Stock assessment for Indo-Pacific sailfish (*Istiophorus platypterus*) in Indian Ocean using Bayesian surplus production model (JABBA)

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SUMMARY

Assessing the status of the Indo-Pacific (IP) sailfish (*Istiophorus platypterus*) in the Indian Ocean remains challenging due to limited data availability. There is lack of reliable information on stock structure, abundance and biological parameters. This report details the ongoing stock assessment for IP sailfish in the Indian Ocean, building upon the methodological framework established in the 2022 assessment. Given the persistent data constraints for this highly migratory species, this assessment employs alternative approaches suitable for data-limited scenarios. The primary objective is to evaluate stock status relative to sustainability reference points to provide science-based management advice.

The core methodology replicates the 2022 approach. Fleet-specific annual length-frequency data are used to estimate the annual Spawning Potential Ratio (SPR), which serves as a key indicator of reproductive health. The normalized annual SPR estimates from major fleets are combined into a single time series, and subsequently used as an index of relative abundance. This derived abundance index forms the primary input to the Bayesian State-Space Surplus Production Model (JABBA). The JABBA framework allows for the estimation of historical and current stock biomass relative to the biomass that can produce Maximum Sustainable Yield (B/B_{MSY}) and fishing mortality relative to the level consistent with MSY (F/F_{MSY}),

The results indicate that there has been a 45.5% decline in SPR since 1970. In the base model (S1), MSY was 34.3 kt (25.8-47.7 kt), the 2023 estimate of B/B_{MSY} was 1.34, and F/F_{MSY} was 0.69. The trajectory of B/B_{MSY} declined consistently from the early-1980s to the most recent estimate in 2023, while F/F_{MSY} gradually increased from 1980, peaking at 0.8 in 2020. Across all scenarios (S1-S9), B/B_{MSY} ranged 1.10-1.85 and F/F_{MSY} < 1 in eight of nine scenarios, with only the S4 indicating a borderline F/F_{MSY} =1.07, which indicating a high probability of being ***not overfished nor subject to overfishing*** for the IP sailfish stock. Sensitivity analyses showed limited influence of ±20% observation error changes but clearer effects of alternative *r* priors on MSY and risk. Ten-year constant catch projections suggest catches at or below approximately 33-34 kt maintain biomass clearly above B_{MSY} with modest stock rebuilding, 34-38 kt keeps the stock near the threshold with rising risk, and catches at or above 40 kt is unlikely to sustain biomass above B_{MSY}.

KEYWORDS

Stock assessment, Billfish, Longline, LBSPR, JARA, Data-limited, JABBA

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1. Introduction

Indo-Pacific sailfish (*Istiophorus platypterus*) is a large, highly migratory apex predator inhabiting tropical and subtropical regions of the Pacific and Indian Oceans, primarily within surface waters above the thermocline (0-200m depth) near coasts and islands (*Nakamura, 1983*). Renowned for its exceptional burst swimming speed (exceeding 110 km/h) and acrobatic jumping behavior, this species exhibits sexual dimorphism in growth and longevity. Females grow faster, reach larger sizes (up to 300cm lower-jaw fork length [LJFL] and >50 kg), and live longer (11–13 years), compared with males (200cm LJFL, >40 kg; and 7–8 years) (*Hoolihan, 2006; Ndegwa & Herrera, 2011)*. Spawning in the Indian Ocean occurs seasonally, peaking in February and June in Indian waters and during warmer months (e.g., December) in subtropical regions such as the Mozambique Channel and Réunion Island (*Nakamura, 1983*). Stock structure remains uncertain. While evidence suggests the presence of isolated populations in the Persian Gulf, limited genetic differentiation elsewhere has led to the assumption of a single pan-ocean stock (*Hoolihan et al., 2004*). For the purposes of assessment, this assumption is maintained.

In 2023, the IP sailfish is primarily caught using gillnets, which accounted for 71.2% of total catches in the Indian Ocean, followed by line (24.4%) and longline (2.2%) (https://iotc.org/WPB/23/Data/02-RC). The majority of reported catches are attributed to vessels flagged to the Islamic Republic of Iran (47%), India (19.3%), and Sri Lanka (6.4%), with the remaining 27.3% distributed across 28 other fleets. According to official statistics and the 2022 stock assessment by the Indian Ocean Tuna Commission (IOTC), the current catches (31,898 t) are substantially higher than the current MSY estimate of 25,905 t (**Figure 1**).

Assessing the status of the IP sailfish in the Indian Ocean is challenging due to the paucity of data. There is lack of reliable information on stock structure and biological parameters (e.g., Maturity, Natural mortality), while catch statistics are classified by the IOTC Secretariat as “best scientific estimates”. Furthermore, stock assessments in the region generally rely on abundance indices to track biomass over time. However, no such index is available for IP sailfish. Consequently, the “data-limited” Catch-MSY method (*Froese et al. 2017*) was applied in 2015 and 2019 (*Sharma 2015; 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 in 2024 (Kobe II Strategy Matrix). It was recommended that target yield levels should not exceed 24,000 t. 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 t. Consequently, the stock status could not be determined, 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 t.

To address the absence of abundance indices for IP sailfish, the 2022 assessment incorporated length-frequency data to estimate annual SPR. Normalized annual SPR estimates were assumed to be proportional to biomass and were used as a relative abundance index in the JABBA model, under the assumption of no long-term trends in annual recruitment (*Parker et al., 2022*). This represents a novel technique developed to mitigate the scarcity of abundance data for this species. The results indicated a 41% decline in SPR since 1970. B/B_{MSY} declined steadily from the early

1980s through the most recent estimate in 2019, while F/F_{MSY} increased gradually over the same period, peaking at 1.1 in 2018. In 2019, B/B_{MSY} was estimated at 1.17 and F/F_{MSY} at 0.98. Based on the weight of evidence available in 2022, the IP sailfish stock is determined not to be overfished nor subject to overfishing, with a 53.7% probability of falling within the "green quadrant".

This paper provides an updated assessment of the IP sailfish stock using the most recent catch and length-frequency data available from the IOTC. The assessment employs an alternative approach developed by *Parker et al. (2022)*, which uses length-frequency data to estimate annual SPR. Normalized annual SPR estimates from two fleets are combined into a single time series, treated as proportional to biomass, and used as an index of relative abundance. This index is then incorporated into the Bayesian state-space surplus production model (JABBA). Building on this validated framework, the present assessment refines the application of the approach with updated data.

