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WESTERN ATLANTIC SAILFISH STOCK STATUS WITH JABBA MODEL

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SUMMARY

*We first attempted to apply the JABBA Models for western Atlantic sailfish (*Istiophorus platypterus*) with the best available data through 2021. Results suggest reasonably robust fits to the data as judged by the presented model diagnostic results. The resulting stock status for 2021 was generally consistent and predicted with high probability that current fishing levels are sufficiently low to preclude overfishing ($F_{2021}< F_{MSY}$), whereas biomass is above the sustainable levels that can produce MSY ($B_{2021}>B_{MSY}$). As such, our models conclusively estimate that stock is not overfished and not subject to overfishing, with probability ranging from 75.1% - 84.6% for the green quadrant of Kobe. Similarly, substantial differences were not observed in biomass and fishing mortality yearly trends among models, with the S2 model indicating a slightly more productive stock.*

RÉSUMÉ

*Nous avons d'abord tenté d'appliquer les modèles JABBA pour les voiliers de l'Atlantique Ouest (*Istiophorus platypterus*) avec les meilleures données disponibles jusqu'en 2021 compris. Les résultats suggèrent des ajustements raisonnablement robustes aux données, comme en témoignent les résultats de diagnostic du modèle présentés. L'état du stock obtenu pour 2021 était généralement cohérent et prédisait avec une probabilité élevée que les niveaux de pêche actuels sont suffisamment faibles pour empêcher la surpêche (F2021< FPME), tandis que la biomasse se situe au-dessus des niveaux durables qui peuvent produire la PME (B2021>BPME). Ainsi, nos modèles estiment de manière concluante que le stock n'est pas surpêché ni victime de surpêche, avec une probabilité allant de 75,1% à 84,6% de se situer dans le quadrant vert de Kobe. De même, aucune différence substantielle n'a été observée dans les tendances annuelles de la biomasse et de la mortalité par pêche entre les modèles, le modèle S2 indiquant un stock légèrement plus productif.*

RESUMEN

*En primer lugar, intentamos aplicar los modelos JABBA para el pez vela (*Istiophorus platypterus*) del Atlántico occidental con los mejores datos disponibles hasta 2021. Los resultados sugieren un ajuste razonablemente robusto a los datos, según los resultados de diagnóstico del modelo presentados. El estado del stock resultante para 2021 fue generalmente coherente y predijo con altas probabilidades que los niveles de pesca actuales son lo suficientemente bajos como para impedir la sobrepesca(F2021< FRMS), mientras que la biomasa permanece por debajo de los niveles sostenibles que pueden producir el RMS (B2021>BRMS). Así, nuestros modelos estiman de forma concluyente que el stock no está sobrepescado y que no se está produciendo sobrepesca, con una probabilidad que oscila entre el 75,1% y el 84,6% de situar al stock en el cuadrante verde del diagrama de Kobe. Del mismo modo, no se observaron diferencias sustanciales en las tendencias anuales de la biomasa y la mortalidad por pesca entre los modelos, indicando el modelo S2 un stock ligeramente más productivo.*

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KEYWORDS

Abundance, Stock assessment, Catch statistics, Western Atlantic, stock status, CPUE fits, biomass model.

1. Introduction

Sailfish (*Istiophorus platypterus*) is an epipelagic species with a pan-tropical distribution (Ferrete *et al*., 2021; Ferrete *et al*., 2023). It is the least oceanic of the Atlantic billfishes, it shows a strong tendency to approach continental coasts, islands and reefs (Nakamura, 1985). Despite of the high uncertainty of stock structure for sailfish in the Atlantic Ocean (Mourato et al., 2010; Ferrete *et al.,* 2021; Ferrete *et al*., 2023), the Standing Committee on Research and Statistics (SCRS) of the International Commission for the Conservation of Atlantic Tunas (ICCAT) has been historically considered the existence of two stocks of sailfish in the Atlantic Ocean: Western Atlantic (WA) and Eastern Atlantic (EA). Historically, the WA sailfish stock has been assessed using surplus production models (SPM), including the ASPIC and Bayesian surplus production models, an integrated age-structured model Stock Synthesis, and catch-only models (ICCAT, 2009; ICCAT, 2016; Mourato and Carvalho, 2017).

The last assessment in 2016 showed different model platforms produced comparable results for the WA sailfish, with the stock being estimated to be not overfished, and overfishing was either not occurring in 2014 (ICCAT, 2016; Mourato and Carvalho, 2017). However, different model runs indicated a declining or increasing trends in 2014 depending on the CPUE series selected. Also, there was a considerable uncertainty, as many models examined had convergence problems, and the maximum likelihood surfaces were flat and not well defined for the ASPIC models (ICCAT, 2016).

While during the 2016 WA sailfish assessment much focus was given to identifying and resolving potential CPUE data conflicts that may arise from fitting of multiple standardized CPUE time series, little attention was given for the biological research, with the available information being characterized to be much more limited. In biomass aggregated models, such as SPMs, somatic growth, reproduction, natural mortality, and associated density-dependent processes are inseparably captured in the estimated surplus production function. Therefore, structural, and biological uncertainty is typical represented in the form of alternative values of r and the shape m of the production function. In the 2016 assessment, the BSP2 models were parametrized using the same lognormal r prior applied to EA sailfish, with a mean of 0.45 and CV of 0.30 (ICCAT, 2016). On the other hand, the Bayesian SPM developed by Mourato and Carvalho (2017) assumed a lognormal distribution with mean 0.16 which is a little higher than the median (r close to 0.13) estimated by Carruthers and McAllister (2011) but with standard deviation equal to 0.25 in order to give more flexibility in parameter estimation. Given the importance of the surplus production function, it was noted that input priors related to the production function should be updated and objectively derived from the simulations in an Age Structured Equilibrium Model (ASEM) (see methodology in Winker *et al*., 2020).

Here we present stock assessment results for WA sailfish stock based on the Bayesian State-Space Surplus Production Model framework, JABBA (Just Another Bayesian Biomass Assessment; Winker *et al.,* 2018), using updated catch and standardized longline CPUE time series for the period 1957-2021. JABBA is a fully documented, open-source R package (www.github.com/JABBAmodel) that has been formally included in the ICCAT stock catalogue (https://github.com/ICCAT/software/wiki/2.8-JABBA).

2. Material and Methods

2.1 Fishery data

Total catch of WA sailfish from 1957-2021 were obtained from the ICCAT Secretariat and includes reported landings (**Figure 1**). 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. For this assessment seven standardized CPUE series were made available: USA (longline and rod & reel), Brazil (longline and rod & reel), Venezuela (longline, gillnet and rod & reel), Japan (longline), Spain (longline) and Chinese Taipei (longline) (**Figure 2**). The Japan index were split into two separate time blocks as agreed in the last stock assessment meeting in 2016 (ICCAT, 2016).

- USA longlines (1993-2021)
- USA rod & reel (1972-2021), with the index fishing power correction (see meeting report for details)
- Brazil longlines (1994-2021)
- Brazil rod & reel (2001-2020)
- Venezuela longlines (1987-2021), with exclusion of year 1987
- Venezuela rod & reel (1961-2001)
- Venezuela gillnet (1991-2021)
- Japan longlines (1960-1993; 1994-2021), with exclusion of year 2005
- Chinese Taipei longlines (2009-2021)
- Spain longlines (2001-2019)

2.2 JABBA stock assessment model fitting procedures

This stock assessment uses the most updated version (v2.2.9) 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, we used 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). Initial depletion was input as a "beta" prior ($\varphi = B_{1957}/K$) with mean = 0.99 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 1957. All catchability parameters were formulated as uninformative uniform priors, while additional observation variances were estimated for index 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 were fixed at 0.05. For all model runs we used a random catch error uncertainty with CV of 0.01.

Initial trials considered six alternative specifications of the Pella-Tomlinson model type based on different sets of r priors and fixed input values of B_{MSY}/K. The input r priors for these six scenarios were objectively derived from age-structured model simulations (see details in Winker *et al*. 2020), based on two different maximum ages of 12 and 15 (Prince *et al.,* 1986; Edhardt amd Devenauex, 2006; ICCAT, 2016) and the growth parameters produced by Edhardt amd Devenauex (2006), and also other updated biological parameters (see **Appendix A**; **Table A1**). This allowed us to approximate the parameterizations of an age structured model based on range of stock recruitment steepness values for the stock-recruitment relationship (h = 0.65, h = 0.75 and h = 0.85), while admitting reasonable uncertainty about the natural mortality M (CV of 20% and the central value mean value of 0.35). Based on sensitivity analysis of these six initial runs, including the 'steepness-specific' r input priors (**Figure A1**), no major differences were found on the estimates of the main reference points (**Figure A2**). In this sense, a r prior with corresponding steepness of h = 0.75 and a maximum age of 15 was selected for the subsequent analysis. This translates to an associated lognormal r prior of $\log(r) \sim N(\log(0.283), 0.223)$ and a fixed input value of B_{MSY}/K = 0.34 (**Table A2**). The following scenarios were selected as candidate models:

- S1: all CPUE
- S2: all CPUE minus Brazilian rod & reel

2.3 Model diagnostics

The evaluation model diagnostics adheres to the recommendations made by Carvalho *et al*. (2021) who suggested that the candidate models be objectively assessed 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. We conducted run tests 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, we also performed a retrospective analysis 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 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 results of the MCMC convergence tests (Heidelberger and Welch, 1992; Geweke, 1992; Gelman and Rubin, 1992), and the visual examination of trace plots, show that all models have adequate convergence a high level of model stability.

