Assessment of Indian Ocean narrow-barred Spanish mackerel (*Scomberomorus commerson*) using data-limited methods

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[1] IOTC Secretariat

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 narrow-barred Spanish mackerel (*Scomberomorus commerson*) from 2013 to 2017, and again in 2020 using data-limited methods (Zhou & Sharma, 2013, 2014; Martin & Sharma, 2015; Martin & Robinson, 2016, Martin & Fu, 2017). In 2017, the C-MSY method was used to assess the status of *S. commerson* using historically catches (Fu 2020). 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 *S. commerson*.

2. Basic Biology

The narrow-barred Spanish mackerel (*Scomberomorus commerson*) (Lacépède, 1800) is part of the Scombridae family. It is an epipelagic predator which is distributed widely in the Indo-Pacific region from shallow coastal waters to the edge of the continental shelf where it is found from depths of 10-70 m (McPherson 1985). It is relatively large for a neritic species with a maximum fork length of 240 cm. Narrow-barred Spanish mackerel is primarily caught by gillnet fleets operating in coastal waters with the highest reported catches form Indonesia, India and I.R. Iran (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, although a number of otolith ageing studies have also been undertaken.

Estimates of growth parameters for S. *commerson*, using either length or age-based information, vary between geographic locations. Estimates of the growth parameter K of the von Bertalanffy equation range from 0.12 (Edwards et al. 1985) to 0.78 (Pillai et al. 1993), however, most studies suggest relatively rapid growth of juveniles (IOTC 2015). Differences may be due to regional variation in growth patterns but may also be due to the different selectivity patterns of gears used to obtain the samples as a variety of drifting gillnets, hooks and lines, trolling and trawl gear are used to catch narrow-barred Spanish mackerel.

3. Catch, CPUE and Fishery trends

Disaggregated nominal catch data were extracted from the IOTC Secretariat database for the period 1950–2021, given that records for 2022 were still incomplete at the time of writing. Gillnet fleets are responsible for the majority of reported catches of *S. commerson* followed by line and purse seine gear, with the majority of catches taken by coastal country fleets (Figure 1). Indonesia, India and I.R. Iran together account for 65% of catches. Figure 2 shows the total catch of narrow-barred Spanish mackerel since 1950, which increased to a peak of 175 559 t in 2016 and has then declined to the 143 597 t in 2018 (Table 1). However, the catch has since again increased to 168 807 t in 2021. In 2019, IOTC endorsed the revisions of Pakistani gillnet catches that introduce some changes in the catches of tropical tuna, billfish, as well as some neritic tuna species since 1987 (IOTC 2019). However, the revision appears to have very minor effects on the Spanish mackerel nominal catch series since the last assessment (Figure 3).

Fu et al. (2019) developed standardised CPUE indices for several neritic tuna species including Spanish mackerel 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 Spanish mackerel tuna showed an increasing trend over time since 2011/12 (Figure 4), with a strong seasonal pattern driven mostly by the productivity cycle in the southern Gulf as well as market conditions (Fu et al. 2019). The annualised indices (by taking the average of the quarterly indices) are included in the assessment method based on the JABBA model (see Section 4.2). As the indices covers up to 2017, an assumption was made in the model that the 2018 index is the same as in 2017.

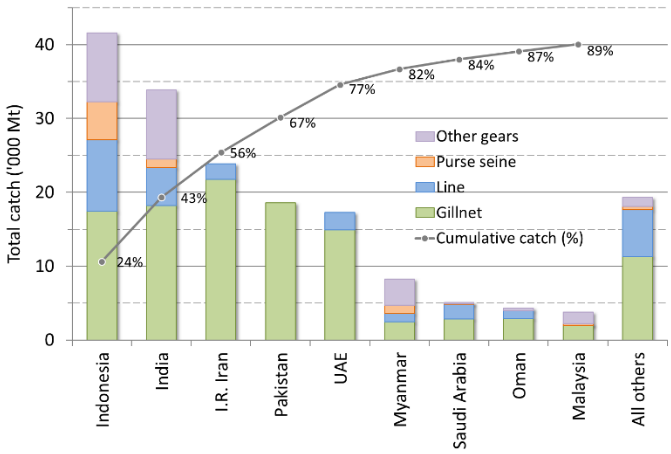

Figure 1: Average catches in the Indian Ocean over the period 2012-2021, by country. by country. The red line indicates the (cumulative) proportion of catches of Spanish mackerel by country.

