Alternative methods to assess the data-limited Indo-Pacific sailfish (*Istiophorus platypterus*) stock

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SUMMARY

Assessing the status of the Indo-Pacific Sailfish in the Indian Ocean is challenging due to the paucity of data. We explore alternative methods to assess the stock status of IP Sailfish by using length-frequency data to estimate annual Spawning Potential Ratio (SPR). Normalised annual estimates of SPR for two fleets are combined into a single SPR time series, which is assumed to be proportional to biomass, and used as an index of relative abundance. This index is incorporated in the Bayesian State-Space Surplus Production model, JABBA. The results indicate that there has been a 41% decline in SPR since 1970. B/B_{MSY} declined consistently from the early-1980s to the latest estimate in 2019, while F/F_{MSY} gradually increased from 1980, peaking in 2018 at 1.1. The 2019 estimate of B/B_{MSY} was 1.17, while the F/F_{MSY} estimate was 0.98. There is a 53,7% probability that the IP sailfish stock falls within the green quadrant - *not overfished nor subject to overfishing*. However, the current catches (average of 30,420 t in the last 3 years, 2018-2020) are substantially higher than the 2019 MSY estimate of 25,905 tons. This suggest overfishing is occurring. Catches should be decreased to below 25,000 tons to avoid further declines.

KEY WORDS

Abundance, billfish, data-limited, JARA, LBSPR, length-based, longline, spawning potential, stock assessment

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1. Introduction

Assessing the status of the Indo-Pacific Sailfish (*Istiophorus platypterus*) in the Indian Ocean is challenging due to the paucity of data. There is lack of reliable information on stock structure and biological parameters, while catch statistics are considered "*best scientific estimates*" by the IOTC Secretariat. Furthermore, stock assessments conducted in the Indian Ocean generally require an index of abundance to capture trends in biomass over time - no such index is available for IP sailfish in the Indian Ocean. As such, the "data-limited" Catch-MSY method (Froese et al. 2016) was applied in 2015 (Sharma 2015) and 2019 (IOTC Secretariat 2019).

In 2015, the IP sailfish stock was considered to be subject to *overfishing* and, if catches remained constant, the stock would likely deplete to *overfished* levels. It was recommended that target yield levels should not exceed 24,000 tons. In the 2019 assessment, estimated management quantities suggested that the stock was *not overfished* but *overfishing* was occurring. However, these estimates were associated with very large uncertainty as estimates of MSY ranged from 14,310 to 65,040 tons. Consequently, the stock status could not be assessed, and it was categorised as "uncertain". Given the uncertainty in the catch estimates, the management advice was that catches should remain below MSY level of 23,900 tons.

Globally, many fisheries do not have the data required for conventional methods of assessment and are categorised as "data-limited". Understanding the level of exploitation in data-limited fisheries is inherently limited. In these fisheries there are challenges obtaining representative catch statistics, while the perceived lower value of the resource typically leads to less funding for scientific surveys and observer programmes (Haupt et al., 2020). Despite this, several methods attempt to understand levels of exploitation in data-poor fisheries depending on the data available.

Here, we explore alternative methods to assess the stock status of IP Sailfish in the Indian Ocean. Specifically, we try to address the lack of a relative index of abundance (e.g., CPUE) by using annual length-frequency data and applying the length based spawning potential ratio (LBSPR) method to get annual spawning potential ratio estimates. When normalised, we assume these annual estimates of SPR are akin to an index of relative abundance.

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 are not available for IP sailfish in the Indian Ocean. Instead, annual fleet-specific length-frequency data were obtained from the IOTC website (IOTC 2018). Data from only two fleets were considered in this assessment, both of which are longline: Japan and Taiwan,China.

When required, lengths of IP sailfish were converted from measured units to lower-jaw fork length (LJFL) using the relationship defined by the IOTC (IOTC 2018). Any lengths reported but considered to be strong outliers, e.g., size was 500 cm, were removed. Furthermore, years with low samples number (i.e., < 200 samples) were removed from the analysis. Thus, the period 1990 – 2016 was removed from the Japanese dataset, while only 2013 data were removed from the Taiwan,China dataset.

2.2. *Methodologies*

2.2.1. *Length-Based Spawning Potential Ratio (LBSPR)*

The length based spawning potential ratio (LBSPR) method has been developed for data-limited fisheries (Hordyk et al., 2016), where few data are available other than a representative sample of the size structure of the vulnerable portion of the population (i.e., the catch) and a limited understanding of the life history of the species. The LBSPR method does not require knowledge of the natural mortality rate (M), but instead uses the ratio of natural mortality and the von Bertalanffy growth coefficient (K) (M/K), which is believed to vary less across stocks and species than M (Prince et al. 2015).

Like any stock assessment method, the LBSPR model relies on several simplifying assumptions. Simulation-testing research has demonstrated that the performance of length-based methods broadly depends on three major factors: (i) life-history characteristics, (ii) exploitation pattern, and (iii) suitability of the size sample. Furthermore, the LBSPR models are equilibrium based, and assume that the length composition data is representative of the exploited population at steady state; often the steady state assumption is violated, but simulations indicate that the SPR metric remains informative regardless. To accurately apply this method the available length data must be of adequate sample size that are representative of the size structure of the vulnerable portion of the stock and there should be accurate life-history information.

There is limited biological information on IP sailfish from the Indian Ocean for this study. Noting LBSPR's use of M/K is more robust to the influence of life history on natural mortality rate (M), attempts were made to obtain this information from other ocean basins. Nevertheless, the lack of ocean-specific life-history information increases uncertainty when estimating annual spawning potential ratio (SPR). Parameter values used for the length based spawning potential ratio analysis are presented in **Table 1**.

