2015	148 251
1981	33 034	2016	151 443
1982	38 629	2017	150 522
1983	35 095	2018	164 133
1984	39 368		

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.

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

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

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

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

Where k_{low} and k_{high} are the lower and upper 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	104 – 1036

4.2. Bayesian Schaefer production model (BSM)

C-MSY imposed strong assumptions on the stock abundance trend. Although the estimate of MSY is generally robust, estimates of other management quantities are very sensitive to the assumed level of stock depletion. Thus, we explored the use of a Schaefer production model (BSM) which utilised the newly available standardised CPUE indices. The BSM was implemented as a Bayesian state-space estimation model that was fitted to catch and CPUE. The model 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. The model allowed for both observation and process errors (see Froese et al. 2016 for details): a lognormal likelihood with a CV of 0.1 was assumed for the CPUE indices. A process error with a prior mean of 0.05 was assumed for the production function. The prior range for r and K was translated into lognormal priors for the Bayesian estimation, with the mean and standard deviation derived from the range values specified in Table 2. The prior range for the initial and final depletion can be applied optionally and are implemented as a penalty on the objective function rather than hard constraints. The initial model made no assumption on the depletion level. However, the initial model (M3) indicated serious conflicts with the input abundance indices Therefore two additional models were conducted which penalise the final depletion outside the range of (1) 0.2–0.6 (M1), and (2) 0.4–0.8 (M2), respectively. A fourth model was also explored which assumed a process error of 0.1 (M4).

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 145 000 t. The KOBE plot indicates that based on the C-MSY model results, kawakawa mackerel is currently overfished ($B_{2018}/B_{MSY}=0.97$) but is not subject to overfishing ($F_{2018}/F_{MSY} = 1.16$). The catches over the last five years are higher than the estimated MSY.

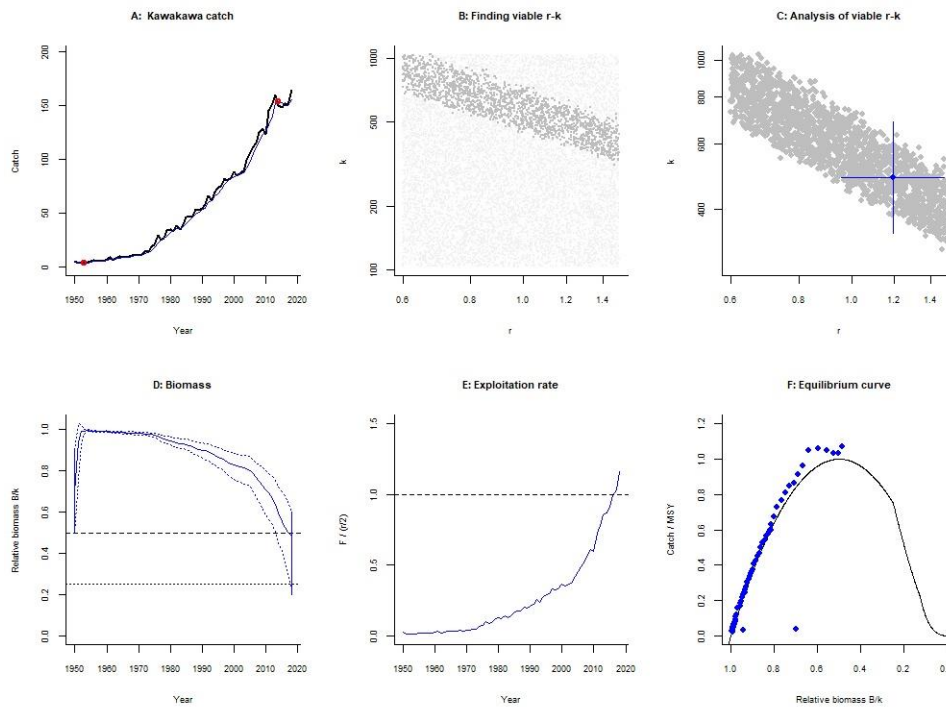


Figure 5. Results of CMSY reference model for kawakawa.

