



An application of the FISHBLICC model to the Indian Ocean skipjack tuna

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Discussions (for information and open discussion):

The paper is to inform meeting members of a length based analysis to support the skipjack tuna stock assessment

Abstract

This paper presents an example analysis of Indian Ocean skipjack tuna (*Katsuwonus pelamis*) length-frequency data using fishblicc, a Bayesian length-based catch curve model. fishblicc can accommodate fisheries with length-frequency data from multiple gears with different selectivities, and offers several alternative model formulations, including flexible selectivity functions that allow for gears targeting different sizes of fish. The model estimates fishing mortality by length bin and gear, as well as the spawning potential ratio (SPR) for the population. Using length-frequency data alone, the four models implemented estimated SPR of approximately 49-71% for 2021-2025. By comparison, the SB/SB0 estimate for 2025 from the full stock assessment ranged from approximately 34% to 71%.

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1. Introduction

FISHBLICC (Bayesian Length Interval Catch Curve Analysis) is a recently developed method for data-limited fisheries stock assessments (Medley 2025; <https://github.com/PaulAHMedley/fishblicc>). Like the LBSPR approach, FISHBLICC utilizes length frequency data from fishery catch samples to estimate key parameters such as fishing mortality and spawning potential ratio (SPR), providing a measure of stock depletion relative to the unfished level (SPR0). However, FISHBLICC provides greater flexibility than LBSPR by accommodating both asymptotic (logistic), dome-shaped selectivity patterns (e.g., double normal selection curves with ascending and descending limbs) which allows for more realistic modeling of fisheries that caught younger, smaller fish, such as the purse seine fishery. The FISHBLICC package further extends selectivity modeling by enabling mixtures of logistic and double normal curves, allowing it to fit complex, multi-modal length frequency distributions. Additionally, FISHBLICC can simultaneously fit length frequency data from multiple fisheries, each with its own selectivity pattern, thereby improving the precision of selectivity and fishing mortality estimates for individual fisheries.

FISHBLICC, like LBSPR, relies on the critical assumption that length frequency data are collected under equilibrium conditions, with no recruitment variability. While life-history parameters (such as the M/K ratio, growth, and maturity) are treated as fixed model inputs, FISHBLICC accounts for uncertainty in fish growth by integrating survivorship over a distribution of L^∞ , assumed to follow a gamma distribution with an estimable coefficient of variation. The model is also implemented using full Bayesian estimation via the RSTAN package, providing robust quantification of parameter uncertainty.

To complement the 2026 skipjack tuna stock assessment (Philips, 2026), FISHBLICC was applied to length-frequency data from the main gear groups, as defined in the Stock Synthesis model. The aim was to examine whether modelling the length data alone can broadly support the stock status estimates from the Stock Synthesis model, which integrates a diverse range of data. The modelling approach in this analysis follows that used in the catch curve analysis of Indian Ocean yellowfin tuna by Medley (2024).

2. Methods

The analysis used the publicly available length-frequency dataset from [IOTC-2026-WPTT28-DATA05](#), which is the same dataset used in the 2026 Stock Synthesis skipjack tuna stock assessment. The data were restricted to the most recent five years and combined across those years. The data were rescaled to by the square root of the sample size to avoid numeric overflow (Medley 2024). The length-frequency data were grouped into seven gear groups: bait boat or pole-and-line (BB), gillnet (GL), line (LI), longline (LL), purse seine free school (PSFS) and purse seine log school (PSLS), the latter consisting mostly of sets on fish aggregating devices (Figure 1-right). It is worth noting that each gear group itself comprises a range of gears or fishing methods with similar characteristics (see Philips, 2026, for the gear group definitions).

For multiple gears, the relative catch in numbers for each gear is required to estimate the relative fishing mortality each gear applies. For IO skipjack tuna, direct estimates of catch weight are available (Figure 1-left), and these have been converted to numbers using the mean weights from the length frequency samples. These gears cover most of the known catch of skipjack in the Indian Ocean.

