UPDATED STOCK ASSESSMENT OF BLUE MARLIN (*MAKAIRA NIGRICANS*) IN THE INDIAN OCEAN USING *JABBA*

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SUMMARY

Three Bayesian State-Space Surplus Production Model scenarios were run to assess blue marlin (*Makaira nigricans*) in the Indian Ocean using the JABBA framework, based on catch and effort data up to and including 2020. A 'drop one' sensitivity analysis indicated that omitting any of the CPUE time-series would not significantly alter the stock status. Similarly, a retrospective analysis produced highly consistent results for stock status estimates back to 2015 and therefore provided no evidence for an undesirable retrospective pattern. The B/B_{MSY} trajectory declined from the mid-1980s to 2007. A short-term increase in B/B_{MSY} occurred from 2007 to 2012, which is thought to be linked to the NW Indian Ocean Piracy period. Thereafter, the B/B_{MSY} trajectory again declines to the current estimate. F/F_{MSY} increased since the mid-1980s and despite a recent decline, F/F_{MSY} remains above 1. Terminal points of the time series fall within the red quadrant of the Kobe plot in all scenarios (61.4% - 74% probability). As such, the blue marlin stock in the Indian Ocean is currently "overfished" and "subject to overfishing". However, the current catches of blue marlin are marginally lower than the estimated MSY for all scenarios.

KEY WORDS

Abundance, Stock assessment, longline, stock status, CPUE fits, biomass model, diagnostics, process error

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1. Introduction

In 2019, the Indian Ocean Commission (IOTC) carried out an assessment for blue marlin (*Makaira nigricans*) using two different model types; the Bayesian Surplus Production Model JABBA (Winker et al., 2018) and the statistical age-structured model Stock Synthesis (Methot and Wetzel, 2013). Prior to the final model being determined by the WPB, a continuity run was developed in JABBA (IOTC-2019-WPB17-20a) to recreate continuity with the previous assessment. The results indicated that JABBA was able to provide a suitable continuity run to the Andrade (2016) assessment as the results are comparable. Continuity of assessments is important to evaluate the efficacy of previous management interventions by the IOTC Commission.

In 2019, the management advice was based on the results from the JABBA model with a Schaefer-type production function, which indicated that the catches in 2017 (12,796 t) were above MSY and that the stock was overfished and subject to overfishing.

Here, we provide an updated (2022) assessment of blue marlin in the Indian Ocean using the Bayesian State-Space Surplus Production Model software 'JABBA' (Winker et al. 2018a; Just Another Bayesian Biomass Assessment). JABBA is implemented as a flexible, user-friendly open-source tool that is hosted on GitHub (https://github.com/jabbamodel) that has also been included in the ICCAT stock catalogue (https://github.com/ICCAT/software/wiki/2.8-JABBA), following a number a number of recent tuna RFMO stock assessments.

2. Material and Methods

2.1. *Fishery data*

Catch time series (1950-2020) were extracted from the IOTC stock assessment dataset repository of the 20th Meeting on of Working Party on Billfish (https://www.iotc.org/WPB/20/Data/03-NC). Indices of relative abundance were made available in the form of standardized catch-per-unit-of-effort (CPUE) time series, which were assumed to be proportional to biomass. Standardized CPUE series were obtained from three fishing fleets operating in the Indian Ocean, all of which were longline: Japan, Taiwan,China and Indonesia (**Figure 3**). The Taiwan,China indices were split into two separate time series, and it was recommended that only the latter index (2005 onwards) be used in the assessment. However, the early index was included in a scenario for continuity with the 2019 assessment:

- Japan North-West (1979-2010)
- Japan Central-East (1979-2020)
- Taiwan,China North-West historical (1979-2004)
- Taiwan,China North-East historical (1979-2004)
- Taiwan,China North-West (2005-2020)
- Taiwan,China North-East (2005-2020)
- Indonesia (2006-2020)

2.2. *JABBA stock assessment model fitting procedures*

This stock assessment uses the most updated version (v2.2.5) of JABBA and can be found online at: https://github.com/jabbamodel/JABBA. JABBA's inbuilt options include: (1) automatic fitting of multiple CPUE time series and associated standard errors; (2) estimating or fixing the process variance, (3) optional estimation of additional observation variance for individual or grouped CPUE time series, and (4) specifying a Fox, Schaefer, or Pella-Tomlinson production function by setting the inflection point B_{MSY}/K and converting this ratio into shape a parameter m.

For the unfished equilibrium biomass K, two values were used depending on the scenario. For the continuity scenarios we assumed the same range of plausible values as in Parker et al. (2019) which approximates those used in Andrade (2016). For the updated scenario, we used the default settings of the JABBA R package in the form of vaguely informative lognormal prior with a large CV of 100% and a central value that corresponds to eight times the maximum total catch and is consistent with other platforms such as Catch-MSY (Martell and Froese, 2013) or SpiCt (Pederson and Berg 2017). Similarly, two values were used as priors for initial depletion. For the continuity scenarios a lognormal prior distribution with mean = 1 and CV of 5% were used, as was the case in Parker et al. (2019). For the updated scenario, the initial depletion was input as a “beta” prior ($\varphi = B_{1950}/K$) with mean = 0.95 and CV of 5%. This distribution is considered more appropriate than a lognormal for initial depletion, given the understanding that there was very little fishing before the starting year of 1950. All catchability parameters were formulated as uninformative uniform priors, while additional observation variances were estimated for indices by assuming inverse-gamma priors to enable model internal variance weighting. Instead, the process error of log(B_y) in year y was estimated “freely” by the model using an uninformative inverse-gamma distribution with both scaling parameters setting at 0.001. Observation error for CPUE estimates was fixed at 0.15 in the continuity scenarios, and 0.25 in the updated scenarios.

All models were run using a Schaefer model type with an associated lognormal r prior of log(r) ~ $N(log(0.4),0.3)$ and a fixed input value of B_{MSY}/K = 0.5. A Schaefer model was preferred for continuity with the 2019 assessment, where the WPB decided a Schaefer model was more appropriate than a Fox (B_{MSY}/K = 0.37) model.

S1 (Cont_hist): Parker et al. (2019) prior formulation; all CPUE

S2 (Cont_new): Parker et al. (2019) prior formulation; remove historical TWN CPUE

S3 (Update): updated K, initial depletion, and observation error prior formulation; remove historical Taiwan,China CPUE

2.3. *Model diagnostics*

The evaluation model diagnostics follows the principles in Carvalho et al. (2021), who recommended to objectively evaluate the base-case candidate model based on the following four model plausible criteria: (1) model convergence (2) fit to the data, (3) model consistency (retrospective pattern) and (4) prediction skill through hindcast cross-validation (Kell et al. 2016; 2021).

JABBA is implemented in R (R Development Core Team, https://www.r-project.org/) with JAGS interface (Plummer, 2003) to estimate the Bayesian posterior distributions of all quantities of interest by means of a Markov Chains Monte Carlo (MCMC) simulation. In this study, three MCMC chains were used. Each model was run for 30,000 iterations, sampled with a burn-in period of 5,000 for each chain and thinning rate of five iterations. Basic diagnostics of model convergence included visualization of the MCMC chains using MCMC trace-plots as well as Heidelberger and Welch (Heidelberger and Welch, 1992) and Geweke (1992) and Gelman and Rubin (1992) diagnostics as implemented in the coda package (Plummer et al., 2006).

To evaluate the JABBA fit to the abundance index data, the model predicted values were compared to the observed indices. Residual plots were used to examine (1) color-coded lognormal residuals of observed versus predicted CPUE indices by fleet together with (2) boxplots indicating the median and quantiles of all residuals available for any given year; the area of each box indicates the strength of the discrepancy between CPUE series (larger box means higher degree of conflicting information) and (3) a loess smoother through all residuals which highlights systematically auto-correlated residual patterns to evaluate the randomness of model residuals. In addition, it depicts the root-mean-squared-error (RMSE) as a goodness-of-fit statistic. Run tests were conducted to evaluate the randomness of residuals (Carvalho et al., 2017). The runs test diagnostic was applied to residuals of the CPUE fit on log-scale using the function runs.test in the R package “tseries”, considering the 1- sided p-value of the Wald-Wolfowitz runs test (Carvalho et al. 2021).

