

# *Practical applications of diagnostic weighing in ensemble models: three case studies, Northern shrimp, Adriatic sole and Gulf of Bothnian vendace*

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E LE BIOTECNOLOGIE  
MARINE

# Why Ensemble Modeling

Current practices in stock assessment consists in comparing different models and choosing the **“best case scenario”**

In this context, discarded models have no effect (weight = 0) on management even if they represent a plausible realization of the truth

The main objective when using an **ensemble of models** in stock assessments is to quantify the **total uncertainty** across all plausible models, where the structural uncertainty is likely to be much greater than the within model uncertainty

Moreover, ensemble forecasting has been shown to generally being able to **improve forecast accuracy** in many fields, particularly in weather forecasting where the method originated and transport science

# Why weighting models in an ensemble

The need to **weigh models** based on information in the available data is well recognised in several sciences but it is often difficult to do so within the context of fisheries stock assessment models

**Model weighting** is a necessary step because assigning the same weight (reliability) to all hypotheses could introduce biases into the management advice if some hypotheses are, in fact, more unlikely than others

**Model diagnostics** have the potential to be used to weight models

# Model diagnostics

1. Felipe Carvalho, Henning Winker, Dean Courtney, Laurence Kell, Maia Kapur, Massimiliano Cardinale, Michael Schirripa, Toshihide Kitakado, Dawit Y. Ghebrehiwet, Kevin R. Piner, Mark N. Maunder, Rick Methot, 2021. A Cookbook for Using Model Diagnostics in Integrated Stock Assessments. Fisheries Research, <https://doi.org/10.1016/j.fishres.2021.105959>.
2. Laurie Kell, Rishi Sharma, Toshihide Kitakado, Henning Winker, Iago Mosqueira, Massimiliano Cardinale, Dan Fu, 2021. Validation of stock assessment methods: is it me or my model talking? ICES Journal of Marine Science, <https://doi.org/10.1093/icesjms/fsab104>.
3. Gorka Merino, Agurtzane Urtizberea, Dan Fu, Henning Winker, Massimiliano Cardinale, Mathew Laretta, Hilario Murua, Toshihide Kitakado, Haritz Arrizabalaga, Robert Scott, Graham Pilling, Ane Laborda, Maite Erauskin-Extramianiana, Josu Santiago 2022. Investigating trends in process error as a diagnostic for integrated fisheries' stock assessments. Fisheries Research, <https://doi.org/10.1016/j.fishres.2022.106478>.

## Diagnostic test category



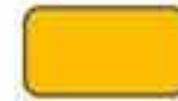
**Goodness-of-fit**



**Information sources  
and structure**



**Prediction skill**



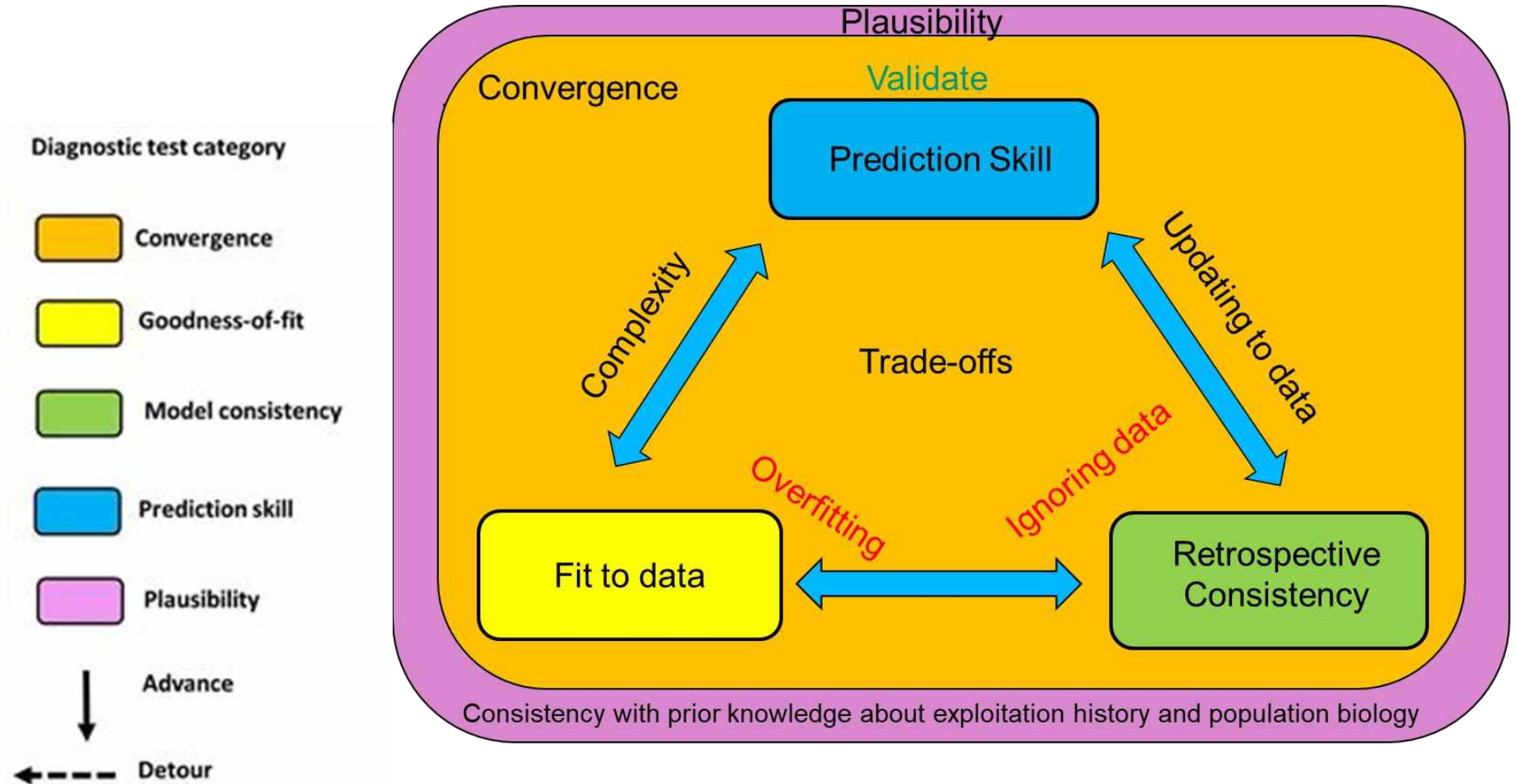
**Convergence**



**Plausibility**

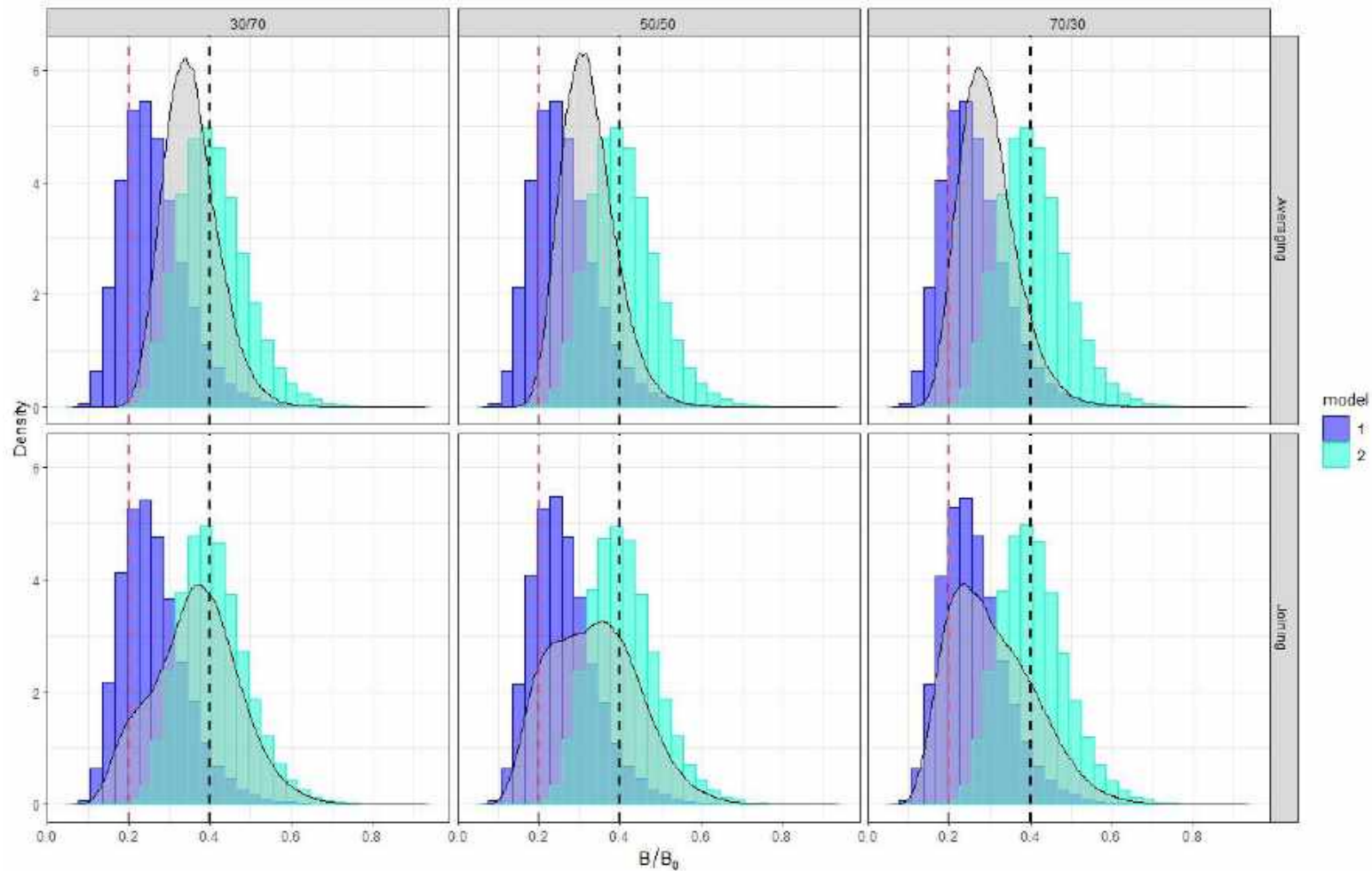
# Model diagnostics

## “Modern” Model diagnostics



When all **model diagnostic** tests are considered together, the power to detect model misspecification improves without a substantial increase in the probability of incorrectly rejecting a correctly specified model

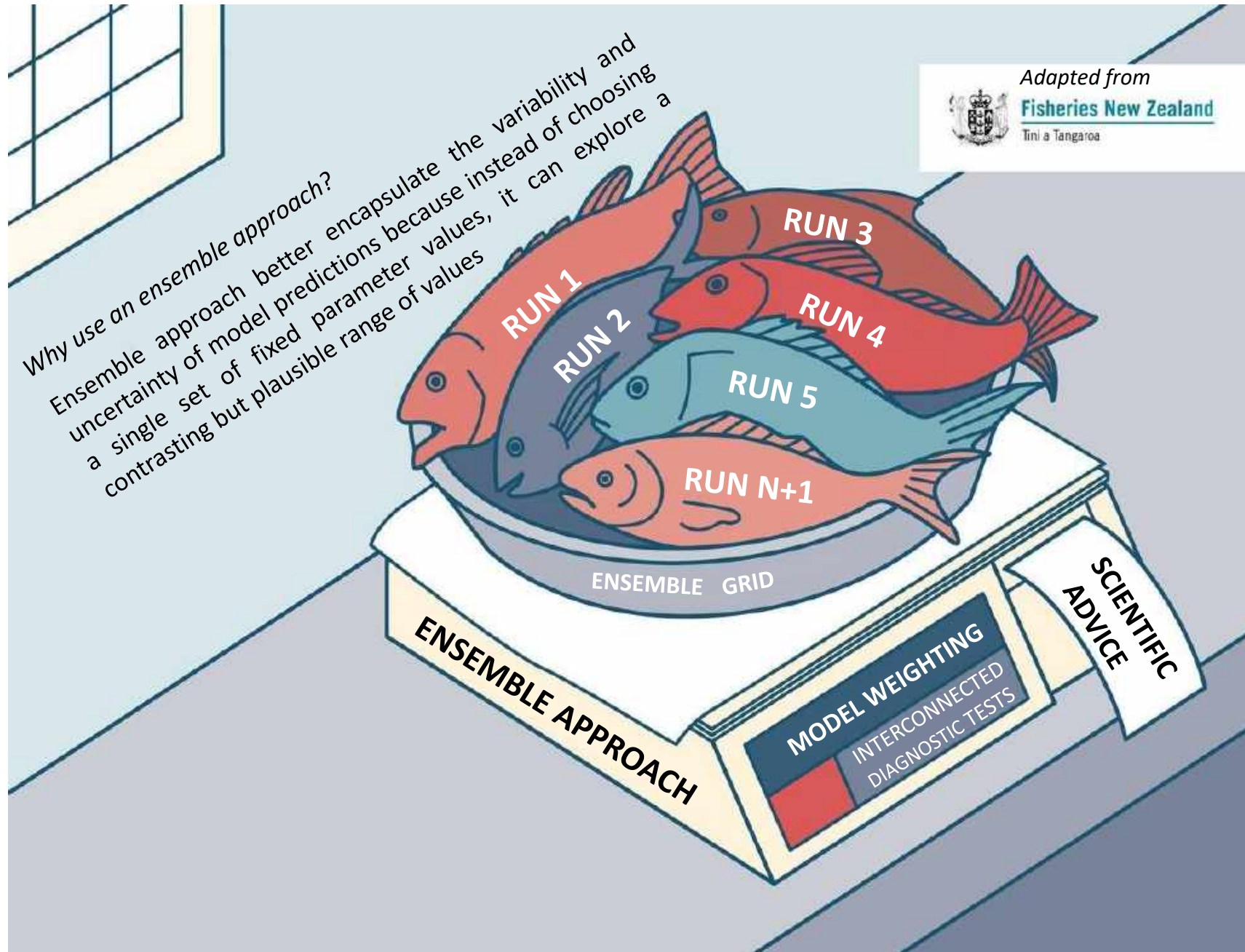
# Model averaging and model stitching



Thus, even if bias divergence is large (even if bidirectional) and correlation between models is also large, then we might lose the benefit of improving accuracy, but we still preserve the tails for a better quantification of risk.

