# Assessing the impact of the growth on estimates of fishing mortality for the Indian Ocean bigeye tuna 

DAN FU ${ }^{1}$

02 MAY 2022


#### Abstract

SUMMARY In 2021, a new growth estimate for bigeye tuna in the Indian Ocean was derived based on otolith aging studies. The new growth estimates represent a size-at-age that is significantly larger than the growth currently used for bigeye tuna stock assessment. This is expected to have a significant impact on the assessment results if included in the model. This report aims to assess the potential impact of the new growth on the estimates of fishing mortality for bigeye tuna by performing an analysis of length composition data based on the assumption that the length distribution is primarily determined by fish growth and mortality. Assuming that growth and natural mortality are known, the analytical method estimates fishing mortality rates and selectivity parameters from the longline length freqeuncy dataset (assuming each length abundance is a steady distribution). The performance of the estimator was validated using simulated data. The analysis shows that longline length frequency data suggest that estimates of annual fishing mortality for new growth are 2-3 times higher than the current growth estimates for bigeye tuna.


## 1. INTRODUCTION

Fish growth is one of the most important life-history traits for quantifying productivity and resilience and is an important component of fish stock assessment (Patrick et al., 2010; Zhou et al., 2018). In modern age-structured, integrated models such as the stock synthesis (Methot 2013) the growth has multiple applications, including translating numbers at age into biomass based quantities, converting length-based selectivity to selectivity-at-age, and calculating expected length compositions (Maunder et al. 2016).

The most recent stock assessment of Indian Ocean bigeye tuna (Fu 2019) used growth estimates by Eveson et al. (2012). Eveson et al (2012) derived estimates of Indian Ocean bigeye tuna growth from otolith age data and tag release/recovery (an updated analysis by Eveson et al (2015) estimated very similar growth parameters for males and females). The growth deviates from a von Bertalanffy growth function with considerably lower growth for quarterly age classes $4-8$. Maximum average length ( $L^{\infty}$ ) was estimated at 150.9 cm . The growth model was unable to reliably estimate the standard deviation of length-at-age; however, the most appropriate level of variation in length for all age classes was considered to be represented by a coefficient of variation of 0.10 (P. Eveson, pers. comm.). In 2021, Farley et al. (2021) estimated age and growth using otoliths collected in the Indian Ocean as part of the 'GERUNDIO' project, based a new method developed to estimate the age and growth of bigeye tuna from counts of daily and annual growth zones in otoliths. The preliminary age validation work

[^0]using otoliths and data from the IOTTP provides evidence that the otolith ageing method used in this study is accurate. The two-stage, VB-LogK growth curve is quite different from the integrated VB-logK curves of Eveson et al. (2012) (Figure 1). The new estimates represent a size-at-age that is significantly larger, with a much higher mean asymptotic length ( $L^{\infty}=168 \mathrm{~cm} \mathrm{FL}$ ). The major difference between the two growth is expected to be a major source of uncertainty in bigeye tuna assessment. Therefore, it is useful to assess the potential impact of the new growth on estimates of some key assessment metrics.

The growth is directly related to the modelling of the length composition data which provides critical information on fishing mortality, recruitment, and growth. As the change in mean size of a fished population relative to the unfished state is usually interpreted by the assessment model as linked to fishery-induced depletion, the lack of large fish in the catch, relative to a higher asymptotic length would imply a higher level of fishing mortality. Estimating mortality from a length frequency distribution corresponds to what is known as a catch curve analysis. Age-based catch curve analysis, such as Chapman-Robson estimators and regression-based methods, can derive mortality from the slope of the relative number of each age class (Dunn et al. 2002). Length-based catch curve estimator generally requires additional information on growth in order to assign mortality to each age group. Beverton and Holt (1956) developed a method to estimate total mortality $(Z)$ from length data assuming good information of $K$ and $L^{\infty}$. The Beverton and Holt model was further developed by Powell (1979) and Wetherall et al (1987) to simultaneously estimate growth and mortality parameter. The Powell-Wetherall method using a regression analysis to provide estimates from each length distribution of $Z / K$ and $Z$ if $K$ is known. Kell et al. (2013) applied the Powell-Wetherall method to the Atlantic white maline

Schnute and Fournier (1980) and Fournier and Breen (1983) developed a procedure for obtaining simultaneous estimates of growth and total-mortality rates from size-frequency distribution. This method formulates the distribution of individual lengths in a population as a product of both the distribution of mean lengths at age (growth) and the age distribution of individual. If the effect of recruitment and migration on the age distribution can be ignored, growth and mortality rate determine the form of the size frequency distribution. Fournier and Breen (1993) suggested the method produced relatively stable and accurate estimates of total mortality rate over a range of conditions, whereas the model does less well at estimating the Brody coefficient $(K)$ which are correlated with the mortality-rate estimates. Fournier and Sibert (1990) showed that better parameter estimates can be obtained by simultaneously analyzing several length frequency data sets obtained at several different times from a fish population. The method of Fournier and Breen (1993) assumes a steady-state age distribution, but random error can be included in the maximum likelihood estimation to explain the potential deviation from the equilibrium distribution.

