Title	Precision of growth curve parameters and biological reference points estimated from the length fish data: A case study of Yellowfin tuna (Thunnus albacares) in Indonesia
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Degree Grantor	北海道大学
Degree Name	博士(食資源学)
Dissertation Number	甲第16520号
Issue Date	2025-03-25
DOI	https://doi.org/10.14943/doctoral.k16520
Doc URL	https://hdl.handle.net/2115/97741
Type	doctoral thesis
File Information	WIWIET_TEGUH_TAUFANI.pdf

Precision of growth curve parameters and biological reference points estimated from the length fish data: A case study of Yellowfin tuna (*Thunnus albacares*) in Indonesia

（体長データから推定した成長曲線パラメータと生物学的管理基準の精度：
インドネシアのキハダマグロ（*Thunnus albacares*）の事例研究）

Hokkaido University Graduate School of Global Food Resources
Division of Global Food Resources　　Doctoral Course

Wiwiet Teguh Taufani
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ABSTRACT

I. General Introduction

Fisheries resources are vital to global food security and the livelihoods of millions of people. As demand for fish continues to rise, ensuring the sustainable use of these resources has become a major focus of fisheries management. Stock assessments play a fundamental role in this effort by providing the necessary information to evaluate fish stock status and guide management decisions. Among the various approaches available, length-based methods are particularly favoured in data-limited situations due to their simplicity, affordability, and ease of application.

Despite their advantages, length-based methods are susceptible to misestimation, especially when the number of data is limited, which can lead to inaccurate stock assessments and potentially compromise management outcomes. Therefore, this research aims to provide a rigorous evaluation of precision through quantitative analysis for estimating growth parameters and biological reference points in data-limited situations. This research will offer new insights into the performance of length-based methods, thereby supporting researchers, policymakers, and fisheries managers in improving data collection and analysis practices. In doing so, it contributes to the sustainable management of fisheries resources, helping to ensure food security through science-based policies and responsible governance.

II. Materials and Methods

Bootstrapping simulations were used to assess the precision of growth parameter estimates and biological reference points (BRPs) under different data scenarios. The dataset consisted of length-frequency data from yellowfin tuna (*Thunnus albacares*) collected over 24 months (2013–2014) in Indonesian Fisheries Management Area 573, with a total of 14,190 individuals. Data scenarios included reducing the number of months (24, 18, 12, 6, and 3 months) and decreasing the number of data per month (100%, 75%, 50%, 25%, and 10%). Each scenario was bootstrapped 1,000 times, generating distributions of growth parameters and BRPs to assess variability.

The von Bertalanffy growth model (VBGM) was applied to estimate growth parameters such as L_∞, K, and t_0. To ensure biological plausibility, estimates with

t_0 values less than -1 were omitted. Subsequently, BRPs such as $F_{0.1}$, $F_{\max}$, and $F_{0.5}$, were calculated. Additionally, the coefficient of variation (*CV*) was used to measure the precision of the parameter estimates, with lower *CV* values indicating more stable results.

III. Results and Discussions of Growth Curve Parameters

The estimates of growth parameters displayed variability with changes in data availability.

In the scenario utilizing full data (24 months 100% data), the estimated mean values were 166.50 cm FL (fork length) for L_∞ and 0.76 y^{-1} for K with *CV*s of 2.55% and 23.04%, respectively. As data availability decreased, the *CV* for these estimates increased, indicating a rise in uncertainty. Notably, in scenarios with 10% of the data, the *CV* for L_∞ increased to 13.36% (a fivefold increase) and for K to 67.72% (a threefold increase) relative to the full dataset. These findings quantitatively demonstrate the critical importance of comprehensive data collection, as limited datasets resulted in variability of up to threefold in the parameter estimates.

Different combinations of L_∞ and K may describe the similar shape of the growth curve. The growth performance index or phi prime (Φ'), which integrates L_∞ and K, was used to assess the difference of shape of the growth curve. The analysis showed that Φ' had lower *CV* compared to L_∞ and K, with *CV*s ranging from 2.35 to 5.13% across scenarios, indicating consistency and reliability. Scenarios with higher Φ' values corresponded to more stable parameter estimates, suggesting its suitability for data-limited fisheries. These results highlight that while length-based methods are practical for evaluating fish growth in data-limited fisheries, the reliability of such methods is heavily dependent on the quality and quantity of available data.

IV. Results and Discussions of Biological Reference Points

Using growth parameters derived from bootstrapping simulations, the estimates values and *CV*s for $F_{0.1}$, $F_{\max}$, and $F_{0.5}$ were calculated. For the full dataset, the mean values were 0.64 for $F_{0.1}$, 1.06 for $F_{\max}$, and 0.50 for $F_{0.5}$, with *CV*s of 21.03%, 18.17%, and 25.31%, respectively. As data availability decreased, the *CV*s for these BRPs increased markedly. For example, in the scenario with 10% of the data, the *CV*s rose to 22.14% for $F_{0.1}$, 78.82% for $F_{\max}$, and 72.81% for $F_{0.5}$, highlighting reduced precision in the estimates under data-limited conditions.

It has been believed that the length-based methods produce imprecise growth curve parameters, which leads to unreliable BRPs. However, our results show that even with 50% of the data, the *CV*s for $F_{0.1}$ and $F_{0.5}$ remained below 30%, indicating fair precision. Notably, in some cases, *CV*s for $F_{0.1}$ and $F_{0.5}$ were much lower than those for K, suggesting that the worse precision of VBGM parameters does not necessarily result in unreliable BRPs. On the other hand, $F_{\max}$ showed much higher variability, with *CV*s exceeding 30% in 50% data. This suggests that $F_{0.1}$ and $F_{0.5}$ are more reliable for stock assessments, while $F_{\max}$ is less suitable due to its low precision.

To determine the minimum data required for reliable estimates, we assessed several scenarios using a 10% threshold below the mean values of $F_{0.1}$ and $F_{0.5}$ from full dataset. Reliable results were achieved in the following scenarios: 24 months at all data percentages; 18, 12, and every 2 months at more than 50%; and every 3 months at 100%. Despite the reduction in data, the *CV* values of $F_{0.1}$ across all scenarios remained low comparing with *CV* of $F_{0.5}$ and $F_{\max}$, providing a precautionary and safe estimate for fisheries management.

V. General Conclusions

This study examines the precision of growth curve parameters and the BRPs using length-based methods, especially in data-limited situations, by using bootstrapping simulations.

The methodology and procedures used in this study, particularly the t_0 filtering approach, are adaptable and can be applied to other species and situations, especially for estimating length-based VBGM parameters. While the findings highlight that yellowfin tuna required specific sampling designs to achieve reliable precision, the necessary data volume may vary depending on the species and context. To ensure practical precision, it is crucial to consider *CV* thresholds for BRPs and Φ', which tend to exhibit lower variability compared to VBGM parameters. Future studies should refine these criteria further, adapting sampling designs to the specific biological and fisheries conditions of the target species.

The results demonstrate that length-based methods estimate the BRPs precisely enough with adequate data. Comprehensive length data collection will support sustainable fisheries management.

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ACKNOWLEDGEMENT

First and foremost, I would like to express my profound gratitude to Alloh Almighty for His boundless mercy, guidance, and blessings throughout my academic journey. Without His will and grace, I would not have had strength and perseverance to complete this doctoral thesis.

I owe a deep debt of gratitude to my main supervisor, Prof. MATSUISHI Takashi Fritz. Ph.D., who graciously allowed me to join the laboratory, treating me not just as a student but as a part of the family. Your continuous mentorship, guidance, and rigorous reviews of my work have shaped my understanding and development throughout these years. Your belief in my potential has opened doors to extraordinary international experiences, which have enriched both my academic and personal growth. For this, I am forever grateful.

To my sub-supervisor, Assoc. Prof. UCHIDA Yoshitaka, Ph.D., and Prof. NABESHIMA Takako, Ph.D., I extend my heartfelt thanks for the constructive criticism and invaluable feedback provided during my study. Your insight was essential in refining the direction of my study and ensuring the quality of this doctoral thesis. The time and effort you invested in reviewing my work and providing guidance have had a lasting impact on me, and for that, I am truly thankful.

I would also like to express my eternal gratitude to my father, H. Markono, and my late mother, Hj. Sri Suwarsi, whose unconditional love, prayers, and support have been my source strength. From the very beginning of my studies until now, your encouragement and belief in me have been constant, and I dedicate this achievement to both of you.

To my beloved family -my wife, Pramesti Budi Widyaningrum, and our sons, Zaydan Nayazka Alfarez, Sarfaraz El Basyar, and Naoki Ryouta Prabananta- thank you for your patience, love, and unwavering support throughout this long journey. Despite the great distance between us, with me studying in Japan and you in Indonesia, your prayers and constant encouragement were always felt, guiding me through the toughest of times. Your understanding and sacrifices have made this possible, and I am forever indebted to you.

My heartfelt thanks also go to my parents-in-law, Dr. H. Apik Budi Santoso and Hj. Dwi Handayani, for their constant prayers, support, and care for my wife and children while I was away. Your unwavering commitment to our family allowed me to focus on my studies with peace of mind, and for that, I am deeply grateful.

To my siblings, Nadiya Endah Kharisa and Fahmi Tri Adi Nasucha, and sibling in-law, Prameswari Budi Kusumaningrum, thank you for your continuous encouragement, prayers, and support throughout this journey. Your faith in my success has been a source of motivation, pushing me to persevere and complete this doctoral thesis.

I would like to extend my gratitude to Universitas Diponegoro (Undip), particularly the Badan Pengembangan Sumber Daya Manusia, for providing the scholarship that supported my studies. Your generosity made this academic pursuit possible, and I am honored to represent Undip in this capacity.

I am also deeply thankful to my colleagues at the Department of Aquatic Resources, Faculty of Fisheries and Marine Science, Undip, for their camaraderie, encouragement, and prayers. Your support has been invaluable throughout this journey, and I am fortunate to have such a dedicated and inspiring group of colleagues.

A special thanks to the members of Matsuishi-ken, MATSUDA Ayaka, Ph.D., KURODA Mika, Ph.D., Suppapong Pattarapongpan, Ph.D., Chonlada Meeanan, Ph.D., KANNO Hayato, Changoma Fransis Marko, Jeeratorn Yuttharax, TAKEUCHI Hayate, SHIBATA Natsumi, NAGURA Nodoka, IKUTA Motoki, TSUCIDA Manami, UMEKITA Hina, ARAKANE Shintaro and YAMADA Kanta for welcoming me into the academic community in Japan. Your friendship, support, and assistance throughout my time here have been critical helping me navigate this academic journey far from home. Thank you to be my family in Japan.

To my international friends, Karn Tippayakraisri, Chalvin Putra Rura, Widhya Nugroho Sastroajie, Muhammad Noorullah, Abdul Ghani, Sobia Nasir, Emmanuel Masautso SAKALA, and all the other international students, thank you for creating a supportive and collaborative environment where could all grow together. Your friendship transcended borders and made this journey less isolating and much more enriching.

Lastly, I extend my sincere gratitude to my Japanese friends, TSUCHIYA Jiro, YAMAGUCHI Keito, KURUSHIMA Rei, OKUMURA Kana, TAKADA Sayaka, UMEKI Yuito, SHICHINOHE Naoya, YAMAMOTO Ritsuka, NAKANO Kuriko, KIKUCHI NOZOMI, and all the others, for treating me not only as a friend but also as a brother. Your warmth, kindness, and support have made my experience in Japan truly memorable and meaningful.

Wiwiet Teguh Taufani

1. GENERAL INTRODUCTION

1.1. Vital Roles of Fisheries Resources

Fisheries resources play a critical role in meeting global animal protein needs, particularly in coastal nations. Fish and other seafood are high-quality protein sources that provide essential nutrients such as omega-3 fatty acid, which are vital for human health, especially for cardiovascular and brain function. In comparison to other animal protein sources, such as red meat, fish is a healthier option due to its lower saturated fat content. This makes fisheries an essential component in global food security, especially in regions that have historically relied on marine resources for their dietary needs (FAO, 2020).

In addition to addressing nutritional requirements, fisheries contribute significantly to global food security by providing accessible animal protein to population across various socio-economic backgrounds. In many countries, particularly in developing regions, fish accounts for more than 20% of animal protein intake. Thus underscores the strategic importance of fisheries in reducing food insecurity and malnutrition, especially in coastal communities where fish is often a dietary staple (FAO, 1989; Peng et al., 2013; FAO, 2022).

Beyond nutrition, the fisheries sector is a crucial driver of economic activity, providing employment opportunities worldwide. It is estimated that over 120 million people globally are employed in fisheries and aquaculture, either directly or indirectly. These jobs span across various stages of the supply chain, including fishing, processing, distribution, and sales. In many coastal communities, fisheries represent the primary source of livelihood, making them vital to local economies and community welfare (FAO, 2022; FAO, 2024).

However, the heavy dependence on fisheries resources presents challenges related to sustainability. Overfishing and poor management practices can lead to significant declines in fish stocks, threatening both the availability of animal protein and the livelihood of millions. Addressing these issues requires the implementation of sustainable, science-based fisheries management strategies to ensure that the balance between resource utilization and conservation is maintained.

Sustainable fisheries management is crucial for ensuring the long-term viability of fisheries in supporting global food security and economic stability. With proper management approaches, fisheries can continue to provide valuable animal protein and create employment opportunities. Thus, collaboration between government, stakeholders, and local communities is important to ensure equitable and sustainable management of these vital resources.

1.2. Fisheries Management and Stock Assessment

Fisheries management and stock assessment are important for maintaining global fishery resources. Effective fisheries management seeks to balance the exploitation of fish stocks with conservation efforts, ensuring that marine ecosystems remain healthy while supporting economic livelihoods. Key strategies include the implementation of the ecosystem-based approach, which considers the broader ecological impact of fishing, and the setting of sustainable catch limits to prevent overfishing. Management measures also involve controlling fishing access through licensing, gear restrictions, and area closures, along with fostering international cooperation to manage migratory species that traverse national boundaries. The maximum sustainable yield (MSY) framework, along with the precautionary approach, provides guidelines to prevent stock depletion and ensure long-term sustainability (Garcia et al., 2003; FAO, 2020).

The success of fisheries management heavily relies on accurate and timely stock assessments. Stock assessment is a scientific process that estimates fish stock abundance, productivity, and exploitation rates. This data is essential for fisheries managers to make informed decisions on harvest limits, fishing seasons, and conservation measures. Techniques used in stock assessment include population dynamics models, catch data analysis, and biological parameters such as growth, reproduction, and mortality rates. Assessment helps classify the status of fish stocks -whether they are overfished, fully exploited, or underutilized- allowing managers to adjust regulations as necessary (Hilborn and Walters, 1992; Quinn and Deriso, 1999).

Despite the importance of stock assessments, several challenges complicate their implementation. Data limitations are a common issue, particularly in regions where resources for scientific research are limited or where fisheries operate in remote or data-poor areas. Environmental variability, such as changes in ocean temperatures or current due to climate change, further compliances stock predictions and assessments. Additionally, the uncertainty inherent in population models, often due to incomplete biological information or variable fishing pressures, poses challenges for accurate and precision stock status determination (Pauly et al., 2002). Continuous refinement of assessment models and improved data collection, including the use of modern technologies, are vital for improving the accuracy, precision, and reliability of stock assessments.

1.3. Data-limited Situation

Data-limited situations in fisheries management present significant challenges, particularly when reliable data on stock size, age structure, growth rates, and mortality are scarce or unavailable. These limitations are often due to the high costs of data collection, lack of scientific capacity, or remote fishing areas where monitoring is difficult. As a result, traditional stock assessment methods, which rely on detailed biological and catch data, cannot be applied effectively, leading to greater uncertainty in estimating stock status and setting sustainable catch limits. The lack of comprehensive data also complicates efforts to apply more advanced management models, which depend on accurate stock assessment for decision-making (Carruthers et al., 2014; Downing et al., 2016; Downing et al., 2019).

Several alternative approaches have been developed to manage fisheries in data-limited contexts in response to these challenges. One common method is the use of length-based stock assessment techniques, which utilize length-frequency data to estimate key biological parameters, such as growth rates and natural mortality, without requiring age data. Tools such as catch-MSY, which estimates sustainable yield based on historical catch data, and depletion-corrected average catch (DCAC) models are also widely used in data-limited fisheries. These methods offer simpler but scientifically valid frameworks for assessing stock status and guiding management decisions in the absence of detailed stock assessments (Froese et al., 2017). The precautionary approach is another widely adopted strategy, where management decisions err on the side of caution to avoid overfishing when data is insufficient.