Both models fit to each standardized CPUE indices are depicted in **Figures 3** and **4**, and appeared to fit CPUE data poorly, with RMSE estimates of 60.3% and 57.8%, respectively (**Figure 5**). Run tests conducted on the log-residuals for scenario S1 indicated that the CPUE residuals may not be randomly distributed for seven of the 11 indices: USA rod & reel, Japan, Venezuelan fleets and Spain (**Figure 3)**. For model S2 it was observed the same pattern with exception of second block of Japan that did pass in runs test **(Figure 4)**. This residual pattern suggests data-conflicts caused by CPUE indices' opposite trends, particularly in the last seven years (2015-2021), in which part of the indices shows an increasing trend while other shows a decreasing pattern in recent years. It was noted that runs tests to the USRR index presented a strong negative residual in the beginning of the time series being, followed for a positive residuals trend after 2000 up to 2021, which indicates a substantial lack of model fit and might suggest the need of a time-block for this index. Indeed, the CPUE data-conflicting situation was also noted in the latest assessment of the WA sailfish stock (ICCAT, 2016), and also for blue and white marlins in the Atlantic Ocean, with high RMSE values (>50%) and poor goodness-of-fit (Mourato *et al*., 2018; Mourato *et al*., 2020). Despite the overall increase in landings since the 2015 and the negative trends of CPUE for most of the fishing fleets in recent years, the estimated process error deviates show a positive trend between 2012 and 2021 in all models (**Figure 6**). Thus, the model might interpret the stock's productivity as having been above average in recent years.

Marginal posterior distributions along with prior densities for all two models are shown in **Figure 7**. The prior to posterior median ratio (PPMR) for *r* in models S1 and S2 were close to 1, indicating that the posterior is heavily influenced by the prior. This was expected, given the low CVs that were estimated in the development of the priors (**Table A2**). On the other hand, the resulting small PPVRs observed in S1 and S2 *K* indicate that the input data was more informative about *K*, which was expected, since the high CVs were applied in the development of these priors. The marginal posteriors for initial depletion (φ) were similar between all models, with both PPMR and PPVR close to 1, which suggests that this parameter was largely informed by the priors.

Summaries of posterior quantiles for parameters and management quantities of interest are presented in **Table 1.** Estimates of *MSY* were very similar between models S1 and S2 (1,459 and 1,483 t, respectively). The marginal posterior median for B_{MSY} varied between 4,141 metric tons (S1) and 4,217 metric tons (S2). The F_{MSY} median estimate for S1 (0.354) was similar to model S2 (0.352) (**Table 1)**. Similarly, no differences were observed between models S1 and S2 in the trends in biomass and fishing mortality (**Figure 8**), with the S2 model indicating slightly more productive stock than S1. The trajectory of B/B_{MSY} showed an overall decreasing trend from 1970 to around 1990, thereafter the decreasing trend stabilized somewhat and has fluctuated slightly around of MSY level until 2005, but increasing again up to 2021, with the current estimates varying between 1.162 and 1.238. The F/F_{MSY} trajectory showed a sharp increase a gradual increasing trend in 2000, followed by a period of decreasing trend with estimates being well below of MSY level up to 2012. After 2023, F/F_{MSY} increased again (**Figure 8**), but current estimates are well below 1 (range: 0.534 (S1) - 0.493 (S2)).

A retrospective analysis for five years was run for both models and the results presented in **Figure 9,** which shows minimal retrospective deviations from the full models. Furthermore, **Table 2** 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 both models was negligible. Hindcasting cross-validation results suggest that USA rod & reel and second block of Japanese longline indices presented MASE scores around 2, which might suggest these indices have no good prediction skills **(Figure 10)**. Overall, the MASE scores for the S2 scenario presented a slight improvement in relation to the S1 model (**Figure 10**). The Jackknife sensitivity analysis of CPUE indices performed on model S1 showed that the USA rod & reel is highly influential with regards to stock status trajectories (**Figure 11**). Removing this index resulted in much more pessimistic stock status trajectories, with biomass level well below B_{MSY}. This is due to the significant increase in the CPUE trend since 2000.

Kobe biplots for all three models are shown in **Figure 12**. A typical anti-clockwise pattern is present, with the stock status moving from underexploited through a period of unsustainable fishing to the overexploited phase and then to the recovery phase after a decrease in fishing mortality. Currently, both models indicate that the stock in the last 15 years has been moving from the "recovery" yellow quadrant into the green quadrant of the Kobe biplot. The resultant stock status posteriors for 2021 from each model have the highest probability falling within the green quadrant (S1 – 75.1% and S2 – 84.6%). Furthermore, the probability that current fishing mortality is sufficiently low enough to facilitate stock rebuilding (yellow + green) is above 99% in each model.

Our results suggest that both models provide reasonably robust fits to the data as judged by the presented model diagnostic results and might be used for management advice. Both models performed very similarly regarding the residual's diagnostics, with a slight improvement in this regard for the S2. Also, it is essential to note that there is a considerable lack of basic life history information for the WA sailfish, including the growth, length at maturity, and natural mortality, making it even more important to admit uncertainty about the stock's productivity. Considering new available information on genetics (Ferrete *et al.*, 2021; Ferrete *et al.*, 2023), we also highlight the high uncertainty on the stock structure for sailfish in the Atlantic Ocean. Thus, we strongly recommend that alternative scenarios for stock structure should be considered for future assessments.

The final models were decided by the Billfish Species Group during the sailfish assessment meeting. The final model's setup and the results are available in the sailfish assessment meeting report.

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Table 1. Summary of posterior quantiles presented in the form of marginal posterior medians and associated the 95% credibility intervals of parameters for the Bayesian state-space surplus production models for WA sailfish.

	S1			S2		
Estimates	***Median***	***2.5%***	***97.5%***	***Median***	***2.5%***	***97.5%***
K	12176	8629	17258	12399	8711	18803
r	0.304	0.214	0.433	0.302	0.204	0.436
σ_{proc}	0.165	0.116	0.205	0.166	0.117	0.205
F_{MSY}	0.354	0.250	0.505	0.352	0.238	0.508
B_{MSY}	4141	2935	5869	4217	2963	6395
MSY	1459	1243	1751	1483	1251	1782
B_{1957}/K	0.921	0.660	1.235	0.919	0.653	1.227
B_{2021}/K	0.395	0.257	0.594	0.421	0.280	0.625
B_{2021}/B_{MSY}	1.162	0.757	1.746	1.238	0.822	1.837
F_{2021}/F_{MSY}	0.534	0.322	0.845	0.493	0.307	0.770

Table 2. Summary of models Mohn's rho statistic computed for a retrospective evaluation period of five years. The larger the threshold the stronger is the retrospective bias.

Model	B	F	B/B_{MSY}	F/F_{MSY}	MSY
S1	-0.076	0.083	-0.078	0.100	-0.016
S2	-0.036	0.040	-0.055	0.065	-0.015

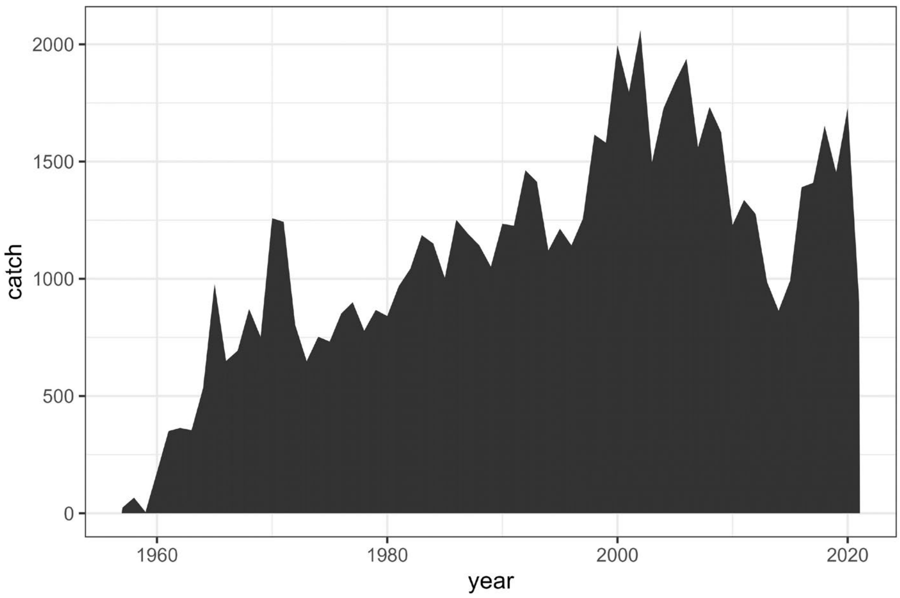

Figure 1. Available catch times series in metric tons (t) for WA sailfish for the period 1957 - 2021.

