IOTC–2026–WPNT16–15

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

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Contents

1. EXECUTIVE SUMMARY

In this stock assessment for kawakawa (*Euthynnus affinis*), a pelagic mackerel from the Scombridae, we have implemented the updated CMSY method (CMSY++; (Froese *et al.*, 2023)) that utilises both CMSY and a Bayesian Schaefer Model (BSM) separately, allowing for abundance indices to be incorporated if available, alongside gear creep (Froese *et al.*, 2023). We also implemented the JABBA model and one length-based method: the length-based spawning potential ratio model (LBSPR, (Hordyk *et al.*, 2015)). The length-based method provides 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.

Estimates from the CMSY++ BSM model suggests that currently the stock of kawakawa in the Indian Ocean is **not overfished** ($B_{2024} > B_{MSY}$) and is **not 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 ~ 155,000 t** which is higher than that estimated by JABBA (**139,000 t**). The 2024 catch (160,841 t) is over that of MSY (from both models) and higher than catches reported for the previous 10-15 years. The final year of catch is the highest ever recorded for kawakawa in the latest iteration of the data, but it is close to previous estimates of catch (e.g. 168,807 t were originally recorded for 2021 prior to revisions). It is likely that the revisions in catch data have driven the stock status to move towards a more optimistic outcome in 2026, given overall these have reduced long-term catches.

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 (most of the catch, and the most representative length data), 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 between 2015-2020, mirroring the upward trend in the CPUE in the same time period, there has been a decrease in SPR from 2020 to 2024.

Based on a weight-of-evidence approach, it is likely that kawakawa is, in 2024, **not overfished** but is **subject to overfishing** in the Indian Ocean, likely through localised depletion. However, there are several caveats to this, stated below:

a) Catch data have undergone significant revisions over time – the long-term reduction in catch over time has likely moved the stock to a more optimistic status, with the terminal year moving the stock into an overfished state (but these catches seem extremely high, compared to the new long-term average).
b) The much higher reported catches in 2024 should be noted, as these represent catches over the estimated MSY, and are unlikely to be sustainable long term.

c) Length-based analyses suggest that the stock is likely to be overfished, however the representativeness of the length data in comparison to the entire Indian Ocean stock(s) needs to be fully evaluated. Additionally, the length-based analyses only cover one fishery grouping (gillnet)

d) Length data are not reported at a fine-enough scale to investigate potential stock dynamics at a finer scale.

e) Additionally, representative abundance indices should be developed that cover a greater spatial area than currently (I.R. Iran).

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 a 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 and Sharma, 2013; Zhou and Sharma, 2014; Fu, 2020, 2023; Zhou, 2020) and using Stock Synthesis (Sharma, Martin and Pierre, 2015). In 2020 the CMSY method (Froese et al. 2016) was used to assess the status of *E. affinis* (Fu 2020). In 2023, the CMSY method was used to assess the status of *E. affinis* using historical catches (Fu, 2023). The 2023 assessment also explored several alternative methods including the Optimised Catch-Only method (Zhou *et al.*, 2018), 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 KAW.

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, alongside 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 Spanish mackerel.

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)).. The 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

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 and Pauly, no date) and generally forms multispecies schools by size with other scombrid species comprising 100 – 5,000 individuals or more (B. B. Collette and Nauen, 1983; B. Collette and 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). The species supports substantial commercial and artisanal fisheries in many countries bordering the Indian Ocean, including Indonesia, India, Iran, Pakistan and Sri Lanka (IOTC 2026). 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).

There is some evidence of stock structure within kawakawa in the western Indian Ocean from three studies (Davies *et al.*, 2020; Feutry *et al.*, 2020; Mzingirwa, McKeown, *et al.*, 2025), and likely seasonal migrations offshore for spawning (Mzingirwa, Okemwa, *et al.*, 2025). These studies are limited in scope due to sampling issues (e.g. samples only from landing sites), but deserve further attention in future assessments, if research provides more information.

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 kawakawa followed by purse seine and then lines, with most of the catch taken by coastal country fleets (Figure 1).

Indonesia, India and I.R. Iran together account for 76 % of catches in 2024. Figure 2 shows the total catch of kawakawa since 1950, which increased to a peak of 135,660 t in 2022, following a plateau of catches at approx. 125,000 t from 2012-2021. The final year of data shows exceptionally high catch (160,840 t, Table 1), mainly from a dramatic increase in purse seine catches (Figure 2). 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 kawakawa nominal catch series between 2020 and 2023 data, flattening the high peak in catches around 2015 (Figure 3).

Of major impact to fishery data has been the endorsed revisions of Indonesia's catches for all historical data, with overall catches increased between 1950-2008 when compared to data used in 2020, after which the revised data shows much lower catches (Figure 3). In comparison to data used in 2023, catches are similar until around 1975, when revised data has overall lower catches of kawakawa in the Indian Ocean up to 2023. In 2024 a sharp increase in catch has been reported (Figure 3), mainly attributed to purse seine catches from Indonesia.

Fu et al. (2019) developed standardised CPUE indices for several neritic tuna species including kawakawa 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 index (2008–2018) for kawakawa shows an increasing trend throughout the time period, with three periods of flatter CPUE (2008-2012, 2012-2016 (slight decreasing trend), and 2016-2018) (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).

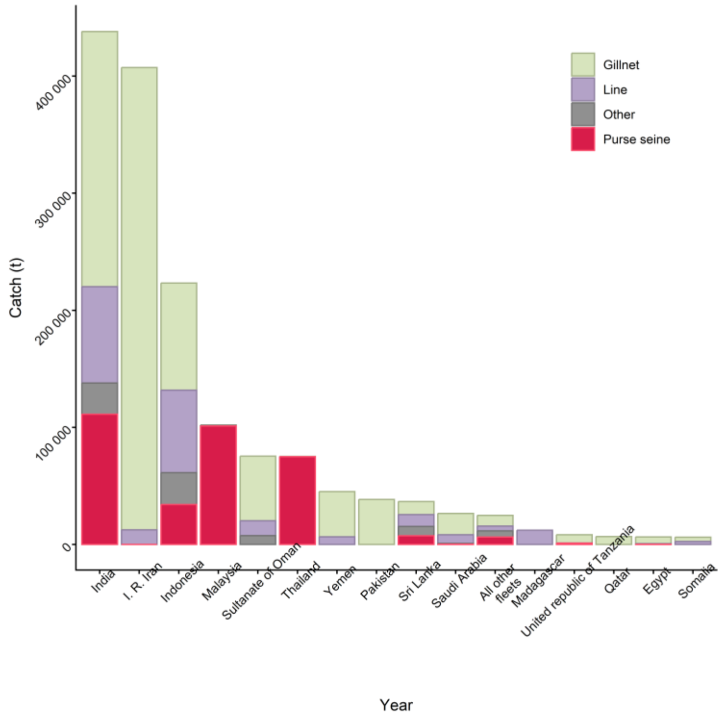

Figure 1: Average catches of kawakawa (*Euthynnus affinis*) in the Indian Ocean over the period 2012-2024, by country, and gear grouping.

