



Empirical selectivity

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Virtual workshop on Model Diagnostics in Integrated Stock Assessments

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Introduction

- Selectivity:
 - Assigning selectivity curves is one of the most important steps in creating contemporary statistical fishery stock assessment models.
 - focus of the first CAPAM workshop in 2013 and the associated special issue in Fisheries Research.
- Selectivity curves in stock assessment models:
 - represent a combination of contact gear selectivity, and
 - availability (e.g. due to the fish behavior of the fish or characteristics of the habitat),
 - this may result in complex selectivity shapes.
 - this is especially true when spatial processes of the dynamic are not modelled in an explicitly spatial model but are rather approximated using an area-as-fleet model.
 - Splines have been used to model selectivities with complex shapes
 - Splines are flexible but complicated to set up

Importance of correctly specifying selectivity

- An incorrectly specified selectivity curve can substantially bias the estimates of
 - estimate of absolute abundance,
 - estimate of fishing mortality,
 - and the consequently result in poor management advice.
- Therefore, it is important to ensure an appropriate selectivity curve is used.
- This is particularly true for the selectivity of old fish:
 - modelling as asymptotic or dome shape can have strong consequences in estimates.

Empirical selectivity

- The “empirical” selectivity diagnostic was recently developed at IATTC (e.g. Mauder et al 2020, Minte-Vera et al 2020, Xu et al 2020)
- Goals:
 - focus on the misfit of composition data for old fish that are more influential, but less abundant in the composition data,
 - used as a weighting metric in the newly developed Risk Analysis

Empirical selectivity

- The empirical selectivity ($T_{a,t}$) is simply the proportion at length l (or proportion at age a) in the catch divided by the proportion at length (or proportion at age) in the population

At length

$$T_{l,t} = \frac{\frac{Cl.t}{\sum_l^L Cl.t}}{\frac{Nl.t}{\sum_l^L Nl.t}}$$

At age

$$T_{a,t} = \frac{\frac{Ca.t}{\sum_a^A Ca.t}}{\frac{Na,t}{\sum_a^A Na.t}}$$

- Proportion in the catch comes from samples
- Proportion in the population comes from a preliminary integrated model fit set up with

Empirical selectivity

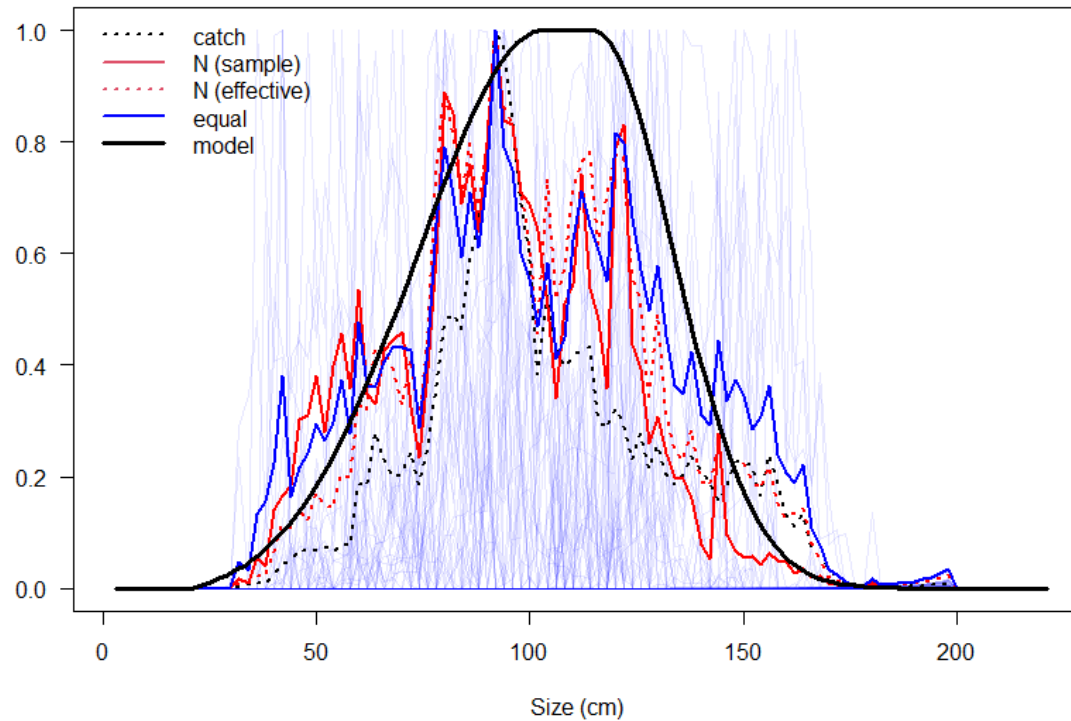
- computed for each time step in the model where there is composition data,
- averaged by period or for the whole time series.
- weighted average:
 - weighted by the composition sample size,
 - weighted by the catches or
 - not weighted
- Implemented in the R package ***empirical.selectivity*** (Oliveros-Ramos 2021)

Empirical selectivity

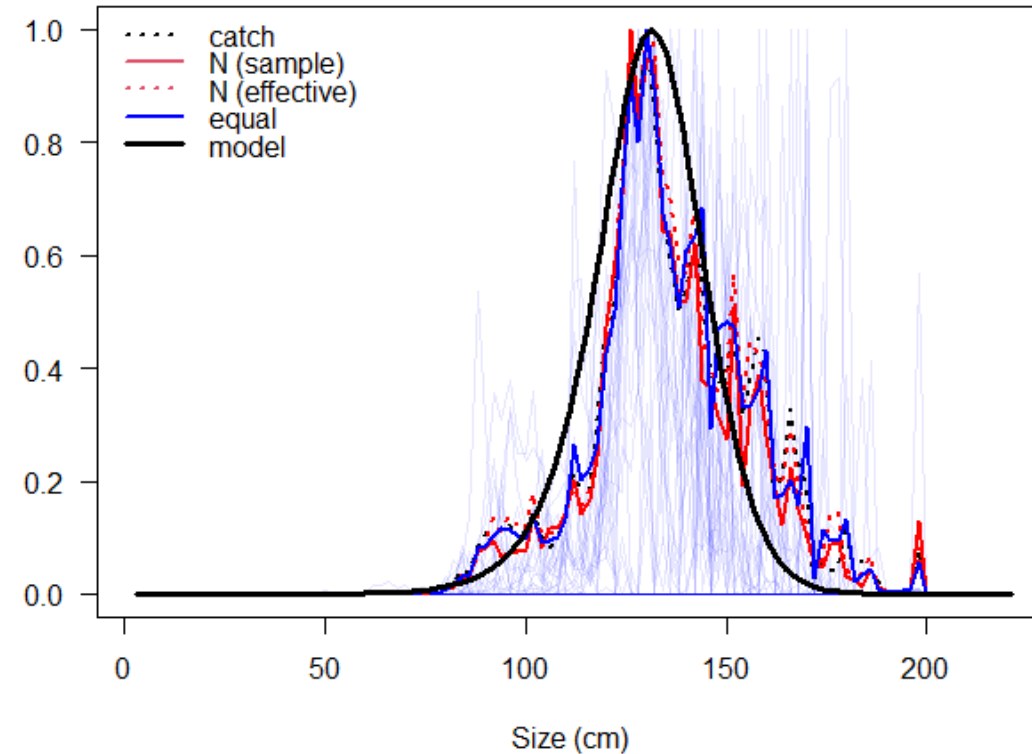
```
remotes::install_github("roliveros-ramos/fks")
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```
remotes::install_github("roliveros-ramos/empirical.selectivity")
```

