# Implementation of an informed creep correction into the Chile Jack Mackerel CPUE index

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## Abstract

The central-southern fleet for the jack mackerel fishery in Chile has experienced technological changes over time, which may not be reflected by other variables already considered in the CPUE abundance index. In this study, we explore different approaches to estimate and include a creep correction factor into the standardization of the Chile CPUE index. From the survey of the JM fishery conducted during 2023, we used fisher's responses to determine the magnitude of perceived changes in fleet efficiency and periods of occurrence to estimate a creep factor. Next, we implemented a GLM, where the inclusion of a creep factor as a dummy variable in the standardization model of the Chile CPUE index showed multicollinearity and aliasing that prevented its use as an additional factor in the model. However, when using the corrected CPUE index by an informed creep factor as the response variable in a GLM, the model exhibited a similar pattern as with the uncorrected CPUE. We discuss the benefits and limitations of this approach, and propose next steps for adjusting and improving its reliability. Next steps, may include an additional survey to collect complementary user data that can improve the robustness of the index standardization process.

## Background

The central-southern fleet for the jack mackerel fishery in Chile has experienced technological changes over time, which may not be reflected by other variables already considered in the CPUE standardization process. To account for these changes, during the Jack Mackerel Benchmark Workshop in 2022, the SPRFMO Scientific Committee agreed to apply a factor of 1% per year to correct the CPUE abundance indexes of Jack Mackerel for the chilean and peruvian fleets. However, there are concerns over the technical implications of a fixed rate, and the exploration of alternative efficiency correction factors was recommended. The impact of effort creep is likely to be minimal over the short term, but could grow more pronounced over time, and additional steps would be required in order to provide a more long-term solution to this problem. Recently, there have been efforts to estimate both the impact of alternative creep correction factors (Hintzen 2023, Zenteno & Payá 2023).

In this study we explore different approaches to estimate and include a creep correction factor into the standardization of the Chile CPUE index. We discuss the benefits and limitations of this approach, and propose next steps for adjusting and improving its reliability.

## Objective

- Analyze different approaches to include the developed survey efficiency factor in the correction of the abundance index based on the CPUE of the central-south zone.
- Assess the statistical viability and applicability of including this efficiency factor in the standardization process of the Chile CPUE index.

## Methodology

### User survey data

During the survey of efficiency changes of the JM fishery, users were asked specifically to quantify the reduction of effort to locate jack mackerel aggregations associated with the use of technological advances and tools, and the period of ocurrence of these improvements in fishing operations. These responses were included in the standardization model of the CPUE index, first as a dummy variable and, since the magnitude of the change in efficiency would prevent a posterior index correction. On a previous analysis, we considered alternative survey responses to construct the creep correction factor (Zenteno & Payá 2023). After a review was conducted, we identified potential limitations associated with the way some of the survey questions were designed. In this sense, the responses incorporated in the efficiency factor in this study address the issues identified.

Survey responses from fishers were used to determine the magnitude of perceived changes in fleet efficiency over two dimensions. First, responses were used to determine the size of the effect of technological changes in the fishing activity, namely the introduction of multibeam sonars and the delivery of oceanographic satellite information to fishing vessels. Second, we used responses to establish the period where these technological improvements were implemented. According to this approach, we were able to design a criteria table, which was used to correct the CPUE data series, to all fishing trips of the fleet were data was available (**Table 1**).

We implemented a GLM parallel to the one used to standardize the CPUE abundance index (**Table 1**), were we defined a CPUE corrected by the effort creep factor as the response variable, according to:

$$\log(\mathrm{CPUE}_{\mathrm{creep}}) = \beta_1 \cdot \mathrm{yearf} + \beta_2 \cdot \mathrm{quarter} + \beta_3 \cdot \mathrm{zone} + \beta_4 \cdot \mathrm{hc}$$

Where $CPUE_creep$ is the creep-corrected index, yearf is the year as a factor, quarter is the quarter as a factor, zone corresponds to fishing zone as a factor and hc is the vessel haul capacity. This GLM is designed with the same explanatory variables as with the GLM used in the current CPUE standardization process (Payá 2025).