To check for model consistency with respect to the stock status estimates, a retrospective analysis was performed on S3 by removing one year of data at a time sequentially (n = 5), refitting the model and comparing quantities of interest (i.e., biomass, fishing mortality, B/B_{MSY}, F/F_{MSY}, B/B_0 and MSY) to the S3 model that is fitted to full time series. To compare the bias between the models, we computed Mohn’s (Mohn, 1999) rho (ρ) statistic and specifically the commonly used formulation Hurtado-Ferro et al. (2015).

To validate a model’s prediction skill, we applied a hindcasting cross-validation (HCXval) technique (Kell et al. 2016), where observations are compared to their predicted future values. HCxval is a form of cross-validation where, like retrospective analysis, recent data are removed, and the model refitted with the remaining data, but HCXval involves the additional steps of projecting ahead over the missing years and then cross-validating these forecasts against observations to assess the model's prediction skill. A robust statistic for evaluating prediction skill is the Mean Absolute Scaled Error (MASE), which scales the mean absolute error of prediction residuals to a naïve baseline prediction, where a 'prediction' is said to have 'skill' if it improves the model forecast when compared to the naïve baseline (Kell et al. 2021). The MASE score scales the mean absolute error of the prediction residuals to the mean absolute error of a naïve in-sample prediction and a score of higher than one can be interpreted such that the average model forecasts are no better than a random walk. Conversely, a MASE score of 0.5 indicates that the model forecasts twice as accurately as a naïve baseline prediction; thus, the model has prediction skill.

3. Results and Discussion

The MCMC convergence tests by Heidelberger and Welch (Heidelberger and Welch, 1992) and Geweke (1992) and Gelman and Rubin (1992), as well as visual inspection of trace plots, indicate adequate convergence in all models. Furthermore, identical model runs produce consistent results, indicating a good level of model stability.

The S3 model fit to each of the five (three fleets, two of which are split by area) standardized CPUE LL indices are shown in **Figure 3.** The S3 model appeared to have a reasonable fit to the CPUE data, and the goodness-of-fit was estimated to be RMSE = 26% (**Figure 2**). There is some conflict in the last 15 years (2005-2020) largely due to this being the period when the most indices are available. Run tests conducted on the log-residuals indicated that the CPUE residuals may not be randomly distributed for two of the five: JPN_NW and TWN_NW (**Figure 4**). Both Northwest indices show residual autocorrelation and the several outliers.

Marginal posterior distributions along with prior densities for all three models are shown in **Figures 6,7** and **8**. The prior to posterior median ratio (PPMR) for *r* in all models are above 1, indicating that the posterior mean is consistently larger than the prior mean (i.e., there is information in the data to suggest that the stock is more productive). The response of the prior to data was expected, given the relatively high CVs of 0.4 that was input (**Table 3**). Similarly, the resulting small PPVRs for *K* observed in all scenarios indicate that the input data was informative about *K*, while the prior was largely uninformative. The marginal posteriors for initial depletion (φ) were similar between S1 and S2, with both PPMR and PPVR close to 1, which suggests that this parameter was largely informed by the priors. For S3, the prior had a different distribution (beta) but the posterior was still heavily influenced by the prior.

Summaries of posterior quantiles for parameters and management quantities of interest are presented in **Table 3** Estimates of *MSY* were very similar between all models (8,456 – 8,837). The marginal posterior median for B_{MSY} varied between 34,370 metric tons (S1) and 37,401 metric tons (S2). The largest variation is seen in the estimate of *K*, which ranged from 68,741 (S1) to 74,802 (S2). Despite the 2020 points estimates being similar between all models, the trends in biomass and fishing mortality, including B/B_{MSY} and F/F_{MSY}, were different for S1 when compared to S2 and S3. This is due to the inclusion of historical TWN CPUE information in S1 (**Figure 9**). The trajectory of B/B_{MSY} showed an overall decreasing trend from the early 1980s to 2007, followed by a substantial increase over a brief period (2008-2012) which is thought to be linked to the NW Indian Ocean Piracy period. B/B_{MSY} has declined since 2014. The lowest level of B/B_{MSY} was observed in 2007 (0.64). The F/F_{MSY} trajectory showed a gradual increasing trend between 1980 and the mid-2000s, and despite a recent declining trend F/F_{MSY} remains above 1 (**Figure 9**). The 2020 estimates of B/B_{MSY} range between 0.73 (S3) and 0.77 (S2), while F/F_{MSY} estimates range between 1.06 (S2) and 1.13 (S2).

A retrospective analysis for five years was run on S3 and the results presented in **Figure 10,** which shows minimal retrospective deviations from the full model. Furthermore, **Table 5** depicts the Mohn's rho statistic computed for a retrospective evaluation period of five years. The estimated Mohn's rho for *B* and B/B_{MSY} fell within the acceptable range of -0.15 and 0.20 (Hurtado-Ferro et al. 2014; Carvalho et al. 2017) and consequently indicated that the retrospective pattern for model S3 was negligible.

The Jackknife sensitivity analysis of CPUE indices performed on model S3 showed that the removal of the JPN_NW index resulted in the most optimistic outcome, in terms of B/B_{MSY}. In contrast, removing either TWN_NE or JPN_CE had a similar, pessimistic, outcome (**Figure 11**). That said, omitting any of the CPUE indices does not alter the 2020 stock status, indicating the lack of a disproportionally influential CPUE timeseries. The two historical CPUE timeseries for TWN were not included in the Jackknife analysis it was recommended they not be included in the final model by the Taiwan,China scientists.

Kobe biplots for all three models are shown in **Figure 12**. All three models indicate that the stock is in the “red” quadrant and therefore *overfished and subject to overfishing*. The resultant stock status posteriors for 2020 from each model have the highest probability falling within the red quadrant (61.4% - 74%). However, the current catches of blue marlin (average of 8,058 t in the last 3 years, 2018-2020) are marginally lower than the estimated MSY for all scenarios (8,456 - 8,837 t).

Our results suggest that all three candidate models are stable and provide reasonably robust fits to the data as judged by the presented model diagnostic results. Scenario S1 includes TWN CPUE information from prior to 2005 that was included only for continuity’s sake, but it was recommended these data be excluded from the final model. There is no evidence to favor either S2 or S3 based on performance alone. Furthermore, continuity exists between the results from the 2019 assessment and the current results in that catches have not decreased enough to facilitate stock recovery.

4. References

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5. Tables

Table 1. Summary of catch-per-unit-effort (CPUE) indices considered in the 2022 JABBA assessment for Indian Ocean blue marlin.

CPUE indices and period	Period	Abbreviation	Scenario
Taiwan,China historical North-West Indian Ocean	1979-2004	TWN_NW_hist	S1
Taiwan,China historical North-East Indian Ocean	1979-2004	TWN_NE_hist	S1
Taiwan,China North-West Indian Ocean	2005-2020	TWN_NW	S1, S2, S3
Taiwan,China North-East Indian Ocean	2005-2020	TWN_NE	S1, S2, S3
Japan North-West Indian Ocean	1979-2010	JPN_NW	S1, S2, S3
Japan Central-East Indian Ocean	1979-2020	JPN_CE	S1, S2, S3
Indonesia	2006-2020	IDN	S1, S2, S3

Table 2. Summary of prior and input parameter assumptions used in the 2022 JABBA Indian Ocean blue marlin.

