



Working Group on Multispecies Assessment Methods (WGSAM)

Bentley, Jacob; Bartolino, Valerio; Kulatska, Nataliia; Vinther, Morten; Gaichas, Sarah; Kempf, Alexander; Lucey, Sean; Baudron, Alan; Belgrano, Andrea; Bracis, Chloe

Total number of authors:
19

Link to article, DOI:
[10.17895/ices.pub.5758](https://doi.org/10.17895/ices.pub.5758)

Publication date:
2019

Document Version
Publisher's PDF, also known as Version of record

[Link back to DTU Orbit](#)

Citation (APA):

Bentley, J., Bartolino, V., Kulatska, N., Vinther, M., Gaichas, S., Kempf, A., Lucey, S., Baudron, A., Belgrano, A., Bracis, C., DeCastro, F., O'Neill, T. D. S., Lehuta, S., McGregor, V., Neuenfeldt, S., Panzeri, D., Soudijn, F. H., Spencer, M. S., & Trijoulet, V. (2019). *Working Group on Multispecies Assessment Methods (WGSAM)*. International Council for the Exploration of the Sea (ICES). ICES Scientific Report Vol. 1 No. 91 <https://doi.org/10.17895/ices.pub.5758>

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WORKING GROUP ON MULTISPECIES ASSESSMENT METHODS (WGSAM)

VOLUME 1 | ISSUE 91

ICES SCIENTIFIC REPORTS

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International Council for the Exploration of the Sea Conseil International pour l'Exploration de la Mer

H.C. Andersens Boulevard 44–46
DK-1553 Copenhagen V
Denmark
Telephone (+45) 33 38 67 00
Telefax (+45) 33 93 42 15
www.ices.dk
info@ices.dk

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ISSN number: 2618-1371 | © 2019 International Council for the Exploration of the Sea

ICES Scientific Reports

Volume 1 | Issue 91

WORKING GROUP ON MULTISPECIES ASSESSMENT METHODS (WGSAM)

Recommended format for purpose of citation:

ICES. 2019. Working Group on Multispecies Assessment Methods (WGSAM).
ICES Scientific Reports. 1:91. 320 pp. <http://doi.org/10.17895/ices.pub.5758>

Editors

Sarah Gaichas • Alexander Kempf

Authors

Jacob Bentley • Valerio Bartolino • Nataliia Kulatska • Morten Vinther • Sarah Gaichas • Alexander Kempf • Sean Lucey • Alan Baudron • Andrea Belgrano • Chloe Bracis • Francisco DeCastro • Thomas Del Santo O'Neill • Sigrid Lehuta • Vidette McGregor • Stefan Neuenfeldt • Diego Panzeri • Floor Soudijn • Michael Spence • Vanessa Trijoulet



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i Executive summary

The Working Group on Multispecies Assessment Methods (WGSAM) works on the development of multispecies and ecosystem models that have potential or actual application for supporting advice on management of fish stocks and fisheries and assessing the implications of multispecies interactions. This report describes key-runs (standardized model runs updated with recent data) of multispecies and ecosystem models for the Baltic and Irish Sea. Model key-runs are used in ICES advice processes, and WGSAM provides critical expert review of these key-runs to recommend appropriate use of results.

WGSAM first formalized a consistent set of review criteria to conduct key-run reviews (https://ices-eg.github.io/wg_WGSAM/ReviewCriteria.html), as these are increasingly requested. WGSAM then applied these review criteria to three potential key-runs: two for the Baltic Sea ecosystem and one for the Irish Sea ecosystem. Any difficulties with the review process were noted to further refine the review criteria and to make future key-run reviews more efficient and effective.

WGSAM notes that streamlining processes for updating data would facilitate future key-runs. From 2020, WGSAM will require draft key-run results and documentation 2–4 weeks before the meeting to allow more thorough review prior to the meeting. This will increase available meeting time for model comparisons, ensemble modelling, and coming to agreement on recommendations.

For the Baltic Sea, multispecies model key-runs estimate predation mortality to provide time-series of natural mortality (M) for use in single species stock assessments for herring and sprat. The review of key-runs from an SMS model (used in the previous 2012 key-run) and a newly developed Gadget model demonstrated that both models provided consistent time-series of M for herring and sprat when using the same assumptions regarding residual natural mortality, despite different representations of cod population dynamics.

WGSAM recommends the use of natural mortality estimates from the Baltic SMS key-run for use in single species stock assessment models of Baltic herring and sprat. Due to issues of stability in the historical period the Gadget model was not selected as a key-run. WGSAM notes that the results of the SMS key-run depend on the outcome of the ICES Eastern Baltic cod assessment. Any bias in this assessment directly influences the predation mortality estimates. Uncertainty estimates for M from SMS should not be used as these assume that the cod population abundance is known without error.

For the Irish Sea, an an Ecopath with Ecosim (EwE) model was reviewed to suggest methods by which some of the outputs could be used to provide an indicator to help inform the choice of F_{target} within the pre-defined F_{msy} ranges. This allows for the incorporation of ecosystem information when setting F_{target} for individual stocks, while remaining within the existing precautionary fisheries management framework and reference point ranges used by ICES. An EwE model key-run was accepted as a basis for generating the indicator(s) but directly use of modelled F_{msy} values in other models or for management was not recommended.

ii Expert group information

Expert group name	Working Group on Multispecies Assessment Methods (WGSAM)
Expert group cycle	Multiannual
Year cycle started	2019
Reporting year in cycle	1/3
Chair(s)	Alexander Kempf, Germany Sarah Gaichas, USA
Meeting venue(s) and dates	14–18 October 2019, Rome, Italy (19 participants)

1 Key-run review criteria

One of the main tasks of WGSAM is the review of so called “key-runs” from multi species and ecosystem models. A ‘key-run’ refers to a model parameterization and output that is accepted as a standard by ICES WGSAM, and thus serves as a quality assured source for scientific input to ICES advice products (e.g., natural mortality estimates as input for single species assessments).

The main focus of the 2019 WGSAM meeting was to find agreement among members on criteria to be applied when reviewing key-runs in a systematic way. Although general criteria already existed from previous meetings and key-runs, more detailed criteria were needed to ensure that a proper skill assessment is carried out.

In the following sections, the new WGSAM review criteria and guidelines will be presented and explained. Afterwards, the reviews carried out during the 2019 WGSAM meeting are documented. In total, three models were reviewed as candidate key-runs (Baltic Sea SMS, Baltic Sea Gadget, Irish Sea Ecopath with Ecosim) by WGSAM in 2019.

Criteria

Draft key-run review criteria were posted online prior to the WGSAM meeting, and were discussed and refined on the first day by all attendees prior to conducting reviews. The refined criteria are posted at https://ices-eg.github.io/wg_WGSAM/ReviewCriteria.html and reproduced below. Each review in following sections uses the same headings to ensure consistent treatment of all reviewed models.

WGSAM Key-run Review Criteria

1.1 Background

This document provides criteria for consistent review of models by the multispecies assessment working group of the International Council for the Exploration of the Sea (ICES WGSAM). For nearly a decade, WGSAM has reviewed model “key-runs” as part of its Terms of Reference. Recently, WGSAM reviewed key-runs for the North Sea SMS model in 2014 and 2017, the North Sea EwE model in 2015, and the Baltic EwE model in 2016. Key-run reviews are scheduled for Baltic Sea Gadget and SMS models and the Irish Sea EwE model in 2019.

WGSAM Term of Reference b) for 2019–2021 reads:

“Update of key-runs (standardized model runs updated with recent data, producing agreed output and agreed upon by WGSAM participants) of multispecies and ecosystem models for different ICES regions. The key-runs provide information on natural mortality for inclusion in various single species assessments. Deliverables: Report on output of multispecies models including stock biomass and numbers and natural mortalities for use by single species assessment groups and external users.”

Because WGSAM is increasingly asked to provide model framework reviews as well as key-run reviews, we have drafted this document to provide consistent guidelines and review crite-

ria for both reviewers and groups submitting models for review. Guidelines are based on experience from past reviews (see WGSAM reports from 2013–2018 as well as, e.g., <https://www.st.nmfs.noaa.gov/science-quality-assurance/cie-peer-reviews/peer-review-reports>) as well as best practices outlined in the literature (NRC, 2007; Kaplan and Marshall, 2016).

