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**Precision and accuracy in estimating biological reference points using length-based fisheries assessment: a bootstrapping approach**

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**Abstract:** Stock assessment is essential for sustainable fisheries management. Biological reference points (BRPs) such as $F_{0.1}$, $F_{\max}$, and $F_{0.5}$ are essential to fisheries management and are estimated from fisheries and biological data. However, research on the precision and accuracy of these estimates remains limited. This study evaluates the precision and accuracy of the BRPs, which are estimated from ELEFAN (Electronic LEngth Frequency ANalysis) and applied to real data using a bootstrapping approach. Additionally, we examined the minimum quantity of data and survey frequency needed. Reliable estimates require either sequentially sampling for more than 12 months or sampling every 2 months across two years, with both strategies requiring 7,000 to 8,000 data points. This research helps to optimize the length-based survey design. Accurate sampling is essential for generating reliable data that informs management decisions and ensures sustainable fishery practices.

**Keywords:** BRPs, ELEFAN, bootstrapping, survey design, length-based method

## Introduction

Accurate estimations of fishery productivity are essential for effective fishery management and, ultimately, for achieving sustainable fisheries. When sufficient data on fisheries are available, managers can conduct precise stock assessments, which allows for scientific control of fisheries (Gabriel and Mace 1999). However, data availability is limited for over 60% of global fishery resources (Costello et al. 2012; Dowling et al. 2018). This challenge is particularly acute in Southeast Asia, where the rapid development of capture fisheries underscores the urgent need for systematic fishery management practices (Matsuishi 2025).

The length-based approach, which focuses on the length distribution of fish within a population, is a widely utilized method in data-limited stock assessments (Pauly 1984; Gulland 1983). This method is especially beneficial for species in tropical areas, where obtaining age data can be difficult (Medeiros-Leal et al. 2023). It provides an index of fishing mortality, known as biological reference points (BRPs), which can be used alongside current fishing mortality data. By comparing current fishing mortality with BRPs, researchers can assess the sustainability of fishery stock and make necessary adjustments to management strategies (Sparre and Venema 1998).

The Thompson and Bell (TB) yield-per-recruit (YPR) model, established by Thompson and Bell (1934), is widely utilized for BRPs in data-limited scenarios. As a specific instance of the TB model, the Beverton and Holt (1957) YPR model ensures that any overarching conclusions are also applicable to the broader Thompson and Bell framework (Sparre and Venema 1998). The TB model assesses stock status and selectivity by utilizing length composition data (Frédou et al. 2009).

The TB model provides biological reference points (BRPs) of fishing mortality, such as $F_{\max}$, $F_{0.1}$ and $F_{0.5}$. $F_{\max}$ is the fully recruited fishing mortality that produces the maximum yield per recruit (Chen et al. 2007). $F_{0.1}$ is a precautionary proxy of $F_{\max}$, which is the fishing mortality rate corresponding to 10% of the slope of the yield-per-recruit curve at the origin (Gulland and Boerema 1973). $F_{0.5}$ is the fishing mortality at which stock attains 50% of the maximum spawning potential that is achieved under conditions of no fishing mortality (Gabriel and Mace 1999).

Beyond its application in fisheries management, the performance of the TB model has been evaluated by Chong et al. 2020, who compared it with other models such as the Length-based Spawning Potential Ratio (Hordyk et al. 2015), Length-based Integrated Mixed Effects

(Rudd and Thorson 2018), and Length-based Risk Analysis (Ault et al. 1998, Ault et al. 2008, Ault et al. 2009) under varying life history, exploitation status, and recruitment errors. However, Chong et al. (2020) did not focus on assessing the precision and robustness of the TB model in terms of different data quantities.

In a related study, Taufani and Matsuishi (2024) explored the accuracy and precision of estimating growth curve parameters using a length-based model with bootstrapping. This research highlights the role of data volume in estimating BRPs to refine predictions from length-based models. It also underscores the importance of sufficient data to ensure reliable fisheries assessments and effective management decisions. BRPs are calculated based on growth curve parameters. However, because the estimation errors of these parameters are not independent, a large error in individual growth curve parameters does not necessarily indicate a large error in BRPs. Therefore, the accuracy and precision of BRPs should be assessed separately.

A bootstrapping approach—an advanced statistical method that involves repeatedly resampling the data to create numerous simulated samples—allows researchers to estimate sample precision (Efron 1979). This method provides several advantages, including the ability to estimate the variability and confidence intervals of model parameters without making strong parametric assumptions. Bootstrapping is particularly useful for complex models where traditional analytical methods are challenging to apply (Davison et al. 1986; Elvarsson et al. 2014). The bootstrapping approach has been widely used in length-based methods (e.g., Elvarsson et al. 2014; Schwamborn et al. 2019; Wang et al. 2020; Schwamborn et al. 2023; Taufani and Matsuishi 2024).

ELEFAN (Electronic LEngth Frequency ANalysis) estimation relies heavily on the quality and quantity of input data, as noted in studies that emphasize the importance of comprehensive sampling for accurate stock assessment (Maunder and Piner 2015; Katsanevakis et al. 2016). It is essential to understand how variation in data quantity, including the number of months and the amount of data per month, affects precision. This study goes beyond previous research by incorporating bootstrapping simulation to evaluate how these variations affect the stability of ELEFAN estimation.

Applying models to real data provides valuable insight into the practical effects of data limitations (Hilborn and Walters 1992; Walters and Martell 2004; Cadrin and Dickey-Collas 2015; Gebremedhin et al. 2021). By emphasizing the role of data quantity and leveraging the bootstrapping approach, this paper makes an important contribution to length-based stock

assessments, particularly in real-world applications, and offers a more refined precision evaluation of the TB model.

