SIOFA Sharks

Annex 4: Length Based Indicators for Centroscymnus coelolepis

DELEGATION OF THE EUROPEAN UNION

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Using length-based indicators (LBIs) over length-based methods (LBMs) offers several advantages, particularly in the context of fisheries management where data limitations and the need for robust, understandable metrics are paramount. This justification draws on the detailed examination of fisheries challenges, the limitations of catch-only methods, and the utility of length data as outlined in the provided text.

Advantages of LBIs Over LBMs

1. Data Availability and Accessibility: Length data are more readily available for many fisheries compared to age-based data required for LBMs. LBIs can utilize data from even a single year to provide snapshots of exploitation levels, making them particularly valuable in data-limited situations.

2. Simplicity and Stakeholder Comprehension: LBIs, being based on direct observations and simple transformations of length frequencies, are easier to explain and understand for non-scientific stakeholders compared to the complex models and assumptions underpinning LBMs. This transparency is crucial for gaining stakeholder trust and compliance with management measures.

3. Robustness to Data Limitations: The reliance on fewer assumptions makes LBIs less susceptible to the biases and inaccuracies that can affect LBMs, especially in data-limited contexts. While LBMs can provide detailed insights, their complexity and the need for specific biological and fishery information can introduce significant uncertainties.

4. Rapid Assessment Capabilities: LBIs allow for quicker assessments of stock status and exploitation levels. They can provide immediate management guidance without the extensive data collection and analysis periods required for effective application of LBMs.

5. Cost-Effectiveness: The implementation of LBIs requires less detailed data and fewer resources than LBMs. This cost-effectiveness is particularly important for managing fisheries with limited financial and technical capacities.

Contextual Considerations

While LBIs offer these advantages, their effectiveness is context-dependent. The choice between LBIs and LBMs should consider the specific management objectives, the nature of the fishery, and the available data. LBIs serve as powerful tools for initial assessments, trend monitoring, and providing priors for more complex models. However, they may not always capture the full dynamics of a fishery as effectively as LBMs.

Conclusion

The preference for LBIs over LBMs in certain situations is justified by their accessibility, simplicity, robustness to data limitations, rapid assessment capabilities, and cost-effectiveness. These attributes make LBIs particularly suitable for data-limited fisheries and those requiring immediate management actions. However, a balanced approach that considers the strengths and limitations of both LBIs and LBMs, potentially integrating them where appropriate, can offer the most robust framework for fisheries management within the Ecosystem Approach to Fisheries.

Catch-only methods have become increasingly popular for evaluating the status of fish stocks in situations where data are limited. These methods attempt to reconstruct historical abundance and assess stock status relative to reference points by making assumptions about productivity and final biomass relative to the unfished state. However, the reliability and accuracy of catch-only models have been a subject of debate, with concerns about their sensitivity to the choice of priors and their inability to validate using observations. This summary highlights the key reasons why catch-only methods are viewed with caution and suggests the integration of length data into biomass dynamic models as a more informative approach.

Critique of Catch-Only Methods

1. **Sensitivity to Heuristics**: Catch-only models rely heavily on heuristics and priors for initial and final depletion based on expert opinion. These assumptions significantly influence the model outputs, making them sensitive to the choice of heuristics. The lack of data for calibration means that results can vary widely based on these initial assumptions.

2. **Limited Validation Capabilities**: One of the fundamental limitations of catch-only models is the difficulty in validation. Since the only observations used are the catches themselves, traditional validation techniques such as cross-validation cannot be employed effectively. This lack of validation undermines the credibility of the models for making management decisions.

3. **Inability to Monitor Management Interventions**: Catch-only models, by their nature, cannot be used as part of management control where data updates are used to monitor the effectiveness of interventions. Without additional data and knowledge, these models offer limited utility in implementing management for data-poor stocks.

4. **Poor Performance in Classification**: Studies have shown that heuristics alone performed nearly as well as catch-only models in classifying stock status, indicating that the models do not significantly improve upon basic assumptions. This suggests that catch-only models might not provide a reliable basis for management decisions.