Another factor that can lead to uncertainty when applying length-based methods relates to differences between the size sample and the selectivity pattern of the main fishery (Pons et al. 2020). The most common cause is differences in capture methods or configuration (e.g., smaller mesh sizes) of surveys when compared to the fishery being assessed. Length data were limited to two different fleets, both of which were longline (JPN, TWN). Furthermore, the default assumption of the LBSPR model is that natural mortality is constant for all size classes and that the selectivity curve is asymptotic (Hordyk et al., 2016). However, it is generally assumed that species-specific selectivity for gillnets is domed-shaped (Horton et al., 2019), but this phenomenon is difficult to identify from size data alone; as is size-dependant natural mortality (Hordyk et al., 2016).

To mitigate the potential error associated with violating the aforementioned fleet selectivity assumptions, as well as overcome the lack of accurate ocean-specific life-history information, the resultant SPR estimates were used as an indicator of relative abundance as opposed to an instantaneous estimate of stock status. This was done by iteratively running the LBSPR analysis over many years to produce a SPR trend and then applying an additional analysis (see JARA section below) to provide Bayesian posterior probabilities of percentage change in annual SPR levels relative to the SPR level estimated in the first year data were available.

2.2.2. *JARA trend analysis*

By estimating annual SPR values and considering these to be a time series of relative abundance, species-specific population change (relative to the first year of available data) could be estimated using Just Another Red List Assessment 'JARA'. JARA is a Bayesian state-space tool (Winker and Shirley 2019; github.com/henning-winker/JARA) that was developed as an IUCN Red List decision-support tool that utilizes formal stock assessment outputs (e.g., trends in SPR), or standardized or nominal CPUE, to calculate the Bayesian posterior probability of the percentage change in a population (Daly et al., 2020; Winker, Pacoureau & Sherley, 2019). While the JARA option to calculate a probability of satisfying each of the Criterion A categories adopted by the IUCN Red List procedure was not applied in this analysis, the distribution of the posterior probability was used to estimated relative change in the population. Here, the JARA approach was applied to IP sailfish using the annual SPR estimates and their associated standard errors, calculated from length data derived from two fleets.

Following the procedure set out by Sherley et al. (2020) - based on the original stochastic growth and extinction model by Dennis et al., (1991) - each fleet-specific SPR time series was assumed to follow an exponential growth model of the form:

$$t+1= t+rt,$$

where *t* is the logarithm of the expected abundance in year *t*, and rt is the normally distributed annual rate of change with the mean r and process variance 2. A noninformative normal prior for ¯r ~ Normal (0, 1000) was used and priors for the process error variance were 2 ~ 1⁄gamma (0.001, 0.001), or approximately uniform in log space, as per Sherley et al., (2020). Finally, the median of the posterior distribution was taken as the percentage change in SPR over the observed period.

2.2.3. *JABBA*

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.

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).

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 typically represented in the form of alternative values of r and the shape m of the production function. Indian ocean specific biological information on IP sailfish is limited and, therefore, the input r value was provided as a range of 0.28 - 0.48 (**Table 2**), which was the probable range of r values estimated from the 2019 assessment (IOTC Secretariat 2019). For the unfished equilibrium biomass K, the probable range of values estimated from the 2019 assessment was also used as a prior: 162,000 – 412,000 tons (IOTC Secretariat 2019). 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 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 0.25.

3. Results and Discussion

3.1. *JARA*

Spawning potential ratio (SPR) is a well-established fisheries indicator and is defined as the proportion of the unfished reproductive potential remaining given any possible level of fishing pressure (Walters and Martell, 2004). Thus, in a pristine fishery the SPR equals 100% and zero in a stock where no spawning can occur (e.g., all mature fish have been removed) (Hordyk et al., 2015). In this assessment, no emphasis was placed on the resultant SPR estimates, but rather the novel combination of SPR and JARA allowed for a reliable estimate of change in SPR for IP sailfish – a 41% decrease since 1970. This decline manifests in a consistent negative trend that, despite missing data (1990 – 2013), provides enough information as a “relative abundance index” to be able to run a surplus production model. The underlying assumption is that the SPR trend is proportional to biomass – an assumption that still requires further investigation.

3.2. *JABBA*

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 model fit to the combined index is shown in **Figure 5.** The fit to the data is reasonable and the goodness-of-fit was estimated to be RMSE = 15%. Run tests conducted on the log-residuals indicated that the index residuals are randomly distributed and there are no outliers. There is a significant period (1990 – 2013) where no reliable length-frequency data are available, and therefore no index information exists.

Marginal posterior distributions along with prior densities are shown in **Figure 8**. The prior to posterior median ratio (PPMR) for r is essentially 1, indicating that r was heavily informed by the prior despite the prior range being reasonably large (0.28 - 0.48). In contrast, the relatively small PPVR observed for K indicates that the input data was more informative about K than the prior. The marginal posterior for initial depletion (φ) had a PPMR and PPVR value that were both close to 1, which suggests that this parameter was largely informed by the prior.

Summaries of posterior quantiles for parameters and management quantities of interest are presented in **Table 3.** The *MSY* estimate was 25,906 (20,789 – 34,168), while the median for B_{MSY} was 138,402 metric tons. The median estimate of *K* was 276,803 (215,921 – 371,953). The trajectory of B/B_{MSY} showed an overall decreasing trend from the early 1980s to the latest estimate in 2019. The F/F_{MSY} trajectory showed a gradual increasing trend from 1980 and peaked in 2018 at 1.1 but dropped below 1 in the following year (**Figure 9**). The 2019 estimate of B/B_{MSY} was 1.17, while the F/F_{MSY} estimate was 0.98.

The Kobe biplot (**Figure 10**) indicates that the IP sailfish stock has the highest probability falling within the green quadrant (53.7%) and is therefore *not overfished nor subject to overfishing*. However, there is also a 38.9% probability that the stock is within the orange quadrant, and *overfishing* may be occurring. The current catches of IP sailfish (average of 30,420 t in the last 3 years, 2018-2020) are substantially higher than the 2019 MSY estimate of 25,905 tons. This suggest overfishing is occurring.