Despite these methods, the uncertainty inherent in data-limited simulations remains high. Environmental factors, such as climate variability, can introduce additional complexity by affecting growth, reproduction, and fish distribution patterns. In response, many fisheries managers have adopted adaptive management frameworks, which allow for regular updates to regulations based on new information or changes in stock status. Collaborative approaches involving local fishers and stakeholders are crucial for improving data collection efforts and supplementing formal scientific data with local ecological knowledge (Berkes et al., 2000).

A key limitation in achieving precise stock assessments is the shortage of data, which often results from constraints in budget allocation and limited availability of human resources. Newly targeted stocks for assessment are particularly vulnerable to data scarcity, as initial sampling efforts may be insufficient to capture their biological and ecological variability (Pilling et al., 2009; Carruthers et al., 2014).

To address the long-term challenges of data-limited fisheries, investments in capacity building and technological advancements are essential. Expanding the use of modern tools can significantly improve data quality and availability in remote areas. Additionally, international cooperation and knowledge sharing among fisheries scientists and managers can help develop more robust models and management strategies tailored to data-limited situations. Through these efforts, the sustainability of fisheries in data-limited contexts can be better ensured, allowing for the continued provision of resources and livelihoods for communities dependent on these fisheries (Costello et al., 2012; FAO, 2020).

1.4. Length-based Method

Length-based methods are widely used in fisheries stock assessments, particularly in data-limited fisheries where age data are scarce or unavailable. These methods rely on the length distribution of fish in a population to estimate key biological parameters such as growth, mortality, and exploitation rates. One of the primary advantages of length-based methods is that length data is easier to collect than age data, which typically requires labour-intensive and costly otolith or scale analysis. As such, length-based assessments provide a valuable alternative for fisheries with limited resources, enabling managers to make informed decisions about stock sustainability (Pauly and Morgan, 1987; Hordyk et al., 2015).

Several widely used length-based methods include length-based stock assessment (LBSA), length-based spawning potential ratio (LBSPR), and length frequency analysis. These techniques utilize the size of the composition of fish samples to estimate parameters like the asymptotic length (L_∞), growth coefficient (K), and natural mortality rate (M). LBSPR, for instance, estimates the proportion of the population that can reproduce based on size at maturity and the size distribution of the stock. This method is particularly useful in data-limited situations, where it can provide insight into the reproductive potential of a fishery and guide sustainable management strategies (Hordyk et al., 2015). Length frequency analysis uses length-frequency data to infer growth patterns over time without the need for direct age measurements (Pauly, 1979).

These length-based methods are integral to fisheries management, especially in tropical and subtropical regions, where fish species often grow rapidly and exhibit high variability in size within populations. By estimating key growth parameters and mortality rates, length-based methods enable managers to assess stock status and implement measures such as catch limits, size restrictions, and gear regulations that are important for preventing overfishing. Moreover, these methods are applicable in small-scale and artisanal fisheries, where age data is typically unavailable, and the costs of conventional stock assessments are prohibitive (Beverton and Holt, 1957; Froese, 2004).

However, while length-based methods offer simplicity and accessibility, they are not without limitations. These methods often assume that environmental factors remain stable and that the length distribution of the sample is representative of the entire population, which may not always be the case. Additionally, the selectivity of fishing gear can skew length data, potentially biasing estimates of stock status. Consequently, it is essential to regularly validate the results of length-based assessments with independent data sources or more comprehensive stock assessments when available (Cope and Punt, 2009). Despite these challenges, length-based methods remain a crucial tool in the management of fisheries, particularly in data-poor regions, where they offer an effective and practical approach to ensuring the sustainability of fish stocks.

1.5. Electronic LEngth Frequency ANalysis (ELEFAN)

Electronic LEngth Frequency ANalysis (ELEFAN) is a method developed by Pauly in the 1980s to analyze length-frequency distribution of fish and estimate growth parameters using the von Bertalanffy growth model. This method is particularly useful in situations where age data is difficult to obtain, making it an essential tool in data-limited fisheries management. ELEFAN works by detecting growth patterns from observed length distribution of fish and estimating key growth parameters (Pauly, 1987). It has been widely applied in tropical and subtropical fisheries (Kaymaram et al., 2014; Haruna et al., 2018; Abobi et al., 2019; Amorim et al., 2020; Ghofar et al., 2021; Barua et al., 2023; Santos et al., 2023). The ELEFAN is perhaps the most commonly used method for modeling the modal progression from length frequency distribution data (LFD) (Zhou et al., 2022).

The ELEFAN process involves collecting length data from fish catches, and the ELEFAN algorithm identifies sinusoidal growth patterns that reflect individual growth within the population. The result is an estimation of growth parameters that can be used to assess the status of fish stocks. Because the method only requires length data, ELEFAN provides an efficient solution in data-limited situations, allowing fisheries managers to make more informed decisions about stock management (Gayanilo et al., 2005). This method also offers opportunities for small-scale or remote fisheries to conduct stock assessments without the need for costly and complex data collection efforts.

However, like other length-based methods, ELEFAN has certain limitations. One major limitation is its sensitivity to the quality and quantity of length data collected. Non-representative data or biased length distribution can affect the accuracy of growth parameter estimates. Therefore, it is important to validate ELEFAN results with additional methods to confirm the reliability of the analysis (Pauly and Morgan, 1987; Taylor and Mildenberger, 2017). In this context, the validation of ELEFAN is often necessary to ensure that growth parameter estimates are robust enough to support sustainable fisheries management.

Despite these challenges, ELEFAN remains one of the most useful methods for stock assessment in data-limited fisheries. Using ELEFAN, fisheries managers can obtain critical growth parameter estimates that inform management measures. The method has also been endorsed by various international organizations as an effective tool for managing fish stocks in tropical waters (Beverton and Holt, 1957; Froese, 2004).

1.6. The Development of Length-based Methods

The development of length-based methods in fisheries science has been accompanied by significant advancements in performance over the decades. Initially introduced as a practical solution for data-limited fisheries, these methods have evolved to become more robust and capable of handling diverse fishery conditions. In the early stages, the performance of length-based methods was somewhat constrained by the quality of and computational limitations. However, as computational tools and statistical models have improved, it has the accuracy and precision of these methods (Beverton and Holt, 1957; Pauly, 1987).

One of the key milestones in improving the performance of length-based methods was the development of ELEFAN algorithm, which enhanced the ability to analyze length-frequency data with greater accuracy. ELEFAN's performance in estimating growth parameters was significantly through refinements in the algorithm, making it more efficient in handling large datasets and complex fish population structures. Subsequent enhancements in software tools, such as FiSAT (FAO-ICLARM Stock Assessment Tools), have further streamlined the process, enabling faster and more accurate stock assessments in data-poor fisheries (Gayanilo et al., 2005).

Another important improvement in performance came with the introduction of LBSPR, length-based Thompson and Bell (TB), length-based integrated mixed effects (LIME), and length-based risk analysis (LBRA). LBSPR models have enabled fisheries managers to assess the reproductive potential of fish stocks and perform well even with extreme conditions in life history and exploitation level recruitment (Hordyk et al., 2015; Chong et al., 2020).

The continuous development of length-based methods has also addressed some of the early performance challenges related to gear selectivity and sampling biases. These factors can skew the length-frequency data, leading to inaccurate estimates of growth and mortality. Modern length-based models now incorporate corrections for such biases, improving their reliability. Additionally, advances in statistical methods, such as bootstrapping and Bayesian approaches, have enhanced the performance of length-based models by providing better uncertainty estimates and allowing for more robust comparisons across different fishery scenarios (Cope and Punt, 2009; Schwamborn et al., 2019; 2023).

However, the overall performance of these methods has steadily improved, making them a cornerstone of fisheries management in regions with limited data availability. The ongoing development of new tools and methodologies will likely continue to enhance the accuracy and reliability of length-based stock assessments in the future (Froese, 2004; Chong et al., 2020; Schwamborn et al., 2023).

1.7. Bootstrapping Approach

Bootstrapping is a general statistical technique that involves resampling a dataset with replacement to create multiple simulated samples. The purpose of this approach is to estimate the variability or uncertainty in parameter estimates without making strict assumptions about the underlying distribution of the data. This approach, introduced by Efron in the 1970s, is particularly valuable in cases where the original dataset is small or does not follow a normal distribution, allowing for more flexible and robust statistical inference (Efron, 1979; Efron and Tibshirani, 1993). Bootstrapping is widely used across various scientific fields, including economics, biology, and particularly fisheries science, where it helps assess the precision of models and predictions.

In fisheries science, the bootstrapping approach plays a critical role in evaluating the robustness of growth parameters, such as those derived from length-based methods or stock assessments. By repeatedly resampling fish length data or other biological variables, bootstrapping enables researchers to generate a range of plausible outcomes, providing confidential intervals around estimated parameters. For example, in the estimation of L_∞ and K using length-frequency data, bootstrapping helps quantify the uncertainty associated with these estimates, which is crucial for making reliable fisheries management decisions (Haddon, 2011). This process also allows for a better understanding of how variability in the dataset influences the model's output, ensuring that conclusions are more robust, even in data-limited situations.

Bootstrapping proves highly valuable when assessing how different data reduction scenarios impact model performance. By generating multiple resampled datasets for each scenario, bootstrapping allowed the comparison of parameter estimates across different data quantities, providing insight into how much data is necessary to maintain precision in stock assessments (Efron and Tibshirani, 1993; Haddon, 2011, Schwamborn et al., 2023).

Furthermore, one of the strengths of the bootstrapping approach is its ability to handle datasets with skewed distributions or outliers, which are often present in fisheries data. Traditional statistical methods that assume normality may not perform well in such cases, but bootstrapping makes fewer assumptions and can still provide reliable estimates of variability and confidence intervals (Manly, 2006).

Overall, bootstrapping has become a critical component of fisheries stock assessments, particularly in data-limited fisheries, where uncertainties in growth or mortality parameters can significantly affect management decisions. By providing a method to estimate the variability in parameter estimates, bootstrapping ensures that the models used are more robust, ultimately supporting sustainable fisheries management practices.

1.8. Growth Curve Parameters

Growth curve parameters refer to specific metrics used to describe the growth patterns of fish populations over time, providing critical insight into their biological characteristics and life history. These parameters are typically derived from mathematical models that relate fish size to age, enabling researchers to understand how fish grow and develop throughout their life cycle. The most widely used model for estimating growth in fisheries science is the von Bertalanffy growth model (Russo et al., 2009; Flinn and Midway, 2021), which is characterized by three parameters; $L_\infty,\ K,$ and t_0. If the growth of the fish follows exactly to the model, L_∞ represents the maximum size a fish can attain; K indicates the rate at which a fish approaches its maximum size; and t_0 represents the hypothetical age at which a fish would be zero length (von Bertalanffy, 1938). Since von Bertalanffy growth model is a theoretical model describing the average growth pattern of the fish population, the three parameters are merely adjustment parameters for determining the shape of the curve, and care is needed as the biological interpretation of the parameters can lead to misunderstandings.

Estimating growth curve parameters involves analyzing length-frequency data, which reflects the size distribution of fish within a population at different points in time. This data can be collected through various sampling methods, and then analyzed using length-based methods like ELEFAN. These methods enable researchers to estimate L_∞, K, and t_0 without the need for direct age data (Pauly, 1987; Gayanilo et al., 2005).

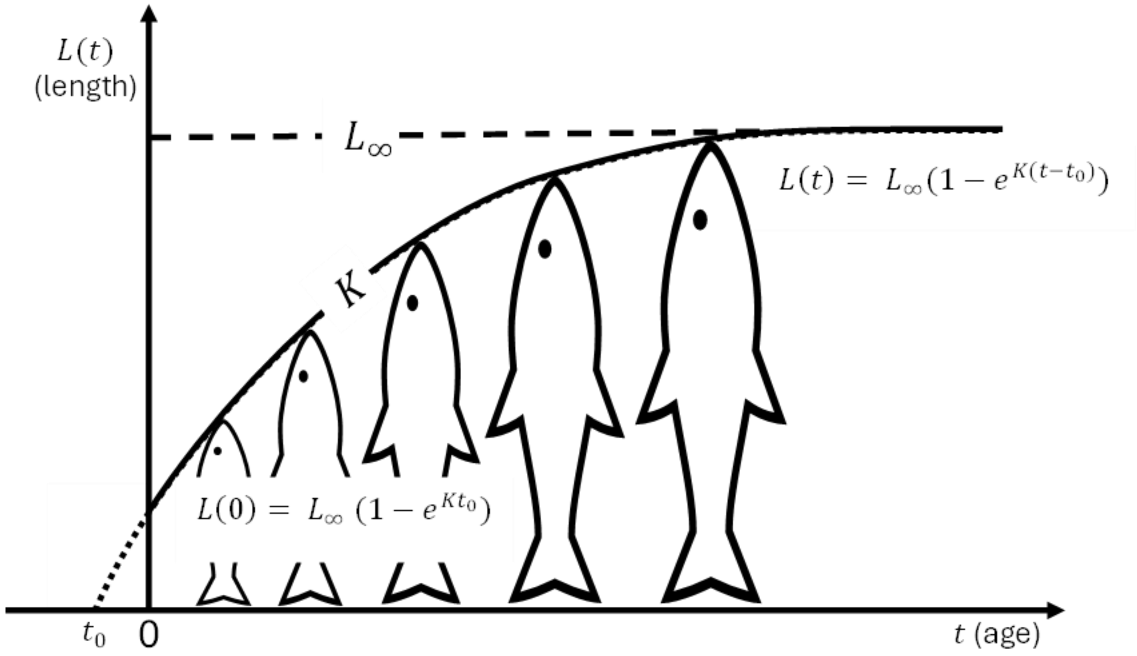

Figure 1. von Bertalanffy growth model. (Source: Sparre and Venema, 1998).

The VBGM effectively models the decelerating growth pattern of many fish species, transitioning from rapid juvenile growth to slower adult growth. Unlike sigmoidal curves, the VBGM represents a strictly convex growth trajectory, accurately reflecting the biological process of diminishing growth rates over time (Pauly, 1980). Its popularity stems from its simplicity, requiring only three parameters (L_∞, K, t_0), and its suitability for length-at-age data, which is commonly available in fisheries research. Additionally, the VBGM supports the calculation of growth performance indices (Φ'), facilitating comparisons across species or stocks. These attributes, combined with its theoretical and empirical robustness, make VBGM an indispensable tool in fisheries science (Flinn and Midway 2021; Katsanevakis, 2006). The reliability of growth curve parameters is influenced by various factors, including the quality and quantity of data collected, the ecological context, and the biological characteristics of the species under study. Environmental variables, such as temperature, food availability, and fishing pressure, can significantly impact growth rate, leading to various in L_∞ and K among populations of the same species (Watson et al., 2022; Lin et al., 2023; Couture et al., 2024). To address this variability, bootstrapping techniques are often employed to assess the uncertainty surrounding growth parameter estimates, generating confidence intervals that provide a clearer picture of growth patterns and their implications for fisheries management (Haddon, 2011, Schwamborn et al., 2023).

1.9. Biological Reference Points

Growth curve parameters are closely linked to biological reference points used in fisheries management, such as $F_{0.1}$ and $F,_{\max}$, which help determine sustainable fishing practices. By accurately estimating growth parameters, fisheries managers can better assess the health of fish stocks in relation to these reference points, allowing for more effective management strategies that ensure the long-term sustainability of fisheries resources. Integrating growth curve parameters with mortality estimates provides a comprehensive understanding of fish stock dynamics, aiding in the development of conservation measures and sustainable harvesting practices (King, 2007).

Biological reference points are quantitative benchmarks used in fisheries management to evaluate the status of fish stocks and guide sustainable fishing practices. These benchmarks are rooted in indices like fishing mortality (F) and biomass or spawning potential ratio (SPR), enabling managers to set thresholds for sustainable exploitation (Gabriel and Mace, 1999). BRPs, including $F_{0.1}$ and $F_{\max}$, offer objective criteria for determining overfishing or stock depletion risks, ensuring long-term resource sustainability. Such benchmarks integrate biological and fishery-specific dynamics, reinforcing their relevance in modern fisheries science (Hilborn and Walters, 1992).

There are two primary categories of biological reference points: thresholds and targets. Thresholds indicate critical levels of biomass or fishing mortality that should not be exceeded to prevent overfishing, while targets represent optimal levels that maximize yield and maintain the reproductive capacity of the population (Caddy and Mahon, 1995).

Biological reference points (BRPs) are essential benchmarks in fisheries management, serving as target or limit values for indices such as fishing mortality (F), yield-per-recruit (YPR), and spawning potential ratio (SPR). These indices assess stock status and guide sustainable fishing practices. F quantifies fishing pressure, YPR evaluates the trade-off between growth and mortality, and SPR measures reproductive capacity under varying fishing intensities. BRPs provide actionable thresholds to maintain stock sustainability (Gulland and Boerema, 1973; Gabriel and Mace, 1999; Chen et al., 2007).