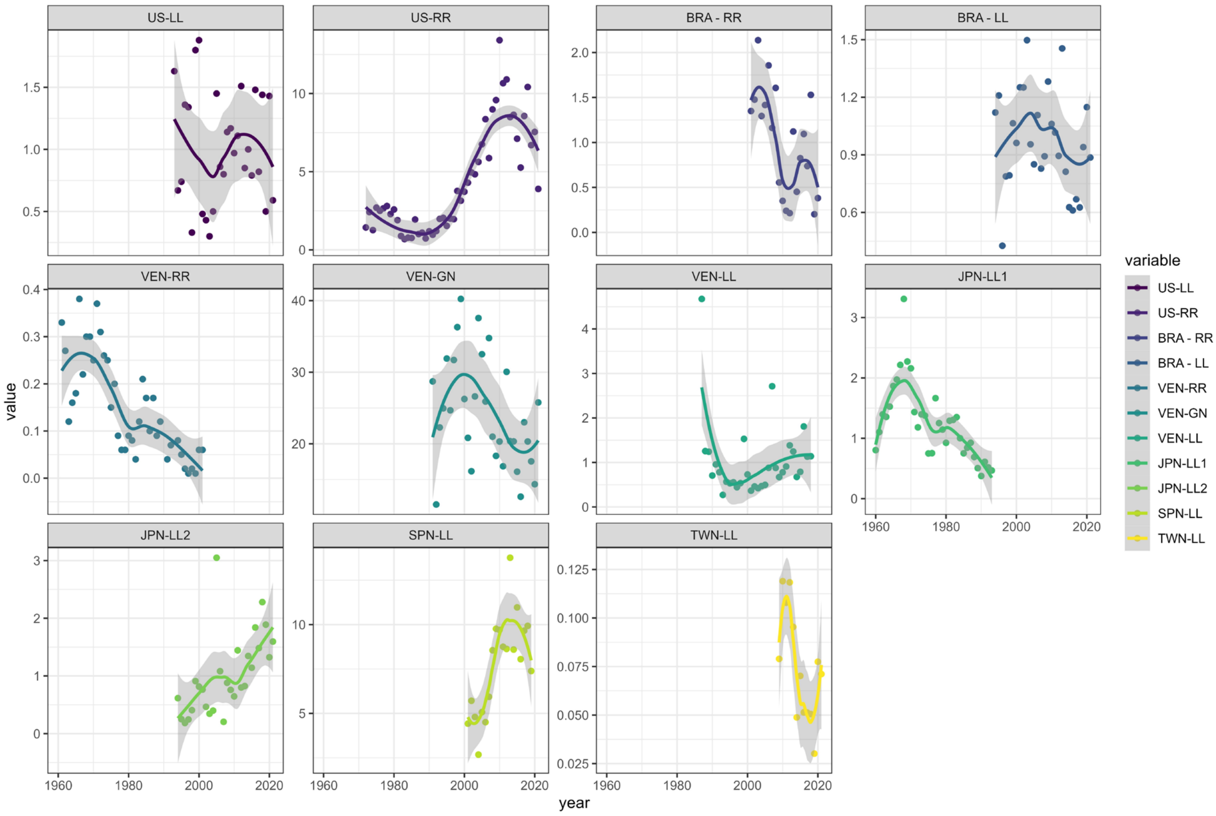

Figure 2. Available standardized CPUE series for WA sailfish assessment. Points are the observed value; Lines and grey shaded area represents the results of smoothing regression analysis.

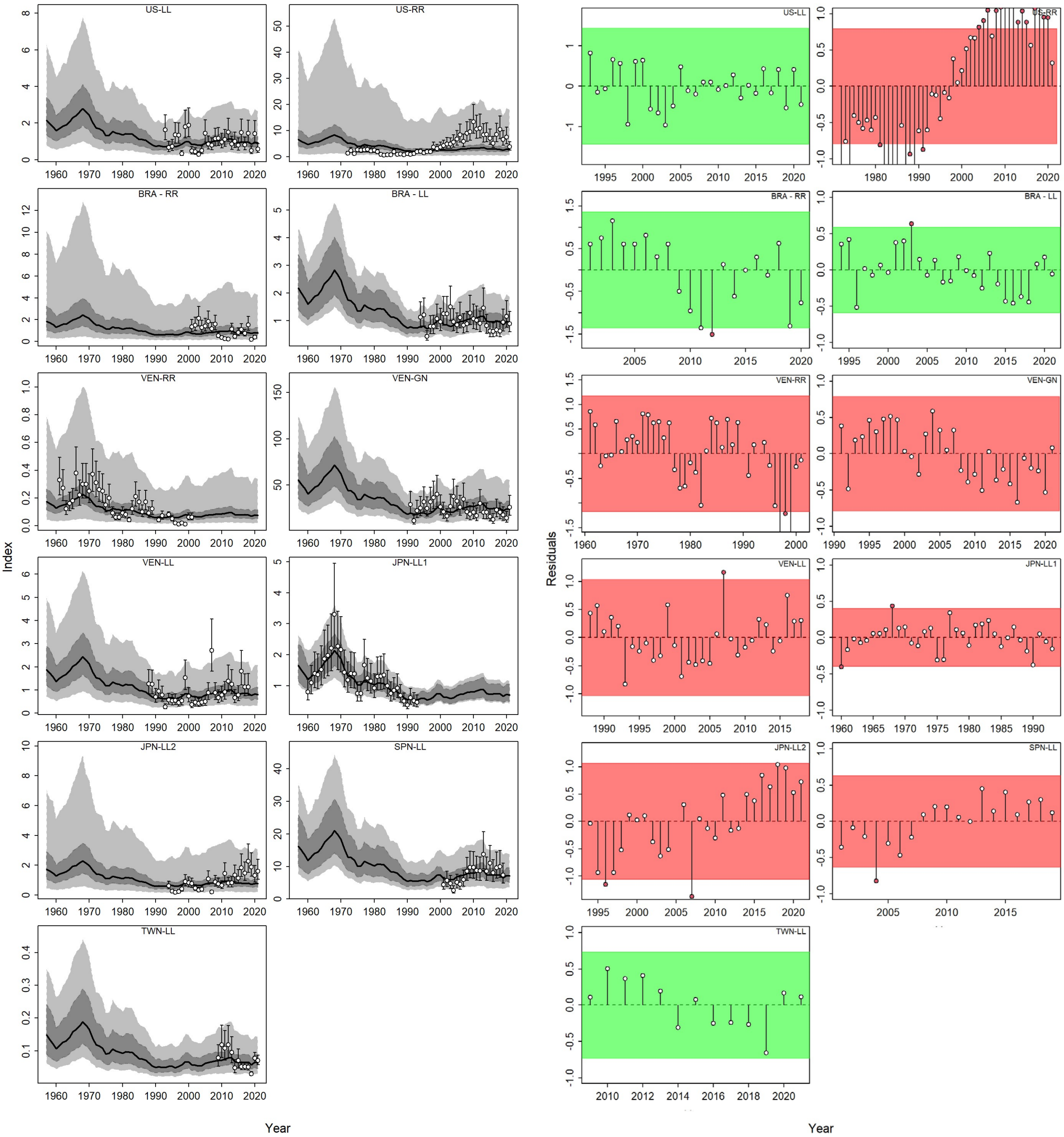

Figure 3: Left panel: Time-series of observed (circle) and predicted (solid line) CPUE of WA sailfish for the JABBA model S1. The Dark shaded grey areas show 95% credibility intervals of the expected mean CPUE, and light shaded grey area denote the 95% posterior predictive distribution intervals. Right panel: Runs tests to evaluate the randomness of the time series of CPUE residuals by fleet for S1. 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).