#### Effort Creep Estimation via Bootstrap Analysis

To quantify the uncertainty associated with the effort creep factor (technological and knowledge-based efficiency gains), a non-parametric bootstrap resampling technique was applied. This procedure allows for the estimation of the variability of a statistic without assuming a prior theoretical distribution of the original data

**Resampling Procedure** We performed $R = 10,000$ iterations with replacement using the data collected from the captain survey (July 2023). For each iteration, a bootstrap sample of the same size as the original ($n = 24$) was generated. To ensure the reproducibility of the results, a pseudo-random seed was set (set.seed(123)).

**Definition of Estimators** Three scenarios were evaluated to determine the creep correction factor: - Unweighted Mean: The arithmetic average of the bootstrap replicates was calculated to obtain a central estimate of the observed factor. - 10th Percentile (P10): The 10th percentile of the bootstrap distribution of means was extracted. This estimator serves as a precautionary (conservative) criterion, representing a scenario where technological growth is lower than the observed average. - Experience-weighted Mean: Acknowledging that the perception of technological change may vary according to the informant's trajectory, a weighted mean was calculated for each replicate. The weight ($w_i$) was defined by each captain's years of experience, following the formula:

$$\bar{x}_w = \frac{\sum_{i=1}^{n}(x_i \cdot w_i)}{\sum_{i=1}^{n} w_i}$$

For this analysis, case resampling (resampling by rows) was performed on a paired data frame to preserve the link between the reported creep factor and the specific experience of the captain.

**Uncertainty Assessment and Timeframes** The standard deviation of the distribution of the $10,000$ calculated means was used as an estimate of the Standard Error (SE) for the factors. Additionally, 95% confidence intervals were calculated using the percentile method.Finally, the corrections were applied to the CPUE historical series considering two distinct time horizons: for the unweighted estimators (Mean and P10), the 2005–2024 period was used; for the experience-weighted estimator, the impact was extended to the 2003–2024 period, reflecting the long-term influence of the most experienced captains in the fleet (**Table 1**).

Table 1: Correction criteria for the CPUE data series of the central-southern fleet. The table compares the base index with three bootstrap-derived factors: unweighted mean, 10th percentile (P10), and mean weighted by captains experience. The correction multiplier is calculated as (1 - creep factor).

| Criteria | Period | Survey creep factor (sd) | Correction multiplier* (sd) |
|---|---|---|---|
| No correction | 1983-2002/04 | 0 | 1 |
| **Bootstrap Unweighted** | | | |
| Mean | 2005-2024 | 0.384 (0.041) | 0.616 |
| Percentile 10 (P10) | 2005-2024 | 0.331 (0.041) | 0.669 |
| **Bootstrap Weighted** | | | |
| Mean (Experience weighted) | 2003-2024 | 0.420 (0.052) | 0.580 |

* Note: sd represents the standard deviation obtained from the bootstrap expansion. The weighted mean accounts for the years of experience of the captains surveyed.

## Results

The use of creep-corrected CPUE indices as the response variable in a GLM, exhibited a similar pattern as with the uncorrected CPUE (**Figure 3**)). The integration of a non-parametric bootstrap resampling procedure ($R = 10,000$) provided a robust framework for quantifying the uncertainty associated with effort creep and its subsequent impact on the standardized CPUE. By moving beyond a fixed annual increment, this approach allowed for the derivation of correction factors based on the empirical distribution of the fishing data. The bootstrap results yielded an unweighted mean correction factor of 0.384, which served as the baseline for adjusting technological efficiency gains within the Generalized Linear Model (GLM) framework.

To evaluate the influence of operator experience on fishing power, a weighted bootstrap analysis was implemented using years of captain experience as a weighting variable. This scenario resulted in a higher mean correction factor of 0.420, suggesting a significant synergy between technological advancement and professional expertise. Furthermore, the 10th percentile ($P_{10}$) of the bootstrap distribution was calculated at 0.331. This value was utilized as a precautionary threshold to evaluate the sensitivity of the abundance index to more conservative effort creep assumptions, effectively accounting for potential overestimation in high-efficiency strata.The application of these bootstrap-derived factors to the abundance index standardization resulted in distinct trajectories for the corrected CPUE. The weighted experience scenario exhibited the most pronounced adjustment, indicating that traditional nominal indices may underrepresent the true impact of efficiency increases when captain experience is omitted.