2. Materials and methods

2.1 Data sources

The catch data were obtained from the IOTC stock assessment dataset repository of the 23rd Working Party on Billfish, covering the period 1950-2023 (https://iotc.org/WPB/23/Data/03-CE). As no Indices of relative abundance are available for IP sailfish in the Indian Ocean, annual fleet-specific length-frequency data were instead obtained from the IOTC website (https://iotc.org/WPB/23/Data/05-sfsfa). For this assessment, 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 (FL) 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 (*Parker et al., 2022*). Accordingly, data from 1990-2016, and 2020 were removed from the Japanese dataset, while data from 2013-2014 were excluded from the Taiwan, China dataset. The final dataset comprised a total of 12,552 samples from Japan and 25,797 from Taiwan, China.

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 (*Hordyket 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* (*Hordyket al., 2015*).

As with other stock assessment methods, the LBSPR model relies on several simplifying assumptions. Simulation studies have shown that the performance of length-based methods broadly depends primarily on three factors: (i) life-history characteristics, (ii) exploitation patterns, and (iii) suitability of the size sample. LBSPR is an equilibrium based model that assumes that the length composition data are representative of the exploited population at steady state. While the steady state assumption is often violated in practice, simulations indicate that the SPR metric remains informative under such conditions. Effective application of the LBSRP method requires length data of adequate sample size that accurately represent the size structure of the exploited stock, along with reliable life-history information.

Biological information on IP sailfish in the Indian Ocean is limited. Given that the LBSPR method relies on the ratio of *M/K*, which is considered more robust to variability in life history than *M* alone, life-history parameters were obtain from other ocean basins. Nevertheless, the absence of ocean-specific life-history information introduces uncertainty into annual SPR estimates. The parameter values used for the LBSPR analysis are presented in **Table 1**. Another source of uncertainty in length-based methods arises from differences between the size composition of samples and the selectivity pattern of the main fishery (*Pons et al. 2020*). Such discrepancies often result from differences in capture methods or gear configuration (e.g., smaller mesh sizes in surveys compared with the fishery being assessed). In this study, length data were restricted to two loneline fleets (Japan and Taiwan, China).

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 (*Huse et al., 1999; Madsen et al., 1999; Stergiou and Erzini 2002*), 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 'JARA'(Just Another Red-List Assessment). JARA is a Bayesian state-space tool (*Winker and Shirley 2019,* https://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, 2020*). 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., (2019)* - 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 t 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., (2019)*. Finally, the median of the posterior distribution was taken as the percentage change in SPR over the observed period.

2.2.3 JABBA model

The stock assessment model uses the most updated version (v1.1) of JABBA (*Winker et al. 2018*), which 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 (abundance index) 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.

The prior and input parameter assumptions used for JABBA are the same as those applied in the 2019 assessment and 2022 assessment (*Froese and Pauly 2015; Parker et al., 2022*) (**Table 2**). 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 t. The input r value was provided as a range of 0.28 - 0.48, which was the probable range of r values estimated from the 2019 assessment. 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(By) 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 relative abundance index estimates were fixed at 0.25.

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*). Log Residual Diagnostic Plots were used to compare the goodness of fit between CPUE observations and estimates in the model. The Root Mean Squared Error (RMSE) and the Deviation Information Criteria (DIC) were used to judge the goodness of fit between CPUE and different model scenarios. The smaller the RMSE and DIC values, the better the model fitting effect.

A retrospective problem (RP) refers to a systematic deviation in estimates of a resource variable (e.g. biomass) for the same year as the time series of the evaluated data increases, manifesting as persistent overestimation or underestimation. To evaluate potential systematic bias of the model, a retrospective analysis was conducted. The model was re-fitted sequentially, removing one year of data at a time for a total of 5 years, and the Mohn's ρ statistic was calculated to cquantify bias between the models. The calculation formula is:

$$\rho = \sum_{t} \frac{X_{(t1:t),t} - X_{(t1:t2),\,t}}{X_{(t1:t),\,t}}$$

Where, $t1$ and $t2$ represent the first and last year of the catch data. t is a year between $t1$ and $t2$. X represents an estimated variable, in this case the amount of biomass. When ρ value is 0, there is no RP, that is, there is no systematic bias estimation, when ρ value is positive, there is a positive RP, that is, the short time series of resources in the same year is greater than the long time series, otherwise, it is negative RP.

2.3 Scenarios

To maintain continuity with previous work, the 2022 assessment model (Schaefer) was retained as the base model (S1) and augmented with targeted refinements based on preliminary diagnostics. These changes were designed to improve performance and probe key structural assumptions without altering the fundamental structure. Specifically (**Table 3**):

1) Examined production-function shape uncertainty by adding a Fox model (S2) and two Pella–Tomlinson variants with B_{MSY}/K=0.40 and 0.60 (S3, S4);

2) Tested alternative observation-error assumptions for relative abundance index by varying the fixed observation error (fixed.obsE) to 0.20 and 0.30 (S5, S6);

3) Evaluated productivity sensitivity by revising the prior for the intrinsic growth rate r: lower-centered (0.20-0.40), higher-centered (0.40-0.60), and a wide prior (0.20-0.60) (S7-S9).

3. Results and analysis

3.1 JARA

SPR is a well-established fisheries indicator, defined as the proportion of unfished reproductive potential that remains under a given level of fishing pressure (*Walters and Martell, 2004*). Thus, in a pristine fishery the SPR equals 100%, whereas in a stock where no spawning occurs (e.g., all mature fish have been removed), SPR equals zero (*Hordyk et al., 2015*). In this assessment, the resultant SPR estimates were not emphasized, but rather the novel combination of SPR and JARA allowed for a reliable estimate of change in SPR for IP sailfish, indicating a 45.5% decrease since 1970 (**Figure 3**). This decline is reflected in a consistent negative trend that, despite missing data (1990-2014), provided sufficient information to serve as a "relative abundance index" for surplus production modeling. The underlying assumption that the SPR trend is proportional to biomass remains to be further validated.

3.2 JABBA Model fitting and diagnosis

The diagnostic analysis of the JABBA assessment for IP sailfish in the Indian Ocean showed reliable convergence and satisfactory model fitting across all model configurations (S1-S9). 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, replicate model runs produced consistent results, further demonstrating model stability (**Figure 4**). The model fit to the combined index is shown in **Figure 5**. The fit to the data was reasonable for the base model (S1), with a goodness-of-fit estimated at RMSE = 27.2% (**Figure 6**). For comparability across scenarios, we summarized the RMSE of the combined index fit and the DIC for all models (**Table 4**). Run tests on the log-residuals indicated that the index residuals were randomly distributed with no apparent outliers. However, a substantial period (1990-2014) without reliable length-frequency data resulted in no index information for those years.