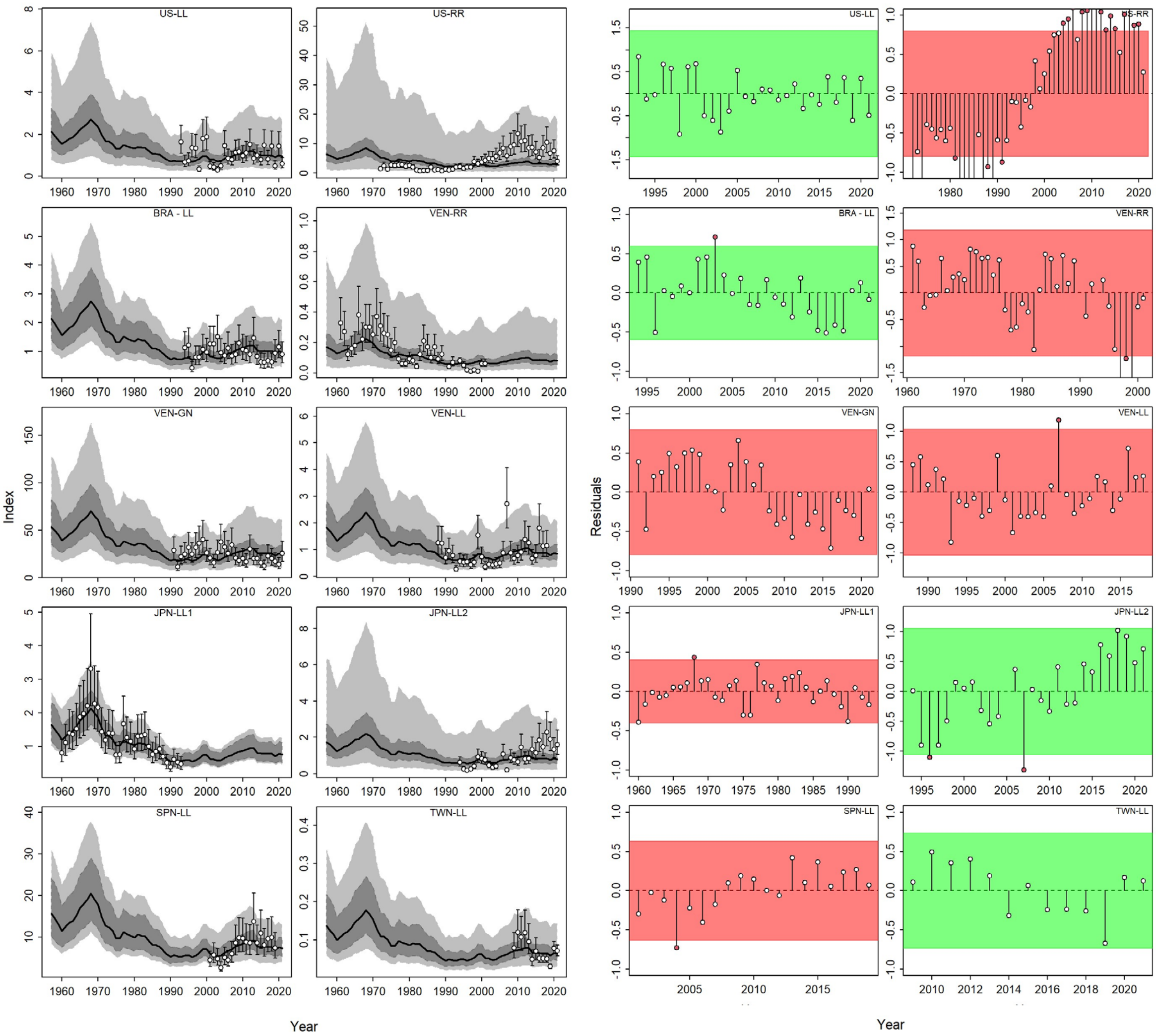

Figure 4: Left panel: Time-series of observed (circle) and predicted (solid line) CPUE of WA sailfish for the JABBA model S2. The Dark shaded grey areas show 95% credibility intervals of the expected mean CPUE, and light shaded grey area denote the 95% posterior predictive distribution intervals. Right panel: Runs tests to evaluate the randomness of the time series of CPUE residuals by fleet for S2. 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).

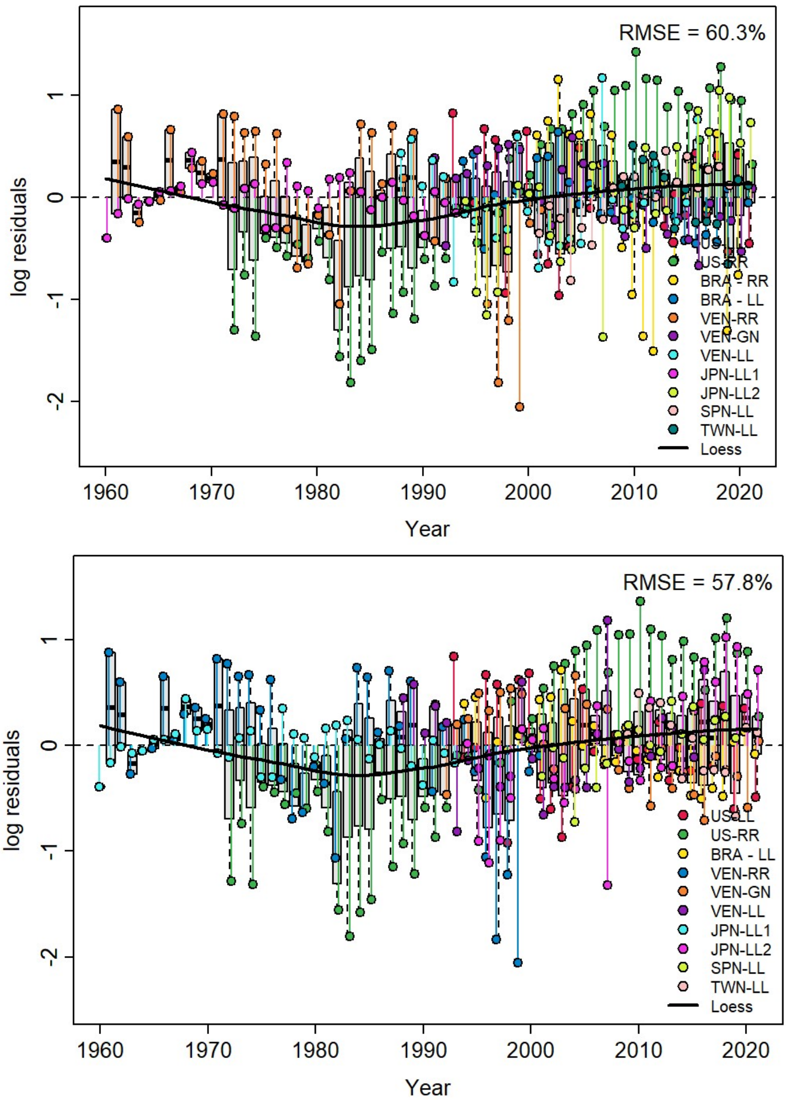

Figure 5. Residual diagnostic plots of CPUE indices for the WA sailfish models S1 (upper panel) and S2 (bottom panel). Boxplots indicate the median and quantiles of all residuals available for any given year, and solid black lines indicate a loess smoother through all residuals.

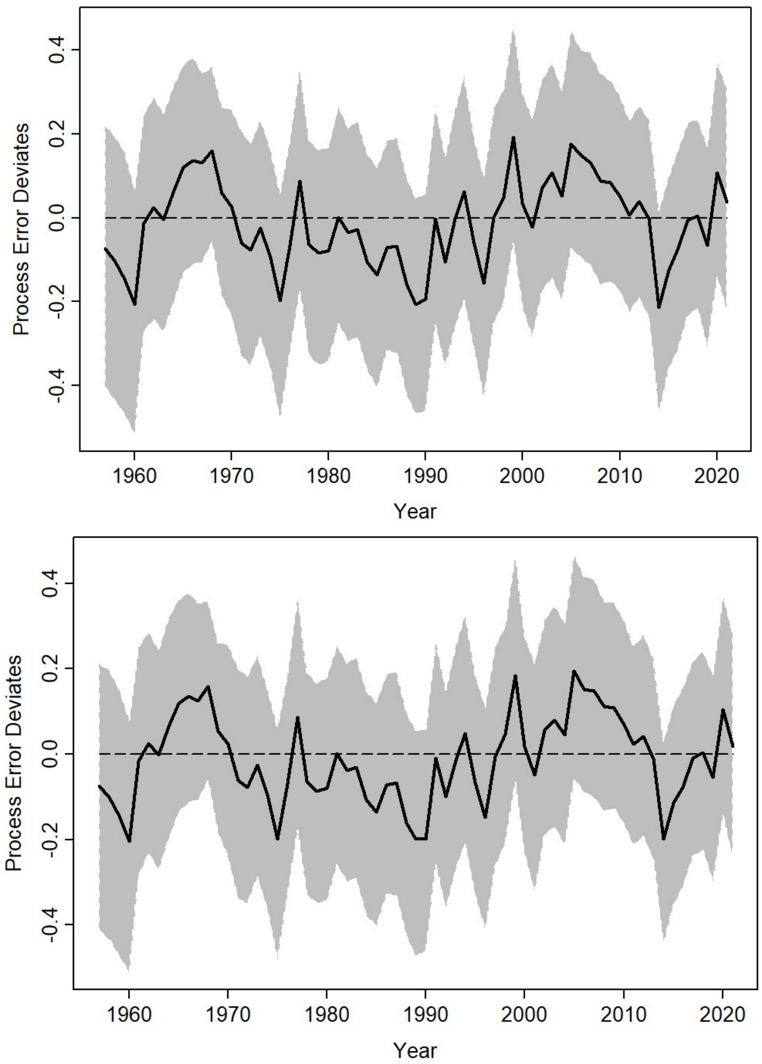

Figure 6. Process error deviates (median: solid line) for the WA sailfish models S1 (upper panel) and S2 (bottom panel). Shaded grey area indicates 95% credibility intervals.

