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# Guidelines for the standardization of catch per unit of effort (CPUE) in SIOFA fisheries

The SIOFA Secretariat / SIOFA SC CPUE informal working group

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| **Abstract** | |

Acting upon a recommendation from the SC8 to add generalised linear model (GLM) standardisations of CPUE to the Overview of SIOFA Fisheries 2024 (Paragraph 56, SC8 report), the Secretariat worked with an informal working group on CPUE standardization composed by SC HoDs. The informal group eventually concluded that the inclusion of (GLM) standardized CPUE in the Overview of SIOFA Fisheries 2024 could not be fully addressed by the Secretariat, and recommended instead that the Secretariat prepares a generic "guideline paper" on CPUE standardization and provide example R code for this purpose.
This paper attempts to guide novel users to CPUE standardization, offering example code and reference to previous attempts at standardization in SIOFA.

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[2] Documents available only to members invited to closed sessions.

| **Recommendations** |
|---|
| The SIOFA Secretariat recommends that the SC9:<br><br>• **notes** the work done by the Secretariat in preparing the guidelines for CPUE standardization in SIOFA Fisheries.<br>• **provides** any comments or edits to this paper.<br>• **considers** how to progress with the CPUE standardization for key stocks in SIOFA and **recommends** how these could be included in the Overview of SIOFA Fisheries 2025. |

# Guidelines for the standardization of catch per unit of effort (CPUE) in SIOFA fisheries

## 1. Introduction

At its 8th annual meeting, the SIOFA Scientific Committee noted that generalised linear model (GLM) standardisations of CPUE would be a useful addition to the Overview of SIOFA Fisheries 2024. The SC requested the Secretariat work with CCPs during the intersessional period to develop, where possible, standardised GLM CPUE indices for each of the main SIOFA fish stocks (Paragraph 56, SC8 report).

The Secretariat followed up on this request by involving all interested parties in an informal working group on CPUE standardization, which conducted its discussion via correspondence during the intersessional period and met virtually once (in September 2023) to discuss the main direction of the group. Smaller meetings were also conducted with the different interested parties to discuss specific issues, when possible.

Eventually, the informal working group on CPUE standardization decided that the inclusion of (GLM) standardized CPUE in the Overview of SIOFA Fisheries 2024 could not be fully addressed by the Secretariat, given that some of the relevant standardization parameters might not be available in the SIOFA databases.

The informal working group on CPUE standardization recommended instead that the Secretariat prepares a generic “guideline paper” on CPUE standardization and provide example R code for this purpose, but without referring to specific data or using data as example in the analysis. References could instead be made to papers previously submitted to the SC (e.g., by the Cook Islands or the EU-Spain) including those figures as examples.

CCPs could then use these guidelines and code as a basis to develop their own standardization procedures and submit the outcomes of such analyses to the SIOFA Scientific Committee. Where a fishery is shared across different CCPs, this could encourage cooperation across members of the Scientific Committee.

## 2. Methods

This paper was composed by reviewing part of the existing scientific literature on CPUE standardization, and the relevant reports that were submitted to the SIOFA SC on the same topic. It also reviewed the available tools/packages that could aid users approaching to this task.

It also draws from draft EU STECF guidelines on CPUE standardization (Bartolino et al. 2010).

All original figures are exclusively presented as examples, and do not reflect analysis of real data. Other figures are not original, and have been included as examples, with specific references to the respective original papers.

Overall, the paper was considered, edited and commented by the SIOFA informal working group on CPUE standardization, prior to its submission to the 9th annual meeting of the SIOFA Scientific Committee (SC9).

# 3. Results

Catch-per-unit-of-effort (CPUE) stands as a fundamental component in evaluations of fisheries stocks. Typically, CPUE is presumed to correlate with abundance, making it an integral part of stock assessments as a relative gauge of abundance.

Given CPUE's significance in numerous stock assessments and the assumption of its proportionality to abundance, it is crucial to eliminate any extraneous factors affecting CPUE from the index. This mitigation process is commonly termed standardizing CPUE. Various methods have been developed for CPUE standardization, with the application of generalized linear models (GLM) being the most prevalent approach.

Before proceeding with CPUE standardization, it is advisable to develop a sufficient understanding of the fishery that will be subject to the analysis. Starting with a description of the fishery and identification of the vessels involved allows for the identification of a consistent time series of fishing effort, conducted with similar fishing gear, within a relevant region that encompasses the known (or assumed) stock boundaries.

A first step would always be to calculate an unstandardized CPUE series based on the catch and effort data. This will provide initial information be also useful as a reference to gauge the effects of the standardization process.

A standardized CPUE (or CPUEs where there are different options) would include the year as an index, plus a set of variables such as location, depth, gear parameters, tow duration or set times, target species and catch composition, month or other appropriate seasonal variables, etc.

## 1.1. Data exploration

The first step should always consist in grooming the data, which involves subsetting to isolate a specific set of data, making sure that there are no gaps (e.g. missing positions) or errors (e.g. positions outside of the assessment area), etc. This step should also involve retrieving any missing information/predictor variable such as e.g. calculating depth of fishing locations or other parameters that might be lacking in the starting dataset.

The second step before fitting a GLM, or any regression model, is usually to explore the distribution of the data and the relation between the response variable and the covariates.

To do so, usually a visual examination of the data histogram (in this case the log of total catch +1) and of the collinearity between predictors is recommended.

The following code and examples illustrate this part of the process:

```
## visual data exploration

# plot frequency histogram of catch

hist(log(yearly_operations_all_catch_cropped$Catch+1))
```