Marginal posterior distributions along with prior densities are shown in **Figure 8**. The model successfully integrated data and priors, demonstrating a highly informative dataset and a robust fit. The posterior for K was sharply concentrated and substantially shifted from its broad, diffuse prior, indicating that the data provided precise information for estimating this parameter. In contrast, the posterior for r is also notably updated and concentrated relative to its prior, reflecting a data-informed estimate. To further examine productivity, we evaluated sensitivity by revising the prior for thethe intrinsic growth rate r which showed varying degrees of influence on the assessment results. However, the change is less pronounced than for K. The marginal posterior for φ had a posterior to prior ratio of means and variances value close to 1, which suggests that this parameter was largely informed by the prior, instead of the data.

Retrospective analysis conducted by sequentially removing the most recent years of data, revealed limited retrospective bias. For the base model (S1), Mohn's ρ values for biomass (B) and B/B_{MSY} were centered around -0.047, indicating minor underestimation bias (**Table 5**). Comparable patterns were observed across the alternative scenarios (S2-S9), which likewise showed small, near-zero ρ values for biomass-related metrics. These results suggest that the JABBA model predictions are robust over time, consistently estimating biomass levels with minimal systematic bias (**Figure 9**).

However, the analysis highlighted a more notable impact on F/F_{MSY}, with Mohn's ρ value of 0.128 under S1, suggesting some fluctuation in fishing mortality estimates attributable to observation error. A similar tendency-greater variability in F/F_{MSY} than in biomass metrics-was also evident across scenarios S2-S9, consistent with the broader pattern in fisheries assessments whereby observation error inflates variability in F/F_{MSY} relative to biomass-related parameters, thereby influencing assessments of overfishing risk.

3.3 Stock status

The summaries of posterior quantiles for parameters and management quantities for 9 scenarios are presented in **Table 6**. In the base model (S1), the MSY was 34,341 t (25,841-47,671), the B_{MSY} had a median of 174,181 t, and K was 348,362 (262,418-477,488). The trajectory of B/B_{MSY} showed an overall decline from the early 1980s through 2023, whereas the F/F_{MSY} trajectory increased gradually from 1980 and peaked at 0.8 in 2020, before declining sharply the following year (**Figure 10**). The 2023 estimate of B/B_{MSY} was 1.34, while the F/F_{MSY} estimate was 0.69. The Kobe plot for S1 (**Figure 11**) indicates that the IP sailfish stock most likely falls within the green quadrant (92.3%), suggesting that it is not overfished nor subject to overfishing.

Across all scenarios (S1-S9), 2023 status is consistently above the B_{MSY} (B/B_{MSY}=1.10-1.85). Fishing pressure is below F_{MSY} in eight of 9 scenarios (F/F_{MSY}= 0.38-0.82), with only the S4 indicating a borderline F/F_{MSY} =1.07. Additionally, the stock status all yielded in the green quadrant, except for S4, indicating the IP sailfish population has not been overfished or subject to overfishing (**Figure 12**). Varying the assumed observation error by ±20% shifts the estimated 2023 status modestly toward to the orange quadrant on the Kobe plot. Revising the prior for the intrinsic growth rate r exerts a clearer influence on MSY and the 2023 stock status. A lower-centered prior (0.20-0.40) has low MSY and the probability falling within green quadrant decline (higher F/F_{MSY}), whereas a higher-centered prior (0.40-0.60) increases MSY and the probability falling within green quadrant increase; the wide prior (0.20-0.60) has no significant effect.

3.4 Projection

Projections (2024-2033) based on S1 over a range of future catches from 28,800 to 43,200 t (±20%), with the 2024 catch set at the 2021-2023 average, are shown in **Figure 13**, where the dashed line denotes B_{MSY}. Across nine scenarios, the magnitude of change varies with model specification. Overall, these projections indicate that catches at or below approximately 33,000-34,000 t are consistent with maintaining biomass clearly above B_{MSY} and fostering modest stock rebuilding. The catches between 34,000-38,000 t expected to maintain the stock near the the threshold with increasing risk over time. And catches at or above 40,000 t are unlikely to sustain biomass above B_{MSY} over the 10-year projection period.

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Tables

Table 1. Parameters used for the LBSPR analysis of IP sailfish. Some of the parameters were sourced from FishBase and are the same as those applied in the 2019 assessment and 2022 assessment (*Froese and Pauly 2015; Parker et al., 2022*).

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. The prior and input parameter assumptions used for JABBA.

Parameter	Description	Prior	*m*	CV
K	Unfished biomass	Range*	162,000-412,000	-
r	Population growth rate	Range	0.28-0.48	-
$\psi(psi)$	Initial depletion (B_{1950}/K)	Beta	0.95	5%
B_{MSY}/K	Ratio Biomass at MSY to K	Fixed	0.5	-

* For parameters marked "Range", the values L, U are implemented as the approximate 95% central interval of a lognormal prior. This prior is not truncated and has support on $(0, \infty)$; therefore, the stated range does not impose hard bounds, and posterior estimates can lie outside L, U. The "Range" should be interpreted as a high-probability prior interval rather than fixed limits.

Table 3. Scenarios setting for Indian Ocean IP sailfish.

Scenarios	Model type	B_{MSY}/K	*fixed.obsE*	*r* Prior	Purpose
S1*	Schaefer	0.5	0.25	0.28-0.48	Base model
S2	Fox	—	0.25	0.28-0.48	Shape sensitivity (left-skew)
S3	Pella	0.4	0.25	0.28-0.48	Shape sensitivity (Fox-like)
S4	Pella	0.6	0.25	0.28-0.48	Shape sensitivity (right-skew)

S5	Schaefer	0.5	0.2	0.28-0.48	Obs. error −20%
S6	Schaefer	0.5	0.3	0.28-0.48	Obs. error +20%
S7	Schaefer	0.5	0.25	0.20–0.40	*r* low (lower-center, narrow)
S8	Schaefer	0.5	0.25	0.40–0.60	*r* high (upper-center, narrow)
S9	Schaefer	0.5	0.25	0.20–0.60	*r* wide (uninformative)

Table 4. Goodness of fitting of S1−S9 scenarios in JABBA for Indian Ocean IP sailfish

Scenarios	RMSE	DIC
S1*	27.2	-365.9
S2	27.3	-366.1
S3	27.3	-366.4
S4	26.9	-366
S5	27.9	-366.2
S6	28.7	-361.3
S7	27.5	-366.9
S8	27.5	-367.6
S9	27.5	-367.2

Table 5. Retrospective patterns of JABBA model for Indian Ocean IP sailfish (S1).