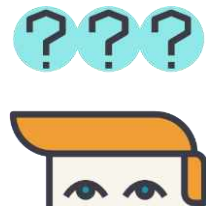


# Assessment model framework: the ensemble approach

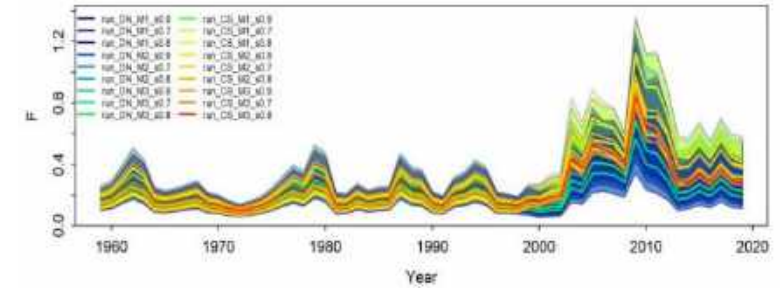
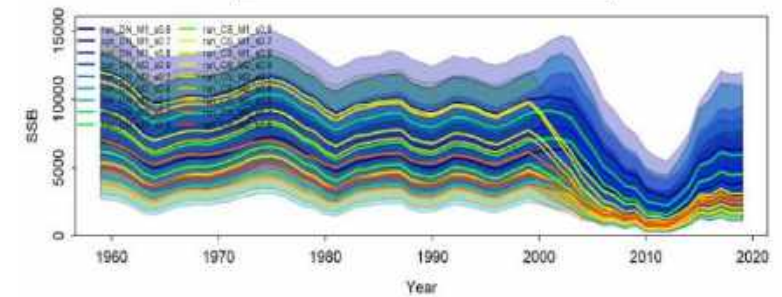


- Stock Synthesis 3 + Ensemble approach (delta-MVLN)**

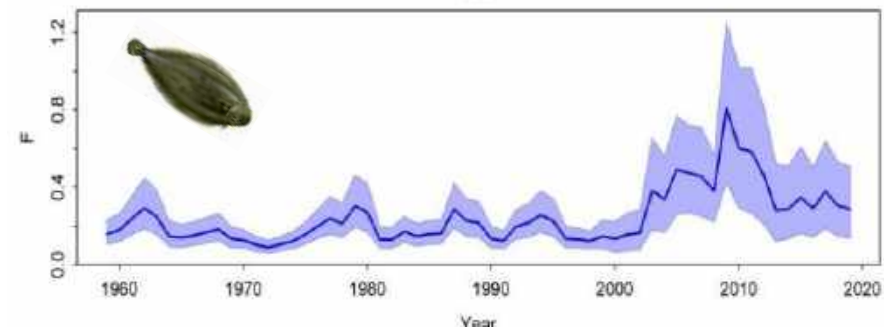
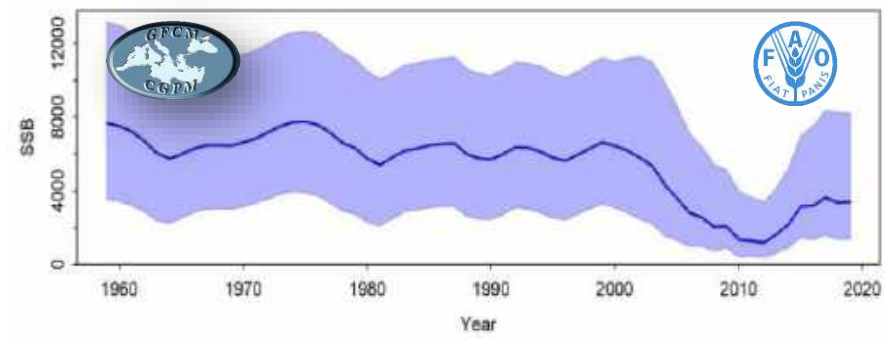
to address structural uncertainties, a range of alternative models was selected through diagnostics, to be stitched together



Grid of alternative runs



Ensemble model

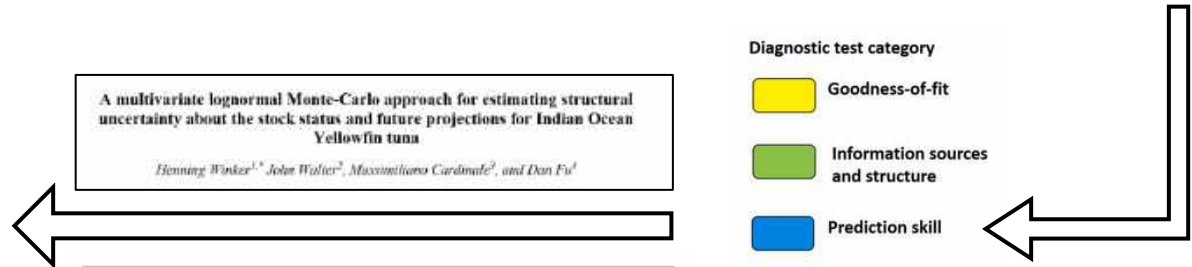


A multivariate lognormal Monte-Carlo approach for estimating structural uncertainty about the stock status and future projections for Indian Ocean Yellowfin tuna  
*Henning Winker<sup>1,\*</sup>, John Walter<sup>2</sup>, Maximiliano Cardinale<sup>2</sup>, and Dan Fu<sup>1</sup>*

Scientific Advisory Committee On Fisheries (SAC)  
 Working Group on Stock Assessment of Demersal Species (WGSAD)  
 Benchmark session for the assessment of common sole in GSA 17

Diagnostic test category

- Goodness-of-fit
- Information sources and structure
- Prediction skill
- Convergence
- Plausibility





The 1<sup>st</sup> application of ensemble modelling in GFCM stock assessment and advice

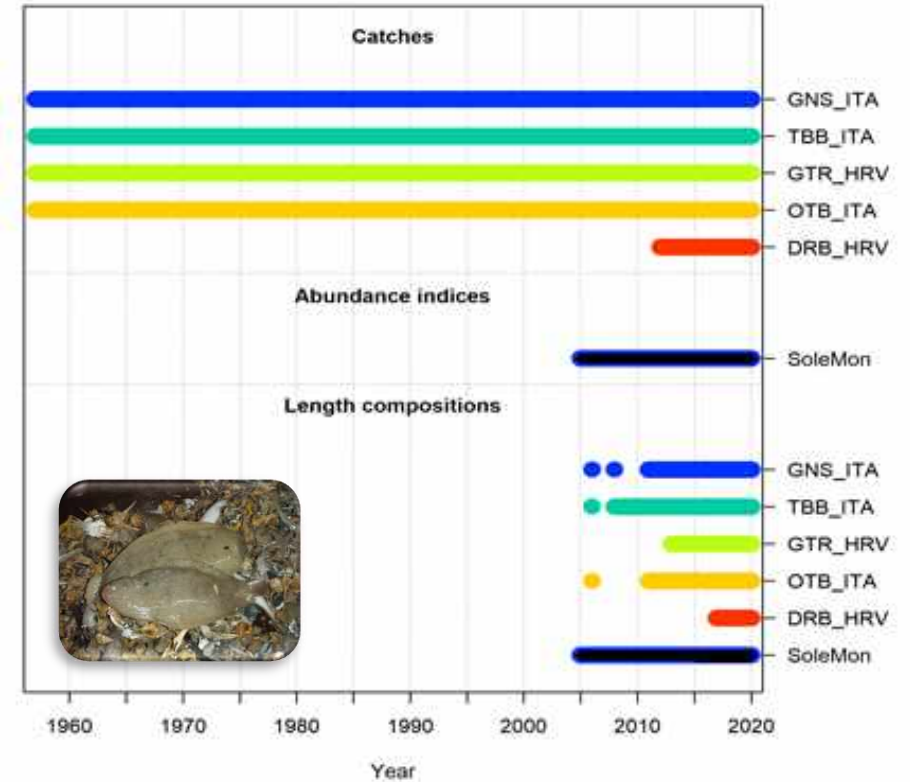
# Adriatic sole

- **Stock Synthesis 3** - Statistical age structured population modelling using a wide range of minimally processed fishery and survey data (Maunder and Punt 2013)



<https://vlab.ncep.noaa.gov/web/stock-synthesis>

*Model structure:* one-area yearly model where the population is comprised of 15+ age-classes with sexes combined



GNS ITA



TBB ITA



GTR HRV



OTB ITA



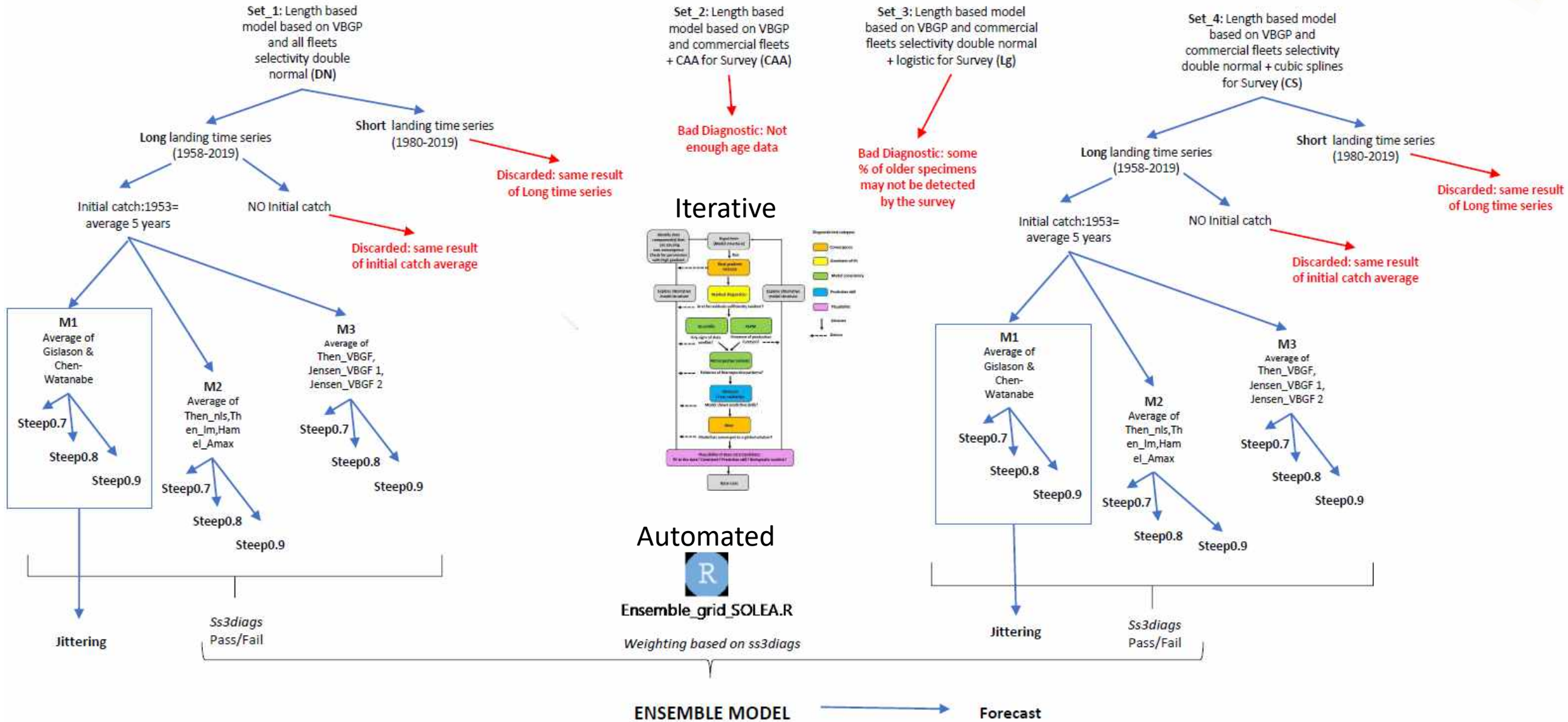
DRB HRV



SoleMon



# Stock Assessment workflow for Benchmark of *Solea solea* in GSA 17



# Diagnostic - Convergence & stability



A cookbook for using model diagnostics in integrated stock assessments

Felipe Carvalho<sup>a,\*</sup>, Henning Winker<sup>b,1</sup>, Dean Courtney<sup>c</sup>, Maia Kapur<sup>d</sup>, Laurence Kell<sup>e</sup>,  
Massimiliano Cardinale<sup>f</sup>, Michael Schirripa<sup>g</sup>, Toshihide Kitakado<sup>h</sup>, Dawit Yemane<sup>i</sup>,  
Kevin R. Piner<sup>j</sup>, Mark N. Maunder<sup>k,1</sup>, Ian Taylor<sup>m</sup>, Chantel R. Wetzel<sup>m</sup>, Kathryn Doering<sup>n</sup>,  
Kelli F. Johnson<sup>m</sup>, Richard D. Methot<sup>m</sup>