The bootstrap analysis of the original sample ($n = 24$) revealed an average effort creep factor of 0.383 (SE = 0.041). The distribution of bootstrap replicates showed minimal bias (0.0005), indicating high stability in the mean estimation. The 95% confidence interval, calculated via the percentile method, ranged from 0.304 to 0.467, suggesting that under random sampling conditions, the average increase in technological efficiency is highly likely to fall within this range. Furthermore, adopting a conservative criterion based on the 10th percentile (P10) resulted in a factor of 0.331, providing a robust lower bound for stock assessment scenarios under a precautionary approach. When incorporating captain experience as a weighting factor, the creep estimator increased to 0.420 (SE = 0.052). This increase relative to the unweighted mean suggests that captains with longer trajectories in the fishery perceive a more significant impact of technological improvements and accumulated knowledge on catching efficiency. Although the variability of this weighted estimator was slightly higher than that of the unweighted model, the results indicate that ignoring informant experience could lead to a 9.6% underestimation of the effort correction factor, highlighting the importance of considering professional profiles when interpreting perception-based surveys.

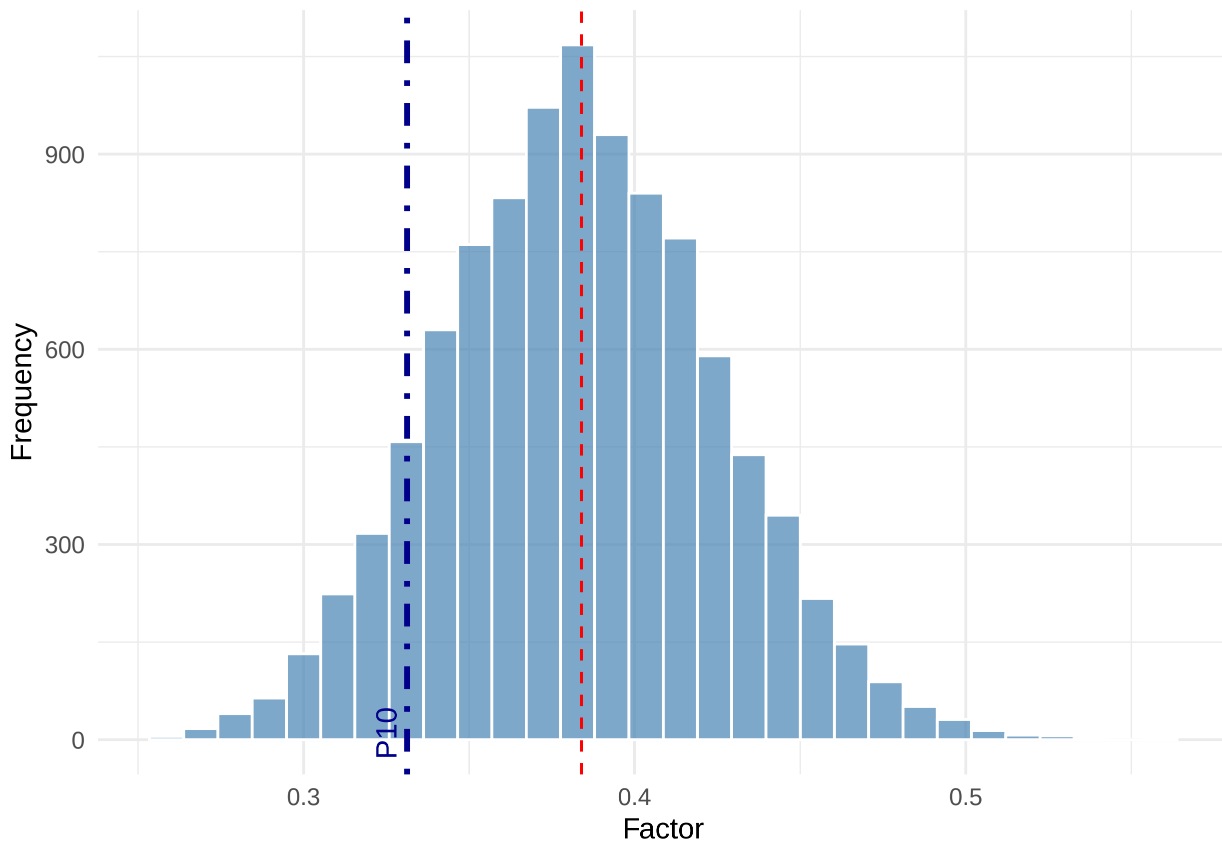


Figure 1: Unweighted bootstrap distribution of the survey technological improvent factor.

## Discussion

An analysis was conducted to continue previous efforts to integrate potential changes in effort of the chilean central-southern fleet, which may not be already accounted for by the current CPUE standardization. To accomplish this, we test the response of the model JM stock biomass over a set of potential effort creep-corrected CPUE index, implemented in the standardization process of the CPUE index of the Chile fleet. When comparing the corrected indexes with the base index (1% correction), we observe similarity in the last 20 years of the series, but an overestimation in the earlier years of the series.

The results provided with the current JJM model (SC 13) show that using a more realistic and informed correction only have minor impacts on estimated biomass. This relative stability suggests that the model's scale is strongly anchored by other data sources, such as the acoustic biomass indices and the age-composition data, which may be filtering the signal provided by the fleet-specific CPUE. By integrating the informed correction, the model achieves a more coherent reconciliation between historical catch levels and the perceived abundance of the stock at that time. Even if the absolute change in total biomass is marginal, the adjustment in the CPUE slope can lead to subtle but critical shifts in the estimation of the Catchability Coefficient ($q$)