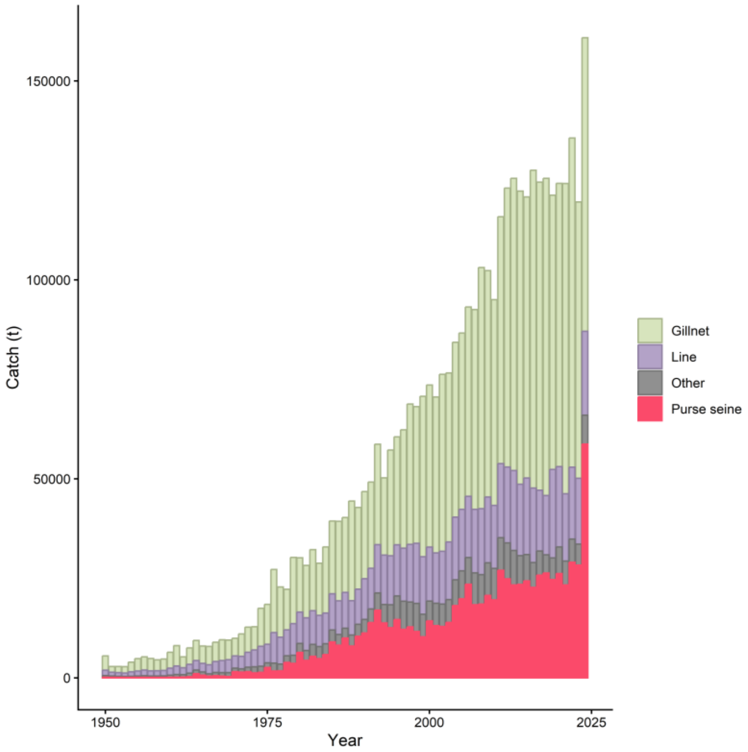

Figure 2: Total nominal catch of kawakawa by gear grouping, 1950 – 2024 (IOTC database).

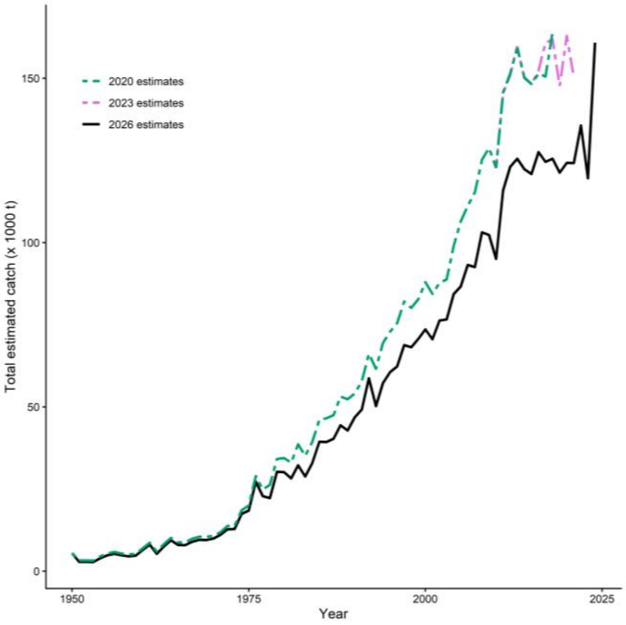

Figure 3: Revisions to IOTC nominal catch data for Spanish mackerel (datasets used for the 2020, 2023, and 2026 assessments, using data up to 2019, 2021, and 2024 respectively).

Figure 4: Standardised CPUE indices (year-quarter) for kawakawa 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 kawakawa (*Euthynnus affinis*) in the Indian Ocean, 1950-2024 (source IOTC Database)

Year	Catch (t)	Year	Catch (t)
1950	5 502	**1988**	44 428
1951	2 853	**1989**	42 812
1952	2 850	**1990**	46 814
1953	2 801	**1991**	49 203
1954	3 950	**1992**	58 704
1955	4 836	**1993**	50 247
1956	5 286	**1994**	57 238
1957	4 846	**1995**	60 546
1958	4 523	**1996**	62 309
1959	4 724	**1997**	68 799
1960	6 433	**1998**	68 145
1961	8 102	**1999**	70 736
1962	5 273	**2000**	73 577
1963	7 533	**2001**	70 580
1964	9 407	**2002**	76 281
1965	7 990	**2003**	76 619
1966	7 912	**2004**	84 338
1967	8 952	**2005**	86 623
1968	9 569	**2006**	93 194
1969	9 494	**2007**	92 534
1970	9 950	**2008**	103 102
1971	11 048	**2009**	102 313
1972	12 750	**2010**	95 041
1973	12 854	**2011**	115 876
1974	17 475	**2012**	123 047
1975	18 459	**2013**	125 528
1976	27 231	**2014**	122 329
1977	22 844	**2015**	120 858
1978	22 247	**2016**	127 551
1979	30 266	**2017**	124 551
1980	30 152	**2018**	125 510
1981	28 251	**2019**	121 281
1982	32 226	**2020**	124 254
1983	28 815	**2021**	124 224
1984	32 909	**2022**	135 660
1985	39 392	**2023**	119 569
1986	39 333	**2024**	160 841
1987	40 303		

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 kawakawa (*Euthynnus affinis*, 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 also allows 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.

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

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

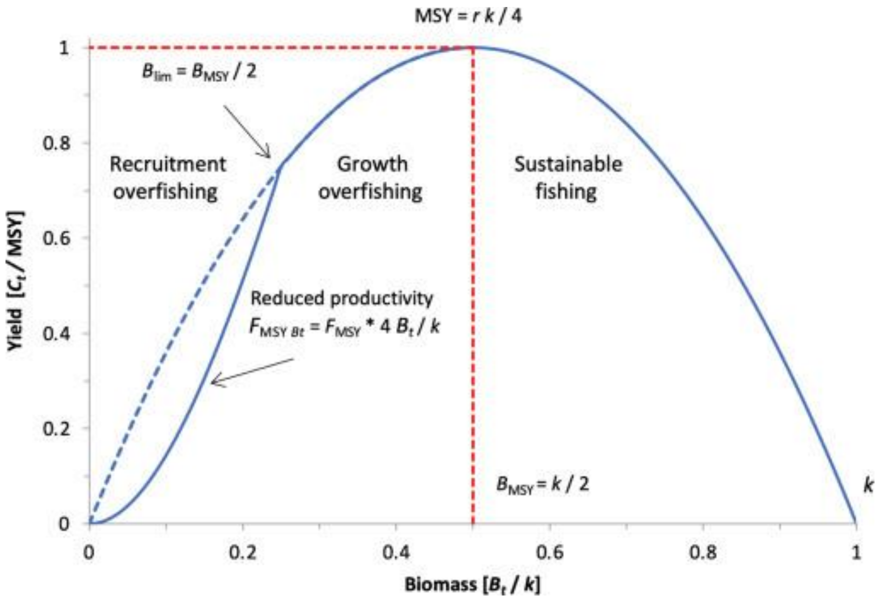

Figure 5: A schematic representation of the modified Schaefer surplus production model used by CMSY and CMSY++ (Figure 2 from Froese et al., 2023), that highlights the reduced productivity of a stock under recruitment overfishing where F_{MSY} reduces linearly with a decline in biomass.

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 kawakawa (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 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), kawakawa 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):

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

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 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 high range of biomass (0.4 – 0.8) assumption for the final depletion level (e.g. lower depletion) in the reference model, considering the continuing increase in total catches throughout the assessment period, with no decline in catches, or catch rates. The same level of biomass was assumed in the intermediate year, and the intermediate year was set to 2021, as this is the year the highest catches were observed (bar the very high catches reported in 2024), after a period of sustained high 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 *E. affinis* 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 kawakawa. 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 kawakawa in the setup of CMSY and CMSY++ reference model

	Initial rel. biomass	**Intermediate rel. biomass**	**Final rel. biomass**	***r***	**Resilience**
Year	1950	2021	2024		
Value	0.5 – 0.9	0.4 – 0.8	0.4 – 0.8	0.6 – 1.5	High

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), $\mathbf{L}^{\infty}$ (and associated variance), and maturity-at-size. These parameters for *E. affinis* were obtained from previously used figures (IOTC (2015)).

