Precision of estimated growth parameters of yellowfin tuna (*Thunnus albacares*) from length-frequency data estimated by bootstrapping

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Abstract

Over 60% of the world's fish stocks suffer from limited data, which hampers effective fisheries management. Researchers have developed stock assessment methods for data-limited fisheries using length-frequency data, but reliability was questionable and not well researched. We evaluated the precision of the widely used length-based method ELEFAN using 24 months of length-frequency data from 14,190 individual yellowfin tuna and sequential and interval data fractions. Using bootstrapping (1000 times) and data reduction, growth parameters and precision L_{∞}, K, and Φ' were estimated. The CVs of L_{∞}, K, and Φ' were 2.55%, 23.04%, and 2.35%, respectively. From the result of data reduction, at least once in 1 or two months and 12 times measurements with 500 data per measurement on average is recommended for achieving high precision with CV of Φ'< 3%.

KEYWORDS

length-based methods, growth curve parameter, yellowfin tuna, bootstrapping, precision, coefficient of variation

1. INTRODUCTION

Fishery resources play crucial roles in providing food and livelihoods for humans, so must be carefully maintained (FAO, 2018). Unfortunately, >60% of global stocks lack sufficient data for effective resource management (Costello et al., 2012; Froese et al., 2018; Sagarese et al., 2019). Length-based methods are rapidly evolving for fisheries management, but poor data raises concerns about reliability of resultant stock assessments (Chong et al., 2020; Downing et al., 2019; Froese et al., 2018; Hordyk et al., 2015).

The popularity of length-based methods arises from their simplicity, affordability, and ease of estimating growth parameters, in contrast to age-based methods, which are often more intricate and costly (Schwamborn et al., 2023). Collecting data on individual body length is relatively straightforward and cost-effective, thereby making it a practical and efficient choice for fisheries research (Zhou et al., 2022). As a result, length-based methods have undergone rapid development (Xu et al., 2022).

Accuracy and precision of length-based methods have been previously evaluated. For example, average-length-based assessment methods were evaluated for their ability to achieve long-term management goals, showing acceptable performance for highly productive Australian demersal trawl species, provided variability in length-at-age is considered (Klaer et al., 2012). Further, the effects of intra-annual recruitment process error on small pelagic fish were evaluated by comparing models with additive recruitment error using quarterly fixed-effects model (QFEM) to seasonal interaction models, showing that QFEM can enhance assessments and management of fast-growing, short-lived species such as small pelagic fish (Canales et al., 2019). Conversely, an evaluation of length-based stock assessment methods emphasized the need to measure precision and apply methods contextually, finding the Thompson and Bell method and length-based spawning potential ratio (LBSPR) to be the most reliable, while length-based risk analysis (LBRA) was precautionary despite bias, length-based integrated mixed effects (LIME) suited longer time-series and all methods struggled with short-lived species (Chong et al., 2020). Finally, bootstrapped length-frequency and length-at-age (otolith) analyses (bootLFA) can reliably estimate growth parameters, which is crucial for fisheries assessment and management when specific recommendations and criteria are followed (Schwamborn et al., 2023).

The length distribution of a fish population at a specific point in time is represented by length-frequency data (LFD) that reflect growth and mortality. First, changes in the length of fish at successive ages reflect annual growth (Batts et al., 2019). Second, variation in length within age groups over a year reflects seasonal growth (Laslett et al., 2004). The distribution and number of fish lengths affect the precision of analytical results for stock assessment (Han et al., 2021; Headley, 2020). Therefore, to ensure accurate results, the number of fish lengths, number of months, and distribution of fish lengths per month must be considered. As a standard, 675 LFD samples from 7 months of sampling showed a low pseudo-$R^2_{Phi`}$, from 54% to 68%, indicating the need for more samples (Schwamborn et al., 2019).

ELEFAN (Electronic LEngth Frequency ANalysis) is a method used to estimate growth parameters from LFD (Pauly and David, 1981), commonly employed for fitting the von Bertalanffy growth function (VGBF; von Bertalanffy, 1938). ELEFAN has been extensively implemented in multiple software tools like FAO-ICLARM fish stock assessment tools (FiSAT; Pauly and Sparre, 1991), FiSAT II (Gayanilo et al., 2005), ELEFAN in R (Taylor & Mildenberger, 2017), and TropFishR (Mildenbelger et al., 2017). ELEFAN has been used to estimate VBGF parameters asymptotic length (L_∞) and growth coefficient (K), especially when data are limited (Chong et al., 2020; Downing et al., 2019).