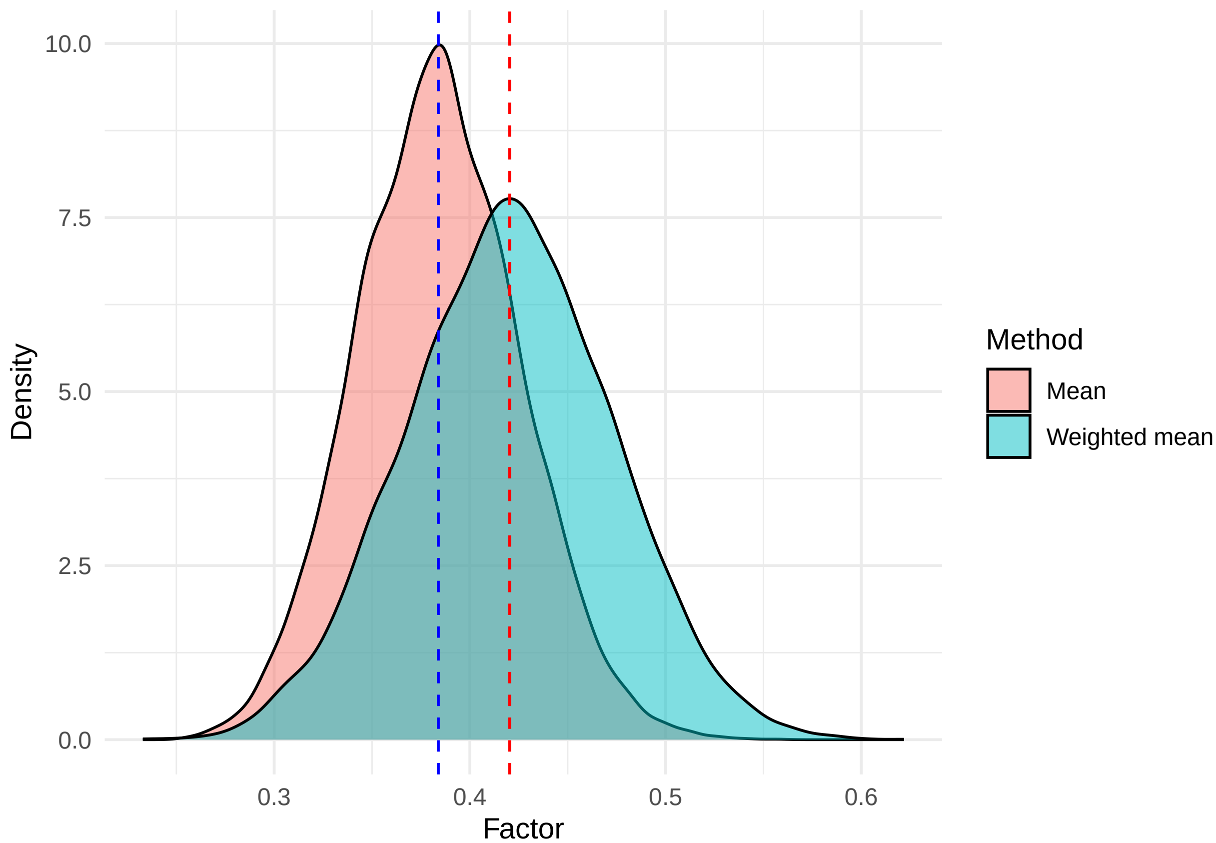


Figure 2: Weighted bootstrap distribution of the survey technological improvent factor.

and Fishing Mortality ($F$).

Integrating Local Ecological Knowledge (LEK) through surveys of captains and shipowners represents a significant step forward in calibrating the effort of the Jack Mackerel fishery. Unlike estimations based purely on technological logs, this approach captures the knowledge that is often the primary driver of catching efficiency gains (effort creep). The primary advantage of applying Bootstrap analysis to this dataset is the ability to generate robust uncertainty metrics from a relatively small sample ($n = 24$). The use of an experience-weighted mean corrected potential bias from less-experienced informants, giving more weight to those who have observed the fleet's technical evolution over decades. Furthermore, utilizing the 10th Percentile (P10) as a correction criterion provides a solid technical alternative to meet the precautionary approach required in modern fisheries management, allowing for scenarios where efficiency gains are not overestimated, thus preventing the assessment is based in potentially biased input data.

However, the methodology has inherent limitations. Since the data is perception-based, there is a risk of recall bias or subjectivity among respondents, who may under- or overestimate changes depending on their interests in the fishery. Additionally, while bootstrap is a powerful tool, it does not replace representativeness; with $n = 24$, results remain sensitive to outliers (as seen in the slight increase in standard error for the weighted