Our results suggest that the model is stable and provides a reasonably robust fit to the index data. The assessments results are slightly more optimistic than previous assessments (IOTC 2019; Sharma 2015). However, the current MSY estimate of 25,905 t is plausible when compared to the 2015 (25,000 t) and 2019 (23,900 t) estimates. The methodology applied here, particularly the conversion of length data into an index of relative abundance, requires further review. Yet, the consistency in MSY estimates across assessments is somewhat reassuring. Catches of IP sailfish should be decreased to below 25,000 tons to avoid further declines in the stock's biomass.

4. References

Carvalho, F., Winker, H., Courtney, D., Kapur, M., Kell, L., Cardinale, M., Schirripa, M., Kitakado, T., Yemane, D., Piner, K.R., Maunder, M.N., Taylor, I., Wetzel, C.R., Doering, K., Johnson, K.F., Methot, R.D. 2021. A cookbook for using model diagnostics in integrated stock assessments. Fisheries Research. 240. doi.org/10.1016/j.fishres.2021.105959.

Carvalho, F., Punt, A.E., Chang, Y.J., Maunder, M.N., Piner, K.R., 2017. Can diagnostic tests help identify model misspecification in integrated stock assessments? Fish. Res. 192, 28–40. https://doi.org/10.1016/j.fishres.2016.09.018

Daly, R., Parker, D., Cliff, G., et al. 2020. Long- term catch trends and risk assessment of the Critically Endangered white-spotted wedgefish (Rhynchobatus djiddensis) from South Africa. Aquatic Conserv: Mar Freshw Ecosyst. 2020;1–12. https://doi.org/10.1002/aqc.3483.

Dennis, B., Munholland, P.L., Scott, M. 1991. Estimation of Growth and Extinction Parameters for Endangered Species. Ecological Monographs, 61(2), 115-143.

Gelman, A., Rubin, DB, 1992. lnference from Iterative Simulation Using Multiple Sequences. Stat. Sci. 7, 457–472. https://doi.org/10.2307/2246093

Geweke, J, 1992. Evaluating the accuracy of sampling-based approaches to the calculation of posterior moments., in: Berger, J.O., Bernardo, J.M., Dawid, A.P., Smith, A.F.M. (Eds.), Bayesian Statistics 4: Proceedings of the Fourth Valencia International Meeting. Clarendon Press, Oxford, pp. 169–193.

Heidelberger, P, Welch, PD, 1992. Simulation run length control in the presence of an initial transient. Oper. Res. 31, 1109–1144. https://doi.org/10.1287/opre.31.6.1109

Hordyk, A.R., Ono, K, Prince, J.D., Walters, C.J. 2016. A simple length-structured model based on life history ratios and incorporating size-dependent selectivity: application to spawning potential ratios for data-poor stocks. Can J Fish Aquat Sci 73:1787–1799. doi: 10.1139/cjfas-2015-0422.

Hordyk, A.R., Ono, K, Valencia, S, Loneragan, N, Prince, J.D. 2015. A novel length-based empirical estimation method of spawning potential ratio (SPR), and tests of its performance, for small-scale, data-poor fisheries. ICES Journal of Marine Science. 72: 217–231. https://doi.org/10.1093/icesjms/fsu004

Mohn, R., 1999. The retrospective problem in sequential population analysis: An investigation using cod fishery and simulated data. ICES J. Mar. Sci. 56, 473–488. https://doi.org/10.1006/jmsc.1999.0481

Plummer, M., 2003. JAGS: A Program for Analysis of Bayesian Graphical Models using Gibbs Sampling, 3rd International Workshop on Distributed Statistical Computing (DSC 2003); Vienna, Austria.

Plummer, M., Nicky Best, Cowles, K., Vines, K., 2006. CODA: Convergence Diagnosis and Output Analysis for MCMC. R News 6, 7–11.

Pons, M., Cope, J.M., Kell, L.T. 2020. Comparing performance of catch-based and length-based stock assessment methods in data-limited fisheries. Canadian Journal of Fisheries and Aquatic Sciences 77: 1026–1037.

Sherley, R.B., Winker, H, Rigby, C.L., et al. 2019. Estimating IUCN Red List popula- tion reduction: JARA—a decision-support tool applied to pelagic sharks. Conservation Letters. e12688. https://doi.org/10.1111/conl.12688

Walters, C.J., and Martell, S.J.D. 2004. Fisheries ecology and management. Princeton University Press, Princeton, USA.

Winker, H., Carvalho, F., Kapur, M., 2018. JABBA: Just Another Bayesian Biomass Assessment. Fish. Res. 204, 275–288. https://doi.org/http://doi.org/10.1016/j.fishres.2018.03.01

Winker, H., Pacoureau, N., Sherley, R.B. 2019. JARA: 'Just another Red List assessment' https://doi.org/10.1101/672899

5. Tables

Table 1: Parameters used for the length based spawning potential ratio analysis of IP sailfish. Some of the parameters were sourced from FishBase and are the same as those applied in the 2019 assessment (Froese and Pauly 2015).

Parameter	Description	Value	Unit
Linf	Maximum length	260	cm
L50	Length-at- 50 percent maturity	160	cm
L95	Length-at- 95 percent maturity	175	cm
SL50	Length-at- 50 percent selectivity	110	cm
SL95	Length-at- 50 percent selectivity	125	cm
M/K	M/K ratio	1.275	-

Table 2. Summary of prior and input parameter assumptions used in the 2022 JABBA Indian Ocean IP sailfish assessment.

