A multi-species ratio approach to estimate eastern little tuna (*Euthynnus affinis*) abundance independent of fishing effort in the Indian Ocean

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Abstract

Catch-per-unit-of-effort (CPUE) as index of abundance can serve as a valuable indicator of trends in stock biomass, particularly for calibrating the stock assessment. However, obtaining a reliable index becomes challenging in fisheries interacted with fish aggregating devices (FADs), as effort is no longer easily defined. FADs are designed to maintain catchability, thereby violating the assumption that CPUE is proportional to stocks size. To address this, a simple alternative approach is proposed that estimates stock abundance using the ratio of catches between target and reference species. The catch-ratio estimator performs well when its assumptions are met, and including multiple reference species can improve estimation accuracy. In this case, yellowfin tuna, particularly when combined with skipjack tuna, appears to be a suitable predictor for eastern little tuna. However, further research is needed before this method can be applied in formal stock assessments.

Keywords: Catch-per-unit-of-effort, data-limited fisheries, purse seine fisheries, stock assessment.

1. Introduction

Indonesia is recognized as a prominent global producer of tuna, accounting for up to 15% of the worldwide tuna catch (Miyake et al., 2010; Sunoko & Huang, 2014). The export volume of tropical, temperate and neritic tuna reached nearly one billion USD in 2022 (Pusat Data, Statistik dan Informasi, 2022), with Japan being the primary destination (Chodrijah et al., 2016). Notably, the Indonesian fleet accounted for about one- third (~210,000 tons) of the total neritic tuna catch in the Indian Ocean (IOTC-WPNT13, 2023). Despite the significance of these tuna species for local industries and household consumption, there is limited knowledge regarding their current dynamics and stock status, particularly at a regional level (Zhou et al., 2019).

Uncertainty in catch and effort data, particularly from small and medium-scale tuna fisheries, poses a significant challenge to fish stock assessment at a regional scale, including Indonesia (Yuniarta et al., 2017). This issue has become a bottleneck in fisheries management within the country. The government's annual historical data has often been criticized by various stakeholders (Duggan & Kochen, 2016; IOTC-WPDCS14, 2018) due to its inconsistency and uncertainty. Many organizations, including NGOs, have been collecting similar data, driven by a lack of trust in the validity of existing data. However, most of these alternative data sources have not been considered when estimating national catch statistics. While some of these data sources could potentially be valuable for determining fish abundance from time series of catch and effort, further investigation is required, particularly when dealing with species like the neritic tuna group (Novianto et al., 2019).

Fish aggregating devices (FADs) are floating objects utilized by fishermen to attract and capture pelagic fish, including tunas, thereby increasing their fishing yield (Moreno et al., 2016). FADs come in two types: drifting FADs (DFAD), primarily utilized by European fleets in the western region of the Indian Ocean, and anchored FADs (hereafter: AFADs), which are equipped with attractors (such as coconut leaves) and secured to the sea floor with concrete blocks. Coastal countries in the eastern part of the Indian Ocean, notably Indonesia, extensively employ AFADs. In most cases, AFADs are used by surface fisheries, for which selectivity bias means that catch-per-unit-of-effort (CPUE) is not proportional to abundance (Bannerot & Austin, 1983). However, changes in catch-rates do not always accurately reflect true changes in the fisheries resource (Walters, 2003), and may therefore lead to poor fishery management (Quirijns et al., 2008). Most fisheries scientists have tried to overcome the issue by removing the impact on catch rates of factors other than abundance and adjusting for changes over time in the composition of effort. This process is referred to as CPUE standardization.

Several approaches have been proposed to standardize the CPUE from FADs associated purse seine fleet, such as: the use of the Associative Behaviour-Based abundance Index (ABBI) (Baidai et al., 2024) as an alternative to conventional indices, applying spatio-temporal analysis (Akia et al., 2022; Kaplan et al., 2024), and inclusion of drifting Fish Aggregating Devices (dFAD) density as a predictor (Akia et al., 2022; Kaplan et al., 2023). However, such methods can only be applied in data-rich environments where all essential data, such as echosounder readings and drifting Fish Aggregating Device (dFAD) positions, are systematically recorded and maintained. In contrast, many coastal nations lack this level of data availability. One way to address this issue is using Robin Hood approach (Punt et al., 2011), by borrowing information from data-rich species assessments.