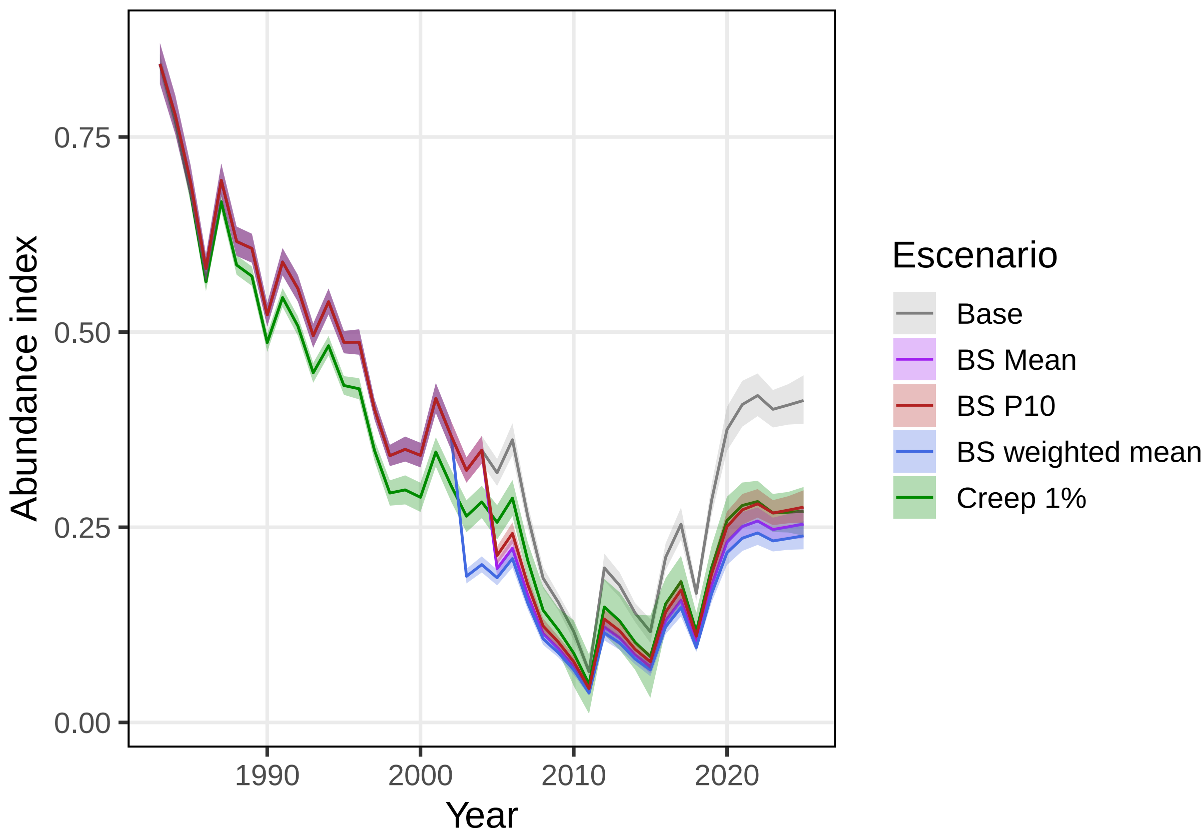


Figure 3: Predicted abundance (CPUE) index of Chilean jack mackerel (*Trachurus murphyi*) fishery of central-southern Chile, for the base GLM model and the bootstrapped creep-corrected CPUEs as response variables. Shaded lower and upper limits represent the standard deviation of the series.

model). While limited, our approach integrates the possibility to include an informed effort creep correction to the jack mackerel abundance index, and relative to the current assumption, it allows for a long-term credible input for the stock assessment procedure.