Parameter	Description	Prior	*m*	CV
K	Unfished biomass	Range	162,000 – 412,000	-
r	Population growth rate	Range	0.28 - 0.48	-
ψ (*psi*)	Initial depletion	Beta	0.95	5%
B_{MSY}/K	Ratio Biomass at MSY to K	Fixed	0.5	-

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 assessment of Indian Ocean IP sailfish.

Estimates	***Median***	***2.50%***	***97.50%***
K	276,803	215,921	371,953
r	0.375	0.293	0.476
ψ (*psi*)	0.964	0.827	0.999
σ_{proc}	0.052	0.034	0.088
F_{MSY}	0.188	0.146	0.238
B_{MSY}	138,402	107,961	185,977
MSY	25,906	20,789	34,168
B_{1959}/K	0.956	0.801	1.084
B_{2019}/K	0.584	0.472	0.709
$B_{2019}/B_{\mathrm{MSY}}$	1.167	0.944	1.417
$F_{2019}/F_{\mathrm{MSY}}$	0.982	0.65	1.421

6. Figures

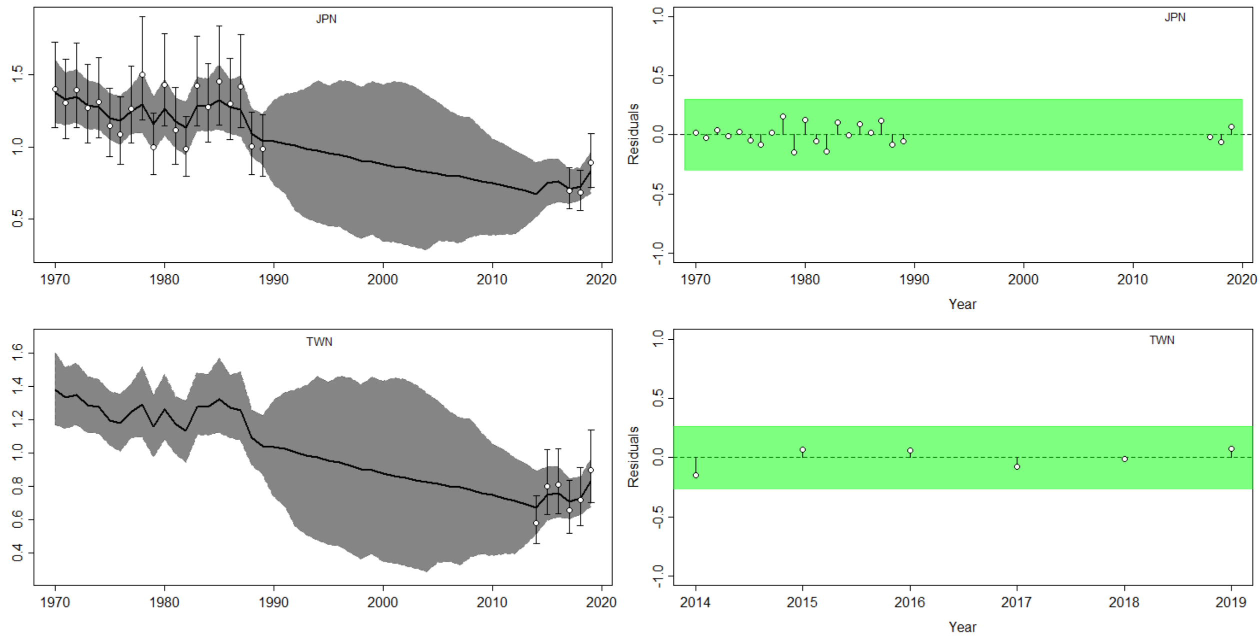

Figure 1: Observed and predicted Spawning Potential Ratio (SPR) trends (left) and associated runs tests (right) for IP sailfish in the Indian Ocean. The top represents the Japanese fleet, while the bottom represents the Taiwan,China fleet. On the left, the circles indicate annual SPR estimates, the black line is the predicted SPR trend, and the grey area is the 95% confidence intervals.

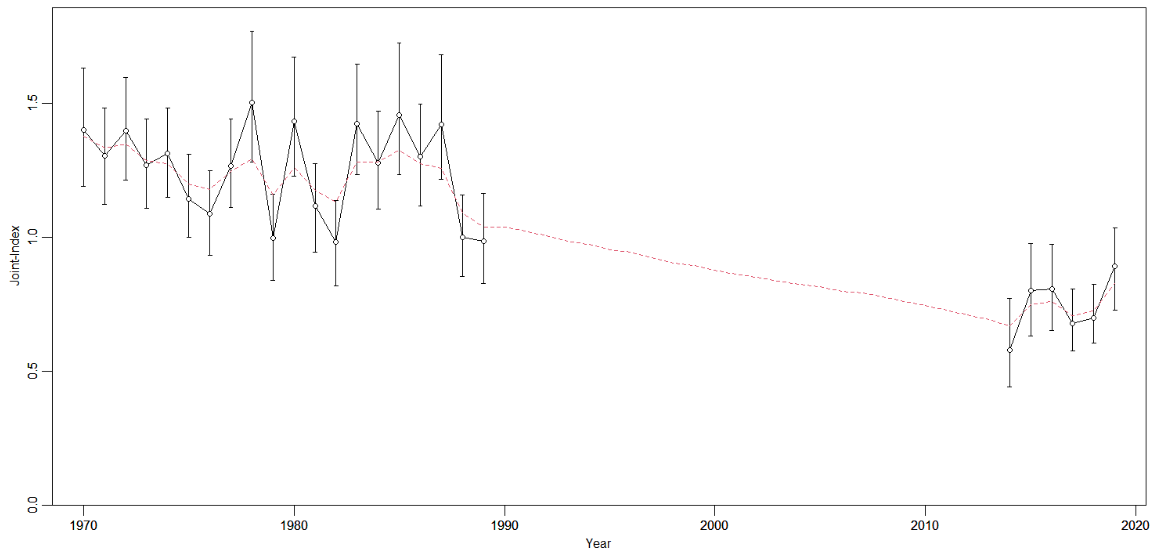

Figure 2: The combined index for IP sailfish, derived from the individual fleet annual SPR estimates.

