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

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1. Introduction ... 2
2. Basic Biology ... 2
3. Catch, CPUE and Fishery trends ... 2
4. Methods ... 5
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 ... 17
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 annually for narrow-barred Spanish mackerel (*Scomberomorus commerson*) from 2013 to 2017 using data-limited methods (Zhou and Sharma, 2013; Zhou and Sharma, 2014; Martin and Sharma, 2015; Martin and Robinson, 2016, Martin & Fu, 2017). In 2017, two data-limited methods were explored to assess the status of *S. commerson*: (i) a C-MSY method (Froese et al. 2016), (ii) an Optimised Catch-Only Method, or OCOM (Zhou et al., 2013). This paper provides an update to the C-MSY assessment based on the most recent catch information. A Bayesian biomass dynamic model was also implemented to include the recently available CPUE indices of Spanish mackerel developed from the Iranian gillnet fishery.

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 (Geehan et al., 2017). 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-WPNT05-DATA14). 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 1950–2018, given that records for 2019 were still incomplete at the time of writing. Gillnet fleets are responsible for the majority of reported catches of *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 185 786 t in 2016 and has then declined to the current catches of 154 785 t in 2018 (Table 1). 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–WPDCS15 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 Bayesian Schaefer production 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.

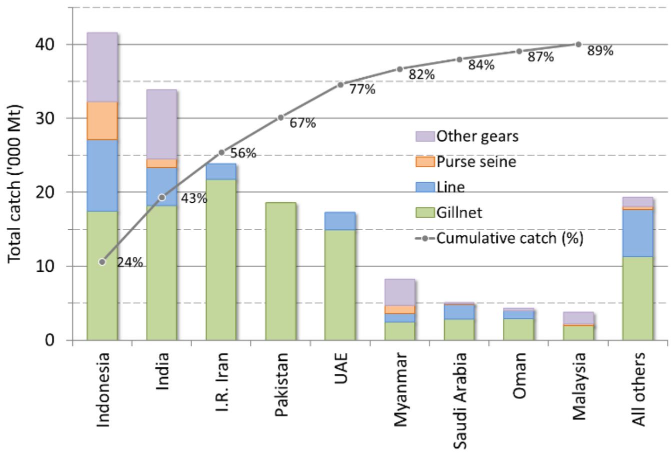


Figure 1: Average catches in the Indian Ocean over the period 2012-2018, by country. by country. The red line indicates the (cumulative) proportion of catches of Spanish mackerel by country.

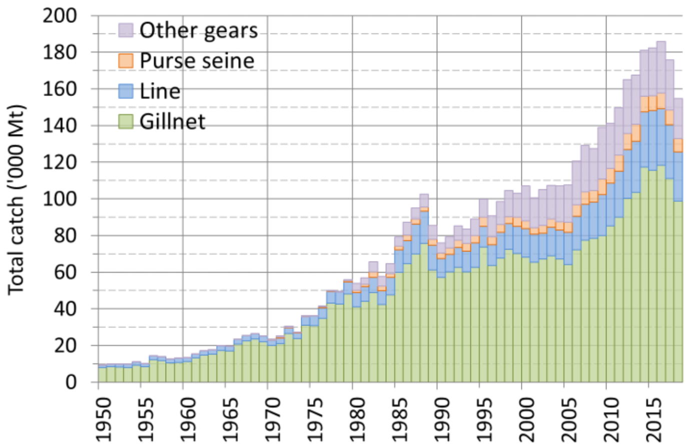


Figure 2: Total nominal catch of Spanish mackerel by gear, 1950 – 2018 (IOTC database).

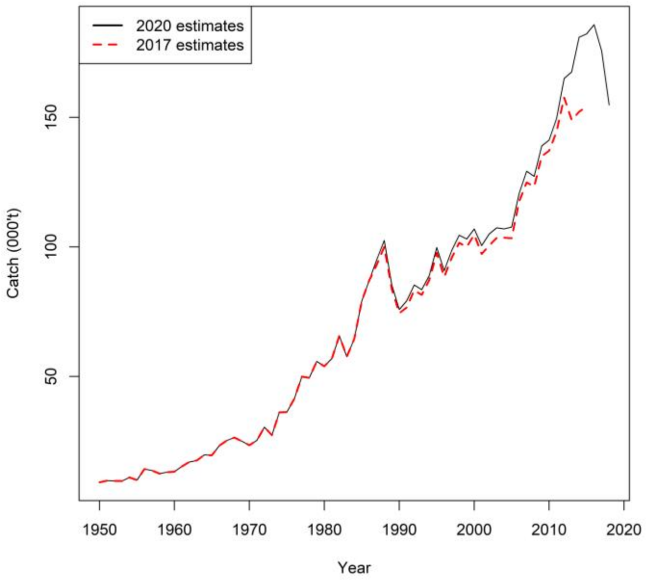


Figure 3: Revisions to IOTC nominal catch data for Spanish mackerel (datasets used for the 2017 and 2020 assessments).