Parameter	Description	Prior	*m*	CV	Scenario
K	Unfished biomass	Lognormal	log(106557.8),0.75)	300%	S1, S2
K	Unfished biomass	Lognormal	95,700	100%	S3
r	Population growth rate	lognormal	0.3	40%	All
ψ (*psi*)	Initial depletion	lognormal	1	5%	S1, S2
ψ (*psi*)	Initial depletion	beta	0.95	5%	S3
s (obs)	Observations error variance	fixed	0.15	-	S1, S2
s (obs)	Observations error variance	fixed	0.25	-	S3
B_{MSY}/K	Ratio Biomass at MSY to K	fixed	0.5	-	All

Table 3. Summary of posterior quantiles presented in the form of marginal posterior medians and associated the 95% credibility intervals of parameters for the JABBA assessments of Indian Ocean blue marlin.

	Scenario 1 (*Cont_hist*)			Scenario 2 (*Cont_new*)		
Estimates	Median	2.50%	97.50%	Median	2.50%	97.50%
K	68 741	46 545	105 547	74 802	48 200	121 940
r	0.491	0.310	0.747	0.474	0.287	0.754
ψ (*psi*)	0.999	0.907	1.099	0.998	0.907	1.103
σ_{proc}	0.137	0.098	0.186	0.124	0.081	0.18
F_{MSY}	0.246	0.155	0.373	0.237	0.144	0.377
B_{MSY}	34 370	23 273	52 774	37 401	24 100	60 970
MSY	8 456	6 895	10 345	8 837	7 189	10 938
B_{1959}/K	0.991	0.743	1.278	0.993	0.76	1.264
B_{2020}/K	0.374	0.266	0.508	0.382	0.276	0.514
$B_{2020}/B_{\mathrm{MSY}}$	0.748	0.533	1.016	0.765	0.552	1.029
$F_{2020}/F_{\mathrm{MSY}}$	1.134	0.759	1.679	1.057	0.715	1.541

	Scenario 3 (*Update*)		
Estimates	Median	2.50%	97.50%
K	71 552	45 734	120 654
R	0.487	0.288	0.784
ψ (*psi*)	0.963	0.819	0.999
σ_{proc}	0.123	0.072	0.183
F_{MSY}	0.243	0.144	0.392
B_{MSY}	35 776	22 867	60 327
MSY	8 735	7 142	10 720
B_{1959}/K	0.947	0.709	1.215
B_{2020}/K	0.364	0.257	0.496
$B_{2020}/B_{\mathrm{MSY}}$	0.728	0.513	0.992
$F_{2020}/F_{\mathrm{MSY}}$	1.125	0.754	1.691

6. Figures

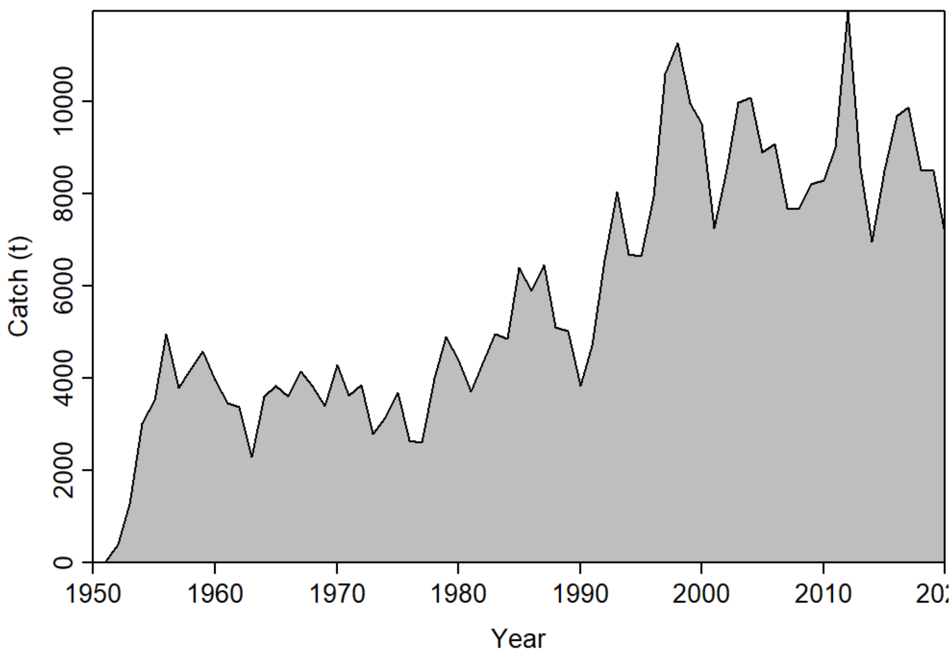

Figure 1: Available catch times series in metric tons (t) for Indian Ocean blue marlin for the period 1950 - 2020.

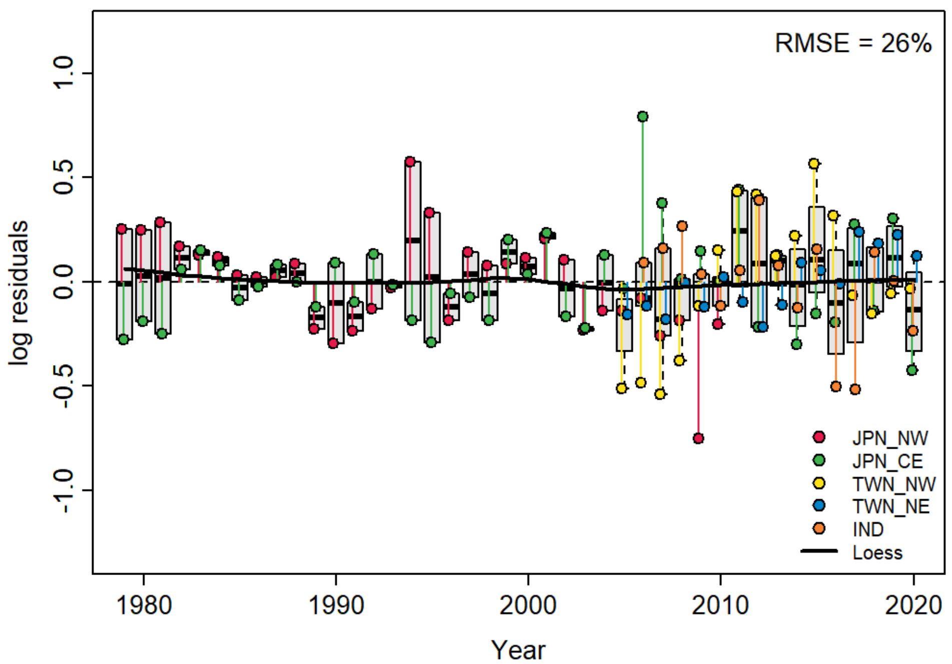

Figure 2. Residual diagnostic plots of CPUE indices for the Indian Ocean blue marlin model S3. Boxplots indicate the median and quantiles of all residuals available for any given year, and solid black lines indicate a loess smoother through all residuals.