Year	B	MSY	B_{MSY}	F_{MSY}	B/B_{MSY}	F/F_{MSY}
2022	-0.012	-0.009	-0.007	-0.004	-0.004	0.017
2021	-0.031	-0.021	-0.013	-0.008	-0.017	0.04
2020	-0.1	-0.065	-0.051	-0.014	-0.05	0.127
2019	-0.15	-0.101	-0.078	-0.024	-0.08	0.21
2018	-0.177	-0.124	-0.102	-0.026	-0.082	0.246
Mean	-0.094	-0.064	-0.05	-0.015	-0.047	0.128

Table 6. Summary of posterior quantiles presented in the form of marginal posterior medians and key management quantities from JABBA.

Estimates	**S1**	S2	S3	S4	S5	S6	S7	S8	S9
K	348,362	320,183	326,658	384,969	341,460	328,976	375,509	306,432	325,778
r	0.395	0.39	0.392	0.4	0.394	0.391	0.325	0.506	0.451
$\psi(psi)$	0.952	0.952	0.964	0.961	0.961	0.964	0.962	0.964	0.959
σ_{proc}	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045
F_{MSY}	0.198	0.39	0.33	0.118	0.197	0.195	0.163	0.253	0.225
B_{MSY}	174,181	117,848	130,657	230,985	170,730	164,488	187,755	153,216	162,889
MSY	34,341	45,744	42,983	27,257	33,433	32,049	30,603	38,650	36,324
B_{1950}/K	0.951	0.951	0.963	0.96	0.961	0.963	0.961	0.963	0.958
B_{2023}/K	0.669	0.679	0.679	0.66	0.649	0.618	0.638	0.694	0.681
B_{2023}/B_{MSY}	1.338	1.846	1.699	1.1	1.299	1.236	1.275	1.388	1.361
F_{2023}/F_{MSY}	0.694	0.377	0.437	1.068	0.735	0.805	0.818	0.595	0.647

Figures

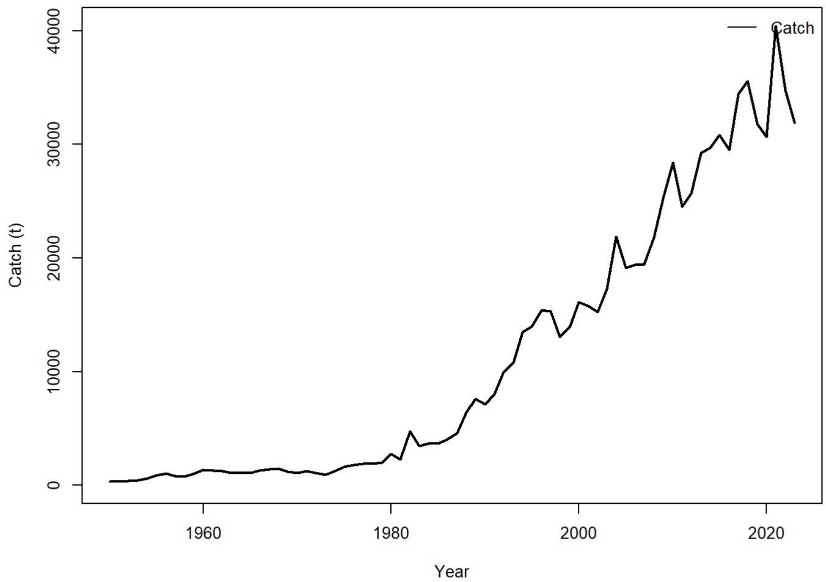

Figure 1. Available catch times series in metric tons (t) for Indian Ocean IP sailfish for the period 1950-2023.

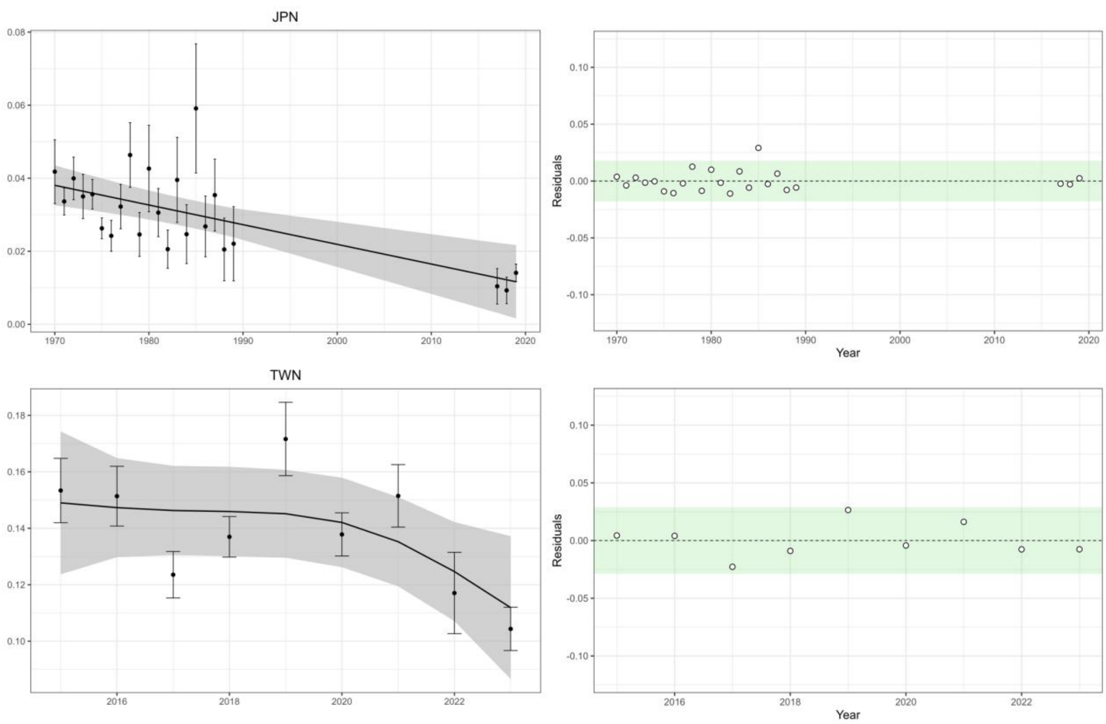

Figure 2. Observed and predicted Spawning Potential Ratio (SPR) trends (left) and associated runs tests (right) for IP sailfish in the Indian Ocean. The top represents the Japanese fleet, while the bottom represents the Taiwan, China fleet. On the left, the circles indicate annual SPR

estimates, the black line is the predicted SPR trend, and the grey area is the 95% confidence intervals.