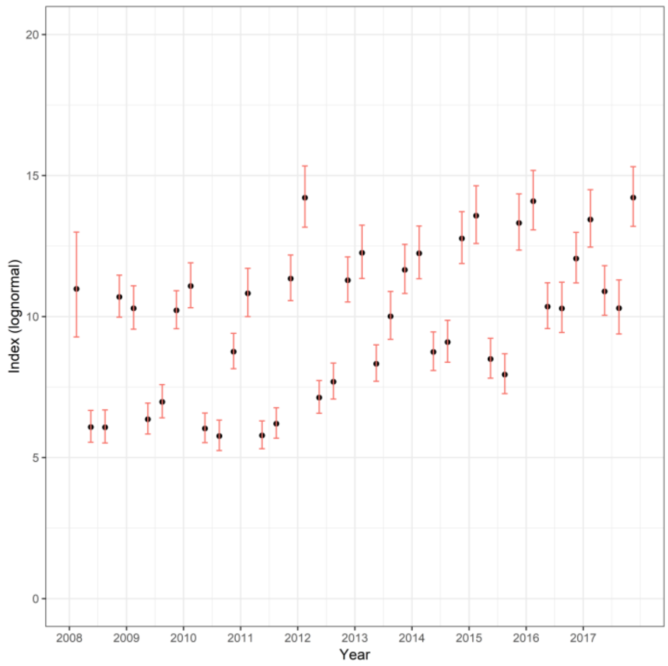


Figure 4: Standardised CPUE indices (year-quarter) for Spanish mackerel 2008–2017 from the GLM lognormal model. See Fu et al. (2019) for details.

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	1985	79 184
1951	9 827	1986	87 184
1952	9 707	1987	95 052
1953	9 687	1988	102 526
1954	11 055	1989	85 421
1955	10 060	1990	75 861
1956	14 291	1991	79 219
1957	13 740	1992	85 317
1958	12 553	1993	83 515
1959	13 076	1994	88 921
1960	13 262	1995	99 801
1961	15 325	1996	90 827
1962	17 035	1997	98 640
1963	17 600	1998	104 521
1964	19 766	1999	103 056
1965	19 618	2000	106 957
1966	23 354	2001	100 514
1967	25 327	2002	104 989
1968	26 430	2003	107 419
1969	25 043	2004	106 979
1970	23 470	2005	107 654
1971	25 387	2006	120 644
1972	30 455	2007	129 252
1973	27 370	2008	127 259
1974	36 180	2009	138 970
1975	36 269	2010	141 245
1976	41 451	2011	149 641
1977	49 986	2012	165 010
1978	49 528	2013	167 549
1979	55 831	2014	180 952
1980	53 927	2015	182 247
1981	56 937	2016	185 786
1982	65 724	2017	175 686
1983	57 647	2018	154 785
1984	64 550		

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.

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

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

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, *S. commerson* 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

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

Where k_{low} and k_{high} are the lower and upper lower bound of the range of *k*, max(C) is the maximum catch in the time series, and r_{low} and r_{high} are lower and upper bound of the range of r values.

The ranges for starting and final depletion levels were assumed to be based on one of possible three biomass ranges: 0.01–0.4 (low), 0.2–0.6 (medium), and high (0.4–0.8), using a set of rules based on the trend of the catch series (see Froese et al. (2016) for details). The prior range for the depletion level can also be assumed optionally for an intermediate year, but this option was not explored in this report. The medium range (0.2 – 0.6) assumption was adopted for for the final depletion level in the model (same as the assumption used in the 2017 assessment). 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	122 – 1220

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 **Error! Reference source not found.**. 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 (M1) 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 (M2), and (2) 0.4–0.8 (M3), 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 389 000 – 801 000 (mean of 558 000). 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 166 000 t. The KOBE plot indicates that based on the C-MSY model results, Spanish mackerel is currently overfished (B2018/BMSY=0.96) but is not subject to overfishing (F2018/FMSY = 0.97). The average catch over the last five years is higher than the estimated MSY. The results are slightly more optimistic than the last assessment (which suggested the stock was subject to overfishing), as a result of the reduced catches in the last few years.