The length frequency data (IOTC-DATASETS-SF-KAW-1987-2024-WIDE-FORMAT) 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 2010 to 2024 (Figure 6) – earlier samples are available, but the size range varies considerably from more recent data. Length data are provided from several gear groupings, but the numbers available are low for gears other than gillnet (Figure 7).

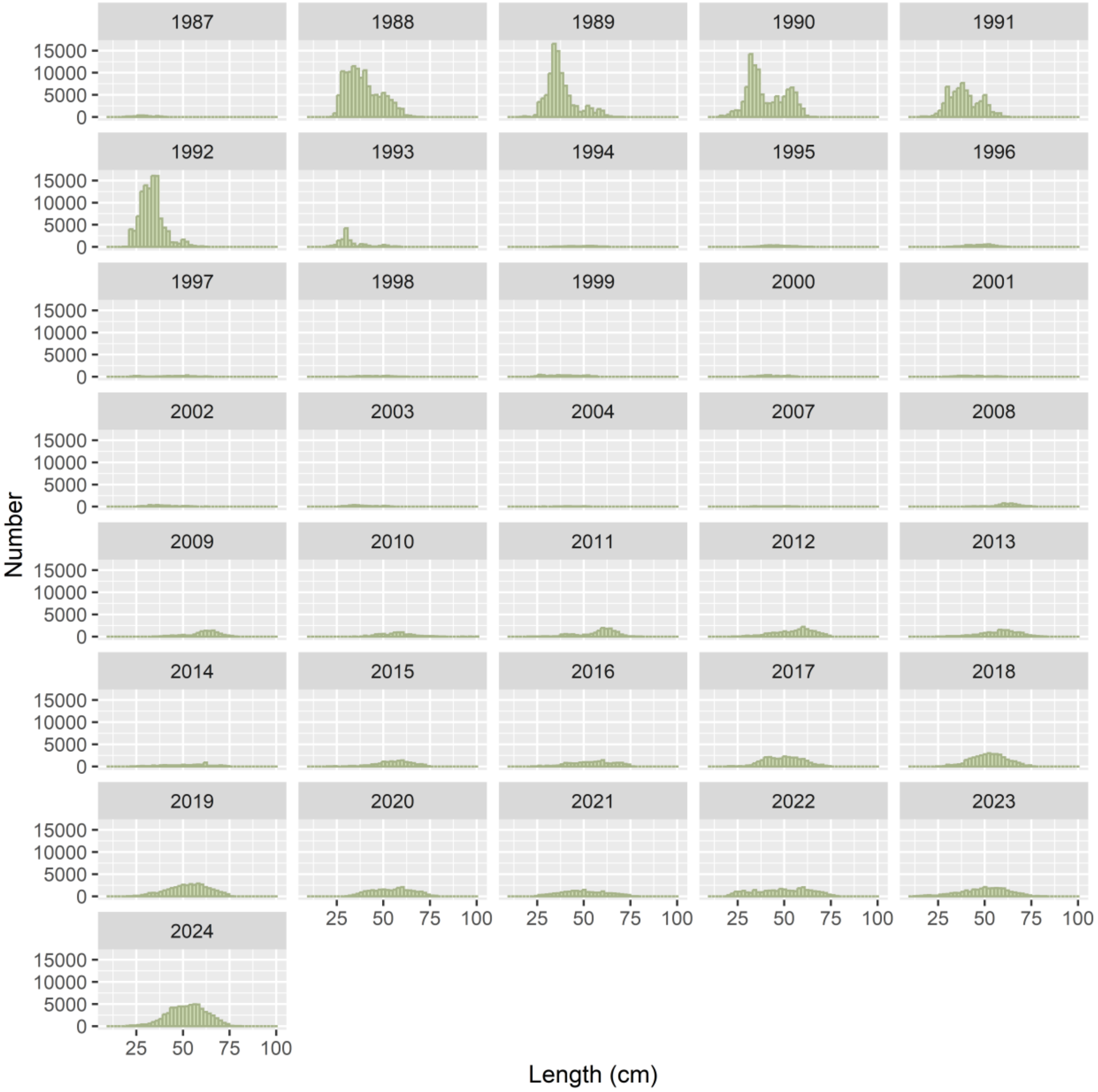

Figure 6: Length frequency data for kawakawa available in 2026 for the assessment (data up to 2024) from gillnet fisheries in the Indian Ocean. Data are aggregated to a "fishery grouping" level and represent data reported to the IOTC from several fisheries across the Indian Ocean, however the overwhelming majority of data are from gillnet fisheries in I.R. Iran. Data were used from 2009 to 2024 in the LBSPR analyses.

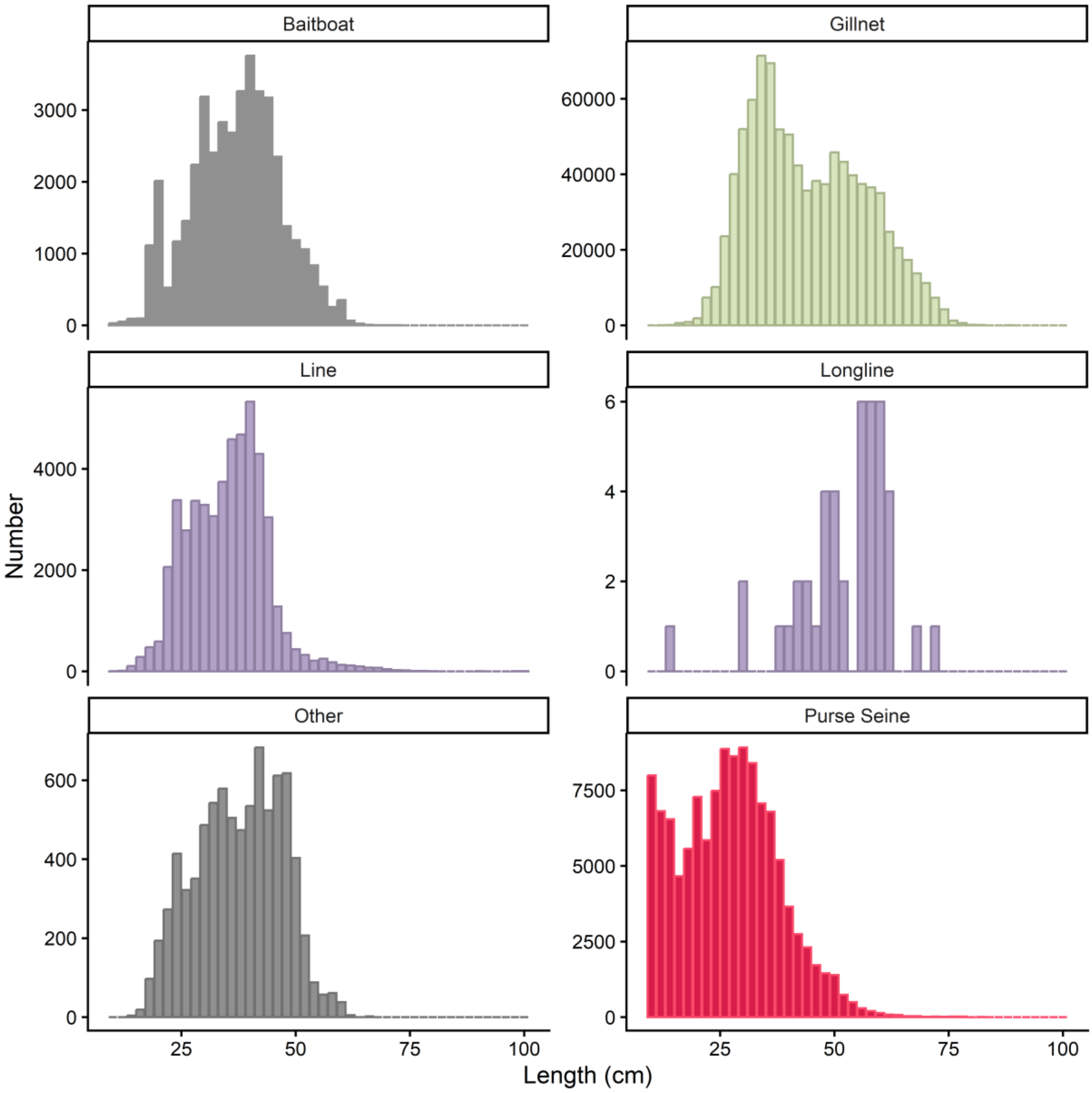

Figure 7: Length frequency data for kawakawa available in 2026 for the assessment (data up to 2024) from all fisheries in the Indian Ocean. Data are aggregated to a gear grouping level and represent data reported to the IOTC from several fisheries across the Indian Ocean. Data were used from 2010 to 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 kawakawa. 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 kawakawa 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 2021 as the intermediate year as this is the final year of high mean catches prior to the terminal year of the assessment. The catch data in 2022 and 2023 appear to deviate from the mean too. 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, after data revision).