Integration of Length Data into Biomass Dynamic Models

To address the limitations of catch-only methods, integrating length data into biomass dynamic models (e.g., JABBA) offers a promising alternative. Length data can provide snapshots of exploitation levels and serve as priors for catch-only methods, potentially improving the robustness of stock assessments. Here are some ways length data can enhance biomass dynamic models:

1. **Improvement in Model Inputs**: Length data can serve as an unbiased estimate of abundance, offering additional information that can be used to refine model inputs and assumptions. This can lead to more accurate assessments of stock status relative to maximum sustainable yield (MSY) reference points.

2. **Enhancement of Model Validation**: Including length data allows for a broader range of validation techniques, including comparisons with data-rich assessments from databases like RAM Legacy. This can help in evaluating the robustness of the assumptions used in models and the benefit of obtaining better priors.

3. **Support for Management Decisions**: Integrating length data into models provides a more detailed picture of stock dynamics, supporting the development of scientific management frameworks that protect marine ecosystems and the well-being of stakeholders. It also allows for the evaluation of the value of obtaining additional information for reducing risk due to loss of yield through adopting a risk equivalence approach.

4. **Transition from Data-Poor to Data-Moderate Assessments**: The use of length data enables a transition from catch-only to data-moderate stock assessments. This gradual integration of more

detailed data can improve the accuracy of stock status estimates and support adaptive management strategies.

In conclusion, while catch-only methods offer a tool for assessing fish stocks in data-limited situations, their limitations necessitate caution in their use for management decisions. Integrating length data into biomass dynamic models presents a viable alternative that can enhance the reliability and validation of stock assessments, supporting more informed and effective fisheries management.

Length Frequency Distributions

IEO

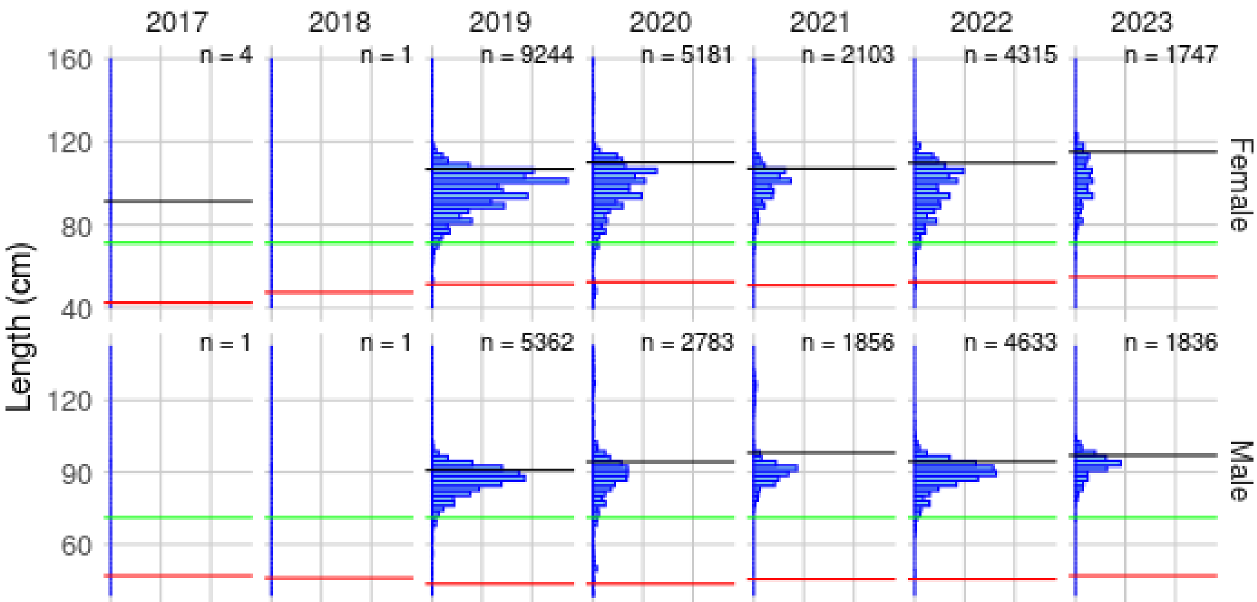

Figure 1 Length distributions by gender for IEO data.