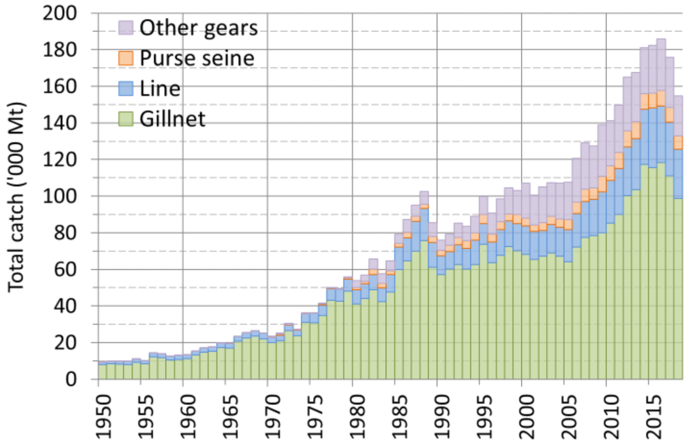

Figure 2: Total nominal catch of Spanish mackerel by gear, 1950 – 2021 (IOTC database).

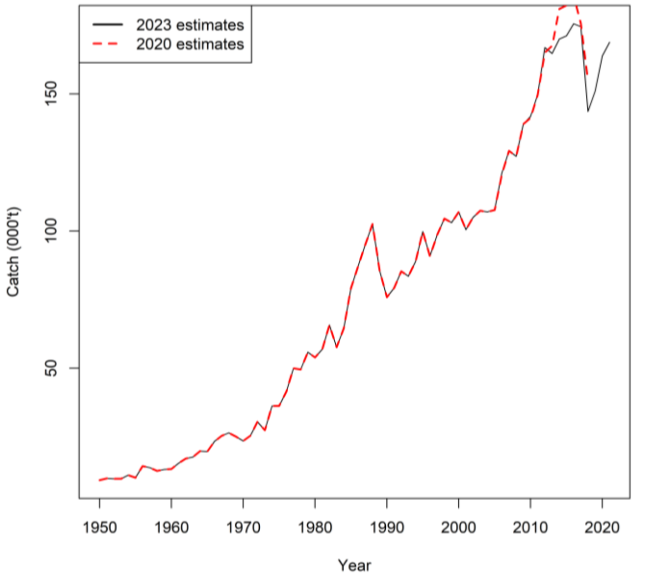

Figure 3: Revisions to IOTC nominal catch data for Spanish mackerel (datasets used for the 2017 and 2021 assessments).

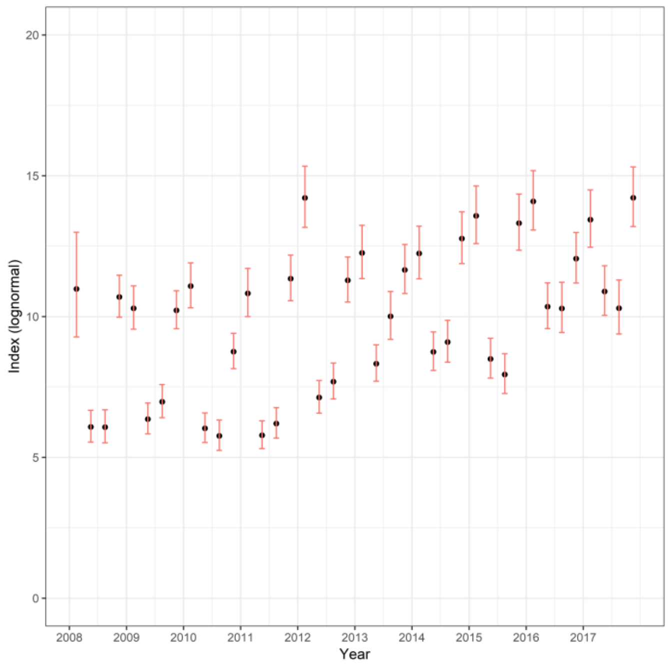

Figure 4: Standardised CPUE indices (year-quarter) for Spanish mackerel 2008–2017 from the GLM lognormal model. See Fu et al. (2019) for details.