A procedure similar to that of Fournier and Breen (1983) was used to assess the effect of growth on estimates of bigeye tuna fishing mortality. In contrast to Fournier and Breen (1893), who seek to estimate both growth and mortality, this analysis assumes that growth is known. This method also estimates the selectivity parameter from the length frequency data.

## 2. METHOD

### 2.1 Estimation model

The analysis assumed independent and stationary annual length frequency distribution determined by the age distribution of a pseudo cohort (i.e., the age distribution obtained by tracking a cohort
overtime). Given an arbitrary, constant recruitment at age zero, $N_{0, y}$ (e.g., 1000,000), the population number at age $a, N_{a, y}$ is calculated as:

$$
\begin{equation*}
N_{a+1, y}=N_{a, y} \exp \left(-M_{a, y}-F_{a, y}\right) \exp \left(\varepsilon_{a, y}\right) \tag{1}
\end{equation*}
$$

Where $M_{a, y}$, and $F_{a, y}$ are the natural and fishing mortality at age $a$ in year $y$ ( $F_{a, y}$ is commonly seperated into an age component $F_{a}$ and a time component $F_{y}$ under separable assumption $F_{a, y}=$ $\left.F_{a} F_{y}\right) . \varepsilon_{a, y}$ is a random error assuming to follow a normal distribution, i.e.,

$$
\begin{equation*}
\varepsilon_{i, y} \sim \operatorname{normal}\left(0, \sigma_{r}\right) \tag{2}
\end{equation*}
$$

$\varepsilon_{a, y}$ incorporates process errors such as recruitment variability in the age structure. Expected catch-at-age is $E\left(C_{a, y}\right)$ is calculated using standard Baranov equation:

$$
\begin{equation*}
E\left(C_{a, y}\right)=\frac{F_{a, y}}{M_{a, y}+F_{a, y}}\left(1-\exp \left(-M_{a, y}-F_{a, y}\right)\right) N_{a, y} \tag{3}
\end{equation*}
$$

Let $C_{l, y}$ denote the catch number from length class $l$ in year $y$, thus expected catch-at-length is calculated as

$$
\begin{equation*}
\mathrm{E}\left(C_{l, y}\right)=\sum_{a} \mathrm{E}\left(C_{a, y}\right) \operatorname{Pr}(l \mid a) \tag{4}
\end{equation*}
$$

Where $\operatorname{Pr}(l \mid a)$ is the probability of the fish being in length class / given its age $a$ and can be inferred directly from the fish growth. Assuming the size at age follows a normal distribution with mean $g(a)$ (e.g., see the Von Bertalanffy, Richard, and VB-LogK growth functions in Farley et al. 2021) and standard deviation $\sigma_{a}$, then

$$
\begin{equation*}
\operatorname{Pr}(l \mid a)=\int_{l_{l o}}^{l_{h i}} \frac{1}{\sqrt{2 \pi \sigma_{a}^{2}}} \exp \left(-\frac{(x-g(a))^{2}}{2 \sigma_{a}^{2}}\right) d x \tag{5}
\end{equation*}
$$

Where $l_{l o}$ and $l_{h i}$ denote the lower and upper bounds of the length class $l$. The objective function (negative log-likelihood) contains two components, one is the robustified multinomial likelihood for the length frequency observations:

$$
\begin{equation*}
L^{C} \propto \sum_{y} \sum_{l}\left[-n_{y}\left(\widetilde{C_{l, y}}+\delta\right) \log \left(E\left(\widehat{\left.C_{l, y}\right)}+\delta\right)\right]\right. \tag{6}
\end{equation*}
$$

Where $\overline{E\left(C_{l, y}\right)}=\frac{E\left(C_{l, y}\right)}{\sum_{l} E\left(C_{l, y}\right)}$, and $\widetilde{C_{l, y}}=\frac{C_{l, y}}{\sum_{l} C_{l, y}}$ is the observed length frequency; $n_{y}$ is the number of fish sampled in year $y ; \delta$ is the robustifying constant (set to 0.001 ). The other component is the penalty on the random errors

$$
\begin{equation*}
L^{P} \propto \sum_{y} \sum_{a}\left[\log \left(\sigma_{r}\right)+\frac{1}{2}\left(\frac{\varepsilon_{a, y}}{\sigma_{r}}\right)^{2}\right] \tag{7}
\end{equation*}
$$

The overall objective function is

$$
\begin{equation*}
L=L^{C}+L^{P} \tag{8}
\end{equation*}
$$

The model was implemented in Template model builder (Kristensen 2016).