Biological reference points are vital tools in fisheries management, helping assess stock sustainability. While BRPs are typically derived from growth parameters and mortality estimates, their effectiveness remains even when growth curve parameters are imprecise. This finding underscores the robustness of BRPs in data-limited scenarios. Regular evaluation of these parameters ensures that BRPs remain relevant as fishery conditions evolve, aiding in the adaptive management of fish stocks (Zhang et al., 2017; Tsai et al., 2020). This is critical in fisheries where data availability is often constrained, necessitating robust methods to ensure the accuracy and precision of growth parameter estimates.

1.10. Purpose of Study

This study focuses on assessing the precision and reliability of estimated growth curve parameters and biological reference points. Utilizing 24-month length data of yellowfin tuna from Indonesia, a length-based method was employed to estimate growth parameters. The research explores how data limitations, both in terms of observation periods and the amount of data per period, affect the reliability of these estimates.

The findings from this research are expected to provide crucial insights for sustainable fisheries management, particularly in data-limited situations. The study offers a methodology that fisheries managers or researchers can use to assess the impact of limited data and to support the development of length-based method especially to enhance our understanding of fish populations.

2. MATERIALS AND METHODS

2.1. Materials

This study utilizes original monthly data of yellowfin tuna (*Thunnus albacares*) caught using longline gear in Fisheries Management Area (FMA) 573, located in the Indian Ocean, and landed at Benoa Port, Bali, Indonesia. This region serves as a case study due to the suitability of the dataset for length-based analysis under data-limited situations. The dataset spans a 24-month period from 2013 to 2014 and comprises 14,235 length and weight measurements. After analyzing the length-weight relationship, 45 outliers that largely deviated from the expected trend were removed, improving the regression fit to ensure accuracy and eliminate anomalies. This left a total of 14,190 length measurements for further analysis, with lengths ranging from 82 to 187 cm FL (fork length). Fork lengths were measured using a standard measuring board by trained personnel, following the protocol described by Itano, 2004. The sample varies from 211 to 1,473 individuals, with an average of 591 per month. The monthly frequency distribution of length data is described in Figure 3.

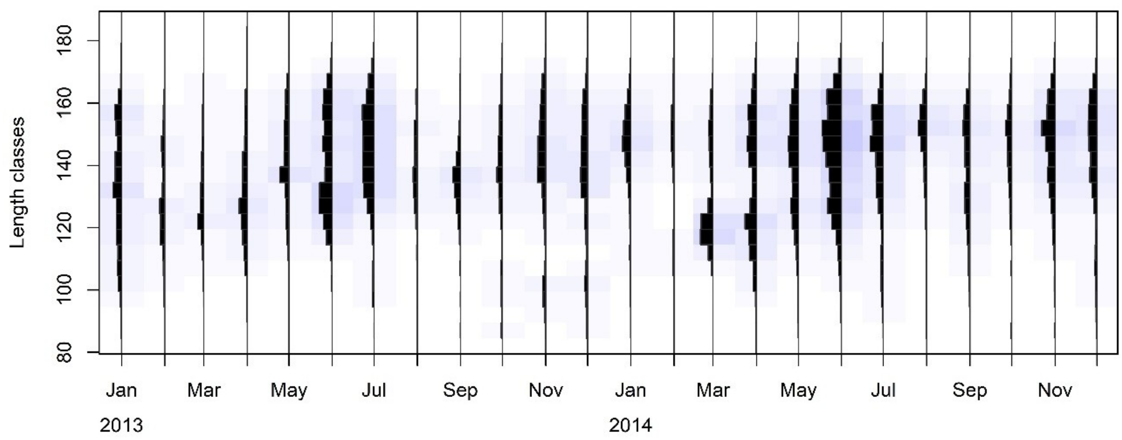

Figure 2. Length-frequency data of yellowfin tuna

2.2. Bootstrapping Approach

The research was initiated with 1,000 bootstrap iterations on the original dataset, employing R packages “boot” (Davidson and Hinkley, 1997; Canty and Ripley, 2024), “dplyr” (Wickham et al., 2023), and “infer” (Couch et al., 2021). This initial step aimed to establish a robust framework for data analysis by generating multiple resampled datasets. To verify the alignment of the bootstrapped data with the original dataset, an additional 10,000 bootstraps were conducted (Appendix 1), ensuring the reliability of the results.

2.3. Simulation Scenarios

A range of scenarios was developed to rigorously assess the sensitivity and reliability of the bootstrapping method. In the first phase, 1,000 bootstrap iterations were conducted using the complete 24 months of data, providing a baseline for subsequent comparisons. The study then explored the impact of two distinct sampling approaches: sequential and interval sampling.

In the sequential sampling scenario, data were progressively reduced by decreasing the number of months considered in the analysis. Starting from the full 24 months, the dataset was narrowed to 18, 12, 6, and 3 months. This approach mimicked a situation where only shorter time frames of data are available or used for assessment.

The interval sampling is designed to simulate more spaced-out data collection efforts. Instead of using consecutive months, data were selected at intervals of 2, 3, 4, 5, and 6 months, respectively. This strategy allowed the study to evaluate how estimates hold up when data are not continuously available but are gathered periodically, reflecting real-world scenarios where sampling may be less frequent.

In addition to varying the temporal scope, the study also investigated the effects of data reduction within each month. Here, the number of observations per month was systematically decreased to reflect different levels of data availability. Five levels of reduction were used: 100%, 75%, 50%, 25%, and 10%. This phase of the analysis aimed to simulate the conditions where data collection is incomplete or only a fraction of the potential data is usable, such as in cases of logistical limitations or sampling inefficiencies. By varying the amount of data available in each month, the study aimed to assess how sensitive the bootstrapped estimates are to reductions in sample size and whether the method can still yield reliable results under more constrained data conditions.

Together, these scenarios provided a comprehensive assessment of how changes in the quantity and temporal distribution of data influence the performance of estimating growth parameters using the bootstrapping method. The selected months and amount of each month's data are available in the appendix.

Table 1. Number of data in all scenarios

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

The research flows are detailed in Figure 3.

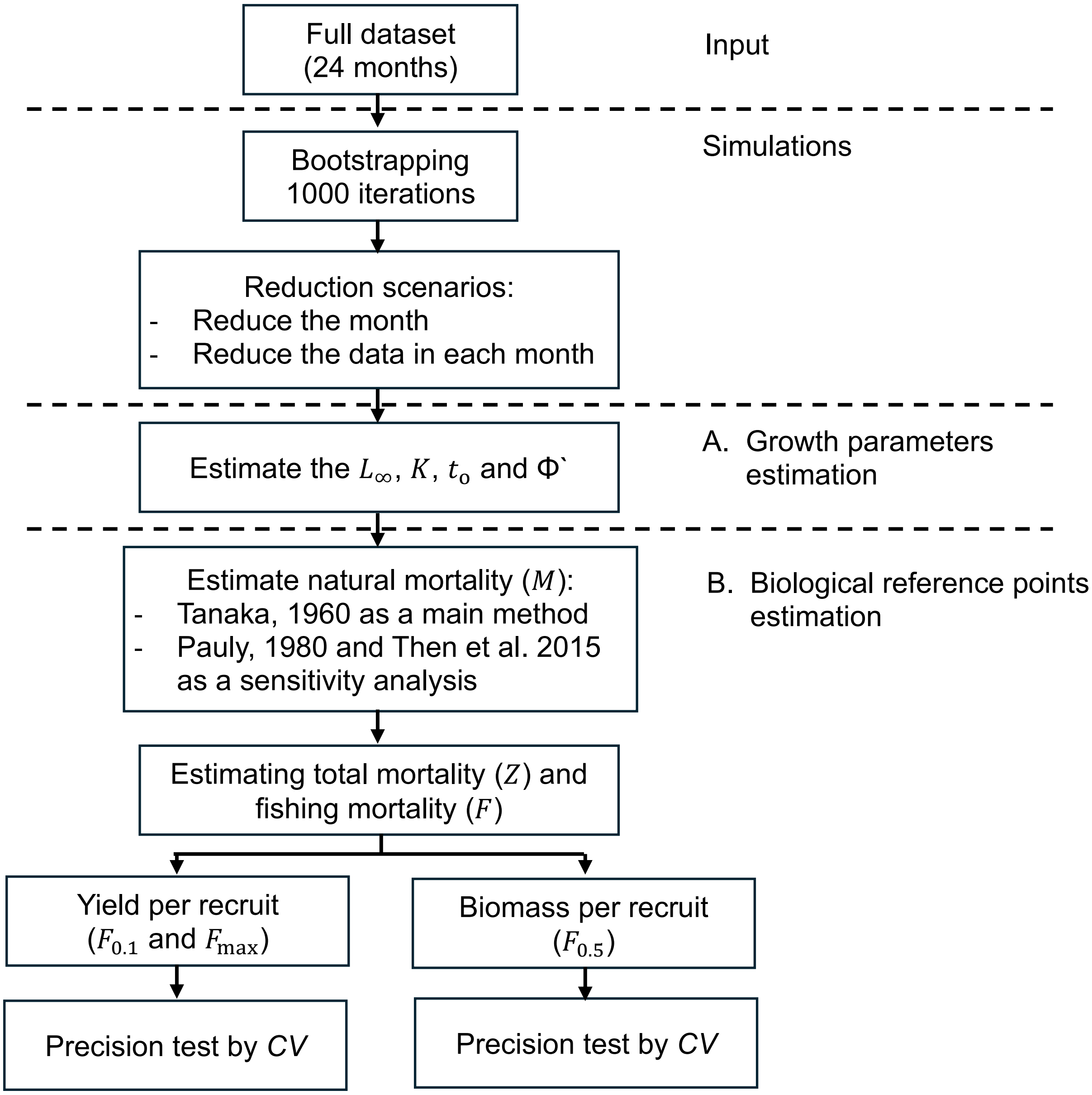

Figure 3. The research flows involve two main processes. **Part A** focuses on estimating growth parameters, while **Part B** centers on calculating biological reference points based on these growth parameter estimates.

2.4. Body Growth Estimation

Body length growth was modelled using the VBGF, a widely used mathematical model to describe growth patterns in aquatic species. The VBGF, (von Bertalanffy 1938) is expressed as:

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

where: L_t is the length of the fish at time t and L_∞, K and t_0 are the growth curve parameters.

To estimate these parameters, the study employed the ELEFAN_SA, function from the TropFishR package (Mildenberger et al., 2017). ELEFAN_SA uses simulated annealing, an optimization technique implemented through the GenSA package (Xiang et al., 2013), to identify the global optimum for parameter estimates. Simulated annealing is particularly useful in this context because it effectively navigates complex solution spaces, ensuring the best fit for the growth model. The flexibility and accuracy of ELEFAN_SA allow for robust parameter estimation even when data are limited or noisy.

In this study, the range of the potential values for L_∞ was set between 120 and 250 cm FL, while the range for K was 0.01 to 1.5, reflecting a wide variety of growth patterns observed in the species. Initial guesses for L_∞ and K were set at 185 cm FL and 0.7, respectively, to guide the optimization process. Seasonalized VBGF was applied, which allows for the modelling of growth variations due to seasonal environmental changes, further refining the accuracy of the growth curve. Each dataset underwent a minute-long iteration process with the setting adjusted for a simulated annealing temperature of 1×10^5 and a moving average of 5. A detailed setting is available at https://github.com/wietteguh89/ELEFAN-Bootstrapping-Simulation/blob/main/ELEFAN_SA.R.

Additionally, the growth performance index (Φ'), developed by Pauly and Munro (1984) was used as a proxy to summarize the growth characteristics of the population. This index integrates both L_∞ and K into a single value, calculated as:

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

The growth performance index provides a comparative measure of growth rates across different population and species, enabling fisheries scientists to evaluate growth dynamics more comprehensively. This combined approach of VBGF estimation and Φ' calculation provides a solid foundation for understanding growth patterns and their implications for fisheries management and population dynamics modeling.

2.5. Parameter Refinement and Filtering Criteria

To ensure the reliability of the growth curve estimates, this study explored filtering approaches based on the t_0, which represents the time before birth when the fish length is considered zero in the VBGF. Since t_0 was not estimated directly through the ELEFAN but rather through an empirical equation proposed by Pauly, 1979, it serves as a derived parameter that can help evaluate the accuracy of estimates for the other growth parameters.

The empirical formula used for calculating t_0 is:

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

This equation leverages the relationship between the L_∞ and K to estimate t_0. The assumption here is that the fish follows the growth curve exactly, and t_0 should reflect the time from embryogenesis to hatching, ideally less than one year. In practice, if t_0 is estimated as being less than -1, it suggests that either L_∞ or K may be misestimated.

To filter out potential misestimates, any growth curves with t_0 values less than -1 were flagged, and their corresponding L_∞ and K estimates were omitted. This approach helps to ensure that the final parameter estimates better reflect the biological growth patterns of fish.

A comparison was then made between the parameter estimates before and after applying this filtering process, examining variation in L_∞, K, and t_0 values. This comparison allowed for the assessment of the filtering approach's impact and ensured the filter's effectiveness in improving the reliability of the growth parameter estimates. By refining the estimates in this manner, the analysis becomes more robust, and the biological relevance of the results is maintained.

2.6. Mortality Estimation

Natural mortality (M) was estimated using Tanaka's method (Tanaka, 1960), which calculates M based on the maximum observed age ($t_{\max}$) of the species. This method is expressed as:

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

This formula is commonly used for species where $t_{\max}$ is known and helps provide a relatively simple estimate of natural mortality. It reflects the biological reality that older fish are more susceptible to natural death due to factors such as predation, disease, or senescence.

For total mortality (Z), the method proposed by Beverton and Holt, 1957 is utilized. This method uses length-frequency data in combination with von Bertalanffy growth parameters to develop a catch-curve-based estimator. The equation is as follows:

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

where $\bar{L}$ is the mean length of the fish sampled, and L_c is the length at first capture, representing the minimum size at which individuals are recruited into the fishery Once the estimates for M and Z are obtained, fishing mortality (F) can be determined using the formula:

$$F = Z - M$$

This calculation assumes that total mortality is the sum of M and F. Understanding these mortality parameters is critical for assessing the sustainability of the fishery, as it allows for the estimation of exploitation rates and informs management decisions on catch limits and fishing effort.

2.7. Yield per Recruit Estimation

The yield per recruit (YPR or Y/R) was calculated using the Beverton and Holt model (Beverton and Holt, 1957), which describes the relationship between F and the growth and survival of fish. The formula of YPR is:

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

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

where t_c is the age at first capture, t_r is the recruitment age, and W_∞ is the asymptotic weight.

This model estimates the biomass a fishery can yield per recruit under different fishing mortality scenarios, incorporating biological and fishery parameters to estimate sustainable harvest rates.

Additionally, the spawning stock biomass per recruit (B/R) was analyzed using the following formula:

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

This formula connects the Y/R to F, allowing for the calculation of the spawning biomass per recruit, which is critical for understanding the reproductive capacity of the fish population under different fishing pressures. By examining both Y/R and B/R, fisheries managers can evaluate the effect of fishing on the population and ensure that fishing practices maintain sustainable stock levels.

2.8. Biological Reference Points

Biological reference points (BRPs) play a crucial role in fisheries management by setting thresholds for fishing mortality that balance sustainable harvests with conservation goals. For YPR, two key BRPs are $F_{0.1}$ and $F_{\max}$ (Chen et al., 2007). $F_{\max}$ represents the fishing mortality rate that maximizes the yield per recruit at a given age of first capture, assuming recruitment remains constant. It serves as a limit BRP, marking the threshold beyond which additional fishing pressure does not significantly increase yield but could harm the population.

$F_{0.1}$ is a more precautionary target BRP. It represents the fishing mortality rate where the slope of the YPR curve drops to 10% of its slope at the origin, a more conservative measure designed to account for uncertainties in estimation (Goodyear, 1993; Zhou et al., 2020). $F_{0.1}$ is recommended as an upper limit for fishing mortality to ensure stock resilience, reducing the risk of overfishing.

For spawning stock biomass per recruit (B/R), BRPs focus on maintaining reproductive capacity. A commonly used BRP is $F_{0.5}$, which identifies the fishing mortality rate that reduces the spawning biomass to 50% of its unfished level. This balance ensures that sufficient stock remains to sustain reproduction and future recruitment (Goodyear, 1993). The long-term productivity of the stock is safeguarded by maintaining biomass at or above this threshold. These reference points allow managers to optimize fishing mortality while keeping population sustainability at the forefront.

All BRP analyses in this study were conducted using the TropFishR package (Mildenberger et al., 2017), which incorporates length-frequency data and von Bertalanffy parameters to estimate mortality rates and other key metrics essential for sustainable fishery management. For detailed script is available in https://github.com/wietteguh89/ELEFAN-Bootstrapping-Simulation/blob/main/ELEFAN_SA.R.