SIOFA

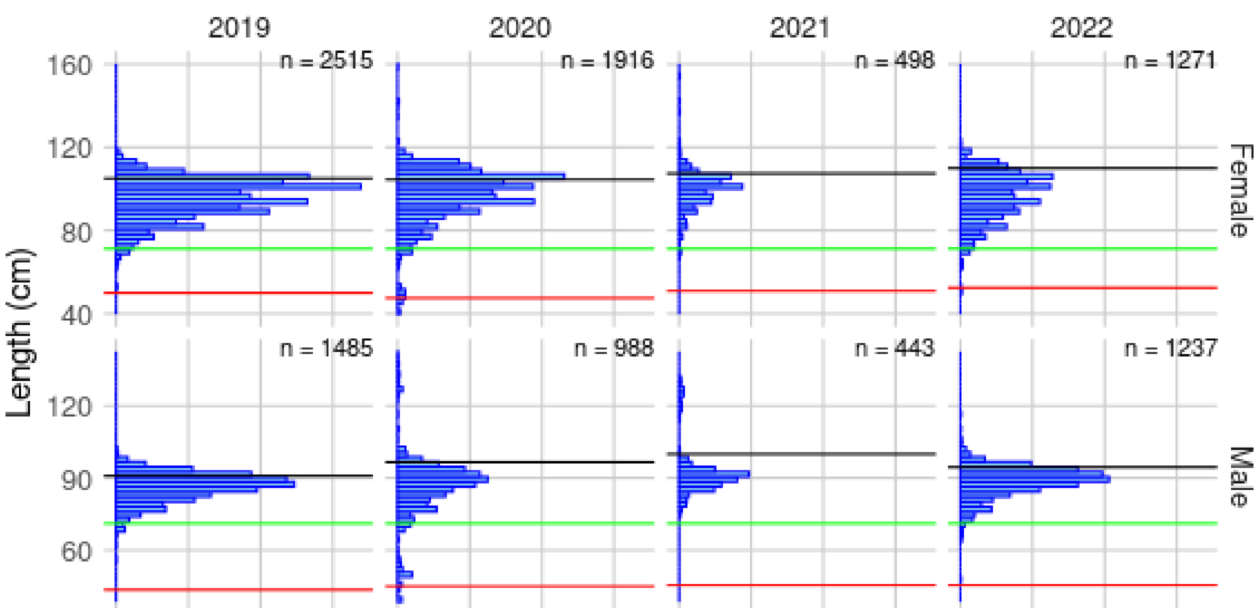

Figure 2 Length distributions by gender for SIOFA data.

Introduction

Applying LBIs requires consideration of species-specific life history traits of sharks and the type of fisheries they are subjected to. Using multiple indicators in tandem is recommended for a comprehensive view of the stock status. Management strategies should be adaptive, considering the ecological roles of sharks, their vulnerability to overfishing, and the socio-economic context of the fisheries.

Diagnostics focusing on checks for model fit, influential observations, and assumption violations: Length-based indicators (LBIs) are useful for assessing shark stocks, based on the size composition of catch or survey data to provide insights into the status of fish stocks. Especially when traditional assessment methods are not applicable due to data limitations.

Here provides a summary of the shark dataset, which includes information on shark captures such as species, length, weight, sex, maturity, and other relevant data. The aim is to understand the diversity of species, the types of data collected, and assess the quality and coverage of the dataset.

Best Length-Based Indicators for Shark Stocks

1. Length Frequency Distribution

- **Description:** Analysis of length frequency distribution can reveal shifts in population structure, indicating changes in recruitment, growth rates, or fishing pressure.
- **Utility:** Helps understand the age structure and can indicate overfishing if larger, older individuals become rare.

2. Mean Length

- **Description:** The average length of individuals in the catch or population over time.
- **Utility:** A declining mean length can indicate heavy fishing pressure or overexploitation.

3. Length at First Capture (L50)

- **Description:** The length at which 50% of individuals are susceptible to capture.
- **Utility:** If L50 is much lower than the length at maturity (Lm), it suggests unsustainable fishing practices.

4. Proportion of Mature Individuals

- **Description:** The percentage of the catch that is mature, assessed through length.
- **Utility:** A decrease over time can indicate overfishing.

5. Large Fish Indicator (LFI)

- **Description:** The proportion of fish above a certain length threshold.
- **Utility:** Useful for detecting shifts towards smaller sizes, indicating overexploitation.