Key parameters like L_∞ and K are important in stock assessment and serve as standard values for estimation and analysis in fisheries management (Cadima, 2003; Hordyk et al., 2015). For instance, asymptotic length is used to determine the minimum catchable size to sustain resource viability (Prince et al., 2023; Xu et al., 2022). Growth rate and theoretical age contribute insights into fishing pressure and fish population structures (Gayanilo et al., 2005; Pauly and David, 1981; Pauly and Sparre, 1991). Imprecise growth parameter estimates create uncertainty that can increase the likelihood of failing to meet target management outcomes, thereby complicating efforts to rebuild depleted stocks and reducing profits from sustainable fishing (Privitera-

Johnson & Punt, 2020). Because growth curve parameters (GCPs) are used for the calculation of Biological Reference Points, such as Yield Per Recruit and Spawning Per Recruit, from which sustainability of fisheries is inferred (Piner et al., 2016), validating these methods under poor data conditions is needed to ensure dependable stock assessment results that support sustainable management policies (Chong et al., 2020; Downing et al., 2019; Privitera-Johnson & Punt, 2020).

The bootstrap method is a statistical resampling technique used to estimate the sampling distribution of a statistic by repeatedly sampling from observed data that has gained widespread recognition as a valuable strategy in statistical analysis (Efron, 1979). Bootstrapping involves resampling with replacement from available data, to quantify uncertainty and estimate confidence intervals for results (Davison et al., 1986; Elvarsson et al., 2014). The primary advantage of bootstrapping lies in its capacity to address inherent data variation, offer a comprehensive view of parameter distributions, and enhance statistical analysis (Rousselet et al., 2023).

In this study, we evaluated the precision of growth curve parameters estimated from the LFD of yellowfin tuna (*Thunnus albacares*), especially the minimum number of length measurements, number of months, and frequency of data collections, using a bootstrap approach for consistent and reliable stock assessment estimates. Through reinforcing stock assessment reliability via bootstrapping and scenario testing, we sought to contribute to shaping adaptive fisheries management policies. Our findings will be useful for establishing a robust foundation for sustainable decision-making, enhancing understanding of fish populations, and supporting global efforts in conserving fisheries resources.

2. MATERIALS AND METHODS

2.1. Data sources

Monthly samples of yellowfin tuna lengths were from longline fishing in the Fisheries Management Area (FMA) 573 of Indonesia in the Indian Ocean. Data were typical for length-based, data-limited fisheries (Abobi et al., 2019; Amorim et al., 2020; Barua et al., 2023; Haruna et al., 2018; Jiang et al., 2022; Kaymaram et al., 2014; Santos et al., 2023). The dataset spanned 24 months during 2013–2014 and included 14,190 length measurements that ranged from 82–187 cm in fork length (FL) and averaged 137 cm FL. The monthly sample included 211–1,473 individuals and an average of 591 individuals per month.

Growth parameters were estimated from LFD using TropFishR (Mildenberger et al., 2021). The optimal bin size (*OBS*) was determined from maximum body length ($L_{\max}$) (Wang et al., 2020; Jiang et al., 2023): $OBS = 0.23\ x\ L_{\max}{}^{0.6}$.