Yellowfin tuna was chosen as the study species because it has significant economic value and is widely distributed in commercial fisheries. This species plays a crucial role in marine ecosystems as a top predator and is in high-demand markets (Mariani et al. 2017; Hare et al. 2020). The management of yellowfin tuna is supported by several international and regional organizations, such as the Western and Central Pacific Fisheries Commission and the International Commission for the Conservation of Atlantic Tuna, which facilitate the collecting and sharing of data (Barclay and Cartright 2007; Sunoko and Huang 2014; Heidrich et al. 2022).

The objective of this study was to evaluate the accuracy and precision of the BPRs ($F_{0.1}$, $F_{\max}$, and $F_{0.5}$) estimated by ELEFAN under varying data quantities, including the number of months and amount of data per month, using a bootstrapping process. This research is crucial because it provides a recommended survey design for enhancing the understanding of fisheries assessment models, which will contribute to better management and conservation.

## Materials and methods

### Overview of ELEFAN and its practical context

The ELEFAN method (Pauly and David 1981) was used to estimate fish growth parameters from length-frequency data. This method is suitable for data-limited fisheries as it does not require age data. ELEFAN detects cohort progression in monthly size distributions to estimate the von Bertalanffy growth parameters $L_\infty$ and $K$. In this study, we used the implementation available in the TropFishR package (Mildenberger et al. 2017), which has been applied in various tropical fisheries. Given that ELEFAN performance can be influenced by data structure and sampling design, we applied a bootstrapping procedure to quantify the variability and precision of growth parameter estimates. We assumed that the samples came from a single stock, which is a common practice in length-based analyses when there is no evidence of separate stocks in the study area (Sparre and Venema 1998; Pauly and Morgan 1987).

### Data sources

Bootstrapping simulations were conducted for 14,190 yellowfin tuna length data points collected over 24 months (Table 1) from longline-caught tuna landed at Benoa Port, Bali, in Fisheries Management Area (FMA) 573, located in the Indian Ocean. The data were obtained from all tuna landings, regardless of vessel size or number. Fork length (FL) was measured by

trained personnel using a standard measuring board (Itano 2004). The data range spans 82 to 187 cm FL. Monthly data quantities vary, ranging from 211 to 1,473 observations per month, with an average of 591 observations per month. The frequency distribution of data for each month is depicted in Fig. 1.

**Procedures for preparing and generating experimental data**

This research began with a data-cleaning process to ensure accuracy and eliminate anomalies. The initial datasets comprised 14,235 length and weight values for yellowfin tuna. Upon analyzing the length-weight relationship, several measurements were found to deviate unrealistically from the expected trend. To improve the quality of the datasets, these outliers were removed. After excluding 45 outliers, a total of 14,190 (full dataset) data points remained for further analysis.

To evaluate the robustness of growth parameter estimates, a resampling procedure using 1000 bootstrap iterations was applied to the full dataset (24 months). Each iteration generated a pseudo-sample by drawing observations with replacement. The growth parameters—asymptotic length ($L_\infty$), and growth coefficient ($K$)—were then estimated from each pseudo-sample using the ELEFAN method.

To assess sensitivity under data-limited conditions, the pseudo-samples were further subjected to systematic data reduction through two steps: (1) temporal reduction, and (2) monthly sample size reduction. For temporal reduction, two sampling strategies were applied: Sequential sampling used continuous months starting from the first month (e.g., 6 months = months 1–6). Interval sampling selected evenly spaced months across the 24 months (e.g., every 2 months = months 2, 4, 6, 8, 10, 12 in the first and second year). See Table 1 for an overview and Online Resource, Table S1 for details.

Each of these reduced-time scenarios was further modified by randomly reducing the number of observations in each selected month to 100%, 75%, 50%, 25%, or 10%, simulating varying levels of data availability.

From each modified pseudo-sample, the ELEFAN method was used to estimate $L_\infty$ and $K$ to compute BRPs. Consequently, the resulting values were treated as random variables arising from the resampling process.

The precision of estimates was quantified using the coefficient of variation (CV), while bias was assessed using percent bias compared to the baseline estimates from the full dataset.

This design allowed for a comprehensive evaluation of how sampling strategy and data availability influence the reliability of growth parameters and BRP estimates.

All procedures were conducted using R packages, including "boot" (Davidson and Hinkley 1997; Canty and Ripley 2024), "dplyr" (Wickham et al. 2023), and "infer" (Couch et al. 2021).

**Growth parameter estimation**

The von Bertalanffy's growth model was used (von Bertalanffy 1938):

$$L_t = L_\infty \left(1 - e^{-K(t - t_0)}\right)$$

The von Bertalanffy's growth model parameters were estimated using the ELEFAN_SA functions within TropFishR (Mildenberger et al. 2017). Implementation of ELEFAN_SA utilized the GenSA package (Schwamborn et al. 2019) to optimize parameters globally (Xiang et al. 2013). The parameters, $L_\infty$ and $K$, were explored within ranges of 120–250 and 0.01–1.5, respectively, with initial values set at $L_\infty$= 185 and $K$ = 0.7. The growth performance index ($\Phi'$; Pauly and Munro 1984) was utilized to synthesize information from $L_\infty$ and $K$, per the formula:

$$\Phi' = Log_{10} K + 2\,\mathrm{Log}_{10} L_\infty$$

**Screening test of the estimated growth parameters**

To estimate the value of $t_0$, the empirical formula proposed by Pauly (1979) was applied:

$$\mathrm{Log}_{10}(-t_0) = -0.3922 - 0.2752\,\mathrm{Log}_{10} L_\infty - 1.038\,\mathrm{Log}_{10} K$$

Under the assumption that fish length follows the growth curve, $t_0$ represents the time from embryonic development to hatching, which generally takes several months to less than one year. Estimated $t_0$ values below $-1.00$ suggested potential misestimations in $L_\infty$and $K$.