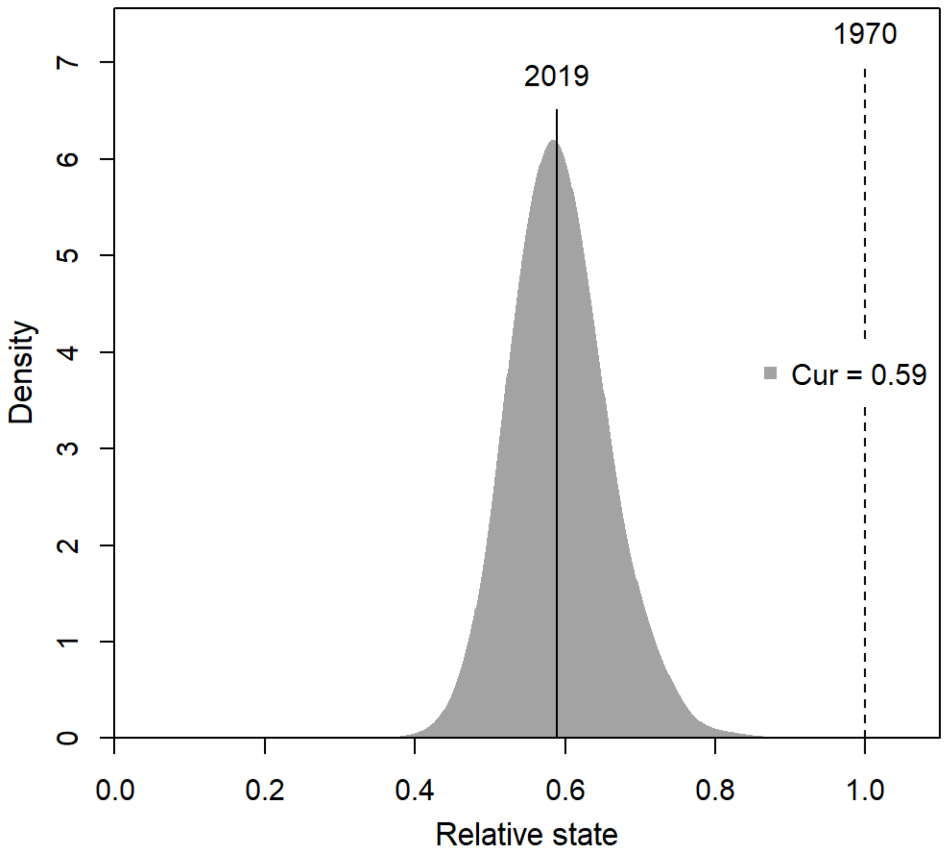

Figure 3: Spawning Potential Ratio (SPR) posterior distributions indicating the relative change in SPR over time for IP sailfish in Indian Ocean. The dashed vertical line indicates the SPR estimates at the beginning of the time series (1970), while the solid vertical line indicates the latest (2019) SPR estimate - the percentage change in SPR is the difference between these two estimates.

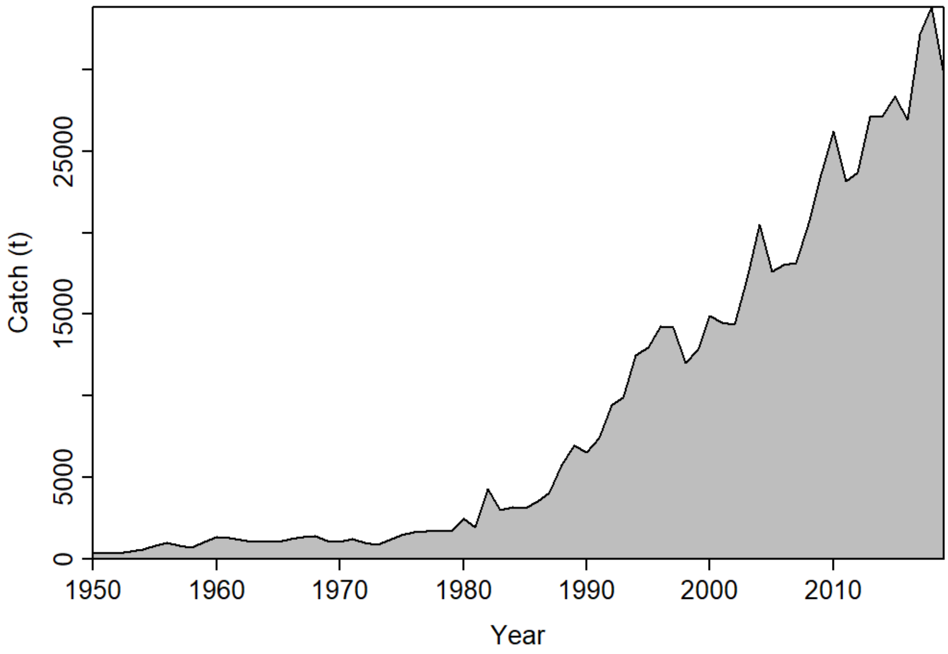

Figure 4: Available catch times series in metric tons (t) for Indian Ocean IP sailfish for the period 1950 - 2019.