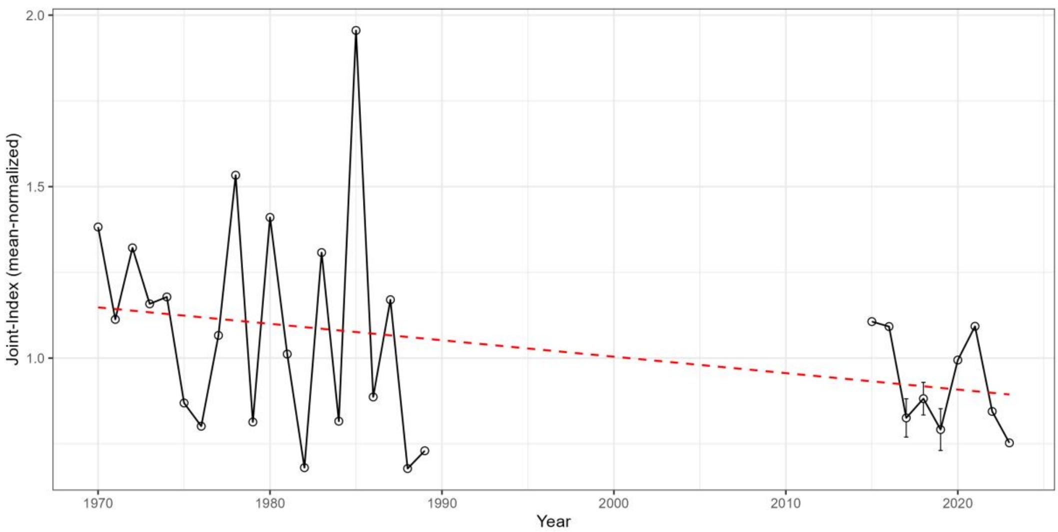

Figure 3. The combined index for IP sailfish, derived from the individual fleet annual SPR estimates.

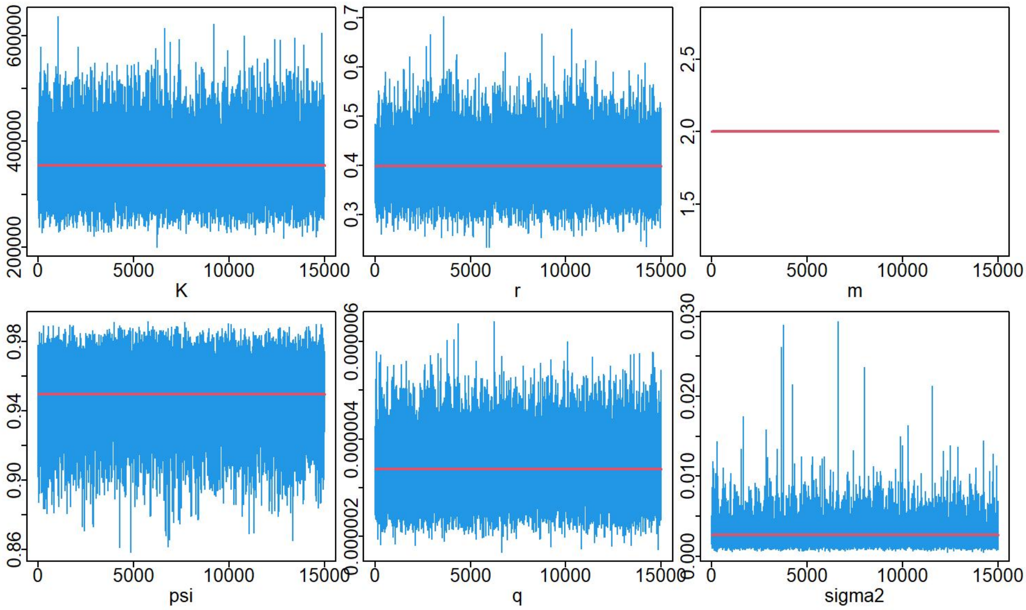

Figure 4. MCMC diagnosis of Indian Ocean IP sailfish for the JABBA model (S1).

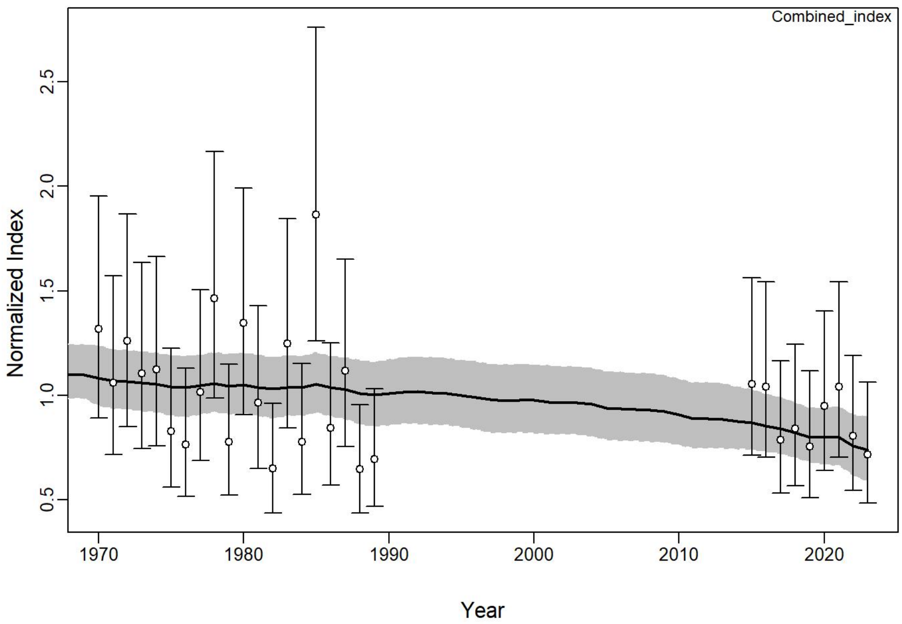

Figure 5. Time-series of combined (circle) and predicted (solid line) Index of Indian Ocean IP sailfish for the JABBA model (S1).