6. Size at Maturity (Lm)

- **Description:** The length at which a certain percentage of the population reaches sexual maturity.
- **Utility:** Important for ensuring sharks reach maturity before being caught.

7. Growth Rates and Maximum Size (L_∞)

- **Description:** Estimated from length-at-age data to understand population dynamics.
- **Utility:** Inform on the health of the stock and the efficacy of current management strategies.

The relationship between L_{max} and L_∞ is a fundamental concept in fishery science, particularly within the context of growth models such as the von Bertalanffy growth function (VBGF). Here's a brief overview:

- L_∞ (Linfinity) is the asymptotic maximum length that an individual of a given species can reach, according to the VBGF. It represents the length towards which the fish grows as age approaches infinity, essentially the maximum theoretical size.
- L_{max} (Lmax) is the maximum observed length from empirical data for individuals of a species within a specific population or study. It's an actual measurement from collected or observed data.

The relationship between the two can be summarized as follows:

1. **Theoretical vs. Empirical**: L_∞ is a parameter from a growth model, while L_{max} is an empirical measurement. L_∞ is often larger than L_{max} because L_{max} is limited by the sizes of individuals that have been observed or caught, and it's unlikely that the largest possible individual of a species (as predicted by the growth model) will have been sampled.
2. **Use in Growth Models**: L_∞ is used in the von Bertalanffy growth function to model the growth of individuals in a population over time. L_{max} can be used to validate or calibrate growth models by providing a reference point or to estimate L_∞ when it cannot be directly calculated from available data.
3. **Indicator of Growth Potential**: Both L_{max} and L_∞ serve as indicators of the growth potential and life history strategy of fish species. Species with large L_∞ values tend to be long-lived, slow-growing, and late-maturing, which has implications for their vulnerability to fishing pressure.
4. **Management Implications**: Understanding the relationship between L_{max} and L_∞ is crucial for fisheries management. It helps in setting appropriate size limits for fishing to ensure that individuals have the opportunity to reproduce before being caught, which is important for the sustainability of fish stocks.

In summary, while L_{max} and L_∞ are related, they are distinct measures. L_∞ provides a theoretical maximum size within the context of a growth model, while L_{max} offers a practical, observed maximum size within a given dataset or study. The two can be used together to enhance our understanding of fish growth, population dynamics, and to inform management decisions.

lmax5(x)

l95(x)

l25(x)

lc50(x)

lmode(x)

lbar(x)

lmean(x)

lmaxy(x, lenwt)

pmega(x, linf, lopt=linf * 2/3)

Bootstrapping an FLQuant object, which contains numbers by length and year for a fish stock, involves resampling the data to create "bootstrap samples." These samples can be used to estimate the variability of stock assessment metrics or indicators. Below, I'll provide a conceptual overview and a basic example of how to perform bootstrapping on an FLQuant object in R using the FLR (Fisheries Library in R) framework.

Conceptual Overview

1. **Bootstrap Sampling**: Randomly resample the FLQuant data with replacement to create a new "bootstrap sample." This involves sampling individual length-at-age data points (or whatever the FLQuant represents) to construct a new dataset of the same size as the original.

2. **Replication**: Repeat the bootstrap sampling process many times (e.g., 1000 or more iterations) to generate many bootstrap samples.
3. **Metric Calculation**: For each bootstrap sample, calculate the stock assessment metric or indicator of interest (e.g., spawning stock biomass, fishing mortality rates, or length-based indicators).
4. **Variability Estimation**: Use the distribution of the calculated metrics across all bootstrap samples to estimate their variability (e.g., standard errors, confidence intervals).

Example Code

This example is hypothetical, as the specific function calls and structure will depend on the details of your FLQuant object and what you're trying to achieve. You'll need to have the FLCore and possibly other FLR packages installed.

Note: This is a simplified example. The actual bootstrapping process will depend on the structure of your data, the metrics you're interested in, and the specific methods used for resampling and analysis. The `calculateMetric` function is a placeholder for whatever analysis you are performing on each bootstrap sample.

Remember, bootstrapping is computationally intensive, especially with large datasets and many bootstrap iterations. Ensure your calculations within the loop are as efficient as possible.