The estimated growth parameters were filtered by omitting results with $t_0 < -1.00$. Taufani and Matsuishi (2024) have validated this approach.

**Estimation of mortality**

Natural mortality ($M$) was estimated using Tanaka's (1960) method:

$$M = \frac{2.5}{t_{\max}}$$

Estimating total mortality ($Z$) using the Beverton and Holt (1957) method involves developing a simple catch-curve-based mortality estimator with length-frequency data and von Bertalanffy parameters.

$$Z = K\frac{L_\infty - \bar{L}}{\bar{L} - L_c}$$

After obtaining the values of $M$ and $Z$, fishing mortality ($F$) is calculated using the formula:

$$F = Z - M$$

**Estimation of yield-per-recruit and spawning-stock-biomass-per-recruit**

The yield per recruit (YPR) was calculated as a function of fishing mortality (Beverton and Holt 1957)

$$Y/R = F\exp[-M(t_c - t_r)]\, W_\infty \left[\frac{1}{Z} - \frac{3S}{Z+K} + \frac{3S^2}{Z+2K} - \frac{S^3}{Z+3K}\right]$$

$$S = \exp\{-K(t_c - t_0)\}$$

The analysis of spawning stock biomass per recruit ($B/R$) was performed using the following equation:

$$B/R = \frac{Y}{R} \times \frac{1}{F}$$

**Estimation of biological reference points**

Biological reference points for YPR included $F_{0.1}$ and $F_{\max}$ (Chen et al. 2007). $F_{\max}$ represents the fishing mortality ($F$) maximizing yield at a specified age at first capture, assuming constant recruitment. $F_{0.1}$ serves as a precautionary BRP for $F$, where the slope of the YPR curve is 10% of the slope at the origin (Goodyear 1993; Zhou et al. 2020). $F_{0.1}$ is a target BRP and recommends an upper limit for fishing mortality considering estimation uncertainties, while $F_{\max}$ is a limit BRP, representing the upper limit without such considerations.

For spawning stock biomass per recruit ($B/R$), BRPs were provided as 0.5, indicating the fishing mortality that reduces spawning stock biomass per recruit to 50% of its unfished level (Goodyear 1993). The concept of $F_{0.5}$ as a biological reference point is used because of its balanced consideration of sustainable fishing and stock conservation. In this study, the unfished $B/R$ level was approximated by using a very low $F$ value ($F$ = 0.001) as a proxy, following the convention used in TropFishR (Mildenberger et al. 2017). All calculations for estimating these biological reference points were performed following the algorithms and procedures implemented in the TropFishR package, ensuring consistency with the formulas described above.

**Evaluation of the precision and accuracy of BRPs**

The variables subject to evaluation included BRPs ($F_{0.1}$, $F_{\max}$, and $F_{0.5}$), for which coefficient of variation (CV) and percent bias were calculated across scenarios:

$$CV = \frac{SD}{Mean}$$

The standard deviation (SD) and mean values were derived from the estimates obtained for each scenario. For the accuracy test, the mean values obtained for each scenario (estimated value) were compared with the mean value of the full dataset (initial value) and calculated using percent bias:

$$\%\ bias = \left(\frac{estimated\ value - initial\ value}{initial\ value}\right) \times 100$$

To evaluate the reliability of the estimates, we applied a 30% CV (NMFS 2004) and 15th percentile threshold (Hesterberg et al. 2003) to assess data precision and accuracy. The 15th percentile threshold was calculated as the ±15th percentile of the %bias distribution from 1,000 bootstrap iterations using the full 24-month dataset.

## Results

### Growth parameter estimation

A summary of the estimated growth parameters is presented in Table 3. In the base scenario with 24 months and 100% of the data, the CV for $\Phi'$ was the lowest among all scenarios, with a value of 2.28%. The CV for $L_\infty$ was 0.58 points higher than that of $\Phi'$, with a value of 2.86%, while the CV for $K$ was ten times higher at 22.82%. In the 12-month scenario with 100% data, the CV for $L_\infty$, $K$, and $\Phi'$ were almost doubled. In comparison with the same number of months, in every 2-month (Ev 2) scenario with 100% data, the CV for $L_\infty$, $K$, and $\Phi'$ were almost two-thirds higher than those from the 12-month dataset.

Furthermore, the mean of $L_\infty$ increased as the dataset size decreased. In the 12-month 100% scenario, the mean of $L_\infty$ increased from 166.39 cm FL (full data) to 170.36 cm FL. In contrast, the mean value of $K$ decreased from 0.76 to 0.61 in the 12-month scenario, with similar declines observed across all scenarios with reduced data coverage. The mean value of $\Phi'$ remained relatively stable, with only slight fluctuations across different scenarios, though it remained marginally lower than the value observed with the full dataset.

### Mortality estimation

Table 4 presents the mean estimated total ($Z$) and fishing ($F$) mortality across all scenarios, where natural mortality ($M$) was assumed to be 0.23 based on the Tanaka method (Tanaka 1960).

### Estimation of $F_{0.1}$, $F_{max}$, and $F_{0.5}$

Table 5 presents the mean of the estimated $F_{0.1}$, $F_{\max}$, and $F_{0.5}$ values from the natural mortality estimation across all scenarios.