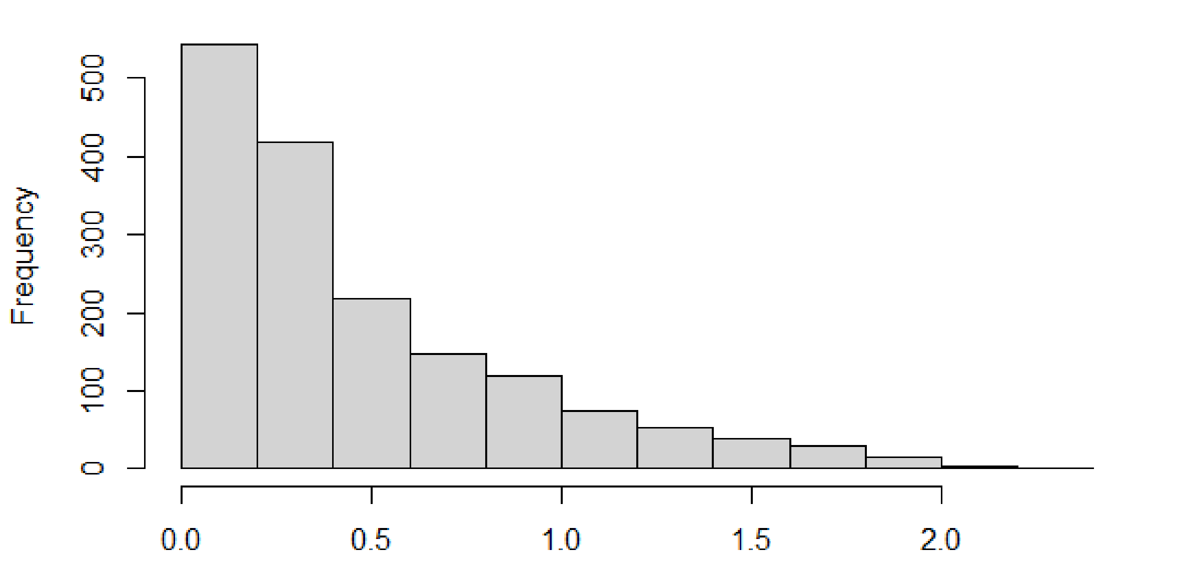


*Figure 1 – Example of a frequency histogram of catch*

```
# visually inspect predictor collinearity
pairs(~ Longitude + Latitude + Depth + Year + Month, data = yearly_operations_all_catch_cropped,
        main = "SIOFA data")
```

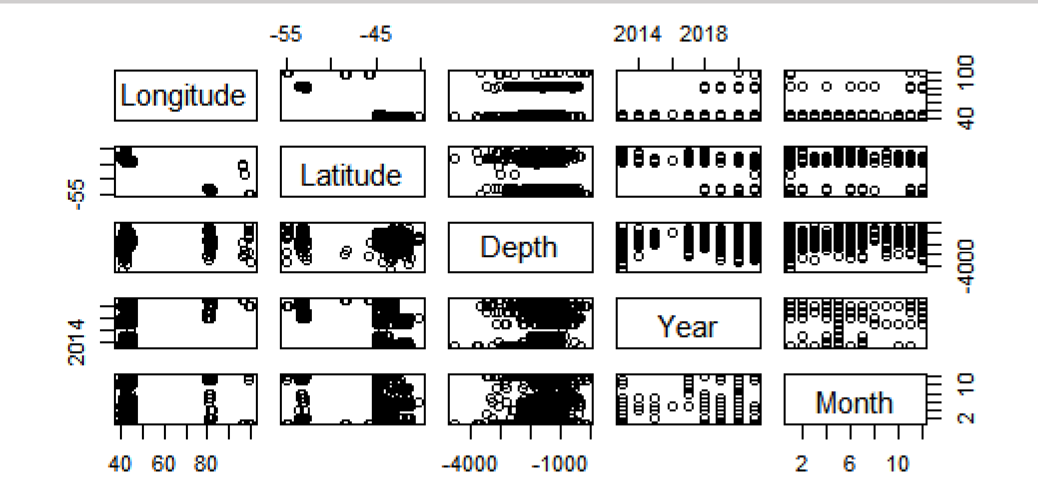


*Figure 2 – Example of a predictor collinearity plot*

```
# calculate and visualize a predictor correlation matrix
cor <- yearly_operations_all_catch_cropped %>%
        as.data.frame() %>%
        dplyr::select(Longitude, Latitude, Depth, Year, Month) %>%
        #as.matrix() %>%
cor()
```

*Table 1 – Example of a predictor correlation matrix*

| | Longitude | Latitude | Depth | Year | Month |
|---|---|---|---|---|---|
| Longitude | 1 | -0.96237 | 0.166714 | 0.241387 | 0.141825 |
| Latitude | -0.96237 | 1 | -0.20958 | -0.24803 | -0.1637 |
| Depth | 0.166714 | -0.20958 | 1 | 0.058137 | 0.094991 |
| Year | 0.241387 | -0.24803 | 0.058137 | 1 | -0.00057 |
| Month | 0.141825 | -0.1637 | 0.094991 | -0.00057 | 1 |

```
# univariate relationships between response and predictors
variab <- c("Longitude", "Latitude", "Depth", "Year", "Month")
png(file="CPUE/SIOFA_ALLcatch_collinearity.png", width=600, height=350)
par(mfrow=c(2,3))
for(i in 1:length(variab)){
  plot(CPUE_analysis[,variab[i]],
      CPUE_analysis$ALLcatch,
      xlab=variab[i], ylab="TOT Catch")}
dev.off()
```

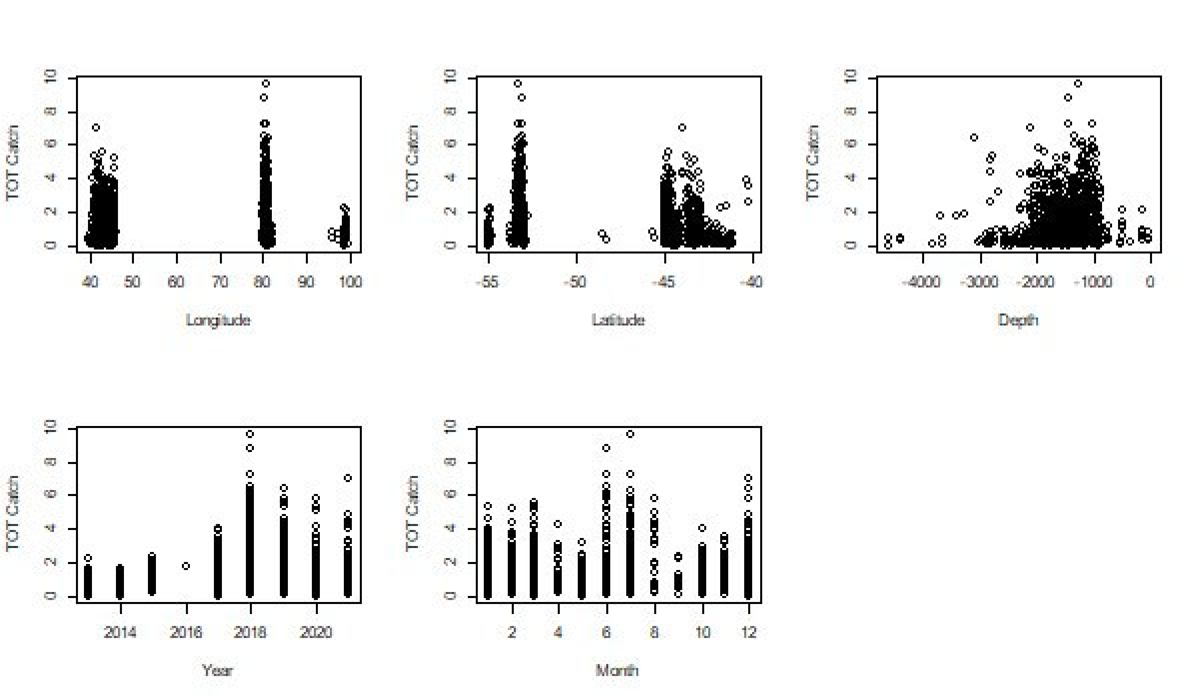


*Figure 3 – Example of response of univariate relationships between response and predictor variables*