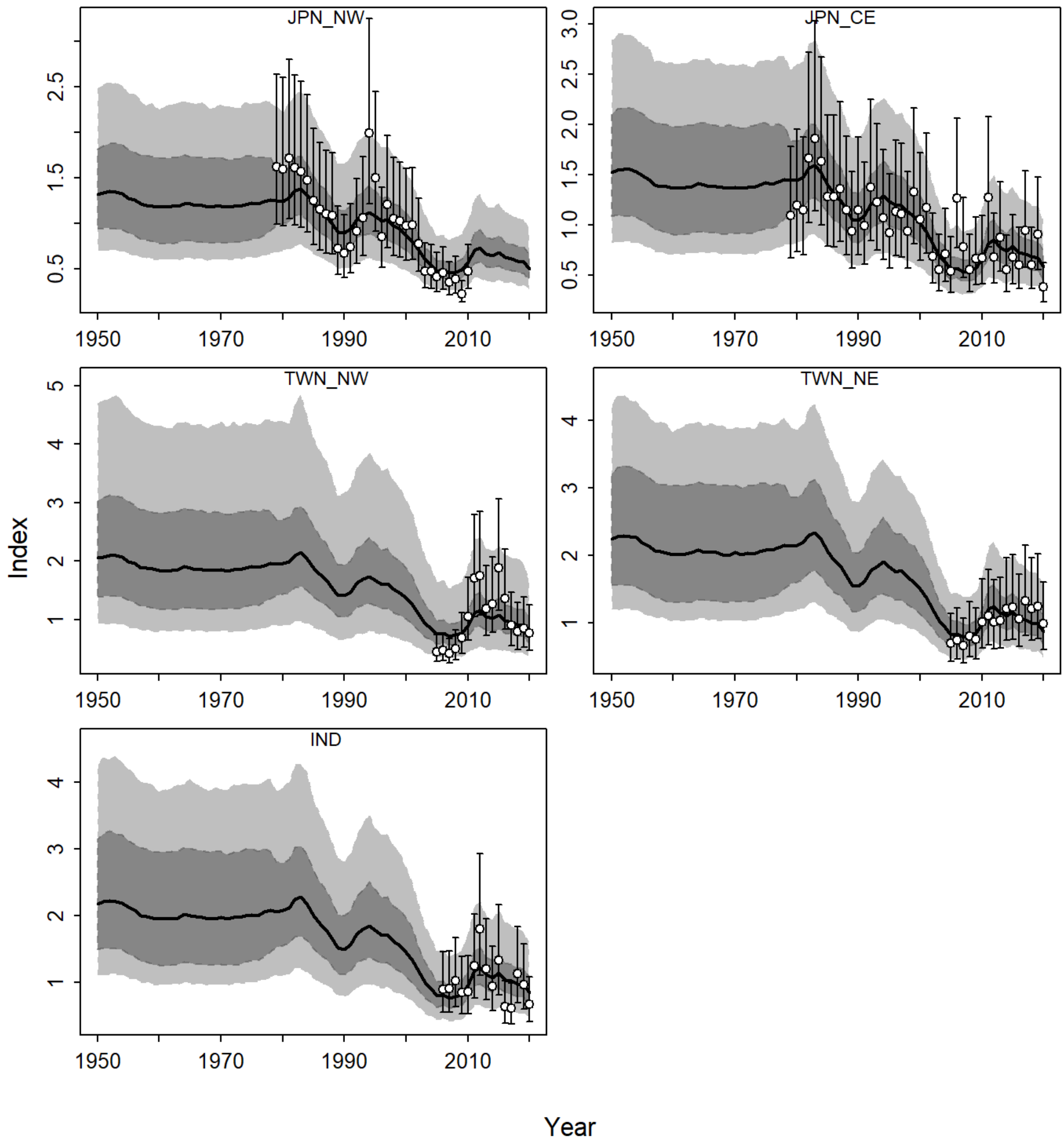

Figure 3: Time-series of observed (circle) and predicted (solid line) CPUE of Indian Ocean blue marlin for the JABBA model S3. The Dark shaded grey areas show 95% credibility intervals of the expected mean CPUE and light shaded grey area denote the 95% posterior predictive distribution intervals.

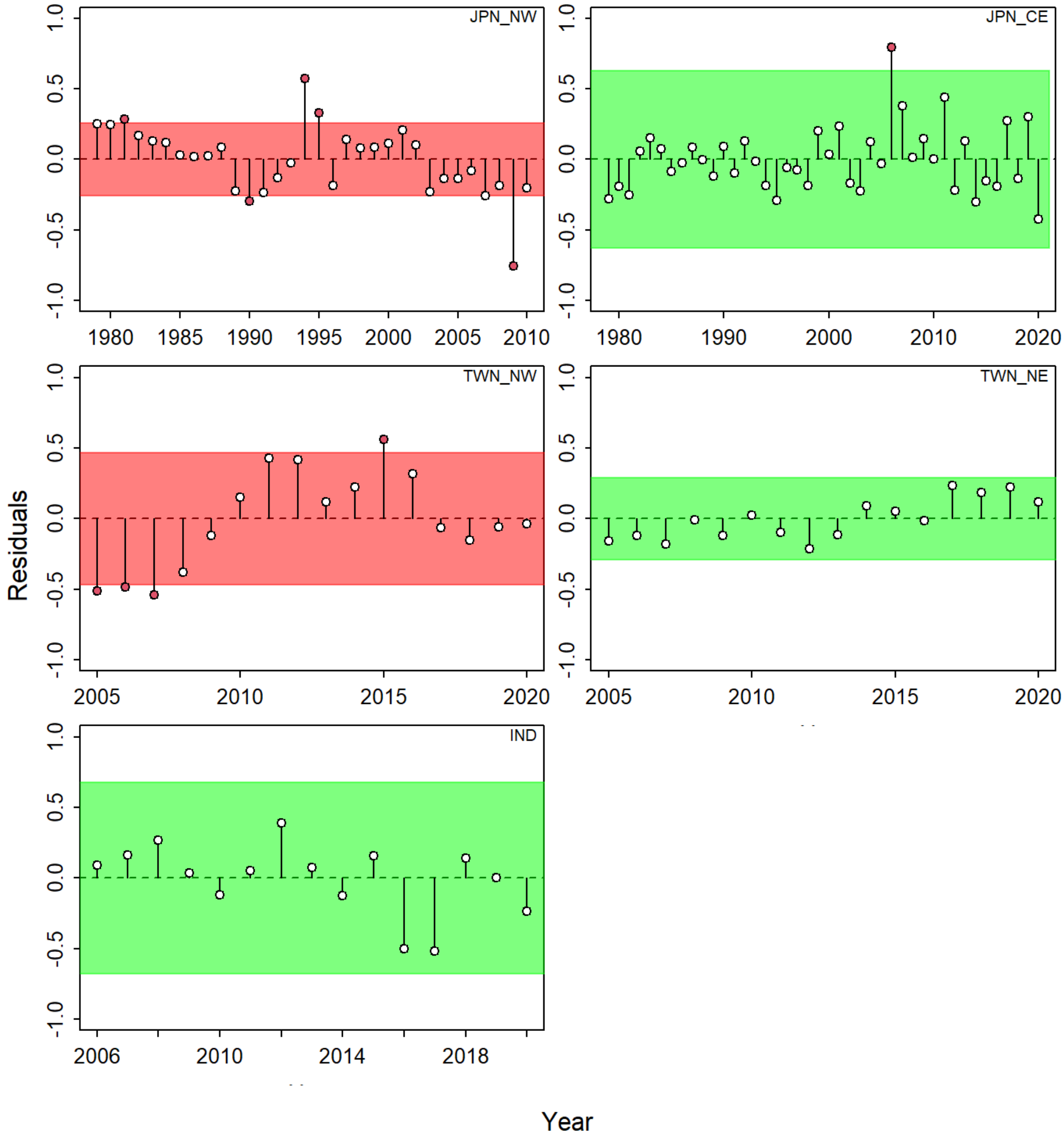

Figure 4: Runs tests to evaluate the randomness of the time series of CPUE residuals by fleet for S3. Green panels indicate no evidence of lack of randomness of time-series residuals (p>0.05) while red panels indicate possible autocorrelation. The inner shaded area shows three standard errors from the overall mean and red circles identify a specific year with residuals greater than this threshold value (3x sigma rule).