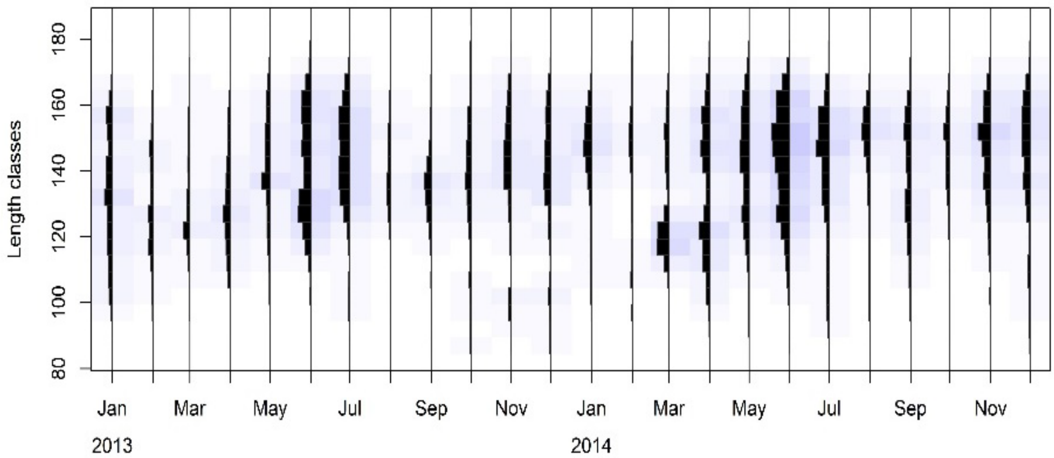

FIGURE 1. Length-frequency distributions of Yellowfin Tuna (*Thunnus albacares*) captured by longline fishing in Fisheries Management Area (FMA) 573 of Indonesia in the Indian Ocean during 2013–2014.

Length-frequency data (Figure 1) were restructured to objectively determine peaks that corresponded to cohorts, without considering the height of peaks or assuming anything about their form (Brey et al., 1988; Gayanilo et al., 2005; Pauly & David, 1981). Restructured LFQ data (Figure 2) aided in determining bin size and incorporated a moving average with a value of five.

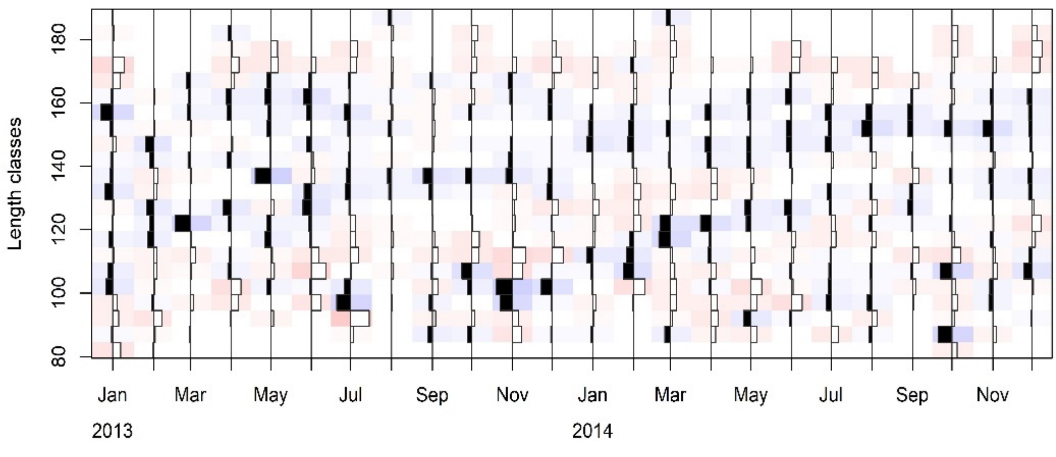

FIGURE 2. Restructured length-frequency distributions of Yellowfin Tuna (*Thunnus albacares*) captured by longline fishing in Fisheries Management Area (FMA) 573 of Indonesia in the Indian Ocean during 2013–2014.

2.2. Research flow

First, 1000 bootstrap samples of source data were drawn using "boot," "dplyr," and "infer" packages in RStudio (Figure 3). Second, to verify that distributions of bootstrapped samples were consistent with the original data, 10,000 bootstrap samples were used (Figure S1). Third, after removing months and samples for each month, growth parameters were estimated using the TropFishR package. Last, precision was indexed using the coefficient of variation (CV).