A3-NOADEL

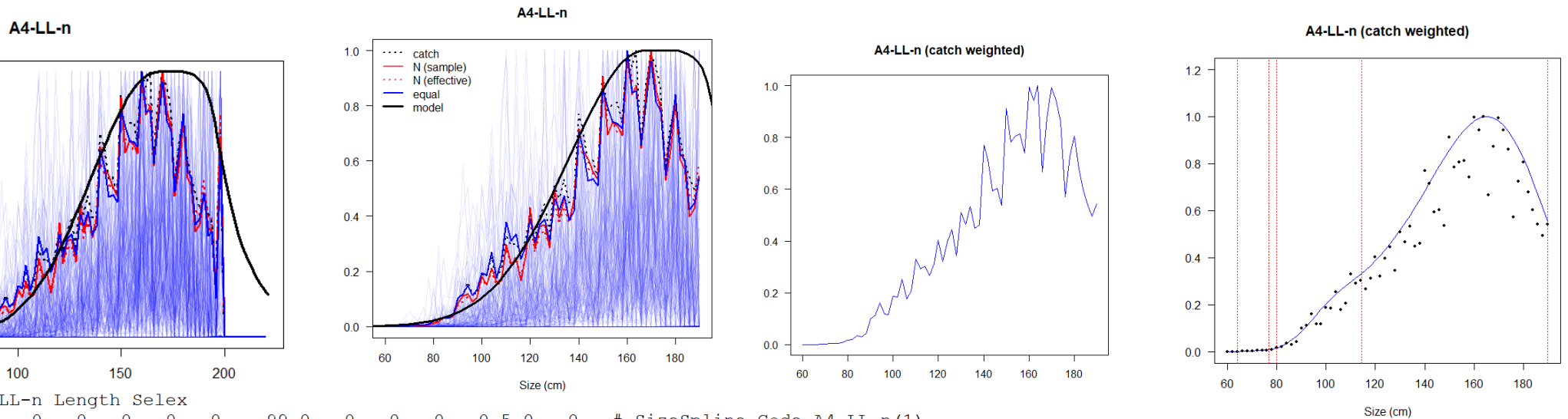


A1-LL-n



Empirical selectivity for model development

- facilitates the choice of the number and position of nodes, by fitting splines to empirical selectivities.
- allows for the choice of meaningful starting values for the spline parameters.



27
fit 12.92564
npar 12.00000

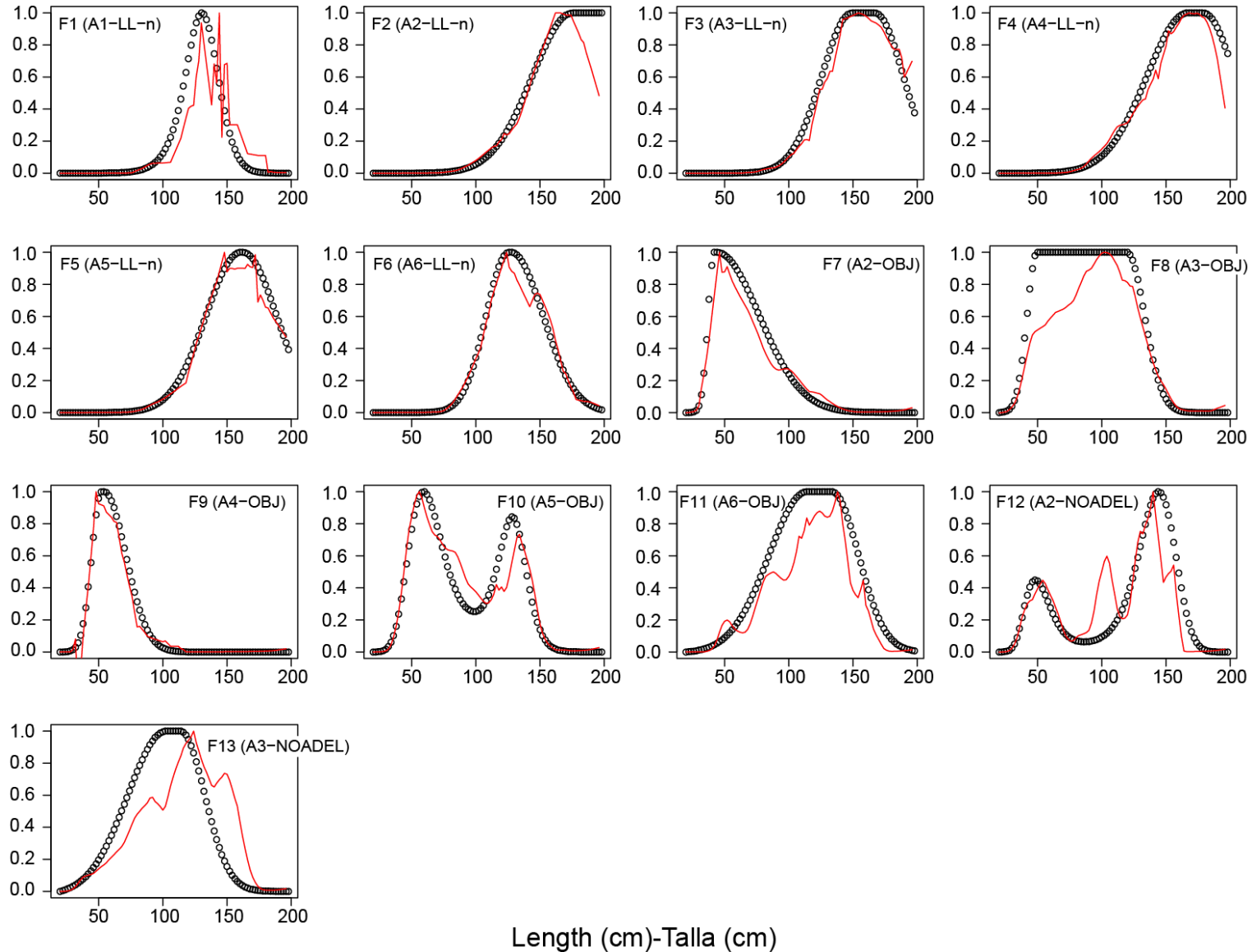
```

1 # A4-LL-n Length Selex
2 0 0 0 0 0 0 -99 0 0 0 0 0.5 0 0 # SizeSpline_Code_A4-LL-n(1)
3 -0.01 1 0.658 0 0.001 1 3 0 0 0 0 0.5 0 0 # SizeSpline_GradLo_A4-LL-n(1)
4 -1 0.01 -0.052 0 0.001 1 3 0 0 0 0 0.5 0 0 # SizeSpline_GradHi_A4-LL-n(1)
5 60 190 64 64 0 0 -99 0 0 0 0 0.5 0 0 # SizeSpline_Knot_1_A4-LL-n(1)
6 60 190 76.748 76.7475911321447 0 0 -99 0 0 0 0 0.5 0 0 # SizeSpline_Knot_2_A4-LL-r
7 60 190 80 80.0000655666902 0 0 -99 0 0 0 0 0.5 0 0 # SizeSpline_Knot_3_A4-LL-n(1)
8 60 190 114.411 114.411292969612 0 0 -99 0 0 0 0 0.5 0 0 # SizeSpline_Knot_4_A4-LL-r
9 60 190 190 190 0 0 -99 0 0 0 0 0.5 0 0 # SizeSpline_Knot_5_A4-LL-n(1)
10 -9 7 -8.026 0 1 1 -2 0 0 0 0 0.5 0 0 # SizeSpline_Val_1_A4-LL-n(1)
11 -9 7 -4.979 0 1 1 2 0 0 0 0 0.5 0 0 # SizeSpline_Val_2_A4-LL-n(1)
12 -9 7 -4.287 0 1 1 -2 0 0 0 0 0.5 0 0 # SizeSpline_Val_3_A4-LL-n(1)
13 -9 7 -1.243 0 1 1 2 0 0 0 0 0.5 0 0 # SizeSpline_Val_4_A4-LL-n(1)
14 -9 7 -0.732 0 1 1 -2 0 0 0 0 0.5 0 0 # SizeSpline_Val_5_A4-LL-n(1)