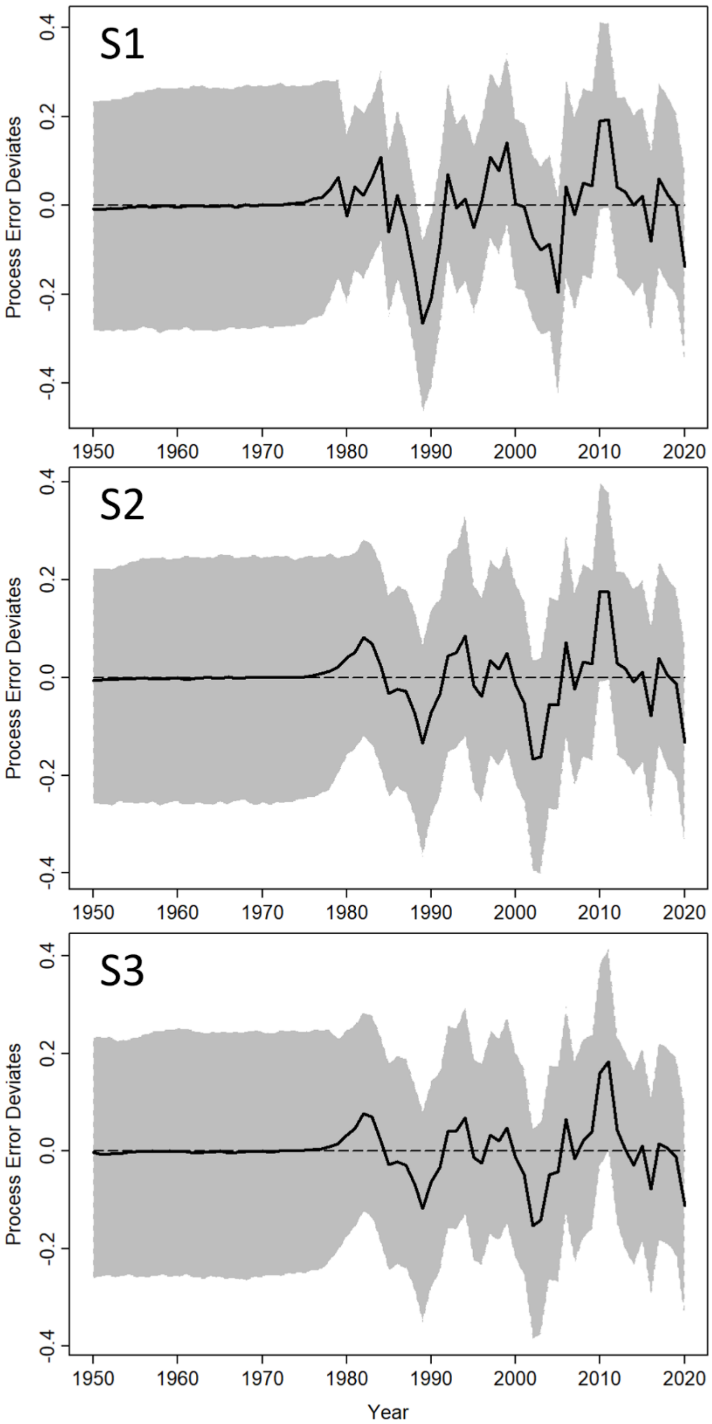

Figure 5: Process error deviates (median: solid line) of Indian Ocean blue marlin for each JABBA model (S1-S3). Shaded grey area indicates 95% credibility intervals.

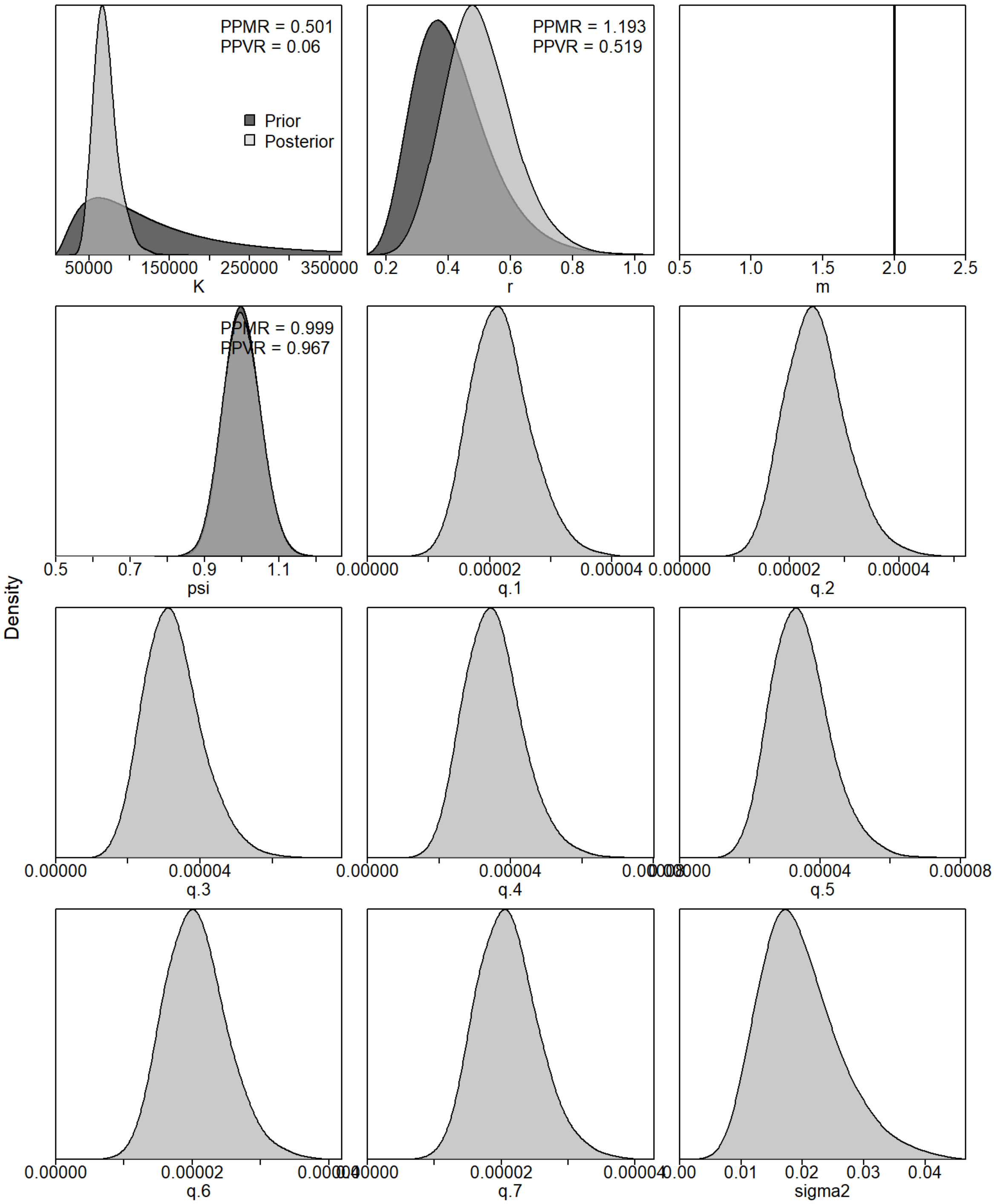

Figure 6: Prior and posterior distributions of various model and management parameters for the JABBA model S1 for Indian Ocean blue marlin. PPRM: Posterior to Prior Ratio of Means; PPRV: Posterior to Prior Ratio of Variances.