[jabbamodel/ss3diags](#) Public

## 1. Convergence & stability

- Positive Hessian
- Jittering

## 2. Goodness of the fit

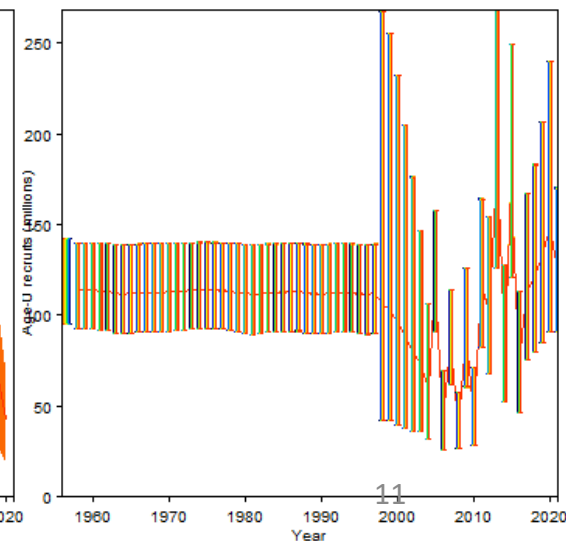
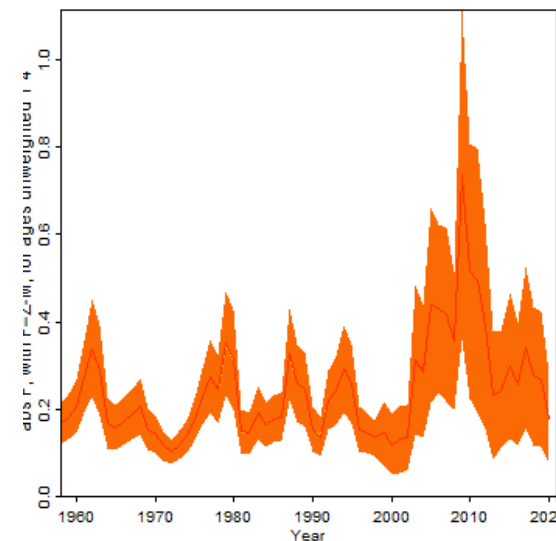
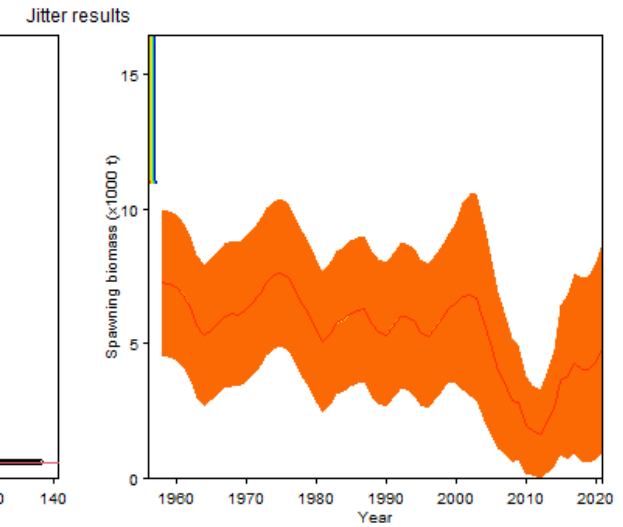
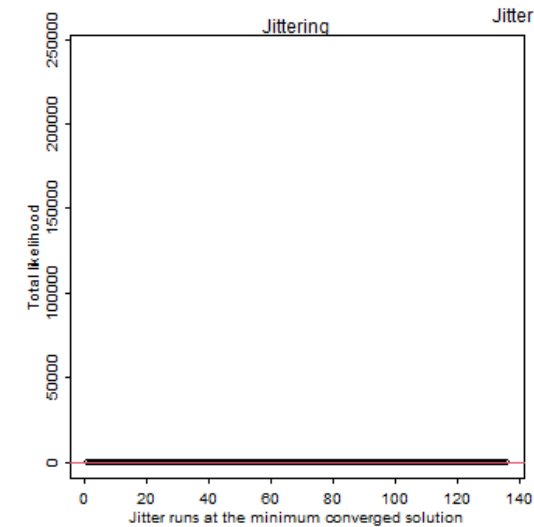
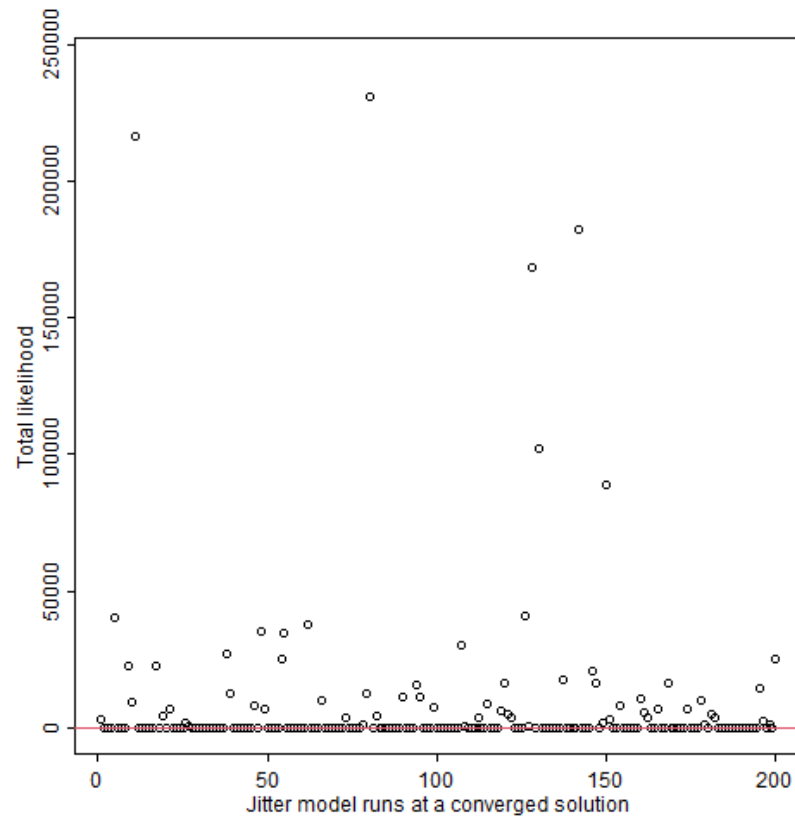
- Joint-residuals
- Runs tests

## 3. Consistency

- Retrospective analysis

## 4. Prediction skills

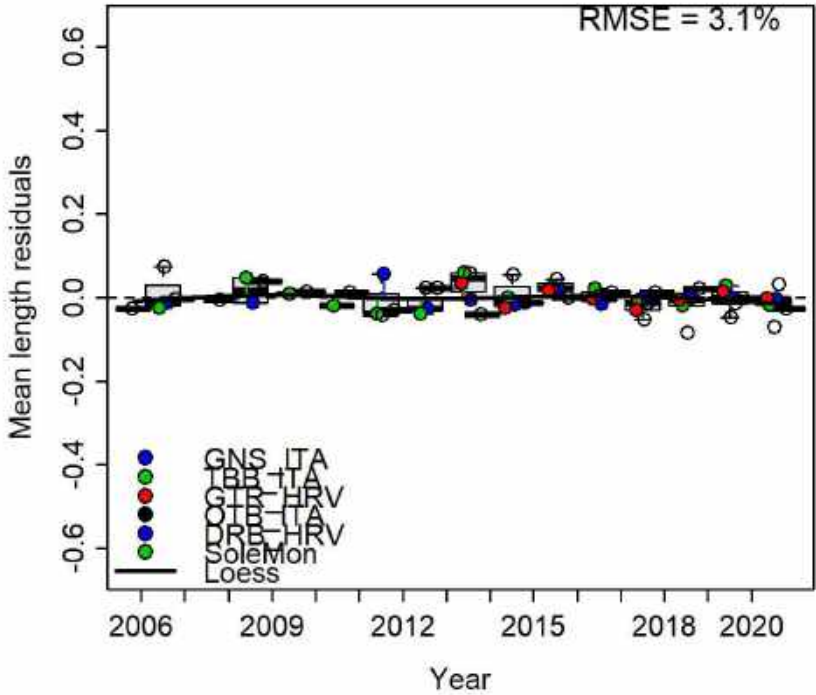
- Hindcasting  
(CrossValidation)



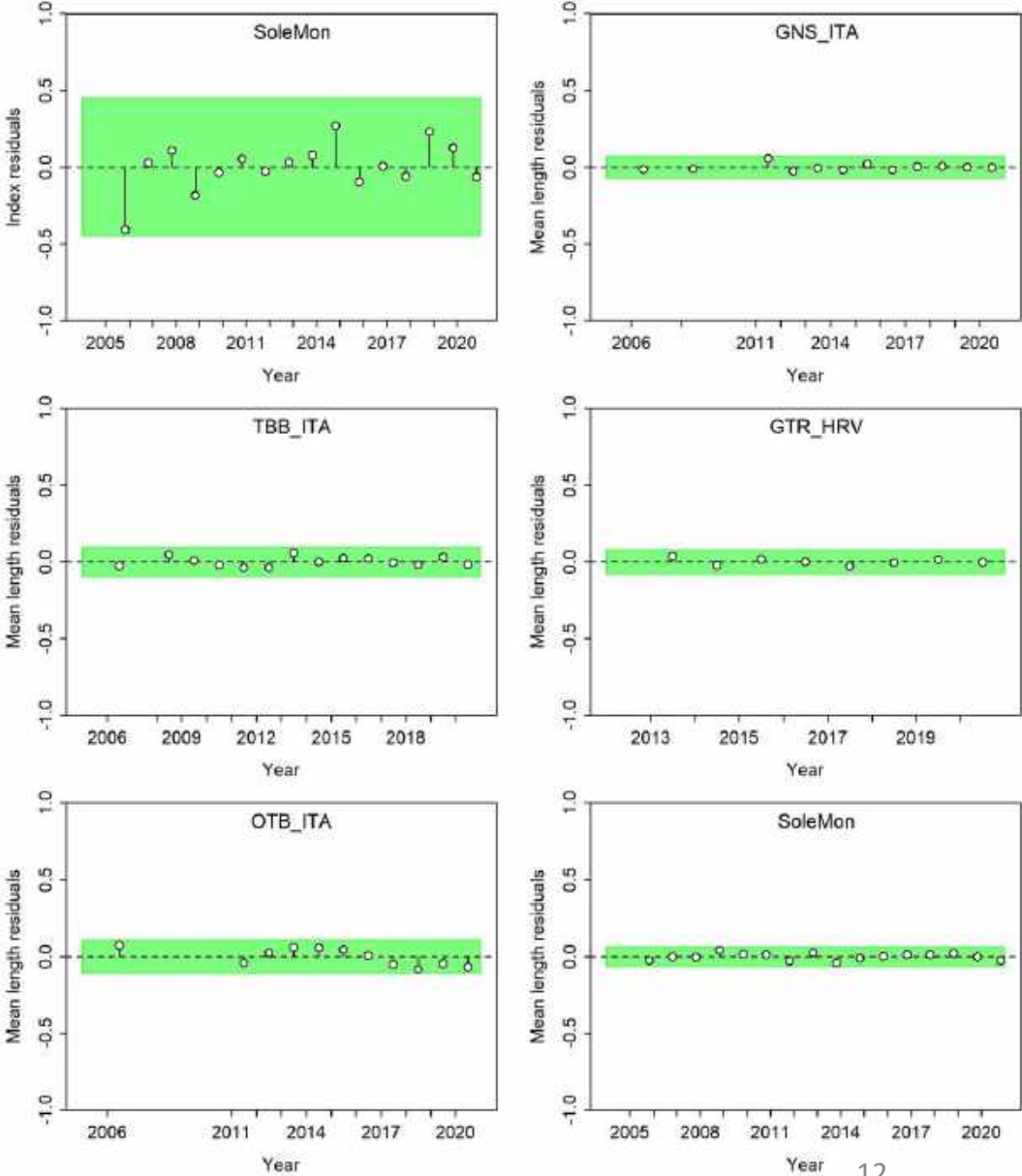
# Diagnostic - Goodness of the fit



Joint-residuals



Runs tests



## 1. Convergence & stability

- Positive Hessian
- Jittering

## 2. Goodness of the fit

- Joint-residuals
- Runs tests

## 3. Consistency

- Retrospective analysis

## 4. Prediction skills

- Hindcasting (CrossValidation)



# Diagnostic - Consistency



## 1. Convergence & stability

- Positive Hessian
- Jittering

## 2. Goodness of the fit

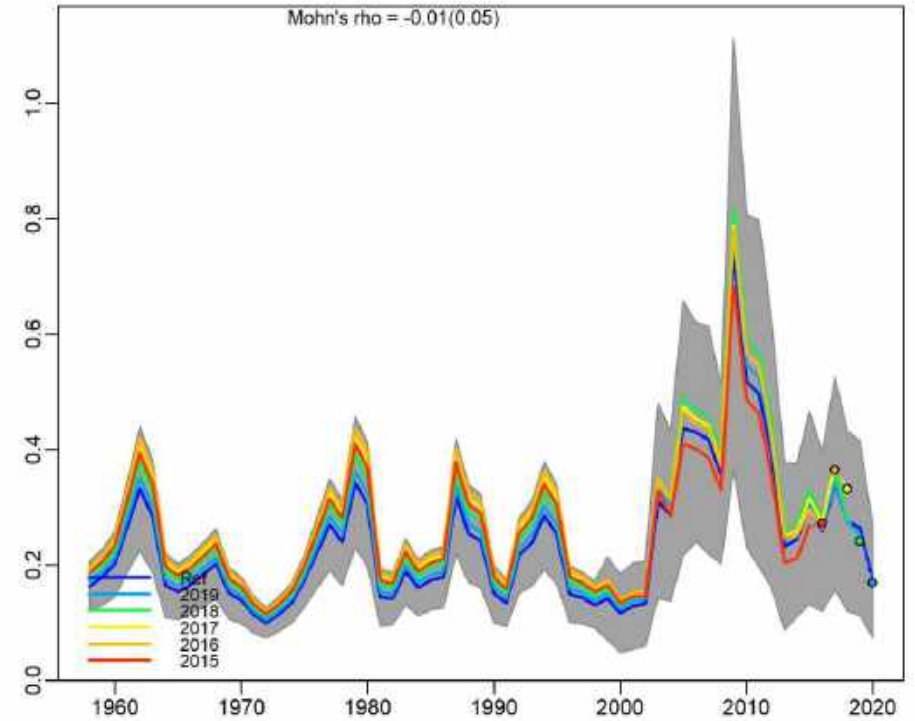
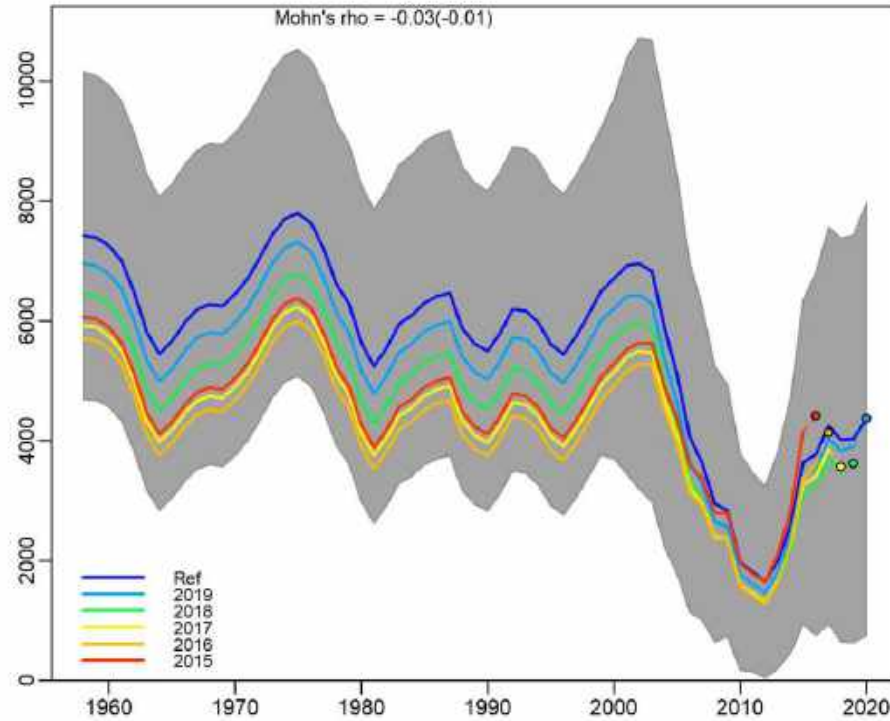
- Joint-residuals
- Runs tests

## 3. Consistency

- Retrospective analysis

## 4. Prediction skills

- Hindcasting  
(CrossValidation)