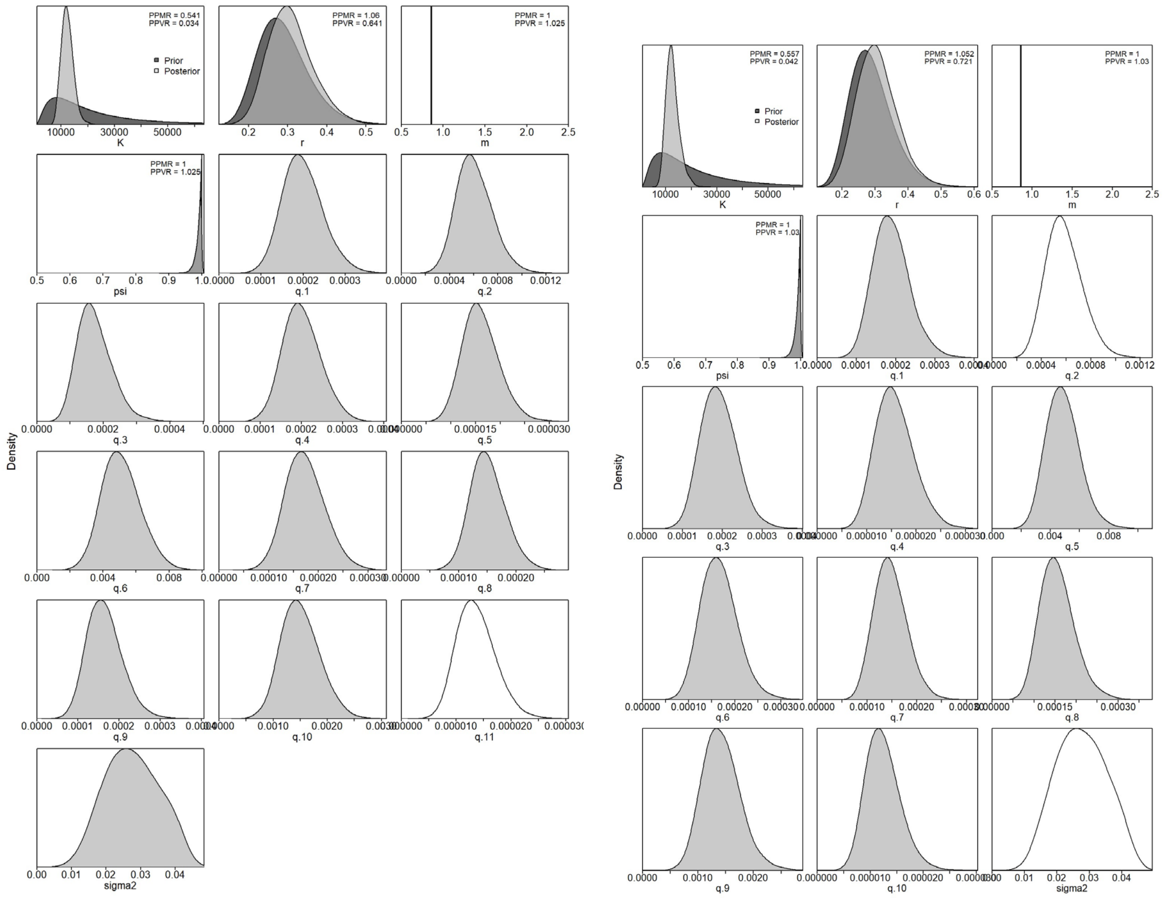

Figure 7. Prior and posterior distributions of various model and management parameters for the JABBA model S1 for WA sailfish models S1 (left panels) and S2 (right panels). PPRM: Posterior to Prior Ratio of Means; PPRV: Posterior to Prior Ratio of Variances.

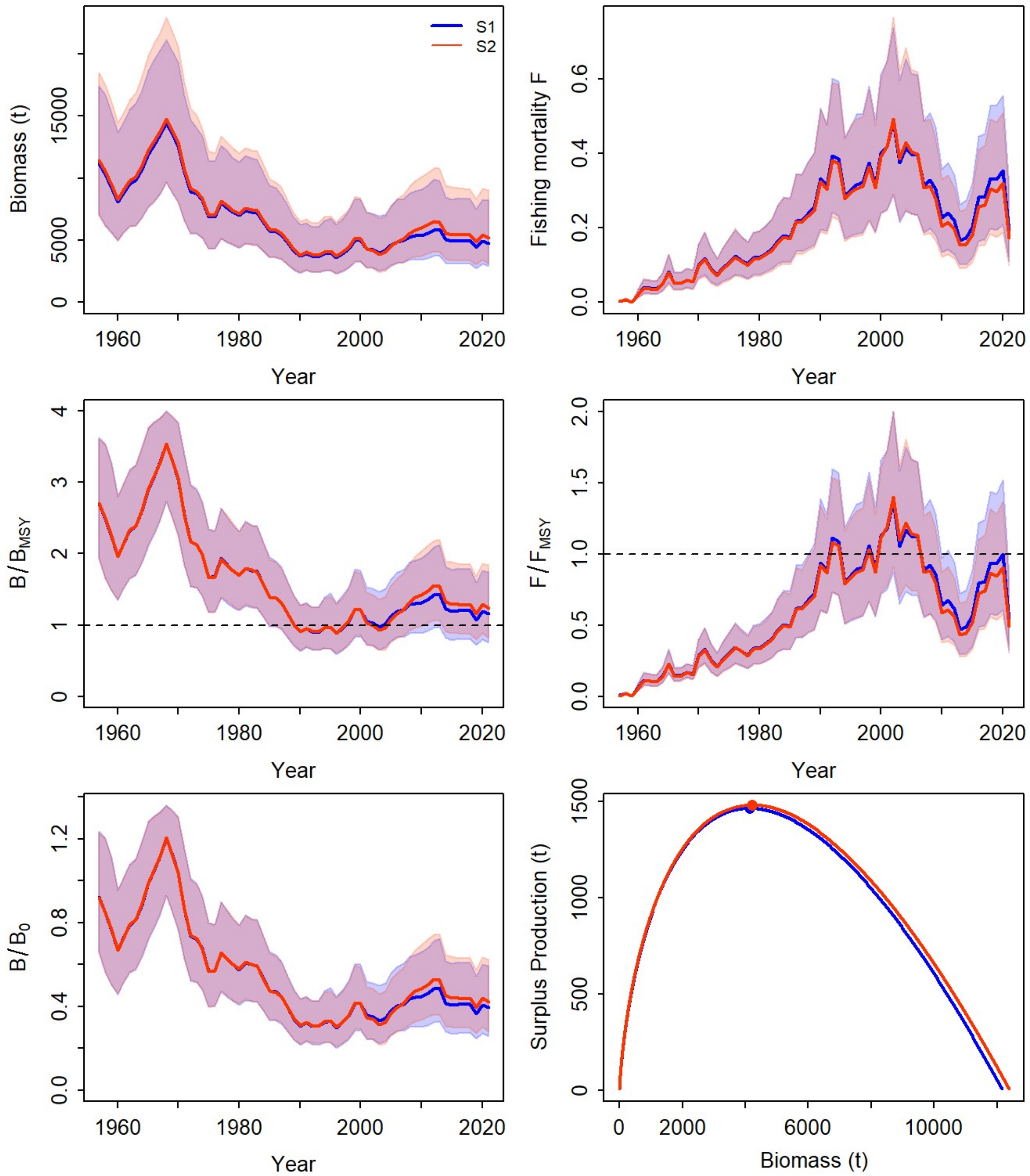

Figure 8. Comparison of biomass, fishing mortality (upper panels), biomass relative to K (B/K) and surplus production curve (middle panels), and biomass relative to B_{MSY} (B/B_{MSY}) and fishing mortality relative to F_{MSY} (F/F_{MSY}) (bottom panels) among JABBA scenarios S1- S2 for WA sailfish.