1.2 Model Life Cycle and Objectives for Evaluation

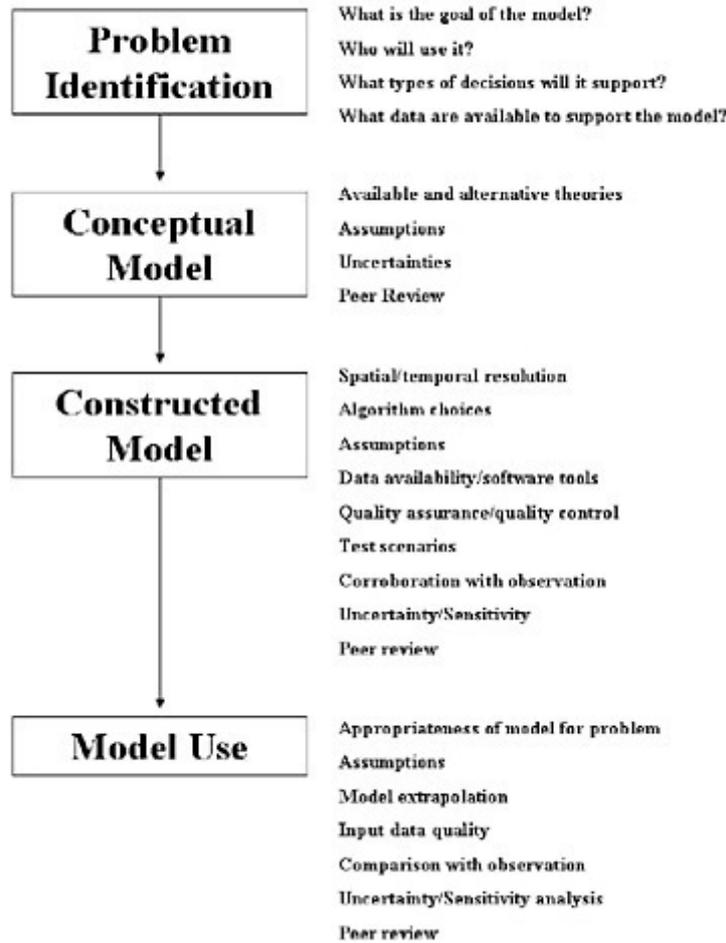
The U.S. National Research Council has summarized the general objectives for model evaluation and tailored them to different stages of the model life cycle with reference to models used in environmental regulation processes (NRC, 2007). The application of multispecies and ecosystem models within fishery management processes is similar enough that this summary provides a useful framework for our criteria.

The general objectives of model review are threefold: (NRC, 2007 p 108)

*Is the model based on generally accepted science and computational methods?
Does it work, that is, does it fulfil its designated task or serve its intended purpose?
Does its behaviour approximate that observed in the system being modelled?*

The model life cycle further specifies review priorities.

Evaluation Issues



Model Life Cycle, NRC 2007

WGSAM receives most requests for model review after the problem identification and conceptual model stage. However, it is important to provide documentation of these processes to reviewers so that the completed model can be evaluated.

In addition, models involved in a management process may face the tradeoff between complexity and transparency, where the need to account for many interactions and processes may render the model harder to explain, and perhaps accept, by decision-makers (NRC, 2007). Because the audience for WGSAM key-runs tends to be other scientists, evaluating the extent to which models are transparent to a scientific, stock assessment oriented audience is appropriate here.

We consider WGSAM reviews to be “peer review”.

Peer review attempts to ensure that the model is technically adequate, competently performed, properly documented, and satisfies established quality requirements through the review of assumptions, calculations, extrapolations, alternate interpretations, methodology, acceptance criteria, and/or conclusions pertaining from a model or its application. (NRC, 2007)

1.3 Key-run Reviews

As described above, model key-runs are currently used to provide inputs to other assessment models; specifically, natural mortality (M) time-series. This places key-runs clearly within the “Model Use” phase of the life cycle. This means that reviews should evaluate (from the figure above):

1. Appropriateness of the model for the problem (problem identification)
2. Assumptions (scientific basis, computational infrastructure; adequacy of conceptual model)
3. Input data quality
4. Comparison with observations
5. Uncertainty/sensitivity analysis
6. Peer review (WGSAM’s role, but consider previous reviews from model construction)

Reviewers will rely on submitted documentation to address these issues. At each point, if documentation is inadequate to address the problem, that will be noted. Review criteria for each point are outlined below, and presentations should include this information.

1.3.1 Is the model appropriate for the problem?

Define the problem, and why this model is (or reviewers to explain why it is not) appropriate.

Define the focal species, spatial, and temporal resolution needed to address the problem.

Current uses:

For example, we are asked to provide M-at-age time-series for North Sea and Baltic herring, cod, whiting, haddock, sprat, sandeel, and possibly other species. Spatial scale is at the stock level and temporal resolution is annual, starting at a stock-specific year and going to 2018.

Therefore, the multispecies model(s) must provide this output and sensitivity in this particular output is most important. However, there are other potential uses for these models that have yet to be defined.

A new use for WKIRISH:

The aim with the Irish Sea Ecopath is to use the model to “fine tune” the quota advice within the predefined EU Fmsy ranges. In “good” conditions you could fish at the top of the range, in “poor” conditions you should fish lower in the range. The range has already been evaluated as giving good yield while still being precautionary, so this should be fine for ICES to use in advice, so any reviewers should have this in mind.

For the Irish Sea EwE model, key outputs will be used to determine where the reference point should be within the MSY range for each species. Therefore, outputs defining Ecosystem conditions and both ecosystem and species productivity under the prevailing conditions are most important.

1.3.2 Is the scientific basis of the model sound?

Is the modelling framework and methodology well established, and has it been previously reviewed and applied? Unless it is not, then WGSAM would use methods outlined for “Constructed Model” review in the flowchart above, or a model framework review.

WGSAM has provided model framework reviews for the LeMans ensemble (2016), FLBEIA (2017), and a multispecies state-space model (2017). Here we outline more general model framework review guidelines for future meetings.

Model frameworks may be at different stages of the model life cycle than the key runs described above, although to date WGSAM has received requests for review closest to the "Constructed Model" phase. This means that reviews should evaluate (from the figure above):

1. Spatial and temporal resolution
2. Algorithm choices
3. Assumptions (scientific basis, computational infrastructure; adequacy of conceptual model)
4. Data availability/software tools
5. Quality assurance/quality control (code testing)
6. Test scenarios
7. Corroboration with observations
8. Uncertainty/sensitivity analysis
9. Peer review (WGSAM's role, but consider previous reviews from prior steps)

1.3.3 Is the input data quality and parameterization sufficient for the problem?

See above defining the problem. Which datasets are adequate, which could be improved, and which are missing?

Show the input data as a simple chart: beginning and end of time-series, gaps, different length of time-series, spatial resolution of data.

Give information on input data pedigree/quality, reference for where it comes from, whether it is survey data or comes from other model output, whether confidence intervals or other uncertainty measures are available and used in the model.

Categorize the assumptions behind modelled ecological or biological processes. Emphasize those related to species interactions (predation, competition), environmental pressures, and also fleet dynamics if needed to address the problem. If the model is spatial, how do these processes happen in space?

Is the parameterization consistent with scientific knowledge (e.g. (PREBAL) diagnostics Link (2010) for general relationships across trophic levels, sizes, etc.).

1.3.4 Does model output compare well with observations?

Here we refer to the more detailed performance criteria developed in Kaplan and Marshall, 2016. We have modified them for our purposes.

Characterize the reference dataset used for comparisons. Has the data been used to construct this model? Is the reference dataset from another model? Describe reference data source(s).

1. (if important to use–projection) All functional groups persist in an unfished unperturbed run.
2. (if important to use–projection) Model stabilizes for the last ~20 years of an unfished, unperturbed 80–100 year run.