```



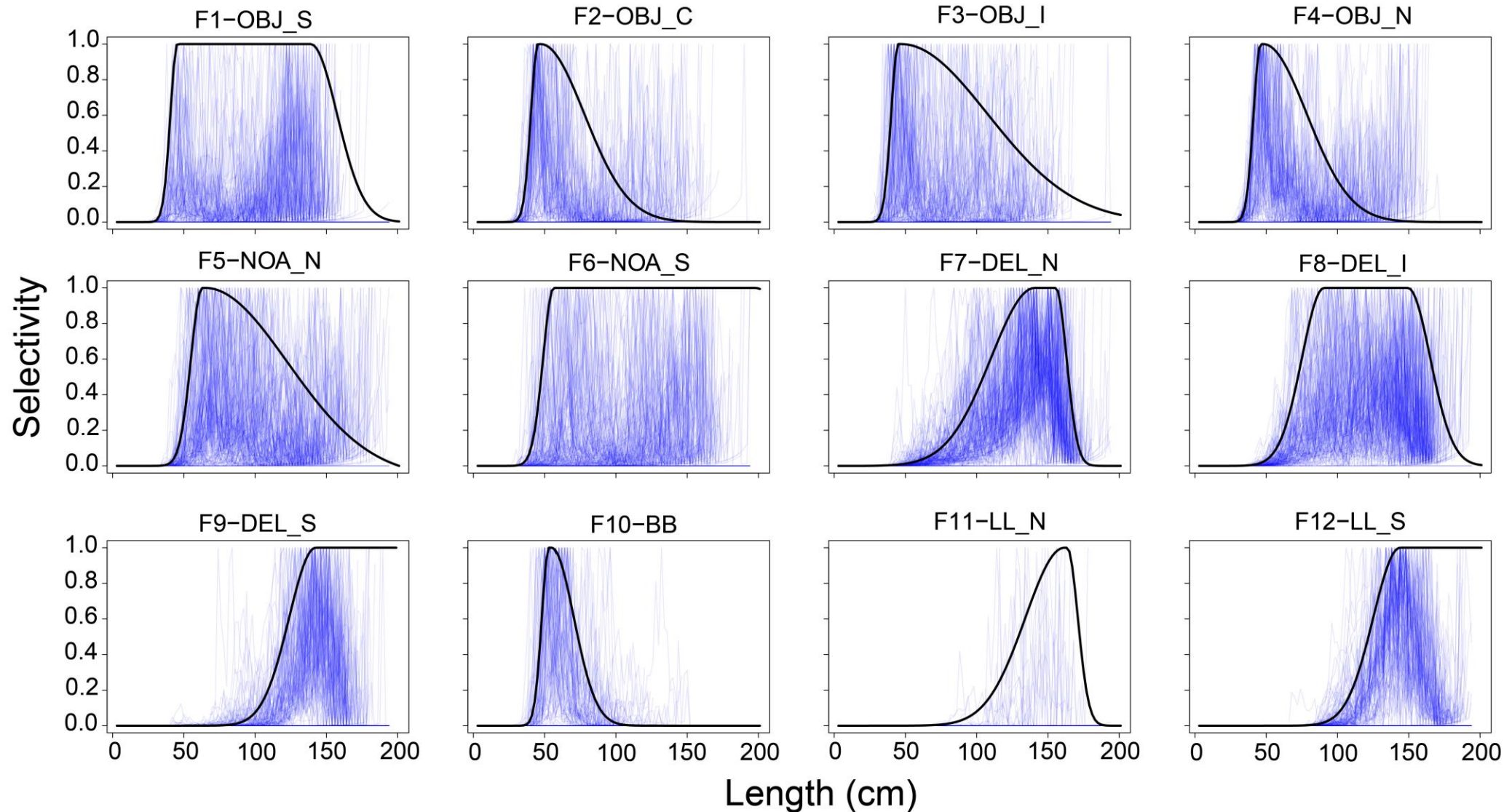
Example: Bigeye tuna in the Eastern Pacific Ocean