This paper develops and tests a simple multispecies catch-ratio approach that uses historical catch data to infer a time series of relative abundance (the fraction of target stock abundance relative to reference abundance) for a data-poor species, given stock assessments from multiple data-rich reference species. We extend the single-reference species approach originally proposed by Maunder & Hoyle (Maunder & Hoyle, 2007) to a multiple-reference species framework. To evaluate its performance, we test both approaches on high-quality and limited-quality data. We then estimate the relative abundance of eastern little tuna (Euthynnus affinis) in the Indian Ocean based on purse-seine catch ratios. For reference abundance indices, we use the most reliable estimators derived from data-rich stock assessments of bigeye tuna (Thunnus obesus), yellowfin tuna (Thunnus albacares), and skipjack tuna (Katsuwonus pelamis).

2. Materials and Methods

2.1. Catch data

For reproducibility, we used purse seine catch data obtained from the Indian Ocean Tuna Commission (IOTC). Two types of data were analysed in this study. The first dataset comprises georeferenced monthly catch data from the European Union (EU) purse seine fleet (Spanish, French, and Mayotte) from 1991 to 2020, representing high-quality data. The second dataset consists of Indonesia's best scientific estimate of yearly historical purse seine catch from 1991 to 2020, representing a data-limited scenario. Both datasets are publicly available on the IOTC website (https://iotc.org/data/browser) under the "CE-CA" and "NC-SCI" sections, respectively.

2.2. Relative abundance references

All reference relative abundances (IOTC-WPTT24, 2022; IOTC-WPTT25, 2023; IOTC-WPTT26, 2024) (henceforth referred as reference abundance) were obtained from recent data-rich stock assessments using the Stock Synthesis model (Fu, 2023; Fu et al., 2022; Urtizberea et al., 2024) for three main tropical tuna species, namely skipjack tuna (SKJ) (Kaplan et al., 2023), bigeye tuna (BET) (Akia et al., 2022), and yellowfin tuna (YFT) (Kaplan et al., 2024) from purse seine associated fleets (Table 1). It is assumed that all standardised CPUEs are proportional to the true abundance of each species, since the effects of floating object densities, spatio-temporal diversities, and all other fishing powers were considered. All reference abundance data were provided in a quarterly format. Therefore, to align with the

Indonesian historical catch data, which were originally in an annual format, we calculated means for each year.

Table 1. List of reference relative abundance indices derived from IOTC data-rich assessments.

Species	Time range	Source	Remarks
Bigeye tuna (BET)	2010-2020	(Akia et al., 2022)	Under floating objects, with emphasis on small bigeye tuna (<10 kg). Used as a sensitivity analysis in the stock assessment.
Yellowfin tuna (YFT)	1991-2020	(Kaplan et al., 2024)	Un-associated floating objects / free schooling, mostly large yellowfin tuna above 10 kg. Used as a sensitivity analysis in the stock assessment.
Skipjack tuna (SKJ)	1991-2020	(Kaplan et al., 2023)	All sizes under floating objects and used in the stock assessment model ensemble.

2.3. Assumption

Let $\mathbf{x} = (x_1, x_2, \ldots, x_n)$ be the catches of n species, and $\mathbf{y} = (y_1, y_2, \ldots, y_n)$ be the abundance. Assume that for each pair of species i, j, the ratio of catches is proportional to the ratio of abundance:

$$\frac{x_i}{x_j} = c_{ij}\frac{y_i}{y_j},$$

for some positive c_{ij}. Suppose that we have assessments of $y_2, y_3, \ldots, y_n$ and want to estimate y_1. Maunder & Hoyle (Maunder & Hoyle, 2007) suggest using a single reference abundance y_2 and

$$y_1 = \frac{1}{c_{12}}\frac{x_1}{x_2}y_2\,. \tag{1}$$

The constant c_{12} is not generally known, so we have an estimate of y_1 up to a multiplicative constant.