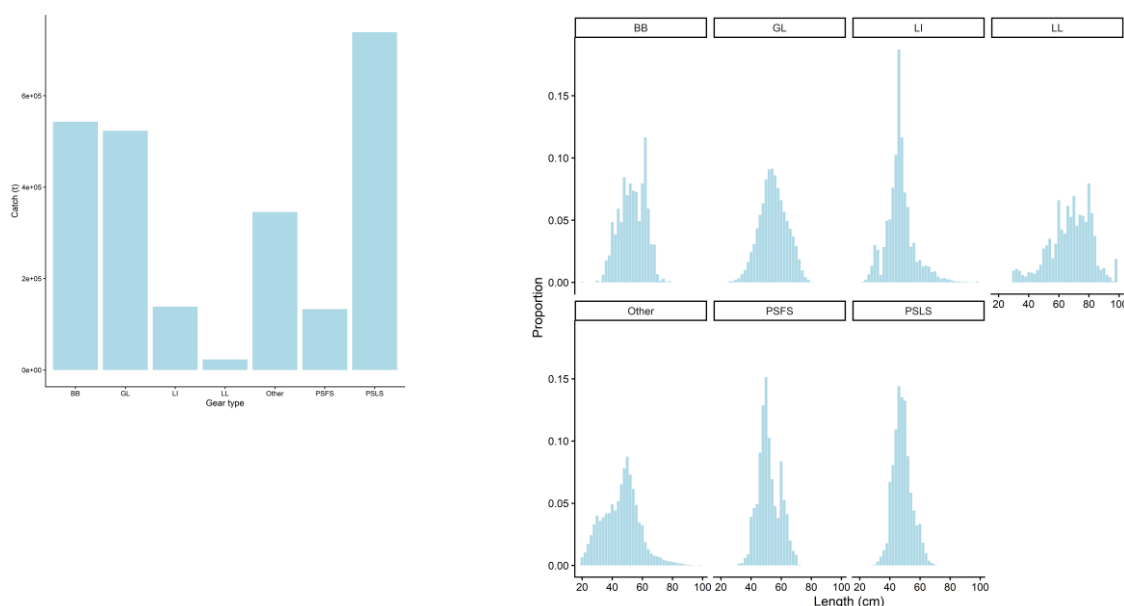


Figure 1: left, total catch weight of skipjack tuna in the Indian Ocean for 2021-2025 by gear type; right, Length frequency data as proportions for each gear.

The following biological parameters (natural mortality, growth, maturity and length-weight relationship) were kept the same as in the Stock Synthesis model:

$$L^{\infty} = 70.35 \text{ cm } (\sigma_{L^{\infty}} = 10)$$

$$M/K = 2.30 \text{ (the ratio of natural mortality } M = 0.8 \text{ to growth rate } K = 0.35)$$

$$L_{50} = 39 \text{ cm (length at 50\% maturity)}$$

$$L_{95} = L_{50} + 10 \text{ cm (length at 95\% maturity)}$$

$$a = 4.97e-006, b = 3.3929 \text{ (length weight relationship)}$$

L^{∞} is an estimable parameter with a lognormal prior, defined by a specified mean and standard deviation. The assumed standard deviation (10) allows the estimate to be strongly influenced by the prior mean while still letting the data inform it. A smaller standard deviation (e.g. < 5) would constrain the parameter so tightly that it effectively acts as a fixed input.

It should be further noted that the stock assessment used the Richards growth model, a generalisation of the standard von Bertalanffy growth model, to allow two-stage growth (juvenile skipjack tuna has been estimated to have faster growth rates). This may explain some of the differences between the full stock assessment and this length-data-only approach.

The following catch curve models were implemented. The models are for illustration only, and the configurations were not exhaustively explored. The main aim was to identify configurations that adequately explain the observations and whether the final estimate of spawning potential ratio (SPR) is sensitive to alternative configurations

- Initial model (M1)

A single selectivity curve separately for each gear, where a double-sided normal is used for all gears except LL for which a logistic curve is used.

- Length-Inverse natural mortality (M2)

A simple length-inverse model was implemented as a sensitivity in which natural mortality is inversely proportional to length: $M_L = \frac{L_1 M_1}{L}$, where L_1 is the reference length and M_1 is the natural mortality at the reference length (set equal to the prior natural mortality). Natural mortality increases below the reference length and decreases above it.

- Independent, mixture selectivity model (M3)

For BB, PSFS and PSLs, selectivity was modelled as a mixture of two normal-like components. The components are independent among the three gear groups, and the weighting of the two components is estimated separately for each gear group.