For each scenario, BRPs were calculated using the growth parameters derived from each of the 1,000 bootstrapped datasets. These repeated estimates allowed for summarizing the distribution of BRPs and evaluating their stability under varying data conditions. The mean of the estimated $F_{0.1}$ values range from 0.41 to 0.65, $F_{\max}$ from 0.92 to 2.32, and $F_{0.5}$ from 0.30 to 0.51. The mean of $F_{0.1}$ generally decreases with a reduction in data quantity, particularly in scenarios with fewer data. Conversely, the mean of $F_{\max}$ exhibits a substantial increase (up to twofold) when data quantity decreases, especially below 50%. The mean $F_{0.5}$ remains relatively constant despite reductions in data quantity. Using the 15th percentile threshold based on percent bias, values within the acceptable range for assessing accuracy are highlighted in the green cells, while those outside the range are shown in red cells (Online Resource, Table S2).

In Fig. 2, the CV for $F_{0.1}$ ranges from 20.05% to 45.77%. For the full dataset, the CV value is 21.03%. A 7.29-point increase occurs when the dataset is reduced to 12 months with 100% data. However, the scenario with the same number of months (Ev 2) yields a lower CV of 22.38% (5.94 points lower). Although no clear trend is observed, CV values generally increase as data availability decreases. For $F_{\max}$, the CV ranges from 18.17% to 92.92%, with the smallest values observed when using the full dataset. Reducing the dataset from 100% to 10% results in a more-than-fourfold increase in CV, from 18.17% to 78.82%. Similarly, the CV for $F_{0.5}$ ranges from 25.31% to 116.44%, with the lowest CV found in the 24-month, 100% data scenario. While incremental increases in CV are seen with dataset reductions to 75%, 50%, and 25%, the most significant jump occurs at 10%, where the CV rises to 72.81%—nearly triple the CV of the 100% dataset. Detailed trends in $F_{0.1}$, $F_{\max}$, and $F_{0.5}$ are provided in the supplementary materials (Online Resource, Fig. S1).

## Discussion

### Mean estimates and precision of Biological Reference Points (BRPs) for $F_{0.1}$, $F_{max}$, and $F_{0.5}$

This study evaluated changes in several variables related to BRPs, which were calculated based on growth parameters estimated by ELEFAN, across different time intervals and data percentages using a field-collected dataset.

According to the 24-month 100% results, which include all data, $F_{0.1}$ is 0.64 and $F_{0.5}$ is 0.50, whereas $F_{\max}$ is almost twice as high at 1.06. $F_{0.1}$ is a precautionary BRP designed with the possibility of overestimating $F_{\max}$ (Chen et al. 2007). Although it is expected that $F_{\max}$ is greater than $F_{0.1}$, the nearly two-fold difference observed suggests that $F_{\max}$ may be overestimated. This overestimation can result from uncertainty in growth and mortality parameters under limited data, which influenced the shape and slope of the yield-per-recruit curve (Quinn and Deriso 1999; Hordyk et al. 2015). Similarly, the estimate of $F_{0.5}$ -a BRP reflecting spawning potential- was lower than $F_{0.1}$, and $F_{\max}$, but still likely overestimated due to the same sensitivity to input parameter variability.

Our results suggest that caution is needed when selecting BRPs, especially under limited data conditions. In our simulation, $F_{\max}$ derived solely from YPR tended to overestimate sustainable fishing levels because it does not account for reproductive capacity. $F_{0.1}$, although generally more precautionary than $F_{\max}$, can still be higher than SPR-based reference points, and thus combinining both YPR- and SPR-based BRPs is essential to achieve a balanced and precautionary approach, particularly in data-limited fisheries (Hodyk et al. 2015).

Our evaluation confirms the robustness of $F_{0.1}$, as it consistently shows lower CV values compared to $F_{\max}$ and $F_{0.5}$, indicating high precision. In addition to its precision, $F_{0.1}$ also exhibits a conservative bias, tending to slightly underestimate fishing pressure relative to actual sustainable levels, which is beneficial under data-limited conditions. This combination of low variability and precautionary bias makes $F_{0.1}$ a suitable BRP for guiding management decisions. Because $F_{0.1}$ estimates generally maintain a CV below the 30% threshold, it serves as both a precise and cautious option for sustainable fisheries management when data availability is limited.

In comparison, $F_{0.5}$ shows greater variability in both mean values and precision. Although some scenarios exhibited high CVs, with an average of 40.49% across all scenarios (Fig. 2), extreme CVs occurred primarily when only 10% of data was used. This indicates that $F_{0.5}$ is more sensitive to data reduction than $F_{0.1}$. These findings emphasize the need for careful selection and interpretation of BRPs to ensure sustainable stock management. A decrease in

these variable values can indicate changes in the condition of fish populations, which must be considered when making management decisions (Hilborn and Walters 1992).

To complement the CV results, Online Resource, Table S2 shows the %bias of each BRP based on 1,000 bootstrap simulations across all data scenarios. This table provides insight into the accuracy of the estimates. Cells highlighted in green represent values within the acceptable range, defined by the 15th percentile thresholds used in this study: 5% for $F_{0.1}$ and $F_{0.5}$, and 28% for $F_{\max}$. Red cells indicate estimates outside these ranges. The base scenario (24 months, 100% data) is shown in white for reference. The results reveal that most scenarios with reduced data tend to produce negative bias, meaning that BRPs are often underestimated. Although positive bias can occur, it is less common. This pattern likely reflects the conservative nature of length-based models under data-limited conditions.

**The impact of data quantity on result reliability**

In determining the appropriate quantity of data for reliable estimation, scenarios were evaluated by applying a 15th percentile threshold of the percent bias and selecting those with a CV below 30% for $F_{0.1}$ and $F_{0.5}$. The following scenarios produced reliable results: 24 months at 100%, 75%, and 50%; 18 months at 100% and 75%; Ev 2 at 100%; and Ev 6 at 100% and 75%.