# Diagnostic - Prediction skills



## MASE Length comp

## MASE CPUE Index

### 1. Convergence & stability

- Positive Hessian
- Jittering

### 2. Goodness of the fit

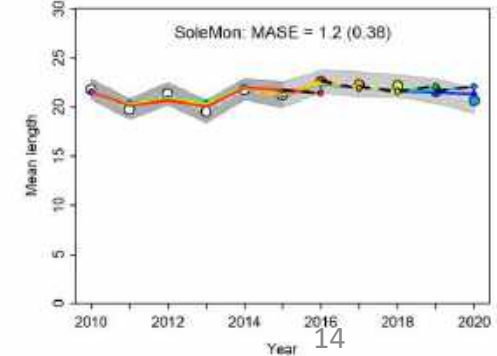
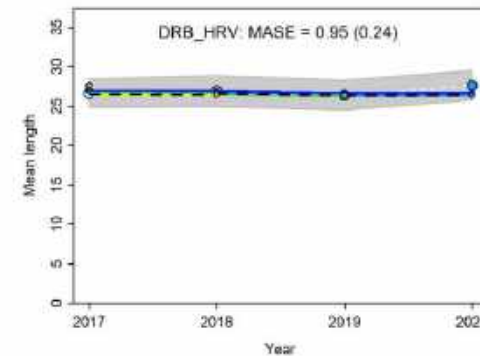
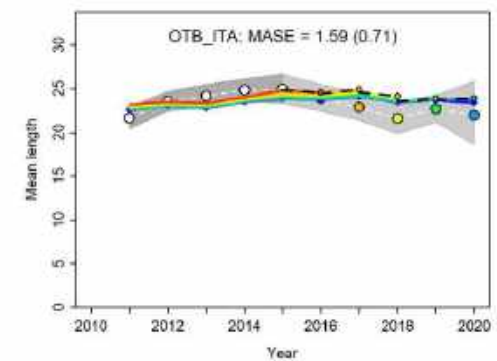
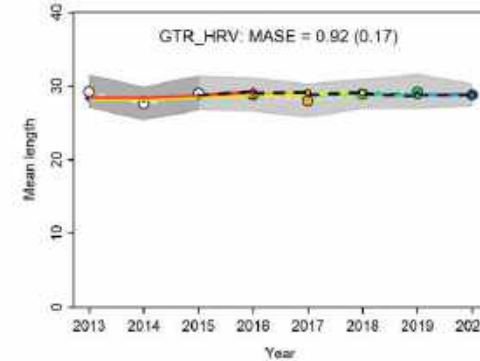
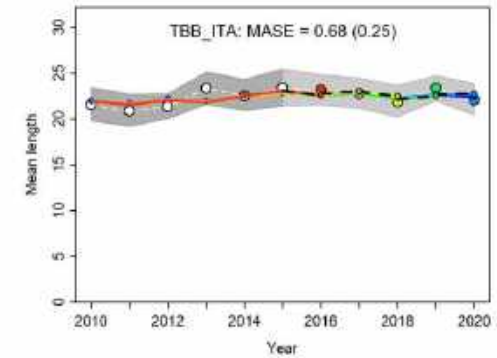
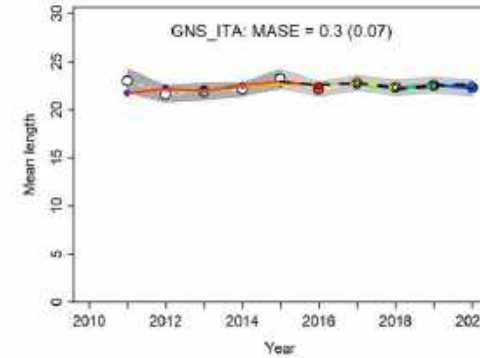
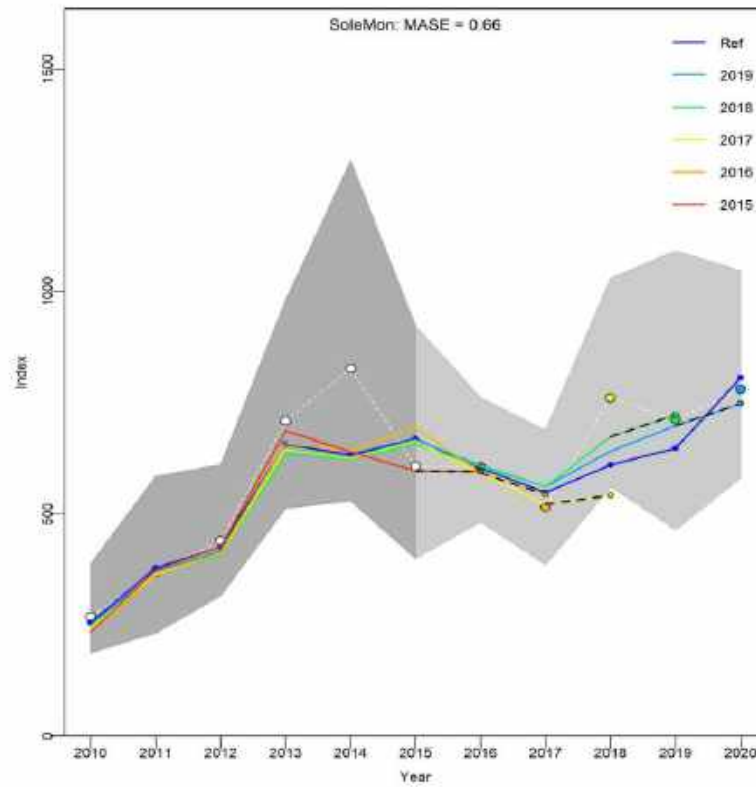
- Joint-residuals
- Runs tests

### 3. Consistency

- Retrospective analysis

### 4. Prediction skills

- Hindcasting  
(CrossValidation)



# Model weighting (diagnostic scores)

$$W(\text{Diagnostics}) = \frac{W(\text{Diags 1}) + W(\text{Diags 2}) + W(\text{Diags 3}) \dots + W(\text{Diags N})}{\text{Num of } W(\text{Diags})}$$



Where Runs test and MASE were aggregated in a single weight (balanced) with a 70% threshold

## 1. Convergence & stability

- Positive Hessian
- Jittering

## 2. Goodness of the fit

- Joint-residuals
- Runs tests

## 3. Consistency

- Retrospective analysis

## 4. Prediction skills

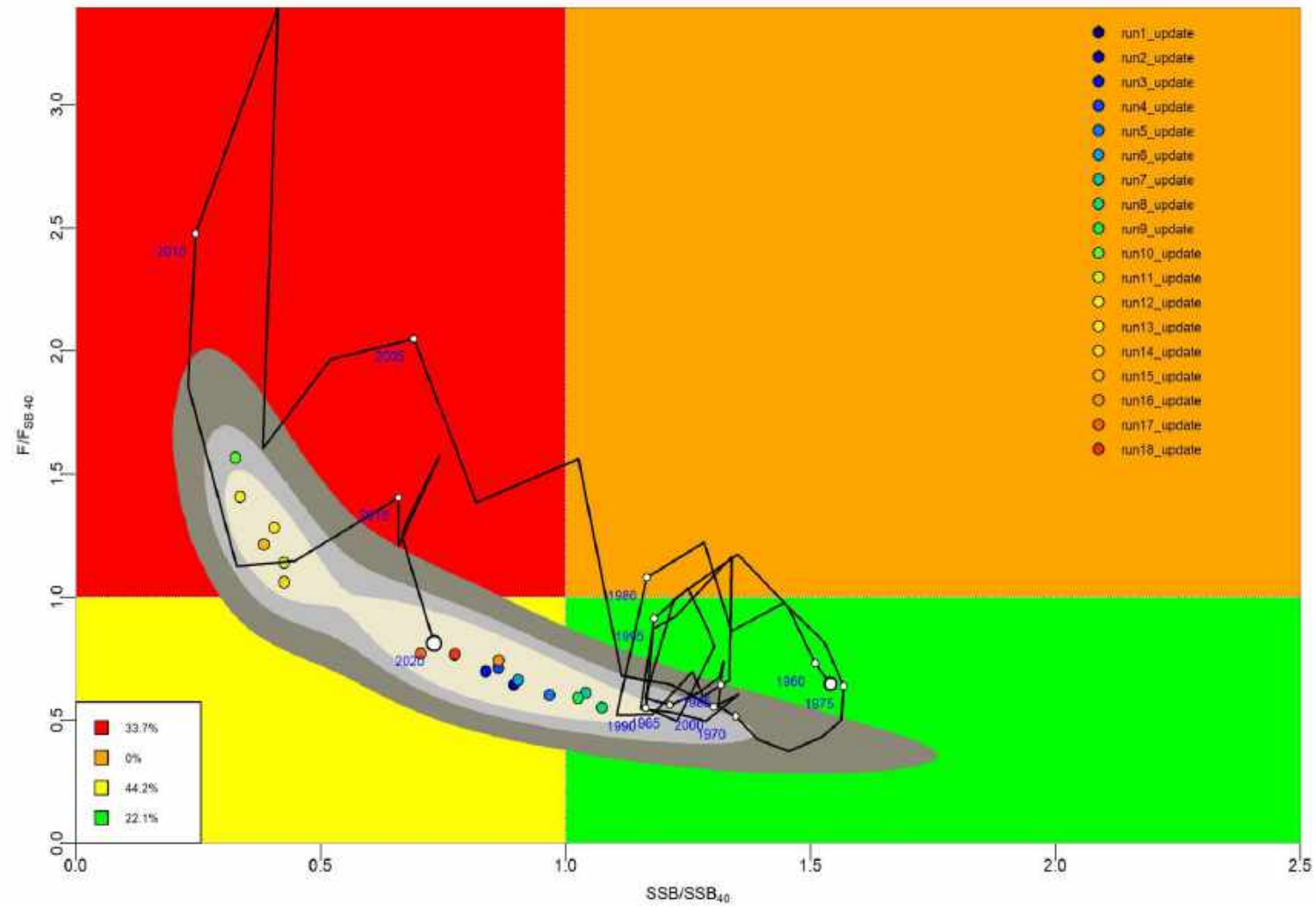
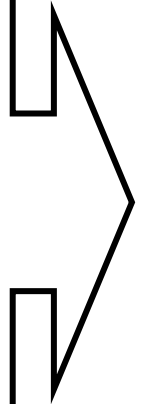
- Hindcasting (CrossValidation)

| Run name | Convergence and stability |           | Goodness of the fit |            |            |            |            |            |                 |        | Consistency            |              |         |            | Prediction skills  |           |          | W(Diagnostics) |
|----------|---------------------------|-----------|---------------------|------------|------------|------------|------------|------------|-----------------|--------|------------------------|--------------|---------|------------|--------------------|-----------|----------|----------------|
|          | Positive Hessian          | Jittering | Run test            |            |            |            |            |            | Joint-residuals |        | Retrospective analysis |              |         |            | Hindcasting (MASE) |           |          |                |
|          |                           |           | Index               | lenGNS_ITA | lenTBB_ITA | lenGTR_HRV | lenOTB_ITA | lenSoleMon | Index           | Length | Retro_SSB              | Forecast_SSB | Retro_F | Forecast_L | Index              | SurveyLen | COMfleet |                |
| Run1     | Passed                    |           | Passed              | Passed     | Passed     | Passed     | Passed     | Passed     | 15.2            | 3.1    | -0.083                 | -0.070       | 0.021   | 0.035      | 0.726              | 0.399     | 0.320    | 1.00           |
| Run2     | Passed                    |           | Passed              | Passed     | Passed     | Passed     | Passed     | Passed     | 14.7            | 3.1    | -0.058                 | -0.054       | 0.026   | 0.052      | 0.863              | 0.363     | 0.312    | 1.00           |
| Run3     | Passed                    |           | Passed              | Passed     | Passed     | Passed     | Passed     | Passed     | 14.9            | 3.1    | -0.061                 | -0.053       | 0.016   | 0.036      | 0.766              | 0.382     | 0.316    | 1.00           |
| Run4     | Passed                    |           | Passed              | Passed     | Passed     | Passed     | Passed     | Passed     | 15.4            | 3.1    | -0.074                 | -0.059       | 0.018   | 0.029      | 0.714              | 0.407     | 0.319    | 1.00           |
| Run5     | Passed                    |           | Passed              | Passed     | Passed     | Passed     | Passed     | Passed     | 14.7            | 3.1    | -0.040                 | -0.036       | 0.014   | 0.040      | 0.842              | 0.370     | 0.312    | 1.00           |
| Run6     | Passed                    |           | Passed              | Passed     | Passed     | Passed     | Passed     | Passed     | 14.9            | 3.1    | -0.036                 | -0.030       | 0.008   | 0.026      | 0.743              | 0.334     | 0.316    | 1.00           |
| Run7     | Passed                    |           | Passed              | Passed     | Passed     | Passed     | Passed     | Passed     | 15              | 3.1    | -0.078                 | -0.064       | 0.034   | 0.047      | 0.744              | 0.410     | 0.317    | 1.00           |
| Run8     | Passed                    |           | Passed              | Passed     | Passed     | Passed     | Passed     | Passed     | 14.4            | 3.1    | -0.037                 | -0.033       | 0.017   | 0.042      | 0.825              | 0.377     | 0.312    | 1.00           |
| Run9     | Passed                    | Passed    | Passed              | Passed     | Passed     | Passed     | Passed     | Passed     | 14.7            | 3.1    | -0.054                 | -0.044       | 0.021   | 0.040      | 0.750              | 0.396     | 0.315    | 1.00           |
| Run10    | Passed                    |           | Passed              | Passed     | Passed     | Passed     | Passed     | Passed     | Passed          | 21.2   | 3.3                    | 0.126        | 0.157   | -0.106     | -0.072             | 0.967     | 0.455    | 0.375          |
| Run11    | Passed                    |           | Passed              | Passed     | Passed     | Passed     | Passed     | Passed     | 20.1            | 3.6    | 0.013                  | 0.003        | -0.009  | 0.041      | 1.362              | 0.450     | 0.351    | 0.93           |
| Run12    | Passed                    |           | Passed              | Passed     | Passed     | Passed     | Passed     | Passed     | 21.1            | 3.4    | 0.083                  | 0.092        | -0.067  | -0.037     | 1.166              | 0.388     | 0.367    | 0.93           |
| Run13    | Passed                    |           | Passed              | Passed     | Passed     | Passed     | Passed     | Passed     | 20.2            | 3.2    | 0.123                  | 0.162        | -0.113  | -0.087     | 0.796              | 0.472     | 0.362    | 1.00           |
| Run14    | Passed                    |           | Passed              | Passed     | Passed     | Passed     | Passed     | Passed     | 19.4            | 3.4    | 0.042                  | 0.043        | -0.040  | -0.001     | 1.098              | 0.464     | 0.344    | 0.93           |
| Run15    | Passed                    |           | Passed              | Passed     | Passed     | Passed     | Passed     | Passed     | 20.1            | 3.2    | 0.086                  | 0.102        | -0.078  | -0.044     | 0.957              | 0.463     | 0.354    | 1.00           |
| Run16    | Passed                    |           | Passed              | Passed     | Passed     | Passed     | Passed     | Passed     | 16.7            | 3.1    | 0.070                  | 0.081        | -0.067  | -0.024     | 0.777              | 0.423     | 0.346    | 1.00           |
| Run17    | Passed                    |           | Passed              | Passed     | Passed     | Passed     | Passed     | Passed     | 16.6            | 3.1    | 0.049                  | 0.051        | -0.045  | 0.001      | 0.887              | 0.421     | 0.340    | 1.00           |
| Run18    | Passed                    |           | Passed              | Passed     | Passed     | Passed     | Passed     | Passed     | 16.7            | 3.1    | 0.062                  | 0.070        | -0.058  | -0.014     | 0.810              | 0.423     | 0.344    | 1.00           |