- Shared, mixture selectivity model (M4)

For BB, PSFS and PSLs, selectivity was modelled as a mixture of two normal-like components. The two components are shared among the three gear groups, and the weighting of the components is estimated separately for each gear group ().

All model configurations are firstly fitted using the Stan optimiser which estimates the maximum posterior density. Then the Markov chain Monte Carlo (MCMC) fit is carried out to obtain the final posterior estimates of parameters.

1. Results

The initial model (M1) estimated some differences in selectivity among gear groups (Figure 2). Asymptotic logistic selectivity was required for the LL gear in order to capture the large fish present in the data. The fits to the length-frequency data were generally reasonable, although some misfits were evident. In particular, the model did not fit the mode of the length distribution for the GI gear well. In addition, the observed length frequencies for some gears (mainly BB and PSFS, and to a lesser extent PSLs) showed multiple distinct modes that were not reproduced by the predictions (see Figure 2). This suggests that selectivity in these fisheries may be more complex than assumed, and warrants investigation of more flexible selectivity forms. The estimated fishing mortality (relative to K) across the gear groups appeared consistent with their relative catch contributions (Figure 3).

Multiple modes in the length-frequency data of a single gear are not unusual and have been observed in many fisheries (Medley 2024). For the BB, PSFS and PSLs gears, the length frequency shows a first peak at around 40 cm, mostly for juveniles and subadults, and a second peak at around 65 cm, for adults. The second peak is very pronounced for BB, weak for PSFS, and minor but still visible for PSLs. The cause of the multimodal distributions in these fisheries is unknown. It could reflect latent selection processes in the gears, whereby fish are caught differently depending on their behaviour or shape (Medley 2024). It could also reflect temporal population processes, such as short-term recruitment variability or long-term migration, which affect the availability of sub-populations. In such cases, a more flexible selectivity function can be obtained by combining (mixing) the basic selectivity functions. Various combinations of shared or independent functions (normal, double-sided normal and logistic) can be tested by trial and error. For these three fisheries, a composite selectivity consisting of two normal components, one for juveniles and one for adults, is a sensible choice to explain the two peaks. Two mixture models were implemented:

- M3: The two components are estimated separately for each of the three gears, assuming that gear selection is completely independent. In total, 10 selectivity functions (20 parameters) are estimated.
- M4: The underlying population processes affecting the availability of each component are assumed to be similar across the three fisheries, so each selectivity component is shared among the three gears, while the

weighting of the two components differs by fishery. In total, 6 selectivity functions (including 2 shared among the three gears) and 12 parameters are estimated.

In both M3 and M4, the selectivity for the GL gear was changed from a double-sided normal to a normal function.

Depending on the assumed selection process, the functional form and relative weighting of the two selectivity components differ between M3 and M4 (Figure 4). Both models substantially improved the fits to the length frequencies, particularly for BB, PSFS and PSLs (illustrated for M4 in Figure 5). Although independent selectivity components among gears are reasonable and justifiable, the data are limited (one length distribution per gear), so there is a risk of overfitting. The shared-selectivity model (M4) is flexible enough to explain the observations while providing a more parsimonious parameterisation.

The results were not particularly sensitive to the alternative natural mortality assumption (length-inverse natural mortality), which produced no obvious improvement or deterioration in the fits.

The final MCMC estimates of SPR for all models are shown in Figure 6, and estimates of key parameters are summarised in Table 1. For M1, the median SPR was approximately 0.59, with an 80% credible interval of 0.43-0.74. The model using length-inverse M estimated a slightly lower SPR (median 0.49), whereas the two mixture-selectivity models estimated higher SPR (median 0.71 for M3 and 0.70 for M4). All models estimated a median L^∞ higher than the prior mean of 0.70, most likely owing to the influence of the large fish caught by the LL fishery. A higher L^∞ is also estimated by the full stock assessment when it is treated as a free parameter rather than fixed.