However, the Ev 6 scenario at 100% and 75% data retention showed unexpectedly lower CV values compared to some reduced-data scenarios. This suggests that the inclusion of all months does not always guarantee higher precision, and certain months may contribute disproportionately to estimate reliability. It is possible that specific months, such as those with high-quality or more informative length compositions, influence the stability of BRP estimates. Conversely, some months might introduce noise, reducing precision when included. Therefore, while the results for Ev 6 at 100% and 75% appear favorable in terms of CV, they should be interpreted with caution. Further analyses using techniques such as Jackknife resampling are recommended to identify critical months that significantly influence parameter estimation. Until then, these results should not be used directly for management purposes.

To ensure reliable outcomes based on threshold CV values, we recommend one of the following sampling designs: full 24-month sampling with approximately 7,000–8,000 total data points, 18-month sampling with similar sample size through higher monthly intensity, or a bimonthly design (i.e., every 2 months for 2 years) totaling around 7,000 data points. These numbers reflect the data quantity that produced consistent and precise BRP estimates in our simulation. The original dataset comprised 14,190 individuals over 24 months (~591 per

month), and these recommended scenarios achieved reliable estimates while using only about half of the full dataset.

In conclusion, the simulation results clearly indicate that data availability plays a crucial role in minimizing the uncertainty of fisheries stock assessment. As the percentage of available data decreases, the risk of imprecise estimates increases, potentially leading to overexploitation of fish stocks. BRP estimates remain better for fisheries management, even when they are derived from scenarios with less reliable or data-limited conditions. While $F_{0.1}$ may be underestimated, this tendency is likely due to the conservative nature of the YPR curve at low fishing mortality rates. In data-limited scenarios, the initial slope of the YPR curve can appear flatter than it actually is, leading to a lower estimated $F_{0.1}$. Despite this, $F_{0.1}$ remains a precautionary reference point that supports more conservative fisheries management. However, the results and conclusions of this study may not be generalizable to all species. Further research on different species is encouraged to enhance the reliability of length-based fisheries management, particularly under data-limited conditions.

**Author contribution statement**

**Wiwiet Teguh Taufani:** Writing: Original draft, formal analysis, methodology, validation, data visualization**. Matsuishi Takashi Fritz:** Conceptualization, validation, Writing: review and editing, supervision.

**Declaration of Competing Interest**

The authors declare that there is no conflict of interest regarding the publication of this article or its funding.

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**Data Availability Statement**

Data will be provided upon request.

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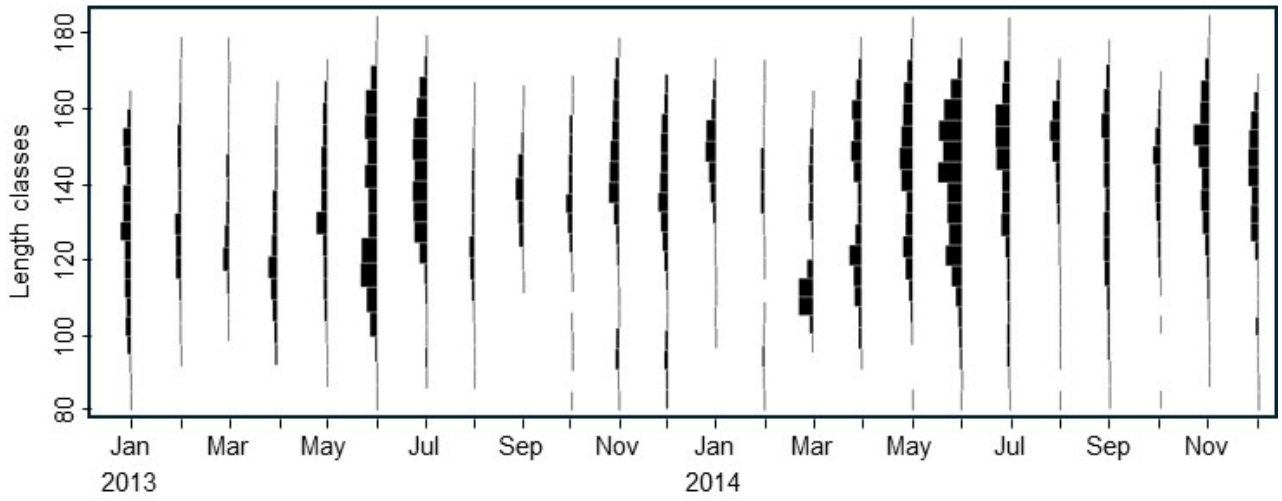