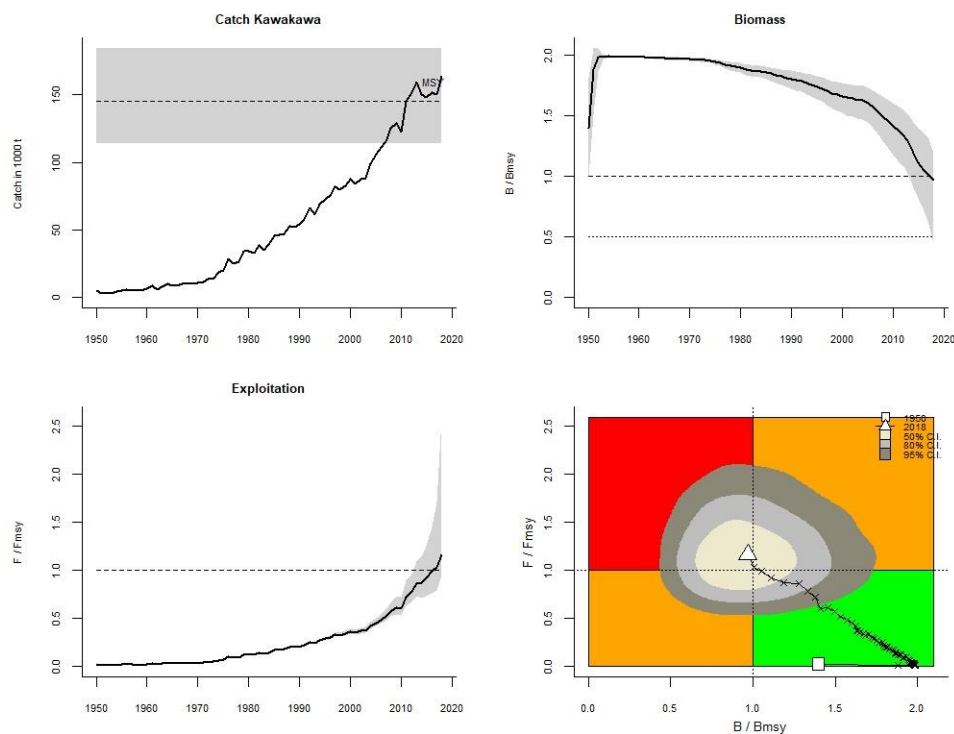


Figure 6. Graphical output of the CMSY reference model of kawakawa for management purposes.

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	2015	2020
Most recent catch estimate (year)	170,181 t (2013)	164,133 t (2018)
Mean catch – most recent 5 years ²	155,468 t (2009 – 2013)	152 919 t (2014 – 2018)
MSY (95% CI)	137,614 (108,233–185,804)	145 000 (114 000 – 185 000)
Data period used in assessment	1950–2013	1950 – 2018
F _{MSY} (95% CI)	0.41 (0.29–0.63)	0.60 (0.48 - 0.74)
B _{MSY} (95% CI)	268,790 (146,419–328,901)	244 000 (173 000 – 343 000)
F _{current} /F _{MSY} (95% CI)	1.19 (0.78–2.17)	1.16 (0.95 – 2.59)
B _{current} /B _{MSY} (95% CI)	0.99 (0.60–1.40)	0.97 (0.44 – 1.19)
B _{current} /B ₀ (95% CI)	0.50 (0.30–0.70)	0.49 (0.22 – 0.60)