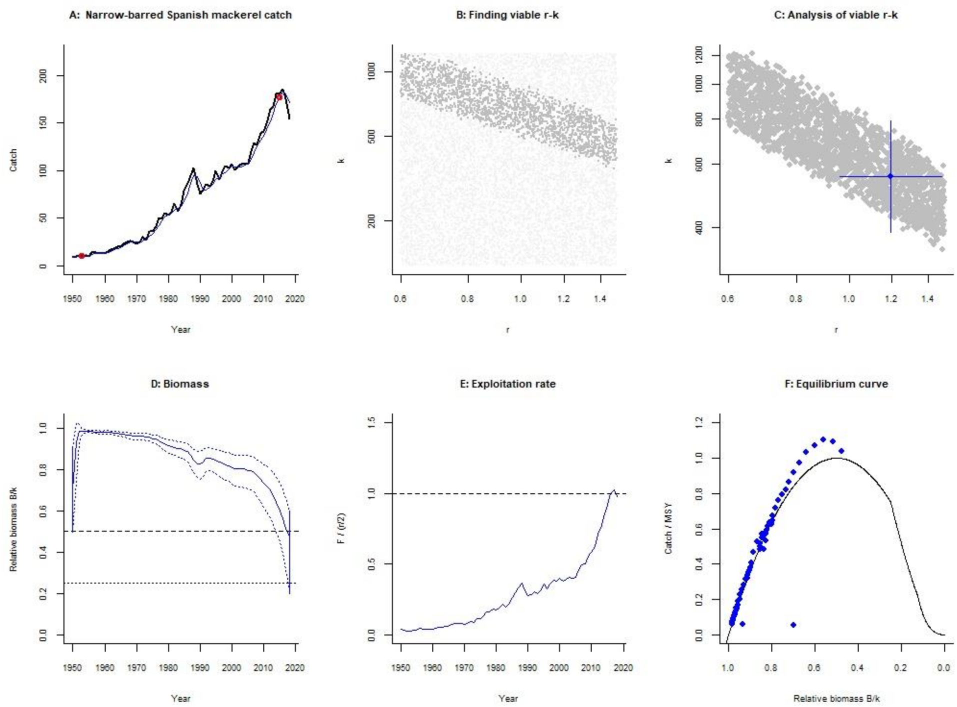


Figure 5. Results of CMSY model for Spanish mackerel.