2.9. Evaluation of Precision

Precision in the estimation process was assessed using the coefficient of variation (*CV*, %), a measure that quantifies relative variability by expressing the standard deviation as a percentage of the mean. The formula used for *CV* is:

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

where *SD* represents the standard deviation, and the mean is the average value derived from each scenario's estimated parameter. By calculating the *CV*, we can gauge the reliability of the growth parameters and biological reference point estimates across different data-reduction scenarios. A lower *CV* indicates more stable and precise estimates.

In the growth parameters estimation, the target *CV* was set to achieve a *CV* of $\Phi' \leq 3\%$, signifying that the variation in growth parameter estimates should be minimal to ensure accuracy. This threshold will help determine the minimum data requirement necessary for a reliable growth curve parameter estimate that can be linked to the biological reference points.

2.10. Comparison among the Natural Mortality Estimation Method

The values applied for M play a crucial role in stock assessment models, directly influencing outputs and subsequent management recommendations (Hoyle et al., 2023). Given this significant impact, handling the uncertainty surrounding M is essential for robust stock assessment. To address this, alternative methods for estimating M were incorporated, namely the widely used Pauly, 1980, and Then et al., 2015 methods, providing a broader perspective on the potential M values.

The Pauly, 1980 method relies on environmental temperature and life-history parameters. The equation is as follows:

$$\log_{10}(M) = -0.0066 - 0.279\log_{10}(L_\infty) + 0.6543\log_{10}(K) + 0.4634\log_{10}(T)$$

or simplified:

$$M = 0.9849\, L_\infty^{-0.279} K^{0.6543} T^{0.4634}$$

where T represents the mean annual environmental temperature, making it useful for species inhabiting various thermal environments.

Then et al., 2015 offer a method that excludes temperature but emphasizes the relationships between growth parameters, defined by the following formula:

$$M = 4.1181\, K^{0.73} L_\infty^{-0.33}$$

This method provides an alternative when temperature data is unavailable, further broadening the applicability of mortality estimates.

After estimating M using both formulas, the values were applied to calculate F, following the same approach as with the Tanaka method. Subsequently, biological reference points such as $F_{0.1}$, $F_{\max}$, and $F_{0.5}$ were determined, to know how sensitive the results after changing M value.

3. RESULTS AND DISCUSSIONS OF GROWTH CURVE PARAMETERS

3.1. Growth Curve Parameters Values

The distribution of growth curve parameter values including L_∞, K, and Φ' after filtering t_0, exhibited considerable variability across the different data reduction scenarios. The estimated parameters were evaluated for both sequential and interval data reduction scenarios.

Table 2. The mean value of estimated growth curve parameters. Ev 2, Ev 3, Ev 4, Ev 5, Ev 6: every 2, 3, 4, 5, 6 months.

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

Table 2 presented several key insights regarding the mean values of estimated growth curve parameters under various data reduction scenarios. For the L_∞, a notable increase is observed as the percentage of available data decreases, especially when fewer months of data are analyzed. For instance, with 24 months of data, L_∞ rises from 166.50 cm FL at 100% data to 194.90 cm FL at 10% data, indicating that reducing the amount of data tends to inflate the L_∞ estimates. In contrast, the K value decreases consistently as the data availability diminishes. For the same 24-month scenario, K drops from 0.76 at 100% data to 0.34 at 10% data. This suggests that a reduction in data leads to lower K estimates. This trend also happens in all scenarios. The changes in growth curve parameters are not only influenced by reductions in the percentage of data within each month but also by the reduction in the number of months.

However, the Φ' appears more stable compared to L_∞ and K, showing minimal changes even with reduced data and fewer months. In the 224-month scenario, Φ' changes from 4.31 at 100% data to 4.01 at 10% data. To assess the level of variation in the estimates across all variables, refer to Table 3 for further details.

3.2. Coefficient of Variation on Growth Curve Parameters

The *CV* values of L_∞, K, and Φ' were compared before and after filtering t_0. Significant differences were observed, for example, in the full dataset scenario (24-months 100% data). The *CV* of L_∞ decreased from 9.32% to 2.55% after filtering. Similarly, the *CV* of K was reduced from 42.16% to 23.04%, while the *CV* of Φ' dropped from 11.64% to 2.35%. A detailed comparison of *CV* values before and after filtering is presented in Table 3.

Table 3. The *CV* value of estimated growth curve parameters

Variables	% data	Months									
		24	18	12	6	3	Ev 2	Ev 3	Ev 4	Ev 5	Ev 6
Before filtering t_0											
	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
L_∞	**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
Φ'	**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
After filtering t_0											
	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	14.4	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

Variables	% data	Months									
		24	**18**	**12**	**6**	**3**	**Ev 2**	**Ev 3**	**Ev 4**	**Ev 5**	**Ev 6**
K	**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
	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	63.4	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
Φ'	**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
	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	4.8	4.59	4.59

0% 50% 100%

The bold values of Φ' indicate the lowest coefficient of variation (CV < 3.00%) across all scenarios.

The application of t_0 filtering significantly improved the stability of growth parameter estimates, as evidenced by consistent reductions in the *CV* for L_∞, K, and Φ' across various data scenarios. As mentioned above, this trend of reduced *CV* was observed not only in scenarios with complete data but also in those with reduced temporal or sampling coverage. Even in data-limited scenarios, such as 10% of the total dataset, filtering t_0 still provided improvements, though the reductions were less pronounced compared to scenarios with full data. However, as the amount of data decreased, the *CV* of K tended to increase, reflecting the higher sensitivity of growth rate estimates to reductions in sample size. This pattern was especially noticeable in six months or fewer scenarios, where greater variability in *CV* values emerged.

3.3. The Relationship between the Estimated L_∞ and K

This study estimates multiple values of L_∞ and K, making it essential to explore the relationship between these two variables across all scenarios. A Kimura plot is used to visualize this relationship effectively. The results indicate that higher L_∞ values tend to correspond with lower K values, and vice versa. Figure 4 illustrates how this relationship shifts as the amount of data decreases.

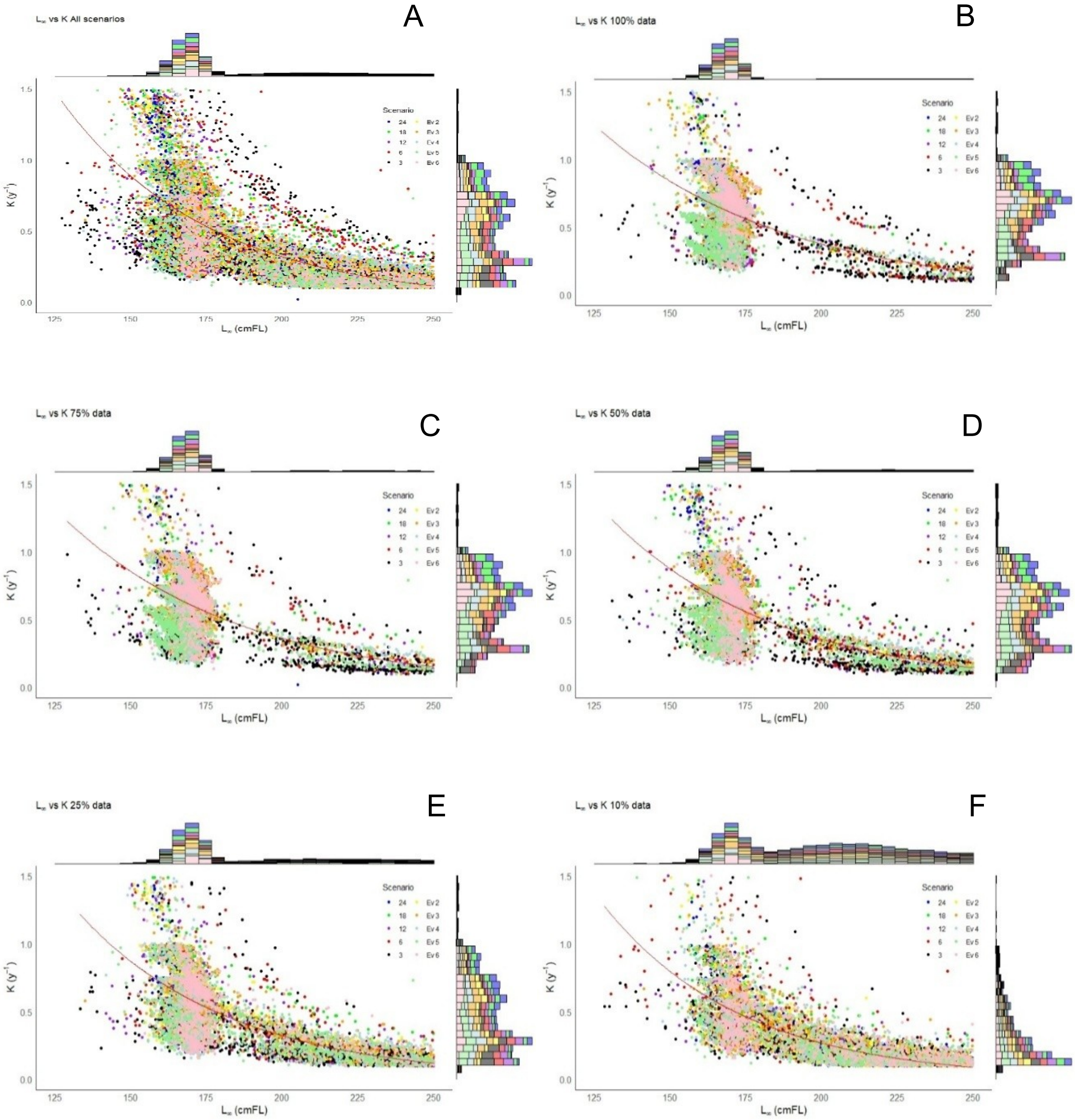

Figure 4. The relationship between L_∞ and K is illustrated using Kimura plots. (**A**) the results from all scenarios combined; (**B**) 100% data; (**C**) 75% data; (**D**) 50% ; (**E**) 25%; (**F)** 10% data.

The relationship trend between the estimated values of L_∞ and K is represented by the red line. The accompanying histograms display the frequency distribution of the estimated values for each variable across all scenarios. The overall trend between the two parameters remains consistent, regardless of the data scenario. However, closer observation reveals that in the scenarios with 100%, 75%, and 50% data, the estimates are concentrated within a similar range, indicating more precise results. In contrast, the 25% and 10% data scenarios show much broader dispersion of estimates, suggesting potential misestimations, either as overestimations or underestimations.

3.4. Discussions

3.4.1. Using Bootstrapped Length Data to Measure Growth Parameter Precision

This study represents the first to utilize over 10,000 original length data points to evaluate the precision of growth parameter estimates using bootstrapping. In comparison, Schwamborn et al., 2019 employed 675 length-frequency distributions (LFDs) to analyze sources of uncertainty in length-based growth estimates, while Schwamborn et al. (2023) used 2,564 length measurements to compare the precision of bootstrapping length data with that of otolith-based methods. By using such a large dataset, this study offers new insights into how sample size affects the stability of growth parameter estimates. *CV* values were calculated across multiple scenarios to assess precision, confirming that the quantity of data plays a crucial role in the reliability of length-based estimation methods.

In this study, the value of t_0 was constrained to be no less than −1 to align with realistic biological principles. This filtering improves the validity of the analysis by preventing biologically implausible estimates and minimizing distortions in the calculation of growth parameters. Without setting specific confidence limits, the value of t_0 was calculated using Pauly's, 1979 empirical equation. The impact of filtering t_0 is evident in the results; for example, in the 24-month scenario with 100% of the data, the *CV* for L_∞ improved significantly, dropping from 9.32% to 2.55% after filtering. Similar trends were observed in other scenarios with a high data fraction (≥50%) and covering half or more of the study period (12–24 months).

However, in interval-based sampling scenarios, the impact of t_0 filtering on *CV* values was less pronounced. In scenarios such as every-3-months sampling with 100%, 75%, and 50% data, or every-4-, 5-, and 6-months sampling with full or near-full data (100%, 75%, and 50%), *CV* values for growth parameters remained relatively consistent before and after filtering. This suggests that the frequency and pattern of data collection can influence how much filtering t_0 affects parameter stability. Filtering appears to be most effective when applied to continuous datasets or those with high data coverage, while interval sampling may reduce the sensitivity of estimates to t_0 adjustments.

These findings emphasize the importance of both data quantity and sampling design in achieving precise and reliable growth parameter estimates. Bootstrapping, combined with careful filtering of t_0, provides a robust approach to address uncertainties in length-based growth models, ensuring that estimation outcomes align with biological realities and improve fisheries management practices.

3.4.2. Evaluation of the Estimation Result

Data reduction significantly influenced the outcomes by altering both the mean values and variability of the estimated growth curve parameters. As shown in Table 2, the mean value of L_∞ increased as the data fraction decreased. For example, in the 24-month scenario, the mean L_∞ increased from 166.50 cm FL with 100% of the data to 194.90 cm FL with 10% data. Additionally, the variability in the estimates, reflected by the *CV* value, rose from 2.55% to 13.36% (filtered data, Table 3). A linear relationship was observed, with the mean L_∞ values and their corresponding *CV*s increasing steadily as the data fraction decreased. These findings suggest that estimates obtained with 100% data are more consistent than those from reduced data fractions.

In contrast to L_∞, the mean K decreased with data reduction, dropping from 0.76 to 0.34 in the 24-month scenario, while the variability (*CV*) increased from 23.04% to 67.22%. This trend indicates that reducing the data fraction widens the distribution of the K estimates, increasing the potential for misestimation. However, this effect was less pronounced in interval sampling schemes, such as those conducted every 6 months, due to the limited data points available.

The precision of L_{∞}, K, and Φ' estimates was assessed using *CV* values across various scenarios (Table 3). For L_{∞}, a reduction in data fraction resulted in increased *CV* values, especially as the sampling period decreased. For example, in the 24-month scenario, the *CV* for 50% of the data nearly doubled (4.51%) compared to 100% data (2.55%). Similarly, *CV* values for 25% and 10% data were 10.17% and 13.36%, respectively. A similar trend was noted in the 18- and 12-month scenarios, where reducing the data fraction to 50% resulted in a near-doubling of *CV* values. However, the mean L_{∞} values showed little variation, suggesting that while the distribution of estimates changed, the underlying pattern remained stable.

To better understand the impact of data reduction, sequential sampling scenarios were compared with interval-based sampling schemes. For example, in the 12-month scenario, the *CV* of L_{∞} increased from 5.29% with 100% data to 14.22% with 25% data. A similar pattern was seen in the every-2-months scenario, where the *CV* rose from 4.85% with 100% data to 12.67% with 25% data. Interestingly, despite differences in *CV* values at 100% data, the *CV*s across scenarios with 10% data remained around 12%, suggesting a maximum variation limit for this dataset. Notably, the *CV* for the every-2-months scenario (4.85%) was lower than that for the 12-month scenario (5.29%) when using 100% data, indicating that more frequent sampling can reduce variability in growth parameter estimates.

A linear trend was also observed when comparing the 6-month and every-4-month scenarios. Although both scenarios showed similar *CV* values (13.04% and 13.22%, respectively) with 10% data, they differed at 100% data, with *CV*s of 10.21% and 7.01%, respectively. A corresponding linear increase in the mean L_{∞} values was also observed (Table 2). For instance, the mean L_{∞} values were similar at 100% data for the 12-month (169.89 cm FL) and every-2-month scenarios (168.08 cm FL), but at 10% data, the mean values increased to 203.20 cm FL and 197.38 cm FL, respectively, reflecting differences in the central distribution of the estimates.

The *CV* values for K were notably higher than those for L_{∞} across all scenarios. As with L_{∞}, the variability in K estimates increased as the data fraction decreased, with *CV* values ranging from 23.04% to 72.26%. A doubling of *CV* values was especially evident when data was reduced from 100% to 10%. The high

CV values for K reflect the broader range of estimates and increased uncertainty, resulting in poor precision and uniformity in K estimation.

These results indicate that reducing the number of months in sampling does not have as substantial an impact on parameter estimates as reducing the data fraction. Additionally, the correlation between the *CV*s of L_∞ and K suggests that high uncertainty in L_∞ estimates often correspond with similar uncertainty in K estimates. A negative correlation between the two parameters was also observed, with higher L_∞ values associated with lower K values, and vice versa (Figure 5). This finding aligns with trends reported in previous studies (Thorson et al., 2017; Schwamborn et al., 2019; Liu et al., 2021; Schwamborn et al., 2023; Ben-Hasan et al., 2024), underscoring the interconnected nature of these growth parameters and their sensitivity to data reduction.