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 close to the full prior range (0.60 – 1.5), ranging from 0.59 – 1.11 (mean = 0.90) while probable ***k*** values ranged from 531,000 – 1,036,000 t (mean = 692,000 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 decline since approx.. 2000 (the intermediate year is marked by the furthest left vertical line).

Panel E shows the corresponding exploitation (harvest) rate from CMSY++ (F/F_{MSY}) showing that although exploitation rates are increasing, currently they are below that of F_{MSY}.

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, but that they have not yet reached C_{MSY} (based on the continuing increase in catches over time, with no substantial decrease or reduction in catches which would suggest that C_{MSY} had been exceeded). However, the final year of catch represents a significant increase towards C_{MSY}. The upper right panel shows the total stock size (biomass) relative to B_{MSY}, suggesting a decreasing stock size, but that the stock is still above 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) has some influence on the trend in fishing mortality (F/F_{MSY}), with sequential removals of data reducing the relative fishing mortality (probably due to the terminal year catch data). There is some impact on the trend in stock status (B/B_{MSY}, right-hand panel) too, although removal of data does not bring the stock biomass below that of B_{MSY}.

The IOTC target and limit reference points for kawakawa 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 155,000 t.

The KOBE plot (**Figure 11**) and management values indicate that based on the CMSY++ model results, kawakawa is currently **not overfished** (B_{2024}/B_{MSY} = 1.31) and is **not subject to overfishing** (F_{2024}/F_{MSY} = 0.74). The average catch over the last five years is lower than the estimated MSY (132,910 t). These results are more optimistic than the last assessment (which suggested the stock was in the middle of the KOBE plot).

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

a) The trend in reported nominal catch of kawakawa over time in the Indian Ocean has been continuing to increase, therefore the catch-only models are estimating that (based on catch data alone), CMSY has not yet been reached, or breached.
b) Revision of reported nominal catch data by Indonesia, which has reduced total catch of kawakawa to levels lower than those in the previous assessment (see Figure 3). Additionally, the reduction in recent years brings the relative catch in the final years of the assessment to a lower proportion of that in the initial years of the fishery. This will reduce the overall fishing mortality (F).

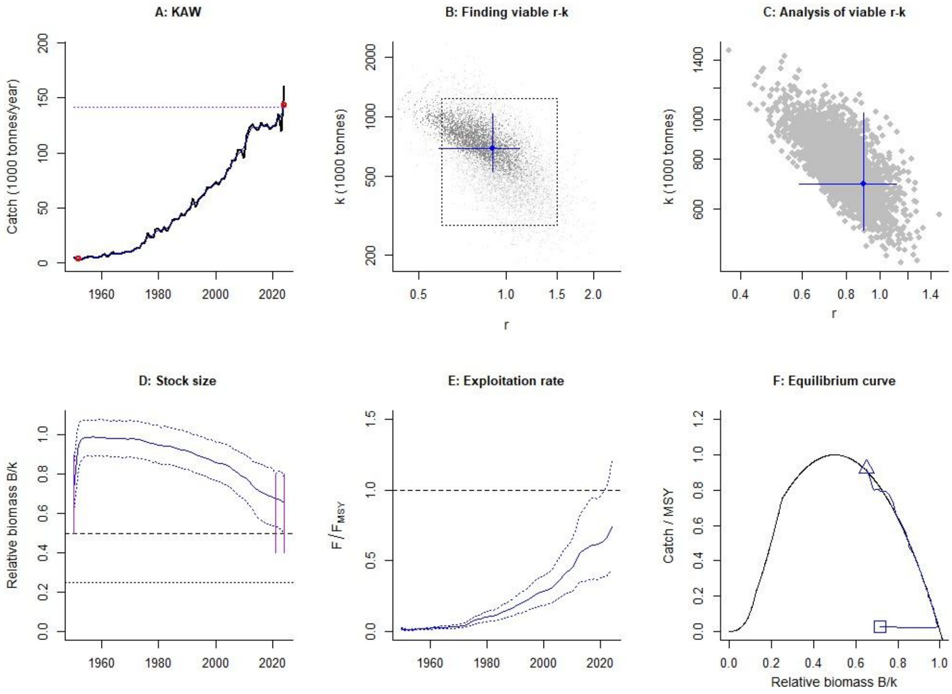

Figure 8. Results of CMSY model for kawakawa. Each lettered panel represents a different output from the CMSY++ model. The red dot in panel A and the furthest left vertical line in panel D represent the intermediate year for the assessment (2021), chosen as this may represent a significant change in the fishery as it is the final year of high mean catches (barring the increase in catch in the final year of data).

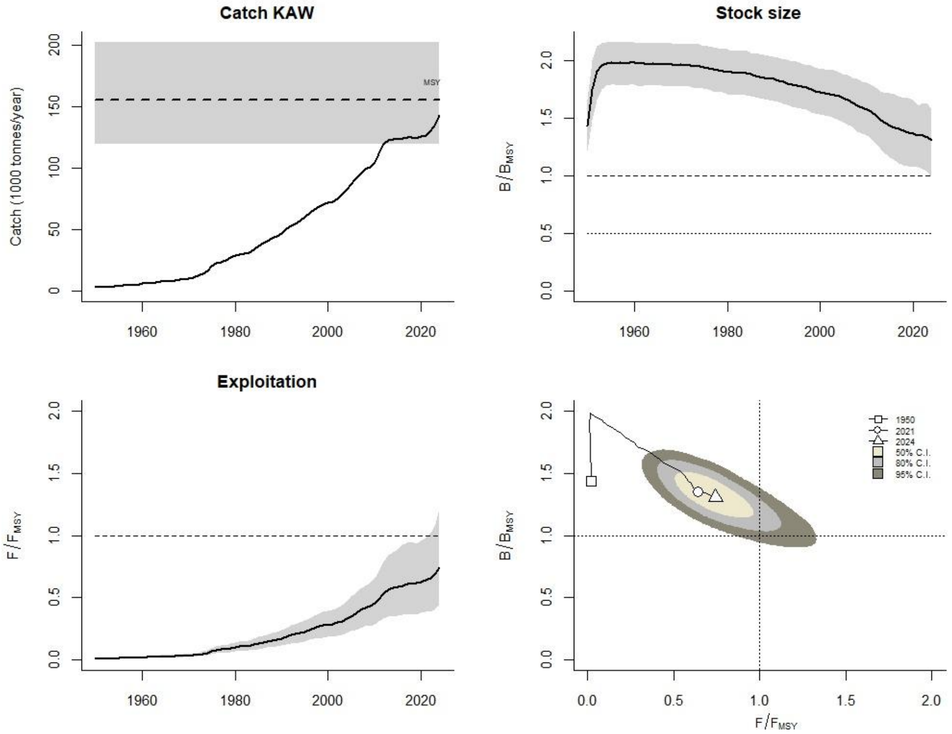

Figure 9. Management quantities from the CMSY++ model of kawakawa.