3. The key-run should define the hindcast time period where agreement with other data sources or assessments is needed. Review will determine if the model fits adequately within that time period. Error ranges are needed for comparison or reference datasets.
4. Focal species should match biomass and catch trends over the hindcast time period. For full system models, species comprising a majority of biomass should also match general hindcast trends. Suggested tests include modelling efficiency, RMSE, etc. (Sterman 1984; Stow *et al.*, 2009; Joliff *et al.*, 2009; Allen and Somerfield 2009; Lehuta *et al.* 2013 and 2016; and Olsen *et al.* 2016).
5. Patterns of temporal variability captured (emergent or forced with e.g. recruitment time-series).
6. Productivity for focal species (or groups totaling ~80% of system biomass in full system models) should qualitatively match life history expectations (prebal diagnostics).
7. Natural mortality decreases with age for majority of groups.
8. Age and length structure qualitatively matches expectations for majority of groups.
9. Diet predicted qualitatively matches empirical diet comp for majority of groups.
10. Spatial distribution of outputs match reference datasets for spatial models (most important if output required at spatial resolution of model, comment if a match in aggregate but not at higher resolution).
11. Ecosystem indicators (relationship between abundance and body size, pelagic to demersal, Large Fish Indicator) match reference data if needed for problem.

1.3.5 Uncertainty

Has uncertainty been assessed in the output of interest? Has sensitivity analysis been performed and how does it affect those outputs?

The key-run should show estimates of uncertainty in the output quantity of interest. Uncertainty analysis is best if possible to estimate confidence intervals. If not possible list key sources of uncertainty, expected bounds on outputs based on those (possibly from sensitivity analysis)—i.e. design sensitivity analysis to approximate uncertainty analysis.

Specific analyses, sensitivity of key output in:

1. Retrospective analysis (5 year peel of all input data)
2. Forecast uncertainty: remove last 3–5 years of survey index only to see how well the model works in forecast mode, given the catch that actually happened.
3. Sensitivity to stomach data and other key or low-confidence data sources
4. Sensitivity to key parameters: consumption rates, residual mortality (M1, M0)
5. Sensitivity to initial conditions

For complex models with long runtimes, simpler ways to address uncertainty may be appropriate (Kaplan and Marshall, 2016).

Best practice is to retain multiple parameterizations that meet the above criteria to allow scenario testing across a range of parameterizations. Parameter uncertainty can be addressed even in complex models. A simple method uses bounding (e.g. base, low bound, and high bound productivity scenarios; Saltelli and Annoni 2010).

1.3.6 Previous peer review

What did they point out and have issues been addressed?

Review of constructed models should have evaluated spatial and temporal resolution, algorithm choices, data availability and software tools, quality assurance/quality control of code, and test scenarios.

1.4 Review recommendations

WGSAM key-run review reports will address the sections above, and then make a recommendation for the appropriate uses of model outputs. WGSAM key-run review reports will also end with a list of recommendations for items to be addressed in future key-runs.

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Refinements to the criteria for future reviews

WGSAM noted that productivity (Section 1.3.4 point 6) is difficult to evaluate for multispecies models when the quantity being estimated (M , F_{msy}) is expected to differ from single species estimates due to the structure of the model. An independent estimate of productivity was difficult to establish during this meeting. For future reviews, modellers could consider comparisons based on individual level survival and longevity, while the portion of productivity related to recruitment levels requires further thought.

Most importantly, WGSAM notes that streamlining processes for updating data would be helpful to facilitate future key-runs. For all meetings after 2019, WGSAM will require draft key-run

results and documentation 1 month to 2 weeks prior to the meeting so that a more thorough review can be completed prior to the meeting, reserving meeting time for model comparisons, ensemble modelling, and coming to agreement on recommendations. This means that data updates must be requested and provided in a timely manner. If the full results and documentation are not available prior to the meeting, no key-run review will be conducted by WGSAM.

2 Irish Sea EwE key-run review

2.1 Overview

2.1.1 Is the model appropriate for the problem?

The aim of the ICES WKIRISH process is to suggest methods by which some of the outputs of the Irish Sea EwE can be used to influence quota setting. The idea is to use the pre-defined single-species based F_{msy} ranges in use within the CFP of the European Union to give flexibility to include ecosystem information. These F_{msy} ranges have already been evaluated using single-species models as giving good yield while meeting ICES precautionary requirements. The aim of WKIRISH is not to use F values directly from the EwE, but rather to use the EwE output as essentially a synthesized ecosystem indicator to help inform the choice of F_{target} within the pre-defined F_{msy} ranges. This method would allow for the incorporation of ecosystem information within the quota setting process, while remaining within the existing precautionary fisheries management framework used by ICES and without disregarding the current reference point ranges.

The original design of the Irish Sea EwE model was to investigate the slower than expected recovery of Atlantic cod; the hypothesis being that environmental factors have complicated the recovery despite reduced fishing pressure. The scope of the model was then expanded by WKIRISH to investigate environmental conditions with respect to fine tuning quota advice within pre-defined EU F_{msy} ranges. Ecopath models allow for the incorporation of environmental covariates as forcing functions and the Irish Sea EwE has been tuned to several. Therefore, the model is appropriate to address the WKIRISH need for synthesis of ecosystem indicators.

2.1.2 Is the scientific basis of the model sound?

Ecopath with Ecosim is an established modelling framework (Christensen and Pauly, 1992; Christensen and Walters, 2004). The strength of Ecopath models is to identify major energy pathways within a system. This makes them well suited for describing the relationships between ecosystem resources and for exploring the direct and indirect effects of management decisions or environmental changes (Plaganyi, 2007).

2.1.3 Is the input data quality and parameterization sufficient for the problem?

The Irish Sea model used data gathered by WKIRISH and updated stock assessments to parameterize 41 functional groups. The model also used information from literature, open access stomach database and local ecological knowledge from stakeholders. The use of fishermen data to flesh out stomach parameters is very novel. This approach should lead to greater acceptance of the final model by stakeholders. The base Ecopath model was parameterized for the 1970s then forced using time-series of fishing effort and environmental covariates to create a model up to 2016. Similar to many Ecopath models, the biomass was estimated for some groups by inputting an ecotrophic efficiency (amount of mortality accounted for in the model) and allowing the model to determine how much biomass would be required to support the food web.

A series of pre-balance (PREBAL) diagnostics were run according to Link (2010). These PREBAL diagnostics check general rules of thumb for full ecosystem models based on observed properties

that adhere to general rules of thermodynamics. These include a general decline of biomass and productivity as trophic level increases. All of the PREBAL diagnostics were within reason.

There is some concern over the productivity to biomass (PB) ratios used for some of the species. In Ecopath models, PB is equivalent to Z . Therefore in general, the reciprocal of PB can be associated with longevity. This means that longer lived species have a lower production to biomass ratio than shorter lived species. In this model of the Irish Sea, Atlantic cod has a PB ratio of 0.820. This would equate with a longevity of 1.22 years. This is a pervasive issue with Ecopath models especially when a F is used from single species assessments for an overfished species without using a negative biomass accumulation term to offset or account for the excess mortality. WGSAM recommended a sensitivity analysis around the cod PB input value. Monte Carlo simulations were run wherein cod PB was permeated between 0.820 (Ecopath value) and 0.1, with and without the AMO driving the recruitment rate of juveniles to the adult stage (Figure 1.5–1). Results suggest that a reduced PB would indeed reduce the recovery rate of cod, however without the inclusion of the AMO as a driver of cod recruitment rate all simulations overestimated the recovery response to reduced fishing effort. This is not necessarily surprising as previous studies have recognised the negative relationship between the AMO and Irish Sea cod recruitment (Planque and Fox, 1998; Beggs *et al.*, 2014).