## 1.2. GLM model fitting

Once relatively confident that we gained a good understanding of the data, the next step is to start fitting our GLM model(s). To fit GLM’s the R function glm can be used, and few different model specifications using the main haul information such as the position, depth, year, month, etc. can be tried out.

A basic initial model (fit1) employs a Gaussian family distribution and an identity link function, akin to fitting a linear regression.

Subsequent models introduce interactions between predictors, indicated by the ∗ symbol in (fit2) and quadratic terms in DEPTH (fit3).

Determining the most suitable model a priori is not evident, and various models must be fitted and compared in a stepwise manner. Similarly, selecting the appropriate predictors and their relationships with the response might prove challenging (e.g. swept area in some trawl fisheries).

```
## GLM model implementation
# only first order effects
fit1 <- glm(CPUE~factor(Year)+factor(Month)+Latitude+Longitude+Depth,
        family=gaussian(link="identity"), data=CPUE_analysis)
# latitude x longitude interaction
fit2 <- glm(CPUE~factor(Year)+factor(Month)+Latitude*Longitude+Depth,
```

```
        family=gaussian(link="identity"), data=CPUE_analysis)
# latitude x longitude interaction and second order effect of DEPTH (~...+x+x^2)
fit3 <- glm(CPUE~factor(Year)+factor(Month)+Latitude*Longitude+Depth+I(Depth),
        family=gaussian(link="identity"), data=CPUE_analysis)
# model summary and diagnostics
AIC(fit1, fit2, fit3)
```

*Table 2 – Example of a model summary and diagnostics through Aikake's Information Criterion (AIC)*

| | df | AIC |
|---|---|---|
| fit1 | 24 | 79190 |
| fit2 | 25 | 79213 |
| fit3 | 25 | 79213 |

```
# summary statistics of the fitted models
summary(fit1)
Deviance Residuals:
    Min        1Q     Median       3Q       Max
-0.0002684  -0.0000588  -0.0000172   0.0000310   0.0008306

Coefficients:
                 Estimate     Std. Error t value          Pr(>|t|)
(Intercept)      -0.00076477287  0.00006189811  -12.36 < 0.0000000000000002 ***
factor(Year)2014 -0.00000289426  0.00000827482   -0.35            0.72653
factor(Year)2015  0.00001307266  0.00000897458    1.46            0.14528
factor(Year)2016  0.00012823011  0.00007446305    1.72            0.08512 .
factor(Year)2017  0.00003767340  0.00000749134    5.03      0.0000005101556 ***
factor(Year)2018  0.00009551794  0.00000606034   15.76 < 0.0000000000000002 ***
factor(Year)2019  0.00002041848  0.00000718533    2.84            0.00451 **
factor(Year)2020  0.00004728760  0.00000684097    6.91      0.0000000000054 ***
factor(Year)2021  0.00007707380  0.00000707597   10.89 < 0.0000000000000002 ***
factor(Month)2   -0.00001770197  0.00000648813   -2.73            0.00639 **
factor(Month)3    0.00009949926  0.00000789356   12.61 < 0.0000000000000002 ***
factor(Month)4   -0.00000700461  0.00000778401   -0.90            0.36823
factor(Month)5   -0.00002403307  0.00000619803   -3.88            0.00011 ***
factor(Month)6    0.00001696519  0.00000758447    2.24            0.02534 *
```

```
factor(Month)7    0.00003718862  0.00000696179    5.34      0.0000000960211 ***
factor(Month)8    0.00008251470  0.00001348517    6.12      0.0000000010125 ***
factor(Month)9    0.00004791746  0.00001871824    2.56            0.01050 *
factor(Month)10   0.00004811896  0.00000938115    5.13      0.0000003015679 ***
factor(Month)11   0.00004704235  0.00000790349    5.95      0.0000000028244 ***
factor(Month)12   0.00003865344  0.00000689464    5.61      0.0000000217588 ***
Latitude        -0.00001810114  0.00000171747  -10.54 < 0.0000000000000002 ***
Longitude        -0.00000099090  0.00000039025   -2.54            0.01114 *
Depth           -0.00000001998  0.00000000441   -4.53      0.0000060555430 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for gaussian family taken to be 0.00000001101)

    Null deviance: 0.000081517  on 5114  degrees of freedom
Residual deviance: 0.000056050  on 5092  degrees of freedom
AIC: -79190

Number of Fisher Scoring iterations: 2

summary(fit2)
Deviance Residuals:
      Min         1Q      Median         3Q        Max
-0.0002955  -0.0000581  -0.0000169   0.0000323   0.0008236

Coefficients:
                    Estimate    Std. Error t value           Pr(>|t|)
(Intercept)        0.0000063636  0.0001677709    0.04            0.96974
factor(Year)2014   -0.0000012151  0.0000082628   -0.15            0.88309
factor(Year)2015    0.0000166097  0.0000089825    1.85            0.06450 .
factor(Year)2016    0.0001335945  0.0000743002    1.80            0.07223 .
factor(Year)2017    0.0000433071  0.0000075605    5.73      0.000000010743 ***
```

```
factor(Year)2018    0.0000980289  0.0000060677   16.16 < 0.0000000000000002 ***
factor(Year)2019    0.0000250148  0.0000072289    3.46            0.00054 ***
factor(Year)2020    0.0000456086  0.0000068337    6.67      0.000000000028 ***
factor(Year)2021    0.0000831594  0.0000071663   11.60 < 0.0000000000000002 ***
factor(Month)2     -0.0000159528  0.0000064829   -2.46            0.01390 *
factor(Month)3      0.0000981508  0.0000078802   12.46 < 0.0000000000000002 ***
factor(Month)4     -0.0000065880  0.0000077666   -0.85            0.39634
factor(Month)5     -0.0000259909  0.0000061965   -4.19      0.000027817068 ***
factor(Month)6      0.0000150663  0.0000075768    1.99            0.04681 *
factor(Month)7      0.0000388428  0.0000069539    5.59      0.000000024475 ***
factor(Month)8      0.0000834436  0.0000134556    6.20      0.000000000604 ***
factor(Month)9      0.0000461782  0.0000186786    2.47            0.01346 *
factor(Month)10     0.0000460149  0.0000093693    4.91      0.000000933345 ***
factor(Month)11     0.0000454283  0.0000078921    5.76      0.000000009109 ***
factor(Month)12     0.0000353451  0.0000069113    5.11      0.000000326797 ***
Latitude           -0.0000025969  0.0000035739   -0.73            0.46748
Longitude          -0.0000158750  0.0000030359   -5.23      0.000000177218 ***
Depth              -0.0000000206  0.0000000044   -4.68      0.000002960176 ***
Latitude:Longitude -0.0000002913  0.0000000589   -4.94      0.000000792109 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for gaussian family taken to be 0.00000001096)

    Null deviance: 0.000081517  on 5114  degrees of freedom
Residual deviance: 0.000055782  on 5091  degrees of freedom
AIC: -79213

Number of Fisher Scoring iterations: 2
```

```
summary(fit3)
Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.0002955  -0.0000581  -0.0000169   0.0000323   0.0008236

Coefficients: (1 not defined because of singularities)
                    Estimate    Std. Error t value          Pr(>|t|)
(Intercept)        0.0000063636  0.0001677709    0.04            0.96974
factor(Year)2014   -0.0000012151  0.0000082628   -0.15            0.88309
factor(Year)2015    0.0000166097  0.0000089825    1.85            0.06450 .
factor(Year)2016    0.0001335945  0.0000743002    1.80            0.07223 .
factor(Year)2017    0.0000433071  0.0000075605    5.73      0.000000010743 ***
factor(Year)2018    0.0000980289  0.0000060677   16.16 < 0.0000000000000002 ***
factor(Year)2019    0.0000250148  0.0000072289    3.46            0.00054 ***
factor(Year)2020    0.0000456086  0.0000068337    6.67      0.000000000028 ***
factor(Year)2021    0.0000831594  0.0000071663   11.60 < 0.0000000000000002 ***
factor(Month)2     -0.0000159528  0.0000064829   -2.46            0.01390 *
factor(Month)3      0.0000981508  0.0000078802   12.46 < 0.0000000000000002 ***
factor(Month)4     -0.0000065880  0.0000077666   -0.85            0.39634
factor(Month)5     -0.0000259909  0.0000061965   -4.19      0.000027817068 ***
factor(Month)6      0.0000150663  0.0000075768    1.99            0.04681 *
factor(Month)7      0.0000388428  0.0000069539    5.59      0.000000024475 ***
factor(Month)8      0.0000834436  0.0000134556    6.20      0.000000000604 ***
factor(Month)9      0.0000461782  0.0000186786    2.47            0.01346 *
factor(Month)10     0.0000460149  0.0000093693    4.91      0.000000933345 ***
factor(Month)11     0.0000454283  0.0000078921    5.76      0.000000009109 ***
factor(Month)12     0.0000353451  0.0000069113    5.11      0.000000326797 ***
Latitude          -0.0000025969  0.0000035739   -0.73            0.46748
Longitude         -0.0000158750  0.0000030359   -5.23      0.000000177218 ***
Depth             -0.0000000206  0.0000000044   -4.68      0.000002960176 ***
I(Depth)                    NA           NA      NA                  NA
Latitude:Longitude -0.0000002913  0.0000000589   -4.94      0.000000792109 ***
```

```
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for gaussian family taken to be 0.00000001096)

    Null deviance: 0.000081517  on 5114  degrees of freedom
Residual deviance: 0.000055782  on 5091  degrees of freedom
AIC: -79213

Number of Fisher Scoring iterations: 2
```