### 2.2 Bigeye tuna longline length frequency data

The model described above is used to estimate fishing mortality rates from the longline length frequency 1976 - 2018 for bigeye tuna (Figure 2, 44 length frequency distributions). The model estimates $F_{y}(y=1976 . .2018)$ and $F_{a}(a=1 \ldots 10)$, where $F_{a}$ is constrain to a logistic function:

$$
F_{a}=\frac{1}{1+19^{\left(\frac{a_{50}-a}{a_{t o 95}}\right)}}
$$

Where $a_{50}$ (the age at $50 \%$ selection) and $a_{t o 95}$ (the number of ages from $a_{50}$ to the age at $95 \%$ selection) are two estimable parameters. The model also estimates $\varepsilon_{a, y}$ (for $a=1 \ldots 10$ and $y=$ $197 \ldots 2018$ ). Ideally, $\varepsilon_{a, y}$ are random effect that should be integrated out, but this has not been very successful. Instead, a penalized likelihood approach was used to provide maximum likelihood estimates of all parameters (total likelihood is penalized by the variability of $\varepsilon_{a, y}$ ). With this approach, $\sigma_{r}$ is assumed known, and was fixed at three different values ( $0.01,0.10$, and 020 ).

Other parameters in the model are assumed known. In particular, $M_{a, y}$ are time-invariant, with $M_{a}=$ $0.8,0.5$ for $a=1,2$, and 0.25 for $a=3 \ldots 10$, following Fu (2019). Respectively, the two alternative growth estimates, namely Evenson et al. 2012 and Farley et al. 2021 (see ) was used to calculate the size-at-age (see equation 5). For each growth estimate, two levels of variability ( 0.10 and 0.05 ) on the mean size-at-age ( $\sigma_{a}$ ) were examined (the value of 0.1 was used by in the bigeye tuna assessment).

In total, 12 models were implemented, corresponding to 2 values of $\sigma_{a}$ and 3 values of $\sigma_{r}$, for each of the two growth estimates (see Table 1)

Simulations were also run to verify the performance of the estimator. The length frequency dataset was simulated using the bigeye tuna population parameters above ( $M_{a}$, growth by Evenson et al. 2012). A total of 10 length frequencies were generated assuming $F_{y}$ linearly increased from 0.2 to 0.3 , and $F_{a}$ follows a logistic selectivity with $a_{50}=3$ and $a_{t o 95}=2$. The simulated data was fitted and estimated $F_{y}$ and $F_{a}$ were compared to the true values.

## 3. RESULTS

Simulation exercises show that if length distribution is primarily determined by growth and mortality, then if growth is known, the model estimates fishing mortality with reasonable accuracy. (Appendix A).

Assuming the growth of Evenson et al. 2012, estimated fishing mortality rates range from 0.03 to 0.58 (a few years with estimated $F_{y}$ of 0 were removed) with an average of 0.27 from 1975 to 2018 (Figure 3). Pre-1990 fishing mortality was much higher than in recent years due to the much smaller average length size (this may reflect the change of sampling method or selectivity, but the analysis does not try to explain the trend in the length frequency). Assuming the growth of Farley et al. 2012, estimated fishing mortality rates range from 0.21 to 1.10 with an average of 0.6 (Figure 3 ). Clearly the fishing mortality derived from the growth of Farley et al. 2021 is significantly higher than that derived from growth of Evenson et al. 2012 - the difference is about 2-3 times in magnitude for $60 \%$ of the length samples. In addition, using growth of Farley et al. 2021 increased the estimated selectivity of fish between age 2 and 5 (Figure 3), as the fast growth results in smaller number of smaller fish in the population.