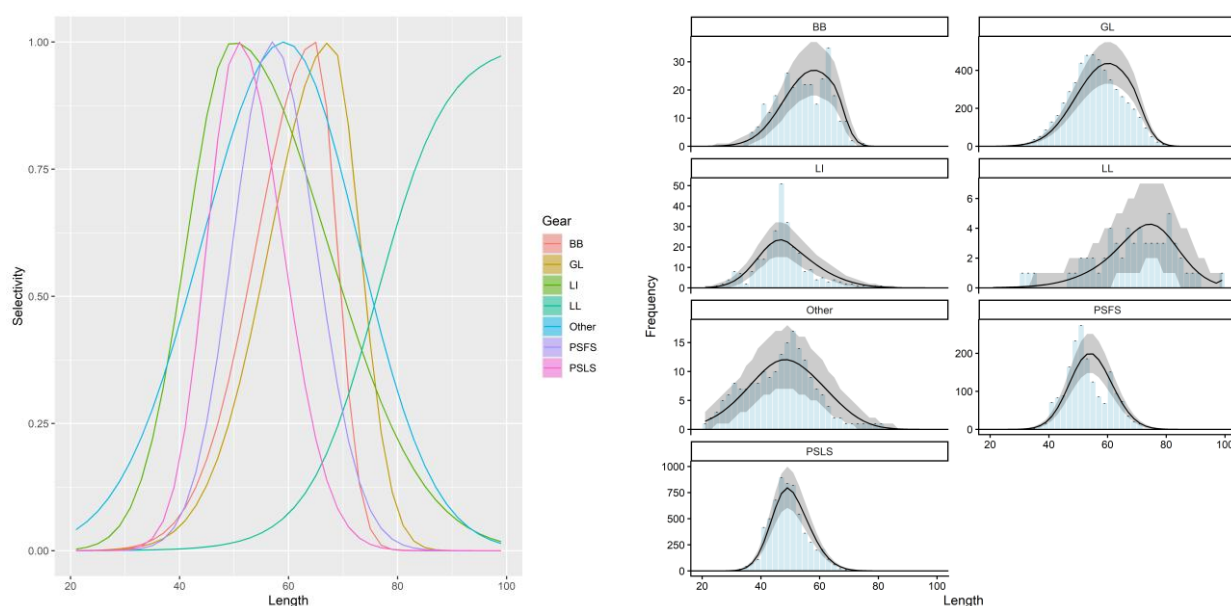


Figure 2: Estimates from the initial model (M1): left, selectivity by gear; right, expected vs observed length frequency.

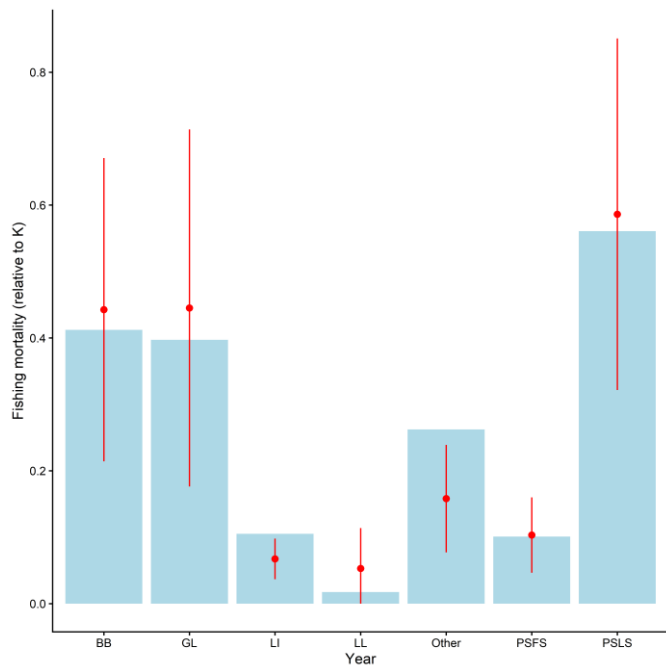


Figure 3: Estimates of fishing mortality F relative to K for each gear, plotted against the catch weight for each gear (normalized to the mean of the fishing mortality for easy comparison) from the initial model (M1) by