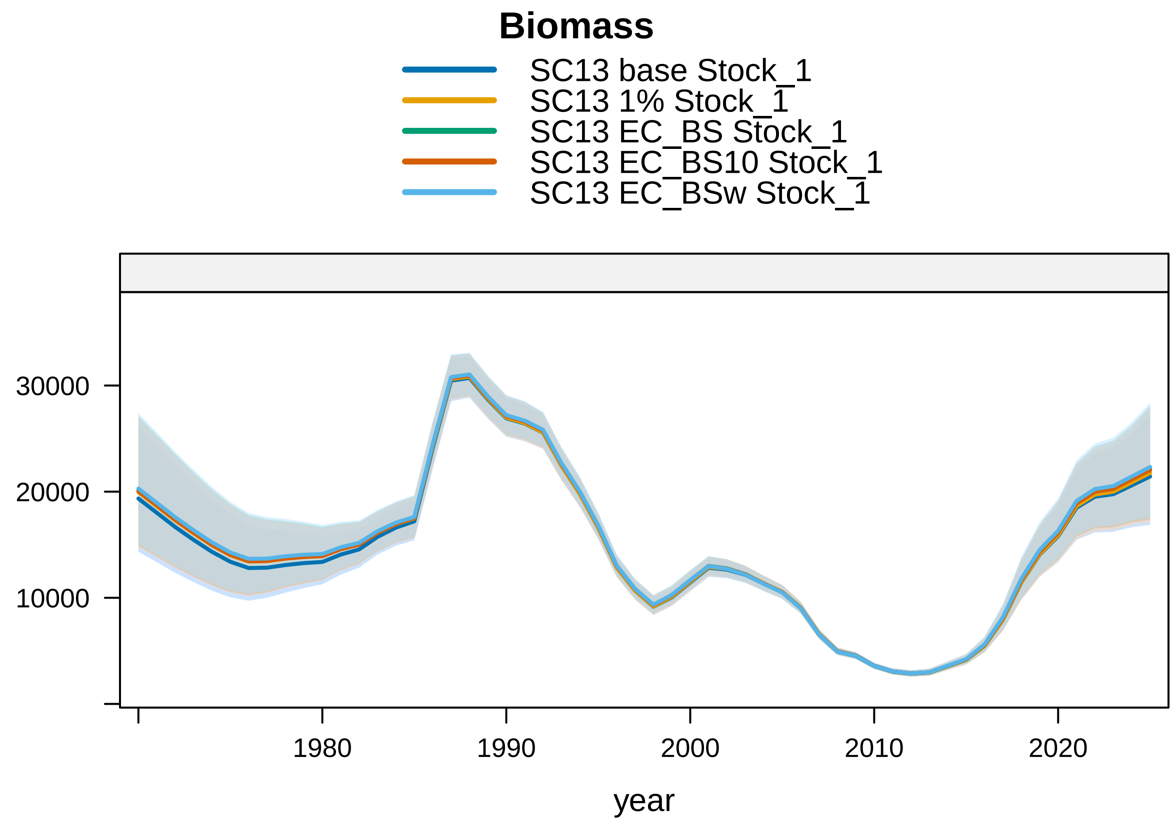


Figure 4: Output biomass (model 1.14) with Chile CPUE index (base index), current creep corrected at 1%, and alternative