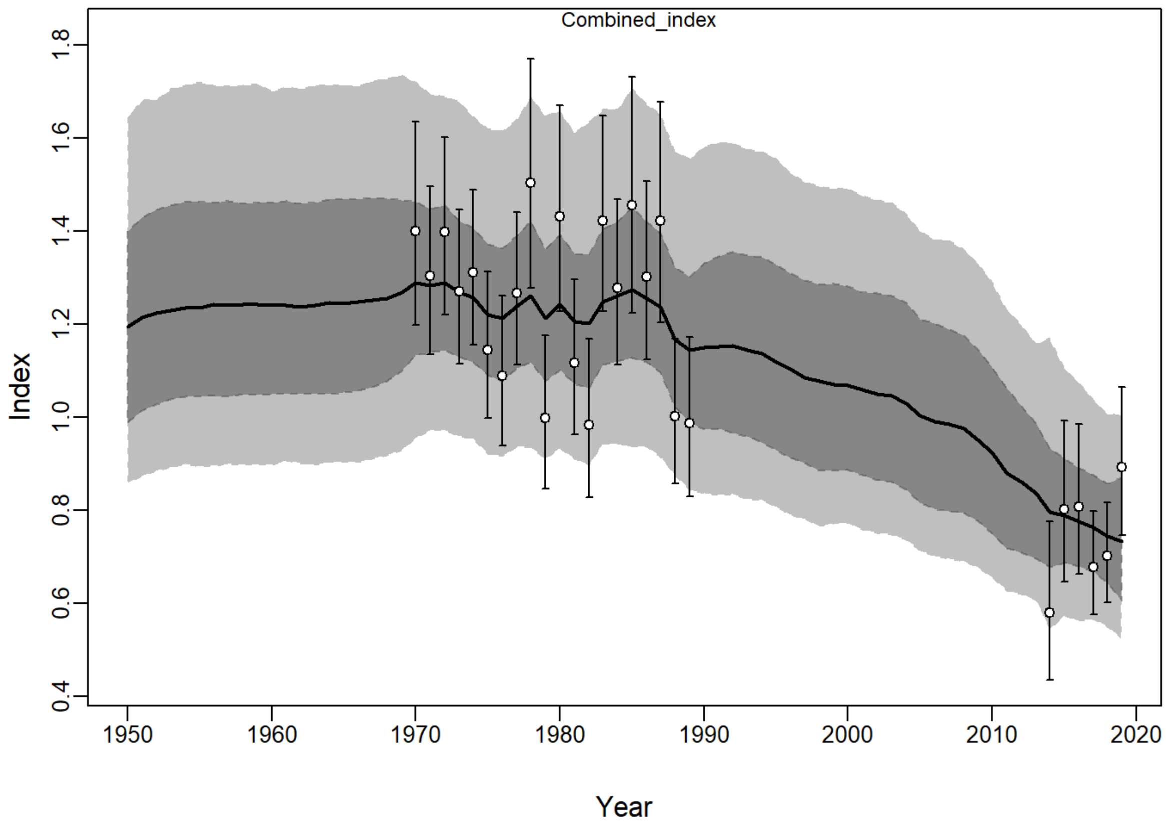

Figure 5: Time-series of combined (circle) and predicted (solid line) Index of Indian Ocean IP sailfish for the JABBA model. The dark shaded grey areas show 95% credibility intervals of the expected mean Index and light shaded grey area denote the 95% posterior predictive distribution intervals.

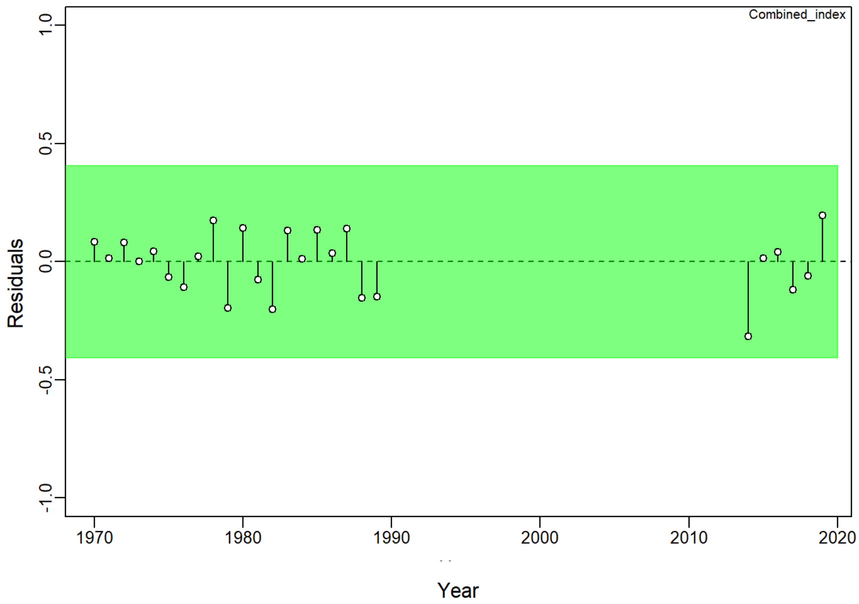

Figure 6: Runs tests to evaluate the randomness of the time series of Index residuals. Green panels indicate no evidence of lack of randomness of time-series residuals (p>0.05) while red panels indicate possible autocorrelation. The inner shaded area shows three standard errors from the overall mean and red circles identify a specific year with residuals greater than this threshold value (3x sigma rule).