2.4. Multiple-species approach

We can extend Equation 1 to a multiple-species approach, as at least three reference relative abundance indices derived from data-rich assessments are available from purse seine fisheries within the Indian Ocean Tuna Commission (IOTC) area of competence (Table 1). Therefore,

$$\log y_1 = -\log c_{12} + \log x_1 - \log x_2 + \log y_2,$$
$$\log y_1 = -\log c_{13} + \log x_1 - \log x_3 + \log y_3,$$
$$\vdots$$
$$\log y_1 = -\log c_{1n} + \log x_1 - \log x_n + \log y_n\,. \tag{2}$$

Adding the rows of Equation 2, and dividing by $n-1$, we obtain the estimator

$$\widehat{\log y_1} = -\frac{1}{n-1}\sum_{\mathrm{i=2}}^{\mathrm{n}} \log c_{1i} + \log x_1 - \frac{1}{\mathrm{n}-1}\sum_{\mathrm{i=2}}^{\mathrm{n}} \log x_i + \frac{1}{\mathrm{n}-1}\sum_{\mathrm{i=2}}^{\mathrm{n}} \log y_i\,. \tag{3}$$

Then exponentiating,

$$\widehat{y_1} = Cx_1\frac{\mathrm{gm}(y_2, y_3, \dots, y_n)}{\mathrm{gm}(x_2, x_3, \dots, x_n)},$$

where gm() denotes the geometric mean, and C is an unknown constant.

2.5. Testing and application to real world datasets

Prior to applying the method, we need to investigate the robustness of the Maunder & Hoyle method (Maunder & Hoyle, 2007) and functions as expected to the real world data. To do so, we tested Equation 1 (single species approach) and Equation 3 (multiple species approach) under high quality and limited quality data. The best model is when the slope of log-log regression between estimated and reference value is equal to 1 with low standard deviation. We selected the best estimators from the models to estimate the relative abundance of eastern little tuna (E. affinis) using Indonesian historical purse seine catch data from 1991 to 2020.

3. Results

3.1. Testing and model performances

The predictive performance of both single-species and multi-species approaches was generally satisfactory when model assumptions were met. Although predicted abundance estimates exhibited consistent positive associations with reference abundance values across all three tuna species, this did not directly translate into high predictive accuracy. In both cases (i.e., high quality and limited quality data), the abundance of yellowfin tuna proved difficult to predict using bigeye or skipjack as sole or combined predictors (**Figure 1**). Similarly, bigeye and skipjack were not reliable predictors of each other, with log–log regression coefficients way below or above 1 (

Table *2*), indicating weak predictive relationships. In contrast, yellowfin tuna performed notably better as a predictor species. When used alone or in combination with skipjack, yellowfin yielded stronger predictions for both bigeye and skipjack abundance, with log–log regression coefficients ranging from 0.82 to 1.38 (

Table *2*).