o Estimated selectivity
— Empirical selectivity

Application: Yellowfin tuna in the Eastern Pacific Ocean

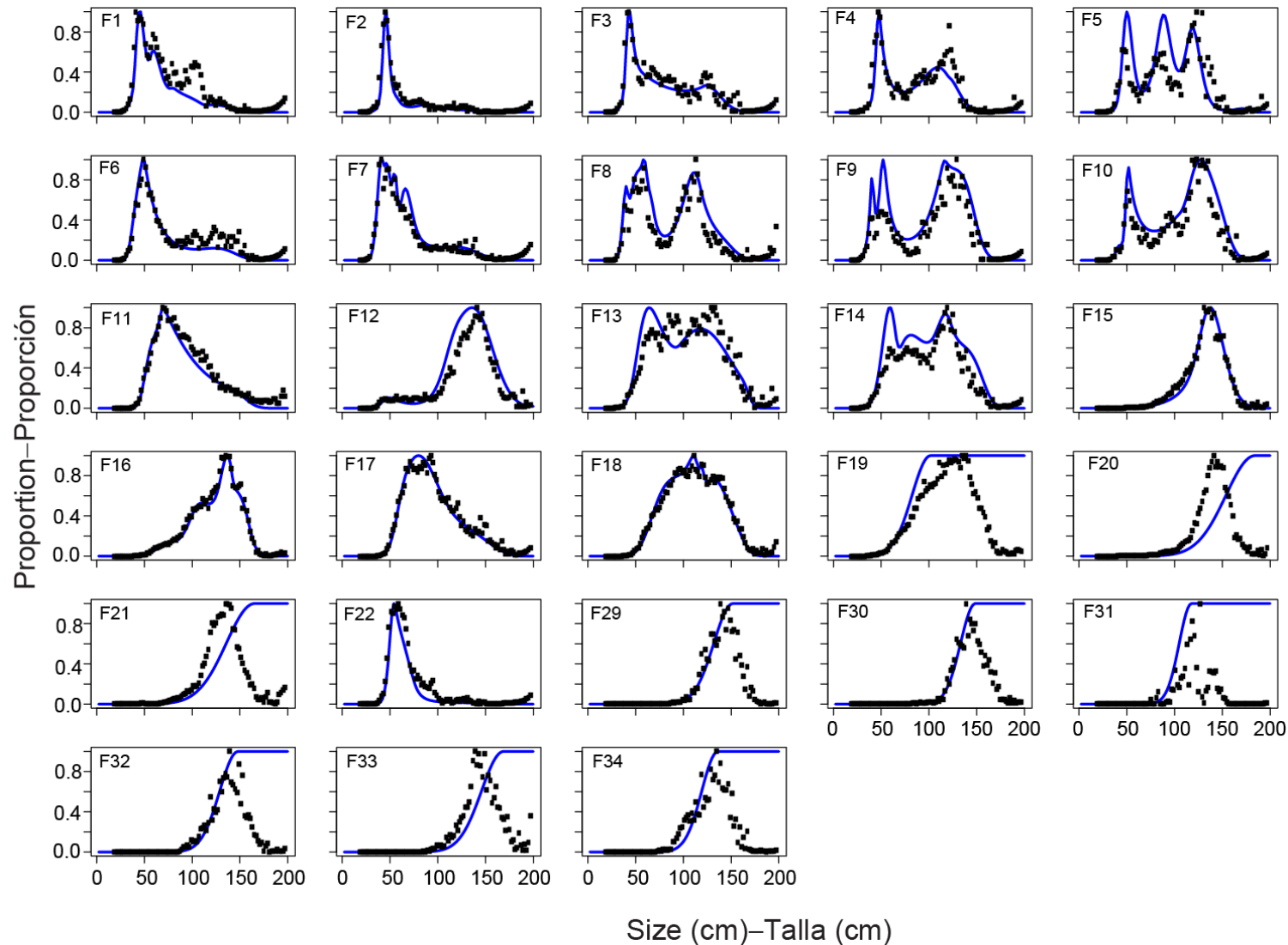
Old model



Application: Yellowfin tuna in the Eastern Pacific Ocean

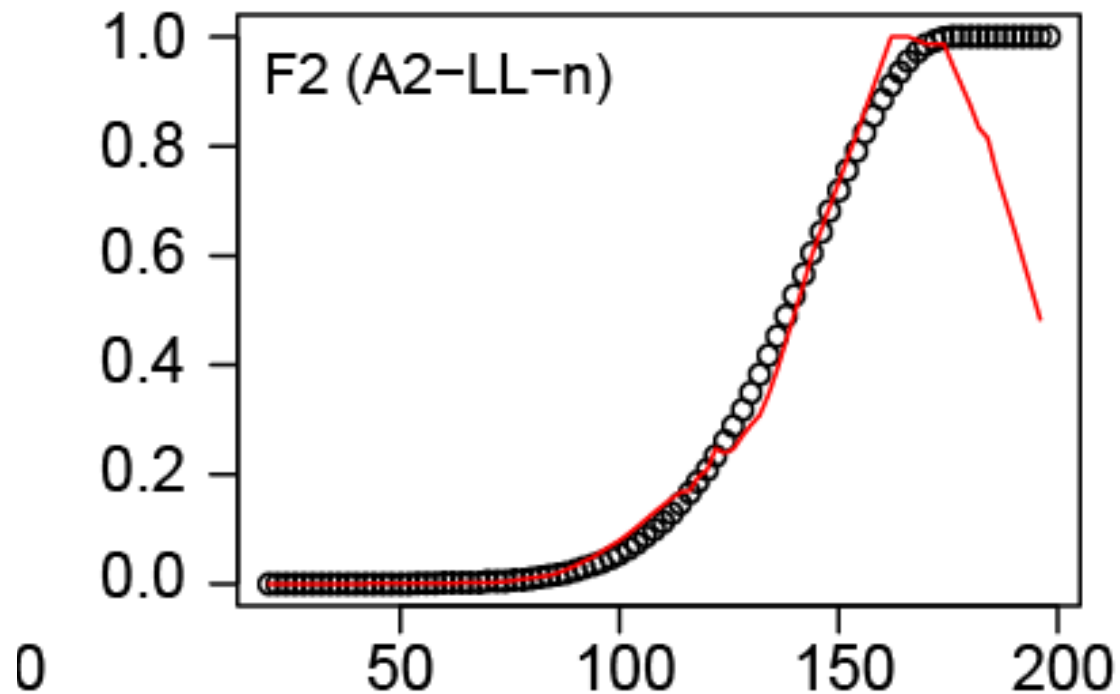
New model

Extensive use of splines



Empirical selectivity used as diagnostic

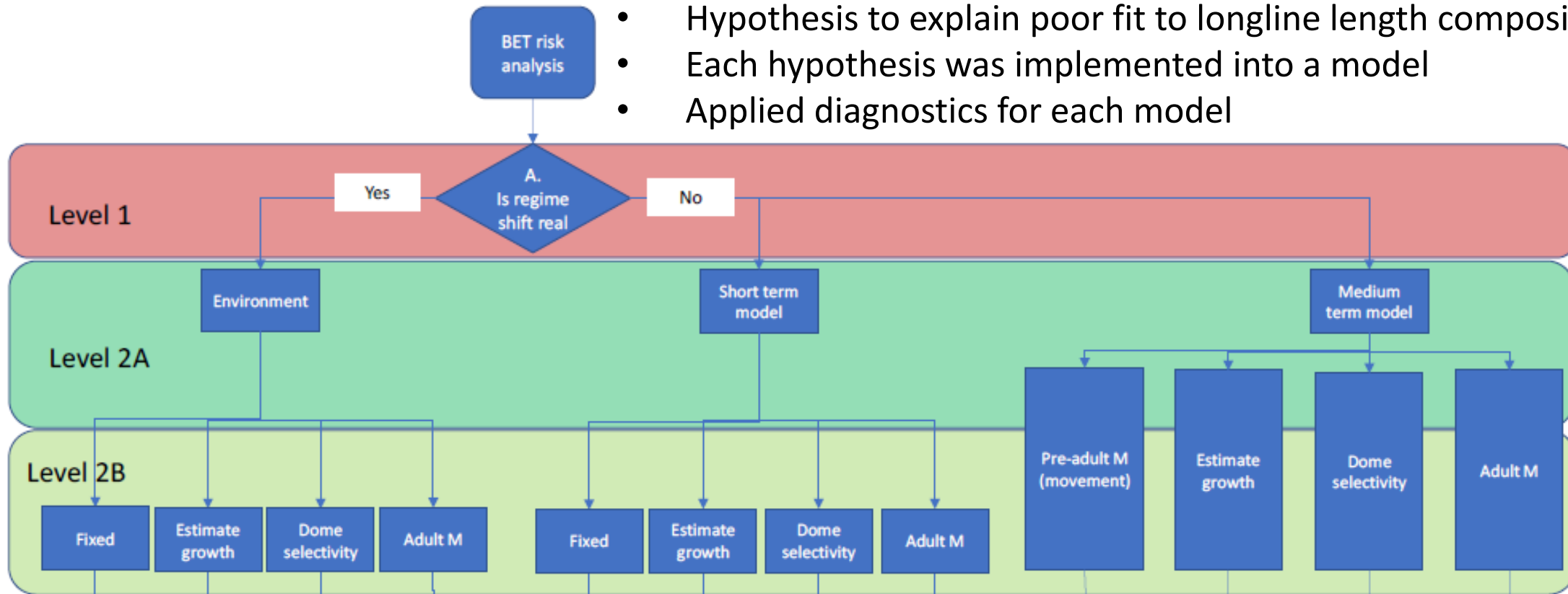
Example: Bigeye tuna in the Eastern Pacific Ocean