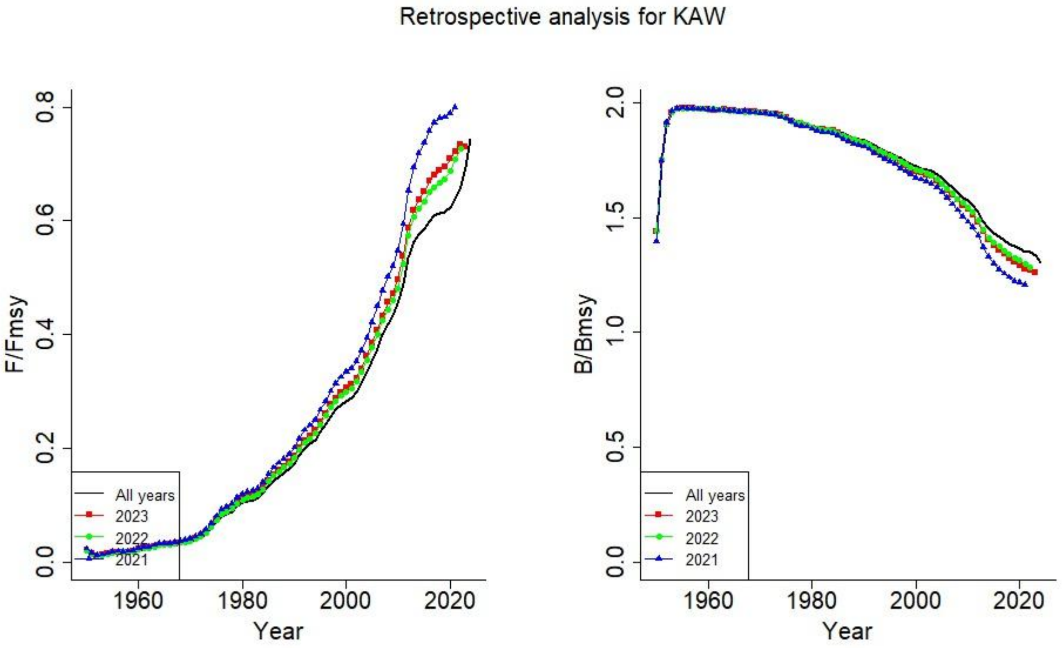

Figure 10. Retrospective analysis for the reference model for kawakawa using CMSY++. Individual years of catch data are sequentially removed from the model. If the catch data in a specific year are significantly influencing the analysis, this analysis will reveal changes to the trajectory or trends in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

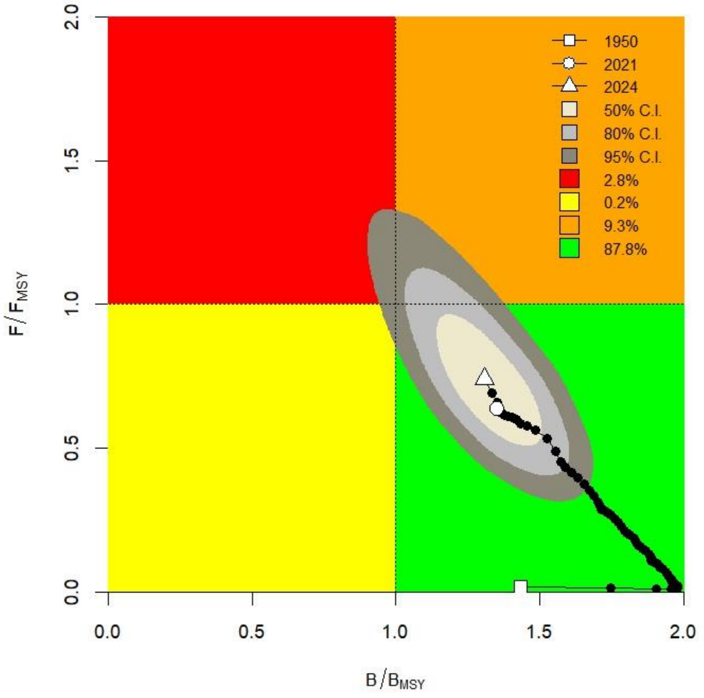

Figure 11: KOBE plot for kawakawa from the output of the CMSY++ reference model.

Table 3. Key management quantities from the CMSY++ stock assessment for Indian Ocean kawakawa. 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)	164 133 (2018)	150 170 (2021)	160 841 (2024)
Mean catch (t) – most recent 5 years[3]	152 919 (2014 – 2018)	156 655 (2017 – 2021)	132 910 (2020 – 2024)
MSY (t) (95% CI)	145 000 (114 000 – 185 000)	154 000 (122 000 – 193 000)	155 000 (120 000 – 203 000)
Data period used in assessment	**1950 – 2018**	**1950 – 2021**	**1950 - 2024**
F_{MSY} (95% CI)	0.60 (0.48 - 0.74)	0.60 (0.48 – 0.74)	0.45 (0.29 – 0.56)
B_{MSY} (95% CI)	244 000 (173 000 – 343 000)	258 000 (185 – 359)	346 000 (266 000 – 518 000)
$F_{current}/F_{MSY}$ (95% CI)	1.16 (0.95 – 2.59)	0.98 (0.82 – 2.20)	0.74 (0.44 – 1.22)
$B_{current}/B_{MSY}$ (95% CI)	0.97 (0.44 – 1.19)	1.00 (0.45 – 1.20)	1.31 (0.98 – 1.56)
$B_{current}/B_0$ (95% CI)	0.49 (0.22 – 0.60)	0.50 (0.22 – 0.60)	0.72 (0.61 – 0.83)

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[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, but in a similar range of estimates to 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. This is partly due to the short CPUE index, and partly due to continually increasing catches (e.g. the model cannot estimate MSY accurately due to a lack of contrast in catch data). 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). Misspecification of this year is likely to cause issues with model fitting, and therefore the usability of the outputs.

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, model 3; **Figure 13**), however, this is achieved by generating a somewhat increasing patterns in the process errors. Additionally, the ***k*** prior range was then set to be narrow – forcing the model to have an estimated carrying capacity of ~ 700 000 t (similar estimate to CMSY++, model 6). 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 and thus the predictive power of the model requires further information.

Estimates of management quantities from model 6 are shown in **Figure 14**. The estimated stock status is less optimistic than the CMSY++ model (likely driven by the CPUE index). The MSY varies between 107,000 and 203,000 t, with an average of 139,000 t which is lower than the estimates from CMSY++. According to the JABBA estimates, the biomass of the spawning stock in 2024 is 8 % higher than B_{MSY}, while the fishing mortality (F_{2024}) is 7 % higher than the F_{MSY} (B/B_{MSY} = 1.08 (0.65 – 1.56), F/F_{MSY} = 1.07 (0.53 – 2.14). Despite the addition of CPUE indices to provide information on relative abundance changes, the information is limited due to the relatively short time series.

The stock trajectory (**Figure 15**) and KOBE plot from the reference model (model 6; **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.