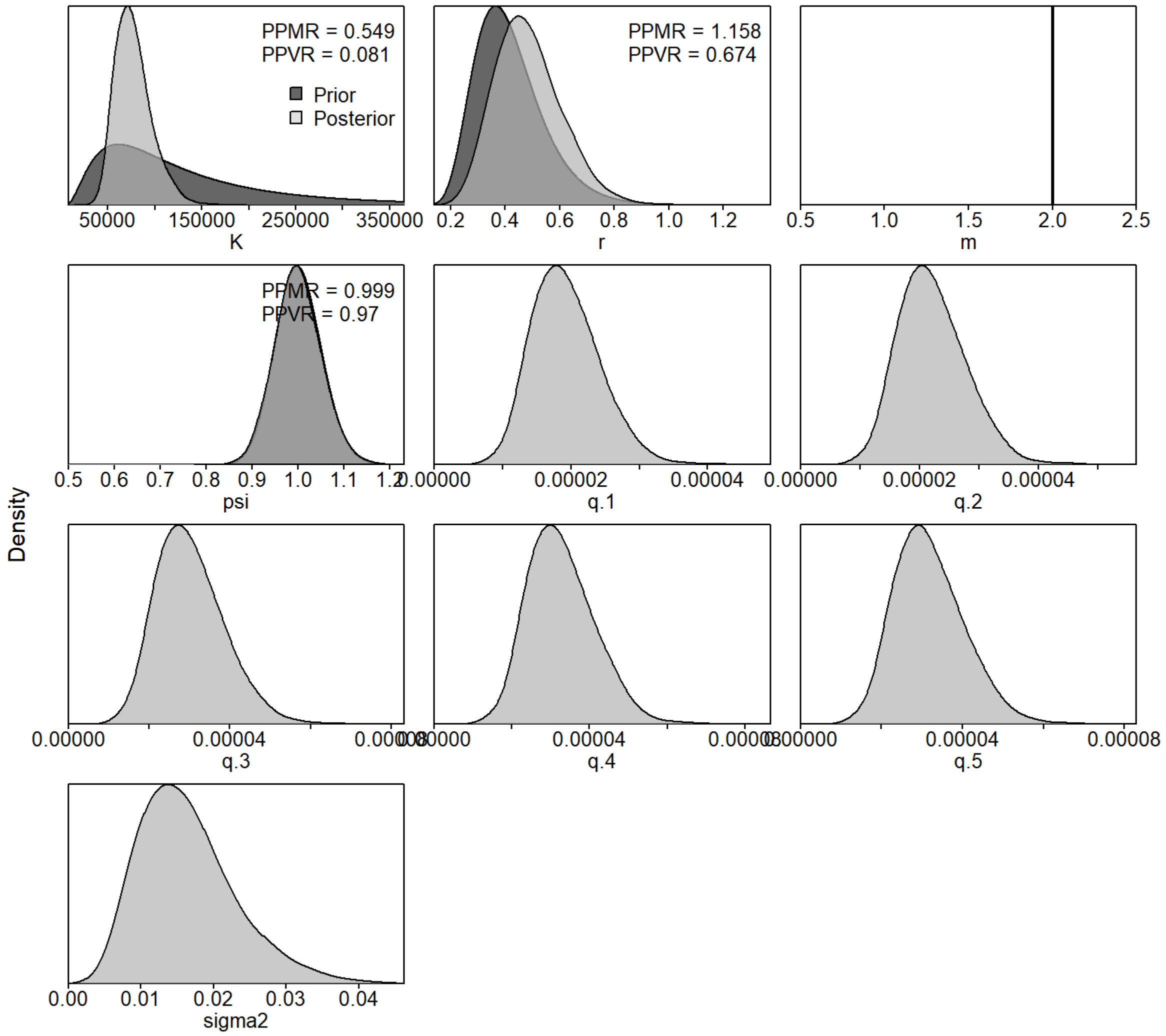

Figure 7: Prior and posterior distributions of various model and management parameters for the JABBA model S2 for Indian Ocean blue marlin. PPRM: Posterior to Prior Ratio of Means; PPRV: Posterior to Prior Ratio of Variances.

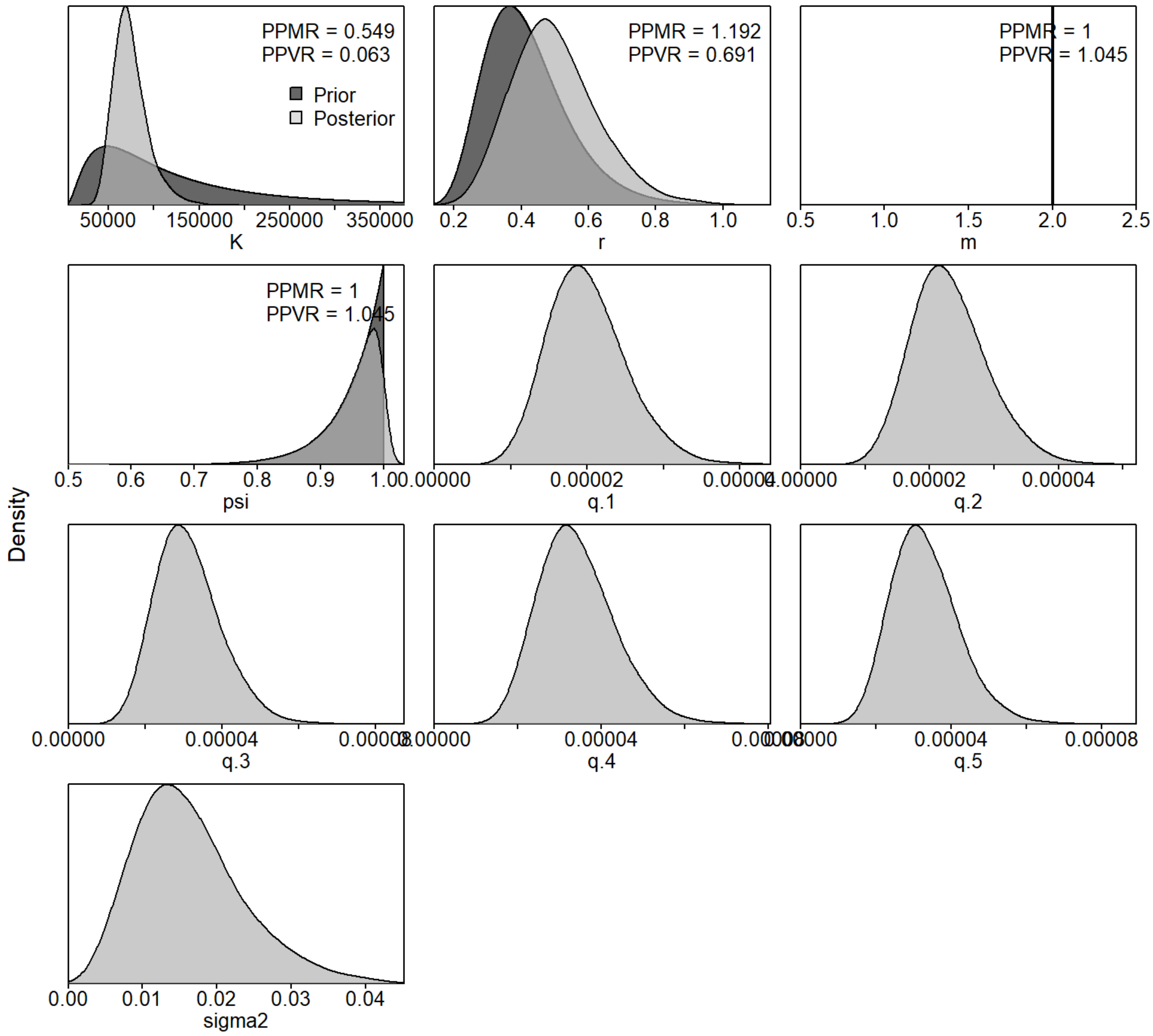

Figure 8: Prior and posterior distributions of various model and management parameters for the JABBA model S3 for Indian Ocean blue marlin. PPRM: Posterior to Prior Ratio of Means; PPRV: Posterior to Prior Ratio of Variances.