**Fig.1** The length distribution of yellowfin tuna

| Variables | % data | Months | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 24 | 18 | 12 | 6 | 3 | Ev 2 | Ev 3 | Ev 4 | Ev 5 | Ev 6 |
| $F_{0.1}$ | 100 | 21.03 | 23.48 | 28.32 | 20.05 | 24.81 | 22.38 | 24.25 | 27.91 | 22.51 | 20.66 |
| | 75 | 25.33 | 23.94 | 28.74 | 21.78 | 27.59 | 23.13 | 24.48 | 27.39 | 25.77 | 22.46 |
| | 50 | 27.19 | 25.73 | 33.96 | 25.29 | 27.45 | 22.65 | 24.45 | 28.48 | 27.92 | 22.21 |
| | 25 | 28.38 | 29.46 | 32.81 | 27.14 | 27.91 | 26.92 | 26.29 | 29.39 | 28.00 | 25.60 |
| | 10 | 22.14 | 25.04 | 21.85 | 33.86 | 23.38 | 22.18 | 22.72 | 22.83 | 45.77 | 26.20 |
| $F_{max}$ | 100 | 18.17 | 23.97 | 24.72 | 53.32 | 55.88 | 25.10 | 29.75 | 34.95 | 50.61 | 31.79 |
| | 75 | 24.11 | 27.10 | 46.11 | 52.43 | 55.08 | 18.65 | 37.38 | 40.42 | 58.70 | 38.54 |
| | 50 | 34.36 | 36.48 | 67.35 | 72.40 | 59.20 | 24.09 | 36.29 | 55.76 | 65.60 | 41.92 |
| | 25 | 73.06 | 69.93 | 80.89 | 70.56 | 64.16 | 72.68 | 67.49 | 84.42 | 81.28 | 62.67 |
| | 10 | 78.82 | 82.84 | 75.17 | 90.50 | 90.85 | 85.70 | 92.92 | 83.91 | 85.59 | 84.19 |
| $F_{0.5}$ | 100 | 25.31 | 28.41 | 33.84 | 26.12 | 34.42 | 26.70 | 30.25 | 30.26 | 27.70 | 25.95 |
| | 75 | 29.73 | 29.21 | 34.63 | 28.77 | 39.34 | 28.06 | 30.54 | 29.93 | 31.41 | 27.93 |
| | 50 | 31.94 | 31.73 | 42.51 | 34.01 | 40.95 | 27.68 | 30.06 | 36.35 | 32.04 | 27.72 |
| | 25 | 33.15 | 36.37 | 48.14 | 43.98 | 47.44 | 34.40 | 34.73 | 42.14 | 51.40 | 32.85 |
| | 10 | 72.81 | 49.86 | 54.93 | 79.96 | 48.45 | 75.57 | 48.27 | 77.46 | 116.44 | 62.78 |

Average across all scenarios:

- $F_{0.1}$ = 25.98
- $F_{max}$ = 56.36
- $F_{0.5}$ = 40.49



18 117

**Fig. 2** CV (%) value of variables $F_{0.1}$, $F_{max}$, and $F_{0.5}$.

**Table 1** Number of samples in each scenario

| Scenario | Months | Remaining data proportion | | | | |
|---|---|---|---|---|---|---|
| | | 100% | 75% | 50% | 25% | 10% |
| Sequential | **24** | 14,190 | 10,643 | 7,095 | 3,548 | 1,419 |
| | **18** | 10,693 | 8,020 | 5,347 | 2,673 | 1,069 |
| | **12** | 6,306 | 4,730 | 3,153 | 1,577 | 631 |
| | **6** | 3,192 | 2,394 | 1,596 | 798 | 319 |
| | **3** | 1,303 | 977 | 652 | 326 | 130 |
| Interval | **Every 2** | 6,967 | 5,225 | 3,484 | 1,742 | 697 |
| | **Every 3** | 5,419 | 4,064 | 2,710 | 1,355 | 542 |
| | **Every 4** | 3,256 | 2,442 | 1,628 | 814 | 326 |
| | **Every 5** | 1,807 | 1,355 | 904 | 452 | 181 |
| | **Every 6** | 3,701 | 2,776 | 1,851 | 925 | 370 |

**Table 2** Parameter symbols used in R scripts for simulation and equations

| Symbol | Description | Value/ Unit |
|---|---|---|
| $\boldsymbol{\Phi'}$ | Growth performance index | |
| $\boldsymbol{a}$ | intercept length-weight parameter[1] | 0.000052 |
| $\boldsymbol{b}$ | Slope length-weight parameter[1] | 2.78 |
| $\boldsymbol{E}$ | Exploitation ratio[2] | |
| $\boldsymbol{F}$ | Fishing mortality | $\text{year}^{-1}$ |
| $\boldsymbol{F_{0.1}}$ | Fishing mortality from the 10 % of the tangent of the YPR curve | $\text{year}^{-1}$ |
| $\boldsymbol{F_{\max}}$ | Fishing mortality from the peak of the YPR curve | $\text{year}^{-1}$ |
| $\boldsymbol{F_{0.5}}$ | Fishing mortality that spares 50% of spawning stock biomass per recruit | $\text{year}^{-1}$ |
| $\boldsymbol{K}$ | Parameter of von Bertalanffy growth function | $\text{year}^{-1}$ |
| $\boldsymbol{L_\infty}$ | Parameter of von Bertalanffy growth function | cm FL |
| $\boldsymbol{L_c}$ | Length at first capture | cm FL |
| $\boldsymbol{L_m}$ | Length at first maturity | cm FL |
| $\boldsymbol{L_t}$ | Mean length at age *t* | cm FL |
| $\boldsymbol{\bar{L}}$ | The average length of those animals longer than $L_c$ | cm FL |
| $\boldsymbol{M}$ | Natural mortality | $\text{year}^{-1}$ |
| $\boldsymbol{t_0}$ | Parameter of von Bertalanffy growth function | year |
| $\boldsymbol{t_\lambda}$ | Age endpoint | year |
| $\boldsymbol{t_c}$ | Age at first capture | year |
| $\boldsymbol{t_{\text{m}}}$ | Age at first maturity | year |
| $\boldsymbol{t_{\max}}$ | Maximum age[3] | 11.1 year |
| $\boldsymbol{t_r}$ | Age at recruitment | year |
| $\boldsymbol{W_\infty}$ | Asymptotic weight | kg |
| $\boldsymbol{Z}$ | Total mortality | $\text{year}^{-1}$ |