3.4.3. The Level of Precision in Relation to the Reliability Result

To assess the performance of the estimated growth curve parameters, the Φ' was calculated across all estimation scenarios. The Φ' values ranged from 2.85 to 4.98, indicating relatively stable outcomes. The associated *CV* values, ranging from 2.35% to 5.13%, reflected high precision with minimal variability. Notably, the *CV*s for Φ' were smaller than those for K, likely because the Φ' estimates exhibited a narrower range, resulting in reduced variability and greater precision. Additionally, the higher precision of Φ' suggests that L_∞ estimates exert a greater influence on Φ' than K, given the generally lower uncertainty in L_∞ estimates.

For instance, in the 24-month scenario with 100% data, the *CV* values for both L_∞ and Φ' were below 3%, while K showed a *CV* exceeding 20%. This discrepancy suggests that the ELEFAN method provides precise estimates for L_∞ but struggles to accurately estimate K. Despite the limitations in K estimation, the stable Φ' values indicate that the overall growth curve shape remains consistent across scenarios.

In scenarios with limited data, particularly the every-6-month sampling, *CV* values remained relatively low. For 100%, 75%, and 50% data, the *CV*s were 3.54%, 4.84%, and 4.84%, respectively. However, caution is advised when interpreting these results due to the limited data and reduced variability. Additional in-depth analyses are recommended to validate these findings, as relying solely on such limited scenarios may lead to unreliable conclusions.

The results further highlight that a sufficient quantity of data is essential for obtaining precise parameter estimates. Specifically, the 12-month scenario with 100% data and the every-2-month scenario (for a total of 24 months) both yielded *CV* values between 4% and 6%. In the 12-month scenario, the *CV* for L_∞ was 5.29%, while in the every-2-month scenario, it was 4.85%. Corresponding *CV*s for K were 46.18% and 27.34%, respectively. Notably, the Φ' value showed better stability in the every-2-month scenario, with a *CV* of 2.79%.

This study aimed to identify the minimum amount of data needed for reliable growth parameter estimation by evaluating changes in *CV* values across scenarios. Considering the characteristics of the estimated variables, a target *CV* of 3% is recommended for the Φ' variable. Based on this threshold, several scenarios met the reliability criterion:

- 24 months: 100%, 75%, and 50% data
- 18 months: 100% and 75% data
- Every 2 months (2 years): 100%, 75%, and 50% data
- Every 3 months (2 years): 100% and 75% data

To ensure reliable results, sampling designs should include either 24 months with 7100 data, 18 months with 8000 data, every 2 months over 2 years with 3500 data, or every 3 months over 2 years with 4100 data. These simulations aim to provide robust information for stakeholders conducting stock assessments.

It is important to note that these findings especially methodology, procedures and filtering t_0 are adaptable and can be applied to other species and situation. Future studies are needed to generalize the results. Additionally, practical decisions on sampling designs must consider the available human resources and financial constraints to ensure feasible implementation.

4. RESULTS AND DISCUSSIONS OF BIOLOGICAL REFERENCE POINTS

This section also uses the growth curve parameter estimates from the previous analysis as input. Therefore, it focuses solely on presenting the results and discussing relevant aspects of the estimation of biological reference points (BRPs).

4.1. Mortality Estimation

Mortality estimation begins with calculating M using the Tanaka method, which requires $t_{\max}$ as input. Since this study did not directly estimate $t_{\max}$, a value from relevant references was used, consistent with the fishing area. The $t_{\max}$ value applied was 11.1 years (Chantawong, 1998), resulting in an estimated M of 0.23. Using this M value, Z and F were then calculated. Table 4 presents the mean estimated mortality values for each scenario.

Table 4. The mean estimated Z and F values for all scenario

Variables	% 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

Since Tanaka's method relies on fixed coefficients and a constant $t_{\max}$, the M value remains consistent across all scenarios at 0.23. However, Z varies between scenarios due to the differing inputs for L_∞ and K. F is also influenced by the variation in Z, given that M remains unchanged across all scenarios.

Tanaka's (1960) method was chosen for estimating M due to its simplicity and applicability in data-limited fisheries. This method uses the maximum observed age $t_{\max}$ as a proxy for M, assuming that the oldest individuals provide the most reliable indicator of mortality. By anchoring mortality estimates to age, it avoids the complexities of models requiring detailed growth, environmental, or reproductive data (Tanaka, 1960).

This approach is practical in fisheries with scarce data, particularly for long-lived species where comprehensive data collection is challenging (Pascual and Iribarne, 1993). In this study, Tanaka's method consistently produced an M value of 0.23 across all scenarios, maintaining stability even under reduced data conditions. However, while effective here, it may not suit all species or ecosystems. More complex models incorporating additional biological factors could offer greater insights, though Tanaka's simplicity remains advantageous for data-limited contexts.

Z was estimated using the Beverton and Holt equation, which utilizes fish length data, making it useful in fisheries with limited age data. Table 4 outlines Z values across scenarios, ranging from 0.6 to 1.17 as data availability decreases from 100% to 10%. The analysis indicates that Z remains stable with 100% or 75% data but becomes more variable at lower data fractions (50%, 25%, and 10%), reflecting increasing estimation uncertainty with reduced data.

Certain scenarios—particularly the every-2-month, 18-month, and 24-month cases—show higher Z values as data are reduced, highlighting the sensitivity of Z to data quantity. The mean F values range from 0.37 to 0.94. The trends in F closely align with those of Z, reflecting the impact of fishing pressure. Additionally, the tendency for higher mortality rates with decreasing data suggests a potential overestimation of mortality under data-scarce conditions (Ricker, 1975; Hilborn and Walters, 1992; Quinn and Deriso, 1999).

4.2. Estimation of $F_{0.1}$, $F_{\max}$, and $F_{0.5}$

The values of $F_{0.1}$, $F_{\max}$, and $F_{0.5}$ were derived using TropFishR based on various inputs, including growth parameters, mortality rates, and the length-weight relationship constants obtained from the literature (Ghofar et al., 2021). This section presents the mean values of each parameter along with their variability, expressed as the *CV* (%).

These estimates provide insights into the optimal fishing effort for sustainable management. $F_{0.1}$ represents the fishing mortality at which the slope of the yield-per-recruit curve is 10% of its initial value, while $F_{\max}$ indicates the point at which yield per recruit is maximized. $F_{0.5}$ reflects the fishing mortality at 50% of the unexploited spawning potential. Presenting the mean and *CV* values helps evaluate the precision of these parameters and assess the robustness of the results across different data scenarios.

Table 5. The mean of estimated $F_{0.1}$, $F_{\max}$, and $F_{0.5}$

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

Table 5 presents the mean of estimated $F_{0.1}$, $F_{\max}$, and $F_{0.5}$ values across all scenarios. The mean of 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 a twofold rise) when the quantity of data decreases, especially below 50%. The mean $F_{0.5}$ remains relatively constant despite reductions in the data quantity. A detailed distribution and trend of these estimates values across all scenarios are provided in the supplementary materials.

The *CV* values for all variables across all scenarios are presented to assess the variation in variable estimates. The *CV* provides a measure of relative variability, helping to identify how consistent the estimates are under different data conditions. Monitoring these variations ensures a better understanding of the precision and reliability of the estimated parameters, which is essential for making informed fisheries management decisions.

Table 6. *CV* value of variables $F_{0.1}$, $F_{\max}$, and $F_{0.5}$

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

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In Table 6, the *CV* for $F_{0.1}$ ranges from 20.05% to 45.77%, indicating substantial variability across different scenarios. In the full dataset (24 months, 100% data), the *CV* is 21.03%, reflecting relatively stable estimates. However, when the dataset is reduced to 12 months with 100% data, the *CV* increases by 7.29 points to 28.32%, demonstrating that halving the observation period introduces more variability. Interestingly, a similar scenario with every-2-month (Ev 2) sampling yields a lower *CV* of 22.38%, which is 5.94 points lower than the 12-month scenario, suggesting that how the data is sampled can influence precision. Although no consistent trend emerges, the overall pattern indicates that *CV* values generally increase as data availability decreases, reflecting growing uncertainty under reduced data conditions.

For $F_{\max}$, the *CV* spans 18.17% to 92.92%, with the smallest value observed in the full dataset. A significant increase in variability is evident as the dataset size decreases reducing data from 100% to 10% causes the *CV* to rise more than fourfold, from 18.17% to 78.82%. This steep increase underscores the sensitivity of $F_{\max}$ estimates to reductions in sample size.

Similarly, the *CV* for $F_{0.5}$ ranges from 25.31% to 116.44%, with the lowest *CV* recorded in the 24-month, 100% data scenario. As data availability decreases to 75%, 50%, and 25%, incremental increases in *CV* are observed. However, the most dramatic jump occurs at 10% data, where the *CV* rises to 72.81%, nearly tripling compared to the full dataset. This sharp increase illustrates the heightened uncertainty in $F_{0.5}$ estimates when data is severely limited, suggesting that more substantial data reduction results in less reliable biological reference points.

These results highlight the impact of both data quantity and sampling strategy on the precision of reference point estimates. While longer sampling periods and higher data completeness yield more consistent and reliable outcomes, reducing either can lead to greater variability, complicating the interpretation of fisheries management parameters.

4.3. Discussions

4.3.1. Mean Estimates and Precision of BRPs

This study evaluates the changes in several biological reference points (BRPs) across different time intervals and data availability percentages, highlighting the critical importance of data quantity in accurately estimating these parameters.

The analysis revealed that the mean $F_{0.1}$ values ranged from 0.41 to 0.65, with *CV*s between 20.05% and 45.77%. For $F_{\max}$, the mean values spanned 0.92 to 2.32, with *CV*s ranging from 18.17% to 92.92%. Meanwhile, $F_{0.5}$ had mean values ranging from 0.30 to 0.51, with *CV*s between 25.31% and 116.44%. These results underscore how the variability in BRPs increases with reduced data, posing challenges for fisheries management under data-limited conditions.

Estimating $F_{\max}$ presents specific challenges, as it often overlooks key ecological factors, such as reproductive capacity, leading to the risk of growth overfishing. Furthermore, environmental fluctuations and recruitment variability complicate the estimation of $F_{\max}$. Traditional models, which assume constant recruitment and mortality, may struggle to reflect the dynamics of real-world fisheries, reducing their reliability (Cooper and Weir, 2006; Lassen et al., 2014; Miyagawa and Ichinokawa, 2024). Given these limitations, more conservative metrics like $F_{0.1}$ are preferred to mitigate the risk of overfishing. Including $F_{0.5}$ in BRP analysis adds further precaution by maintaining spawning stock biomass at 50%, offering a safer benchmark for sustainable fisheries management compared to $F_{0.5}$.

The findings confirm the robustness of $F_{0.1}$ as a reliable indicator for management decisions under limited data conditions. A safety threshold of 0.57 (10% below the baseline mean) was identified, highlighting the suitability of $F_{0.1}$ for guiding management strategies with minimal risk of overexploitation. With *CV*s generally staying below 30%, a widely accepted precision threshold, $F_{0.1}$ proves both precise and effective for fisheries management in data-limited scenarios. Its conservative bias ensures that it serves as a precautionary tool, especially when data availability is low.

In contrast, $F_{0.5}$ displayed greater variability in both mean values and precision, reflecting its sensitivity to reductions in data. Applying the same 10% threshold produced a lower bound of 0.45 from the full dataset's mean value.

Although some scenarios showed acceptable variability, the average *CV* for $F_{0.5}$ was 40.5%, with extreme *CV*s appearing primarily in scenarios with 10% data. This underscores the greater sensitivity of $F_{0.5}$ to data limitations compared to $F_{0.1}$, reinforcing the need for careful interpretation of results when data are scarce.

These findings emphasize the importance of selecting BRPs suited to the data context to ensure sustainable stock management. Shifts or fluctuations in these parameters can signal changes in fish population health, which must be considered when formulating management policies (Hilborn and Walters, 1992). By integrating both conservative metrics like $F_{0.1}$ and additional precautionary indicators like $F_{0.5}$, fisheries managers can create adaptive strategies to maintain stock sustainability. This balanced approach ensures that management decisions remain effective even in data-limited conditions while minimizing the risk of stock depletion.

4.3.2. Comparison of the Natural Mortality Estimation Methods

The sensitivity analysis of estimation methods for M and F, along with the effects of data quantity, revealed significant differences in how these methods respond to data reduction (appendix 5). The Pauly method exhibited high sensitivity to diminishing data, with a sharp decline in M estimates and a substantial increase in F when data availability dropped to 10%. This sensitivity arises from Pauly's reliance on the empirical relationship between fish growth, natural mortality, and environmental temperature (Pauly, 1980). When critical data—especially related to body length and temperature—are scarce, the method's accuracy declines, leading to inflated estimates.

In contrast, the Then et al., (2015) method showed moderate sensitivity, although it also experienced increasing F estimates under limited data conditions. Despite being more stable than Pauly's method, it depends heavily on parameters like maximum fish age $t_{\max}$, making it susceptible to data reduction. On the other hand, the Tanaka method demonstrated the highest stability across all scenarios, with minimal changes in M and F estimates even as data availability decreased. Tanaka's stability can be attributed to its reduced dependence on empirical generalizations, making it more reliable in data-limited situations (Kenchington, 2014).

The interplay between M and F plays a crucial role in determining sustainable fishing levels. The sensitivity analysis of biological reference points (BRPs) such as $F_{0.1}$, $F_{\max}$ and $F_{0.5}$ highlighted the influence of M on these estimates, particularly as data availability decreased from 100% to 10%. With complete datasets, the methods by Pauly, Then et al., and Tanaka produced stable results. However, as data availability dropped below 50%, the Pauly and Then et al. methods displayed notable shifts in F estimates (Appendix 6). The decline in M with reduced data amplified fishing mortality values, making $F_{0.1}$ and $F_{0.5}$ more sensitive to data scarcity.

While Tanaka's method was more stable for $F_{0.1}$ and $F_{0.5}$, $F_{\max}$ estimates showed a sharp increase under limited data conditions, suggesting an optimistic bias. This bias reflects the model's reliance on underlying assumptions when M is uncertain, increasing the risk of overestimating sustainable fishing limits (Carruthers et al., 2014). The Pauly method, which depends heavily on precise M estimates, showed a steep rise in $F_{0.5}$ when data fell below 25%, further illustrating the challenges posed by incomplete data (Kenchington, 2014).

These findings underscore the complexities of managing fisheries with limited data, where the choice of model becomes critical. Reduced data not only increases model uncertainty but also introduces the risk of inaccurate mortality estimates. Methods like Tanaka's, with minimal reliance on broad empirical relationships, provide more reliable outcomes in data-limited contexts (Mangel and Levin, 2005). In contrast, models like Pauly's are highly sensitive to fluctuations in M and recruitment, complicating fisheries management decisions when data is incomplete (Pilling et al., 2002; Carruthers et al., 2014).

Thus, selecting appropriate BRPs that align with the data context is essential to ensure sustainable fisheries management. $F_{0.1}$, with its conservative bias and lower sensitivity to data reductions, offers a more reliable benchmark for guiding decisions under uncertain conditions. Meanwhile, incorporating $F_{0.5}$ provides an additional layer of precaution by maintaining 50% spawning stock biomass, though its precision is more affected by data scarcity. Careful consideration of both M and F dynamics is necessary to minimize risks and maintain sustainability (Pauly, 1980; Hilborn and Walters, 1992; Then et al., 2015).

4.3.3. The Quantity and Its Impact on Result Reliability

In evaluating the appropriate data quantity for robust estimations of $F_{0.1}$ and $F_{0.5}$, scenarios were tested using a 10% threshold below the mean values of these parameters. Several scenarios yielded reliable outcomes:

- 24 months at all data percentages,
- 18 months at 100%, 75%, and 50%,
- 12 months at 100%, 75%, and 50%,
- Ev 2 (every two months over two years) at 100%, 75%, and 50%, and
- Ev 3 (every three months over two years) with 100% data.

These scenarios demonstrated sufficient precision, meeting the mean value threshold and producing acceptable *CV* values, indicating stable estimates suitable for fisheries management.

However, some anomalies were noted. The scenario with 10% data in Ev 5 produced mean values that satisfied the threshold, but the *CV* was excessively high, rendering the estimates unreliable. A similar issue was observed in the Ev 6 scenario at 100%, 75%, and 50%, suggesting that even with seemingly adequate data, the variability may be too great to draw definitive conclusions. These irregularities highlight the need for careful interpretation of the results and the importance of further in-depth analysis to validate their reliability. Data-limited scenarios should be approached cautiously, and results should not be used in isolation for management decisions.

To ensure reliable outcomes that balance precision and uncertainty, we recommend the following sampling designs:

- 24 months with 4,000 data points,
- 18 months with 5,000 data points,
- 12 months with 6,000 data points,
- Every 2 months over 2 years with 4,000 data points, or
- Every 3 months over 2 years with 5,000 data points.

These designs aim to optimize data availability while minimizing uncertainty, offering stakeholders actionable insights for stock assessments. Ensuring comprehensive data collection will reduce the risk of overexploitation and improve the reliability of biological reference point (BRP) estimates.