# Ensemble model Results



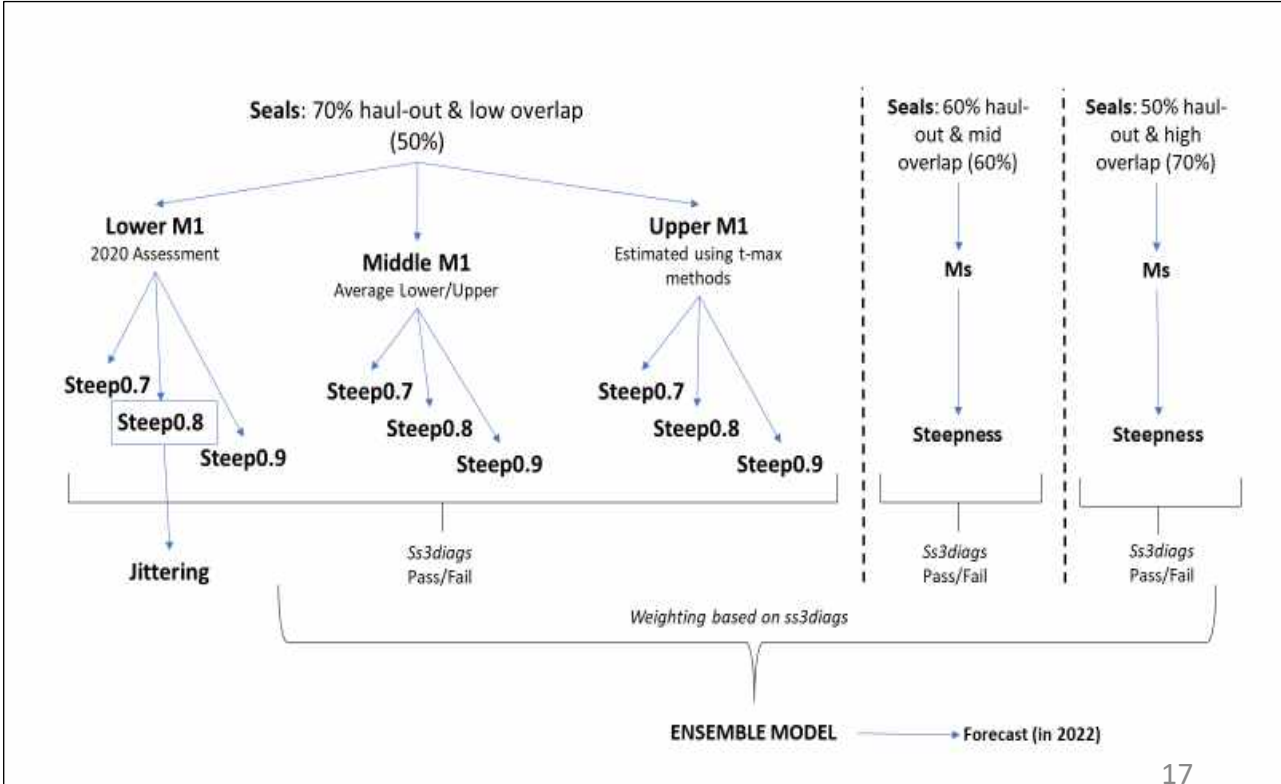
| Name  | Selectivity | M  | h   | Weighting |
|-------|-------------|----|-----|-----------|
| run1  | DN          | M1 | 0.9 | 1.00      |
| run2  | DN          | M1 | 0.7 | 1.00      |
| run3  | DN          | M1 | 0.8 | 1.00      |
| run4  | DN          | M2 | 0.9 | 1.00      |
| run5  | DN          | M2 | 0.7 | 1.00      |
| run6  | DN          | M2 | 0.8 | 1.00      |
| run7  | DN          | M3 | 0.9 | 1.00      |
| run8  | DN          | M3 | 0.7 | 1.00      |
| run9  | DN          | M3 | 0.8 | 1.00      |
| run10 | CS          | M1 | 0.9 | 1.00      |
| run11 | CS          | M1 | 0.7 | 0.93      |
| run12 | CS          | M1 | 0.8 | 0.93      |
| run13 | CS          | M2 | 0.9 | 1.00      |
| run14 | CS          | M2 | 0.7 | 0.93      |
| run15 | CS          | M2 | 0.8 | 1.00      |
| run16 | CS          | M3 | 0.9 | 1.00      |
| run17 | CS          | M3 | 0.7 | 1.00      |
| run18 | CS          | M3 | 0.8 | 1.00      |



# Bothnian Sea vendace



- The model uses a weighted median of plausible scenarios
  - In total 27 scenarios, exploring 3 x 3 x 3 levels of
    - Seal predation
    - Basal Natural mortality
    - Steepness



# Bothnian Sea vendace



## 1. Convergence & stability

- Positive Hessian
- Jittering

## 2. Goodness of the fit

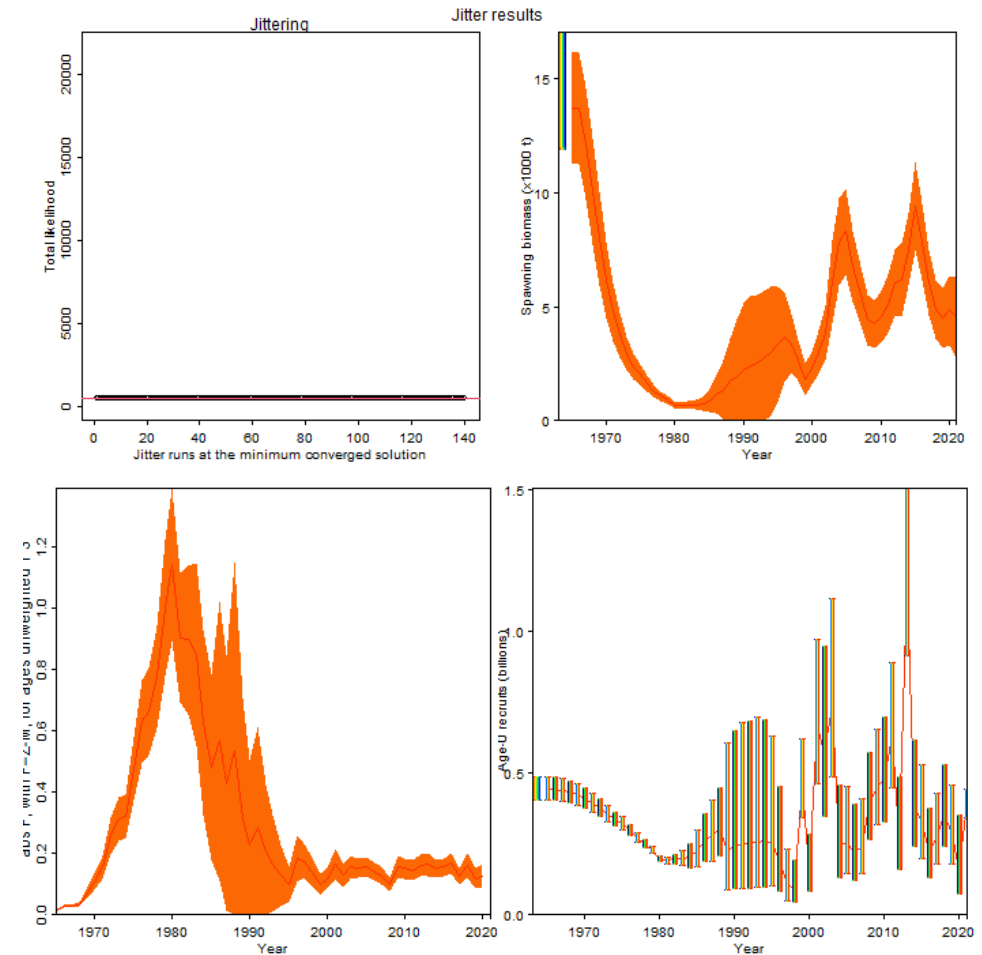
- Joint-residuals
- Runs tests

## 3. Consistency

- Retrospective analysis

## 4. Prediction skills

- Hindcasting  
(CrossValidation)





# Model weighting

Where Runs test and MASE were aggregated in compartmental weight but no threshold



| Ensemble scenario | Convergence & stability | Goodness of fit |        |              |                 |               |                        | Consistency |           |              |                    | Prediction Skill |       |        |          |              |             | Weight |                |                 |
|-------------------|-------------------------|-----------------|--------|--------------|-----------------|---------------|------------------------|-------------|-----------|--------------|--------------------|------------------|-------|--------|----------|--------------|-------------|--------|----------------|-----------------|
|                   |                         | Runs test       |        |              | Joint residuals |               | Retrospective analysis |             |           |              | Hindcasting (MASE) |                  |       |        |          |              |             |        |                |                 |
|                   |                         | CPUE            | Survey | Length catch | Length Seal     | Length survey | Index                  | Length      | SSB retro | SSB forecast | F retro            | F forecast       | CPUE  | Survey | Combined | Length catch | Length Seal |        | Lengthy Survey | Length combined |
| Run1              | Passed                  | Passed          | Passed | Passed       | Passed          | Passed        | 38.2                   | 3.5         | 0.005     | -0.133       | 0.122              | 0.274            | 0.689 | 1.605  | 1.062    | 0.497        | 0.400       | 0.243  | 0.469          | 0.83            |
| Run2              | Passed                  | Passed          | Passed | Passed       | Passed          | Passed        | 36                     | 3.4         | 0.138     | 0.096        | -0.102             | -0.088           | 0.977 | 0.704  | 0.866    | 0.506        | 0.218       | 0.224  | 0.423          | 0.94            |
| Run3              | Passed                  | Passed          | Passed | Passed       | Passed          | Passed        | 34.8                   | 3.4         | 0.135     | 0.096        | -0.110             | -0.087           | 0.982 | 0.692  | 0.864    | 0.500        | 0.233       | 0.252  | 0.424          | 0.94            |
| Run4              | Passed                  | Passed          | Passed | Passed       | Passed          | Passed        | 37.6                   | 3.5         | 0.092     | -0.012       | 0.009              | 0.107            | 1.230 | 1.213  | 1.223    | 0.509        | 0.215       | 0.174  | 0.425          | 0.78            |
| Run5              | Passed                  | Passed          | Passed | Passed       | Passed          | Passed        | 35.9                   | 3.4         | 0.125     | 0.088        | -0.097             | -0.086           | 0.983 | 0.702  | 0.869    | 0.511        | 0.236       | 0.209  | 0.432          | 0.94            |
| Run6              | Passed                  | Passed          | Passed | Passed       | Passed          | Passed        | 34.6                   | 3.4         | 0.117     | 0.080        | -0.101             | -0.083           | 0.962 | 0.697  | 0.854    | 0.520        | 0.243       | 0.236  | 0.441          | 0.94            |
| Run7              | Passed                  | Passed          | Passed | Passed       | Passed          | Passed        | 37.3                   | 3.4         | 0.124     | 0.072        | -0.078             | -0.069           | 0.963 | 0.826  | 0.907    | 0.502        | 0.224       | 0.196  | 0.423          | 0.94            |
| Run8              | Passed                  | Passed          | Passed | Passed       | Passed          | Passed        | 35.8                   | 3.4         | 0.126     | 0.093        | -0.100             | -0.090           | 0.988 | 0.704  | 0.872    | 0.513        | 0.242       | 0.203  | 0.435          | 0.94            |
| Run9              | Passed                  | Passed          | Passed | Passed       | Passed          | Passed        | 34.7                   | 3.4         | 0.126     | 0.089        | -0.106             | -0.084           | 0.976 | 0.700  | 0.864    | 0.503        | 0.239       | 0.244  | 0.428          | 0.94            |
| Run11             | Passed                  | Passed          | Passed | Passed       | Passed          | Passed        | 36.3                   | 3.4         | 0.153     | 0.111        | -0.110             | -0.099           | 0.976 | 0.706  | 0.867    | 0.505        | 0.217       | 0.217  | 0.422          | 0.94            |
| Run12             | Passed                  | Passed          | Passed | Passed       | Passed          | Passed        | 34.9                   | 3.4         | 0.146     | 0.107        | -0.116             | -0.095           | 0.980 | 0.679  | 0.857    | 0.499        | 0.232       | 0.248  | 0.422          | 0.94            |
| Run13             | Passed                  | Passed          | Passed | Passed       | Passed          | Passed        | 38                     | 3.5         | 0.115     | 0.047        | -0.064             | -0.047           | 0.923 | 0.834  | 0.887    | 0.495        | 0.212       | 0.175  | 0.414          | 0.94            |
| Run14             | Passed                  | Passed          | Passed | Passed       | Passed          | Passed        | 36.2                   | 3.4         | 0.135     | 0.098        | -0.102             | -0.093           | 0.981 | 0.705  | 0.869    | 0.510        | 0.235       | 0.203  | 0.431          | 0.94            |
| Run15             | Passed                  | Passed          | Passed | Passed       | Passed          | Passed        | 34.8                   | 3.4         | 0.139     | 0.100        | -0.113             | -0.096           | 0.957 | 0.682  | 0.845    | 0.518        | 0.236       | 0.244  | 0.437          | 0.94            |
| Run16             | Passed                  | Passed          | Passed | Passed       | Passed          | Passed        | 37.7                   | 3.5         | 0.126     | 0.073        | -0.080             | -0.076           | 0.966 | 0.757  | 0.881    | 0.500        | 0.222       | 0.170  | 0.421          | 0.94            |
| Run17             | Passed                  | Passed          | Passed | Passed       | Passed          | Passed        | 36.1                   | 3.4         | 0.150     | 0.114        | -0.110             | -0.102           | 0.985 | 0.698  | 0.868    | 0.507        | 0.228       | 0.224  | 0.428          | 0.94            |
| Run18             | Passed                  | Passed          | Passed | Passed       | Passed          | Passed        | 34.9                   | 3.4         | 0.152     | 0.113        | -0.120             | -0.099           | 0.974 | 0.684  | 0.856    | 0.500        | 0.231       | 0.252  | 0.423          | 0.94            |
| Run19             | Passed                  | Passed          | Passed | Passed       | Passed          | Passed        | 39                     | 3.6         | 0.135     | 0.053        | -0.061             | -0.038           | 0.875 | 0.872  | 0.874    | 0.483        | 0.198       | 0.177  | 0.401          | 0.94            |
| Run20             | Passed                  | Passed          | Passed | Passed       | Passed          | Passed        | 36.5                   | 3.4         | 0.158     | 0.118        | -0.113             | -0.105           | 0.967 | 0.710  | 0.862    | 0.503        | 0.222       | 0.214  | 0.423          | 0.94            |
| Run21             | Passed                  | Passed          | Passed | Passed       | Passed          | Passed        | 35                     | 3.4         | 0.167     | 0.126        | -0.128             | -0.107           | 0.974 | 0.677  | 0.853    | 0.496        | 0.224       | 0.258  | 0.419          | 0.94            |
| Run22             | Passed                  | Passed          | Passed | Passed       | Passed          | Passed        | 38.4                   | 3.5         | 0.135     | 0.070        | -0.073             | -0.063           | 0.926 | 0.818  | 0.882    | 0.496        | 0.213       | 0.198  | 0.415          | 0.94            |
| Run23             | Passed                  | Passed          | Passed | Passed       | Passed          | Passed        | 36.4                   | 3.4         | 0.151     | 0.113        | -0.109             | -0.102           | 0.977 | 0.702  | 0.865    | 0.507        | 0.230       | 0.212  | 0.428          | 0.94            |
| Run24             | Passed                  | Passed          | Passed | Passed       | Passed          | Passed        | 34.9                   | 3.4         | 0.174     | 0.137        | -0.129             | -0.113           | 0.953 | 0.692  | 0.847    | 0.518        | 0.234       | 0.261  | 0.437          | 0.94            |
| Run25             | Passed                  | Passed          | Passed | Passed       | Passed          | Passed        | 38.1                   | 3.5         | 0.191     | 0.145        | -0.093             | -0.093           | 0.951 | 0.747  | 0.868    | 0.491        | 0.212       | 0.219  | 0.411          | 0.94            |
| Run26             | Passed                  | Passed          | Passed | Passed       | Passed          | Passed        | 36.3                   | 3.4         | 0.141     | 0.106        | -0.105             | -0.099           | 0.981 | 0.705  | 0.869    | 0.511        | 0.241       | 0.195  | 0.434          | 0.94            |
| Run27             | Passed                  | Passed          | Passed | Passed       | Passed          | Passed        | 35                     | 3.4         | 0.133     | 0.096        | -0.110             | -0.089           | 0.972 | 0.677  | 0.852    | 0.502        | 0.243       | 0.225  | 0.428          | 0.94            |