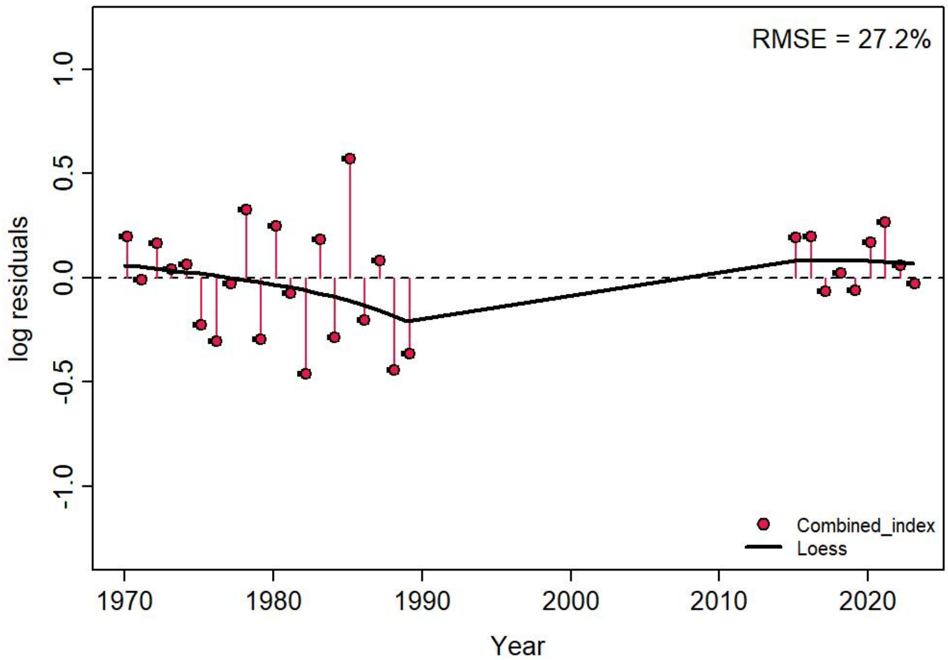

Figure 6. Runs tests to evaluate the randomness of the time series of Index residuals (S1).

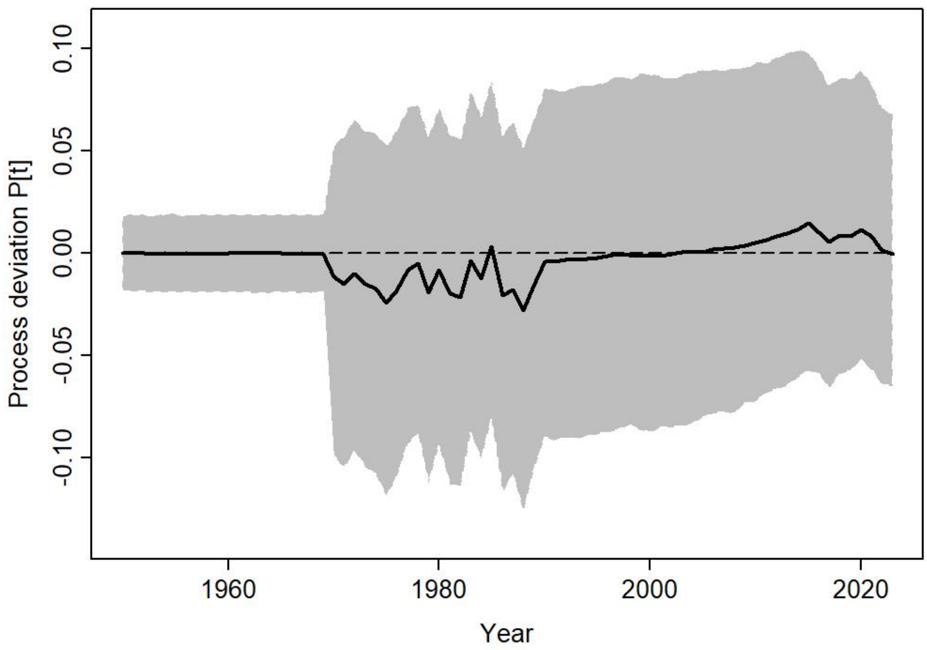

Figure 7. Process error deviates (median: solid line) of Indian Ocean IP sailfish for the JABBA model. Shaded grey area indicates 95% credibility intervals (S1).

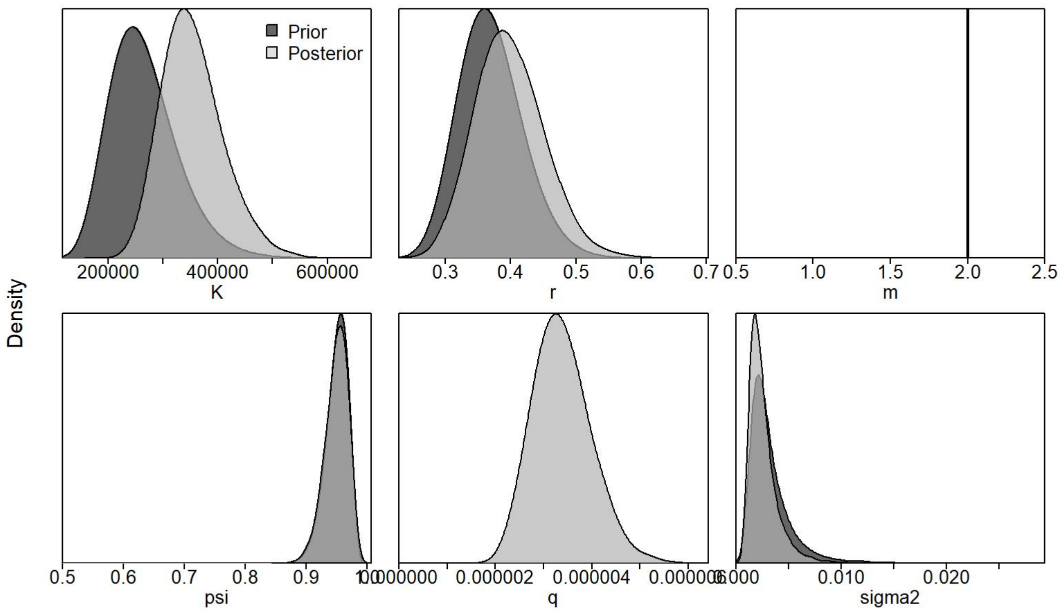

Figure 8. Priors (dark) and posteriors (light) of parameters of Indian Ocean IP sailfish for the JABBA model (S1).