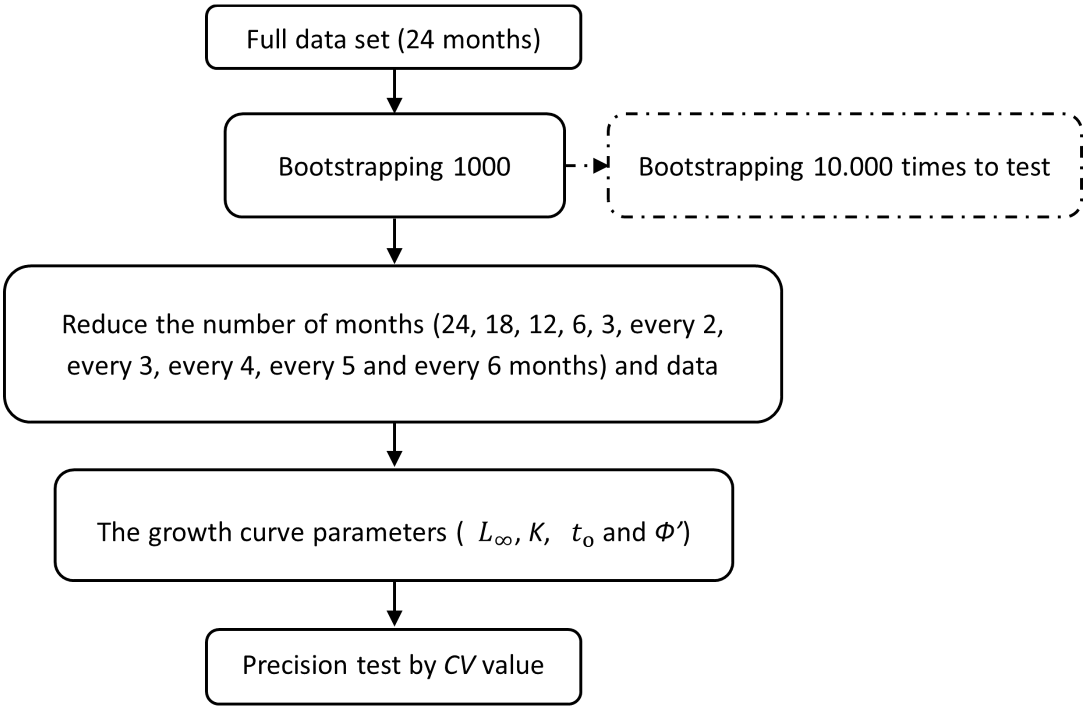

FIGURE 3. Research workflow for evaluating the precision of growth parameters for Yellowfin Tuna (*Thunnus albacares*) captured by longline fishing in Fisheries Management Area (FMA) 573 of Indonesia in the Indian Ocean during 2013–2014.

2.3. Simulation scenarios

Multiple scenarios were used to assess the sensitivity of bootstrapping reliability, including sequential and interval sampling protocols (Table 1). Initially, 1000 bootstrap samples of lengths were drawn from 24 months of samples. For sequential sampling, the number of months was reduced to 18, 12, 6, and 3 months from the start of the data set. For interval sampling, data were sampled at intervals of 2, 3, 4, 5, and 6 months from the start of the data set (Table S2). Effects of the amount of data were examined by selecting 100%, 75%, 50%, 25%, and 10% random samples from the original data (Table S1). The Kruskal-Wallis test is used to evaluate the significance of differences across various scenarios.

TABLE 1. Number of length measurements sub-sampled sequentially and by intervals of Yellowfin Tuna (*Thunnus albacares*) captured by longline fishing in Fisheries Management Area (FMA) 573 of Indonesia in the Indian Ocean during 2013–2014.

Scenario		Percentage of data				
Months		100%	75%	50%	25%	10%
Sequentially	**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

Note: The percentages shown in this table refer to the proportion of data used for analysis.

2.4. Growth parameter estimation

Growth in length was estimated using the von Bertalanffy (1938) growth formula:

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

where L_∞ = asymptotic length, K = the growth coefficient, and t_0 = the theoretical age at length = 0, as tuning parameters for changing the form of the growth curve. VBGF parameters were estimated using ELEFAN_SA (Electronic LEngth Frequency ANalysis Simulated Annealing) in TropFishR, employed through the GenSA package (Schwamborn et al., 2019) to approximate the global optimum (Xiang et al., 2013). Applying the seasonal VBGF and a moving average of 5 required one minute per iteration for each dataset. The growth performance index Φ' (Pauly and Munro, 1984) was used to integrate L_∞ and K (Schwamborn et al., 2023):

$$\Phi' = \log_{10} K + 2\log_{10} L_\infty$$

2.5. Parameter filtering

To remove biologically implausible estimates of growth parameters, t_0 values less than −1.00 were omitted. t_0 was not estimated using ELEFAN, but rather by using the empirical equation (Pauly, 1979):

$$\log(-t_0) = -0.3922 - 0.2752 \log L_\infty - 1.038 \log K.$$

If fish length followed the growth curve exactly, t_0 would reflect the time from embryogenesis to hatching and should be less than 1 year (Batts et al., 2019). Therefore, if an estimated t_0 was less than −1.00, L_∞ and K were also considered to be biologically implausible. Growth parameters estimated before and after filtering were compared to ensure reliability of the t_0 filter.