## 1. Convergence & stability

- Positive Hessian
- Jittering

## 2. Goodness of the fit

- Joint-residuals
- Runs tests

## 3. Consistency

- Retrospective analysis

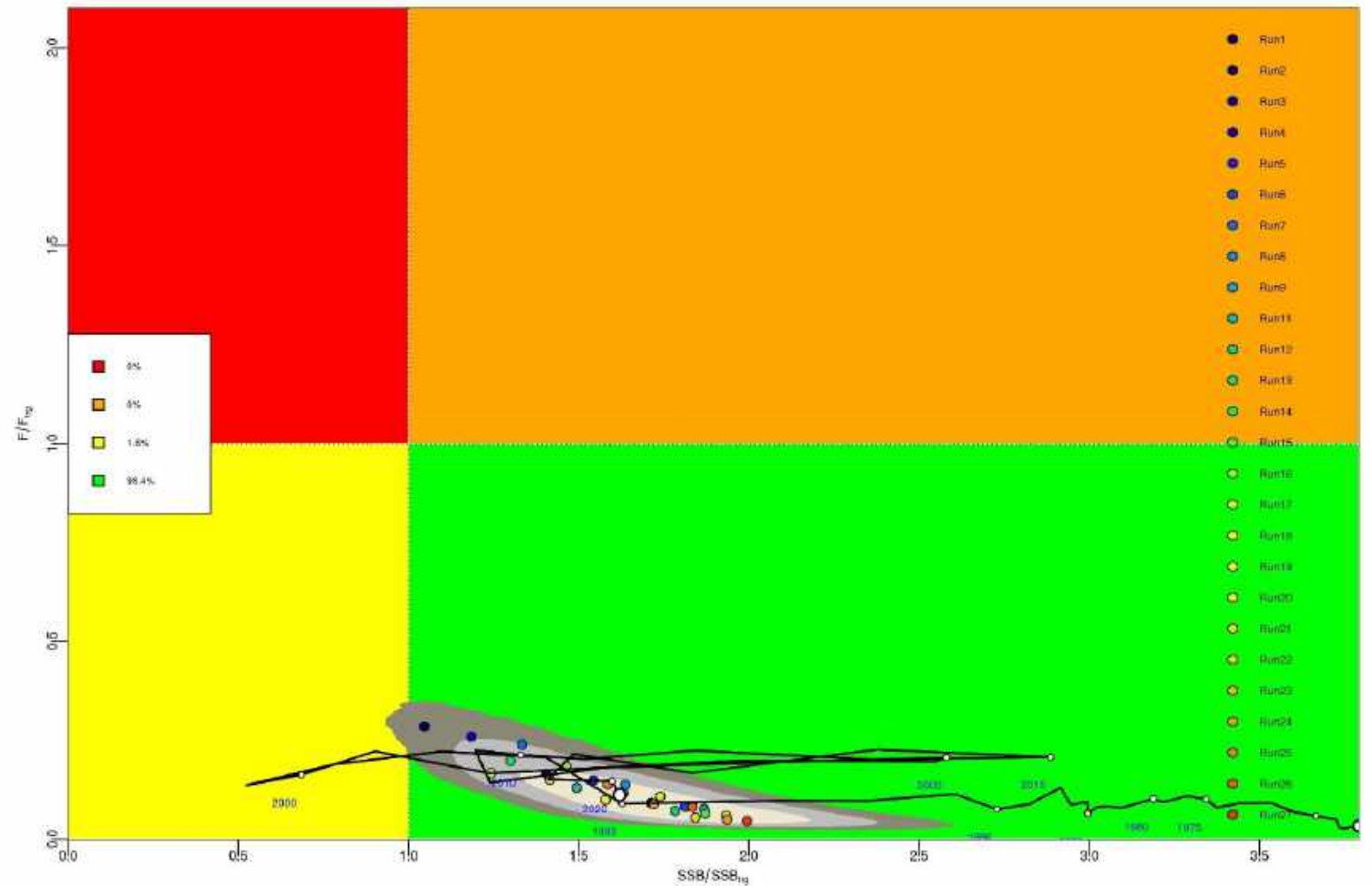
## 4. Prediction skills

- Hindcasting (CrossValidation)

# Ensemble model results



| Name  | Seals  | Natural Mortality | Steepness | Weight |
|-------|--------|-------------------|-----------|--------|
| run1  | low    | M1 low            | 0.7       | 0.83   |
| run2  | low    | M1 middle         | 0.7       | 0.94   |
| run3  | low    | M1 high           | 0.7       | 0.94   |
| run4  | low    | M1 low            | 0.8       | 0.78   |
| run5  | low    | M1 middle         | 0.8       | 0.94   |
| run6  | low    | M1 high           | 0.8       | 0.94   |
| run7  | low    | M1 low            | 0.9       | 0.94   |
| run8  | low    | M1 middle         | 0.9       | 0.94   |
| run9  | low    | M1 high           | 0.9       | 0.94   |
| run10 | middle | M1 low            | 0.7       | 0.83   |
| run11 | middle | M1 middle         | 0.7       | 0.94   |
| run12 | middle | M1 high           | 0.7       | 0.94   |
| run13 | middle | M1 low            | 0.8       | 0.94   |
| run14 | middle | M1 middle         | 0.8       | 0.94   |
| run15 | middle | M1 high           | 0.8       | 0.94   |
| run16 | middle | M1 low            | 0.9       | 0.94   |
| run17 | middle | M1 middle         | 0.9       | 0.94   |
| run18 | middle | M1 high           | 0.9       | 0.94   |
| run19 | high   | M1 low            | 0.7       | 0.94   |
| run20 | high   | M1 middle         | 0.7       | 0.94   |
| run21 | high   | M1 high           | 0.7       | 0.94   |
| run22 | high   | M1 low            | 0.8       | 0.94   |
| run23 | high   | M1 middle         | 0.8       | 0.94   |
| run24 | high   | M1 high           | 0.8       | 0.94   |
| run25 | high   | M1 low            | 0.9       | 0.94   |
| run26 | high   | M1 middle         | 0.9       | 0.94   |
| run27 | high   | M1 high           | 0.9       | 0.94   |



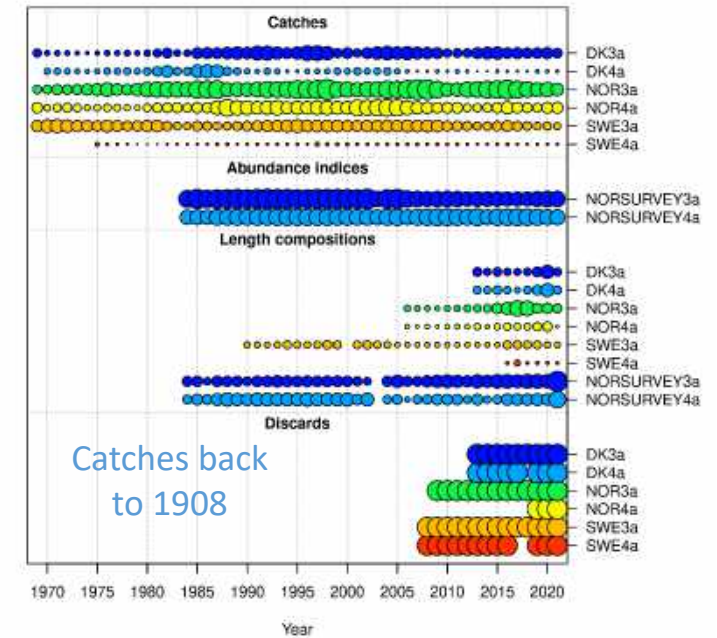
# Northern shrimp



The 1<sup>st</sup> application of ensemble modelling in ICES stock assessment and advice



Two area/age-based using SS3



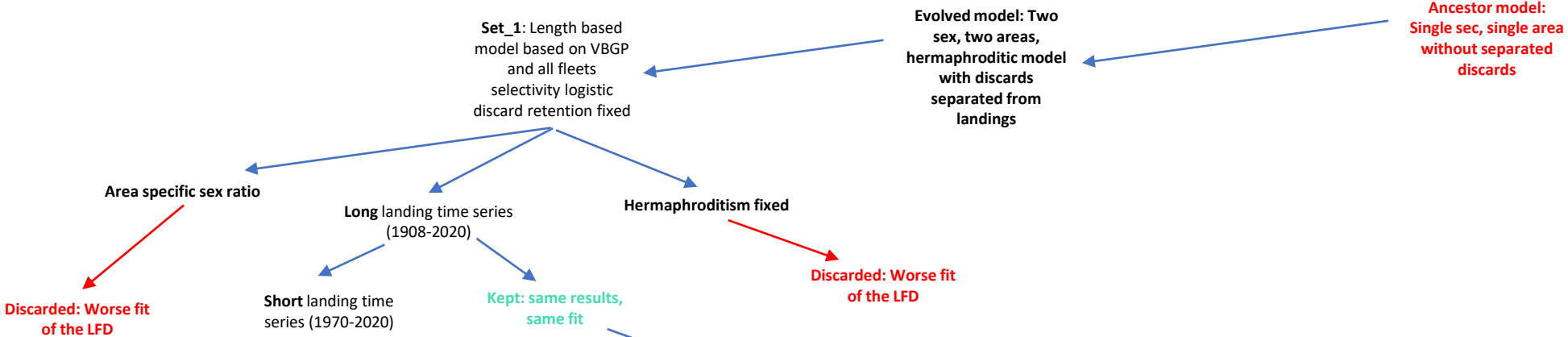
ICES Advice on fishing opportunities, catch, and effort  
Greater North Sea ecoregion  
Published 09 May 2022



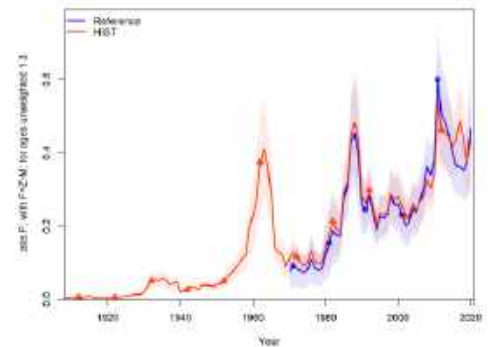
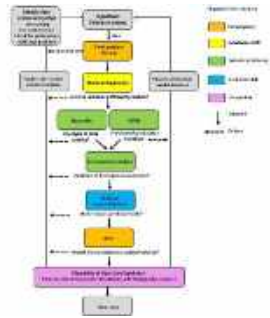
Northern shrimp (*Pandalus borealis*) in divisions 3.a and 4.a East (Skagerrak and Kattegat and northern North Sea in the Norwegian Deep)



# ICES Benchmark of *Northern shrimp* in 3a and 4a east



## Iterative



Jittering and MCMC

Ss3diags  
Pass/Fail

M1  
(base, h=0.7)

M2  
(low, h=0.89)

M3  
(high, h=0.52)

Predation M  
(h=0.91)

Weighting based on ss3diags

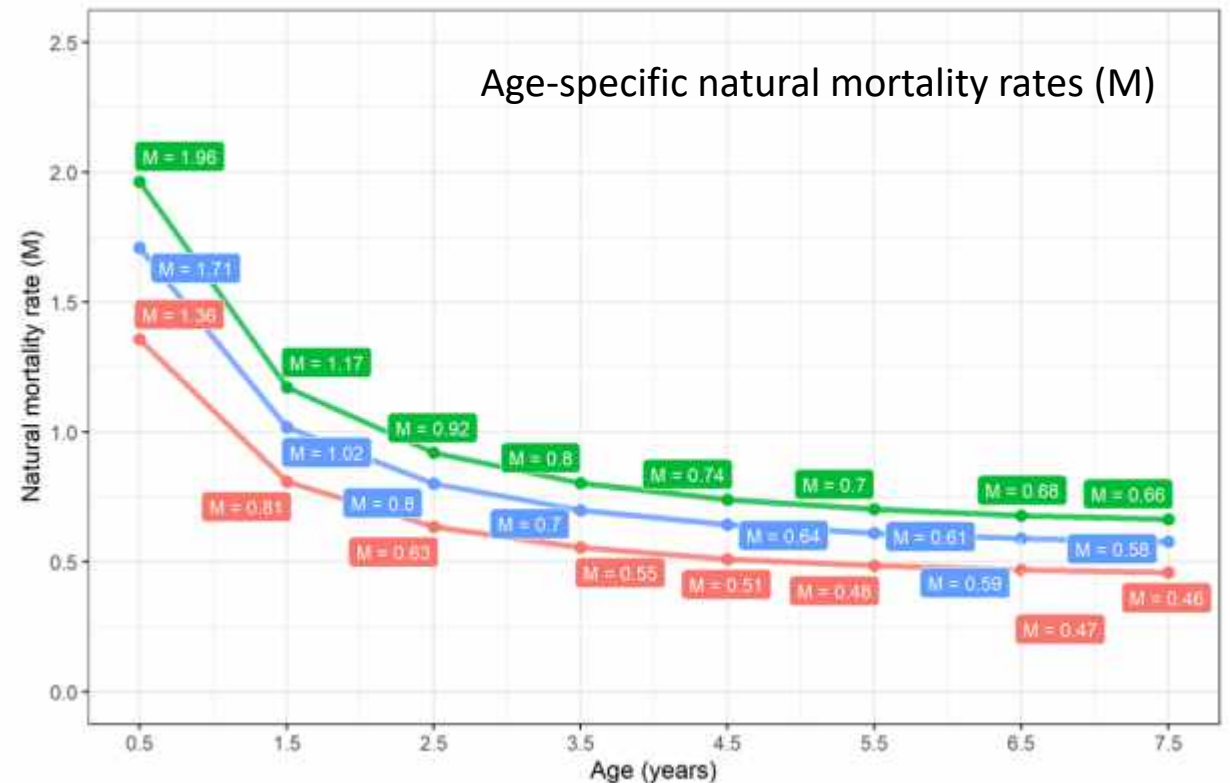
ENSEMBLE MODEL

Forecast

# Why use an ensemble of M?



- Pandalus is an important prey species in the North Sea
- Eaten by a range of predators including cod and saithe (Jørgensen et al., 2014; Skorda, 2018)
- Despite this, we remain uncertain about the levels of natural mortality (M)
- Ensemble modelling allows us overcome this and incorporate 3 different but equally plausible scenarios for M (median, high and low) in our assessment of the stock