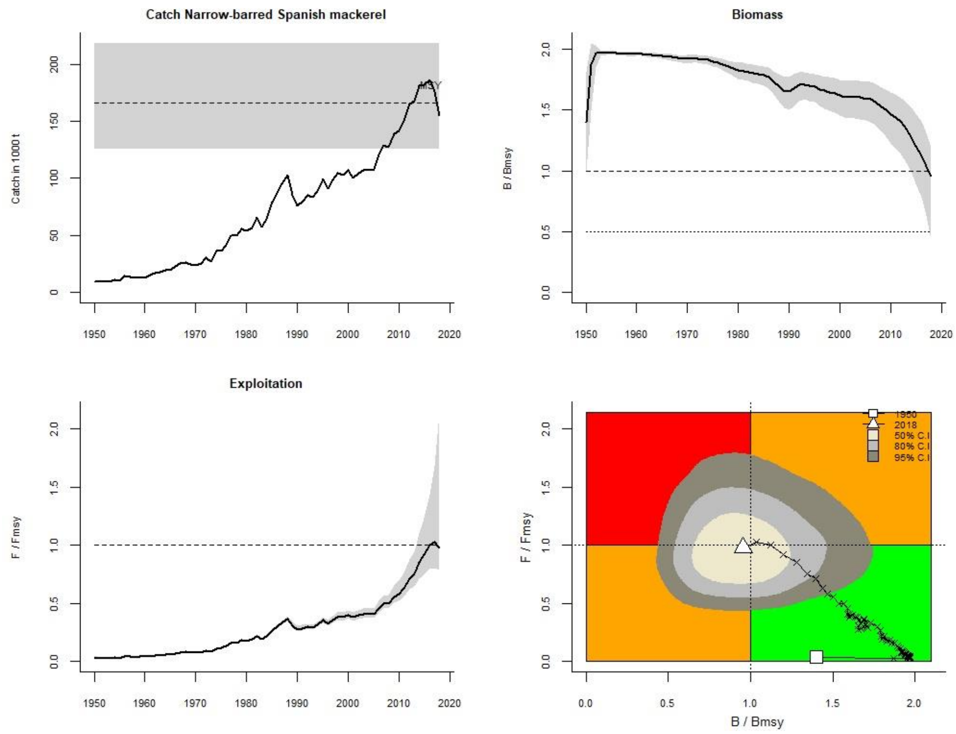


Figure 6. Graphical output of the CMSY model of Spanish mackerel for management purposes.

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.

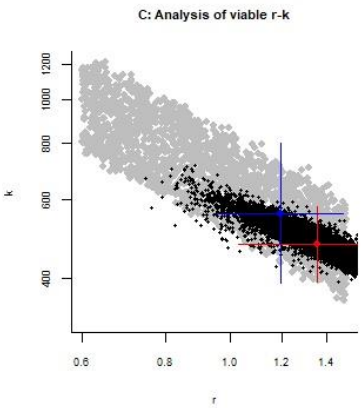
Management Quantity	**2017**	**2020**
Most recent catch estimate (year)	149 177 t (2015)	154 785 t (2018)
Mean catch – most recent 5 years[2]	144 724 t (2011 - 2015)	175 891 t (2014 – 2018)
MSY (95% CI)	138 000 (104 000 to 183 000)	166 000 (126 100 – 218 000)
Data period used in assessment	1950 – 2015	1950 – 2018
F_{MSY} (95% CI)	0.60 (0.48 - 0.74)	0.60 (0.48 - 0.74)
B_{MSY} (95% CI)	232 000 (161 000 – 333 000)	277 000 (194 000 – 396 000)
$F_{current}/F_{MSY}$ (95% CI)	1.19 (0.94 – 2.59)	0.97 (0.78 – 2.14)
$B_{current}/B_{MSY}$ (95% CI)	0.95 (0.43 – 1.19)	0.96 (0.44 – 1.19)
$B_{current}/B_0$ (95% CI)	0.47 (0.22 - 0.60)	0.48 (0.22 – 0.60)

[2] Data at time of assessment

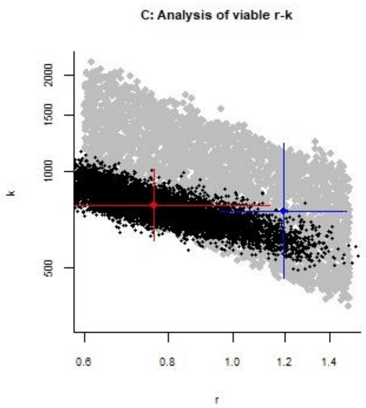
5.2. Bayesian Schaefer production model (BSM)

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, (

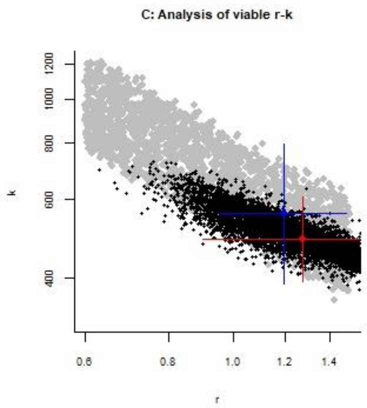
M1



M2



M3



M4

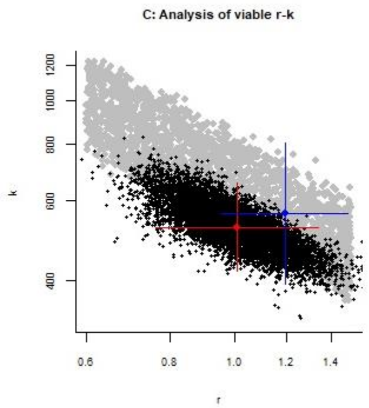
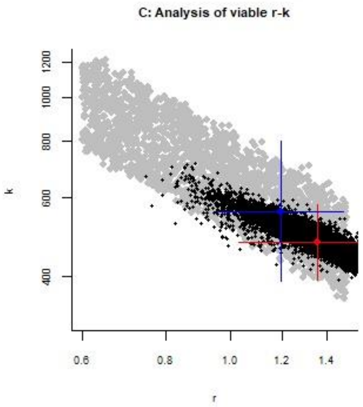
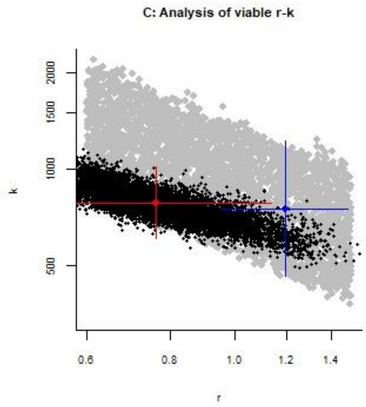