## 1.3. Further GLM model diagnostics

GLM model diagnostics are complex, and involve an evaluation of model performance on multiple levels, the following code attempts to provide a couple of simple visual tools to evaluate model fit.

```
# diagnostic plots
png(file="CPUE/SIOFA_CPUE_fit1_diagnostics.png",
    width=600, height=350)
par(mfrow=c(2,2))
plot(fit1)
dev.off()
```

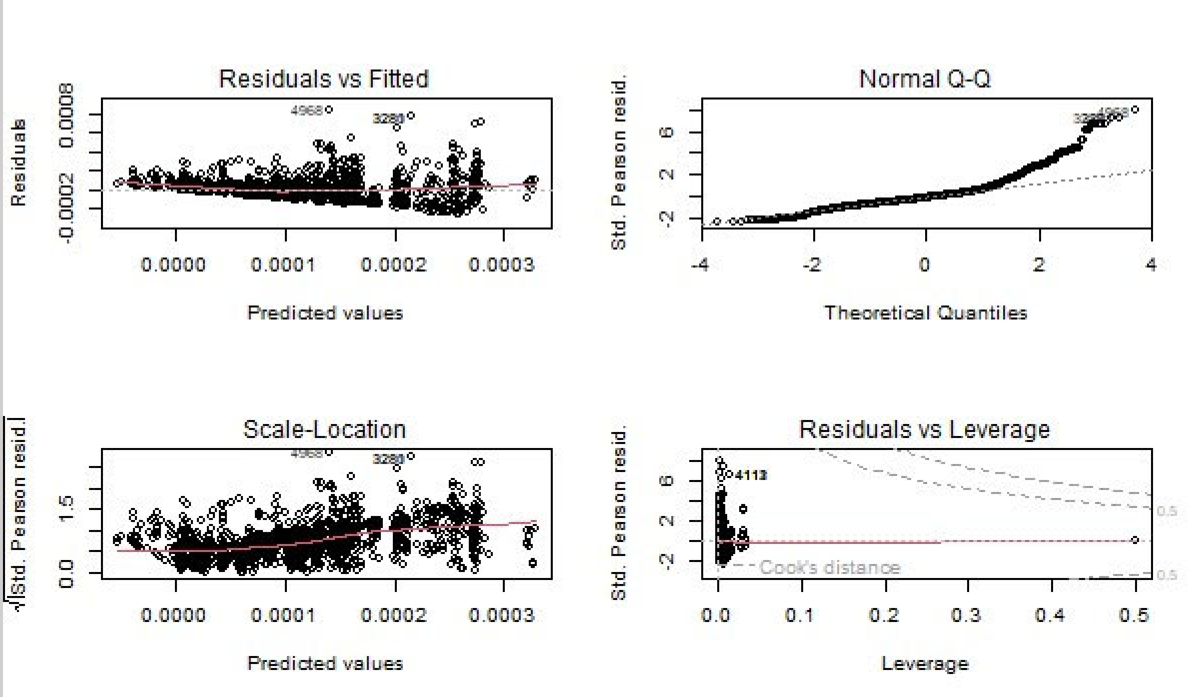


*Figure 4 – Example of diagnostics plot for model 1*

A Residuals vs Fitted plot illustrates the relationship between residuals and fitted values. An increasing spread of residuals for larger fitted values suggests heterogeneity.