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

Year	Catch (t)	Year	Catch (t)
1950	9 188	1987	95 052
1951	9 827	1988	102 526
1952	9 707	1989	85 425
1953	9 687	1990	75 863
1954	11 055	1991	79 219
1955	10 060	1992	85 320
1956	14 291	1993	83 518
1957	13 740	1994	88 921
1958	12 553	1995	99 804
1959	13 076	1996	90 831
1960	13 262	1997	98 642
1961	15 325	1998	104 521
1962	17 042	1999	103 056
1963	17 600	2000	106 957
1964	19 766	2001	100 514
1965	19 618	2002	104 990
1966	23 354	2003	107 419
1967	25 327	2004	106 980
1968	26 430	2005	107 793
1969	25 043	2006	121 163
1970	23 470	2007	129 252
1971	25 387	2008	127 259
1972	30 455	2009	138 969
1973	27 370	2010	141 779
1974	36 180	2011	149 720
1975	36 269	2012	166 867
1976	41 451	2013	164 736
1977	49 986	2014	169 995
1978	49 528	2015	171 166
1979	55 831	2016	175 559
1980	53 927	2017	174 520
1981	56 937	2018	143 597
1982	65 724	2019	150 963
1983	57 658	2020	163 872
1984	64 550	2021	168 807
1985	79 184		
1986	87 184		

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 Spanish mackerel. The C-MSY method represents a further development of the Catch-MSY method of Martell and Froese (2012), with several 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 *S. commerson (*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, *S. commerson* has a high level of resilience (0.6–1.5) (Froese and Pauly 2015), which is similar to 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). For the current assessment, it was decided to adopt the medium range (0.2 – 0.6) assumption for the final depletion level in the reference model, considering the recent reduction in total catches. 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 Spanish mackerel tuna in the C-MSY analysis reference model

Species	Initial B/K	Final B/K	*r*	*K (1000 t)*
Reference model	0.5–0.9	0.2–0.6	0.6–1.5	116 - 1158

4.2. OCOM model

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

4.3. JABBA

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

The LBSPR method (Hordyk et al. 2014) estimates the Spawning Potential Ratio (SPR) of a stock directly from the size composition of the catch. The SPR of a stock is defined as the proportion of the unfished reproductive potential (often approximated by spawning biomass) left at any given level of fishing pressure (Hordyk et al. 2014) and is commonly used to set target and limit reference points for fisheries. The $F_{40\%}$, i.e., the fishing mortality rate that results in SPR at 40% of unfished level, is considered risk adverse for many species. The LBSPR establish that how length compositions and spawning ratios are determined by fishing mortality and life history ratio, which are known to be less variant across species. The LBSPR uses maximum likelihood methods to estimate relative fishing mortality (F/M) and selectivity-at-length that minimize the difference between the observed and the expected length composition of the catch and calculates the SPR (Hordyk et al. 2014). The LBSPR model requires the following parameters: an estimate of the ratio M/k (i.e., the individual values of the M and k parameters may be unknown), L^{∞} (and associated variance), and maturity-at-size. These parameters for *S. commerson* 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 Spanish mackerel 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 393 000 – 746 000 (mean of 542 000). 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 Spanish mackerel 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 161 000 t. The KOBE plot indicates that based on the C-MSY model results, Spanish mackerel is currently overfished (B2021/BMSY=0.98) and is subject to overfishing (F2021/FMSY = 1.07). The average catch over the last five years is higher than the estimated MSY. The results are slightly more pessimistic than the last assessment (which suggested the stock was not subject to overfishing), as a result of the increasing catches in the last few years.