- Fishery A2-LL-n is the longline fishery that has catches the highest proportion **of large bigeye**
- It is therefore assumed in a reference model to have **asymptotic selectivity**
- However, the **empirical selectivity suggests** the selectivity of A2-LL-n is **dome-shaped**

Empirical selectivity used as diagnostic

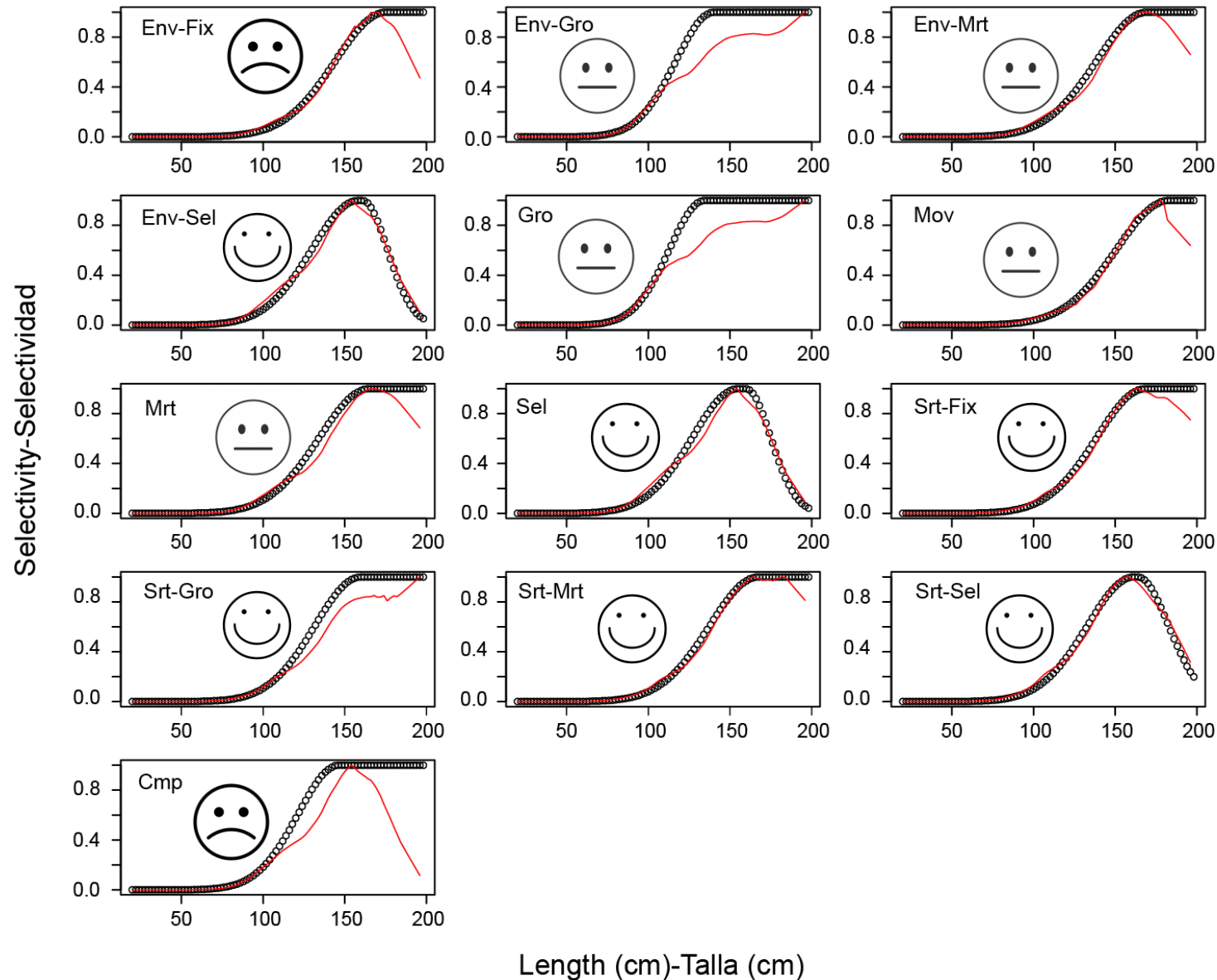
- Hypothesis to explain poor fit to longline length composition
- Each hypothesis was implemented into a model
- Applied diagnostics for each model