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

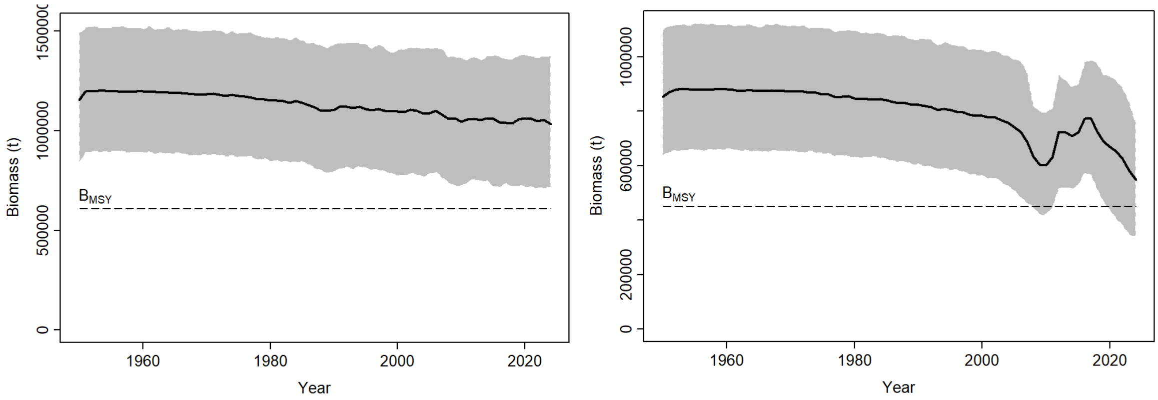

Figure 12: Biomass estimates (median and 95% CI) from JABBA model 1 (left, no prior on final depletion), and the reference model, model 6 (right, a normal prior on final depletion with mean of 0.4 and CV of 10%, corresponding to an approximate range 0.2 – 0.6). Dashed line indicates median B_{MSY}.

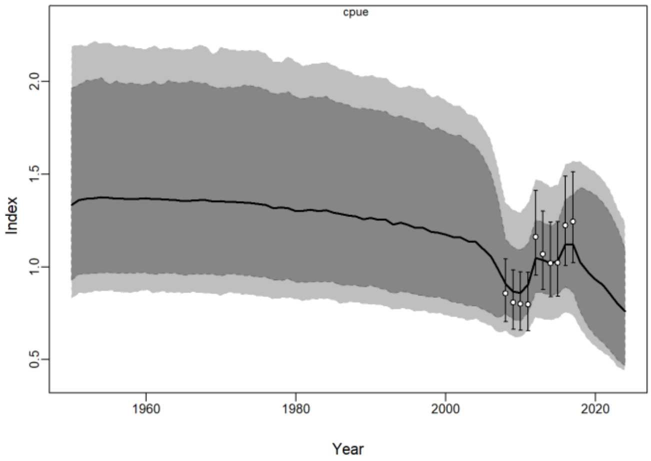

Figure 13: Fits to CPUE indices 2008–2017 from the JABBA reference model. Shaded areas indicates 50% and 95% CI, vertical lines indicate observation errors.

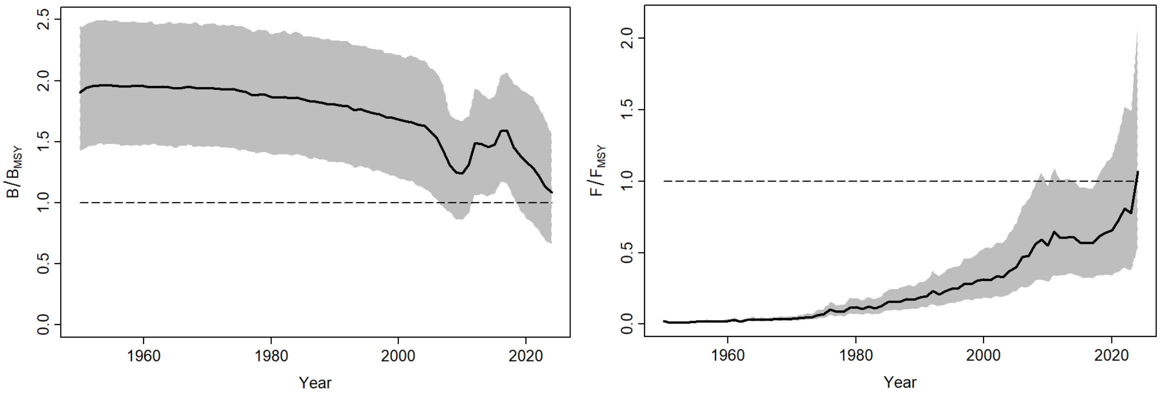

Figure 14: Estimates of management quantities from the JABBA reference model (B/B_{MSY} and F/F_{MSY}).

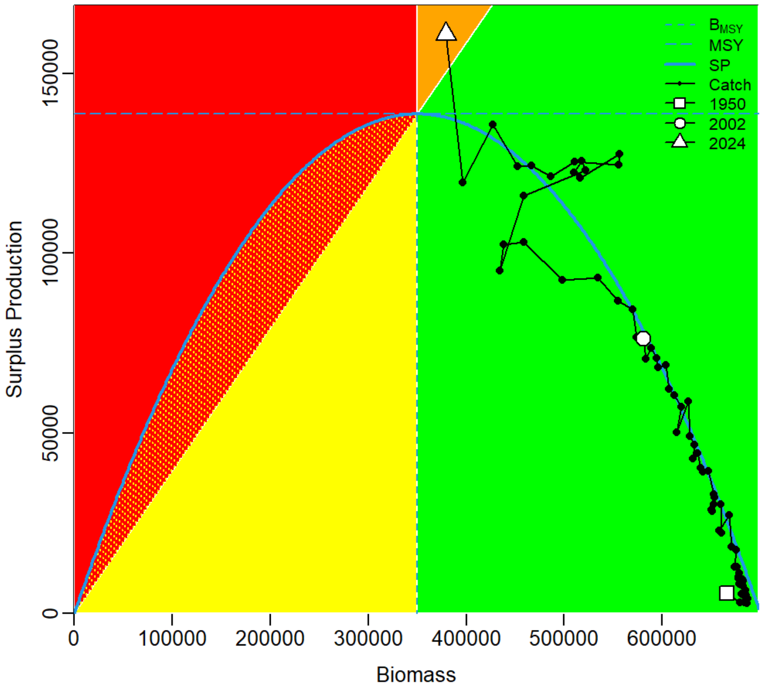

Figure 15: Trajectory of the stock against the Schaefer surplus production model from 1950 to 2024. The intermediate year (2002) has been estimated by the JABBA model.

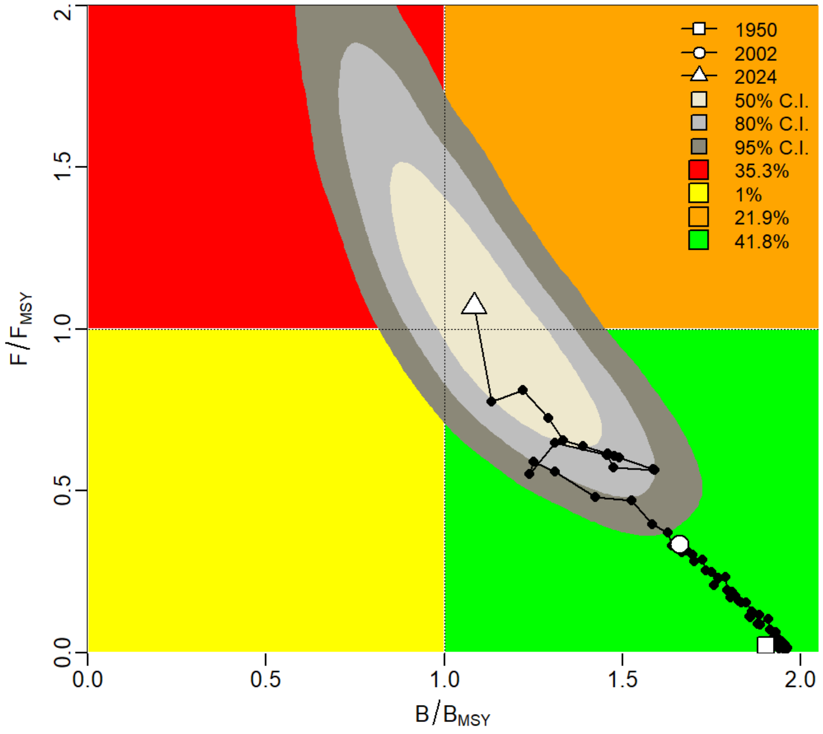

Figure 16: KOBE plot from the JABBA reference model, showing the stock trajectory. The stock is found within the orange quadrant of the KOBE plot, which represents a fishery that is not overfished, but is subject to overfishing.