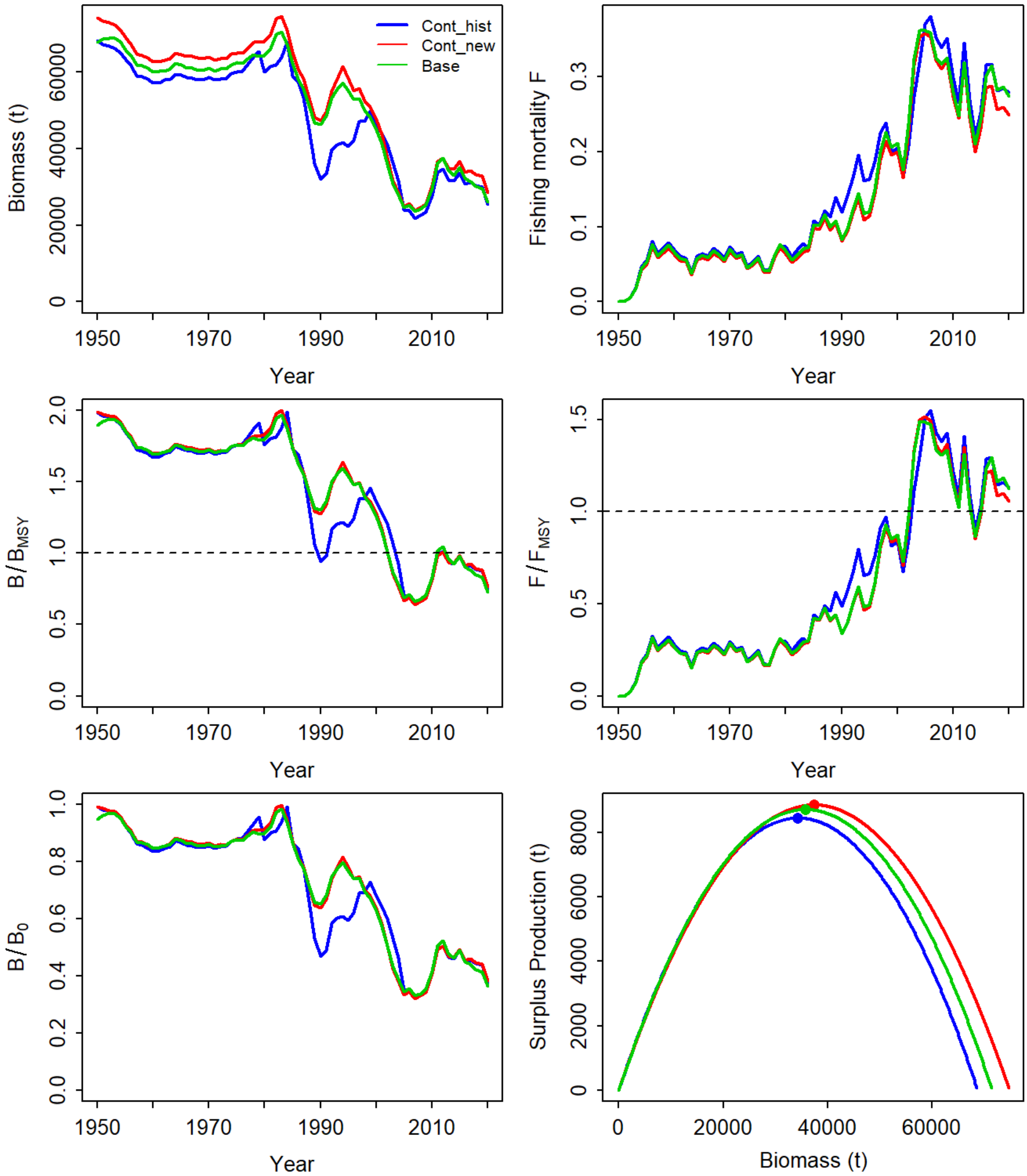

Figure 9: Comparison of biomass, fishing mortality (upper panels), biomass relative to *K* (*B/K*) and surplus production curve (middle panels), and biomass relative to B_{MSY} (B/B_{MSY}) and fishing mortality relative to F_{MSY} (F/F_{MSY}) (bottom panels) among JABBA scenarios S1- S3 for Indian Ocean blue marlin.

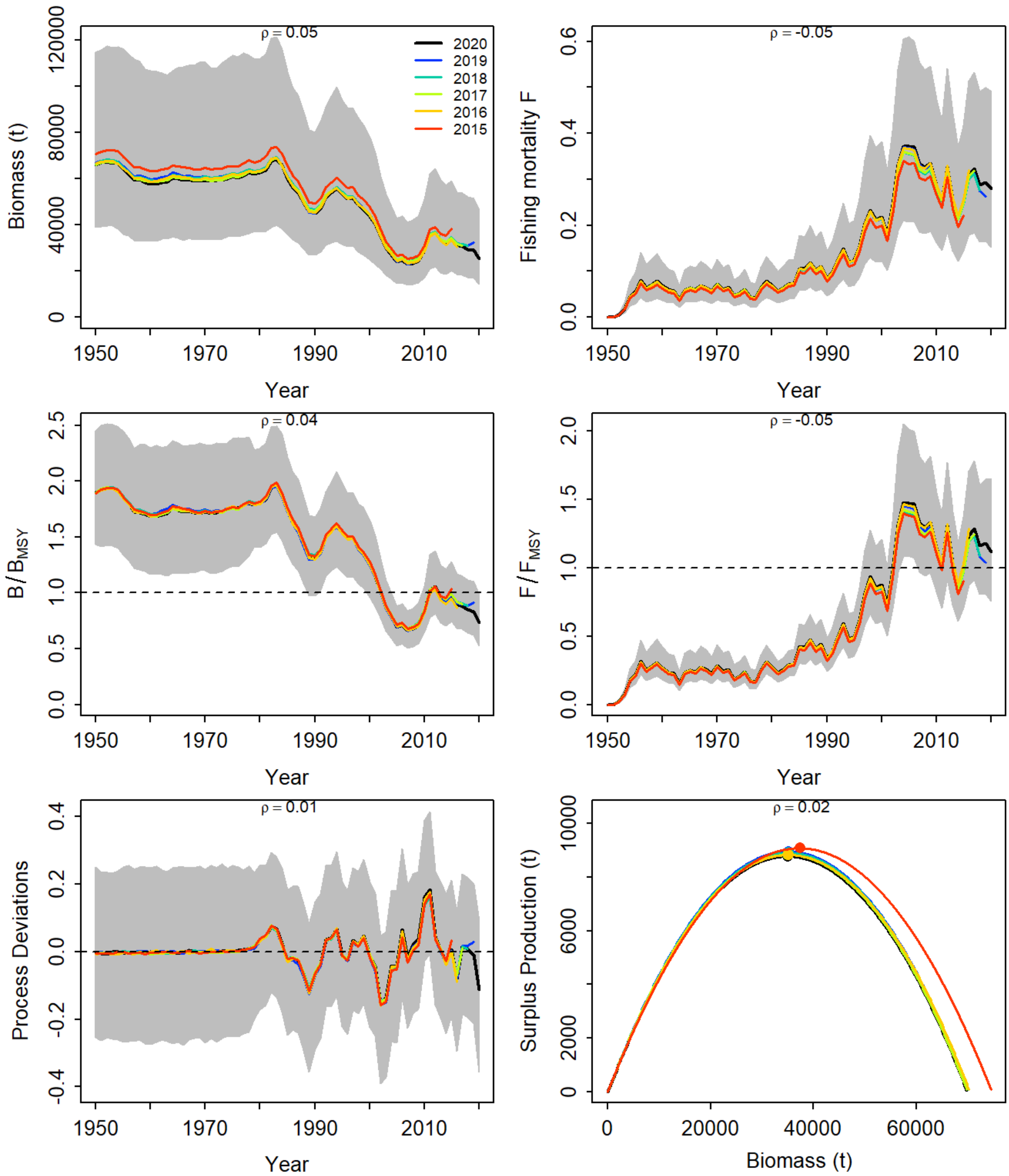

Figure 10: Retrospective analysis performed to the S3 JABBA model of the Indian Ocean blue marlin assessment, by removing one year at a time sequentially (n=5) and predicting the trends in biomass and fishing mortality (upper panels), biomass relative to B_{MSY} (B/B_{MSY}) and fishing mortality relative to F_{MSY} (F/F_{MSY}) (middle panels) and biomass relative to K (B/K) and surplus production curve (bottom panels).