According to the additional analysis, the estimates are less sensitive to the amount of process errors in the age distribution but estimated $F_{y}$ is usually lower with a higher $\sigma_{r}$ (Figure 4). As expected, estimated $F_{y}$ is very sensitivity to the $\sigma_{a}$, the variability of the mean size at age. For both growth estimates, a lower $\sigma_{a}$ will significantly reduce the estimate of fishing morality (a large $\sigma_{a}$ implies more larger fish expected to be present). Assuming a $\sigma_{a}$ of 0.05 , the growth of Farley et al. 2001 yielded similar level of $F_{y}$ estimates to the growth Eveson et al. 2012 assuming with a $\sigma_{a}$ of 0.10 (Figure 4).

The models fitted the annual length frequencies very well (Figure 5). Estimated $\varepsilon_{a, y}$ generally spread near zero and appear to spread more with a higher $\sigma_{r}$ (Figure 6).

## 4. DISCUSSIONS

This paper seeks to assess the effect of the newly available growth on the estimation of fishing mortality for the bigeye tuna using a frequency analysis. The model fits to a time series of length frequencies (the longline length dataset), but assumes that each length frequency is an independent, stationary distribution of a pseudo cohort and is therefore different to a typical sequential population model such as VPA which assumes that the number of fish at age $a$ in year $y$ depends on age $a-1$ in year $y-1$. The stationary distribution is not a realistic assumption but is not expect to influence the main conclusion on the magnitude of changes on the estimation of fishing mortality that may be caused by underlying growth changes. A more thorough assessment of the impact of growth on fishing mortality can be performed more easily within an integrated stock synthesis model. However, the advantage of using the integrated model is that the interactions between different demographic processes such as growth, recruitment, and migration, and the different data contained in the model complicate the interpretation. An independent analysis, such as that performed in this report, provides a rational and efficient assessment of the important indicators. indicators. Compared to other regression-based catch curve methods, the method adapted from Fournier and Breen in 1983, was able to fit to the full length distribution. The maximum likelihood estimator provides a statistically robust approach for estimating fishing mortality from length observation, taking into account the uncertainty of various sources (both process and observation error).

## 5. REFERENCES

Fu, D., Langley, A., Merino, G., Urtizberea, A. 2018. Preliminary Indian Ocean Yellowfin Tuna Stock Assessment 1950-2017 (Stock Synthesis). IOTC-2018-WPTT20-33.

Chapman, D.G., Robson, D.S. 1960. The Analysis of a Catch Curve. Biometrics Vol. 16, No. 3 (Sep., 1960), pp. 354-368.

Beverton, R., Holt, S. review of method for estimating mortality rates in exploited fish populations, with special reference to sources of bias in catch sampling. Rapports et Proces-Verbaux., 140(1):6783, 1956.

Dunn A., Francis, R.I.C.C., Doonan, I. 2002. Comparison of the Chapman-Robson and regression estimators of $Z$ from catch-curve data when non-sampling stochastic error is present. Fisheries Research. Volume 59, 2002, 149-159.

Eveson, P., Million, J., Sardenne, F., Le Croizier, G. 2012. Updated growth estimates for skipjack, yellowfin and bigeye tuna in the Indian Ocean using the most recent tag-recapture and otolith data. IOTC-2012-WPTT14-23.

Eveson, P., Million, J., Sardenne, F., Le Croizier, G. 2015. Estimating growth of tropical tunas in the Indian Ocean using tag-recapture data and otolith-based age estimates. Fisheries Research 163, 5868,

Farley et al. 2021. Estimating the age and growth of bigeye tuna (Thunnus obesus) in the Indian Ocean from counts of daily and annual increments in otoliths. IOTC-2021-WPTT23.

Fournier, D. A., Breen, P. A. 1983. Estimation of abalone mortality rates with growth analysis. Trans. Am. Fish. Soc. 1 12: 403411.

Fournier, D. A., Sibert, J.R., Majkowski, J. Hampton, J. 1990. MULTIFAN a Likelihood-based method for estimating growth parameters and age composition from multiple length frequency data sets illustrated using data for southern bluefin tuna (Thunnus Maccoyii). Can. J. Fish. Aquat. Sci. Vol. 47. 1990.

Fu, D. 2019. Preliminary Indian Ocean Bigeye Tuna Stock Assessment 1950-2018 (Stock Synthesis). IOTC-2019-WPTT21-61.

Kell, L. T., Palma, C., DeBruyn, P. 2013. Length based catch curve analysis for white marlin. Collect. Vol. Sci. Pap. ICCAT, 69(3): 1225-1229 (2013).

Kristensen, K., Nielsen, A., Berg, C.W., Skaug, H., Bell, B.M., 2016. TMB: automatic differentiation and laplace approximation. J. Stat. Softw. 70.