Figure 7–M3). The results are very similar to Model M1, which constrained the final depletion to be in the medium range of 0.2–0.6 through a penalty function (

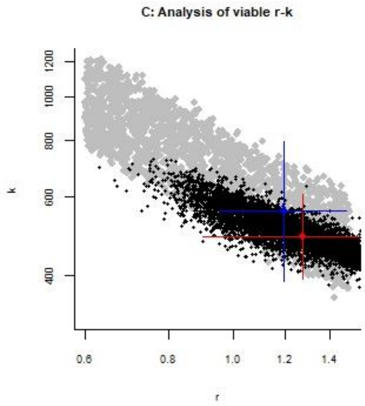
M1

M2





M3 **M4**



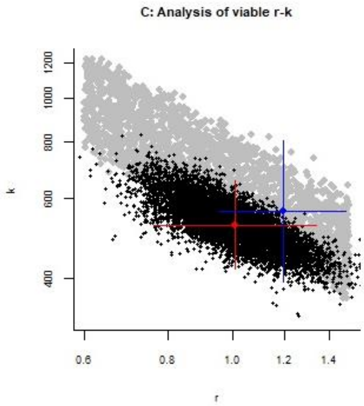
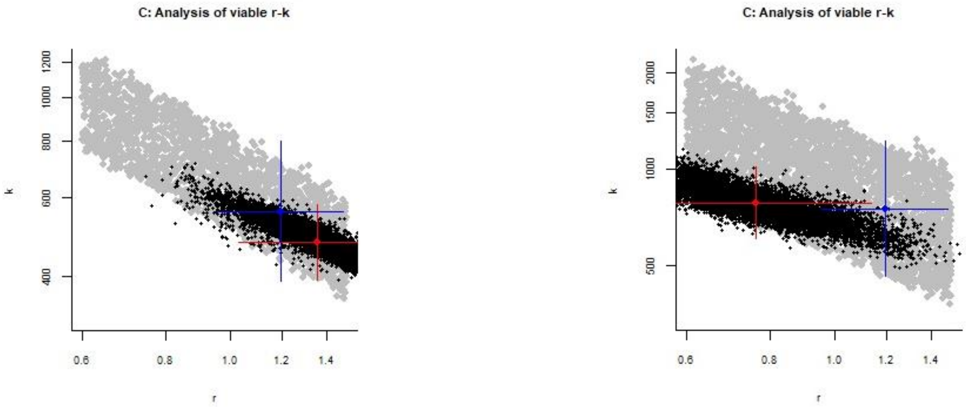


Figure 7–M1). This suggested the medium depletion range appears to be more coherent with the assumed stock productivity. However, neither model is able to fit the CPUE indices, with the predicted biomass trend being in opposite direction of the indices (Figure 8 – M1, M3), suggesting the CPUE is in conflict 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 F2018 to be 0.99 FMSY; Model M1 estimated B2018 to be 0.97 BMSY and M3 estimated B2018 to be 1.01 BMSY (Table 4). The conclusion of model M1 is similar to the CMSY: the stock is overfished but is not subject to overfishing.

Additional model configurations were investigated to account for the increasing trend in the CPUE indices (assuming it is representative of the recent stock trend). Model M2, which assumed a high final depletion level (0.4 – 0.8) appears to fit the CPUE indices very well (Figure 8 – M2), the model achieved this by shifting the r-k pairs more towards the higher k and lower r values range (