2.6. Evaluation of precision

Precision was indexed using the coefficient of variation (*CV*):

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

The standard deviation (*SD*) and mean were estimated for growth parameters generated for each scenario. The evaluation results guided the determination of the minimum data required to estimate growth curve parameters, by targeting a *CV* for Φ\` ≤ 3%.

3. RESULTS

3.1. Parameter estimates

Sample size significantly affected estimates and variability of growth parameters of yellowfin tuna. Mean L_∞ increased and *CV* decreased as the sampling fraction was reduced (Table 2). For example, with 24 months of samples, the mean length increased significantly from 166.50 cm FL to 194.90 cm FL as the sampling fraction decreased from 100% to 10% ($p<0.001$, Kruskal-Wallis test). Precision decreased correspondingly, with *CV* increasing significantly from 2.55% to 13.36% ($p< 0.001$) (Table 3B; Figure S3). Mean K declined significantly from 0.76 to 0.34 with 24 months of samples as the sampling fraction declined ($p<0.001$), while *CV* increased significantly from 23.04% to 67.22% ($p<0.001$). However, a pattern was not apparent for scenarios with data collected every 6 months, likely due to limited data in interval sampling.

Mean L_∞ increased as the sampling interval increased from every 2 months to every 6 months (Table 2). Mean L_∞ with 100% of the data was similar for 12-month (169.89 cm FL) and 2-month interval samples (168.08 cm FL), but higher with 10% of the data for 12-month (203.20 cm FL) and 2-month (197.38 cm FL) interval samples. For all data sampling strategies, the *CV* of K was larger than for L_∞, but followed a similar pattern as the number of months decreased and the sampling fraction increased. The *CV* of K nearly doubled from 23.04% with 100% of the data to 72.26% with 10% of the data.

TABLE 2. Mean estimated growth parameters, L_∞, K, and Φ, over a range of sample fractions and months, after filtering t_0

Variables	% data	Months									
		24	**18**	**12**	**6**	**3**	**Ev 2**	**Ev 3**	**Ev 4**	**Ev 5**	**Ev 6**
L_∞ (cm FL)	**100**	166.50	168.66	169.89	174.46	186.16	168.08	170.34	169.76	169.84	170.30
	75	167.12	168.80	172.91	176.47	187.86	168.71	171.15	171.56	174.98	171.13
	50	167.42	170.88	178.78	183.71	193.86	170.18	174.73	175.75	181.07	171.13
	25	173.22	179.45	188.37	194.04	199.90	180.05	182.42	184.14	190.82	179.20
	10	194.90	197.93	203.20	198.78	203.27	197.38	194.57	196.80	200.10	194.91
K (y^{-1})	**100**	0.76	0.79	0.58	0.48	0.42	0.73	0.66	0.61	0.44	0.68
	75	0.74	0.79	0.58	0.48	0.41	0.72	0.65	0.58	0.42	0.66
	50	0.74	0.74	0.54	0.46	0.37	0.69	0.61	0.56	0.41	0.66
	25	0.62	0.61	0.45	0.39	0.32	0.56	0.53	0.49	0.37	0.52
	10	0.34	0.34	0.26	0.32	0.27	0.33	0.37	0.33	0.31	0.37
Φ'	**100**	4.31	4.33	4.17	4.12	4.08	4.30	4.26	4.21	4.07	4.28
	75	4.30	4.33	4.18	4.12	4.07	4.29	4.25	4.18	4.07	4.26
	50	4.30	4.31	4.16	4.12	4.05	4.28	4.24	4.18	4.08	4.26
	25	4.22	4.23	4.10	4.08	4.02	4.19	4.18	4.14	4.06	4.17
	10	4.01	4.02	3.95	4.01	3.97	4.01	4.06	4.01	4.01	4.06

Ev 2, Ev 3, Ev 5, Ev 6: every 2, 3, 5, 6 months

165.00 205.00 0.25 0.80 3.80 4.40

TABLE 3. Coefficient of variation (*CV* %) for growth parameters, L_{∞}, K, and Φ, before (A) and after (B)filtering t_0, for yellowfin tuna (*Thunnus albacares*) captured by longline fishing in Fisheries Management Area (FMA) 573 of Indonesia in the Indian Ocean during 2013–2014.