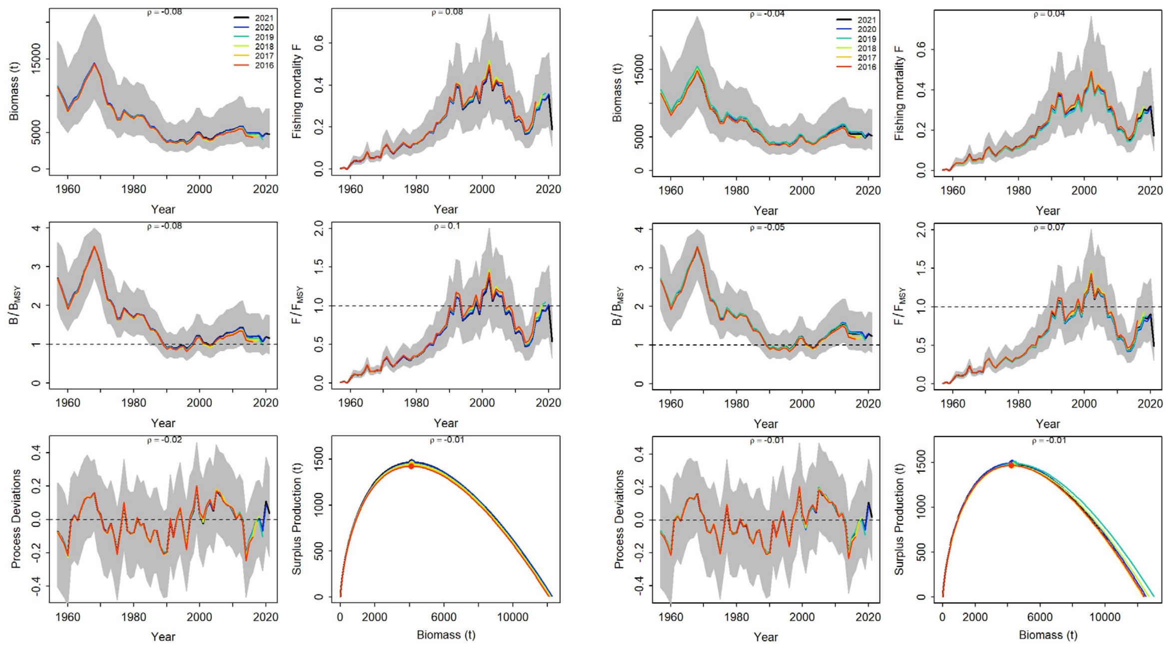

Figure 9. Retrospective analysis performed to the S1 (left panels) and S2 (right panels) JABBA models for the WA sailfish assessment, by removing one year at a time sequentially (n=5) and predicting the trends in biomass and fishing mortality (upper panels), biomass relative to B_{MSY} (B/B_{MSY}) and fishing mortality relative to F_{MSY} (F/F_{MSY}) (middle panels) and biomass relative to K (B/K) and surplus production curve (bottom panels).

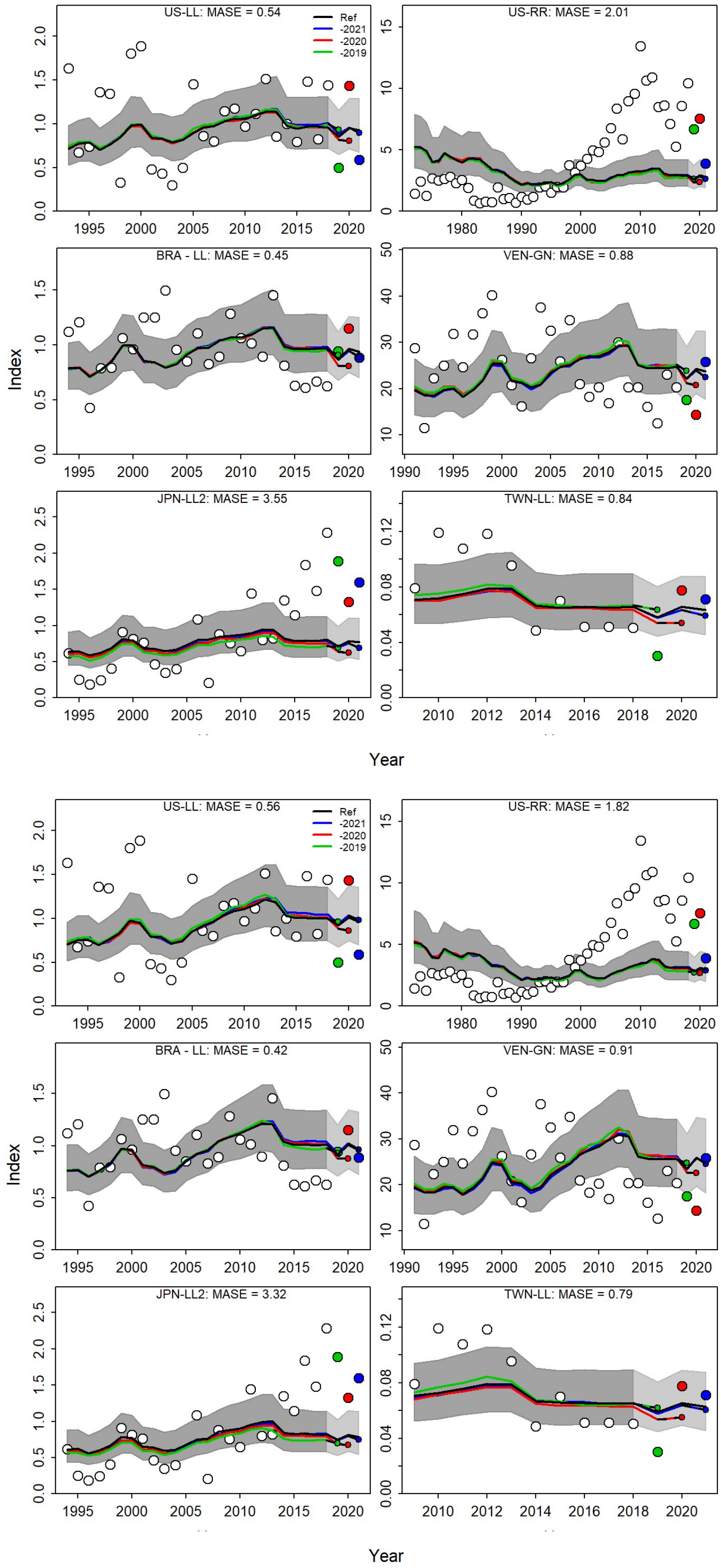

Figure 10. Hindcasting cross-validation results for the JABBA models for the WA sailfish (S1 – upper panels and S2 – lower panels), showing one-year-ahead forecasts of CPUE values (2017-2021), performed with five hindcast model runs relative to the expected CPUE. The CPUE observations, used for cross-validation, are highlighted as color-coded solid circles with associated light-grey shaded 95% confidence interval. The model reference year refers to the end points of each one-year-ahead forecast and the corresponding observation (i.e. year of peel + 1).