² Data at time of assessment

5.2. Bayesian Schaefer production model (BSM)

The estimated posterior distributions of r - k for the BSM models 1 – 4 are shown in Figure 7, and the estimated biomass trend overlaid with CPUE indices (scaled by estimated coachability) for these models are shown in Figure 8. For Model M3, which made no assumption on the final depletion level, estimated r - k pairs are located in the tip region of the viable r - k triangle from the CMSY analysis, (Figure 7–M3). The results are very similar to Model M1, which constrained the final depletion to be in the medium range of 0.2–0.6 through a penalty function (Figure 7–M1). This suggested the medium depletion range appears to be more coherent with the assumed stock productivity. However, neither model is able to fit the CPUE indices, with the predicted biomass trend being in opposite direction of the indices (Figure 8– M1, M3), suggesting the CPUE is in conflict with model assumptions and/or catch history. For both models, estimated stock status are very close to be in the centre of the Kobe quadrant (Figure 9– M1, M3). Both M1 and M3 estimated the stock is not overfished ($B_{2018}/B_{MSY} = 1.06$), but is subject to overfishing ($F_{2018}/F_{MSY} = 1.09$) (Table 4). The conclusion of model M1 is slightly more optimistic than the CMSY analysis which suggested the stock is also overfished.

Additional model configurations were investigated to account for the recent CPUE trend, which declined to 2015 but increased in the last two years. Model M2, which assumed a high final depletion level (0.4 – 0.8) appears to more in line with the CPUE (Figure 8 – M2), and the model achieved this by shifting the r - k pairs more towards the higher k and lower r values range (Figure 7–M2). Consequently, Model M2 estimated that the stock is in the green KOBE quadrant (Figure 9 – M2), with B_{2018} estimated to be about 1.25 B_{MSY} and F_{2018} to be 0.89 F_{MSY} .

Alternatively, Model M4 also fitted the CPUE indices well by assuming a higher process error (twice the value assumed in other models) (Figure 9 – M4). As such, the model attributed the increase of recent abundance to other sources of variations of the population which have not been incorporated by the production function (e.g. recruitment variability, etc.). Model M4 estimated the stock is not overfished ($B_{2018}/B_{MSY} = 1.07$) but is subject to overfishing ($F_{2018}/F_{MSY} = 1.02$) (Table 4, Figure 8 – M4).