The simulation results clearly indicate that data availability plays a critical role in minimizing uncertainty in fisheries stock assessments. As data availability decreases, the risk of imprecise estimates increases, which can lead to inaccurate management decisions and the potential overexploitation of fish stocks. These findings emphasize the importance of precautionary approaches in fisheries management, particularly under data-limited conditions. Reliable and comprehensive data collection efforts are essential to ensure long-term sustainability and prevent unintended overfishing.

However, it is important to note that the methodology and procedures from this study can be applied to all fish species. Fisheries management frameworks often require species-specific assessments to account for differences in biological and ecological traits. Therefore, further research on other species is encouraged to enhance the reliability of length-based stock assessments, particularly in data-limited fisheries. This approach will help refine management strategies, ensuring sustainable exploitation while accommodating variability across different fish populations.

5. GENERAL CONCULSIONS

This study investigates the growth curve parameters and biological reference points (BRPs) for yellowfin tuna (*Thunnus albacares*) using length-based methods, a common approach in fisheries science. By employing bootstrapping simulations, we found that the quality and availability of data are paramount for precisely estimating these critical parameters. The analysis revealed that even slight variations in data collection can significantly influence the reliability of the assessments, reinforcing the notion that high-quality data is essential for effective fisheries management.

To enhance precision while managing uncertainty in stock assessments, we recommend several robust sampling designs. Specifically, we suggest collecting data over 24, 18 and 12 months with 7,000; 8,000; and 9,000 data, respectively. Alternatively, sampling every 2 months over 2 years with 5,000 data or every 3 months over the same period with 6,000 data could be effective. Implementing these sampling designs will facilitate comprehensive data collection, crucial for minimizing overfishing risks and improving the precision of growth curve parameters and BRPs estimation.

Additionally, we conducted a comparison analysis on M to examine how variations in this parameter affect the estimation of BRPs. Understanding the sensitivity of BRP estimates to changes in natural mortality is crucial, as it informs fisheries managers about the robustness of their decisions under varying ecological conditions.

The findings from this research such as methodology, procedures, particularly filtering t_0 are adaptable and can be applied to other fish species. Such research could contribute to a more comprehensive understanding of fish population dynamics and aid in the development of more effective management strategies.

The results of this study further highlight the significant impact of data availability on fisheries stock assessments. Insufficient data can lead to imprecise estimates, increasing the likelihood of poor management decisions that may result in the overexploitation of fish stocks. Therefore, establishing reliable and thorough data collection methods is vital for ensuring the long-term sustainability of fisheries management practices. Ultimately, this research contributes valuable insights that can aid policymakers, researchers, and stakeholders in making informed decisions that promote sustainable fishing practices and conserve aquatic resources.

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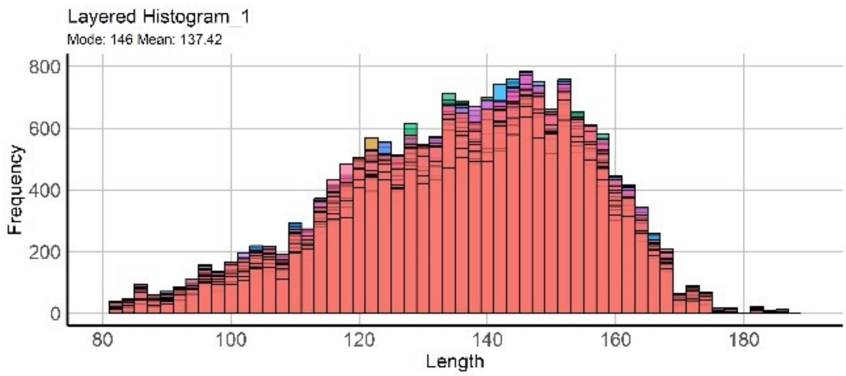
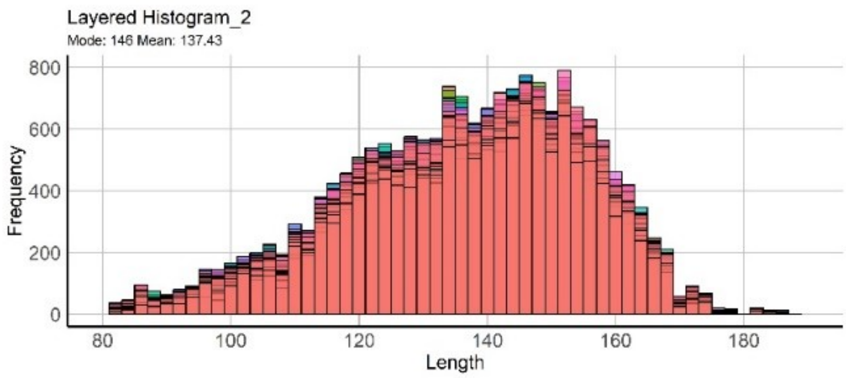
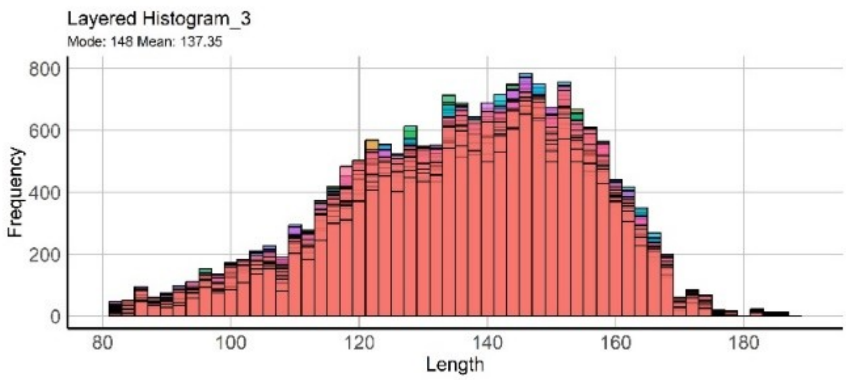
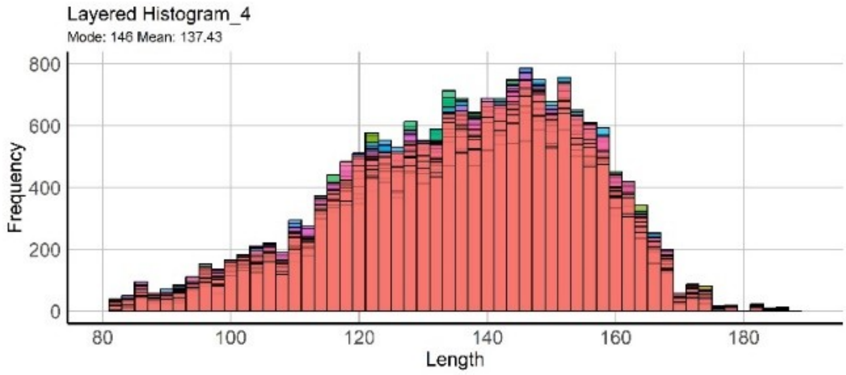
APPENDICES

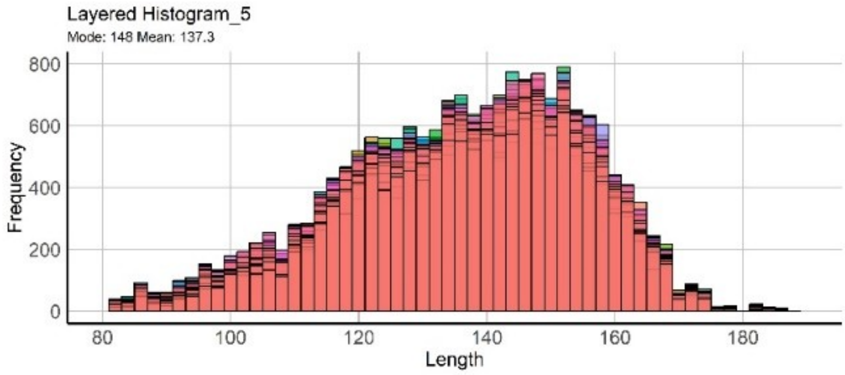
Appendix 1. Bootstrapping 10,000 iterations. Every figure has 1,000 bootstrap iterations and includes values for the mode and mean.








Layered Histogram_4
Mode: 146 Mean: 137.43
Frequency
0
200
400
600
800
80
100
120
140
160
180
Length


Layered Histogram_5
Mode: 148 Mean: 137.3
Frequency
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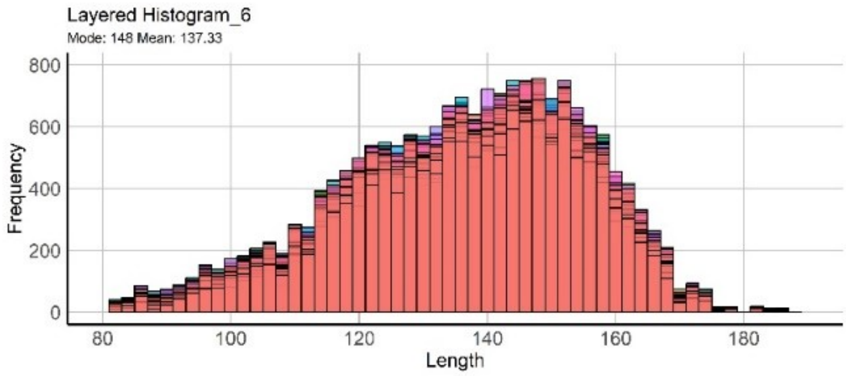
200
400
600
800
80
100
120
140
160
180
Length


Layered Histogram_6
Mode: 148 Mean: 137.33
Frequency
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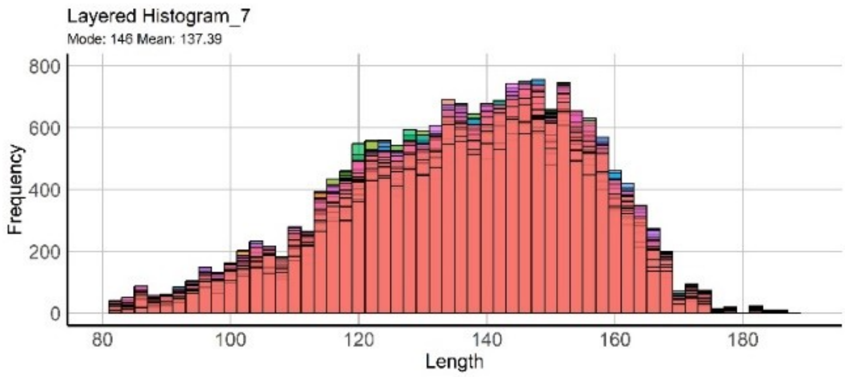
200
400
600
800
80
100
120
140
160
180
Length


Layered Histogram_7
Mode: 146 Mean: 137.39
Frequency
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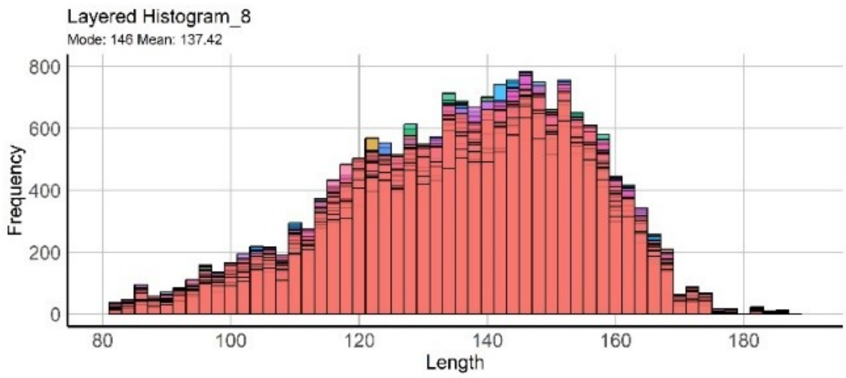
200
400
600
800
80
100
120
140
160
180
Length


Layered Histogram_8
Mode: 146 Mean: 137.42
Frequency
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80
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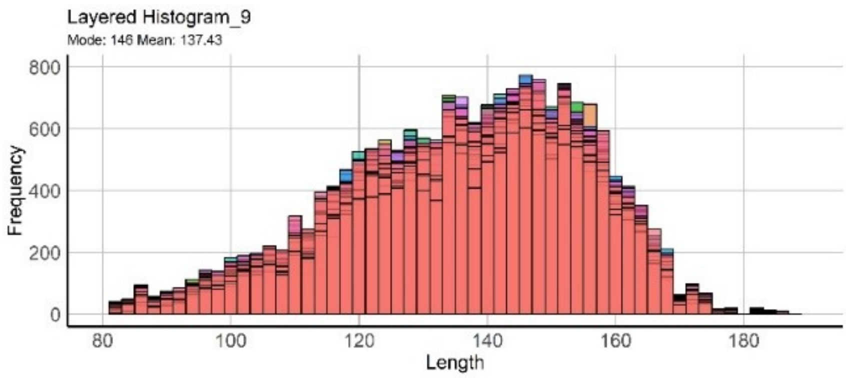
160
180
Length


Layered Histogram_9
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Frequency
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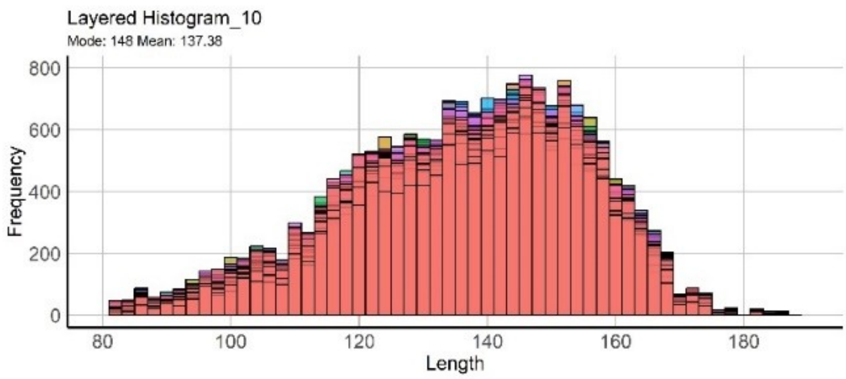
180
Length


Layered Histogram_10
Mode: 148 Mean: 137.38
Frequency
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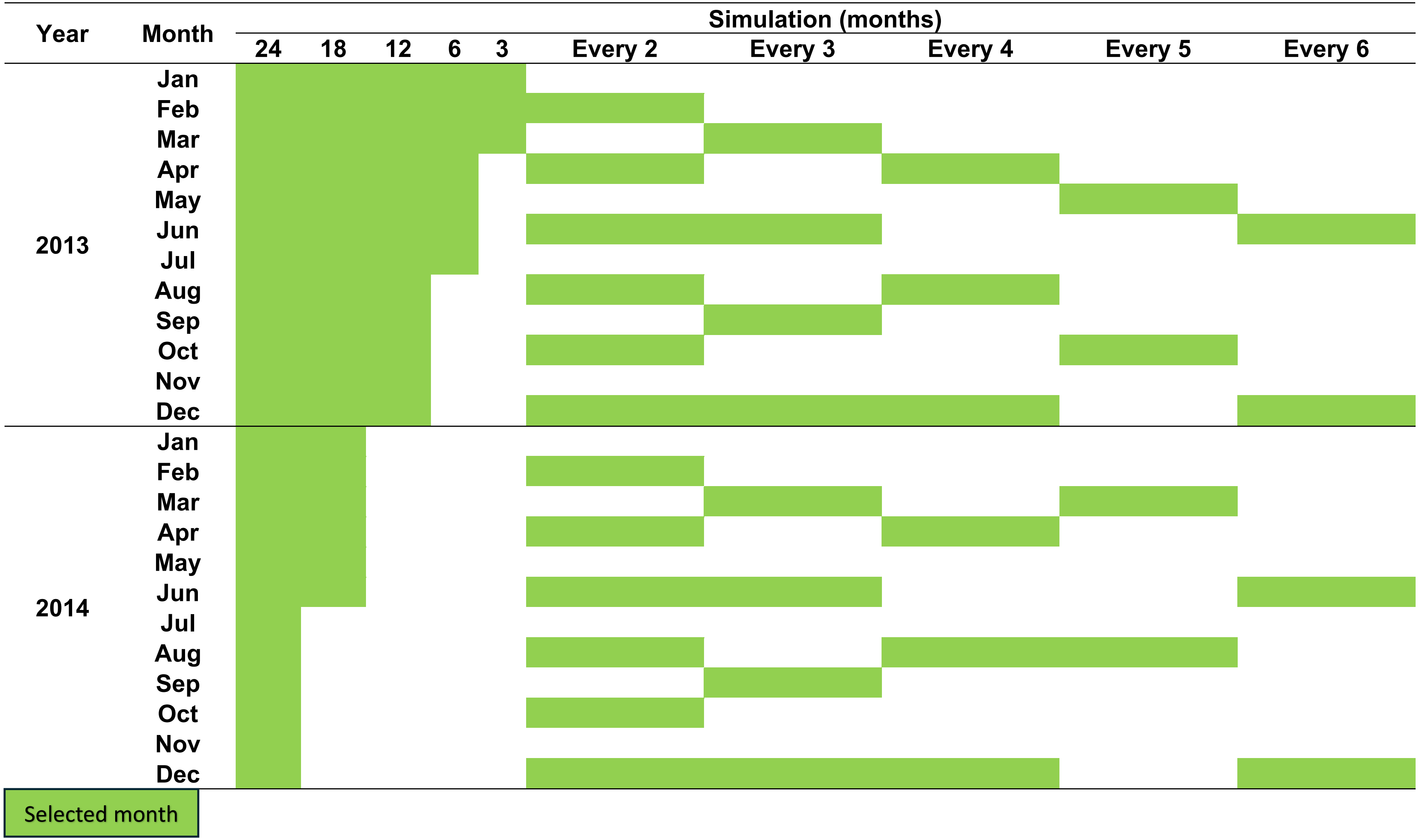
800
80
100
120
140
160
180
Length