M1 **M2**



M3 **M4**

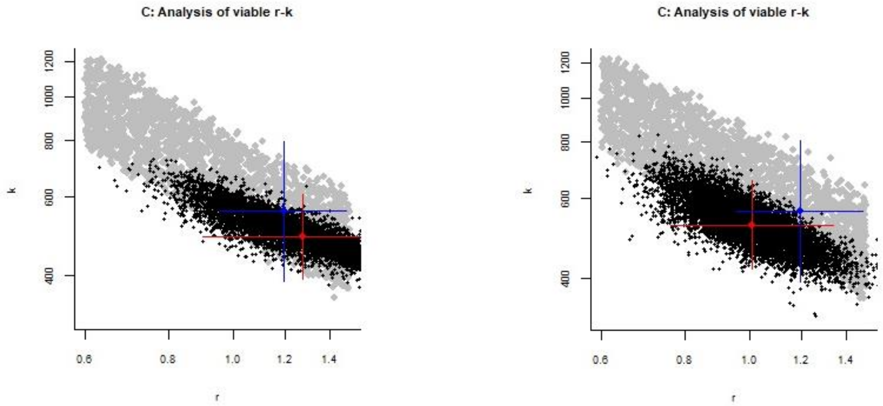


Figure 7–M2). Consequently, Model M2 estimated that the stock is in the green KOBE quadrant (Figure 9 – M2), with B2018 estimated to be about 1.29 BMSY and F2018 to be 0.80 FMSY.

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 (B2018/BMSY=1.14) but is subject to overfishing (F2018/FMSY=1.02) (Table 4, Figure 8 – M4).

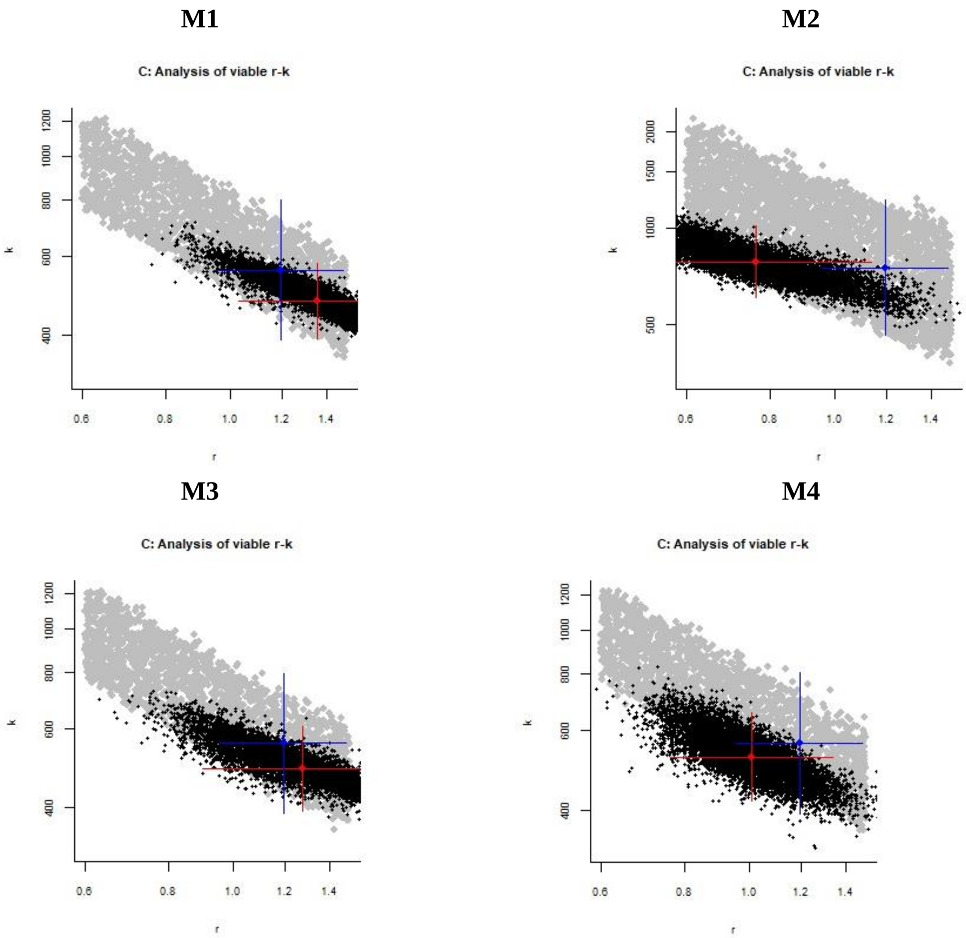


Figure 7: Results of BDM models 1–4 for Spanish mackerel: posterior estimates of *r* and *K* (black dots) and the 95% CI (the red cross), overlaid with the viable r-k pairs as well as the probable range from the CMSY analysis (grey dots and the blue cross); right – median and 95% CI of the posterior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