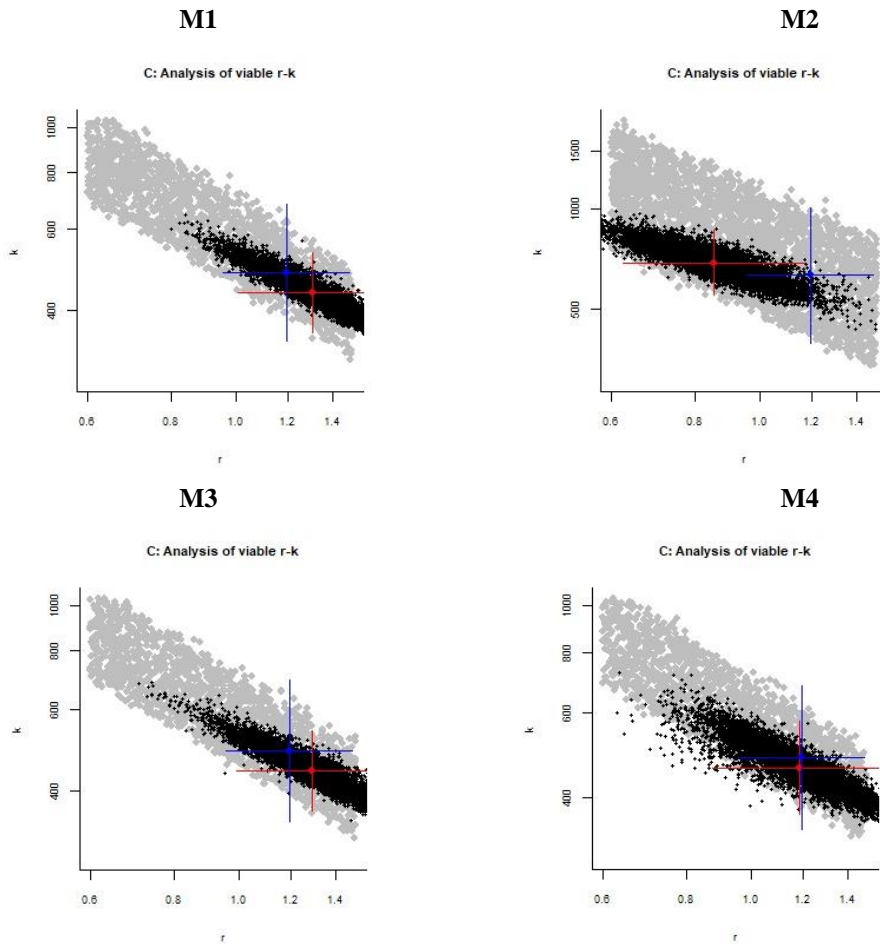


Figure 7: Results of BDM models 1–4 for kawakawa: posterior estimates of r and K (black dots) and the 95% CI (the red cross), overlaid with the viable r - k pairs as well as the probable range from the CMSY analysis (grey dots and the blue cross); right – median and 95% CI of the posterior estimates of biomass, overlaid with the standardised CPUE indices 2008–2017 with observation errors (red).