4.3. LBSPR

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

4.3.1. Gillnet

Selectivity has decreased throughout time from 2009 to 2024 (**Figure 17**). The fishing mortality is estimated to have decreased (**Figure 17**) but was 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 for the whole period of the fishery, 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), and although the SPR increased between 2015-2020, mirroring the upward trend in the CPUE in the same time period, there has been a decrease in SPR from 2016 to 2024.

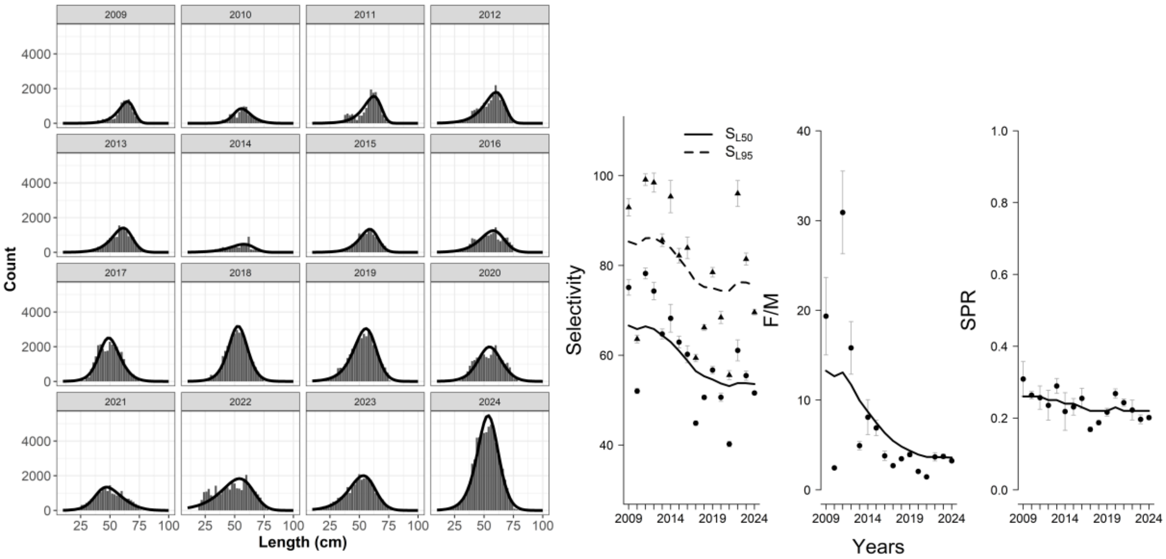

Figure 17: Results of LBSPR method applied to the length samples from the gillnet fishery for kawakawa: Fits to the length frequency in 2009–2024 (black dots) right – estimates (with 95% CI) of annual logistic selectivity parameters (L50 and L95), F/M, and spawning potential ratio (SPR) over time.

5. DISCUSSION

The CMSY++, JABBA, and LBSPR methods have all been investigated in this report to evaluate the status of Indian Ocean kawakawa. 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 kawakawa in the Indian Ocean is **not overfished** ($B_{2024} > B_{MSY}$) and is **not 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 ~ 155,000 t** which is higher than that estimated by JABBA (**139,000 t**). The 2024 catch (160,841 t) is over that of MSY (from both models) and higher than catches reported for the previous 10-15 years. The final year of catch is the highest ever recorded for kawakawa in the latest iteration of the data, but it is close to previous estimates of catch (e.g. 168,807 t were originally recorded for 2021 prior to revisions). It is likely that the revisions in catch data have driven the stock status to move towards a more optimistic outcome in 2026, given overall these have reduced long-term catches.

The CPUE data suggest increasing biomass, as the index is increasing, while over the same time period, catches are remaining constant (and high). As the previous assessment stated, it is likely that the stock is approaching being fished at MSY levels, and higher 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 kawakawa, there appears to be inconsistency between the CPUE indices, 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 kawakawa 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, particularly as there is evidence of stock structure in kawakawa (Mzingirwa, McKeown, *et al.*, 2025).

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 between 2015-2000, mirroring the upward trend in the CPUE in the same time period, there has been a decrease in SPR from 2000 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). Although gillnets used to capture kawakawa are size-selective, kawakawa length samples from gillnet fisheries have similar size ranges or distributions to those from line fisheries (asymptotic selectivity), making it difficult to quantify the degree of possible doming in gillnet selectivity.

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, especially as recent evidence suggests monsoon seasons can impact size structure (Mzingirwa, Okemwa, *et al.*, 2025).

6. CONCLUSIONS

Based on a weight-of-evidence approach, it is likely that kawakawa is, in 2024, **not overfished** but **may be subject to overfishing** in the Indian Ocean, likely through localised depletion. However, there are several caveats to this, stated below:

a) Catch data have undergone significant revisions over time – the long-term reduction in catch over time has likely moved the stock to a more optimistic status, with the terminal year moving the stock into an overfished state (but these catches seem extremely high, compared to the new long-term average).
b) The much higher reported catches in 2024 should be noted, as these represent catches over the estimated MSY, and are unlikely to be sustainable long term.
c) Length-based analyses suggest that the stock is likely to be overfished, however the representativeness of the length data in comparison to the entire Indian Ocean stock(s) needs to be fully evaluated. Additionally, the length-based analyses only cover one fishery grouping (gillnet)
d) Length data are not reported at a fine-enough scale to investigate potential stock dynamics at a finer scale.

e) Additionally, representative abundance indices should be developed that cover a greater spatial area than currently (I.R. Iran).