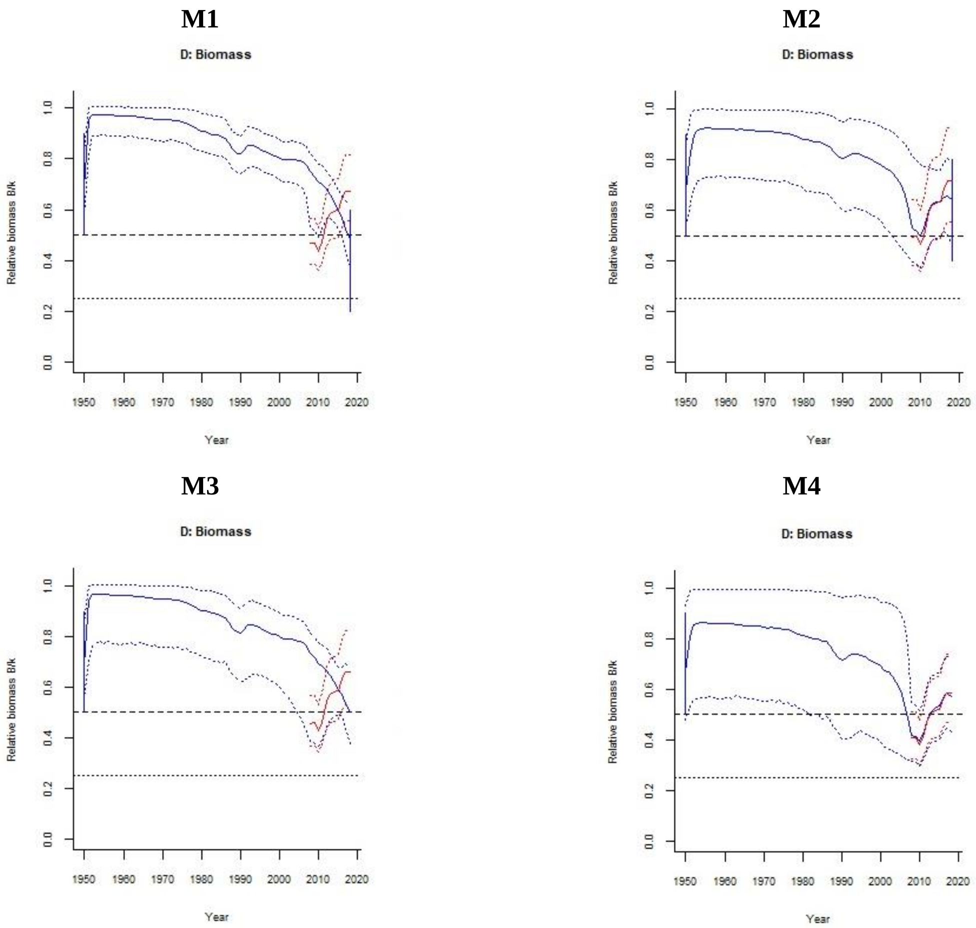


Figure 8: Results of BDM models 1–4 for Spanish mackerel: median and 95% CI of the posterior estimates of biomass, overlaid with the standardised CPUE indices 2008–2017 with observation errors (red).