(A)

Variables	% data	Months									
		24	**18**	**12**	**6**	**3**	**Ev 2**	**Ev 3**	**Ev 4**	**Ev 5**	**Ev 6**
	100	9.32	8.89	7.86	10.97	14.58	11.90	6.48	7.01	10.76	3.54
	75	10.00	9.69	10.57	11.51	14.72	12.47	6.87	8.90	13.05	4.84
$\boldsymbol{L_{\infty}}$	**50**	11.23	10.84	12.71	13.06	14.31	12.03	9.81	11.80	15.03	4.84
	25	12.28	12.89	13.54	13.62	13.68	13.29	13.00	14.59	14.99	11.51
	10	13.59	12.85	12.08	13.05	13.38	12.78	13.66	13.67	13.58	14.08
	100	42.16	43.05	59.67	55.21	70.53	104.10	31.40	38.08	37.15	24.12
	75	46.65	47.97	64.37	61.54	73.07	102.91	31.93	40.43	41.27	29.08
K	**50**	55.09	57.95	76.64	74.04	84.01	86.99	35.01	45.08	48.27	29.08
	25	61.28	70.15	85.19	80.78	92.73	76.60	47.19	58.01	58.32	44.53
	10	87.44	88.72	90.12	84.73	82.04	87.21	65.61	77.35	78.23	64.41
	100	11.64	12.22	12.51	12.03	12.17	22.47	2.96	4.11	3.27	2.85
	75	12.62	13.75	13.64	13.39	12.96	22.16	2.98	4.25	3.44	3.37
$\boldsymbol{\Phi'}$	**50**	14.56	15.38	15.57	15.15	14.38	20.69	3.16	4.25	3.74	3.37
	25	14.28	15.72	15.12	14.78	15.09	16.37	3.92	4.80	4.25	4.28
	10	10.70	11.16	10.72	10.68	10.86	10.93	5.08	5.50	5.26	4.94

(B)

Variables	% data	Months									
		24	18	12	6	3	Ev 2	Ev 3	Ev 4	Ev 5	Ev 6
	100	2.55	3.35	5.29	10.21	14.99	4.85	6.48	7.01	10.76	3.54
	75	3.52	4.38	9.10	11.32	15.20	6.08	6.87	8.90	12.97	4.84
L_∞	50	4.51	7.04	12.4	13.62	14.91	7.32	9.81	11.75	14.89	4.84
	25	10.17	12.34	14.22	14.40	13.91	12.67	12.9	14.39	14.68	11.35
	10	13.36	12.83	12.09	13.04	13.01	12.59	13.22	13.22	13.32	13.81
	100	23.04	24.33	46.18	41.06	58.13	27.34	31.4	38.08	37.15	24.12
	75	25.58	24.72	47.57	44.41	58.71	30.17	31.93	40.43	41.09	29.08
K	50	28.34	30.85	53.95	51.33	66.09	31.26	35.01	44.98	47.81	29.08
	25	38.31	44.85	63.40	59.37	71.84	47.79	46.84	57.31	56.07	44.15
	10	67.72	70.37	72.26	72.18	70.33	67.99	61.47	69.75	71.21	61.66
	100	2.35	3.01	5.05	4.14	4.72	2.79	2.96	4.11	3.27	2.85
	75	2.86	2.89	4.98	4.21	4.66	2.88	2.98	4.25	3.41	3.37
Φ'	50	2.81	3.34	5.02	4.36	4.73	3.06	3.16	4.23	3.69	3.37
	25	3.78	4.28	5.13	4.27	4.51	4.13	3.86	4.71	3.96	4.23
	10	4.93	5.13	4.49	4.66	4.23	4.88	4.61	4.80	4.59	4.59

Note: The columns highlighted by the red rectangle indicates CV values less than or equal to 3, representing highest precision.

Ev 2, Ev 3, Ev4, Ev 5, Ev 6: every 2, 3, 4, 5, 6 months

0% 50% 100%

3.2. Precision of parameter estimates

The *CV* of growth parameters L_∞, K, and Φ' increased as the sampling fraction decreased (Figure S2), especially when the number of months was reduced (Table 3 and Table S3). For example, with 24 months of samples, the *CV* for the 50% sampling fraction was nearly double (4.51%) that of the 100% sample (2.55%), and the *CV* was even higher for 25% (10.17%) and 10% (13.36%) sampling fraction. Filtering t_0 was found to improve the precision of parameter estimates. For instance, in the 24-month scenario with 100% data, *CV* of L_∞ decreased from 9.32% for unfiltered t_0 to 2.55% for filtered t_0. A similar trend was observed in scenarios with more than 50% data, although *CV* values remained stable in interval sampling. Additionally, the *CV* also increased for 100% and 50% sampling fractions with 18 and 12 months of samples. Despite small variation in mean L_∞ among sampling scenarios, the overall pattern consistently indicated that more data led to higher precision of estimated L_∞ (Table S3).