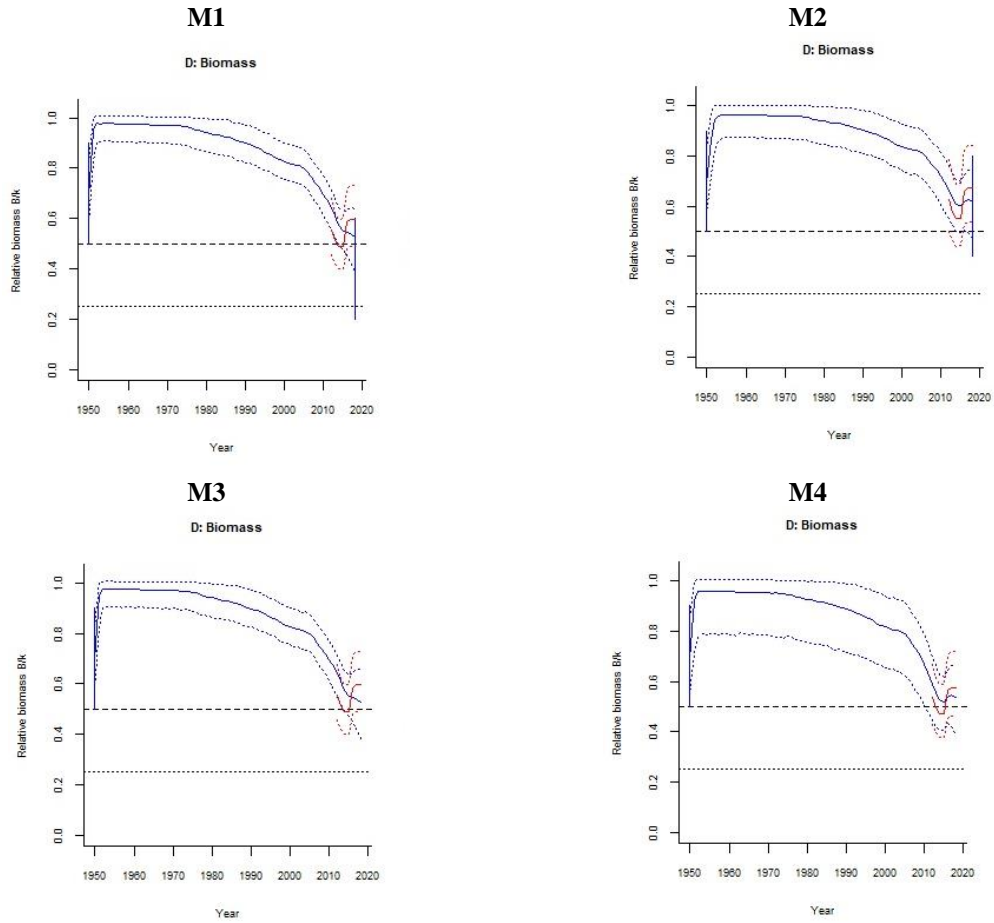


Figure 8: Results of BDM models 1–4 for kawakawa: median and 95% CI of the posterior estimates of biomass, overlaid with the standardised CPUE indices 2008–2017 with observation errors (red).