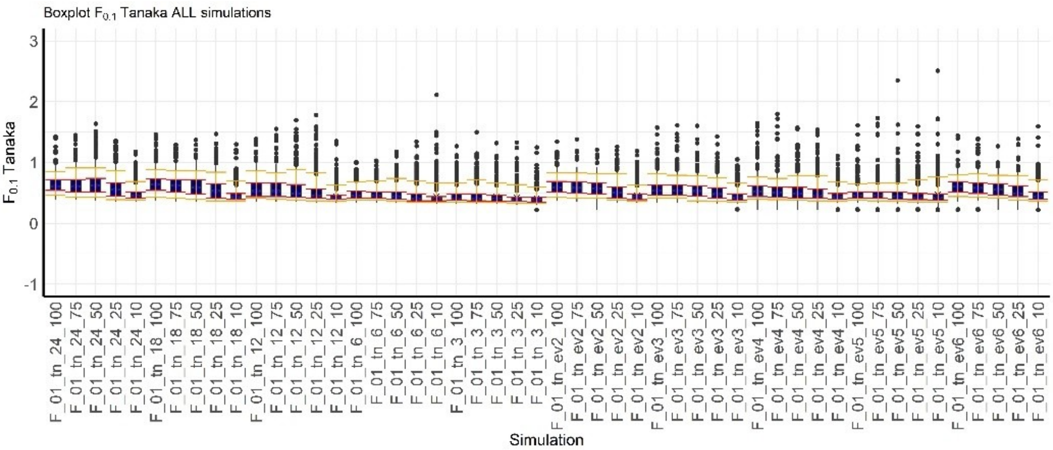
Appendix 2. Simulation framework

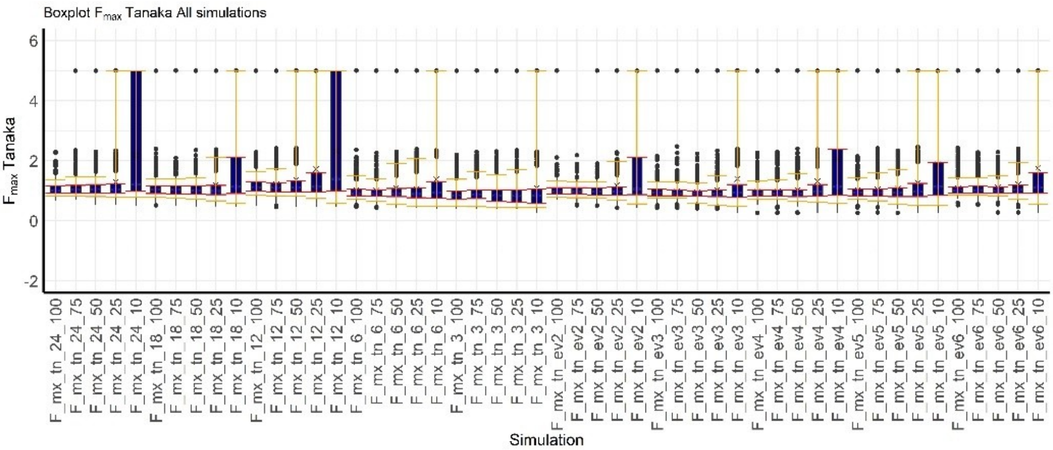


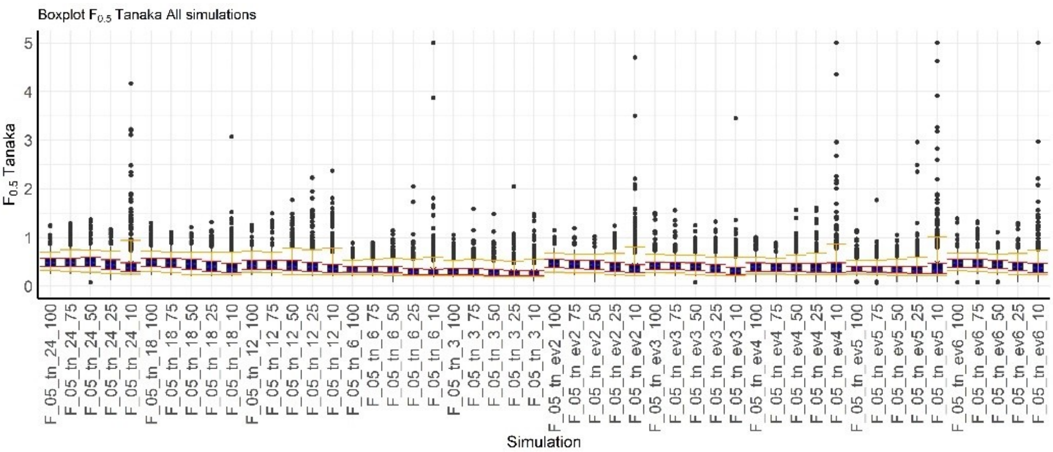
Appendix 3. The amount of each month. Reduction of data from 100% to 75%, 50%, 25%, and 10%.

Year	Month	Percentage				
		100	75	50	25	10
2013	Jan	675	506	338	169	68
	Feb	336	252	168	84	34
	Mar	292	219	146	73	29
	Apr	465	349	233	116	47
	May	466	350	233	117	47
	June	958	719	479	240	96
	July	958	719	479	240	96
	Augst	258	194	129	65	26
	Sept	328	246	164	82	33
	Oct	368	276	184	92	37
	Nov	601	451	301	150	60
	Dec	601	451	301	150	60
2014	Jan	447	335	224	112	45
	Feb	211	158	106	53	21
	Mar	589	442	295	147	59
	Apr	879	659	440	220	88
	May	788	591	394	197	79
	June	1473	1105	737	368	147
	July	849	637	425	212	85
	Augst	384	288	192	96	38
	Sept	509	382	255	127	51
	Oct	365	274	183	91	37
	Nov	721	541	361	180	72
	Dec	669	502	335	167	67
Total		14190	10643	7095	3548	1419

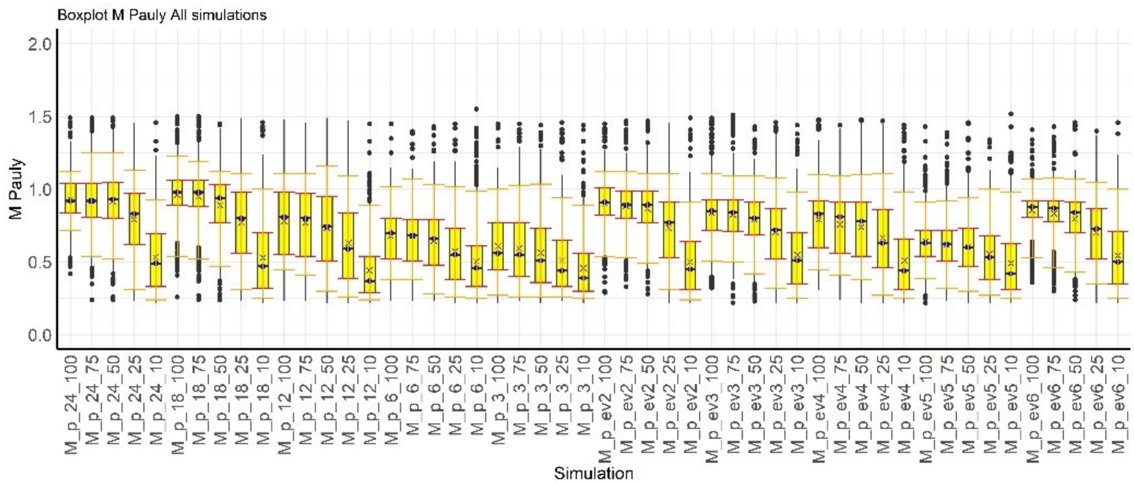
Appendix 4. Distribution of $F_{0.1}$, $F_{\max}$, and $F_{0.5}$ across all scenarios. The dark blue boxplot represents the distribution of estimated values from Tanaka method. Each boxplot includes red lines indicating the 25th and 75th percentiles, yellow lines indicating the 5th and 95th percentiles, black dots representing the mean values, and blue X's representing the median values.

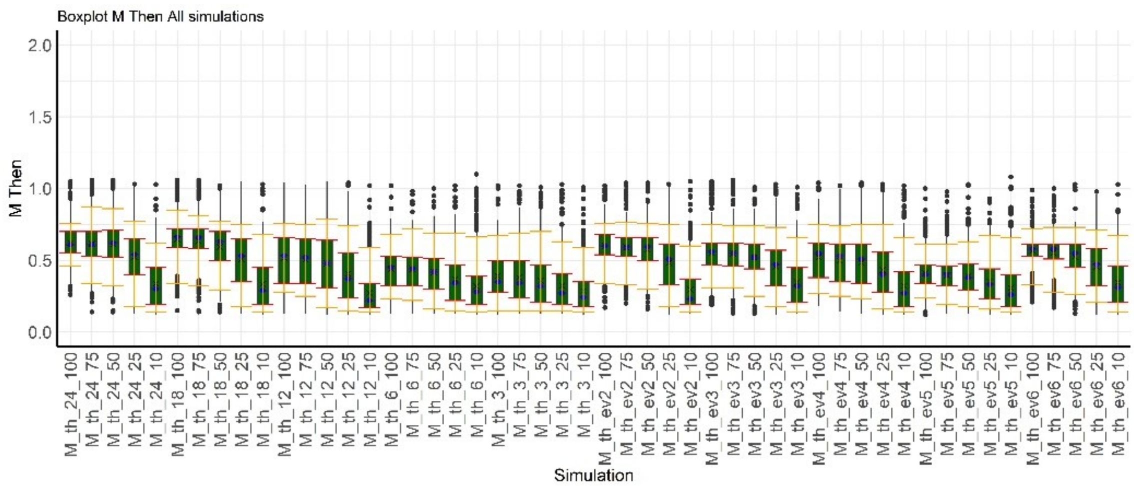


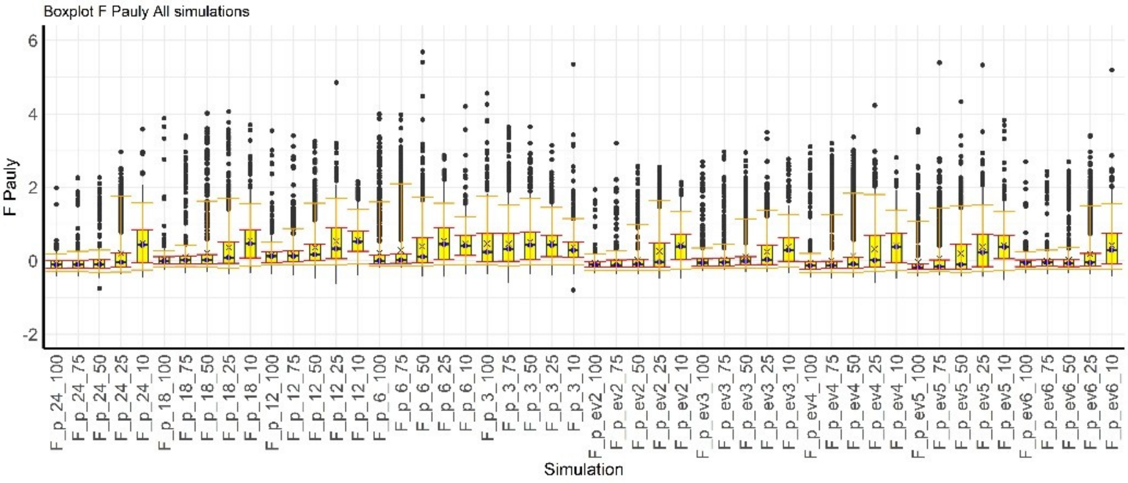


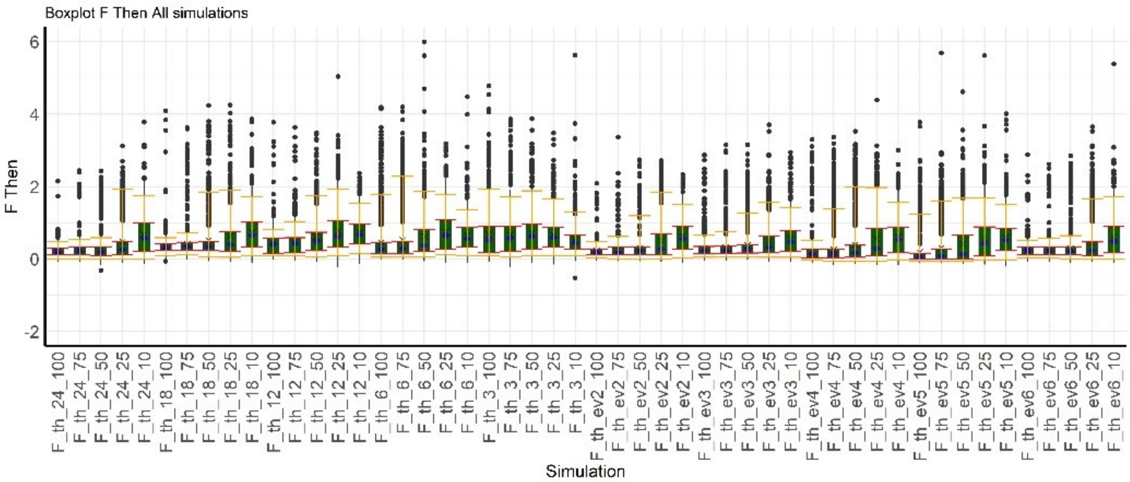


Appendix 5. M and F of Pauly and Then et al., methods. The yellow boxplot represents the distribution of estimated values from Pauly method; the dark green boxplot represents the distribution of estimated values from Then et al method. Each boxplot includes red lines indicating the 25th and 75th percentiles, yellow lines indicating the 5th and 95th percentiles, black dots representing the mean values, and blue X's representing the median values.