# Weights



- As with vendace and sole, the model uses a weighted median of the 3 plausible scenarios based on ss3diags (Carvalho et al. 2021)

[jabbamodel / ss3diags](#) Public

A cookbook for using model diagnostics in integrated stock assessments

Felipe Carvalho<sup>a,\*</sup>, Henning Winker<sup>b,\*</sup>, Dean Courtney<sup>c</sup>, Maia Kapur<sup>d</sup>, Laurence Kell<sup>e</sup>,  
Massimiliano Cardinale<sup>f</sup>, Michael Schirripa<sup>g</sup>, Toshihide Kitakado<sup>h</sup>, Dawit Yemane<sup>i</sup>,  
Kevin R. Piner<sup>j</sup>, Mark N. Maunder<sup>k,l</sup>, Ian Taylor<sup>m</sup>, Chantel R. Wetzel<sup>m</sup>, Kathryn Doering<sup>n</sup>,  
Kelli F. Johnson<sup>m</sup>, Richard D. Method<sup>m</sup>

- The weights are assigned based on 4 criteria:

1. Convergence and Stability
2. Goodness of fit
3. Consistency
4. Predictive skill

Positive  
Hessian/MCMC  
Jittering

Joint residuals  
Runs test

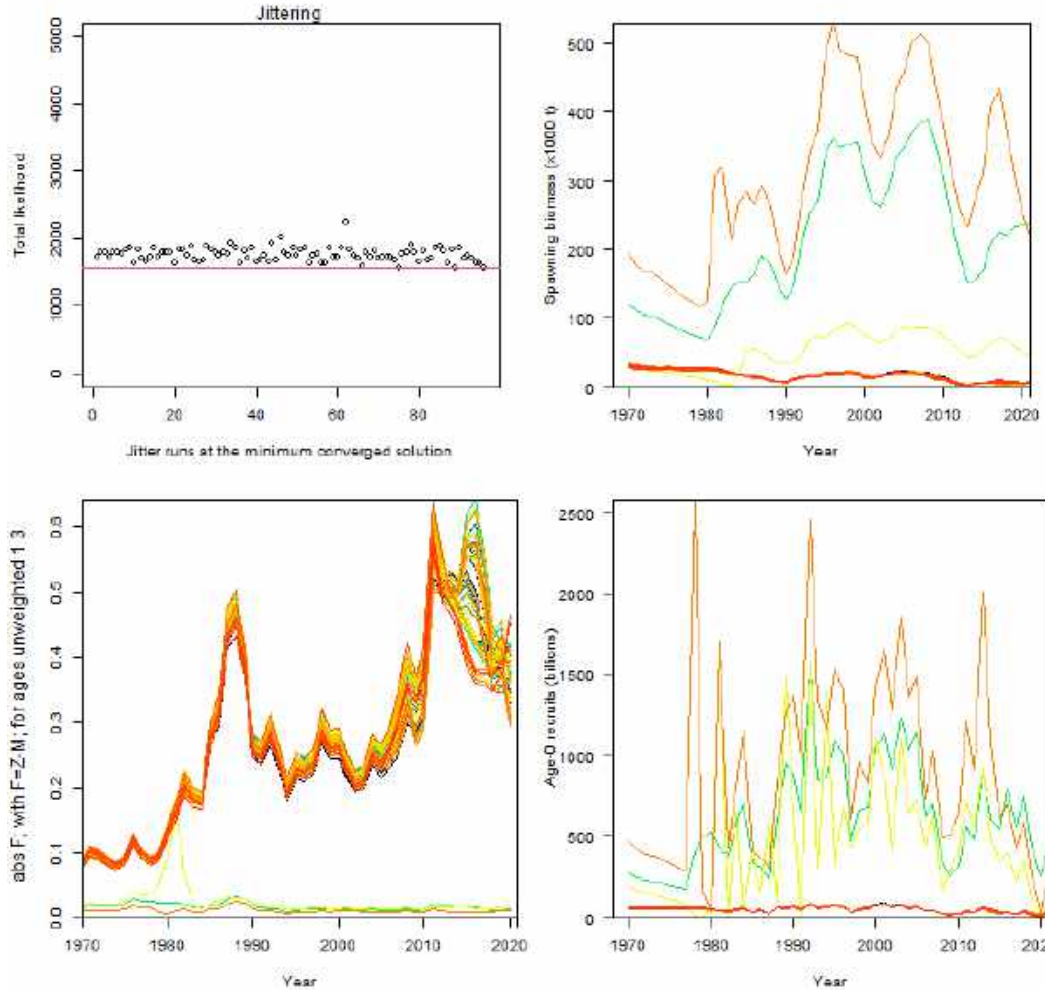
Retrospective  
analysis

Hindcasting  
(Cross Validation)

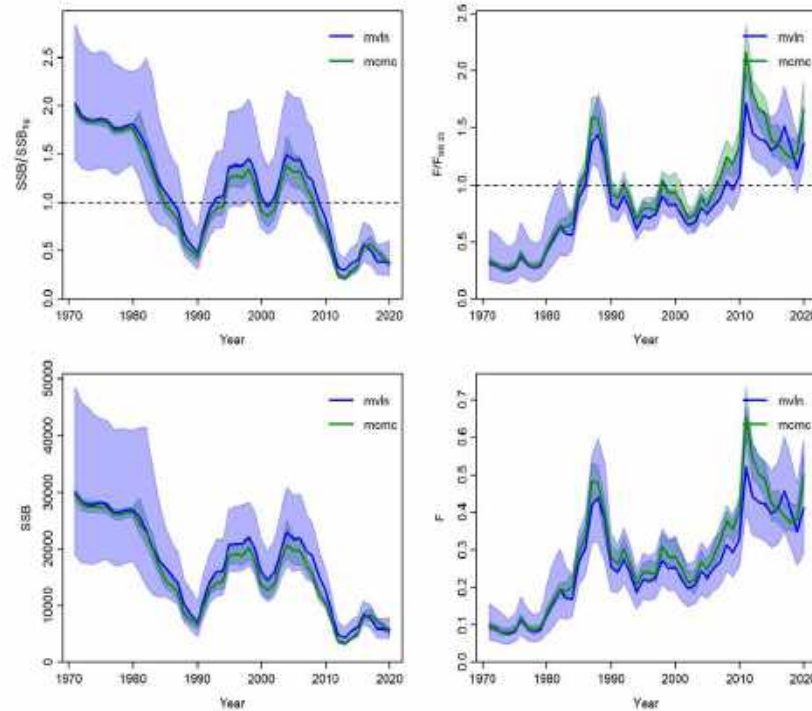
# Convergence and Stability



## Jittering



## MCMC



Positive  
Hessian/MCMC  
Jittering

# Model weights

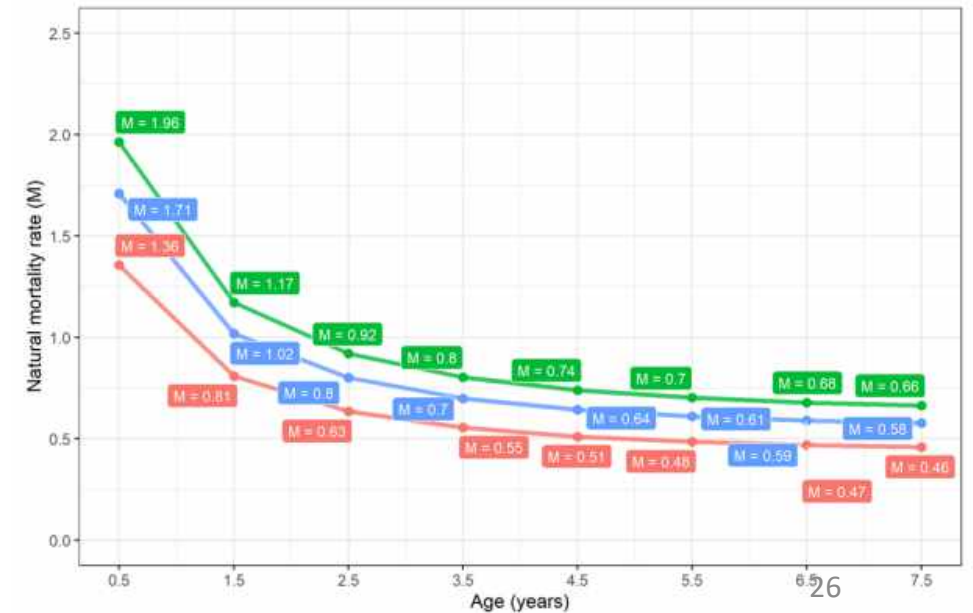
Where Runs test and MASE were not aggregated in a single weight (plain) (no threshold)

| Run name | Convergence and stability |           | Goodness of the fit |        |        |        |        |        |          |        |        |        |        |        |           | Consistency            |         |            |  |
|----------|---------------------------|-----------|---------------------|--------|--------|--------|--------|--------|----------|--------|--------|--------|--------|--------|-----------|------------------------|---------|------------|--|
|          | Positive Hessian          | Jittering | Run test            |        |        |        |        |        | Run test |        |        |        |        |        |           | Retrospective analysis |         |            |  |
|          |                           |           | CPUE1               | CPUE2  | Len1   | Len2   | Len3   | Len4   | Len5     | Len6   | Len7   | Len8   | Index  | Length | Retro_SSB | Forecast_SSB           | Retro_F | Forecast_F |  |
| Run1     | Passed                    |           | Passed              | Passed | Failed | Passed | Failed | Passed | Failed   | Passed | Passed | Failed | Passed | Passed | Passed    | Passed                 | Passed  | Passed     |  |
| Run2     | Passed                    | Passed    | Passed              | Failed | Failed | Passed | Failed | Passed | Failed   | Passed | Passed | Failed | Passed | Passed | Passed    | Passed                 | Passed  | Failed     |  |
| Run3     | Passed                    |           | Passed              | Passed | Passed | Passed | Failed | Passed | Failed   | Failed | Passed | Failed | Passed | Passed | Passed    | Passed                 | Passed  | Passed     |  |

| Prediction skills  |         |        |        |        |         |         |         |         |         |         |         |         |
|--------------------|---------|--------|--------|--------|---------|---------|---------|---------|---------|---------|---------|---------|
| Hindcasting (MASE) |         |        |        |        |         |         |         |         |         |         |         |         |
| Survey3a           | Surve4a | Joint  | Len3a  | Len4a  | lenA1S1 | lenA1S2 | lenA1S3 | lenA1S4 | lenA2S1 | lenA2S2 | lenA2S3 | lenA2S4 |
| Passed             | Passed  | Passed | Passed | Passed | Passed  | Passed  | Passed  | Passed  | Passed  | Passed  | Failed  | Passed  |
| Passed             | Passed  | Passed | Passed | Passed | Passed  | Passed  | Passed  | Passed  | Failed  | Passed  | Failed  | Passed  |
| Passed             | Passed  | Passed | Passed | Passed | Passed  | Passed  | Passed  | Passed  | Passed  | Passed  | Passed  | Passed  |



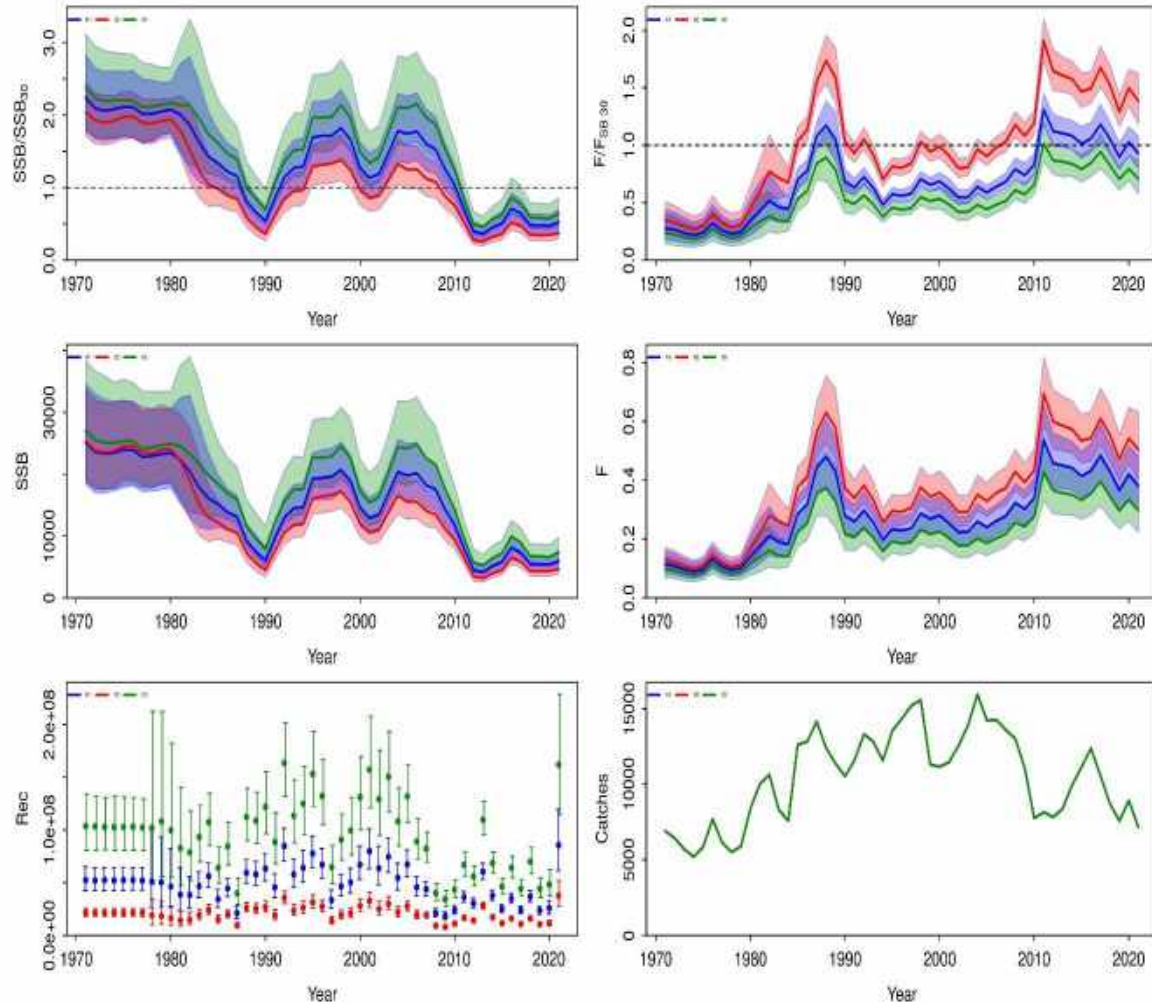
| Model      | Ensemble weight |
|------------|-----------------|
| R1 (blue)  | 0.78            |
| R2 (red)   | 0.66            |
| R3 (green) | 0.72            |