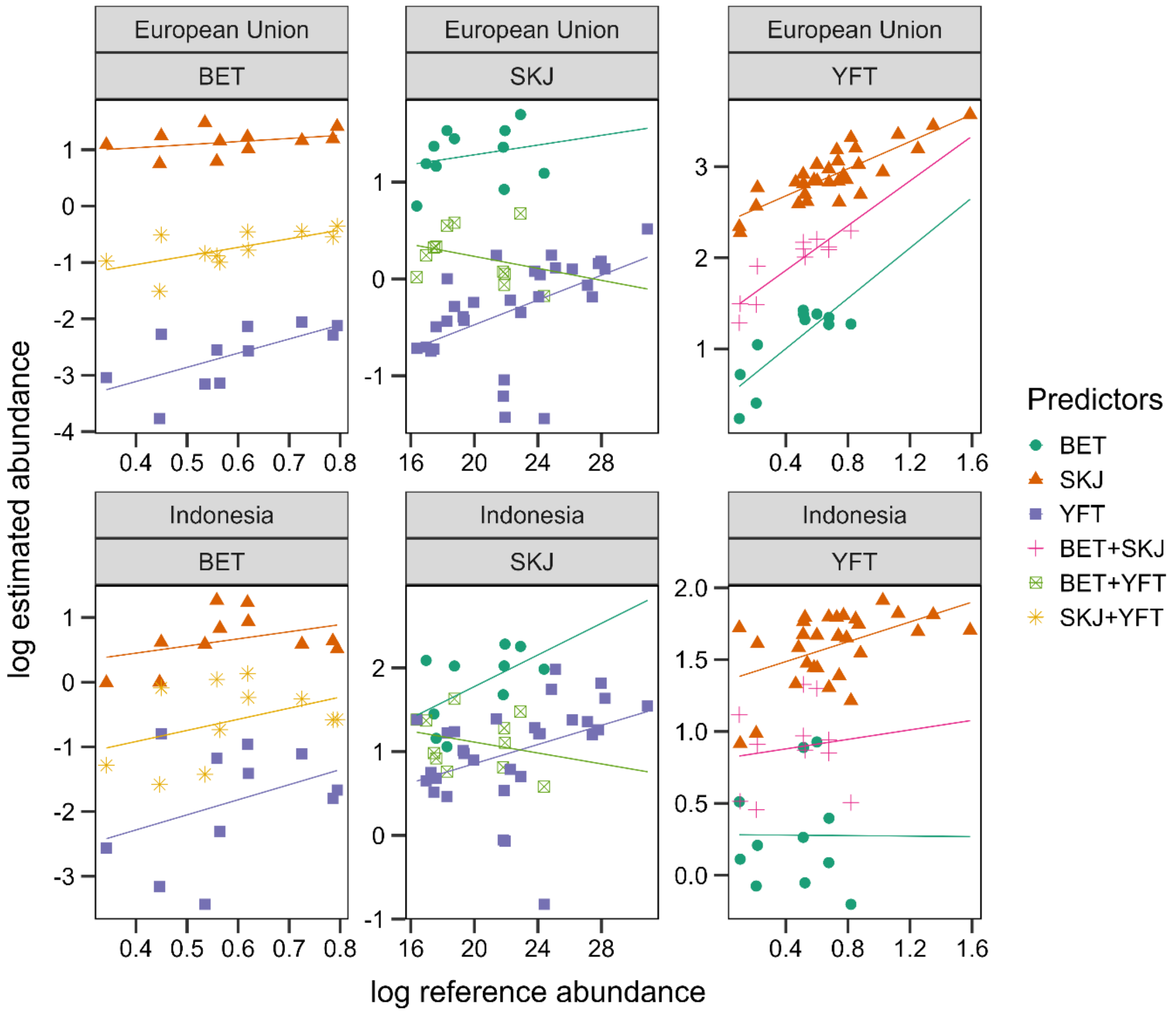

Figure 1. Comparison between target and reference abundance for bigeye (BET), skipjack (SKJ), and yellowfin (YFT) tuna using single-species and multi-species predictors on European Union (upper panel) and Indonesian (lower panel) purse seine fishery. Each panel

represents estimated abundance (y-axis) versus reference abundance (x-axis) for one focal species. Coloured symbols and lines denote the predictor combinations, whereas orange triangles represent combined species predictors.

Table 2. Model performances of log-log regression between estimated and reference abundance values on European Union and Indonesia data. Numbers in bold indicate strong predictive relationship (i.e., regression coefficients closer to 1).