To bootstrap a length frequency distribution from your vector, you can use the `sample()` function in R to randomly resample the length categories with replacement, simulating the process of drawing new samples from the original dataset. This approach allows you to estimate the variability of your statistics (e.g., mean length, total abundance) and can be repeated many times to create a distribution of these statistics.

Here's a basic outline of how you might perform this bootstrap procedure for your length frequency data:

1. **Prepare Your Data**: First, ensure your length frequency data is in a suitable format, such as a vector or data frame where lengths are associated with their frequencies.
2. **Define the Bootstrap Function**: Write a function to resample your data and calculate the statistic(s) of interest (e.g., mean length).
3. **Perform the Bootstrap**: Use a loop to repeatedly apply the bootstrap function, storing each replicate's results.

Below is an example R code snippet that demonstrates this process for bootstrapping the mean length from your dataset. This example assumes your length frequency data is stored in a data frame called `length_freq` with columns `len` for length categories and `freq` for their frequencies.

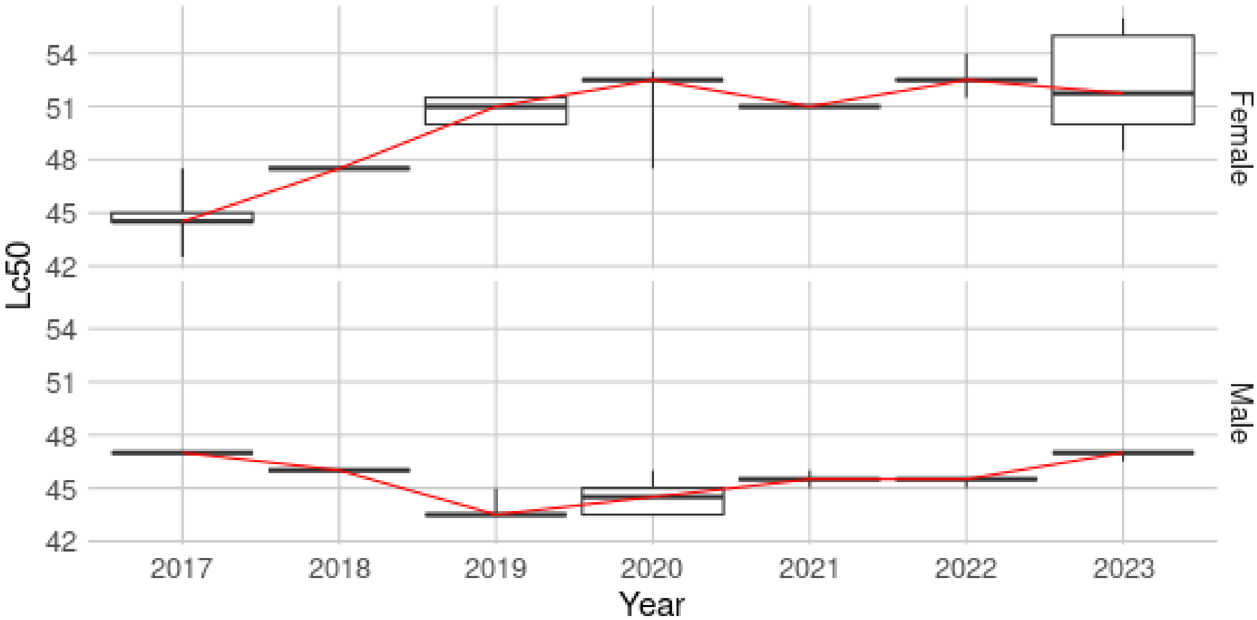

Figure 3 .