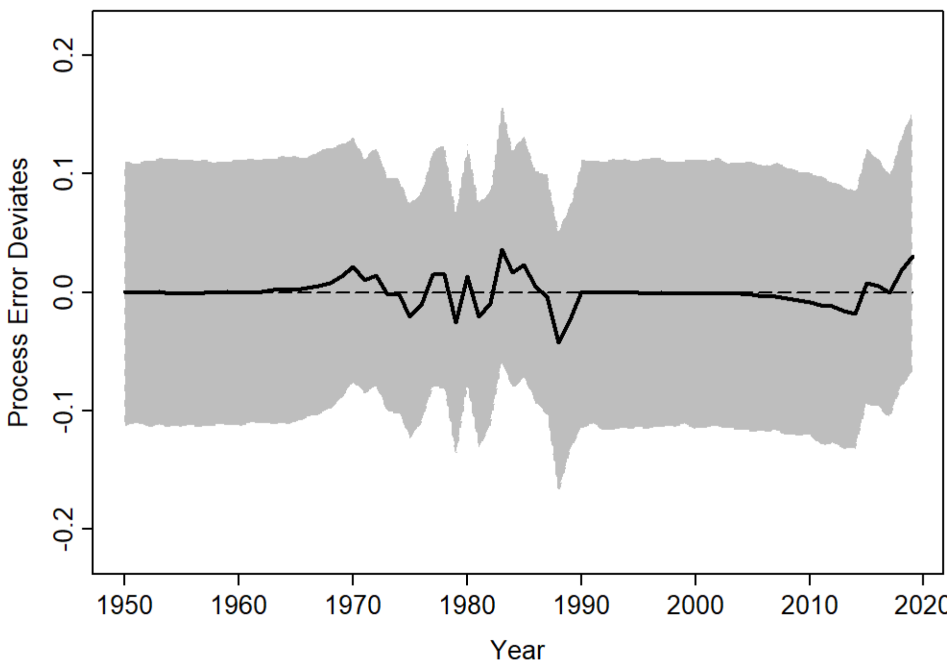

Figure 7: Process error deviates (median: solid line) of Indian Ocean IP sailfish for the JABBA model. Shaded grey area indicates 95% credibility intervals.

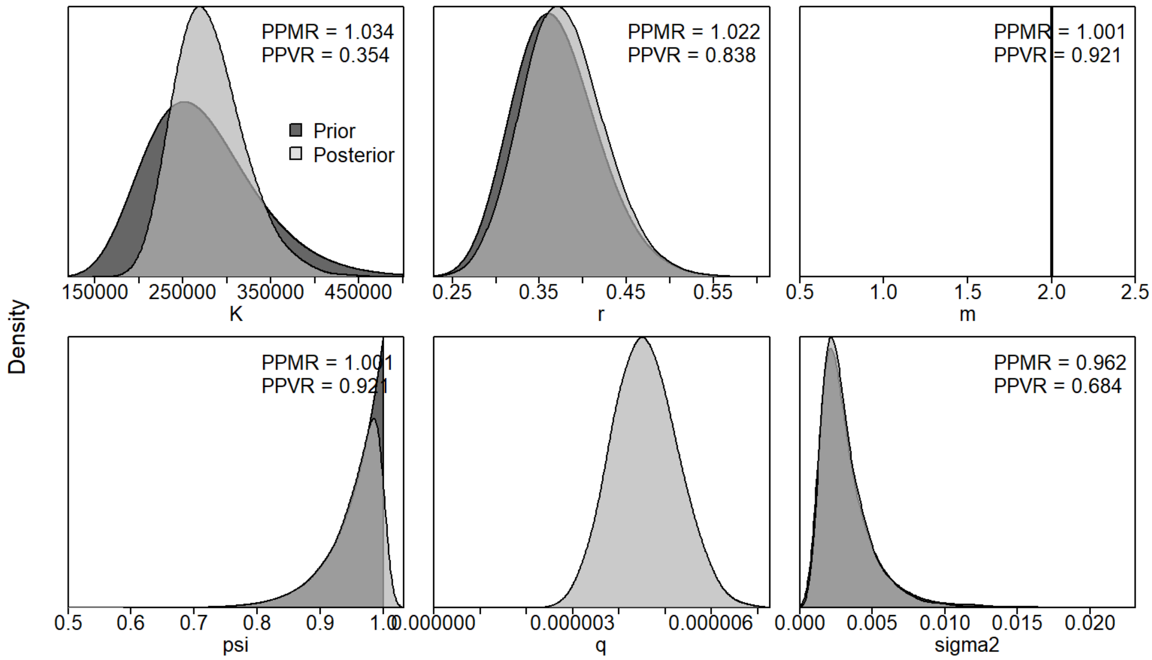

Figure 8: Prior and posterior distributions of various model and management parameters for the IP sailfish JABBA model. PPRM: Posterior to Prior Ratio of Means; PPRV: Posterior to Prior Ratio of Variances.