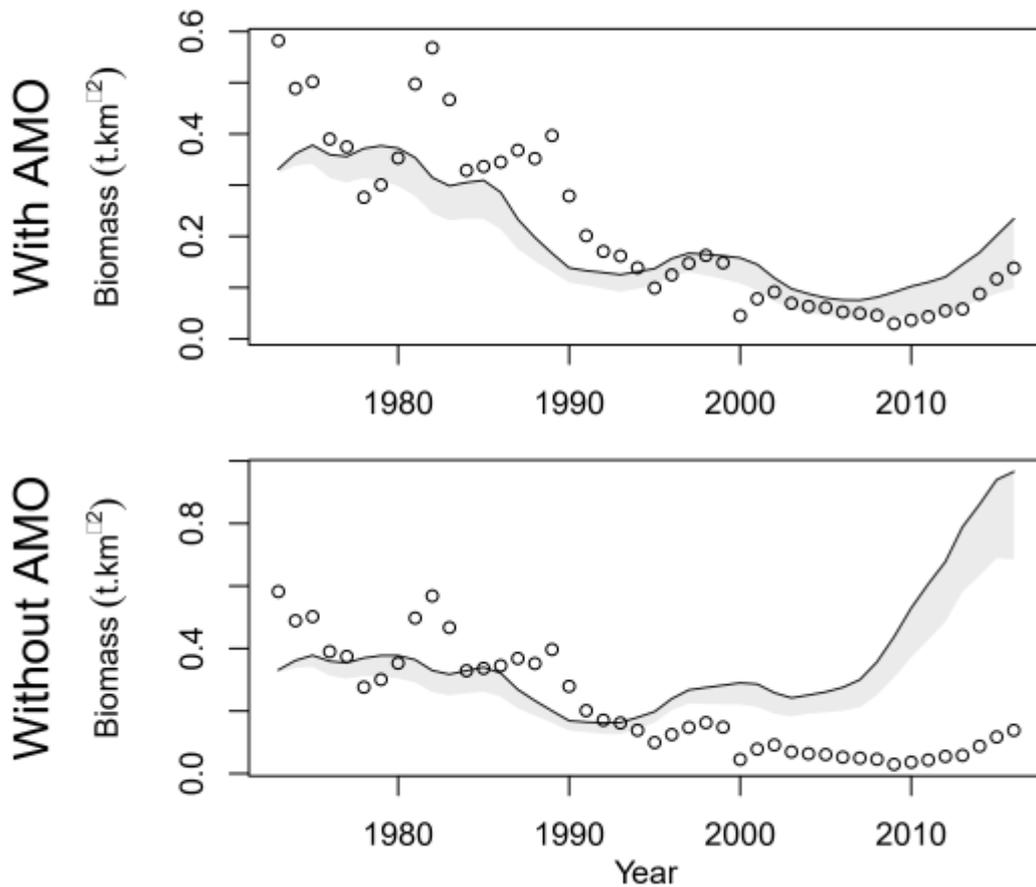


Figure 1.5-1. Sensitivity analysis of cod biomass simulations in the Irish Sea with PB permeated between 0.82 and 0.1. Black lines indicate initial model simulations (PB = 0.82), grey areas indicate the range of possible projections with a reduced PB, and dots refer to the 2018 stock assessment trend.

2.1.4 Does model output compare well with observations?

1. All functional groups persist in an unfished unperturbed run. This is not an issue for EwE models as that is a fundamental aspect of their construction.
2. Model stabilizes for the last ~20 years of an unfished, unperturbed 80–100 year run. Once again, this is a fundamental aspect of EwE models and therefore not an issue.
3. The key-run should define the hindcast time period where agreement with other data sources or assessments is needed. The hindcast for the Irish Sea EwE model is 1973–2016.
4. Focal species should match biomass and catch trends over the hindcast time period. For full system models, species comprising a majority of biomass should also match general hindcast trends. The Irish Sea model identified six key species: Atlantic cod, haddock, Atlantic herring, whiting, plaice, and *Nephrops*. Using a visual analysis and sum of squared deviation calculation, the trends for Atlantic cod, herring, and *Nephrops* were sufficient. The modelled biomass for whiting was low in the early part of the hindcast but matched well with more contemporary data. Modelled catch for plaice initially over-estimated catch based on observations. However the modellers were able to partition

landings and discards to fleets differently which alleviated this issue. Finally haddock failed to match the variable recruitment observed in nature but did get the general trend correct which may be the best one could hope for given the sporadic recruitment events in the stock. WGSAM does suggest testing these fits using methods outlined in Olsen *et al.* (2016).

5. Patterns of temporal variability captured (emergent or forced with e.g. recruitment time-series). The rates of recruitment for cod and whiting in this model are driven by the AMO which helps with the cod and whiting fit and general trend of haddock in response to changes in cod predation pressure.
6. Productivity for focal species (or groups totaling ~80% of system biomass in full system models) should qualitatively match life history expectations (prebal diagnostics). As noted above under 1.1.3, the model passes the PREBAL diagnostics but there are some concerns about the PB ratios used.
7. Natural mortality decreases with age for majority of groups. This is not really relevant for an EwE model as they are not age-structured. However, the Irish Sea model does have several multistanza groups which perform as expected.
8. Age and length structure qualitatively matches expectations for majority of groups. This is not relevant for an EwE model that is not age or length structured.
9. Diet predicted qualitatively matches empirical diet comp for majority of groups. Diet is an input to EwE models. WGSAM does suggest checking to see if the modelled diet composition seems reasonable to the stakeholders who had sketched out conceptual versions of diet for two different time periods.
10. Spatial distribution of outputs match reference datasets for spatial models (most important if output required at spatial resolution of model, comment if a match in aggregate but not at higher resolution). This EwE model does not contain an Ecospace component so spatial distributions are irrelevant.
11. Ecosystem indicators (relationship between abundance and body size, pelagic to demersal, Large Fish Indicator) match reference data if needed for problem. Several ecosystem indicators were examined and appear to be sufficient. Fitting all bumps and drops within a time-series is not necessary as long as the general global assessment of the ecosystem is represented.

2.1.5 Uncertainty

Uncertainty was addressed in this model through a Monte Carlo Markov Chain (MCMC) simulation. Ecopath models have a pedigree that is entered that allows the user to specify their level of confidence in an input parameter. The Irish Sea model was run 1,000 times with a uniform distribution around input parameters based on data pedigree. The dynamic variables (i.e. vulnerabilities) were not included. No retrospective analysis was performed nor does WGSAM think that it is relevant at this time. However, when the procedure for using model outputs in the management process is more clearly specified, the model's ability to provide stable estimates of ecosystem state over a range of data endpoints could be evaluated.

WGSAM does suggest that some sensitivity analysis be performed with respect to the PB ratios for groups other than cod. These values could have a fundamental impact on the interpretation of the model.

2.1.6 Previous peer review

The implementation of EwE for the Irish Sea has several peer reviewed publications already:

Technical report:

- Bentley, J. W., Serpetti, N., Fox, C. J., Reid, D. and Heymans, J. J. 2018. Modelling the food web in the Irish Sea in the context of a depleted commercial fish community. Part 1: Ecopath Technical Report., Scottish Association for Marine Science, Report no., p. 147, <https://doi.org/10.6084/m9.figshare.6323120.v1>.

Published papers:

- Bentley, J. W., Serpetti, N., Fox, C., Heymans, J., Reid, D., G. 2019. Fishers' knowledge improves the accuracy of food web model predictions, ICES Journal of Marine Science, 76, 4, pp. 897–912, <https://doi.org/10.1093/icesjms/fsz003>
- Bentley, J. W., Hines, D., Borrett, S., Serpetti, N., Fox, C., Reid, D. G. and Heymans, J. J. 2019. Diet uncertainty analysis strengthens model-derived indicators of food web structure and function, Ecological Indicators, 98, pp. 239–250. <https://doi.org/10.1016/j.ecolind.2018.11.008>
- Bentley, J. W., Hines, D. E., Borrett, S. R., Hernández-Milián, G., Serpetti, N., Fox, C. J., Heymans, J. J. and Reid, D. 2019. Combining scientific and fishers' knowledge to co-create indicators of food web structure and function, ICES Journal of Marine Science. <https://doi.org/10.1093/icesjms/fsz121>

Relevant WKIrish reports:

- ICES 2018. Report of the Workshop on an Ecosystem based Approach to Fishery Management for the Irish Sea (WKIrish5). 5–9 November 2018, Dublin, Ireland. ICES CM, 2018/ACOM: 66.
- ICES 2018. Report of the Workshop on stakeholder input to, and parameterization of, ecosystem and foodweb models in the Irish Sea aimed at a holistic approach to the management of the main fish stocks (WKIrish4), 23–27 October 2017, Dún Laoghaire, Ireland. ICES CM 2017/ACOM:54, 35.