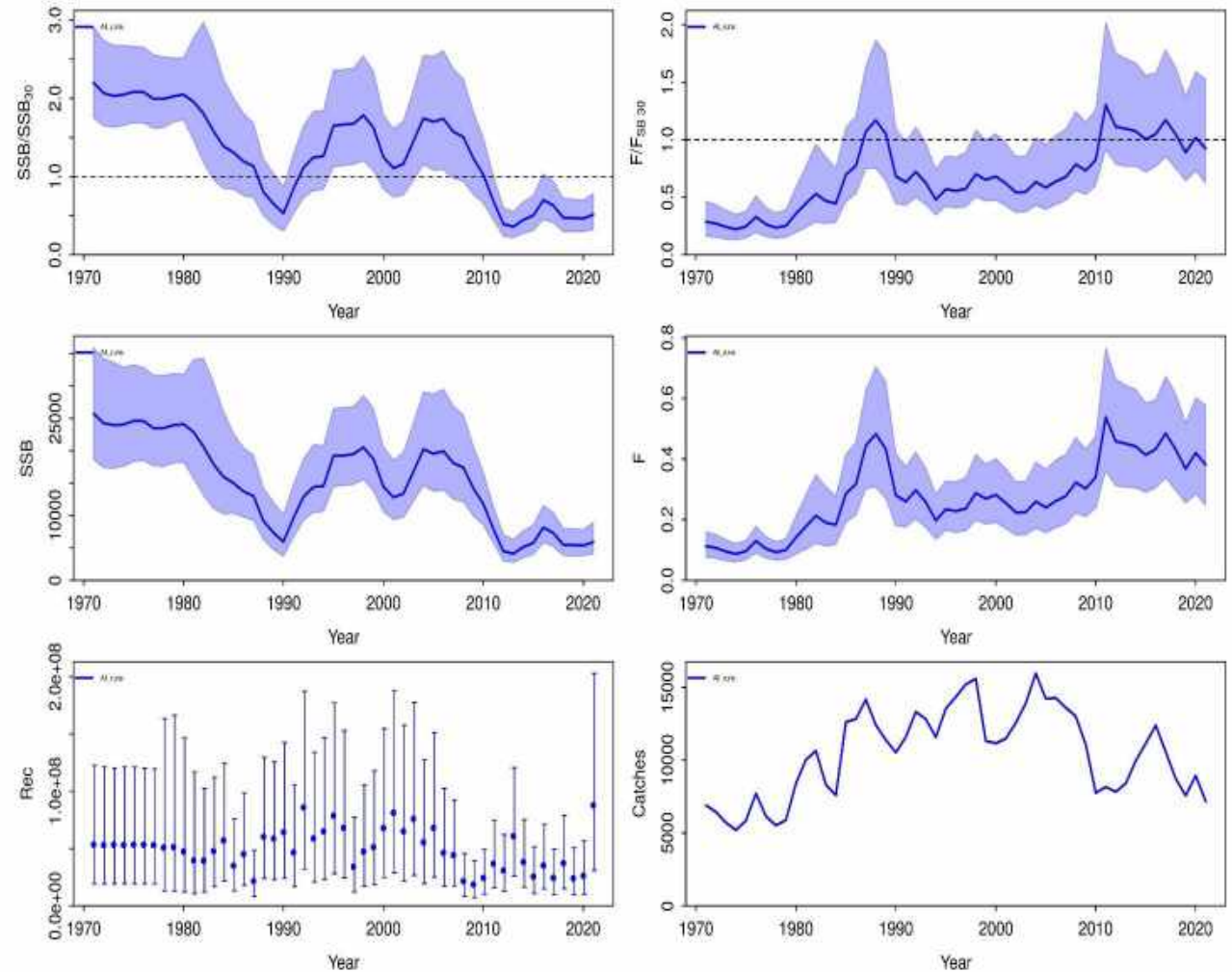
# Results



## Multi-model estimates


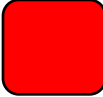
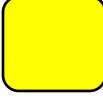



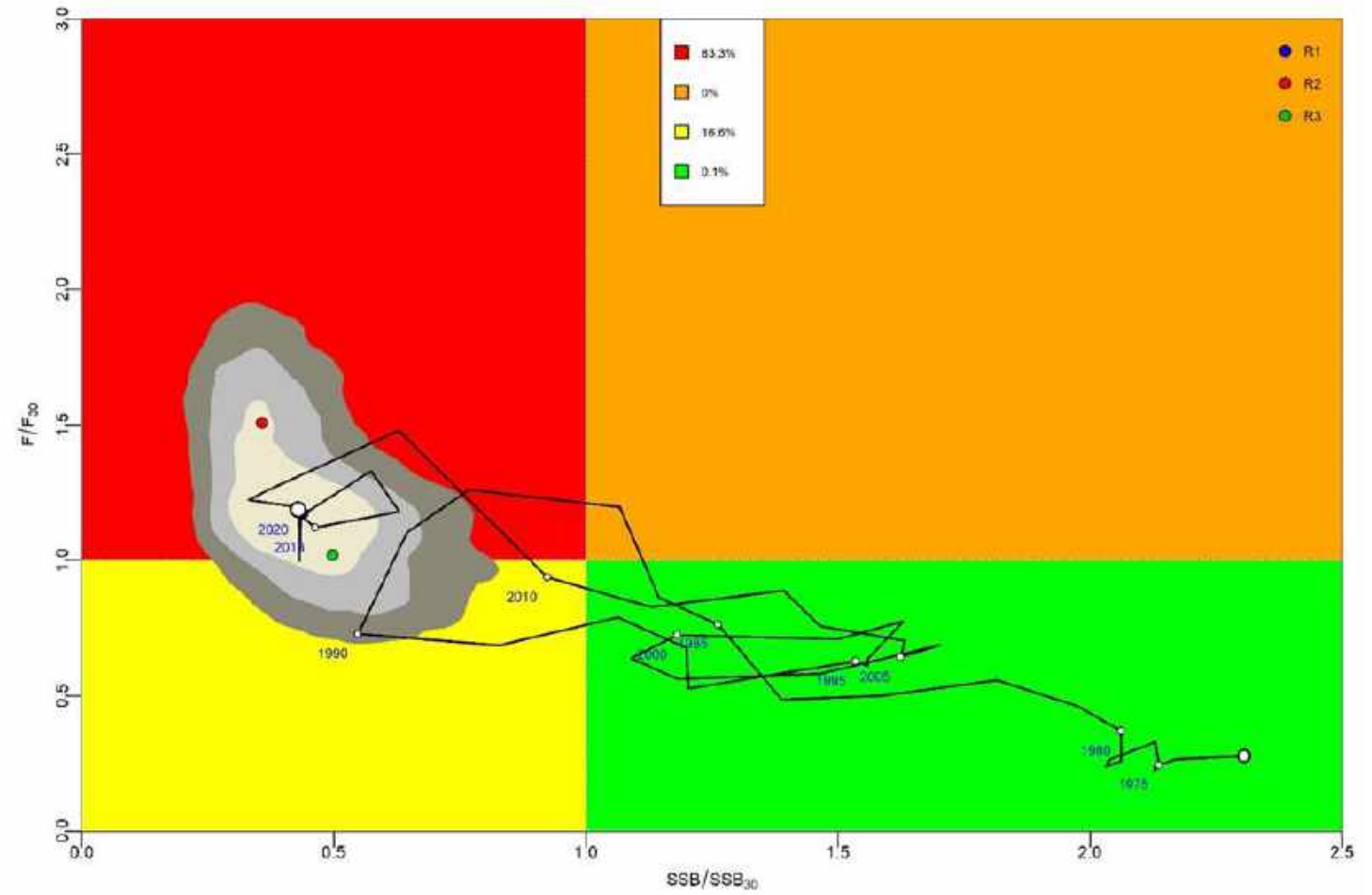
## Ensemble model estimates



# Results

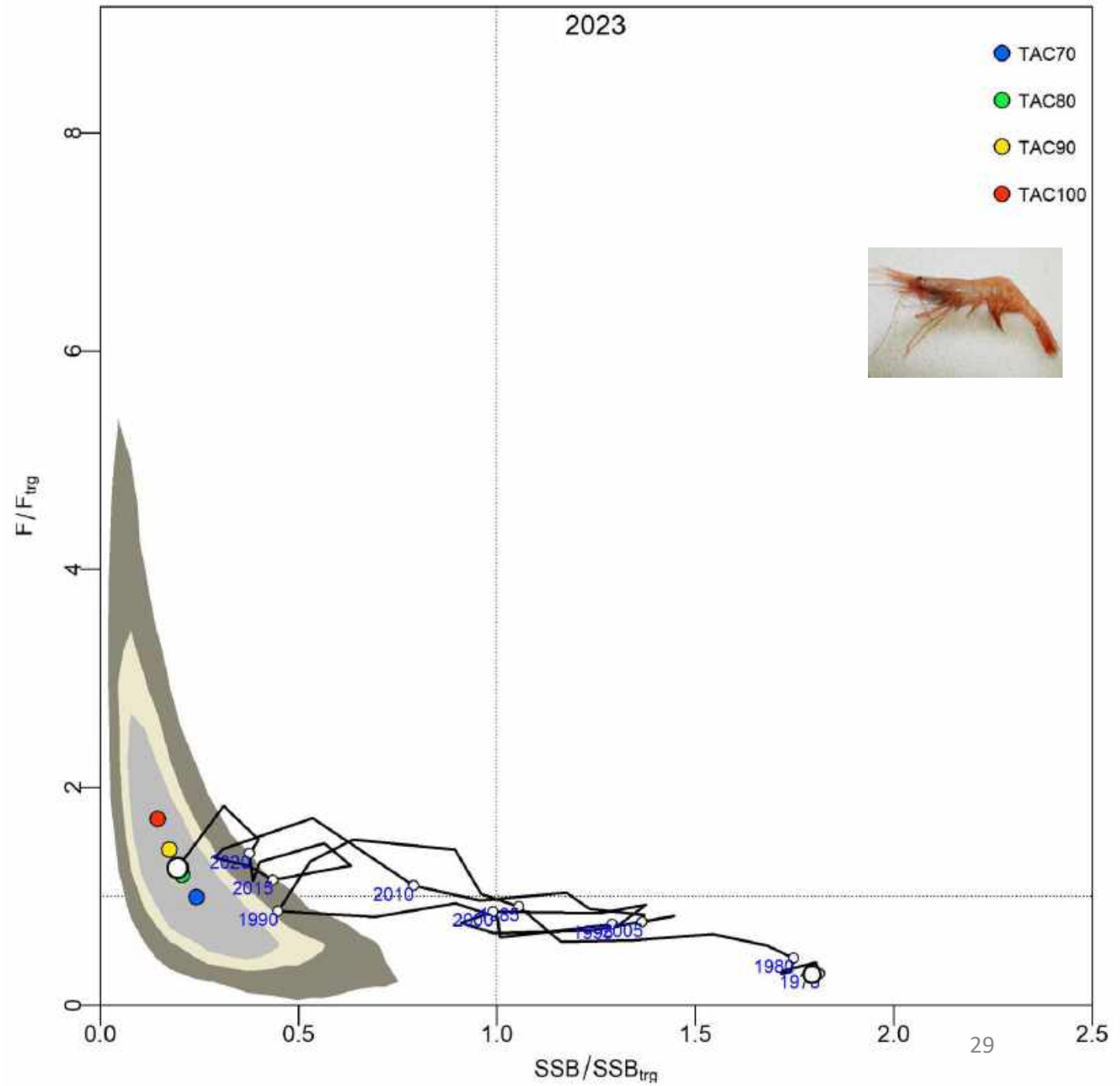


-  Healthy stock size being depleted by over fishing
-  Ongoing overfishing, stock too small to produce MSY
-  Biomass is small and still recovering, a reduction in F is needed
-  Target area for management, sustainable F and healthy stock size





# Predictions uncertainty



# Why weighting

The entire process of stock assessment is pervaded by weighting

When weighting, the simple questions we asked to ourselves was: would we prefer a model that can predict the CPUE trend or a model the persistently overestimates the trend? Or a model that is retrospectively stable instead of one that is not?

From a “tactical” perspective, model weights are parameters to be chosen in such away as to achieve best predictive performance. No specific interpretation of the model is attached to the weights; they must only perform

As rarely models pass all diagnostics and model performances might change with time, we preferred to weight than to exclude or equally weight

# Lessons learned

1. The development of a reference model is the key aspect of the ensemble process
2. A weighting scheme must be agreed beforehand to avoid cherry picking
3. A pass/fail system works well for stock assessment models for which diagnostics is used to weigh the single models in the ensemble
4. Differences in diagnostics performances between models is often small
5. Model stitching preserve the tails for a better quantification of risk
6. Combine diagnostics as for example MASE and run tests into a single value to create more balanced weighting scheme
7. Needs for simulations testing



# Building Web Applications

WITH SHINY

```
1 library(shiny)
2 library(ggplot2)
3
4 load("movies.RData")
5
6 # Define UI for application that plots features of movies
7 ui <- fluidPage(
8   # Sidebar layout with a input and output definitions
9   sidebarLayout(
10    # Inputs: Select variables to plot
11    sidebarPanel(
12      # Select variable for y-axis
13      selectInput(inputId = "y",
14                  label = "Y-axis:",
15                  choices = c("imdb_rating", "imdb_num_votes", "critics_score", "audience_score"),
16                  selected = "audience_score"),
17      # Select variable for x-axis
18      selectInput(inputId = "x",
19                  label = "X-axis:",
20                  choices = c("imdb_rating", "imdb_num_votes", "critics_score", "audience_score")
21            ),
22    ),
23    # Output: Show scatterplot
24    mainPanel(
25      plotOutput(outputId = "scatterplot")
26    )
27  )
28
29 # Run the application
30 runApp()
```



app.R

<https://framasnadi.shinyapps.io/AppSOL/>

<https://maxcardinale.shinyapps.io/Ensemble/>

[https://maxcardinale.shinyapps.io/Ensemble\\_vendace/](https://maxcardinale.shinyapps.io/Ensemble_vendace/)