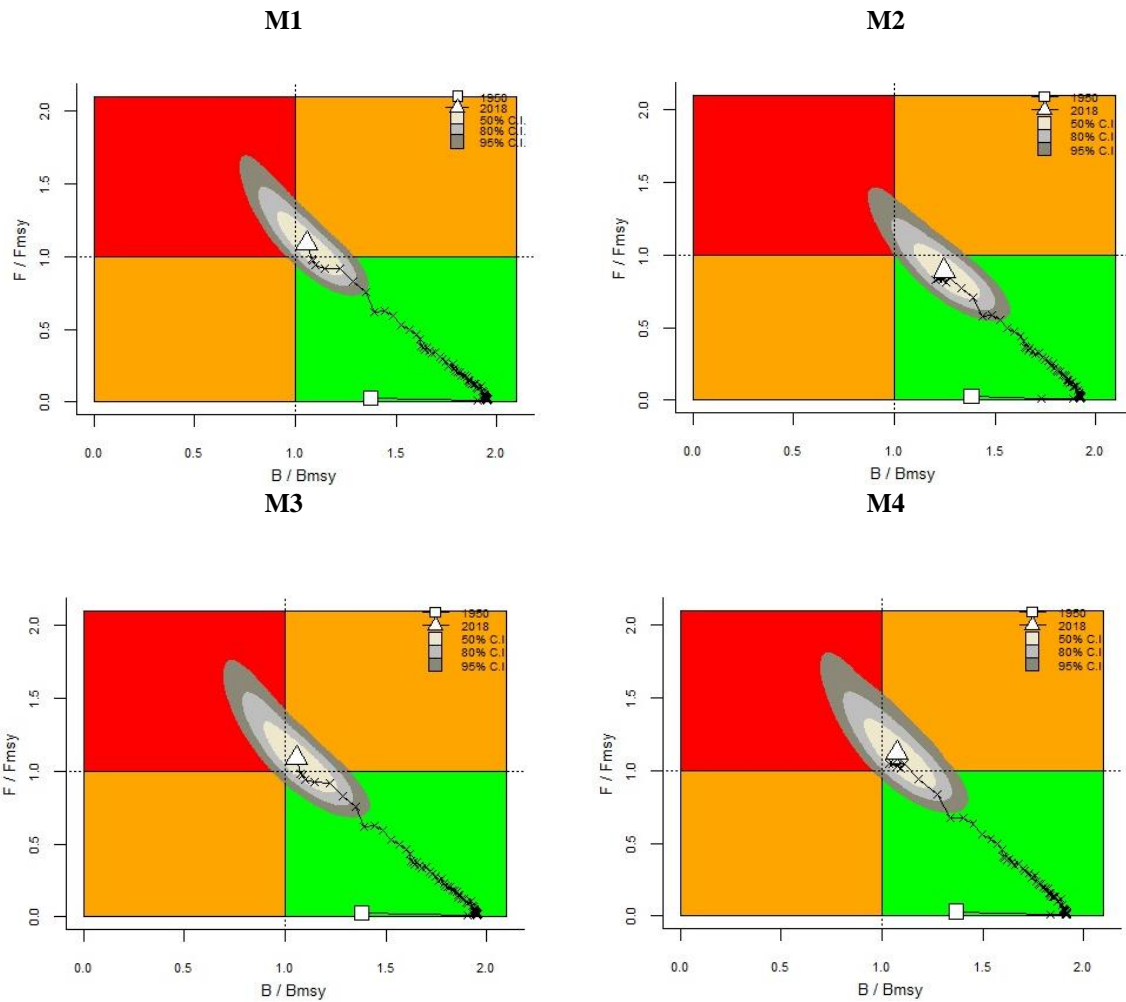


Figure 9: Kobe plots for the BDM models M1 – M4.



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Table 4: Management quantities from the Bayesian Schaefer production model (BSM) – models 1–4 for Indian Ocean kawakawa, means and 95% confidence interval.

Management Quantity	Model 1	Model 2	Model 3	Model 4
MSY (95% CI)	143 000 t (130 010 – 157 000)	148 000 t (125 000–175 000)	143 000t (128 000–158 000)	136 000 t (118 010 – 157 000)
Data period	1950 – 2018	1950 – 2018	1950 – 2018	1950 – 2018
F_{MSY} (95% CI)	0.65 (0.51 – 0.84)	0.43 (0.31–0.59)	0.64 (0.50–0.84)	0.59 (0.44 – 0.80)
B_{MSY} (95% CI)	219 000 t (179 000– 268 000)	346 000 t (277 000–432 000)	221 000t (181 000–270 000)	230 000 t (185 000– 287 000)
$F_{current}/F_{MSY}$ (95% CI)	1.09 (0.90 – 1.46)	0.89 (0.75–1.17)	1.09 (0.88–1.5)	1.12 (0.91 – 1.55)
$B_{current}/B_{MSY}$ (95% CI)	1.06 (0.79 – 1.27)	1.25 (0.95–1.48)	1.06(0.77–1.31)	1.07 (0.78 – 1.32)
$B_{current}/B_0$ (95% CI)	0.53 (0.39 – 0.64)	0.62 (0.47–0.74)	0.53 (0.38–0.66)	0.54 (0.39 – 0.66)

6. Discussion

In this report we have explored two data-limited methods in assessing the status of Indian Ocean kawakawa: C-MSY and Bayesian Schaefer production model (BSM), both of which are based on an aggregated biomass dynamic model. The C-MSY requires only the catch series as model input and uses simulations to locate feasible historical biomass that support the catch history. The BSM has incorporated time series of relative abundance indices, and estimated model parameters and management quantities in a Bayesian framework. Estimates from the C-MSY model suggested that currently the stock of kawakawa mackerel in the Indian Ocean is overfished ($B_{2018} < B_{MSY}$) and is subject to overfishing ($F_{2018} > F_{MSY}$). 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.

On the other hand, the BDM model utilised the standardised CPUE indices to provide information on abundance trend, and as such, the model is less reliant on some of the subjective assumptions. However, for kawakawa, there appears to be some inconsistency between the CPUE indices, and the catch history, and productivity assumptions of the species. In order to reconcile the increasing CPUE trend with the recent high catches, higher levels of stock productivity need to be assumed to allow the stock to sustain the large catches. Such assumptions tend to lead to more optimistic estimates of current stock status (e.g. Model M3 estimated the stock to be in green Kobe quadrant when assuming a high final depletion). Alternatively, 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). It remains a question whether the CPUE indices derived from the Iranian coastal gillnet fleets can index the abundance trend of kawakawa in the Indian Ocean (the CPUE has various caveats even as a local index for the Iranian coastal waters, see Fu et al. (2019)). Nevertheless, the availability of the standardised CPUE as a potential abundance index and its incorporation in the assessment represents a marked improvement in the development of more robust methods to assess IOTC neritic tuna species in the context of data deficiency. Future assessments could consider develop more realistic population models, including age structured models that could utilise more biological and fishery data beyond simple catch series.

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