The Normal Q-Q plot assesses data normality, with a departure from the line indicating non-normality. A heavy tail suggests a violation of normality, prompting consideration of a log link or log transformation for improved fit.

The Scale-Location plot, akin to Residuals vs Fitted but with standardized residuals (square-root transformed and weighted by leverage), indicates heterogeneity in residuals spread.

The Standardized vs Leverage plot identifies potentially influential observations with high leverage, where leverage signifies how distinct an observation is concerning explanatory variables.

Cook's distance gauges the influence of a point on estimated parameters; typically, action is warranted for Cook's values exceeding 1.

Between the AIC, the summary tables and the diagnostics plots we should be able to select the best fitting model. Once selected the best fitting model, we can produce a predicted CPUE and compare it with the observed data.

```
png(file="CPUE/SIOFA_CPUE_fit1_termplot.png",
   width=600, height=350)
par(mfrow=c(1,2))
termplot(fit1, TOP_CPUE_analysis, "Year", se=TRUE)
dev.off()
```

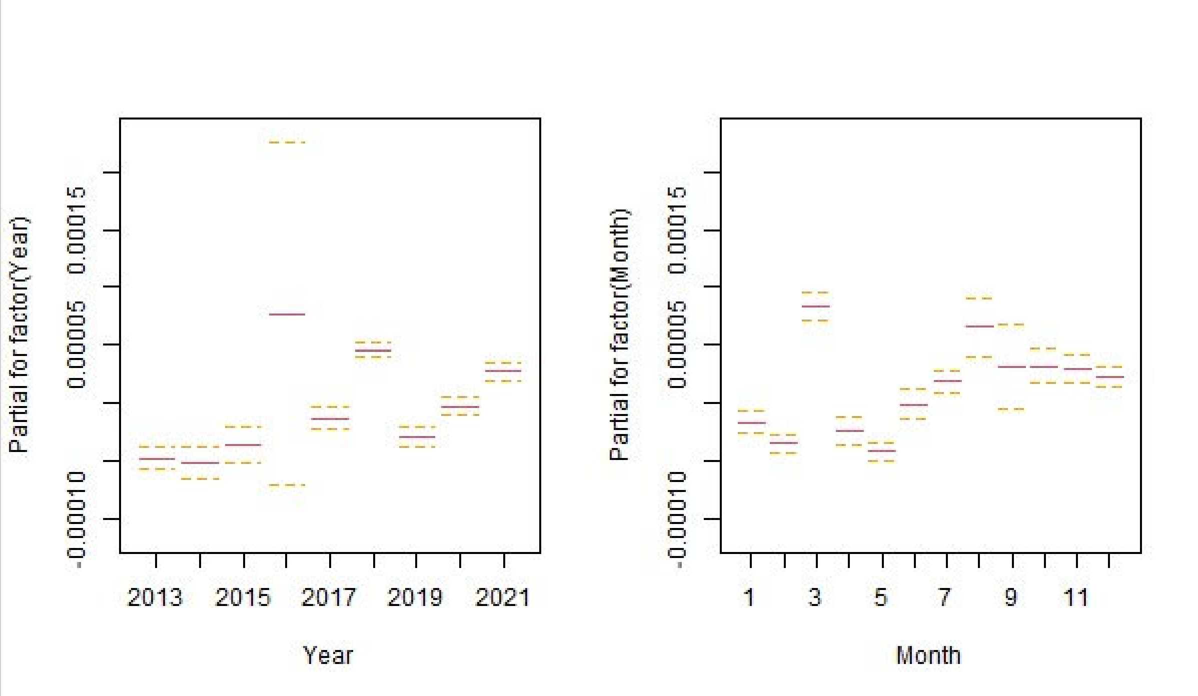


*Figure 5 – Example of Year and Month effect plot (termoplot) for model 1*

More tools are available to visually explore the model performance.

https://github.com/trophia/influ A package for the R language which generates step plots, influence plots, coefficient-distribution-influence (CDI) plots, and influence metrics for linear models as described in Bentley et al. 2011. The package includes a very useful vignette and even a quick rundown of the usage in the GitHub page.