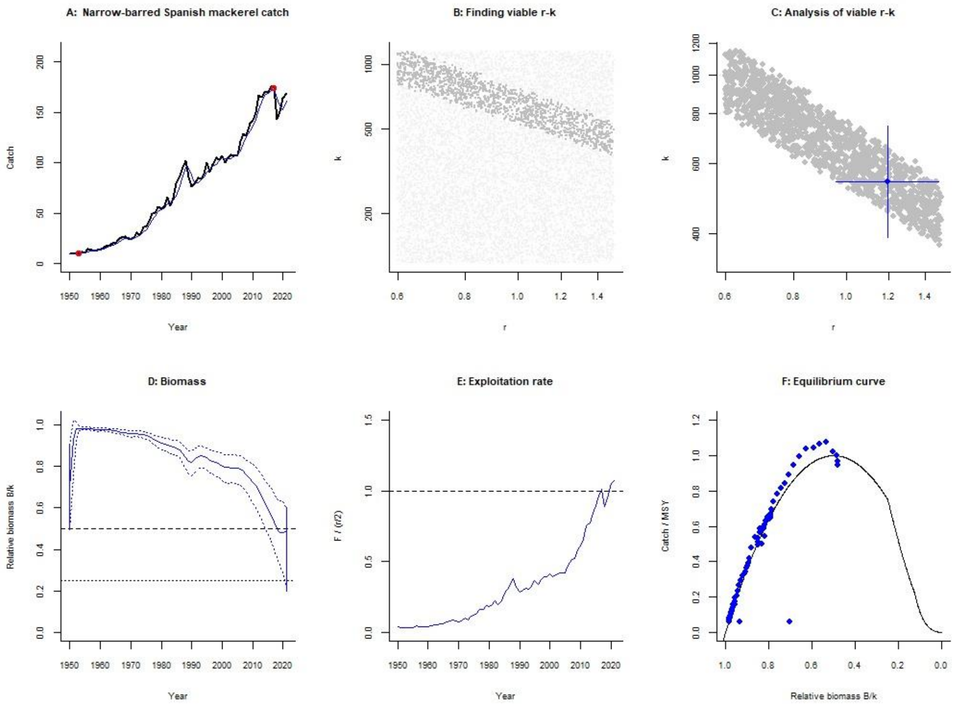

Figure 5. Results of CMSY model for Spanish mackerel.

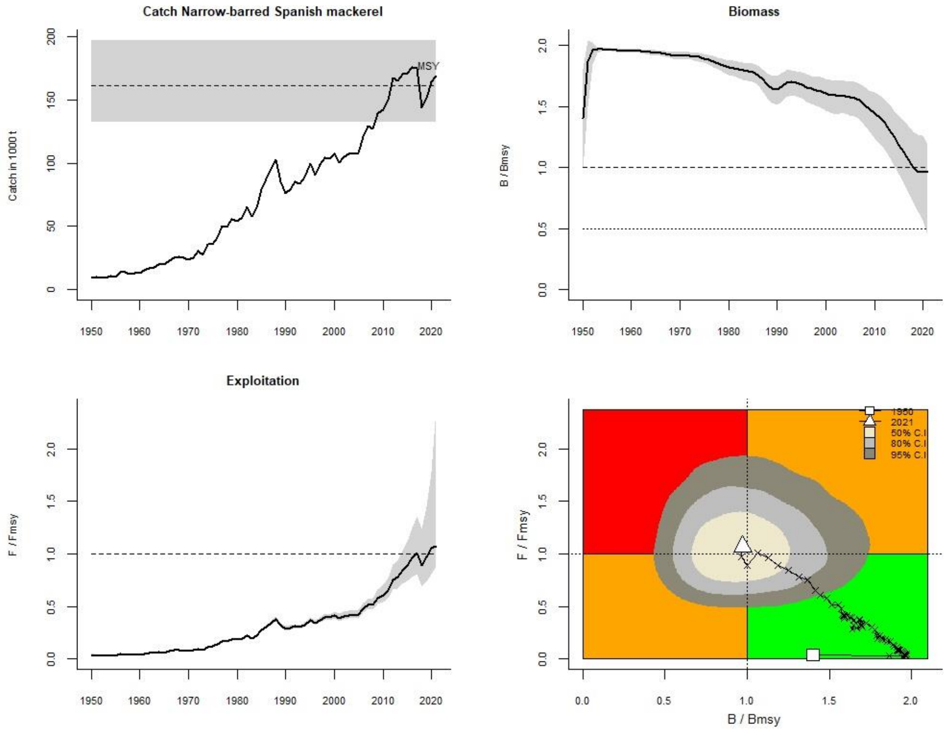

Figure 6. Graphical output of the CMSY model of Spanish mackerel for management purposes.