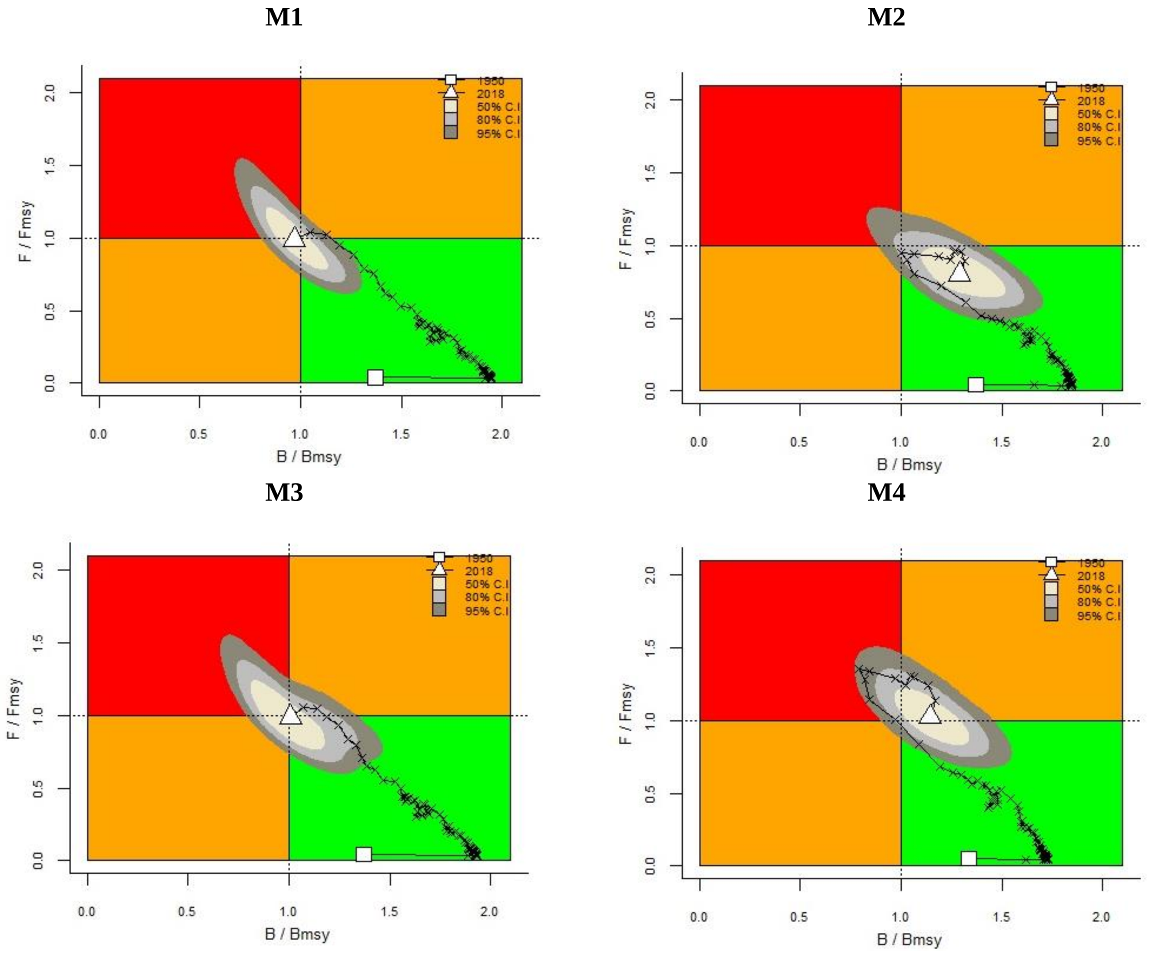


Figure 9: Kobe plots for the BDM models M1 – M4.

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

Management Quantity	**Model 1**	**Model 2**	**Model 3**	**Model 4**
MSY (95% CI)	161 000 t (143 010 – 182 000)	149 000 t (119 010 – 188 000)	156 000 t (130 010 – 186 000)	132 000 t (110 010 – 158 000)
Data period	1950 – 2018	1950 – 2018	1950 – 2018	1950 – 2018
F_{MSY} (95% CI)	0.68 (0.52 – 0.89)	0.38 (0.26 – 0.57)	0.64 (0.45 – 0.90)	0.51 (0.38 – 0.67)
B_{MSY} (95% CI)	238 000 t (197 000– 289 000)	392 000 t (303 000– 508 000)	245 000 t (197 000– 304 000)	262 000 t (209 000– 328 000)
$F_{current}/F_{MSY}$ (95% CI)	0.99 (0.78 – 1.29)	0.80 (0.66 – 1.11)	0.99 (0.73 – 1.32)	1.02 (0.81 – 1.36)
$B_{current}/B_{MSY}$ (95% CI)	0.97 (0.75 – 1.23)	1.29 (0.93 – 1.58)	1.01 (0.75 – 1.36)	1.14 (0.86 – 1.44)
$B_{current}/B_0$ (95% CI)	0.49 (0.37 – 0.62)	0.65 (0.47 – 0.79)	0.50 (0.38 – 0.68)	0.57 (0.43 – 0.72)

6. Discussion

In this report we have explored two data-limited methods in assessing the status of Indian Ocean Spanish mackerel: 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 Spanish mackerel in the Indian Ocean is overfished (B2018 < BMSY) but is not subject to overfishing (F2018 < FMSY). 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 Spanish mackerel, 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 (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). It remains a question whether the CPUE indices derived from the Iranian coastal gillnet fleets can index the abundance trend of Spanish Mackerel 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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