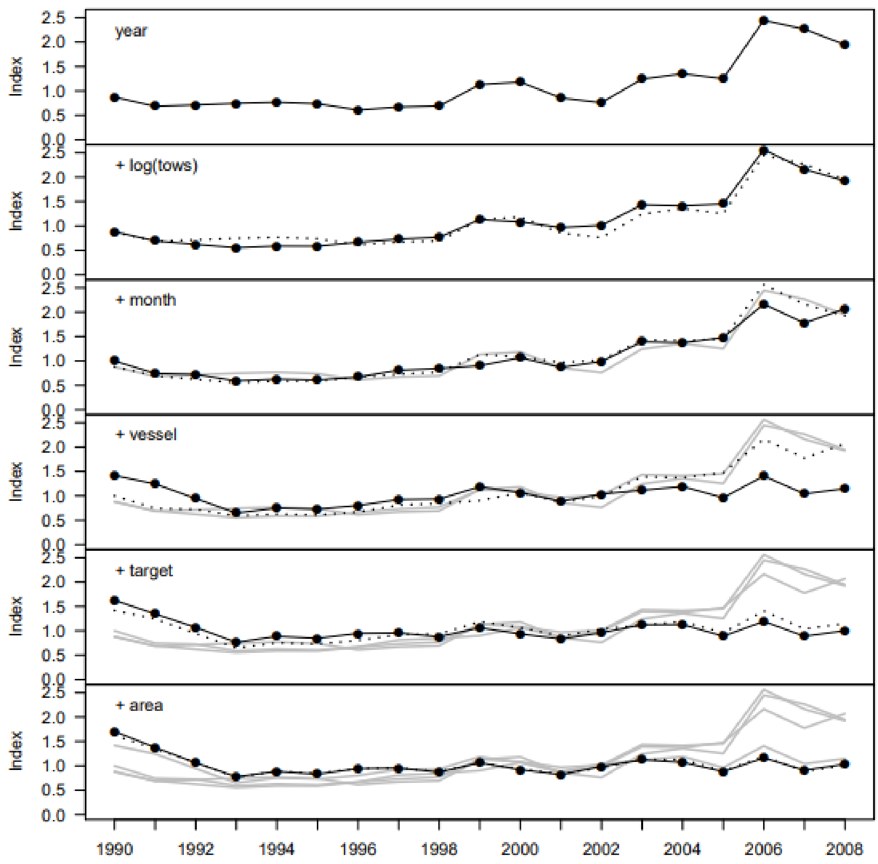


*Figure 6 – Example of a step plot from the vignette of the R package 'influ'*

https://github.com/quantifish/influ2 is a Bayesian version of the influ package. It has been developed for use with brms. It works with population-level or group-level effects, the Bayesian equivalents of fixed-effects and random-effects. It contains functions for extracting coefficients, calculating the influence of terms, generating CDI plots, step plots, and other diagnostic plots.

## 1.4. Examples of CPUE standardization from SIOFA fisheries

So far two standardizations were attempted for SIOFA fisheries.

In 2020, the European Union (Spain) and France (on behalf of its overseas territories) presented a CPUE standardization for the toothfish fishery in paper SERAWG-02-11 (restricted paper).

The initial aim of SERAWG-02-11 was to use all available data provided by the four Parties which have historically fished in this region, but was then limited to the French and Spanish datasets for the period 2010-2019, due to the availability of explanatory variables such as depth, fishing location, or soak time.

Different models and combinations of variables were tested, and the chosen model as well as the step-wise model selection process are given in Equation (1) and Table 3. Second order effect of depth and the soak time were tested as their relationship was expected to be not linear with CPUE. Further included were interactions between the nationality of the vessels and the depth and soak time effects, which could reflect different fishing strategies by different vessels or fleets. Vessel effect on its own was not included since only few vessels fished more than once in the area making it impossible to dissociate the year effect from the vessel effect. Ultimately, the best fit model (Table 3, Equation 1) was selected based on its AIC (reverse 'StepAIC' procedure from R 'MASS' package).

$$\log(CPUE) \sim Depth + Depth2 + Soaktime + Soaktime2 + Country + Year + Depth \times Country + Depth2 \times Country + Soaktime \times Country + Soaktime2 \times Country \quad (1)$$

*Table 3 – Model results for the saturated model and reverse stepwise model selections when on parameter was removed at a time using generalized linear models from SERAWG-02-11*

| Model | Residual Deviance | AIC |
|---|---|---|
| Saturated | 0.52 | 1249 |
| - Country:Depth | 0.53 | 1252.3 |
| - Country:I(Depth^2) | 0.52 | 1252.5 |
| - Soaktime:Country | 0.53 | 1255.1 |
| - Country:I(Soaktime^2) | 0.54 | 1257.5 |
| - factor(Year) | 0.59 | 1293.8 |

SERAWG-02-11 also calculated a standardized CPUE index, as show in Figure 7.

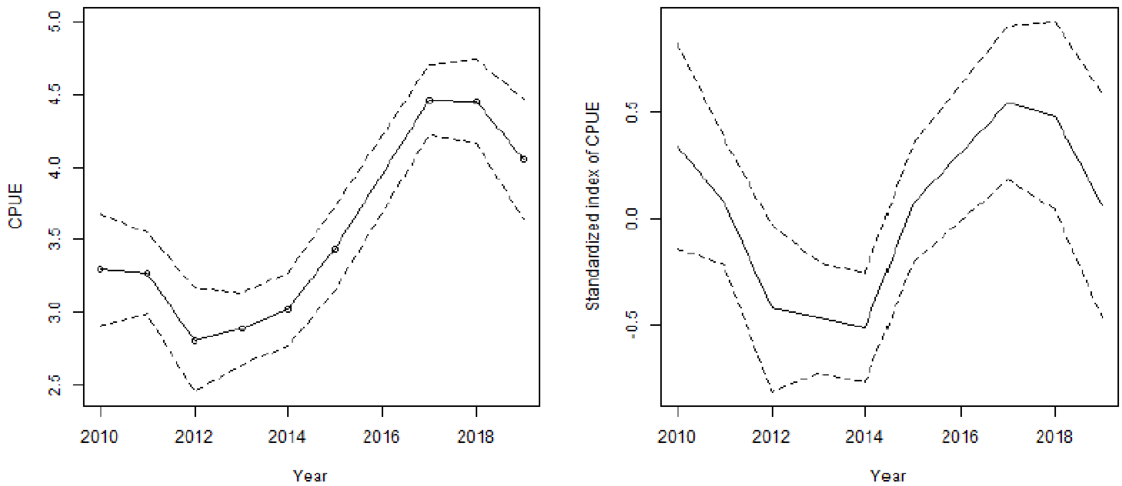


*Figure 7 – CPUE (left, kg/1000 hooks) and standardized index of CPUE scaled to a geometric mean of 1 (right), from SERAWG-02-11.*

In 2023, The Cook Islands presented a CPUE standardization for the alfonsino fishery in paper SC-08-INFO-14.

Two alternative data sets were considered for the alfonsino CPUE analysis. The first was the full data set that included all catch (Figure 57 of SC-08-INFO-14) and the second was only sets with positive alfonsino catch (Figure 58 of SC-08-INFO-14). The influence of removing sets with no alfonsino substantially reduced the catch proportion of orange roughy, and removed a high proportion of orange roughy target sets. This had little impact on the spatial distribution of the catch, and slightly reduced the catch proportion of spiky oreo. Due to the removal of many orange roughy target sets, the alfonsino positive sets only data set, was considered more appropriate.

The one step change plot (Figure 8) suggests that the standardisation did not have a large effect, with the biggest one step change occurring with the introduction of the alfonsino catch proportion and latitude, both of these lowering the index through the mid-2000s. Few other factors resulted in substantial changes to the index.