For 12 months of samples, as the sampling fraction decreased, *CV* increased from 5.29% with 100% of the data to 14.22% for 25% of the data (Table 3). Similarly, *CV* increases with sequential 2-month samples from 4.85% with 100% of the data to 12.67% with 25% of the data. Although *CV* varied when reducing the sampling fraction from 100% to 10%, *CV* remained around 12%, which suggested 12% was the maximum variation possible for the data (Figure S2). The *CV* for the every-2-month scenario (4.85%) was lower than for the 12-month scenario (5.29%) with 100% of the data. *CV* increased linearly between 6-month and 4-month sampling intervals, with a *CV* of 13% with 10% of the data, but differed with 100% of the data, wherein the *CV* was 10.21% for the 6-month sampling interval and 7.01% for the 4-month sampling interval.

3.3. Relationship between L_∞ and K

The relationship between L_∞ and K was illustrated in (Figure 4), with K estimates ranging from 0.1 to 1.5 and L_∞ estimates from 127.29 to 250.00. The trend shows that larger L_∞ estimates correspond to smaller K estimates and vice versa. Unrealistic overlayed estimates often arise from scenarios with limited data availability, highlighting the influence of sample size on the reliability of parameter estimation.

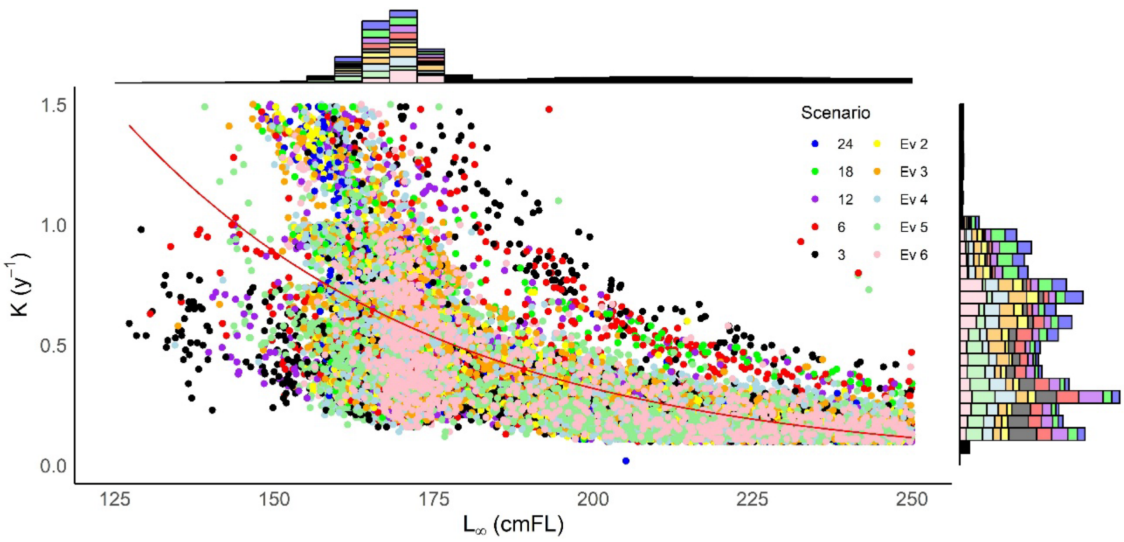

FIGURE 4. Kimura plots of K versus L_∞ for yellowfin tuna (*Thunnus albacares*) captured by longline fishing in Fisheries Management Area (FMA) 573 of Indonesia in the Indian Ocean during 2013–2014. Ev 2, Ev 3, Ev4, Ev 5, and Ev 6 represent scenarios where data is collected every 2, 3, 4, 5, and 6 months, respectively, to evaluate the impact of reduced temporal sampling on the parameter estimation. ELEFAN_SA estimates for each scenario are shown as coloured points. The relationship between L_∞, and K is shown by the red line. Histograms illustrate the frequency distribution of estimated values for each variable across all scenarios. Another Kimura plot illustrating data reduction in each scenario is provided in the supplementary material.