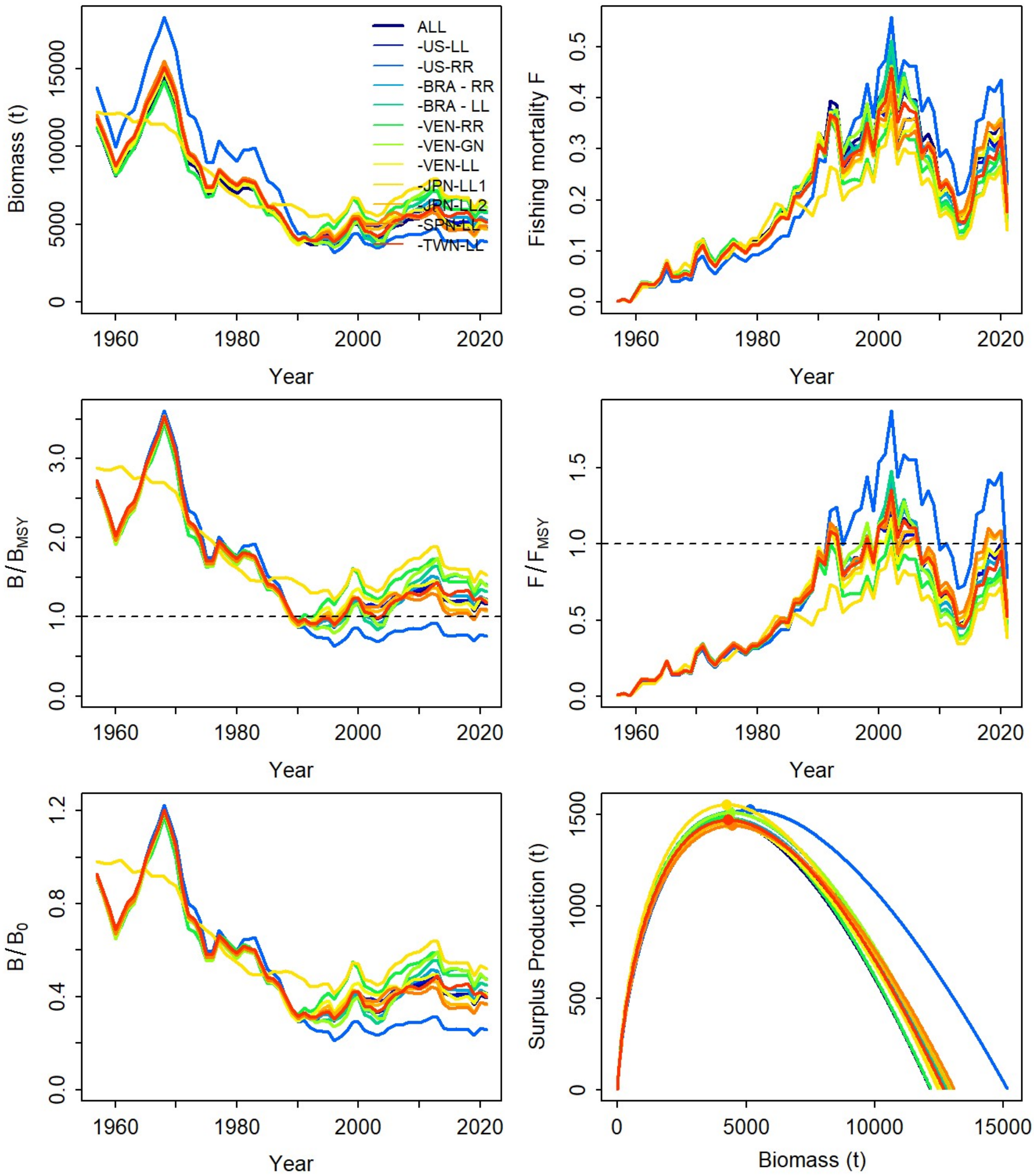

Figure 11. Jackknife index analysis performed to the S1 JABBA model of the WA sailfish assessment, by removing one CPUE fleet at a time and predicting the trends in biomass and fishing mortality (upper panels), biomass relative to B_{MSY} (B/B_{MSY}) and fishing mortality relative to F_{MSY} (F/F_{MSY}) (middle panels) and biomass relative to K (B/K) and surplus production curve (bottom panels)

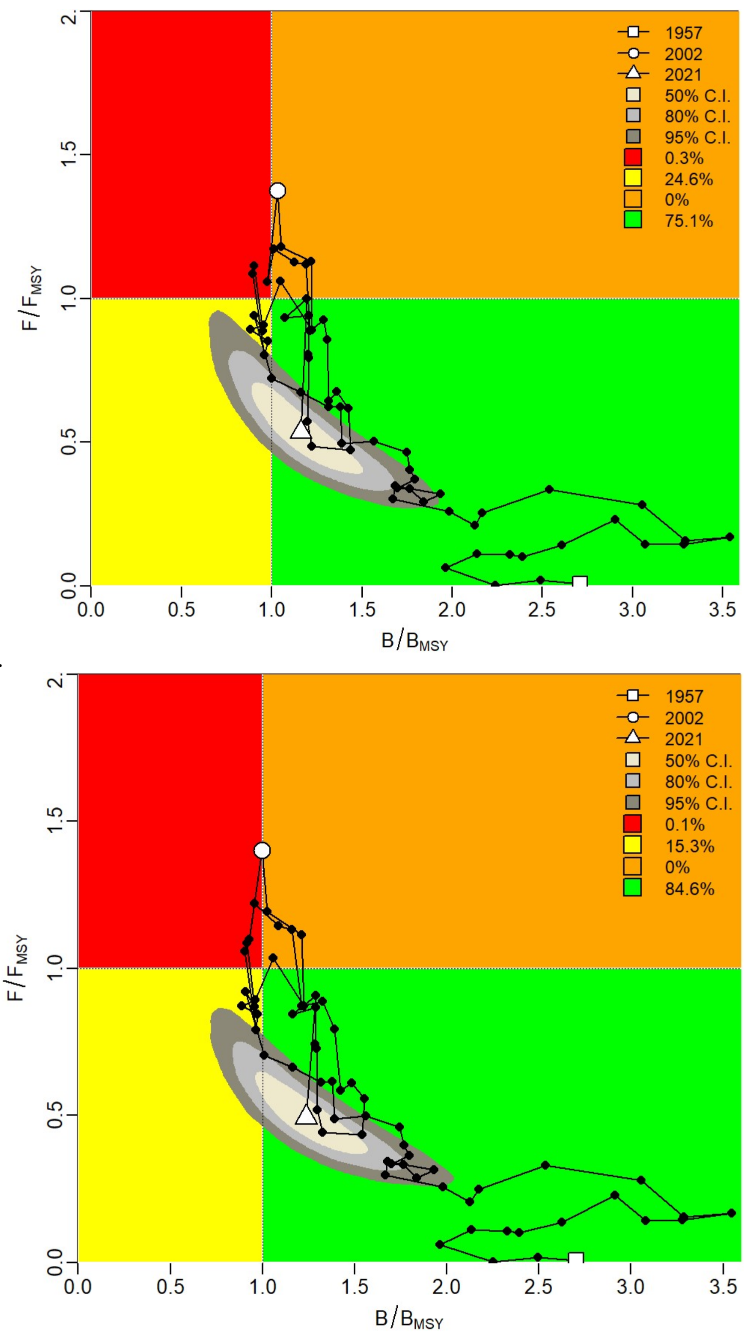

Figure 12. Kobe phase plot showing estimated trajectories (1957-2021) of B/B_{MSY} and F/F_{MSY} for the WA sailfish assessment (S1 – upper panels and S2 – lower panels). Different grey shaded areas denote the 50%, 80%, and 95% credibility interval for the terminal assessment year. The probability of terminal year points falling within each quadrant is indicated in the figure legend.

Appendix A

Table A1. Life history parameters used to estimate r prior distributions and median shape parameter with corresponding B_{MSY}/K values of the WA sailfish assessment. The priors are generated using an Age-Structured Equilibrium Model (ASEM).

Parameter	Mean	CV	Distribution	Description	Source
M	0.35	0.2	Lognormal	Natural Mortality (1/year)	ICCAT (2016)
L_{inf} (cm) female	221	0.1	Lognormal	Von Bertalanffy asymptotic length	Edhardt amd Devenauex, 2006
L_{inf} (cm) male	160.8				
K female	0.617	0.1	Normal	Von Bertalanffy growth parameter	Edhardt and Devenauex, 2006
K male	0.583				
t_o female	0	0.2	Normal	Von Bertalanffy age at zero length	Edhardt and Devenauex, 2006
t_o male	0				
a female	0.00000114	-	Exponential	Weight at length parameter (GG-LJFL)	ICCAT (2016)
a male	0.00000114				
b female	3.26	-	Exponential	Weight at length parameter (GG-LJFL)	ICCAT (2016)
b male	3.26				
L_{50} (cm) female	146.12	0.2	Lognormal	Length at 50% maturity	Mourato *et al*. (2018)
L_{50} (cm) male	146.12				
D	L_{50} x0.05	0.2	Lognormal	Logistic maturity ogive	Knife-edge
t_{max} (y)	12 and 15	0.2	Lognormal	Longevity	ICCAT (2016) and Prince *et al* (1986)
L_c (cm)	119	fixed	Fixed	Length at 50% selectivity	25th percentile LF
h	0.65, 0.75, and 0.85	fixed	Range	Steepness	-

Table A2. Results for r prior distributions and median shape parameter with corresponding B_{MSY}/K values generated an Age-Structured Equilibrium Model (ASEM).

steepness	*maximum age*	*mean r*	*sd of log (r)*	B_{MSY}/K	*shape m*
0.65	12	0.266	0.144	0.36	0.94
0.75	12	0.297	0.202	0.35	0.93
0.85	12	0.338	0.228	0.37	1.03
0.65	15	0.254	0.165	0.35	0.91
0.75	15	0.283	0.223	0.34	0.9
0.85	15	0.323	0.25	0.36	0.99