Hypotheses for the poor fit of longline compositions

- Random error in observations (**Fixed** – fix growth and natural mortality)
- Growth is mis-specified (**Estimate growth** – estimate the Richards growth curve and its variability)
- Longline selectivity is dome-shaped (**Dome selectivity** – use the double-normal selectivity curve)
- Adult natural mortality is mis-specified (**Adult M** – estimate the natural mortality of age 26+ quarters)
- longline compositions are unrepresentative (not shown) – down-weight longline compositions

Empirical selectivity used as diagnostic



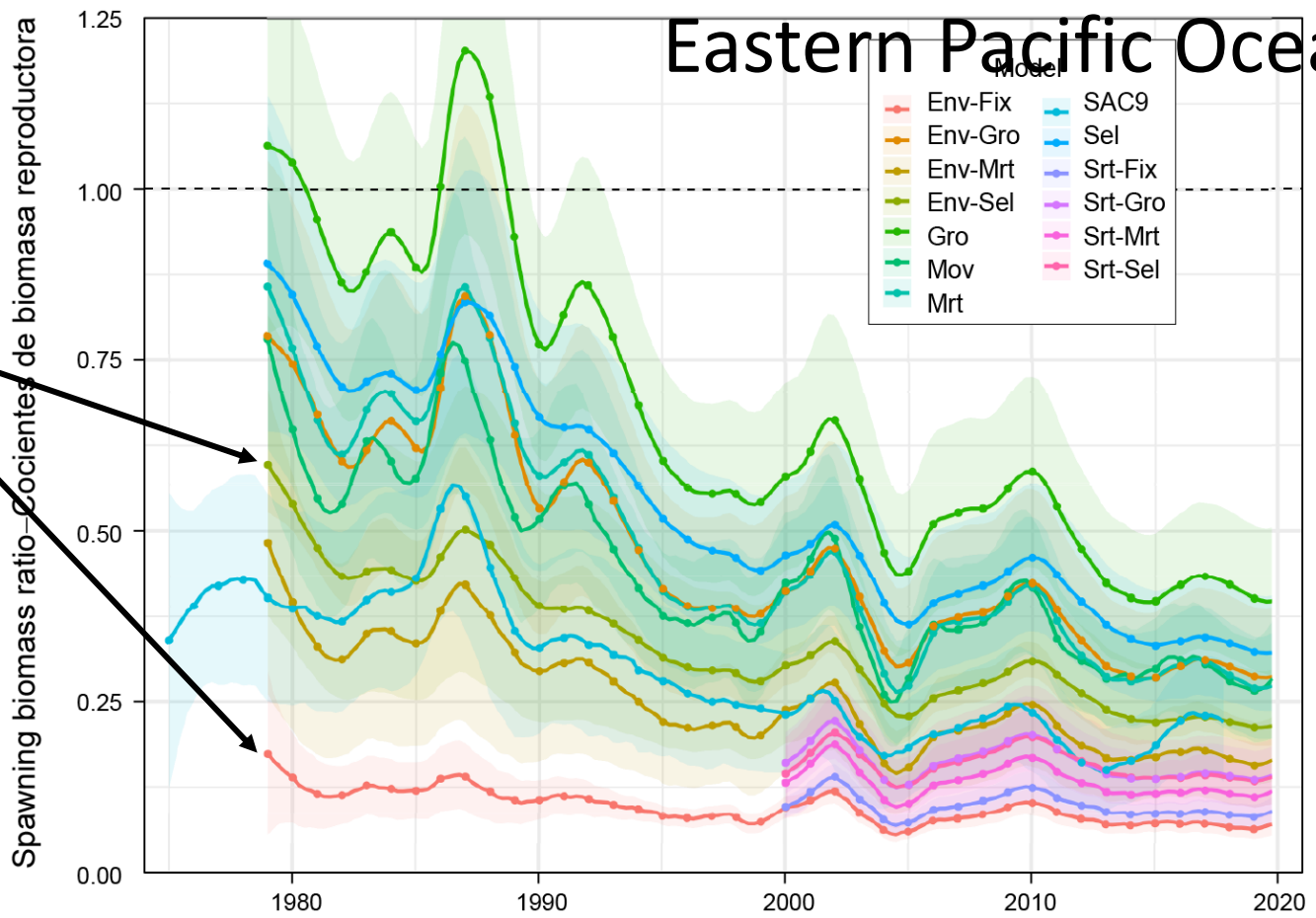
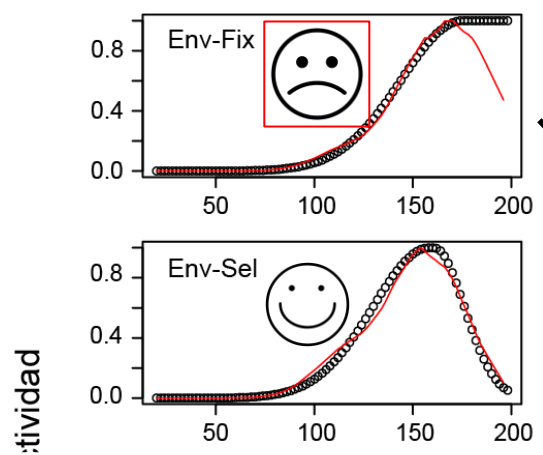
Bigeye tuna in the Eastern Pacific Ocean