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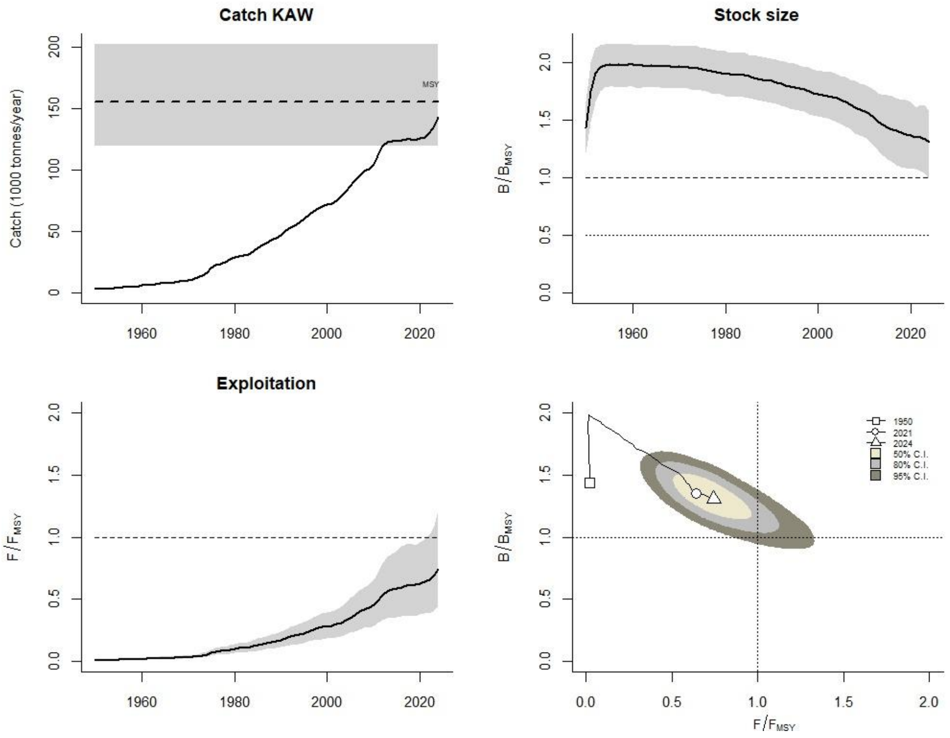
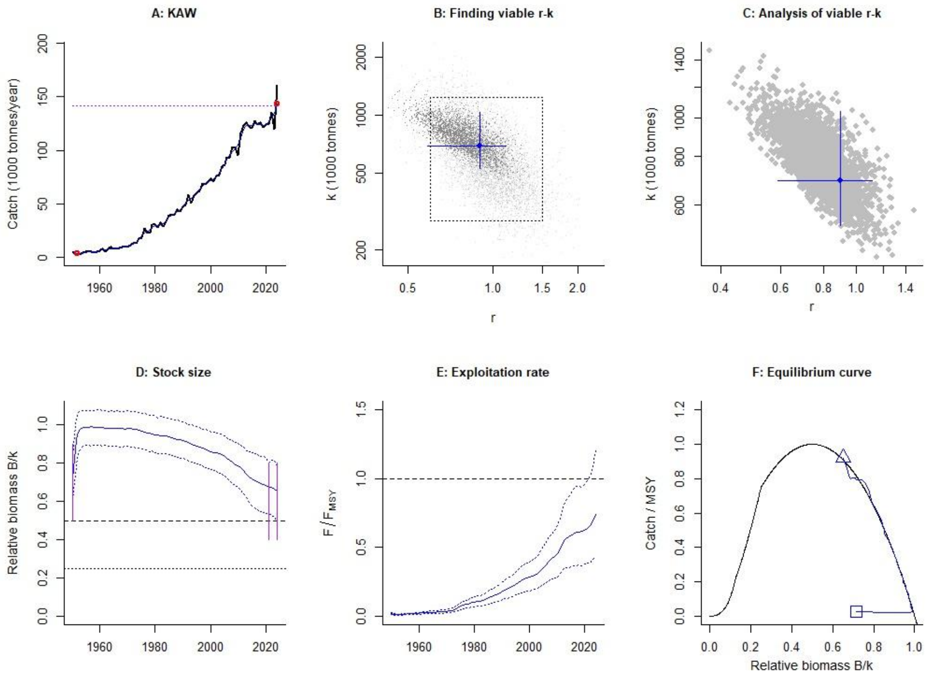
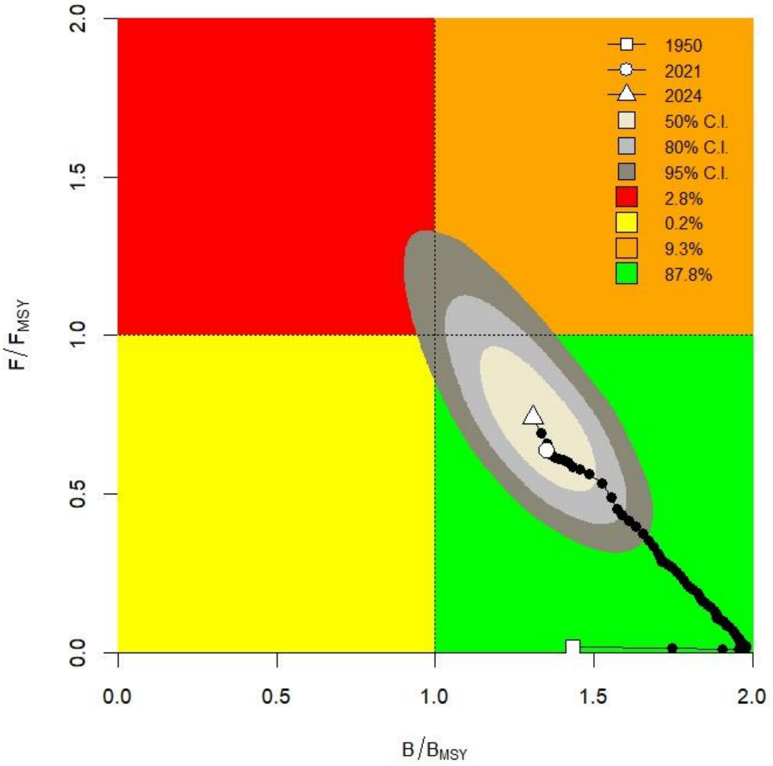
8. APPENDIX

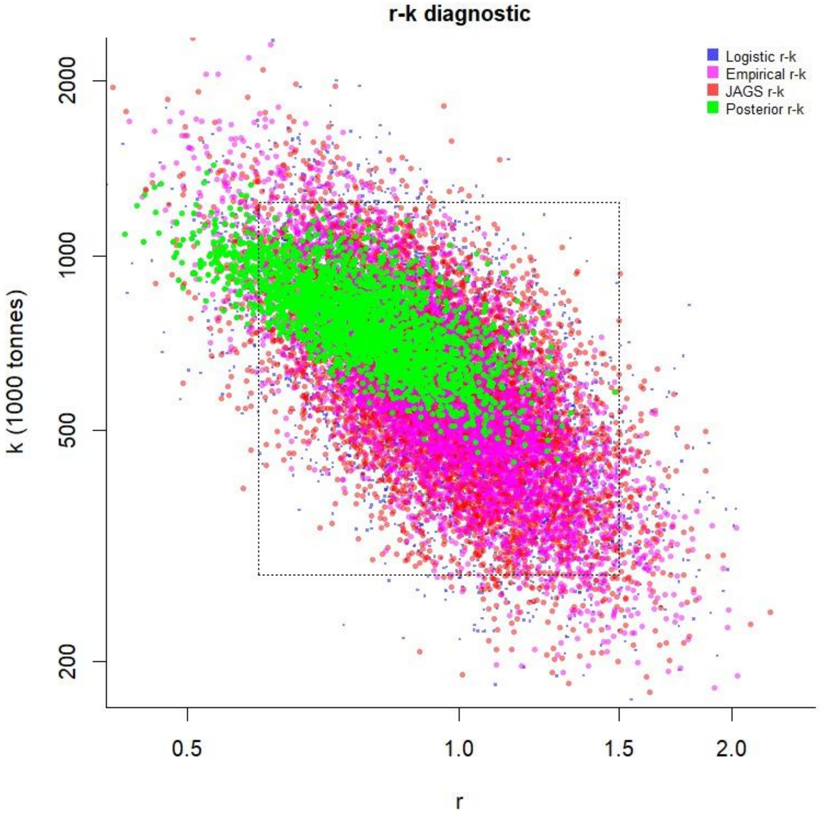
8.1. Comparison of outputs from CMSY++ and CMSY for the reference model

1) Outputs from CMSY++






1950
2021
2024
50% C.I.
80% C.I.
95% C.I.
2.8%
0.2%
9.3%
87.8%
F/F_MSY
B/B_MSY
0.0
0.5
1.0
1.5
2.0


r-k diagnostic
Logistic r-k
Empirical r-k
JAGS r-k
Posterior r-k
k (1000 tonnes)
200
500
1000
2000
r
0.5
1.0
1.5
2.0

2) Outputs from CMSY (v9f)