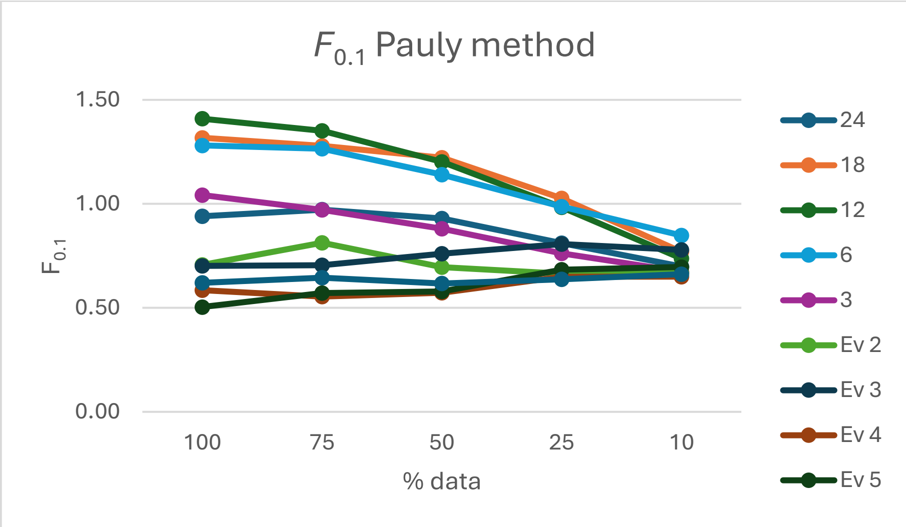


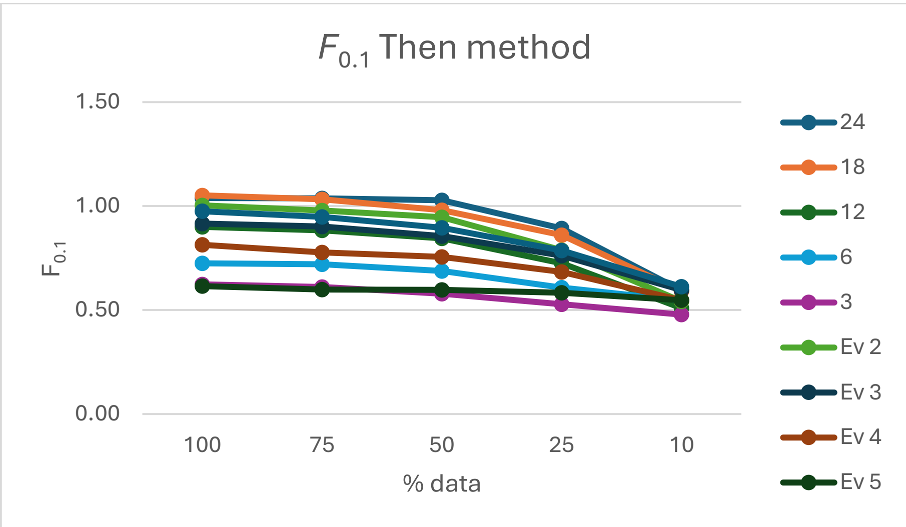


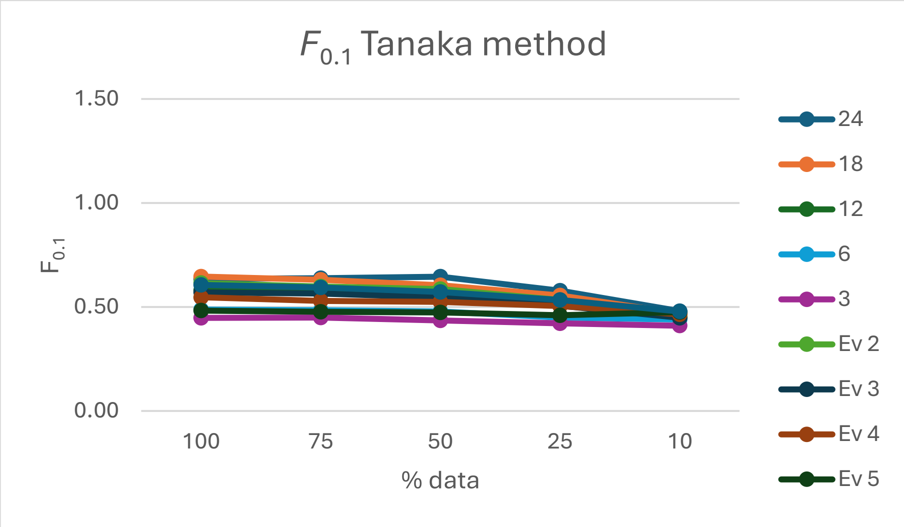

Boxplot F Pauly All simulations
F Pauly
6
4
2
0
-2
F_p_24_100
F_p_24_75
F_p_24_50
F_p_24_25
F_p_24_10
F_p_18_100
F_p_18_75
F_p_18_50
F_p_18_25
F_p_18_10
F_p_12_100
F_p_12_75
F_p_12_50
F_p_12_25
F_p_12_10
F_p_6_100
F_p_6_75
F_p_6_50
F_p_6_25
F_p_6_10
F_p_3_100
F_p_3_75
F_p_3_50
F_p_3_25
F_p_3_10
F_p_ev2_100
F_p_ev2_75
F_p_ev2_50
F_p_ev2_25
F_p_ev2_10
F_p_ev3_100
F_p_ev3_75
F_p_ev3_50
F_p_ev3_25
F_p_ev3_10
F_p_ev4_100
F_p_ev4_75
F_p_ev4_50
F_p_ev4_25
F_p_ev4_10
F_p_ev5_100
F_p_ev5_75
F_p_ev5_50
F_p_ev5_25
F_p_ev5_10
F_p_ev6_100
F_p_ev6_75
F_p_ev6_50
F_p_ev6_25
F_p_ev6_10
Simulation

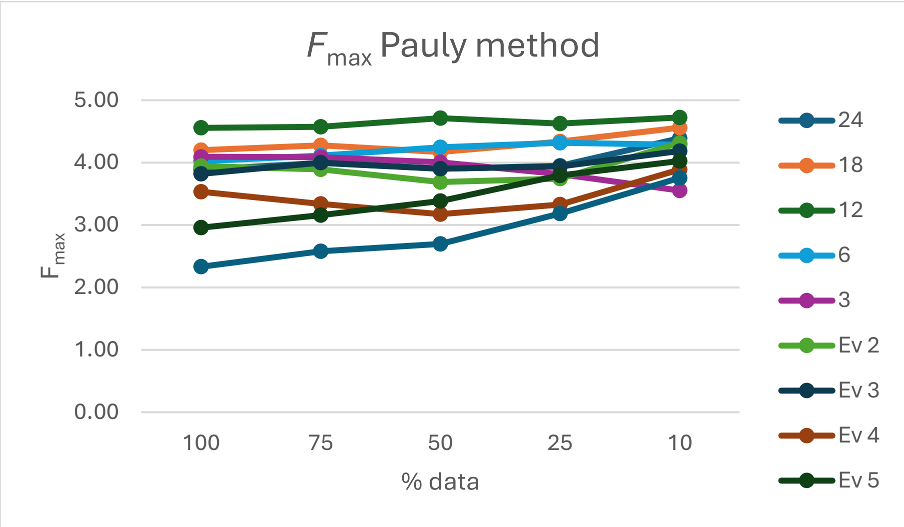

Boxplot F Then All simulations
F Then
6
4
2
0
-2
F_th_24_100
F_th_24_75
F_th_24_50
F_th_24_25
F_th_24_10
F_th_18_100
F_th_18_75
F_th_18_50
F_th_18_25
F_th_18_10
F_th_12_100
F_th_12_75
F_th_12_50
F_th_12_25
F_th_12_10
F_th_6_100
F_th_6_75
F_th_6_50
F_th_6_25
F_th_6_10
F_th_3_100
F_th_3_75
F_th_3_50
F_th_3_25
F_th_3_10
F_th_ev2_100
F_th_ev2_75
F_th_ev2_50
F_th_ev2_25
F_th_ev2_10
F_th_ev3_100
F_th_ev3_75
F_th_ev3_50
F_th_ev3_25
F_th_ev3_10
F_th_ev4_100
F_th_ev4_75
F_th_ev4_50
F_th_ev4_25
F_th_ev4_10
F_th_ev5_100
F_th_ev5_75
F_th_ev5_50
F_th_ev5_25
F_th_ev5_10
F_th_ev6_100
F_th_ev6_75
F_th_ev6_50
F_th_ev6_25
F_th_ev6_10
Simulation

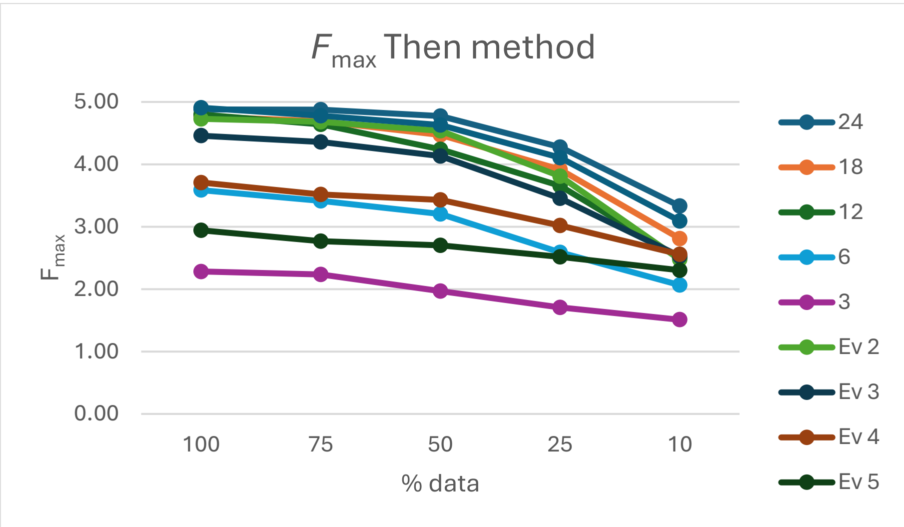
Appendix 6. $F_{0.1}$, $F_{\max}$, and $F_{0.5}$ of Pauly, Then et al., and Tanaka methods. The mean estimates of $F_{0.1}$ range from 0.50 to 1.41 with the Pauly method and 0.48 to 1.05 with the Then et al., method. The mean estimates of $F_{\max}$ range from 2.33 to 4.72 with the Pauly method and 1.51 to 4.91 with the Then et al., method. For $F_{0.5}$, the mean estimates range from 0.25 to 1.23 with the Pauly method and 0.35 to 0.85 with the Then et al., method.

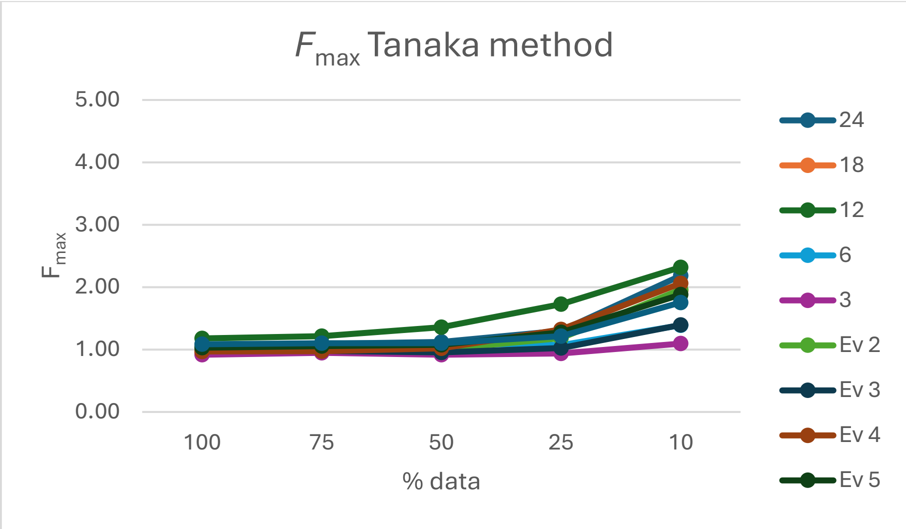


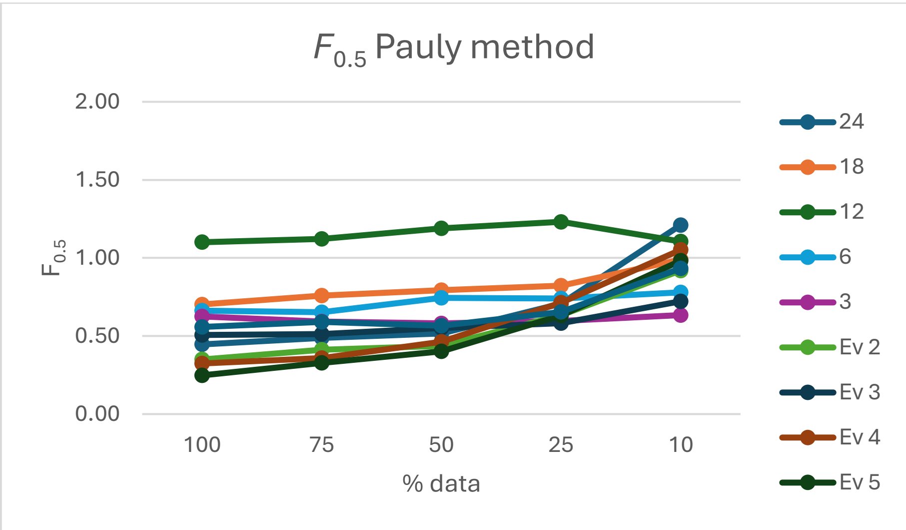


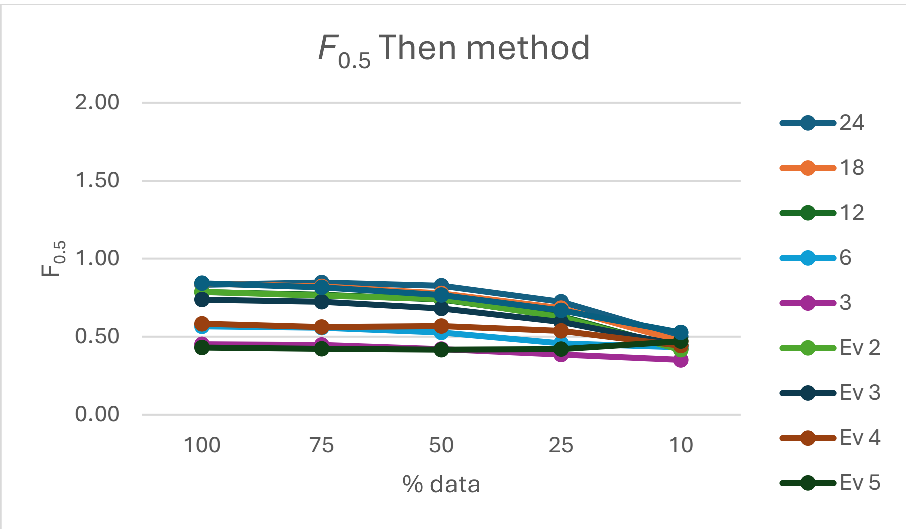

$F_{0.1}$ Tanaka method
1.50
1.00
0.50
0.00
$F_{0.1}$
100
75
50
25
10
% data
24
18
12
6
3
Ev 2
Ev 3
Ev 4
Ev 5

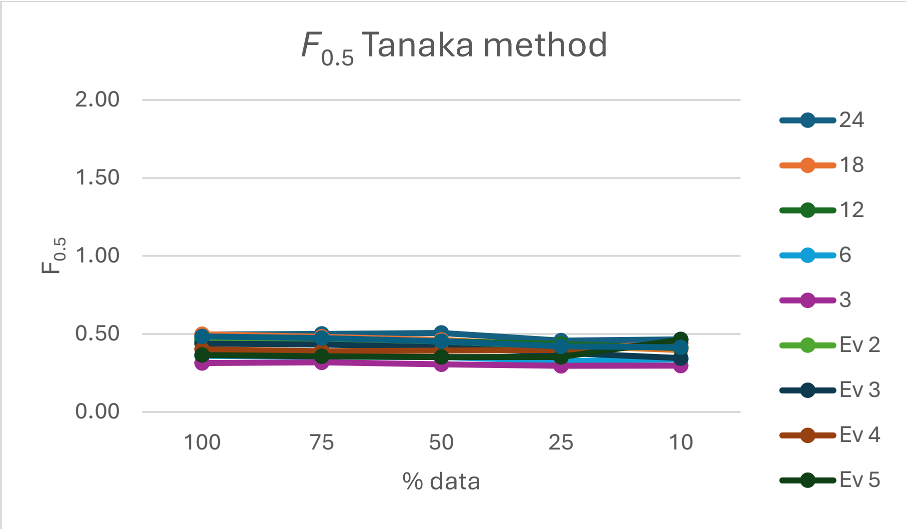

F_{max} Pauly method
5.00
4.00
3.00
2.00
1.00
0.00
F_{max}
100
75
50
25
10
% data
24
18
12
6
3
Ev 2
Ev 3
Ev 4
Ev 5


F_{max} Then method
5.00
4.00
3.00
2.00
1.00
0.00
F_{max}
100
75
50
25
10
% data
24
18
12
6
3
Ev 2
Ev 3
Ev 4
Ev 5


F_{max} Tanaka method
5.00
4.00
3.00
2.00
1.00
0.00
F_{max}
100
75
50
25
10
% data
24
18
12
6
3
Ev 2
Ev 3
Ev 4
Ev 5


$F_{0.5}$ Pauly method
2.00
1.50
1.00
0.50
0.00
$F_{0.5}$
100
75
50
25
10
% data
24
18
12
6
3
Ev 2
Ev 3
Ev 4
Ev 5


$F_{0.5}$ Then method
2.00
1.50
1.00
0.50
0.00
$F_{0.5}$
100
75
50
25
10
% data
24
18
12
6
3
Ev 2
Ev 3
Ev 4
Ev 5



$F_{0.5}$ Tanaka method
2.00
1.50
1.00
0.50
0.00
$F_{0.5}$
100
75
50
25
10
% data
24
18
12
6
3
Ev 2
Ev 3
Ev 4
Ev 5

Appendix 7. *CV* distribution of $F_{0.1}$, $F_{\max}$, and $F_{0.5}$ of Pauly, Then et al., and Tanaka methods. Blue dot represents Pauly method, green dot represents Then et al., method and red dot represents Tanaka method across all scenarios.