Table 3. Key management quantities from the Catch MSY assessment for Indian Ocean Spanish mackerel. 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)	154 785 t (2018)	168 807 (2021)
Mean catch – most recent 5 years[2]	175 891 t (2014 – 2018)	160 351 (2017 – 2021
MSY (95% CI)	166 000 (126 100 – 218 000)	161 000 (132 000 – 197 000)
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)	277 000 (194 000 – 396 000)	271 000 (197 000 – 373 000)
$F_{current}/F_{MSY}$ (95% CI)	0.97 (0.78 – 2.14)	1.07 (0.88 – 2.38)
$B_{current}/B_{MSY}$ (95% CI)	0.96 (0.44 – 1.19)	0.98 (0.44 – 1.19)
$B_{current}/B_0$ (95% CI)	0.48 (0.22 – 0.60)	0.49 (0.22 – 0.60)

[2] Data at time of assessment

5.2. OCOM model

Figure 7 shows the strong correlation of r and K parameter values retained by the biomass dynamics model. 80% posterior range of r is 0.70 – 1.42 and is mostly overlap with the prior. Esimated K ranges from 447 000 to 846 000. 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 580 000 t in 1950 and declined to approximately 230 000 t by 2015 (Figure 7). The estimated MSY associated with this projection is 155 000 t and ranges from approximately 149 000 t to 162 000 t based on the assumed maximum depletion level (Figure 7). The model estimated that the stock is currently overfished (B2021/BMSY=0.84) and is subject to overfishing (F2021/FMSY = 1.30). 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

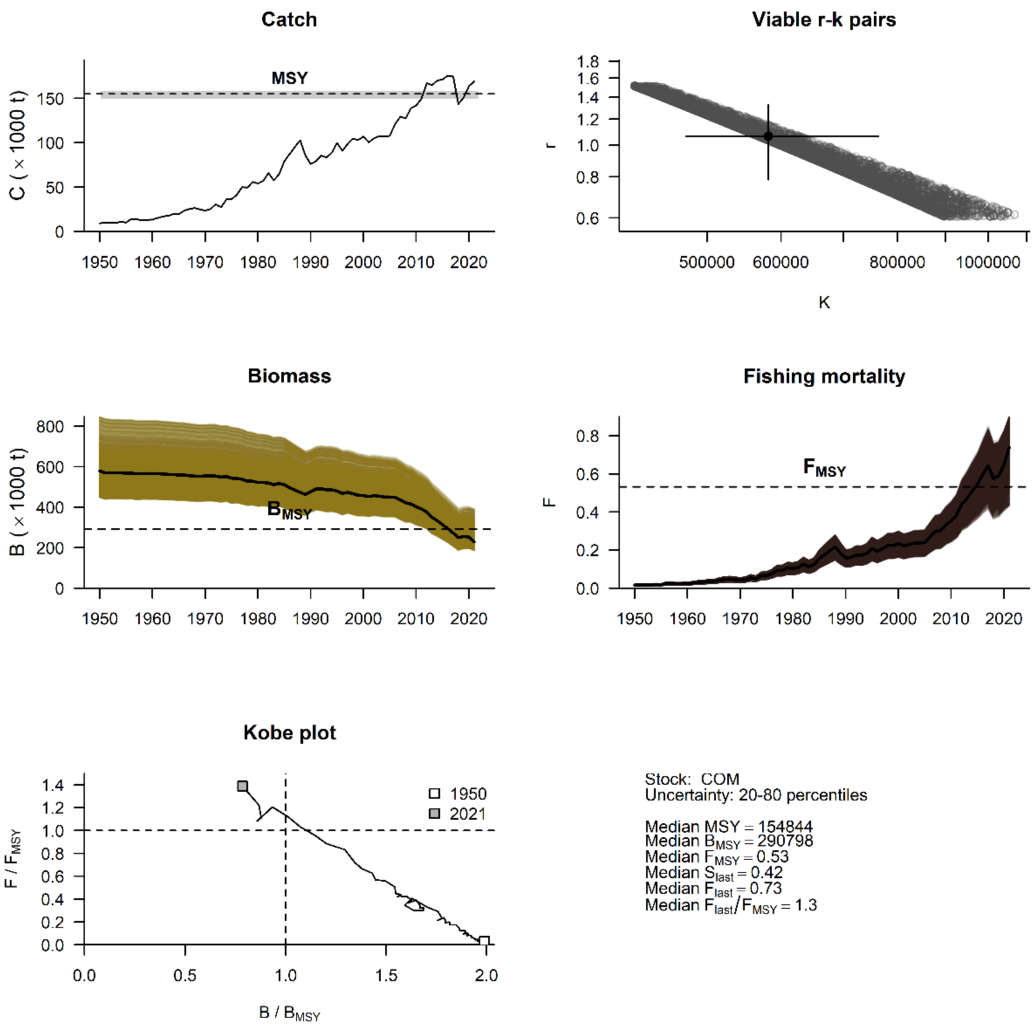

Figure 7: Graphical output of management quantities from the OCOM reference model of Spanish mackerel