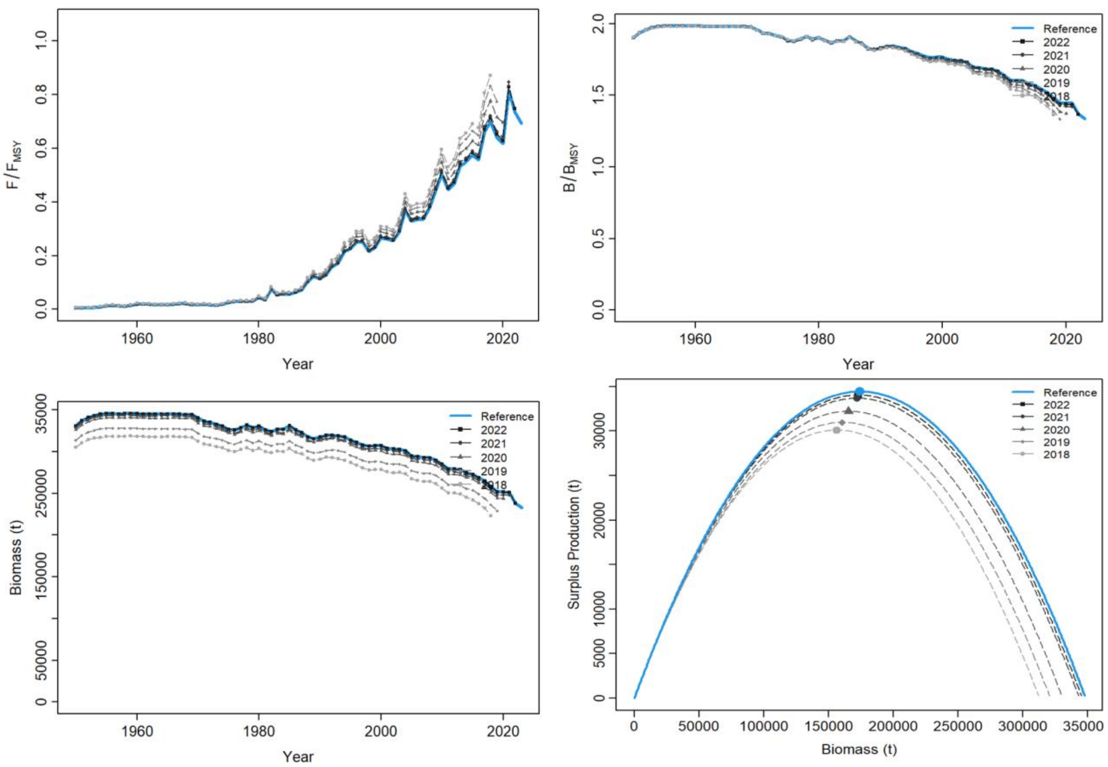

Figure 9. Retrospective analysis of B, B/B_{MSY}, F/F_{MSY} and surplus production for JABBA model of Indian Ocean IP sailfish (S1).

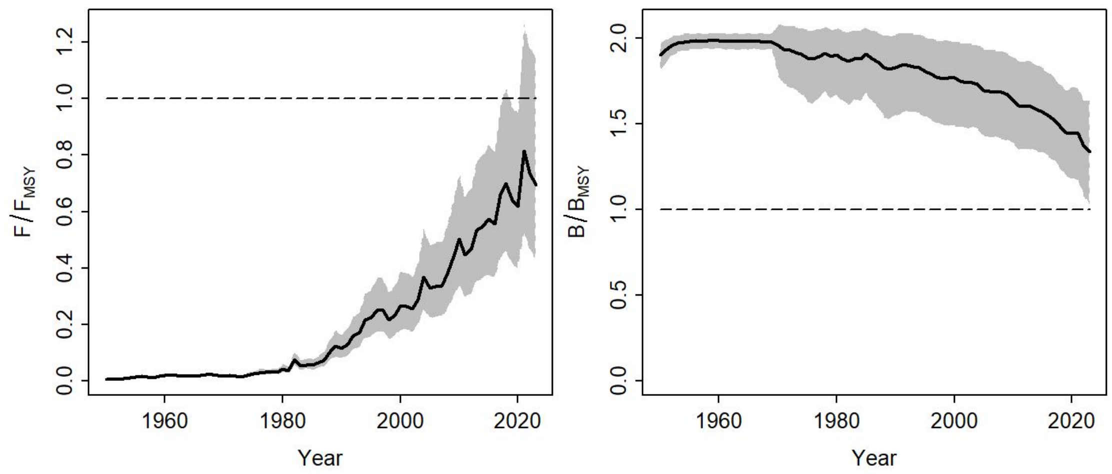

Figure 10. Trends in biomass relative to B_{MSY} (B/B_{MSY}) and fishing mortality relative to F_{MSY} (F/F_{MSY}) for JABBA model of Indian Ocean IP sailfish (S1).

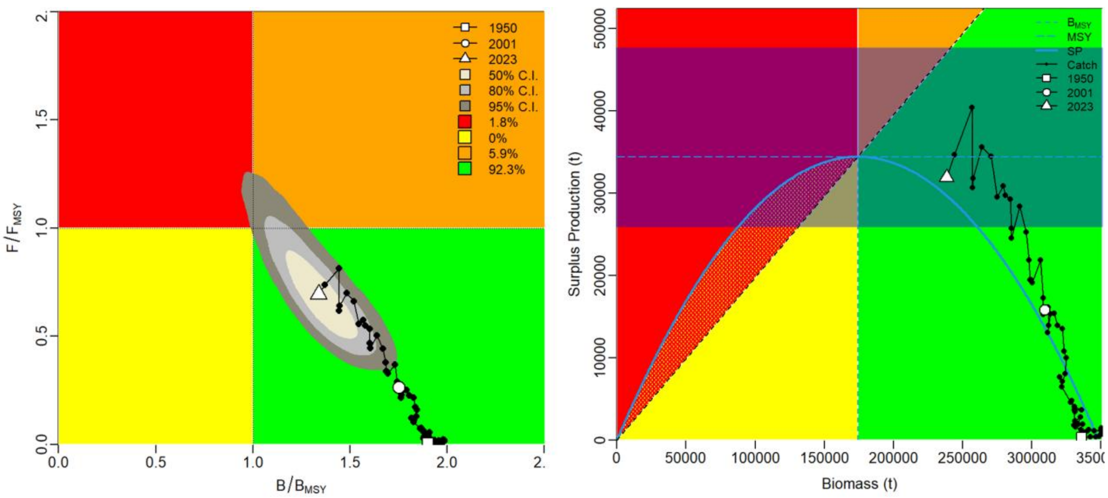

Figure 11. Kobe plot showing estimated trajectories (1950-2023) of B/B_{MSY} and F/F_{MSY} for JABBA model of Indian Ocean IP sailfish (S1). Different grey shaded areas denote the 50%, 80%, and 95% credibility interval for the terminal assessment year. The probability of terminal year points falling within each quadrant is indicated in the figure legend.