2.2 Review recommendations

WGSAM approves the Irish Sea EwE model as a key-run, and recommends that it be made publicly available through ICES.

WGSAM notes that an aim of the ICES WKIRISH process is to suggest methods by which some of the outputs of the Irish Sea EwE can be used to influence quota setting. The idea is to use the pre-defined single-species based Fmsy ranges in use within the CFP of the European Union to give flexibility to include ecosystem information. These Fmsy ranges have already been evaluated using single-species models as giving good yield while meeting ICES precautionarity requirements. The aim of WKIRISH is not to use F values directly from the EwE, but rather to use the EwE output as essentially a synthesized ecosystem indicator to help inform the choice of Ftarget within the pre-defined Fmsy ranges. This method would allow for the incorporation of ecosystem information within the quota setting process, while remaining within the existing precautionary fisheries management framework used by ICES and without disregarding the current reference point ranges.

WGSAM would urge extreme caution in directly transferring F_{msy} values from the EwE model into other models or for direct use in management. However, WGSAM finds that the Irish Sea EwE model does provide a basis for producing indicator(s) which could be used to inform the selection of fishing pressure within a pre-defined range of F values evaluated as precautionary using the single species assessment models. WGSAM encourages WKIRISH 6 to conduct simulations using the single species models to evaluate potential impacts on yields and stock development of the use of the EwE outputs in this manner.

The model can be used describe favourable or unfavourable environmental conditions for stocks but cannot predict when those conditions will be present in the future. WGSAM noted that while environmental covariates help drive the model towards observations, it is always advisable to clarify the underlying mechanism, and advised further investigation into the environmental impacts on stocks. Considerable work has already been done and is demonstrated in the EwE model annex. Correlation analyses that corrected for autocorrelation were used to identify links between the environment and biological trends in productivity and recruitment. The model was tested with and without the inclusion of environmental drivers to clarify the role played by the environment. The underlying mechanisms are described in the literature and fully explored for the Irish Sea model in a paper currently under review.

During initial review, it was noted that a high cod PB ratio could account for the inability of the model to replicate the decline of cod without environmental drivers also included. Subsequent sensitivity analyses, found that low PB cod simulations were similarly unable to replicate observed trends when environmental drivers were absent (Figure 1–5.1), strengthening the argument for the inclusion of environmental drivers. Nevertheless, future work could consider overall model sensitivity to PB ratios for major species.

Finally, WGSAM notes that the model is tuned through 2016. Any relevant advice would be occurring well after this period. It is therefore advisable to update the model to most recent data available before using in a management context.

For future work WGSAM recommends the following:

1. PREBAL diagnostic check on aggregate guilds rather than individual predators and prey.
2. Examine sensitivity of ecological indicator status over a range of PB values (all groups).
3. Update tuning to include most recent data for management advice.

2.3 References

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- Bentley, J. W., Serpetti, N., Fox, C., Heymans, J. J., and Reid, D. G. 2019b. Fishers' knowledge improves the accuracy of food web model predictions. *ICES Journal of Marine Science*, 76: 897–912.
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- Planque, B. and Fox, C.J., 1998. Interannual variability in temperature and the recruitment of Irish Sea cod. *Marine Ecology Progress Series*, 172, pp.101–105.

3 Baltic Sea SMS key-run review

3.1 Overview

3.1.1 Is the model appropriate for the problem?

The SMS model will be used to provide natural mortality estimates by age and year as input to single species assessments of Eastern Baltic herring (Subdivisions 25–29 and 32 (excluding Gulf of Riga)) and Baltic sprat (Subdivisions 22–32). Natural mortality estimates are only used as input for the historic part and no forecast is needed. M estimates by age and quarter are a direct output of the model. However, an assumption is needed for residual mortalities $M1$ while the predation mortalities $M2$ are estimated ($M = M1 + M2$). The model is able to provide estimates for the years 1974 to 2018.

The Baltic SMS model is in general parameterized for subdivisions 25–29 (Eastern Baltic). There are minor components of the ICES cod stock “*Cod (Gadus morhua) in subdivisions 24–32, eastern Baltic stock (eastern Baltic Sea)*” outside that area. Similarly, the sprat stock area, SD 24–32, extends also outside the model area. No correction has been made to take this into account, however, the impact on the results (especially $M2$) is believed to be minor.

Cod is no longer a dynamic predator in the SMS model due to age reading problems and only length based input as catch at length can be provided for recent years. Such input cannot be handled in SMS. Instead numbers at certain length classes from the length based Eastern Baltic cod assessment are used as known input without error. Therefore, cod is treated as so called “Other predator”.

Overall, the model is appropriate to provide information on natural mortalities as input for the assessments of Eastern Baltic herring and Baltic sprat. However, results depend to a larger extent on the input from the Eastern Baltic cod assessment. Since these are assumed to be known without error, SMS uncertainty estimates around M are an underestimate and not very informative any more.

3.1.2 Is the scientific basis of the model sound?

The SMS model is an established and reviewed model that is also applied in the North Sea to provide input for assessments of commercially important stocks (e.g., North Sea cod and herring). The Baltic SMS model has been reviewed in ICES WKMULTBAL (2012) and ICES WGSAM (2012).

3.1.3 Is the input data quality and parameterization sufficient for the problem?

Data quality

SMS uses the same data as used for input to the single species assessments (catch at age, mean weights, proportion mature, survey indices). These data have been benchmarked and therefore no further review on these data has been carried out. However, while single species assessments start with age 1 as recruits, SMS starts with age 0. Given that predation mortalities are important for age 0, this is understandable. But e.g., the mean weight at age is highly uncertain for the 0 group. In general, the assumption that mean fish weight in the catch equals the mean fish weight

in the stock is a major assumption that can have an influence on model results. SMS finally uses smoothed quarterly values as input for the age 0 (Q3 & Q4) and age 1 (Q1 & Q2). Even though there is a large uncertainty around the input values for weight at age in the sea, especially for the youngest ages.

Additional data needed to parameterize SMS are stomach data. A new stomach data set for cod became available in recent years. The stomachs have been collected mainly by the Latvian institute and provide very detailed information based on individual stomachs. The dataset provides information for the period 1974–2014. Overall 64 000 stomachs can be used as input for SMS. This dataset is regarded to be more informative than previously used datasets because data are given by individual cod and the predator size classes are in mm or cm. The previously used dataset was based on pooled data, e.g. aggregated data from all cod 40–45 cm in SD 25 sampled by Poland, and prey length was given by rather large length classes, e.g. sprat 5–10–25 cm. Also the time-series is longer in the new data set. Although in general the eastern Baltic is well covered, sampling focuses to some extent around the Latvian coast and there are some gaps in space especially during the 90ies. The main distribution areas for cod are SD 25, 26 and 28 and stomachs from these areas are used by SMS both in this new key-run and the keyring made in 2012. All three subdivisions have not been sampled in all years. Due to the better quality of the new stomach contents data, this data sets was applied as default. A comparison of SMS runs using either the new or old, or combined new and old data sets gave similar results for M2 (Figure 9.4–2 in Annex 4).

Consumption rates have been recalculated based on the cylinder gastric evacuation rate model from Andersen and Beyer (2005a, b). In order to consider recent changes in cod consumption rate, the relationship between average quarterly consumption rate and total length (a priori parametrized as $C=aL^b$ with C the average quarterly consumption rate and L total length) was estimated separately for three different periods (1974–1989, 1990–1999, 2000–2014).

Overall, the data quality is considered as good as possible to provide input to the model. That the model uses key input from the single species assessments can be seen as strength because these data have been already through a full benchmark process in ICES.