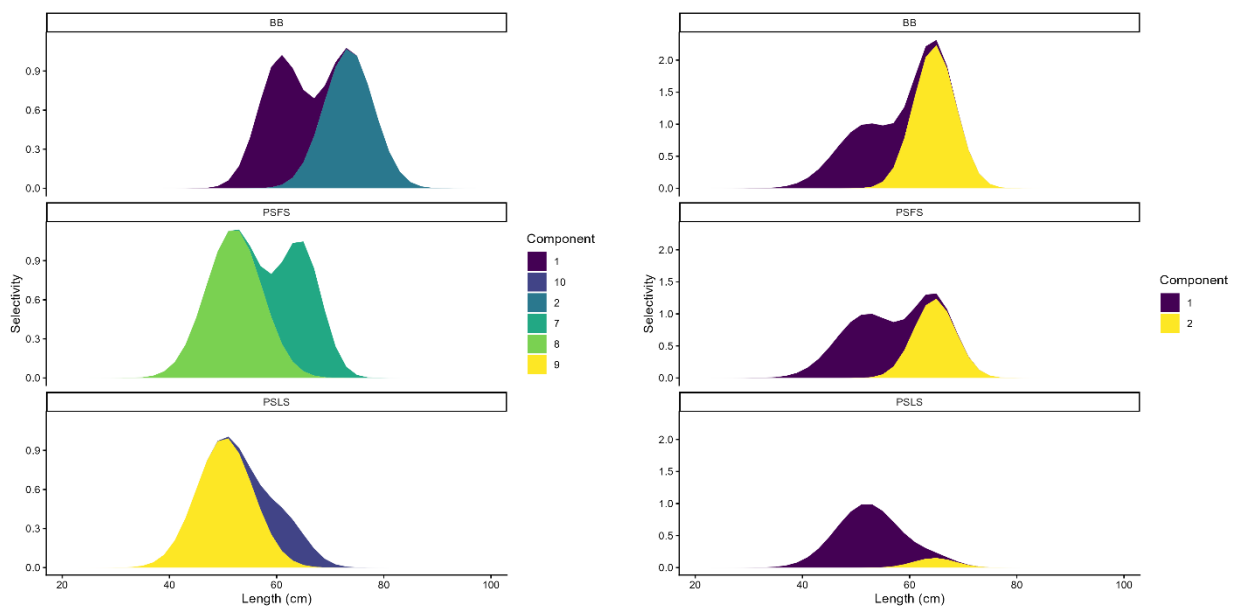


Figure 4: Selectivity mixture components consisting of two normal functions for BB, PSFS, and PSLs: left, for model M2 where all components are estimated independently; right, for model M3 where the each component is shared amongst the three gear groups.

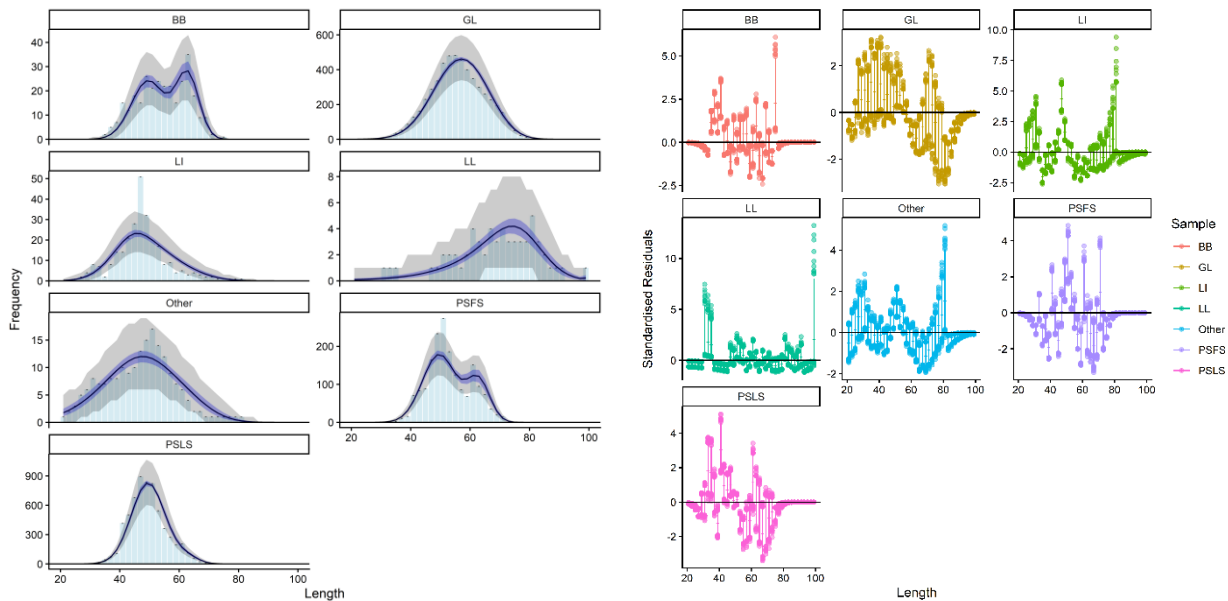


Figure 5: left, Estimated vs observed length frequency from the shared mixture selectivity model (M4); right.