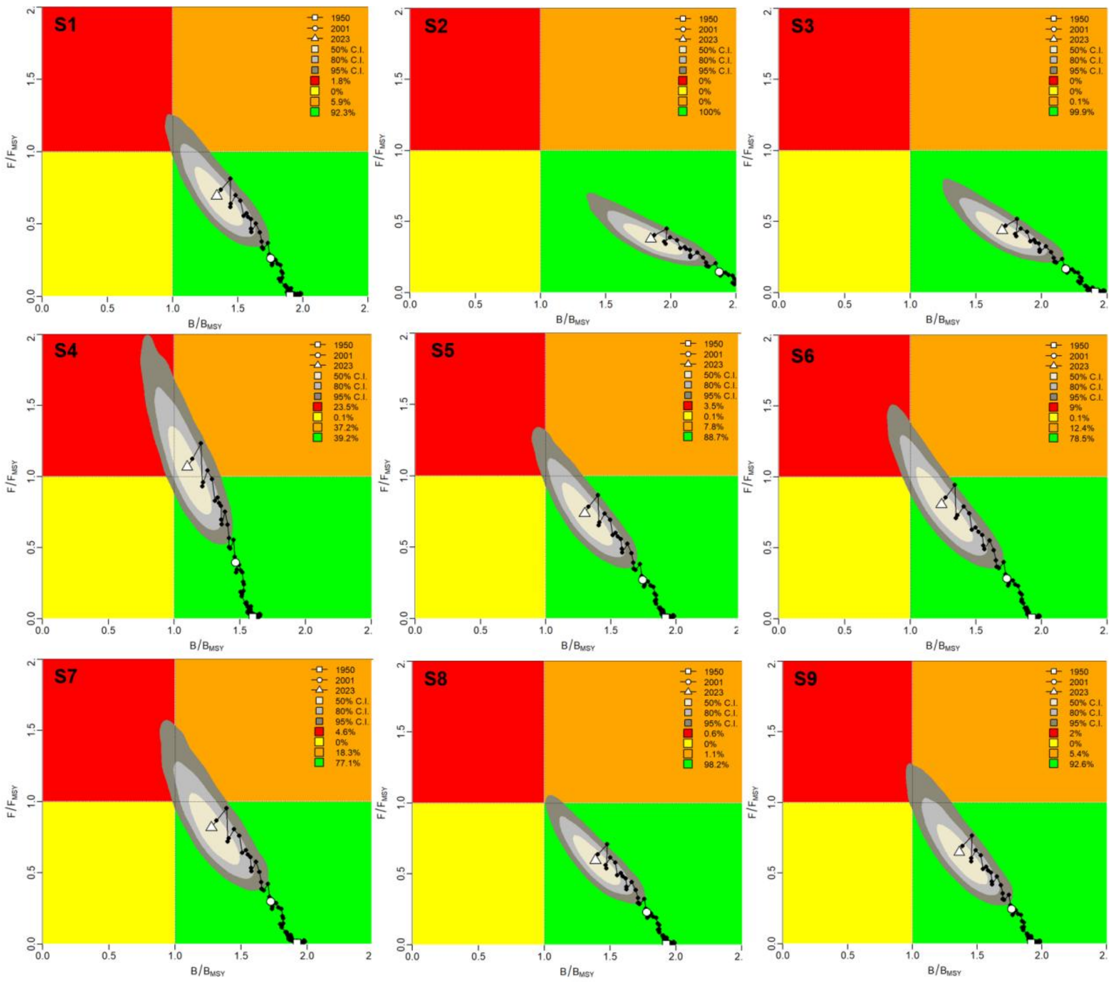

Figure 12. Kobe plots from different scenarios (S1-S9) for JABBA stock assessment of Indian

Ocean IP sailfish.

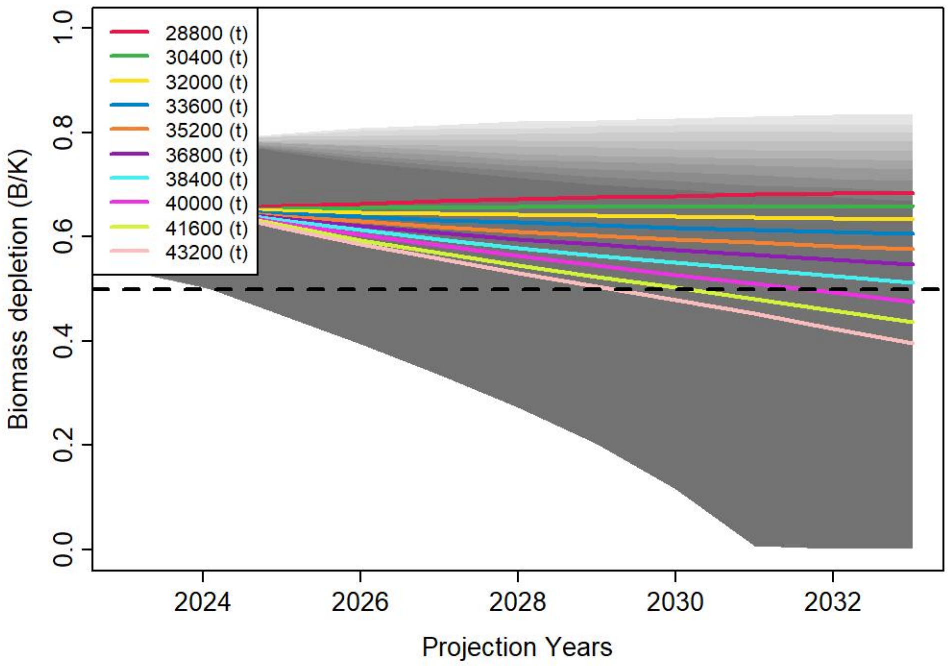

Figure 13. 10-year projections from base model S1 for JABBA model of Indian Ocean IP sailfish.