5.3. JABBA model

The abundance estimates were exceedingly uncertain with a very wide posterior range (upper range of K surpassed 4 500 000 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 shows a declining trend in overtime, which is to the contrary of the CPUE trend from 2008 to 2017 (Figure 9), indicating some inconsistency between the CPUE and recent catch history. Further exploration shows that the model can fit the increasing CPUE by assuming a much lower observation error for the index (reducing from 0.25 to 0.1), however, this is achieved by generating a somewhat increasing patterns in the process errors.

Estimates of management quantities from model 2 are shown in Figure 10. The estimated stock status is more optimistic to the CMSY model (apparently driven by the CPUE index). The MSY varies between 195 000 and 555 000 t, with an average of 140 000 t. According to estimates, the biomass of the spawning stock in 2021 is 26% higher compared to the BMSY, and the fishing mortality is roughly about 32% lower than the FMSY (B/BMSY = 1.26, F/FMSY = 0.68). Compared to the CMSY analysis, the confidence bounds for most estimations are wider. Despite the addition of CPUE indices to provide information on relative abundance changes, the information is limited due to the relatively short time series and lack of contrast between the CPUE and catch series.

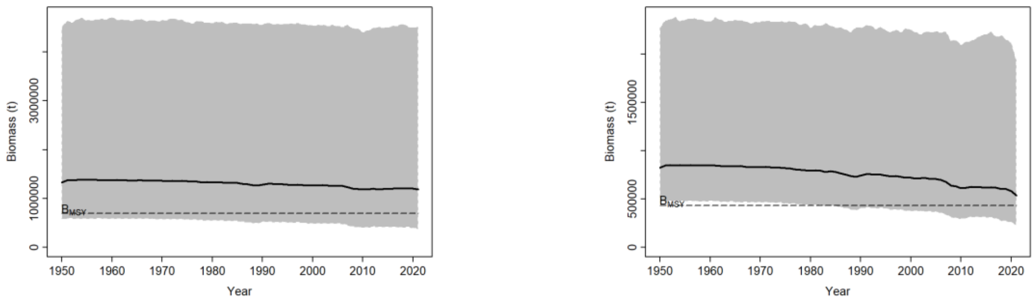

Figure 8: Biomass estimates (median and 95% CI) from JABBA model 1 (left, no prior on final depletion), and model 2 (right, a normal prior on final depletion with mean of 0.4 and CV of 25%, corresponding to an approximate range 0.2 – 0.6). Dashed line indicates median BMSY.

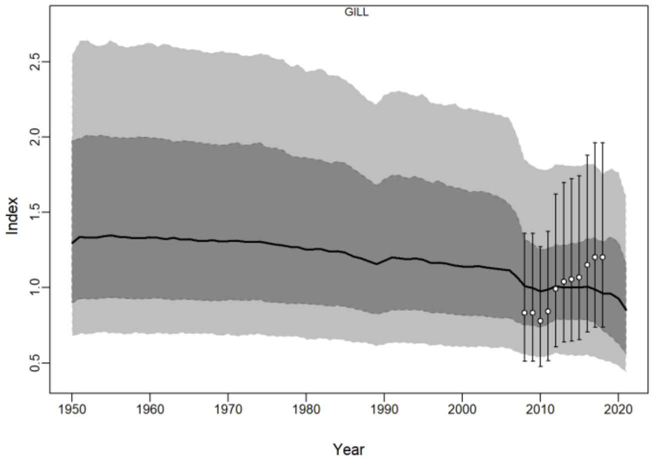

Figure 9: Fits to CPUE indices 2008–2017 form JABBA model 2. Shaded areas indicates 50% and 95% CI, vertical lines indicates observation errors.