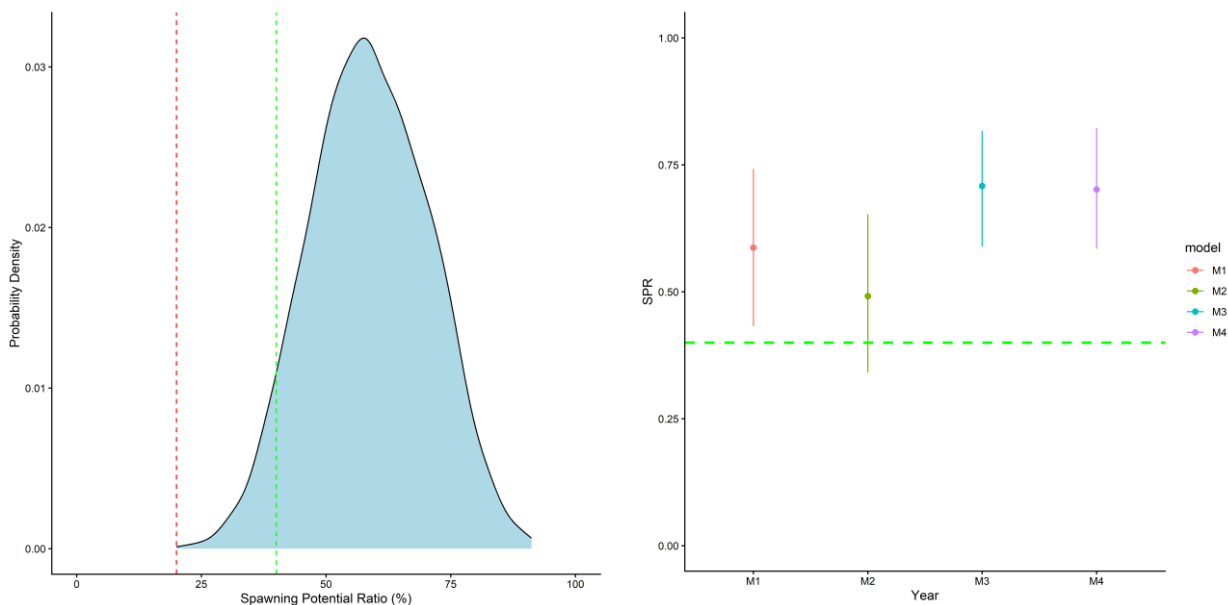


Figure 6: MCMC estimates of Spawning potential ratio (SPR): left, the estimated posterior distribution of SPR for model M1; right, median and 80% credible intervals of SPR for each model.

Table 1: MCMC estimates for the estimated parameters for models M1 – M4. Fk[1-7] are the fishing mortality (relative to K) for gear group BB, GL, LI, LL, Other, PSFS and PSLs respectively. Galpha is the parameter that determines the variability of growth ($CV = 1/Galpha^{1/2}$, i.e., Galpha of 100 corresponds to CV of 10%)