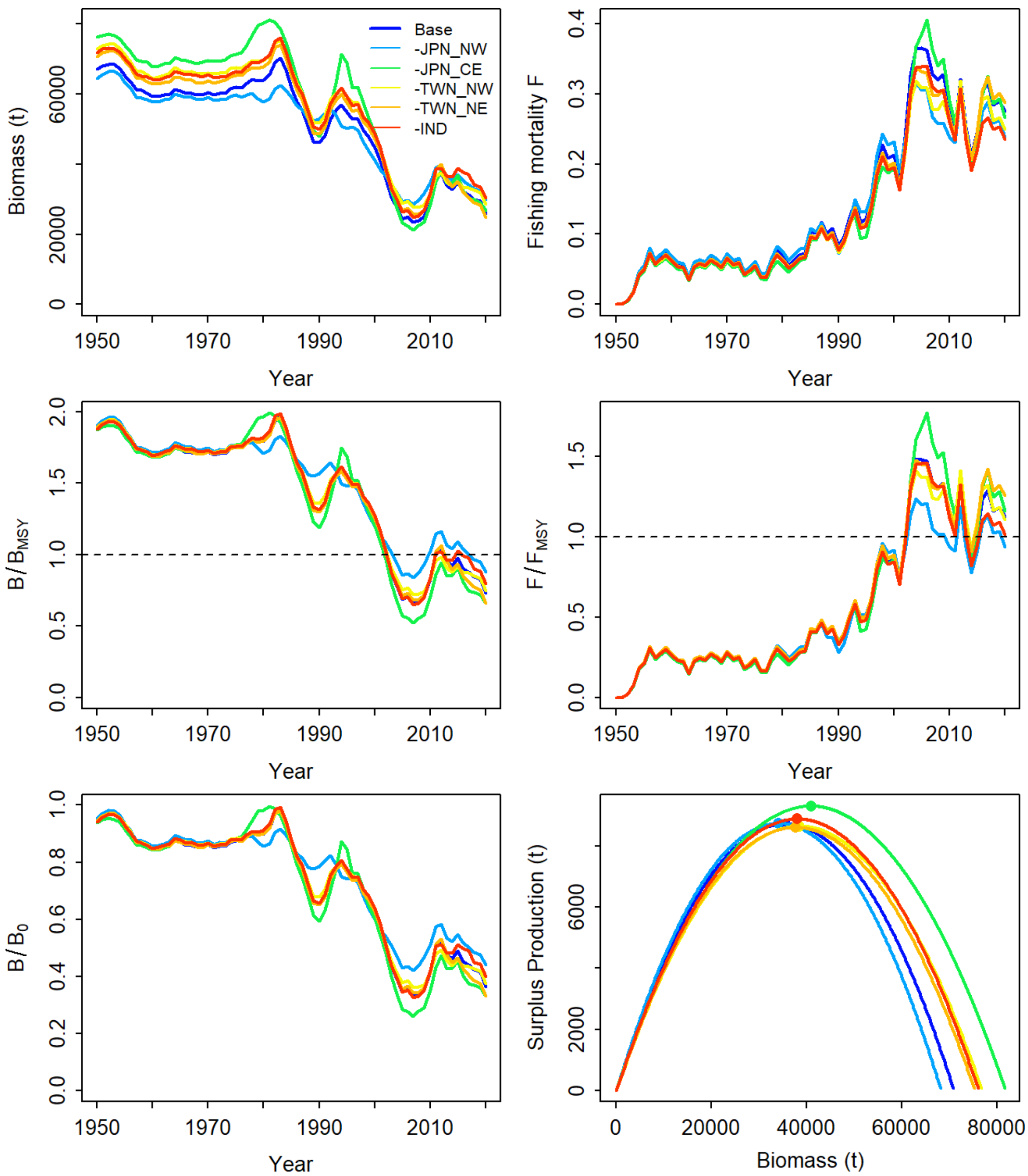

Figure 11: Jackknife index analysis performed to the S3 JABBA model of the Indian Ocean blue marlin assessment, by removing one CPUE fleet at a time and predicting the trends in biomass and fishing mortality (upper panels), biomass relative to B_{MSY} (B/B_{MSY}) and fishing mortality relative to F_{MSY} (F/F_{MSY}) (middle panels) and biomass relative to K (B/K) and surplus production curve (bottom panels)

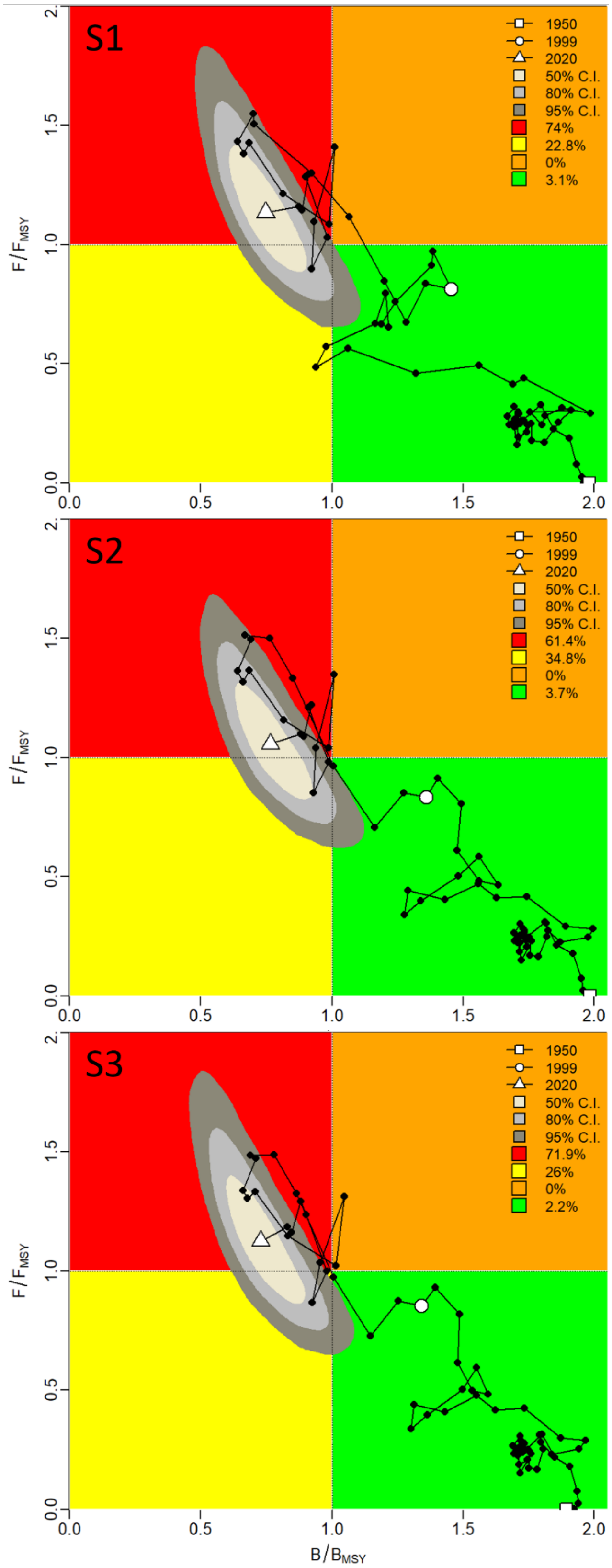

Figure 12: Kobe phase plot showing estimated trajectories (1950-2020) of B/B_{MSY} and F/F_{MSY} for the three JABBA models (S1-S3) for the Indian Ocean blue marlin assessment. Different grey shaded areas denote the 50%, 80%, and 95% credibility interval for the terminal assessment year. The probability of terminal year points falling within each quadrant is indicated in the figure legend.