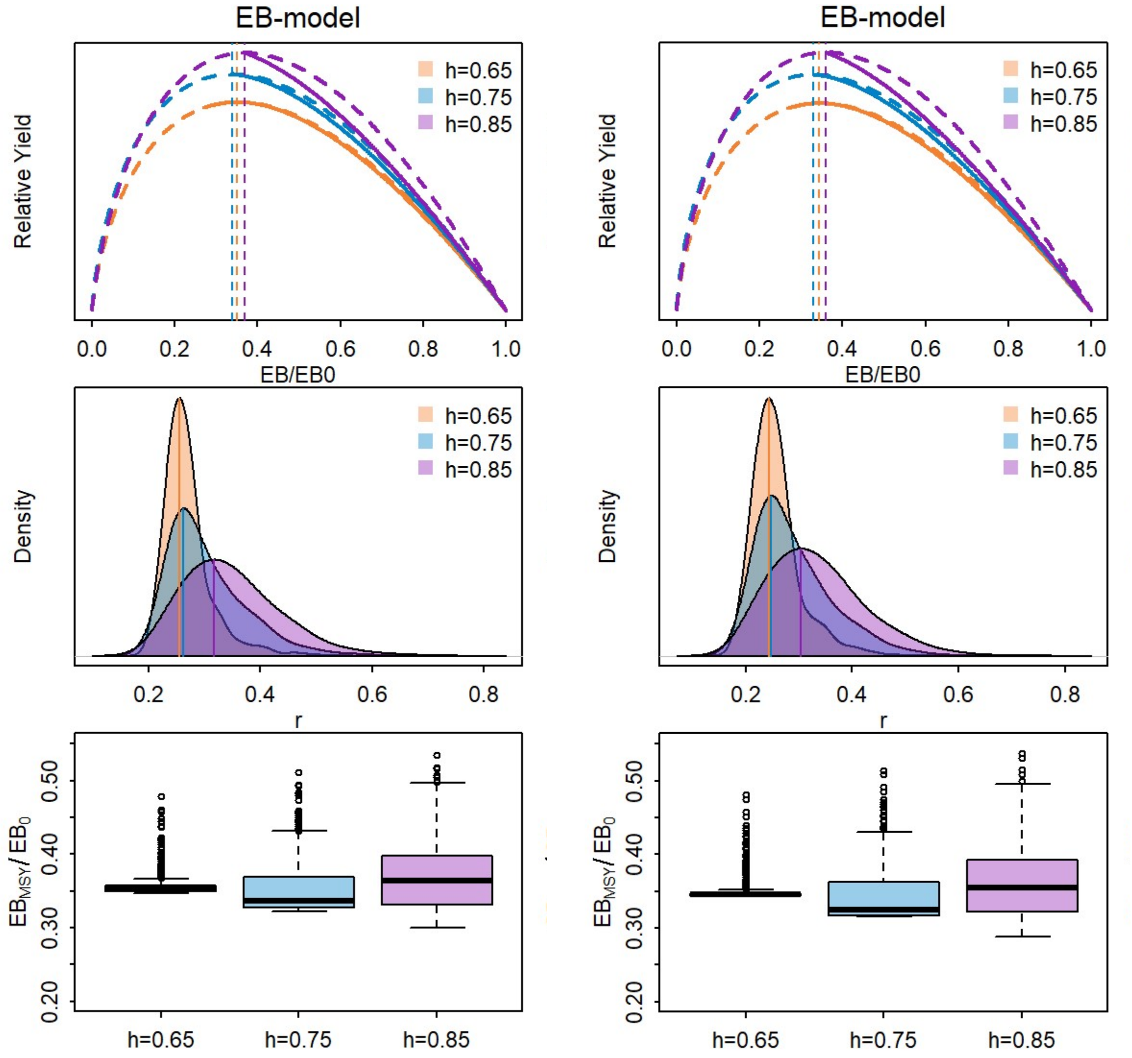

Figure A1. (Top Panel) Showing the functional from of the yield curves produced from the Age-Structured Equilibrium Model (ASEM; solid line) and the JABBA formulation of the Surplus Production function (solid) as a function of EB/EB_0 for a range of fixed steepness values of the spawning recruitment relationship (h = 0.65, h = 0.75, h = 0.85) (top panel); (Middle Panel) density distributions of simulated r values from Monte-Carlo simulations; and (Lower Panel) boxplot generated inflection points of EB_{MSY}/EB_0 for each of the fixed steepness h input values.

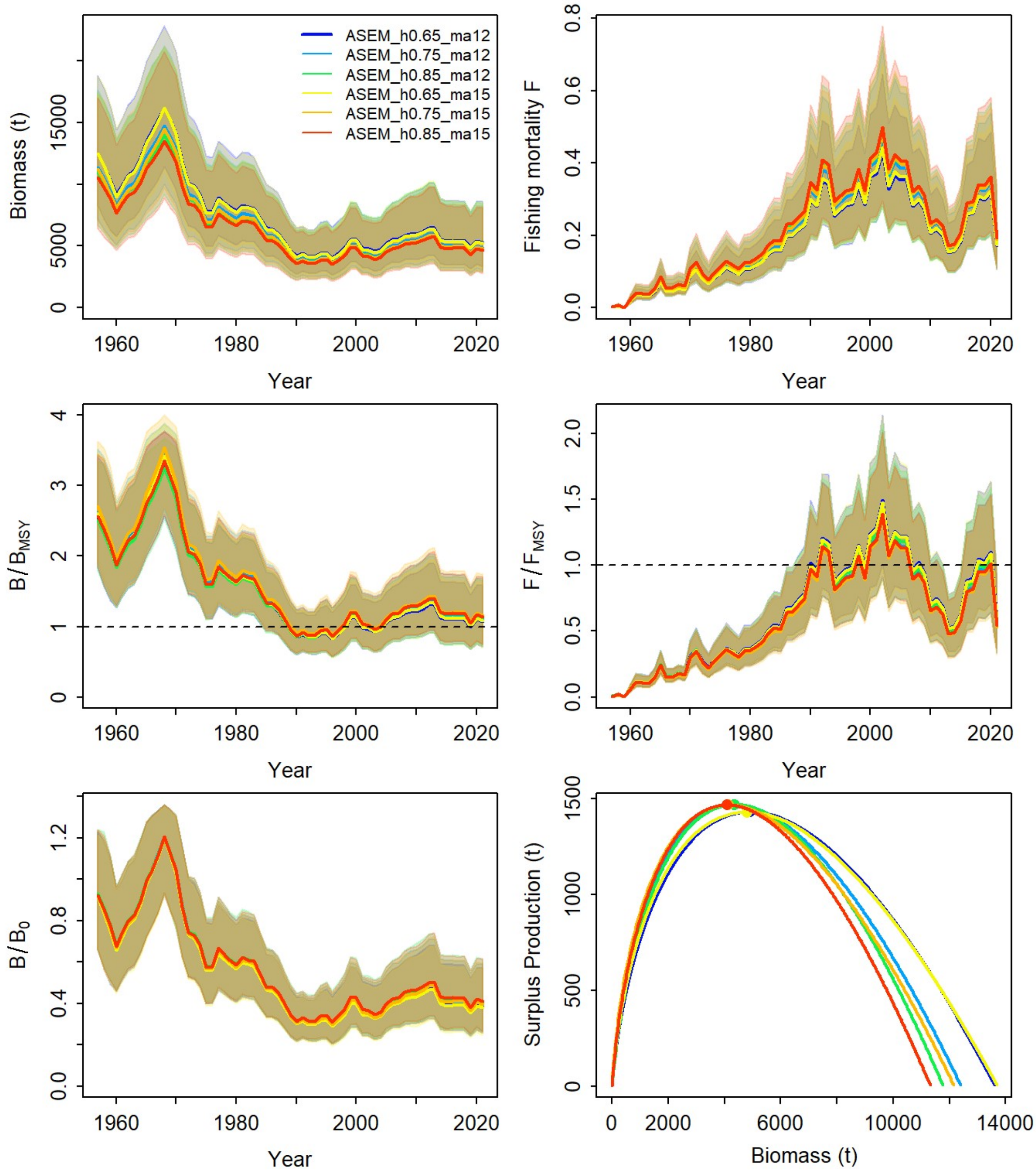

Figure A2. Comparison of biomass, fishing mortality (upper panels), biomass relative to *K* (*B/K*) and surplus production curve (middle panels), and biomass relative to B_{MSY} (B/B_{MSY}) and fishing mortality relative to F_{MSY} (F/F_{MSY}) (bottom panels) among six r prior JABBA for WA sailfish.