	Parameter	Mean	SD	10%	50%	90%
M1	Linf	84.52	4.86	78.40	84.50	90.99
	Galpha	91.95	25.29	62.23	89.31	124.25
	Mk	2.29	0.23	2.00	2.28	2.60
	Fk[1]	0.45	0.20	0.22	0.42	0.72
	Fk[2]	0.49	0.24	0.22	0.45	0.80
	Fk[3]	0.06	0.03	0.03	0.06	0.10
	Fk[4]	0.16	0.25	0.03	0.10	0.32
	Fk[5]	0.19	0.11	0.08	0.17	0.32
	Fk[6]	0.10	0.05	0.05	0.09	0.16
	Fk[7]	0.53	0.22	0.28	0.51	0.82
	SPR	0.59	0.12	0.43	0.59	0.74
M2	Linf	77.50	3.69	72.89	77.50	82.23
	Galpha	100.58	25.59	70.58	97.73	134.53
	Mk	2.29	0.22	2.01	2.27	2.58
	Fk[1]	0.37	0.16	0.19	0.35	0.59
	Fk[2]	0.38	0.19	0.17	0.35	0.65
	Fk[3]	0.06	0.02	0.03	0.06	0.09
	Fk[4]	0.07	0.19	0.01	0.04	0.13
	Fk[5]	0.14	0.07	0.07	0.13	0.23
	Fk[6]	0.09	0.04	0.04	0.08	0.14
	Fk[7]	0.50	0.18	0.28	0.49	0.73
	SPR	0.49	0.12	0.34	0.48	0.65
M3	Linf	75.61	2.79	72.21	75.51	79.14
	Galpha	112.65	24.77	83.92	109.90	144.54
	Mk	2.26	0.23	1.97	2.24	2.57
	Fk[1]	0.14	0.07	0.06	0.12	0.22
	Fk[2]	0.12	0.05	0.06	0.11	0.18

	Fk[3]	0.03	0.01	0.02	0.03	0.04
	Fk[4]	0.10	0.68	0.01	0.02	0.17
	Fk[5]	0.06	0.02	0.03	0.06	0.09
	Fk[6]	0.03	0.01	0.01	0.03	0.05
	Fk[7]	0.20	0.09	0.07	0.20	0.33
	SPR	0.71	0.09	0.59	0.71	0.82
M4	Linf	76.35	2.85	72.84	76.29	79.88
	Galpha	113.72	24.67	84.66	111.10	146.01
	Mk	2.24	0.23	1.96	2.23	2.54
	Fk[1]	0.09	0.03	0.05	0.08	0.13
	Fk[2]	0.12	0.05	0.06	0.11	0.18
	Fk[3]	0.03	0.01	0.02	0.03	0.04
	Fk[4]	0.07	0.21	0.00	0.02	0.13
	Fk[5]	0.06	0.02	0.03	0.06	0.09
	Fk[6]	0.03	0.01	0.02	0.03	0.04
	Fk[7]	0.26	0.09	0.15	0.26	0.39
	SPR	0.70	0.09	0.58	0.70	0.82

2. DISCUSSIONS

The application of fishblicc to Indian Ocean skipjack tuna estimated a median spawning potential ratio (SPR) of approximately 49-71% for 2021-2025 across the four models implemented. By comparison, the median SB/SB0 estimate for 2025 from the full stock assessment (Philips 2026) was 53% (90% CI: 34-71%) across a grid of 48 models.

This application demonstrated several useful features of fishblicc: the flexibility to adopt a range of selectivity functions (asymptotic or dome-shaped), and the ability to fit length data from multiple gears or fisheries simultaneously. This allows more accurate estimation of fishery-specific selectivity and can reduce bias in SPR estimates.

When mixture selectivity functions are used, the peak of the overall composite selectivity is not constrained and can be greater or less than 1. This does not affect model estimates of reference points such as SPR or yield per recruit (YPR). However, the estimated fishing mortality (expressed relative to K) is not comparable across gear groups, because it is confounded with the selectivity function, a well-known identifiability issue. The F estimates for models M3 and M4 should therefore not be interpreted on their own (Table 1).

fishblicc is not designed to model length frequencies as a time series, with each length-frequency sample assumed to represent an equilibrium condition. The model does not account for the dynamics between sampling periods or the cumulative effects of fishing. In this analysis, samples were therefore aggregated over the most recent five years, and the estimates represent a snapshot of population status under the equilibrium assumption. Short-term population



dynamics, such as variability in recruitment, growth and mortality, may undermine this assumption. This is particularly relevant for a short-lived species like skipjack tuna, which is known for fast dynamics and large interannual recruitment variability, so the equilibrium condition may have been violated. Nevertheless, the skipjack length samples appear reasonably stable over recent years. The model can therefore still provide useful information on the recent population status, provided the length-frequency samples are mainly influenced by fishing.

3. REFERENCES

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