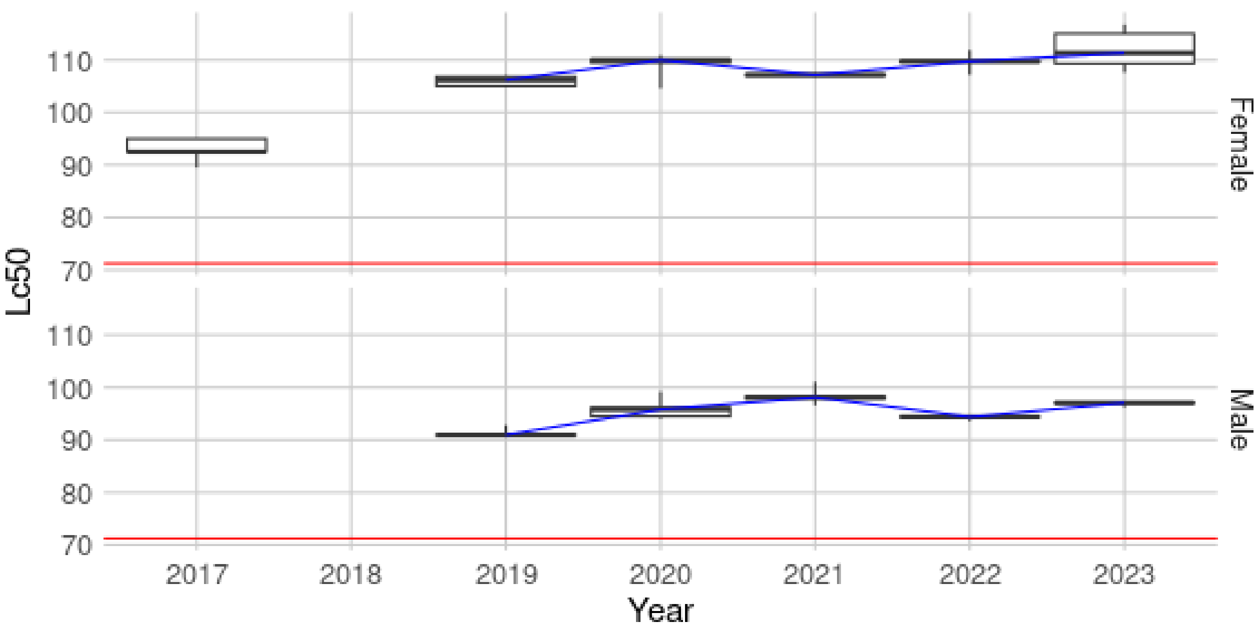

Figure 4 .

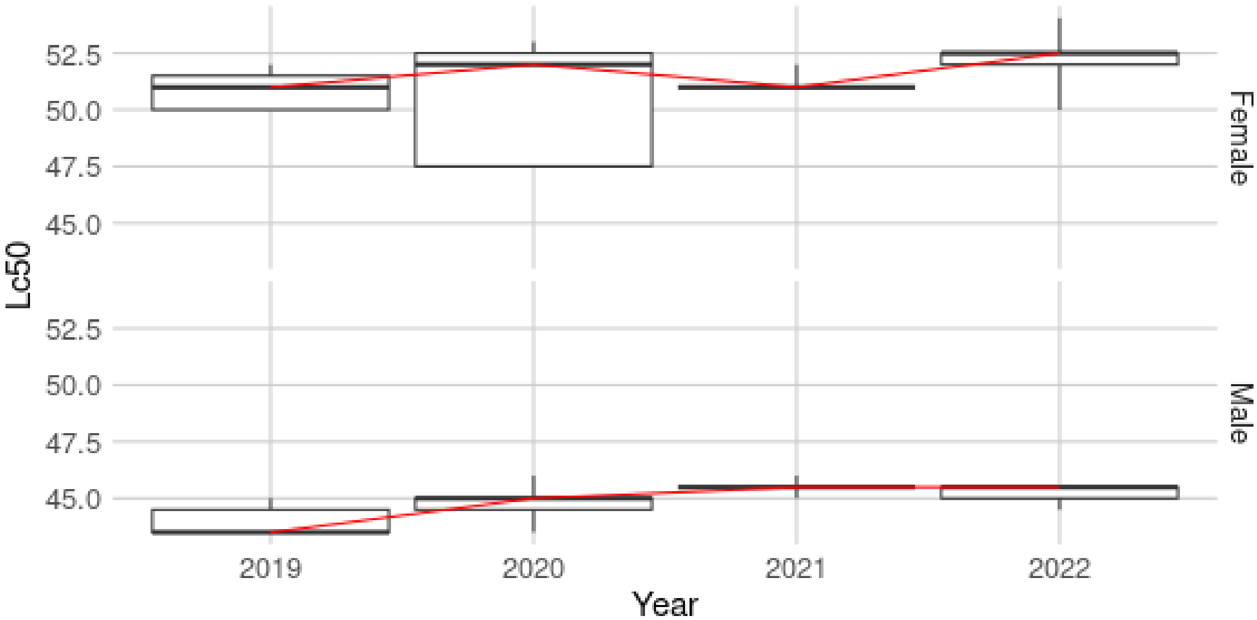

Figure 5 .