1) Ghofar et al. 2021
2) $E = F/Z$
3) Chantawong 1998

**Table 3** Estimated growth parameters for all scenarios.

| Scenarios | | Growth Parameters | | | | | |
|---|---|---|---|---|---|---|---|
| | | $L_\infty$ | | $K$ | | $\Phi'$ | |
| | | **Mean** | **CV(%)** | **Mean** | **CV(%)** | **Mean** | **CV(%)** |
| **24** | **100** | 166.39 | 2.86 | 0.76 | 22.82 | 4.31 | 2.28 |
| | **75** | 166.75 | 4.41 | 0.75 | 30.36 | 4.30 | 3.02 |
| | **50** | 167.44 | 5.87 | 0.75 | 31.99 | 4.30 | 3.15 |
| | **25** | 176.15 | 12.27 | 0.62 | 44.73 | 4.22 | 4.04 |
| | **10** | 192.21 | 12.87 | 0.36 | 62.98 | 4.03 | 4.76 |
| **18** | **100** | 168.12 | 4.44 | 0.81 | 25.76 | 4.34 | 2.86 |
| | **75** | 169.39 | 6.15 | 0.79 | 27.74 | 4.33 | 3.01 |
| | **50** | 172.48 | 9.35 | 0.73 | 33.47 | 4.30 | 3.46 |
| | **25** | 180.12 | 12.61 | 0.60 | 46.72 | 4.23 | 4.28 |
| | **10** | 196.04 | 12.76 | 0.36 | 67.60 | 4.04 | 5.04 |
| **12** | **100** | 170.36 | 6.65 | 0.61 | 45.39 | 4.19 | 4.93 |
| | **75** | 172.61 | 9.26 | 0.60 | 46.47 | 4.19 | 4.88 |
| | **50** | 178.32 | 12.29 | 0.56 | 54.23 | 4.17 | 5.02 |
| | **25** | 187.95 | 13.82 | 0.46 | 62.48 | 4.11 | 5.05 |
| | **10** | 201.33 | 12.53 | 0.28 | 69.91 | 3.96 | 4.42 |
| **6** | **100** | 174.45 | 10.20 | 0.49 | 42.70 | 4.13 | 4.25 |
| | **75** | 176.25 | 11.23 | 0.49 | 43.97 | 4.13 | 4.21 |
| | **50** | 183.17 | 13.50 | 0.46 | 49.96 | 4.13 | 4.35 |
| | **25** | 192.96 | 14.27 | 0.40 | 58.86 | 4.09 | 4.29 |
| | **10** | 197.02 | 13.53 | 0.34 | 72.26 | 4.02 | 4.66 |
| **3** | **100** | 185.31 | 14.78 | 0.43 | 56.07 | 4.09 | 4.70 |
| | **75** | 187.16 | 15.10 | 0.42 | 59.82 | 4.08 | 4.79 |
| | **50** | 192.25 | 15.17 | 0.39 | 65.10 | 4.07 | 4.88 |
| | **25** | 196.79 | 14.36 | 0.34 | 70.36 | 4.03 | 4.59 |
| | **10** | 198.93 | 13.23 | 0.29 | 70.06 | 3.97 | 4.42 |

**Table 3 (continued)** Estimated growth parameters for all scenarios.

| Scenarios | | Growth Parameters | | | | | |
|---|---|---|---|---|---|---|---|
| | | $L_\infty$ | | $K$ | | $\Phi'$ | |
| | | **Mean** | **CV(%)** | **Mean** | **CV(%)** | **Mean** | **CV(%)** |
| **Ev 2** | **100** | 168.08 | 4.84 | 0.73 | 27.31 | 4.30 | 2.78 |
| | **75** | 168.71 | 6.07 | 0.72 | 30.14 | 4.29 | 2.88 |
| | **50** | 170.18 | 7.31 | 0.69 | 31.23 | 4.28 | 3.05 |
| | **25** | 180.05 | 12.66 | 0.56 | 47.76 | 4.19 | 4.13 |
| | **10** | 197.20 | 12.62 | 0.33 | 67.80 | 4.01 | 4.88 |
| **Ev 3** | **100** | 170.34 | 6.48 | 0.66 | 31.39 | 4.26 | 2.96 |
| | **75** | 171.15 | 6.87 | 0.65 | 31.91 | 4.25 | 2.98 |
| | **50** | 174.73 | 9.80 | 0.61 | 35.00 | 4.24 | 3.16 |
| | **25** | 182.42 | 12.89 | 0.53 | 46.81 | 4.18 | 3.85 |
| | **10** | 194.26 | 13.25 | 0.37 | 61.24 | 4.06 | 4.62 |
| **Ev 4** | **100** | 169.76 | 7.00 | 0.61 | 38.07 | 4.21 | 4.11 |
| | **75** | 171.56 | 8.89 | 0.58 | 40.41 | 4.18 | 4.25 |

| Scenarios | | Growth Parameters | | | | | |
|---|---|---|---|---|---|---|---|
| | | $L_\infty$ | | $K$ | | $\Phi'$ | |
| | | **Mean** | **CV(%)** | **Mean** | **CV(%)** | **Mean** | **CV(%)** |
| | **50** | 175.75 | 11.75 | 0.56 | 44.96 | 4.18 | 4.23 |
| | **25** | 184.09 | 14.39 | 0.49 | 57.21 | 4.14 | 4.70 |
| | **10** | 195.59 | 13.24 | 0.34 | 68.98 | 4.02 | 4.82 |
| | **100** | 169.71 | 10.63 | 0.44 | 37.02 | 4.07 | 3.27 |
| | **75** | 174.98 | 12.97 | 0.42 | 41.07 | 4.07 | 3.41 |
| **Ev 5** | **50** | 180.65 | 14.78 | 0.42 | 47.44 | 4.08 | 3.69 |
| | **25** | 190.19 | 14.70 | 0.38 | 55.85 | 4.06 | 3.96 |
| | **10** | 198.52 | 13.45 | 0.32 | 70.93 | 4.01 | 4.64 |
| | **100** | 170.30 | 3.53 | 0.68 | 24.11 | 4.28 | 2.85 |
| | **75** | 171.13 | 4.84 | 0.66 | 28.68 | 4.26 | 3.28 |
| **Ev 6** | **50** | 172.20 | 6.59 | 0.62 | 32.87 | 4.23 | 3.70 |
| | **25** | 179.17 | 11.34 | 0.52 | 44.12 | 4.17 | 4.23 |
| | **10** | 194.44 | 13.84 | 0.37 | 61.40 | 4.06 | 4.62 |

Ev 2, Ev 3, Ev 4, Ev 5, Ev 6: every 2, 3, 4, 5, and 6 months, respectively. The CV represents the minimum and maximum values of the estimated results.