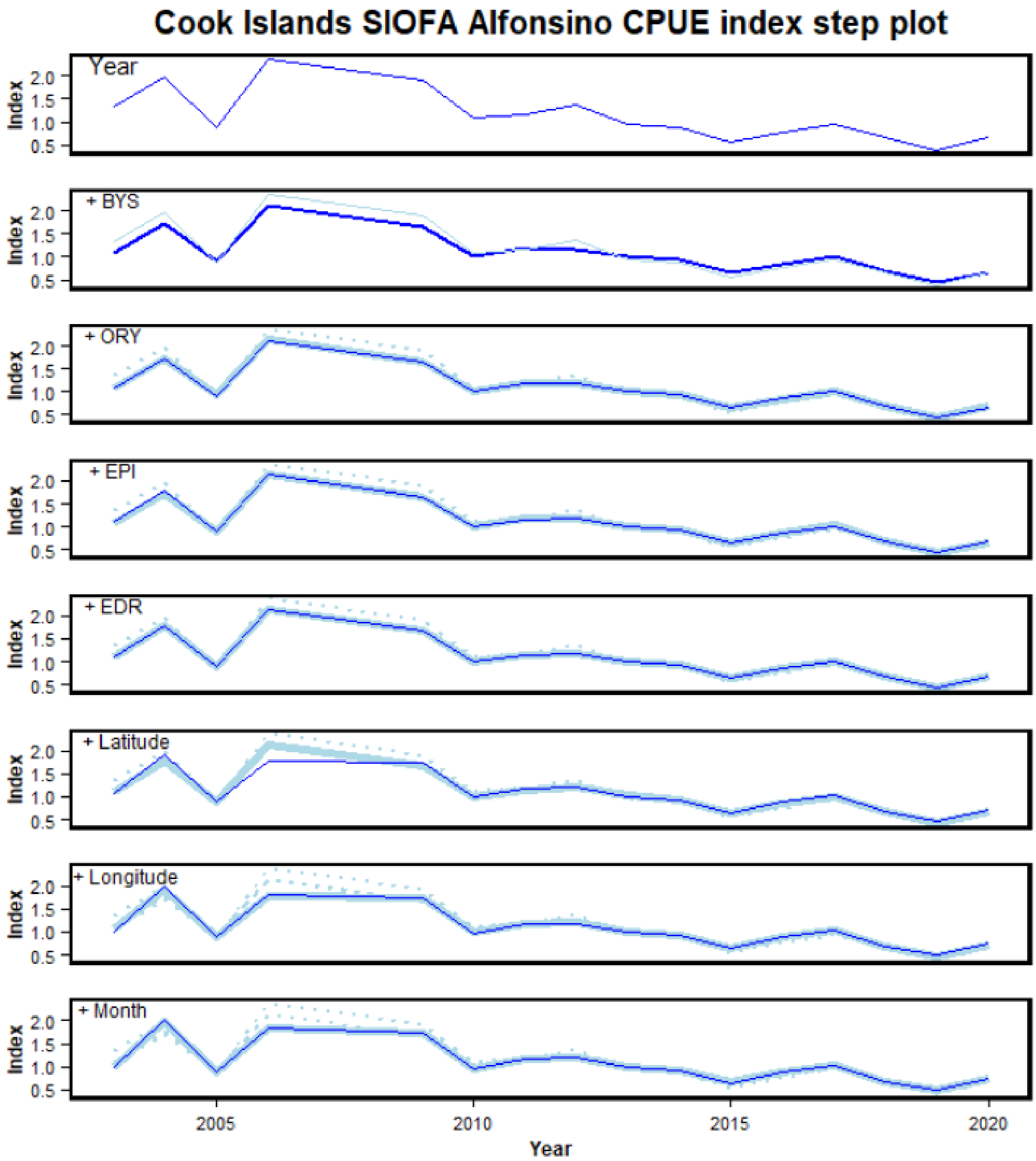


*Figure 8 – One change step plot showing the sequential standardisation effects. Blue line is the index, light blue and light blue dashed lines are the previous models, from SC-08-INFO-14.*

Alfonsino catch proportion has a large influence during the early period of the index but the catch remained consistently high per set throughout the time period (Figure 9). The effects of orange roughy catch proportions, black cardinal fish and pelagic armourhead, latitude, longitude and month were also explored.