Comparison the difference across reference models

Estimated selectivity vs. **empirical selectivity** for fishery A2-LL-n

Stock status is very sensitive to selectivity assumption

Bigeye tuna in the Eastern Pacific Ocean



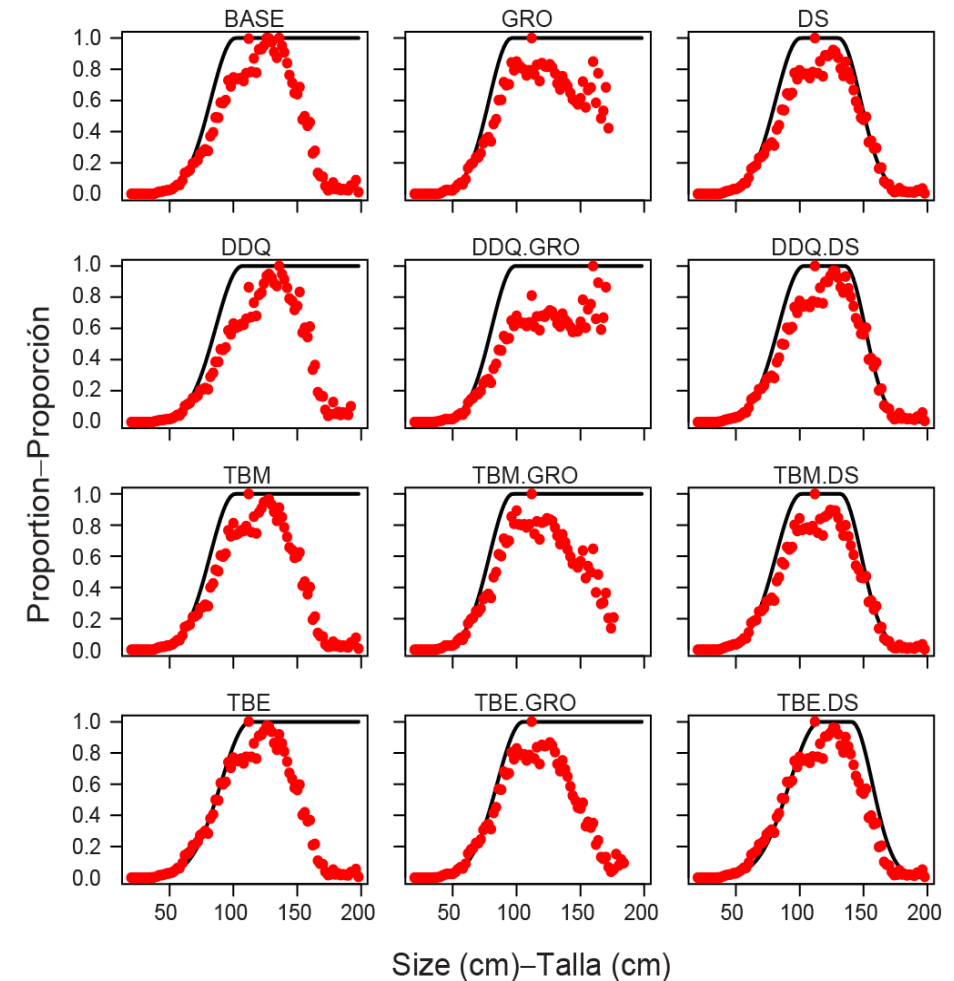
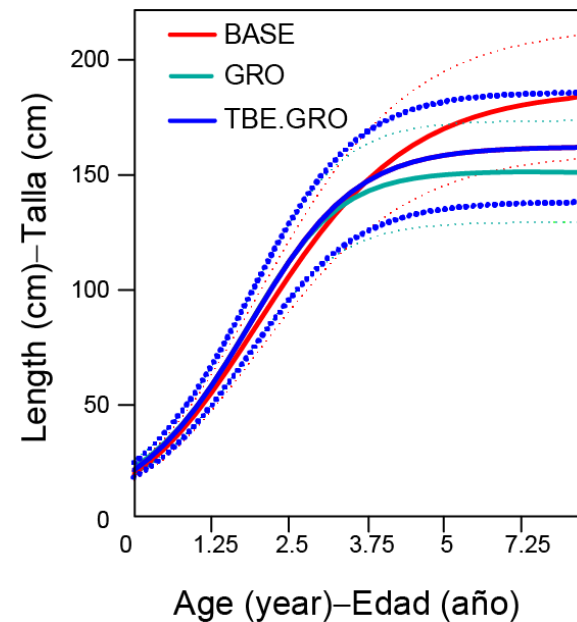
The only difference between the two models is in the selectivity assumption for A2-LL-n

Due to the high sensitivity of stock status to this selectivity assumption, the empirical selectivity diagnostics can have a large impact on ensemble mean through model weighting