Assumptions and parameterization

The parameterization of the diet selection sub-model is based on several assumptions. First there is only one vulnerability parameter per interaction for the full model time-series. The assumption of constant vulnerability may be violated if e.g. the spatial predator-prey overlap may change. Given an assumed constant overlap, the implied Holling type II functional feeding response as used in SMS is well known to lead to instability when prey items become low in abundance and makes them vulnerable to extinction in the model. However, this is mainly an issue for forecasts when trying to make predictions outside the range of observations.

Another important assumption is a constant biomass pool of “Other Food” in time. If the availability of important Other Food prey items changes over time, this can lead to biased predictions of relative stomach contents and therefore predation mortalities. As shown under section 3.2.4 and 3.2.5 this could be an issue for this key-run.

There are several options in SMS how the size selection of the predators is modelled (see Annex 4, appendix 1). In total three options have been tested:

1. log-normal size selection
2. Uniform size selection within range defined by input
3. Constraint uniform size selection by input defined by min and max regression parameters to exclude “outliers”

It was decided to use option 1 as this option provided the best total model likelihood. The “constraint uniform” option performed well in the 2012 key-run, but that was with the use of the “old” stomach data set with its wide size classes. With application of the “new” stomach data set with its narrow size classes, the predator/prey size ratio becomes more precise, such that the cutting of “outliers” had unintended effects. With the new data, the full range of observations should probably be used, if a uniform size selection option is used.

Overall, the parameterization and assumptions are consistent with scientific knowledge. However, some of the assumptions regarding constant vulnerabilities and Other Food may be relaxed in future key-runs and further investigations are needed to fully utilize the extensive time-series of stomach data (also in relation to spatial patterns) to optimise the parameterisation of the diet selection sub-model.

3.1.4 Does model output compare well with observations?

The SMS key-run was able to estimate total catch over time sufficiently well for herring and sprat (Figure 9.1–1 in Annex 4). The main features of the time-series are well covered by the model even though there are clear clusters of positive and negative residuals for the quarterly catch at age observations (Figure 9.1–2 in Annex 4).

The fit to survey data captures the main trends (Figure 9.1–3 in Annex 4). There are clear “year effects” (consistent under- or overestimation in a given year), however this is often seen in acoustic surveys. Overall, no sign of overfitting to a particular data source is apparent.

The fit to stomach data reveals residual patterns. There is a consistent over- or underestimation of Other Food, sprat and herring in certain time periods (see Figure 9.1–4 in Annex 4). This points towards additional processes so far not captured by the model such as non-constant vulnerabilities or availability of Other food.

Predation mortality (M_2) decreases in general by prey size (age) as expected (Figure 9.1–10 in Annex 4); however for sprat M ($M_2 + \text{constant } M_1$) is estimated to be highest for age 1. This pattern might be explained by a lower spatial overlap between the very small sprat and cod, or may be an effect of the rather uncertain mean weight at age applied for the 0-group. However, the M values needed for the single species assessments start with age 1 and therefore it is less critical. Never the less, the impact of using the SMS key-run with first age set to one may be tested in the future.

3.1.5 Uncertainty

The uncertainty around M can be estimated by SMS via the inverse Hessian. However, because cod numbers at length are used as input and assumed without errors, these are underestimated. SMS estimates for example a CV well below 10% for most M estimates (Figure 9.1–13 in Annex 4). Only for the last year a CV around 10% is reached.

To get a better idea on true uncertainties several sensitivity runs were carried out:

1. Retrospective analysis (5 year peel of all input data)
2. Sensitivity to stomach data (old vs. new stomach data set)
3. Sensitivity towards using an overlap index for Other Food
4. Sensitivity towards consumption rates
5. Sensitivity towards using different assumptions for size selection (see under 3.1.3)
6. Comparison with the old 2012 key-run
7. Comparison with the Gadget model run.

The final key-run was able to provide consistent M estimates in the retrospective analysis and therefore the input (natural mortalities) to the single species assessment models can be regarded as robust towards the addition of data points (see Annex 4 for details).

There was limited sensitivity towards using the old stomach data, the old and new stomach combined, and new stomach data only (the key-run). (Figure 9.4–2 in Annex 4). The sensitivity was highest for the early time period when predation was strongest and for younger age groups.

Including an estimated overlap index for Other Food, *Saduria entomon*, only had a minor impact on residual patterns in the fit for stomach data (see Figure 9.7–1 in Annex 4), but positive and negative residuals are less clustered when the input overlap index is applied. The model fit was slightly worse compared to the run without overlap index. When including the overlap index for other food the estimated predation mortalities would be to some extent higher after 1985 and lower in the early time period (Figure 9.7–2 in Annex 4).

Reducing input consumption rates by nearly the half (53%, as estimated within the SMS model) would lead to a slightly better likelihood. M would be estimated lower throughout the time-series (Figure 9.8–1 in Annex 4). The M estimates, however, differed less than the reduction in consumption rate and differs between prey species. The huge reduction in consumption rate estimated by SMS may indicate that the used consumption rates and estimated M2 values from the keyrun are too high.

Model estimates of M2, mean F and SSB (Figure 9.5–2 and 9.5–2 in Annex 4) are quite sensitive to the choice of size selection option. It seems as if the “constraint uniform” option excludes predator-prey interactions from medium sized cod on larger herring such that M2 on herring ages 4–8 becomes very low. The (unconstraint) “uniform” options includes the full observed predator/prey size ratio which results in a higher M2 for the older herring than for the “constraint uniform” option.

The “constraint uniform” option was used in the 2012 key-run, however there is difference in the quality of stomach contents data used in the old and the new 2019 key-run. The old key-runs made use of stomach contents data with large size classes for predator preys, e.g. sprat 5–10–15 cm, while the new stomach data uses a much smaller size classes, e.g. by cm group for sprat. With wider size classes, the predator/prey size ratio becomes imprecise, such that the cutting of “outliers” by the “constraint uniform” options had a limited effect. With the new data, the full range of observations should probably be used, if a uniform size selection option is used.

Even though the 2012 and the 2019 key-run are based on different stomach data, different assumption about the only predator species and different M1, the two key-runs shows quite similar results for the summary output recruitment, SSB and mean F (Figure 9.9–1 in Annex 4). Herring F and SSB are similar, while recruitment is considerably higher in the beginning of the time-series in the 2019 key-run, probably as an effect of the assumed larger cod stock. For Sprat, the trend in SSB and F is the same in the two runs, but F in the 2019 key-run is consistently estimated lower and SSB higher.

The difference in M2 for the two key-runs is more pronounced, especially for herring (Figure 9.9–2 in Annex 4). Herring M2 is now estimated higher for all ages, and much higher for the first part of the time-series. The difference is probably due to the assumption of a larger cod stock (especially of larger cod in the first part of the time-series) in the 2019 key-run, and the application of the predator-prey size selection model in the new key-run, whereas the old version used a uniform size selection. Herring M2 follows better the stock size of cod in the new run which may indicate that the uniform size selection option was not the best choice for the 2012 key-run.

The predation mortality estimates from Gadget the last day of WGSAM are similar to the ones from SMS (Figure 9.10–1 and 9.10–2 in Annex 4). This is encouraging provided that both models have a different model structure.

3.1.6 Previous peer review

The SMS methodology has been reviewed in ICES WKMULTBAL (2012) and WGSAM (2015).

3.2 Review recommendations

WGSAM accepts the model output from SMS as key-run with the settings given in the Stock Annex (see Annex 4).

Key-run summary sheet

AREA	BALTIC SEA
Model name	SMS
Type of model	Age-length structured statistical estimation model
Run year	2019
Predatory species	Assessed species: Herring, Sprat
Prey species	Herrnig, Sprat
Time range	1974–2018.
Time step	Quarterly
Area structure	Eastern Baltic Sea, ICES sub-divisions 25–29, excl Gulf of Riga
Stomach data	Cod: 1974–2014
Purpose of key-run	Making historic data on natural mortality available and multispecies dynamics
Model changes since last key-run	All time-series updated. More stomach data included. Cod is now an external predator estimated by WGBFAS Stock-synthesis model. Daily food ration of changed for the predator cod.
Output available at	Sharepoint/data/Eastern Baltic SMS key-run and https://github.com/ices-eg/wg_WGSAM
Further details in	Report of the Working Group on Multispecies Assessment Methods 2019

WGSAM considers the key-run as currently best possible run with SMS to provide natural mortality estimates. WGSAM recommends to use these values as input to single species stock assessments. The full time-series should be used and not only an update for the years after the last key-run in 2012.