Maunder, M. N., Crone, P. R., Punt, A. E., Valero, J. L., and Semmens, B. X. 2016. Growth: Theory, estimation, and application in fishery stock assessment models. Fisheries Research, 180:1-3.

Methot, R.D., Wetzel, C.R. 2013. Stock synthesis: A biological and statistical framework for fish stock assessment and fishery management. Fisheries Research 142 (2013) 86-99.

Powell, D. G. 1979. Estimation of mortality and growth parameters from the length frequency of a catch [model]. Rapports et Proces-Verbaux des Reunions, 175, 1979.

Wetherall, J., Polovina,J., Ralston, S., 1987. Estimating growth and mortality in steady-state fish stocks from length-frequency data. In ICLARM Conf. Proc, pages 53-74, 1987.

Patrick, W. S., Spencer, P., Link, J., Cope, J., Field, J., Kobayashi, D., Lawson, P., et al. 2010. Using productivity and susceptibility indices to assess the vulnerability of united states fish stocks to overfishing. Fishery Bulletin, 108: 305-322.

SCHNUTE, J., FOURNIER, D. 1980. A new approach to length frequency analysis: growth structure. J. Fish. Res. Board Can. 37: 1337-1 351.

Zhou, S., Punt, A. E., Smith, A. D. M., Ye, Y., Haddon, M., Dlchmont, C. M., and Smith, D. C. 2018. An optimized catch-only assessment method for data poor fisheries. ICES Journal of Marine Science, 75: 964-976.

Table 1: Configurations of 12 model runs, corresponding to $\mathbf{3}$ levels of random process error on age distribution ( $\sigma_{\mathrm{r}}$ ), and two levels of growth variability $\left(\sigma_{\mathrm{a}}\right)$ for each of the two growth estimates, Evenson et al. 2012 and Farley et.al. 2021.

| Model | Growth | $\sigma_{r}$ | $\sigma_{a}$ |
| :--- | :--- | :--- | :--- |
| 1 | Evenson et al. 2012 | 0.01 | 0.10 |
| 2 | Evenson et al. 2012 | 0.01 | 0.05 |
| 3 | Evenson et al. 2012 | 0.10 | 0.10 |
| 4 | Evenson et al. 2012 | 0.10 | 0.05 |
| 5 | Evenson et al. 2012 | 0.20 | 0.10 |
| 6 | Evenson et al. 2012 | 0.20 | 0.05 |
| 7 | Evenson et al. 2021 | 0.01 | 0.10 |
| 8 | Evenson et al. 2021 | 0.01 | 0.05 |
| 9 | Evenson et al. 2021 | 0.10 | 0.10 |
| 10 | Evenson et al. 2021 | 0.10 | 0.05 |
| 11 | Evenson et al. 2021 | 0.20 | 0.10 |
| 12 | Evenson et al. 2021 | 0.20 | 0.05 |



Figure 1: Growth estimates by Eveson et al. 2012 (VB-LogK function), and by Farley et al. 2021 (VBLogK function). Shaded distribution represents the assumed variability of mean size-at-age in the bigeye tuna stock assessment.


Figure 2: Longline length frequency distribution of bigeye tuna 1975-2018. The length frequency data is aggregated across all fleets (Taiwanese and Seychelles data excluded).


Figure 3: Estimated fishing selectivity by age (left) and fishing mortality rate by year (1975-2018) for model 3 (Eveson et al. 2012 growth) and 9 (Farley et al. 2021 growth). See table 1 for model configurations.


Figure 4: Comparison of estimated fishing mortality rates between models assuming different levels of $\sigma_{r}$ (Left; model 1, 3, 5), and models assuming different variability ( $\sigma_{a}$ ) on the mean size-at-age (right; model $3,4,9,10$ denoted as ' 0 ').


Figure 5: fits to the bigeye tuna annual longline length frequency 1975-2018 for model 3 and 9.


Figure 6. Estimated process error $\varepsilon_{a, y}$ by year from models assuming different levels of $\sigma_{r}$ (models 3 and 5).

## Appendix A. Results from the model applied to simulated observations



Figure A1: Model fits to the simulated length frequency -fits (line) and observations (' 0 ') are aggregated over the $\mathbf{1 0}$ (years) length distributions.


Figure A2: Estimated fishing selectivity by age (left) and fishing mortality rate by year from model fits to the simulated length data (2011-2020). ' $e$ ' indicates model estimates (lines are the $\mathbf{9 0 \%} \mathbf{C I}$ ) and ' $\mathbf{o}$ ' indicates assumed true values.


[^0]:    ${ }^{1}$ IOTC Secretariat, Dan.Fu@fao.org;