Target	Predictor	European Union		Indonesia	
		Estimate	Std. Error	Estimate	Std. Error
Bigeye	Skipjack	0.29	0.27	0.75	0.47
Bigeye	**Yellowfin**	**1.35**	**0.34**	**1.34**	**1.07**
Skipjack	Bigeye	0.55	0.66	1.89	0.84
Skipjack	**Yellowfin**	**1.38**	**0.46**	**1.20**	**0.59**
Yellowfin	Bigeye	0.49	0.09	0.02	0.16
Yellowfin	Skipjack	0.37	0.05	0.19	0.06
Bigeye	**Skipjack & Yellowfin**	**0.82**	**0.34**	**1.04**	**0.69**
Skipjack	Bigeye & Yellowfin	-0.58	0.65	-0.63	0.77
Yellowfin	Bigeye & Skipjack	0.42	0.05	0.08	0.13

3.2. Model selection and its application on eastern little tuna (*E. affinis*)

The estimated abundance trends of eastern little tuna (*E. affinis*) from 1990 to 2020 based on different predictors were relatively consistent across models. However, starting from 2011, the predicted trends began to diverge. Models using yellowfin tuna alone, and in combination with skipjack and bigeye tuna, showed similar trends. Predictions based on bigeye tuna alone diverged from the others toward the end of the time series. Predictions using skipjack tuna remained relatively flat with low contrast throughout the period. Overall, the findings underscore the robustness of yellowfin-based predictors, particularly in combination, while highlighting limitations in using skipjack or bigeye tuna alone in recent years.

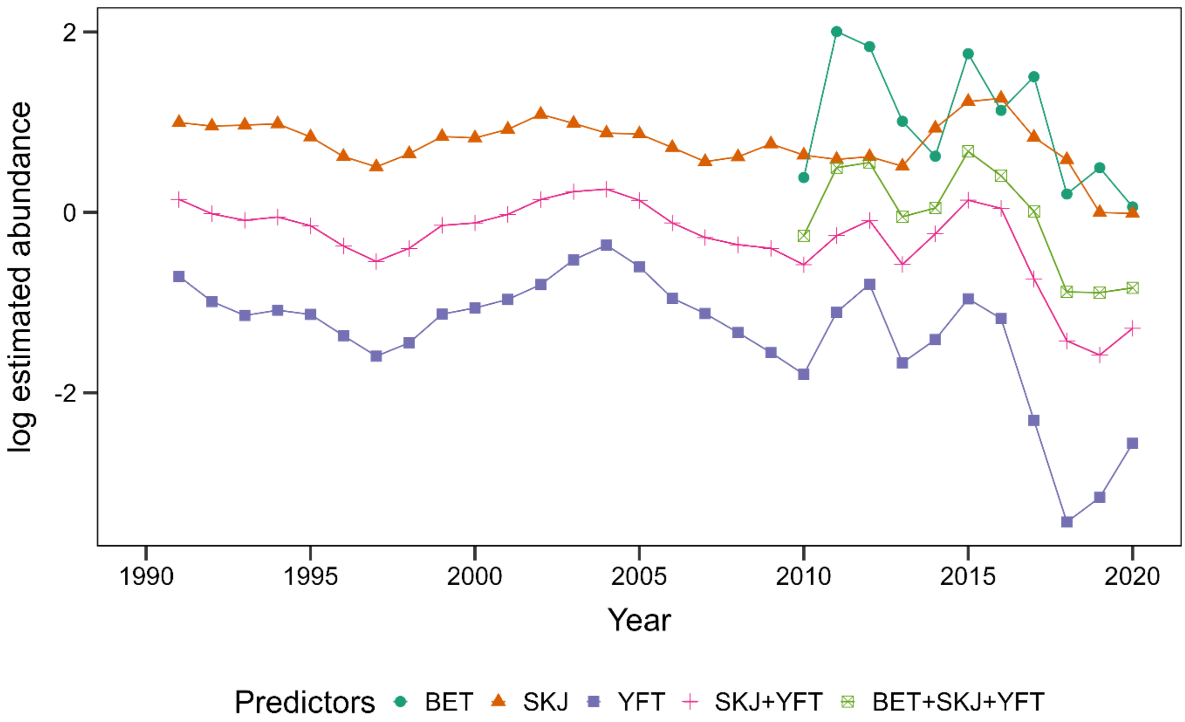

Figure 2. Application of single-species and multiple-species approaches to eastern little tuna (*E. affinis*) from western and southern parts of Indonesian water.

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