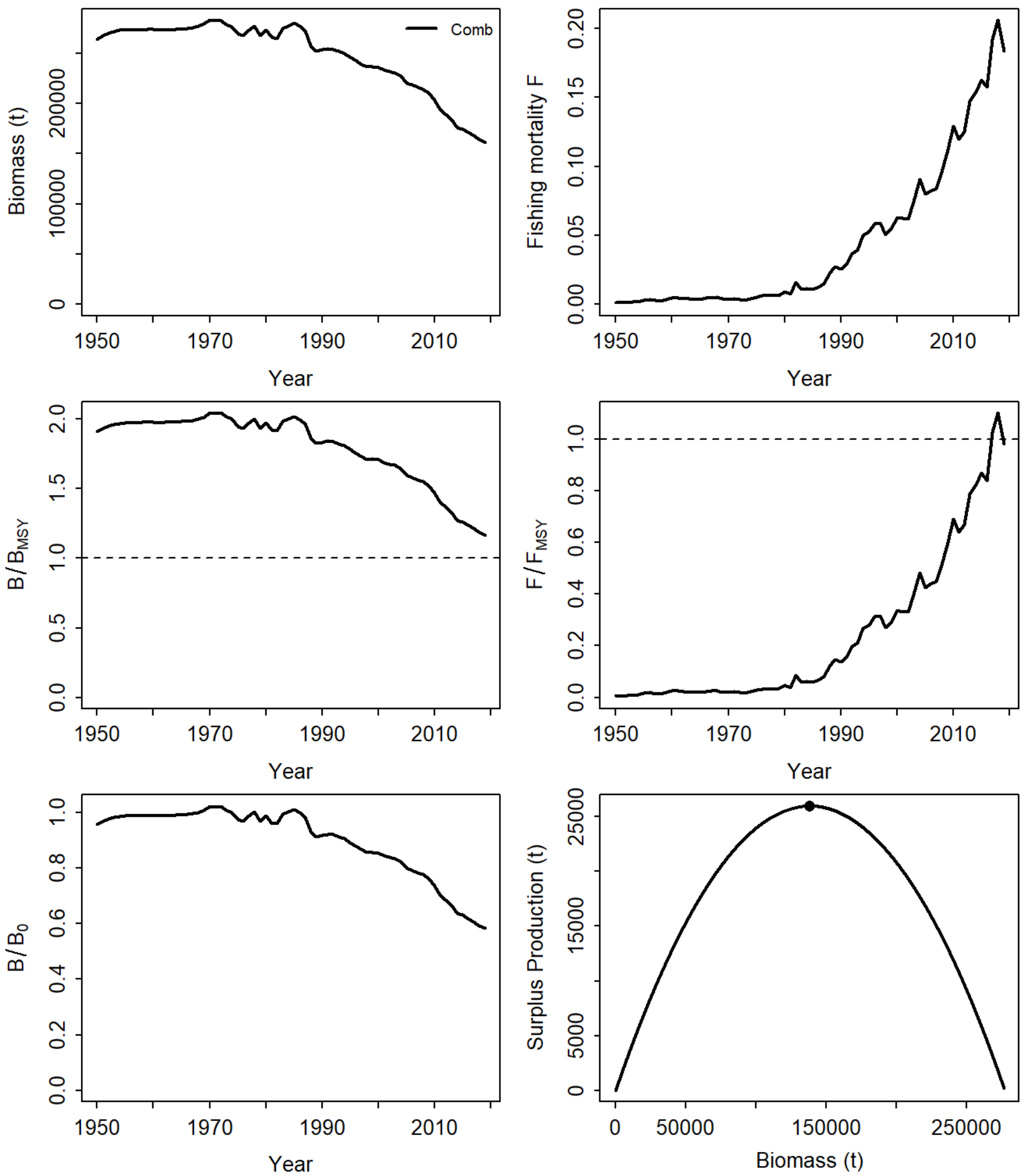

Figure 9: Trends in biomass, fishing mortality (upper panels), biomass relative to K (B/K) and surplus production curve (middle panels), and biomass relative to B_{MSY} (B/B_{MSY}) and fishing mortality relative to F_{MSY} (F/F_{MSY}) (bottom panels) for the IP sailfish assessment.

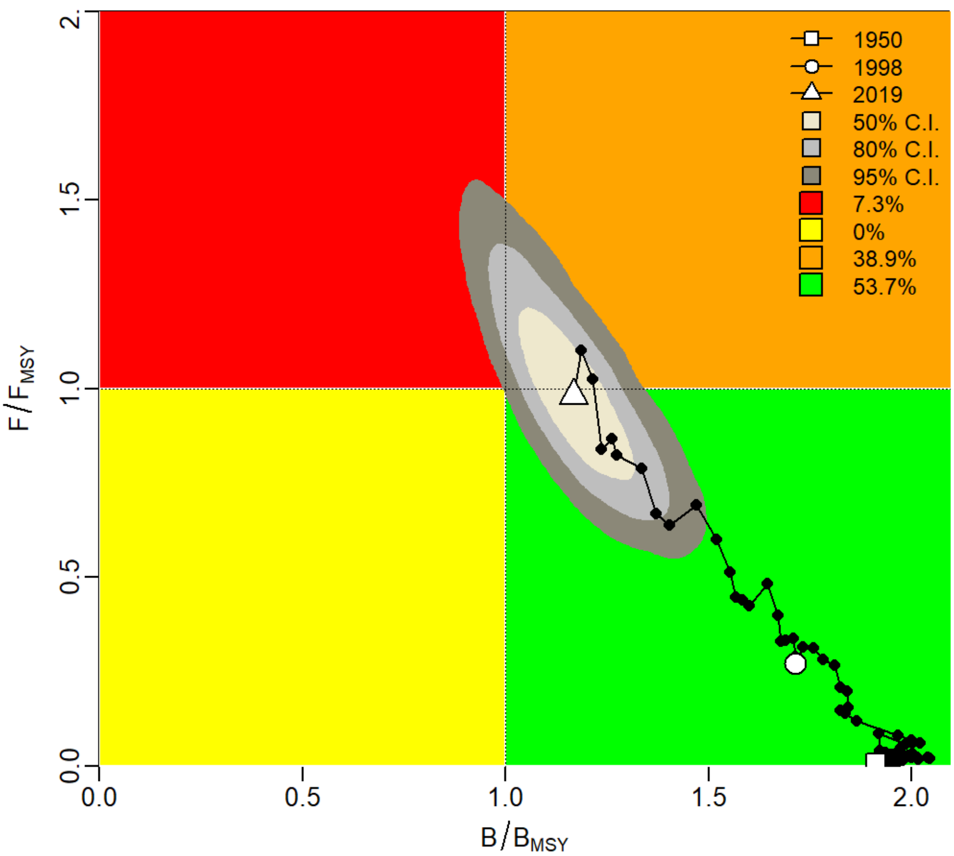

Figure 10: Kobe phase plot showing estimated trajectories (1950-2019) of B/B_{MSY} and F/F_{MSY} for the IP sailfish assessment. Different grey shaded areas denote the 50%, 80%, and 95% credibility interval for the terminal assessment year. The probability of terminal year points falling within each quadrant is indicated in the figure legend.