**Table 4** The mean estimated $Z$ and $F$ values for all scenarios.

| Variable | % data | Months | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **24** | **18** | **12** | **6** | **3** | **Ev 2** | **Ev 3** | **Ev 4** | **Ev 5** | **Ev 6** |
| | **100** | 0.84 | 1.00 | 0.94 | 0.90 | 1.08 | 0.83 | 0.85 | 0.74 | 0.60 | 0.82 |
| | **75** | 0.86 | 1.05 | 0.97 | 0.96 | 1.05 | 0.86 | 0.85 | 0.76 | 0.70 | 0.83 |
| ***Z*** | **50** | 0.87 | 1.10 | 1.10 | 1.04 | 1.08 | 0.88 | 0.89 | 0.88 | 0.80 | 0.81 |
| | **25** | 0.99 | 1.14 | 1.17 | 1.11 | 1.00 | 0.99 | 0.95 | 0.99 | 0.93 | 0.89 |
| | **10** | 1.01 | 1.07 | 1.01 | 0.97 | 0.83 | 0.93 | 0.92 | 0.93 | 0.92 | 0.96 |
| | **100** | 0.61 | 0.77 | 0.71 | 0.67 | 0.85 | 0.61 | 0.62 | 0.51 | 0.37 | 0.59 |
| | **75** | 0.64 | 0.82 | 0.74 | 0.73 | 0.83 | 0.63 | 0.63 | 0.54 | 0.47 | 0.60 |
| ***F*** | **50** | 0.65 | 0.87 | 0.87 | 0.81 | 0.86 | 0.66 | 0.67 | 0.66 | 0.58 | 0.58 |
| | **25** | 0.77 | 0.91 | 0.94 | 0.89 | 0.77 | 0.77 | 0.73 | 0.76 | 0.70 | 0.66 |
| | **10** | 0.79 | 0.85 | 0.78 | 0.74 | 0.60 | 0.70 | 0.70 | 0.71 | 0.69 | 0.74 |

**Table 5** The mean of the estimated $F_{0.1}$, $F_{\max}$, and $F_{0.5}$ values for all scenarios.

| Variables | % data | Months | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **24** | **18** | **12** | **6** | **3** | **Ev 2** | **Ev 3** | **Ev 4** | **Ev 5** | **Ev 6** |
| **F 0.1** | **100** | 0.64 | 0.65 | 0.58 | 0.49 | 0.45 | 0.61 | 0.57 | 0.55 | 0.48 | 0.61 |
| | **75** | 0.64 | 0.63 | 0.57 | 0.48 | 0.45 | 0.60 | 0.56 | 0.53 | 0.48 | 0.59 |
| | **50** | 0.65 | 0.60 | 0.56 | 0.48 | 0.44 | 0.59 | 0.55 | 0.52 | 0.47 | 0.57 |
| | **25** | 0.58 | 0.56 | 0.52 | 0.45 | 0.42 | 0.53 | 0.51 | 0.51 | 0.46 | 0.53 |
| | **10** | 0.48 | 0.47 | 0.45 | 0.44 | 0.41 | 0.45 | 0.45 | 0.46 | 0.47 | 0.48 |
| **F max** | **100** | 1.06 | 1.06 | 1.18 | 1.03 | 0.92 | 1.03 | 0.98 | 0.97 | 1.03 | 1.08 |
| | **75** | 1.09 | 1.05 | 1.21 | 1.00 | 0.95 | 1.01 | 0.98 | 0.98 | 1.05 | 1.10 |
| | **50** | 1.12 | 1.06 | 1.36 | 1.10 | 0.92 | 1.00 | 0.95 | 1.02 | 1.07 | 1.10 |
| | **25** | 1.30 | 1.20 | 1.73 | 1.07 | 0.94 | 1.18 | 1.03 | 1.32 | 1.28 | 1.22 |
| | **10** | 2.18 | 1.94 | 2.32 | 1.39 | 1.10 | 1.96 | 1.39 | 2.06 | 1.88 | 1.76 |
| **F 0.5** | **100** | 0.50 | 0.50 | 0.46 | 0.36 | 0.31 | 0.48 | 0.44 | 0.40 | 0.36 | 0.48 |
| | **75** | 0.50 | 0.48 | 0.45 | 0.35 | 0.32 | 0.46 | 0.43 | 0.39 | 0.36 | 0.47 |
| | **50** | 0.51 | 0.46 | 0.45 | 0.35 | 0.30 | 0.45 | 0.41 | 0.39 | 0.35 | 0.45 |
| | **25** | 0.46 | 0.43 | 0.44 | 0.33 | 0.30 | 0.41 | 0.38 | 0.40 | 0.35 | 0.42 |
| | **10** | 0.46 | 0.40 | 0.41 | 0.34 | 0.30 | 0.42 | 0.35 | 0.44 | 0.46 | 0.41 |