However, there are also clear limitations with the approach and results have been shown to be sensitive to e.g., consumption rates, assumptions regarding M1 and treatment of “Other Food” as well as the size selectivity of cod. In addition, the results depend to a large extent on the outcome of the ICES Eastern Baltic cod assessment. Any bias in this assessment directly influences the predation mortality estimates. Assumptions around other food and constant vulnerabilities may also bias the natural mortality estimates to some extent. Contrarily, the similar results from the Gadget model run are encouraging.

WGSAM does not recommend to use the uncertainty estimates around M as these are underestimated due to the assumption that the cod population is known without error.

For further work WGSAM recommends the following:

1. More analyses on stomach data to get a better process understanding what is driving the systematic changes in relative stomach contents.
2. A split of Other Food in parts where the time dynamic can be taken into account (e.g., flatfish and *Saduria entomon*) and a part that still needs to be assumed constant in time may be beneficial.
3. The inclusion of spatial dynamics (either directly or via overlap coefficients) may improve the fit to data sources.
4. A run with age 1 as recruits could be tried because input for the 0 group is highly uncertain.
5. Account for the uncertainty in cod numbers in the model.

3.3 References

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4 Baltic Sea Gadget key-run review

4.1 Overview

4.1.1 Is the model appropriate for the problem?

Gadget is an age-length structured multispecies model that is implemented on a quarterly time step tracking the dynamics of Baltic cod, herring, and sprat, with a fixed “other food” pool. Similar to the SMS model, the Gadget model can potentially be used to provide natural mortality estimates by age and year as input to single species assessments of Eastern Baltic herring (her.27.25–2932) and Baltic sprat (spr.27.22–32). In addition, dynamics are estimated for Eastern Baltic cod (cod.27.24–32) in the Gadget model, relying on various assumptions from the current cod assessment, especially on M and growth. M estimates for herring and sprat by age and quarter are a direct output of the model. Similarly to SMS, an assumption is needed for residual mortalities $M1$ (which is assumed constant through time) while the predation mortalities $M2$ are estimated dynamically given variable predation intensity by the cod stock ($M = M1 + M2$). As with SMS, the Gadget model provides estimates for the years 1974 to 2018. Therefore, it is appropriate for the problem.

4.1.2 Is the scientific basis of the model sound?

Gadget is an established modelling framework (Begley and Howell, 2004) that has been used to reconstruct single species (Taylor *et al.*, 2007; Bartolino *et al.*, 2011) and multispecies (Pérez-Rodríguez *et al.*, 2016; Kulatska *et al.* 2019) stock dynamics in other regions, perform stock assessments (i.e., hake in the Bay of Biscay (ICES 2019a)) and management strategy evaluation (Howell and Bogstad, 2010; ICES 2017; Elvarsson *et al.* 2018). The modelling approach is considered sound and therefore suitable for the implementation of a key-run. WGSAM will comment on this specific implementation for the Baltic.

4.1.3 Is the input data quality and parameterization sufficient for the problem?

Data Quality

Much of the discussion above for the SMS model is also relevant here, because datasets used to parameterize Gadget and SMS were selected to align as much as possible their implementation. Gadget datasets for each species are identical to stock assessment inputs with the exception of survey numbers at length and age-length keys for the two clupeids, which were recalculated from individual Country data. Gadget Annex (see Annex 5) shows the temporal extent of the input time-series for each species.

Some data are not available at the quarterly model timestep. Prior to 1995, catch at age data is annual for herring and sprat; from 1995 to 2018 verified catch at age is available by quarter. Annual data were partitioned to quarters using the proportions from the 2012 SMS Baltic key-run. Total quarterly catch and quarterly weight at age of herring and sprat prior to 1995 were taken from the 2012 SMS Baltic key-run input data.

Gadget uses two stomach data input files, one informing about the species composition in the stomachs and the other about the size composition of herring and sprat in the stomachs. The first data component is calculated as the prey weight ratio in the stomachs of five cod length groups (i.e., 16–25, 25–35, 35–60, 60–80 and 80–112 cm). The second data component is calculated as the frequency of occurrence using same cod length groups (i.e., 16–25, 25–35, 35–60, 60–80 and 80–112 cm). Exploratory analysis has shown that at least 20 stomach per timestep and length group are needed to represent prey species and length compositions of cod diet. Only those samples that satisfied this requirement were used. Although information on cod diet is retrieved from the same stomach data for both Gadget and SMS, the actual input data differs in the two models. Spatial coverage of stomachs was most sparse in 1994–2003 (Gadget Annex 5). Due to the incomplete spatial coverage of stomach sampling, only quarters 1 and 4 stomachs are used in the Gadget key-run.

As with SMS, much input data quality for Gadget is considered identical to that used in stock assessments for Baltic herring, sprat, and cod, and therefore sufficient for the problem. Both SMS and Gadget share the stomach dataset, which has some issues with spatial and temporal coverage.

Assumptions and Parameterization

A conceptual model representing the sequence of events for each species in each quarter is available in the Gadget Annex Figure 1. Different surveys occur in each quarter prior to natural mortality and fishing mortality. Recruitment of age 0 fish happens in the third quarter for each species. The conceptual model is reasonable and nicely lays out the exact model steps.

The multispecies Gadget model is parameterized by first fitting each species as a single species model, then linking the models using predation on herring and sprat by cod. The cod dynamics are fixed to the single species model estimation, while for herring and sprat, growth parameters are the only parameters not re-estimated after adding cod predation. A shift in weight at age is noted in the data for all Baltic species, so Gadget models the weight at length relationship of clupeids in three time blocks. Therefore, observed changes in weight at age are assumed to be entirely driven by changes in the length-weight relationship, not changes in the growth model. This assumption was not confirmed with data.

Residual mortality (M_1) was assumed to be 0.2 for sprat and 0.1 for herring in Gadget based on the assumption that approx. 50% of stock assessment M was accounted for by predators other than cod. This assumption could be further evaluated using comparisons with diet data or full food web models such as EwE (Bauer *et al.*, 2019; Kulatska *et al.*, 2019).

Consumption is modelled in terms of biomass (kg preys per month). Maximum consumption was assumed independent of temperature and estimated using the 97th percentile of consumption rates estimated from a gastric evacuation model. It was further scaled down divided by feeding level to represent the actual consumption at the population level scale instead of maximum potential consumption.

Parameters of the predator-prey size selection function in Gadget were estimated in the model but suffered of a certain degree of instability.

Baltic cod were modelled dynamically in Gadget, in contrast to the SMS model, which used some Baltic cod stock assessment results (growth parameters, natural mortality and parameters of length-weight relationship) as inputs known without error. Because cod is the only predator driving predation mortality for herring and sprat, this is a key difference between approaches.

4.1.4 Does model output compare well with observations?

The Gadget model is evaluated using fits to input data series, which were used to estimate the Gadget model parameters. This is the typical process for stock assessment models. In addition, comparisons are made between Gadget outputs and single species stock assessment outputs. While model output is not an “observation”, this is a relevant comparison for cod, as Gadget represents an alternative structural model to the stock assessment performed in SS3. This is also a reasonable comparison for herring and sprat, since those single species assessments are informed by SMS-estimated natural mortality from the 2012 key-run. However, we make no assumption that single species assessments are “correct;” we simply note differences and evaluate whether these differences are to be expected given the different approaches, or outside expectations and thus a cause for concern or further investigation.

The reference dataset used for fitting is as described above, with most time-series being the same as those used for single species models, and some as used in the previous (2012) SMS key-run. Sources are listed in Gadget Annex (see Annex 5). Gadget outputs are also compared to the most recent stock assessments for each species (ICES 2019b).