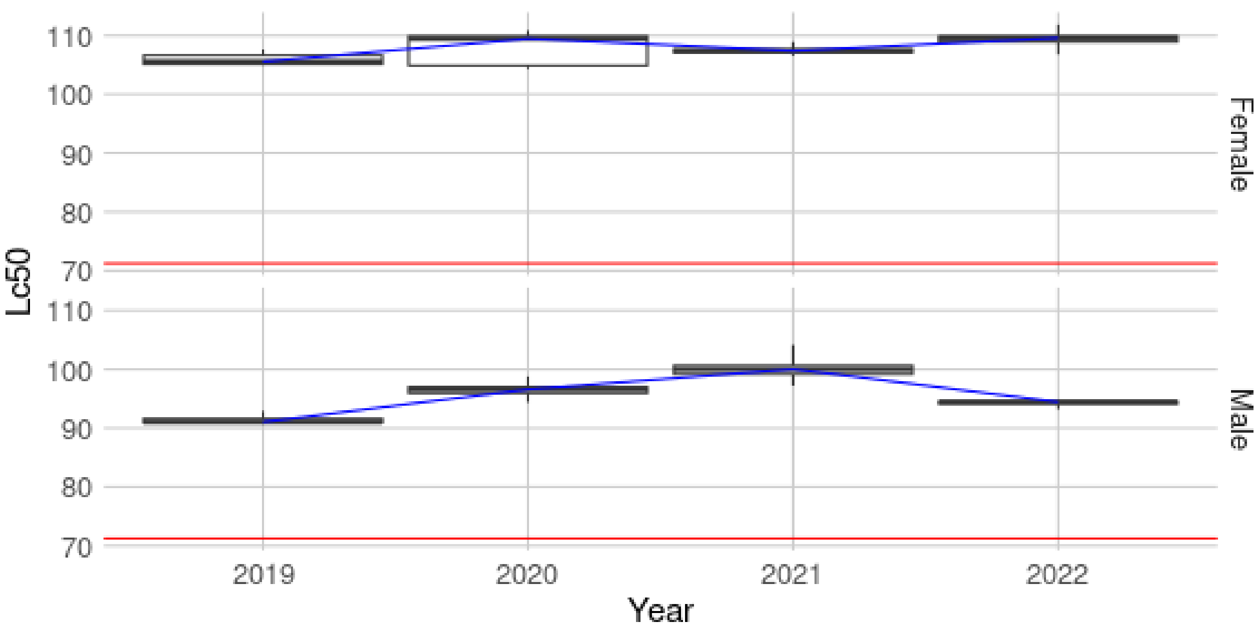

Figure 6 .

The empirical relationship between L_∞ (asymptotic length, the maximum length towards which the individuals in a population converge as they become infinitely old) and L_{max} (the maximum observed length in a population) is an area of interest in fishery science, particularly for assessing fish growth and population dynamics.

While both L_∞ and L_{max} provide insights into the growth potential of a species, they are distinct parameters.

L_∞ is a theoretical parameter derived from growth models (e.g., the von Bertalanffy growth function), whereas L_{max} is an empirical observation from field data.

Several studies have attempted to establish empirical relationships between these two metrics to facilitate the estimation of one parameter from the other, especially in data-poor situations. However, it's important to note that any empirical relationship may be species-specific and influenced by environmental factors, fishing pressure, and the methodological approaches used in studies.

A commonly cited rule of thumb is that L_{max} is often observed to be approximately 0.95 to 0.99 times L_{∞}, acknowledging that most individuals in a population do not reach or exceed the asymptotic length due to natural mortality, predation, or fishing pressure. This approximation allows researchers to estimate L_{∞} from L_{max} when growth model parameters are unknown or cannot be directly calculated due to lack of data.

However, relying on a fixed ratio or empirical relationship without considering species-specific life history traits, ecological conditions, and the quality of the available data can lead to inaccuracies. Therefore, when such empirical relationships are used, they should be applied with caution and, if possible, validated against more comprehensive data sets or models specific to the species and region of interest.