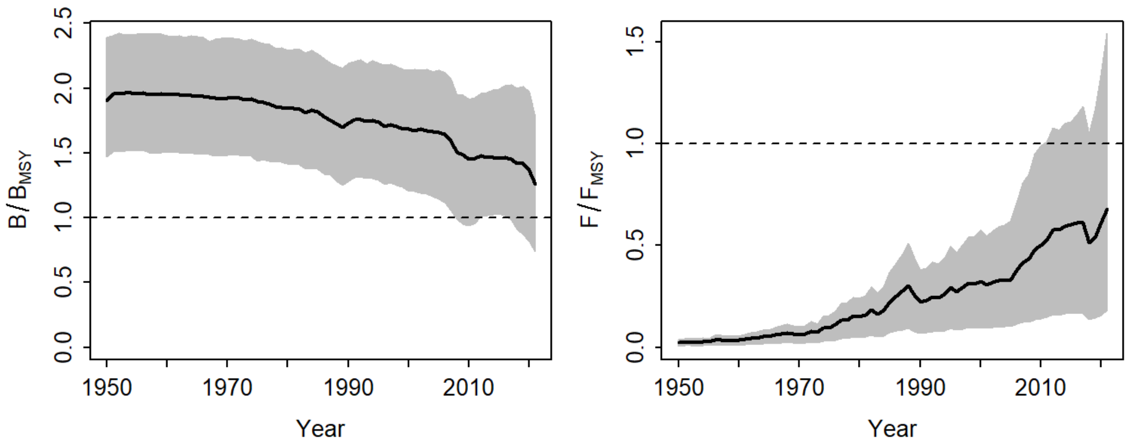

Figure 10: Estimates of management quantities of the JBBBA model 2 (B/BMSY and F/FMSY).

5.4. LBSPR method

The length distribution from the gillnet fishing is well fitted (Figure 11). Selectivity slightly decreased from 2009 to 2013 and then slightly increased after that (Figure 11). The fishing mortality was estimated to have decreased (Figure 11) but was above the potential FMSY (0.87M was regarded a realistic approximation of FMSY for teleost, see Zhou et al., 2012). Estimated spawning potential ratio throughout the time series was 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). But the SPR seems to have been increasing since 2009, mirroring the upward trend in the CPUE, which indicates that the abundance may have been increasing recently. The estimated SPR were also below 0.4 when LB-SPR was applied to length samples from line fisheries (Figure 12).

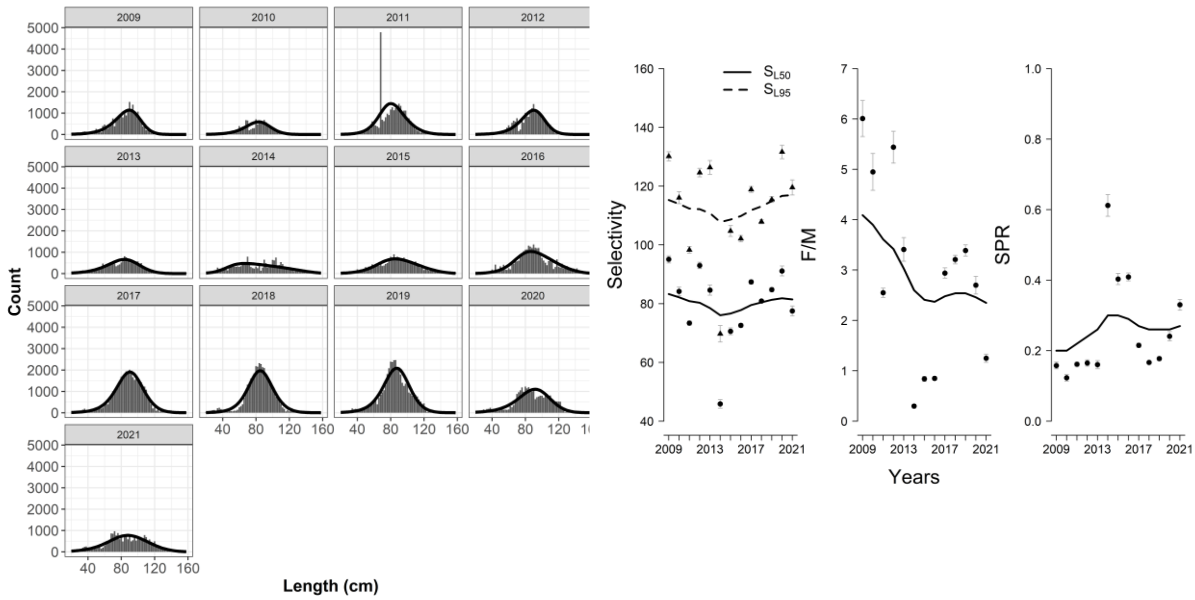

Figure 11: Results of LB-SPR method applied to the length samples from the gillnet fishery for Spanish mackerel: Fits to the length frequency in 2009–2021 (black dots) right – estimates (with 95% CI) of annual logistic selectivity parameters (a50 and a95), F/M, and spawning potential ratio (SPR) over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