4. DISCUSSION

Our study is the first to utilize more than 10,000 original length measurements to examine the precision of growth parameter estimates using bootstrapping. In contrast, Schwamborn et al. (2019) used 675 length measurements to assess sources of uncertainty in length-based estimates of body growth, and Schwamborn et al. (2023) used 2,564 length measurements to compare bootstrapping length data with otolith data. The precision of estimated growth parameters increased with the number of length measurements for all scenarios in our study, which confirms that sample size influences precision or parameter estimates used in length-based stock-assessment methods.

In our study, t_0 was limited to −1.00 to ensure growth parameter estimates were biologically plausible. Especially due to limited data and gear size selectivity, small (young) fish are often lacking from length-frequency and age-frequency samples, which thereby prevents accurate estimation of t_0 (Ono et al., 2015; Zhou et al., 2020; Zhou et al., 2022) (i.e., larger minus t_0 and larger errors in estimated growth parameters). Thus, we conclude that filtering t_0 is necessary to reduce bias and improve the accuracy of ELEFAN analysis. We also found that filtering t_0 improved the precision of parameter estimates.

We found that reducing the number of months of samples had less effect than reducing the sampling fraction in each month. The relationship between CV of L_∞ and K suggested that high uncertainty and low precision of estimated L_∞ often led to similar uncertainty in K. Additionally, K tended to decrease as L_∞ increased, and vice versa, as has been found elsewhere (Ben-Hasan et al., 2024; Liu et al., 2021; Schwamborn et al., 2019; Schwamborn et al., 2023; Thorson et al., 2017).

Growth parameters for yellowfin tuna, based on the Growth Performance Index (Φ`), were estimated within a narrow range (2.85 to 4.98) and with high precision (*CV* between 2.35% and 5.13%). Higher precision of Φ` was likely due to more accurate estimates of L_∞ than K, which suggests that L_∞ has a greater impact on Φ` than *K*. With 24 months of samples and 100% of the data, *CV* was <3% for both $L_\infty$ and Φ` but exceeded 20% for K, which indicates that ELEFAN estimates L_∞ well but not K, although Φ` suggests that growth parameter estimates were stable (Pauly and Munro, 1984).

Because of small sample sizes and low data variability, the *CV* for 6-month sampling intervals was relatively low with 100% of the data (3.54%), 75% of the data (4.84%), and 50% of the data (4.84%). However, we advise caution in interpreting these results, until confirmed by additional further in-depth simulations.

Two of our scenarios produced *CVs* with *CV*s of 4–6%, which we consider an optimal amount of data for obtaining acceptable precision of growth parameter estimates: 12 months of samples with 100% of the data and a 2-month sampling interval with 100% of the data (24 total months). With 12 months of samples and 100% of the data, the *CV* was 5.29% for L_∞ and 46.18% for *K*, and with a 2-month sampling interval and 100% of the data, the *CV* was 4.85% for L_∞ and 27.34% for *K*. The CV of Φ` (2.79%) was lower for the 2-month sampling interval and 100% of the data.

In conclusion, our study evaluated changes in the *CV* of growth parameter estimates in relation to a range of sampling strategies, to identify the minimum amount of data required for reliable estimates. We recommend using a target *CV* for Φ` of 3% when designing sampling programs to collect fish for growth estimation. We conclude that 24 months of samples with 100%, 75%, and 50% of the data; 18 months of samples with 100% and 75% of the data; sampling every 2 months with 100%, 75%, and 50% of the data; and sampling every 3 months with 100% and 75% of the data, meet this criterion. We also recommend sampling at least once every 1–2 months, with 12 samples per year, and an average of 500 length measurements per sample, to achieve high precision of growth parameter estimates (CV of Φ` <3%). Consequently, to obtain reliable growth parameter estimates, a sampling design must cover 24 months with 7100 length measurements, 18 months with 8000 length measurements, sampling every 2 months over 2 years with 3500 length measurements, or sampling every 3 months over 2 years with 4100 length measurements. Ultimately, we aimed to provide fishery managers with information for reliable stock assessment. While our study was based solely on specific data for yellowfin tuna, our methodology and the pattern of results may be generalizable to other species, and equally important, decisions should consider available human resources and financial resources for sampling enough data.

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Data availability:

Data will be made available on request, R script repositories at https://github.com/wietteguh89/ELEFAN-Bootstrapping-Simulation

Statement of conflict of interest and its founding:

We have read and approved the manuscript and take full responsibility for its content. We have no conflict of interest regarding this research or its funding.

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