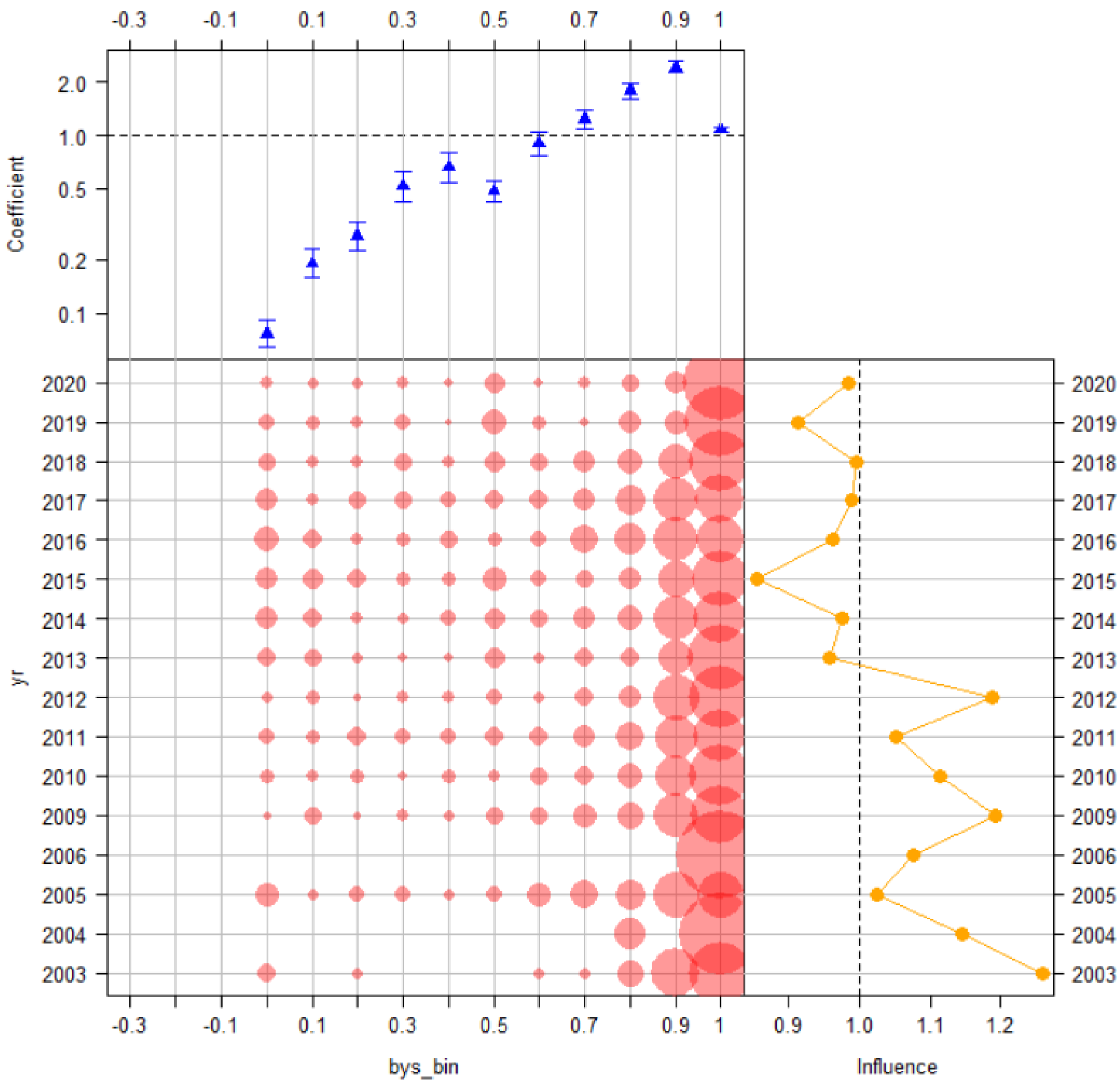


*Figure 9 – Influence of alfonsino catch proportion for the Cook Island fleet (bubble plot; bubbles scaled by catch) on CPUE; influence (right hand plot) shows the standardising effect (a positive effect reduces the standardised CPUE by the equivalent amount); and the estimated coefficients are provided in the top panel, from SC-08-INFO-14.*

The final model is presented in Figure 10. This shows a stronger standardisation effect at the start of the series, likely due to the inconsistent latitude, longitude and months fished at the start of the series.

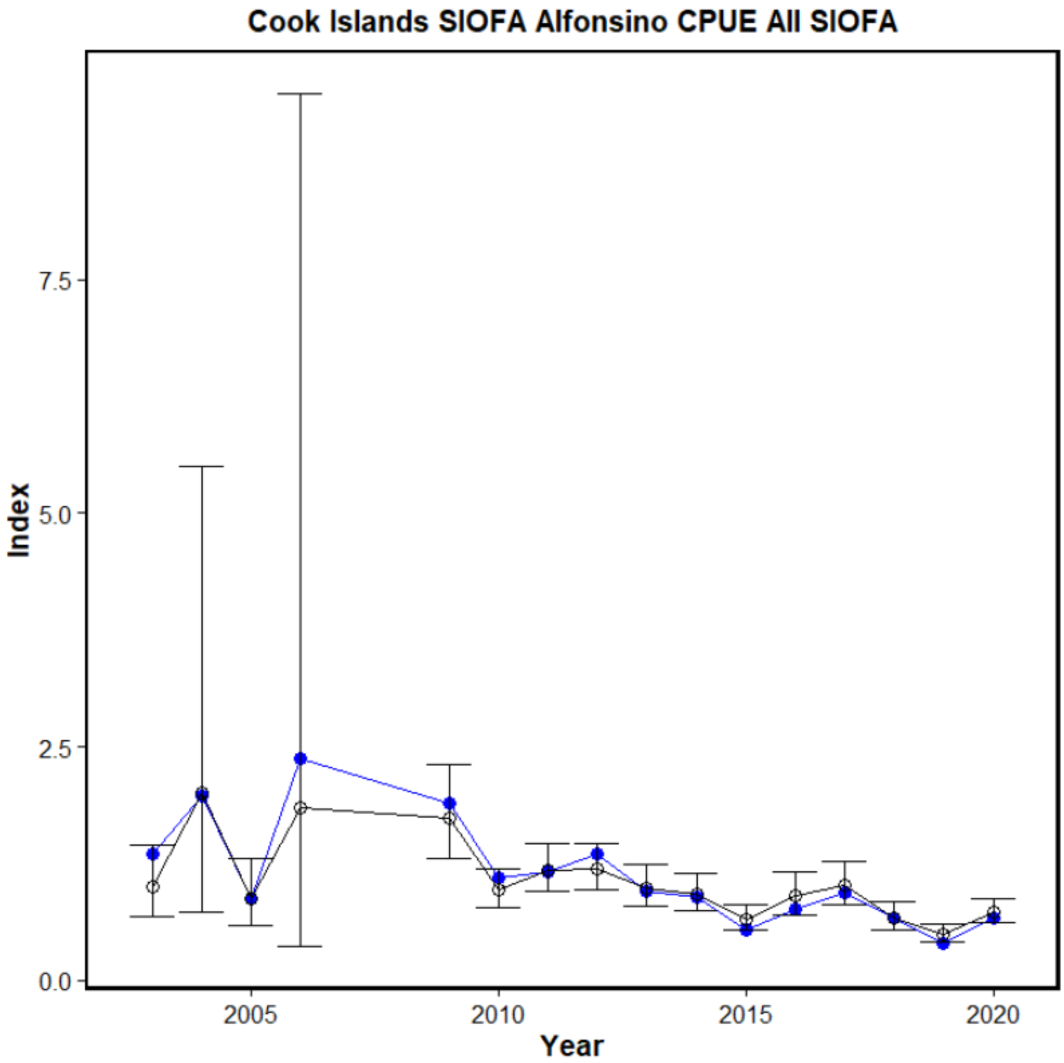


*Figure 10 – CPUE final model with the unstandardised (blue) and standardised (black) indices for alfonsino from the Cook Islands fleet fishing in SIOFA from 2001-2020, from SC-08-INFO-14.*

## 1.5. Additional resources

R packages have been developed to ease the application of GLM to e.g. fisheries survey indexes, and could be a good resource for less experienced users:

https://rdrr.io/github/rooperc4/GLMGAMRF/ The purpose of this code is to make GLM, GAM and Random Forest models based on habitat variables. These models are then used to compute model-based estimates of abundance for fishes in the Aleutian Islands and Gulf of Alaska. The code takes bottom trawl survey data and habitat variables from RacebaseExtract.R code. The package produces annual abundance estimates with errors (either by the Delta method or bootstrapping), and has a handy vignette to understand its operation.

https://github.com/casperwberg/surveyIndex was developed to calculate survey indices, but is fundamentally applying a GLM to survey data. Might require a bit of adaptation and unfortunately, it does not include a vignette so it could be more challenging for less-experienced users.

## 4. Acknowledgments

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## 5. References

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