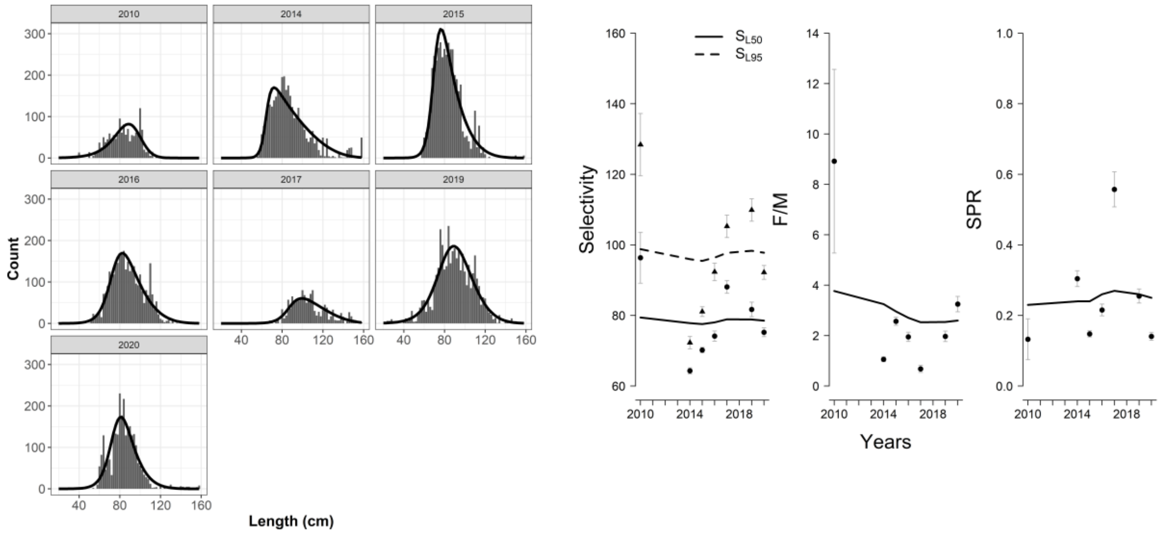

Figure 12: Results of LB-SPR method applied to the length samples from the Line fishery for Spanish mackerel tuna: Fits to the length frequency in 1987–2020 (black dots) a; right – estimates (with 95% CI) of annual logistic selectivity parameters (a50 and a95), F/M, and Spawning Potential Ratio over time.

6. Discussion

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

The C-MSY estimated an average MSY of about 161,000 tons and had a relatively wide range (the other two methods estimated comparable MSY). The 2021 catch was very close to the historical peak and was above the estimated MSY. The high catches appear to coincide with the increasing CPUE in recent years. Despite the significant uncertainties outlined in this paper, this suggests that stocks are approaching being fished at MSY levels and that higher catches may not be sustainable. A precautionary approach to management is recommended.

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 Spanish mackerel, there appears to be inconsistency between the CPUE indices, and the catch history, and productivity assumptions of the species. The increasing CPUE can be attributed to other (unknow) 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 Iranian coastal gillnet fishing fleets can index abundance of Spanish 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. Nonetheless, the SPR estimated by the LB-SPR method was much below the $SPR_{40\%}$, and fishing mortality is much higher than FMSY, corroborating the result of the C-MSY which suggested that the stock is currently overfished and is subject to overfishing. On the other hand, the SPR seems to have been increasing since 2009, mirroring the upward trend in the CPUE, which indicates that the abundance may have been increasing recently. 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). Although the gillnet is known to be size-selective, Spanish mackerel length samples from gillnet fisheries have similar size ranges or distributions to those from line fisheries, making it difficult to quantify the degree of possible doming in gillnet selectivity.

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