bootstrapped creep-corrected CPUE indices.

## References


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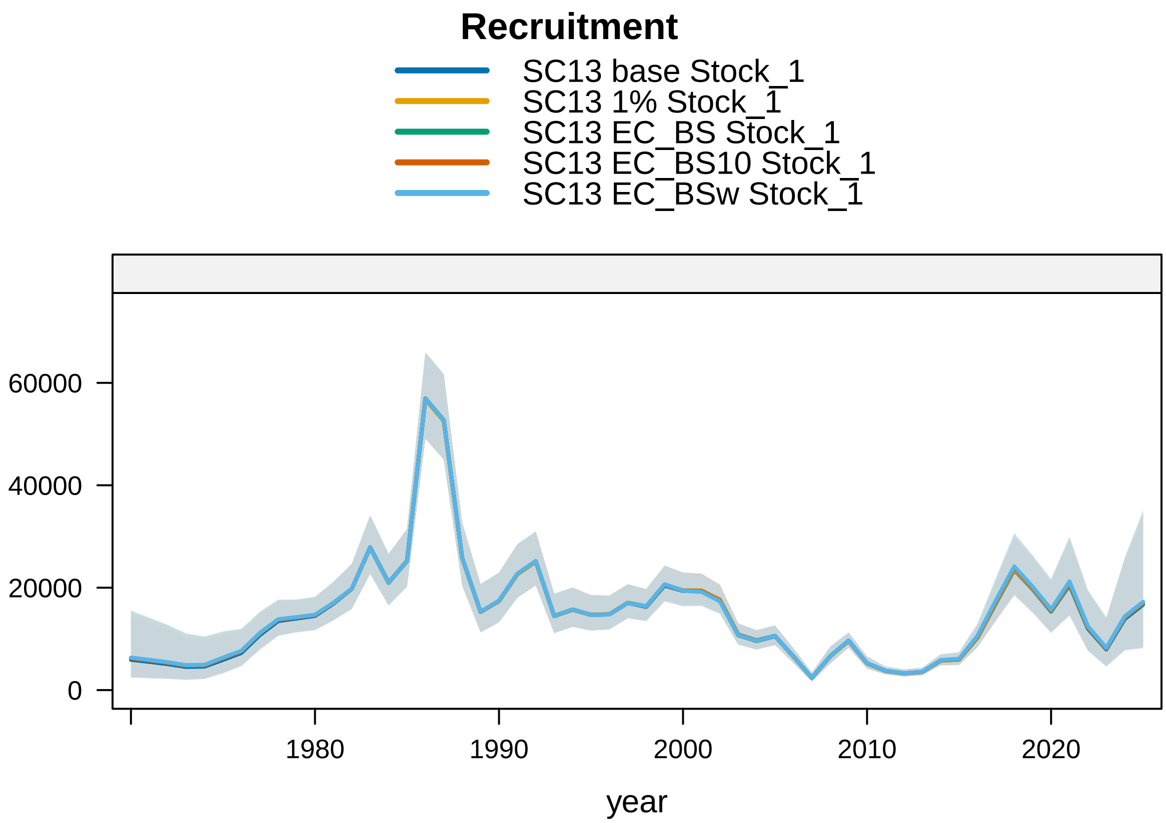