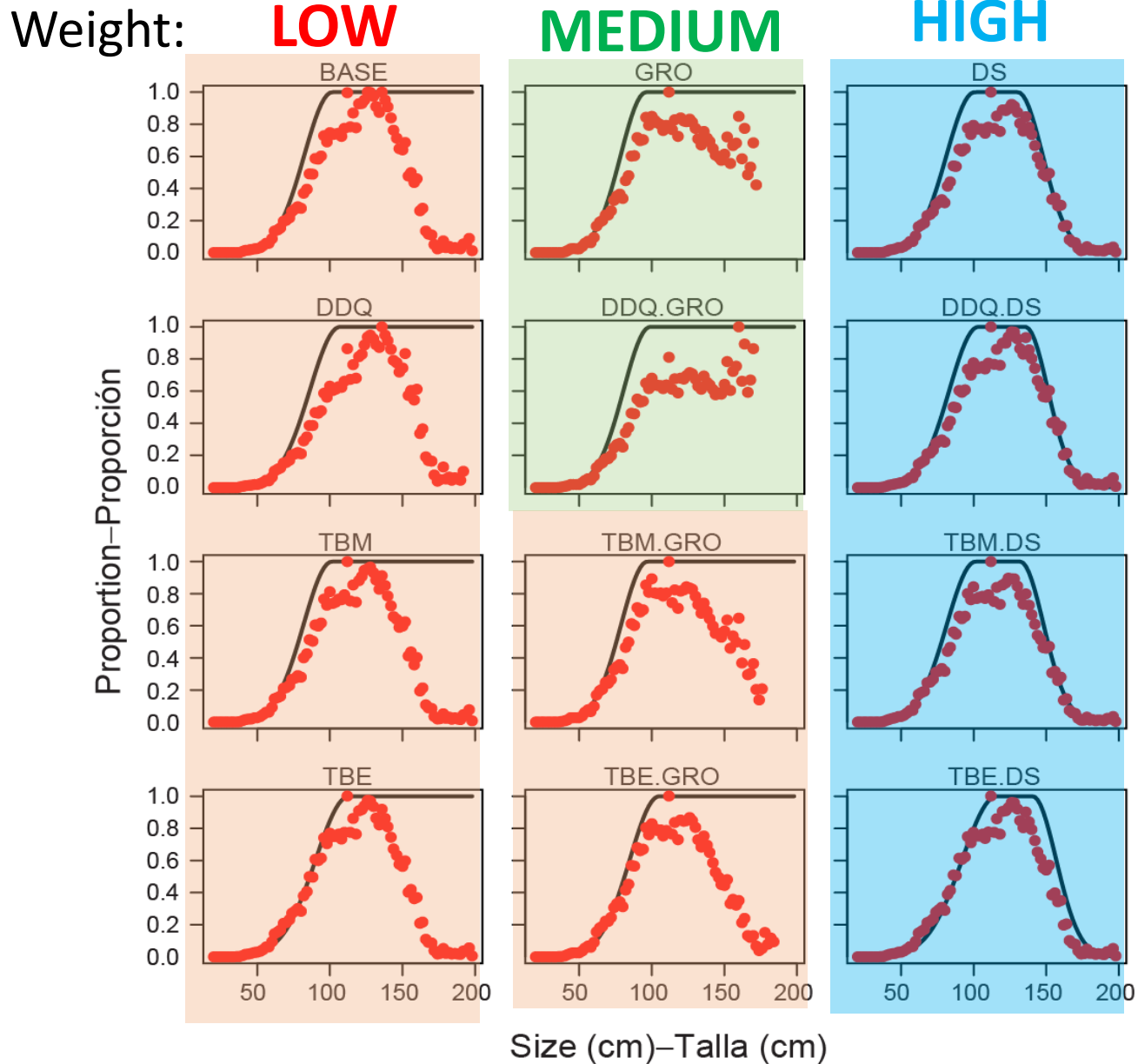
Empirical selectivity used for weighting models

Example: Yellowfin tuna in the Eastern Pacific Ocean

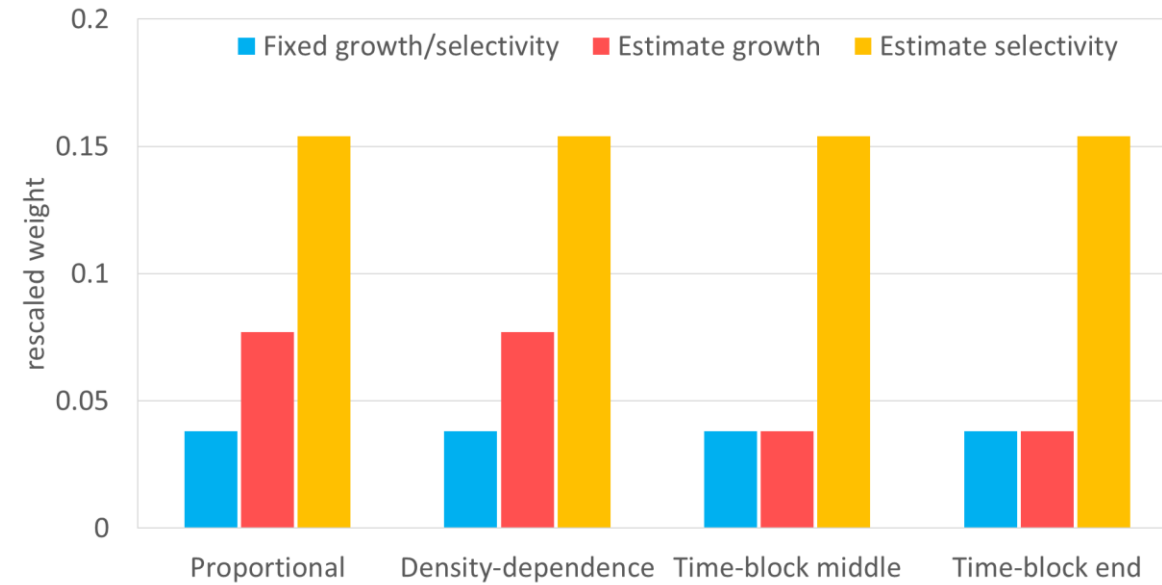
- Hypothesis to explain poor fit to purse-seine sets on dolphin length composition
- Each hypothesis was implemented into a model
- Applied diagnostics for each model



Empirical selectivity used for weighting models



Fishery F19-DEL_P



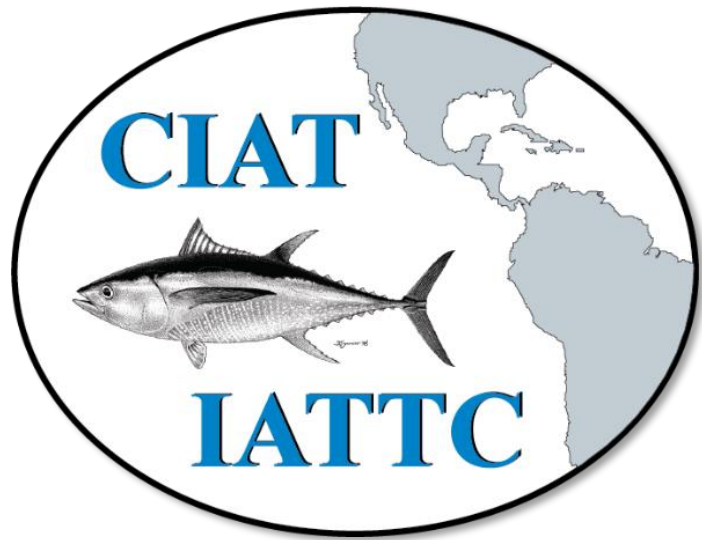
Empirical selectivity

For model development:

- Facilitate the implementation of complex selectivities
- Need the use of an external R library:
 - Compares selectivity functions
 - Optimally select number of knots and positions for splines
 - Provides initial values for selectivity parameters in correct SS3 format

For diagnostics/weighting models:

- Allows categorization of models by visual comparison
- Still subjective
- Needs quantitative metric :
 - to compare the fits of empirical selectivity
 - to compute impact of misfit



Thank you