Figure 5: Output biomass (model 1.14) with Chile CPUE index (base index), current creep corrected at 1%, and alternative bootstrapped creep-corrected CPUE indices.

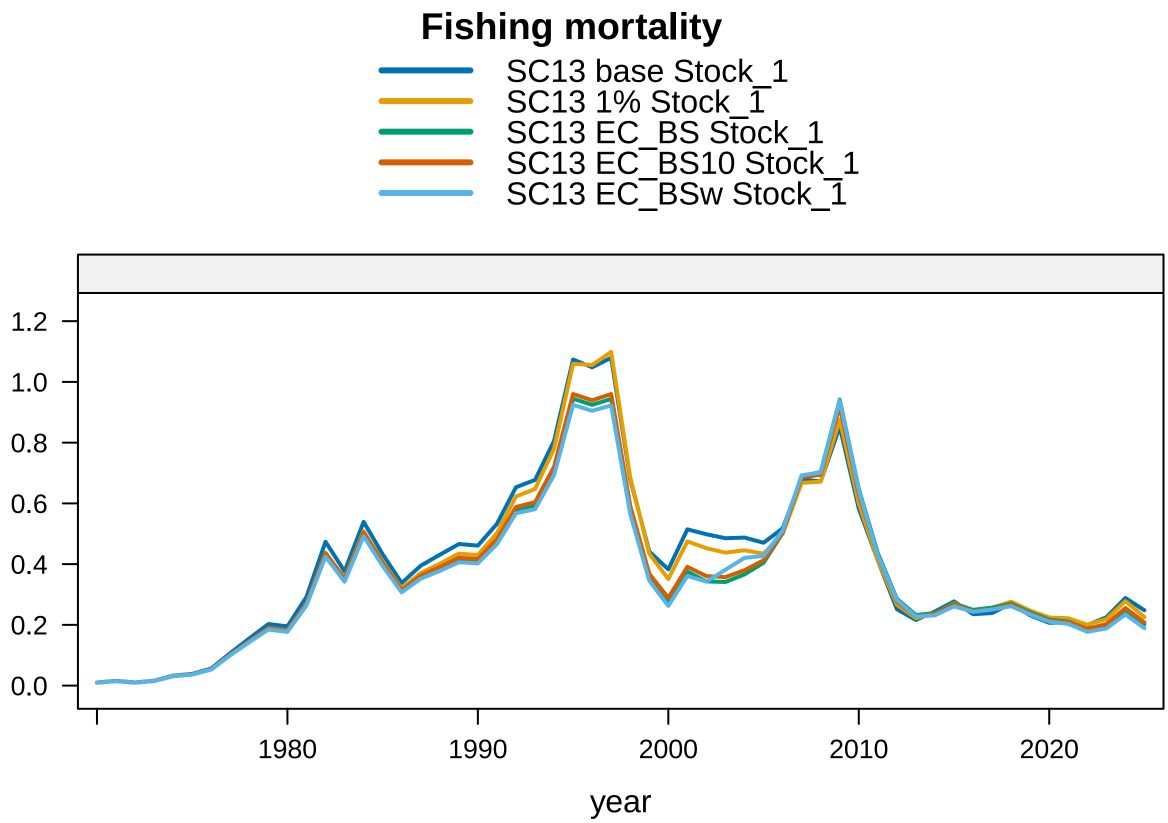


Figure 6: Output biomass (model 1.14) with Chile CPUE index (base index), current creep corrected at 1%, and alternative bootstrapped creep-corrected CPUE indices.