Because the model is to be used to estimate historical M time-series, rather than project, persistence and stability in the absence of fishing (important for projection) were not evaluated.

Gadget model fits to indices of abundance and length/age compositions were presented. These were considered reasonable by WGSAM, Commercial catch at age had reasonable fits for all species, similar to commercial catch at length (available only for cod). Comparison with SS3 fits for cod may be useful in the future. Gadget fits to survey lengths were poorest at the beginning of the time-series for cod, and survey length fit for herring was somewhat inconsistent. Sprat lengths from Gadget seemed to track survey lengths better than for herring. There was bias observed in model-estimated (constant across time), age length keys relative to data for herring older ages, but the Gadget estimated age-length key but covers the observed range for sprat. The largest likelihood components related to the age-length key data for herring and sprat, reflect these poorer fits.

Similar to SMS, Gadget tended to underestimate the proportion of herring prey in cod stomachs relative to the data for cod 35–60 cm after the mid-1990s. However, SMS compensated with sprat proportions being high relative to observations, where Gadget compensates with other food proportions being too high relative to observations.

Single species stock assessment results were generally consistent with Gadget model outputs, however WGSAM noted some differences. Gadget cod numbers at age generally matched SS3 outputs, aside from a notable difference in the middle of time-series for ages 4–8+. This pattern could not be immediately explained. Gadget cod SSB was higher relative to SS3, while estimated recruits were similar, and F was lower. In Gadget, growth parameters such as Linf and k were taken from SS3 for consistency with the assessment, but these parameters may be not entirely compatible between the two models and the implementation of growth may still be different (i.e., Gadget represents variation around an average growth based on a beta-binomial distribution). The result is that the length structure reconstructed by the two models may be more different from that observed by comparing the number-at-age.

For herring and sprat, SSB, recruitment, and F time-series from Gadget were not substantially different from single species assessment outputs (which included time-varying M from the SMS 2012 Baltic key-run). However, additional tests performed after the meeting revealed instability in the reconstruction of the clupeids population size in the historical time period (1974 – end 1980s), prior the beginning of the survey. In particular, the model struggles in the estimation of

the initial population of clupeids which trades-off with estimation of the parameters in the predator-prey size selection, during the historical period when no length data is available from the survey or commercial fleet. Such instability makes estimation of clupeids (especially sprat) population size unreliable during the period prior the 1990s with obvious consequences on the estimation of predation mortality.

There was concern about overfitting the age-0 (recruitment) index for both herring and cod. Comparisons with the cod stock assessment that uses the same input data do not show similar overfitting of the recruitment index (Figure 4.1.4.1). Additional tuning of the model (fixing to 1 the slope of fitting function to age0 survey abundance indices resolved the issue for the age0 index of both herring and cod. This however caused cod numbers at age to become unrealistically high for recent periods, which does not match the stock assessment. The issue was considered more problematic than overfitting of the age0, as cod numbers at age will have a more direct impact on prey mortalities. A more appropriate visualization that respects the log-linear nature of the fitting of survey indices (Figure 4.1.4.2), gives a different perception where overfitting of the age0 group is not a severe issue as initially thought, while the fitting of the IBTS index appear quite poor.

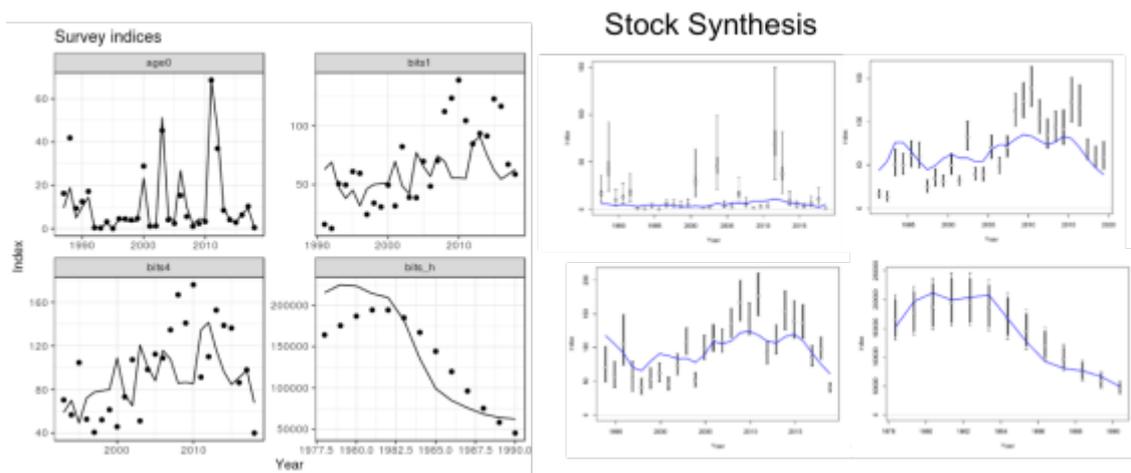


Figure 4.1.4.1. Comparison of fits to cod indices from Baltic Gadget (left) and Baltic cod stock assessment (right).

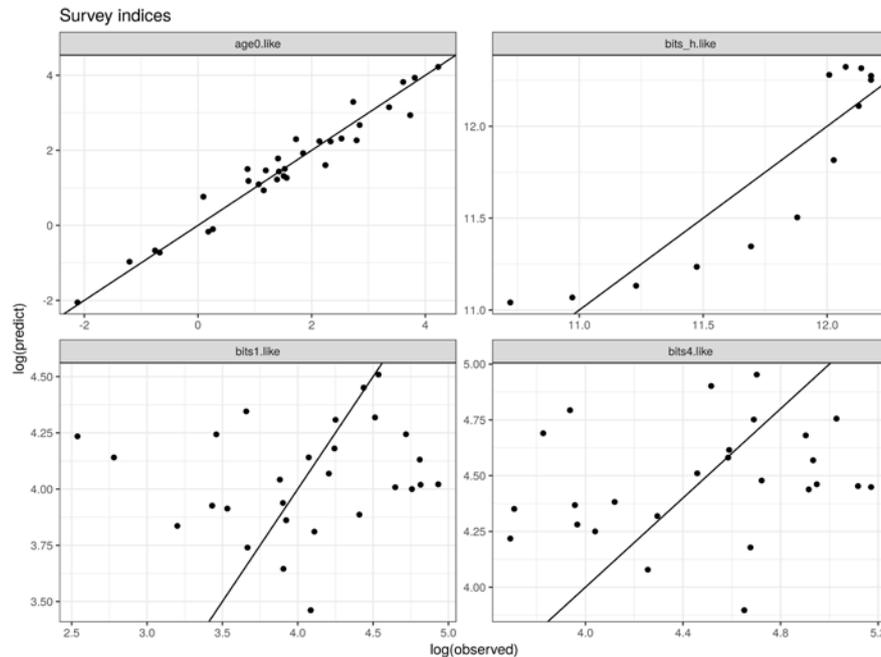


Figure 4.1.4.2. Comparison of log-transformed observed and predicted cod survey abundance indices.

Time-series of M output from Gadget met expectations for decreasing M with age aside from those for age 0. Because age 0 herring and sprat are only present in the model for part of a year, M should be scaled up for comparison; however, even considering this it still appeared too low to WGSAM. There was discussion that both Gadget and SMS probably don't need to include age 0 M estimated since they are not used in stock assessments where recruitment happens at age 1.

4.1.5 Uncertainty

Several sensitivity runs were completed and shown for Gadget, and results are discussed below. However, a larger issue is that in its current configuration, Baltic Gadget is unable to estimate uncertainty in parameter estimates or outputs of interest (M). Future work should evaluate methods currently used in single species Gadget models (bootstraps, etc.) to estimate uncertainty in outputs.

Sensitivities explored:

1. Estimating size selectivity by cod and the fishery initially made little difference in results, but further work estimating selectivities revealed model instability.
2. Using different quantiles to estimate maximum consumption had the slightly larger impacts on model estimates of M for herring than for sprat. In general 95th, 97th and 99th quantiles performed similarly, with a bit lower M for age 1–2 herring and a bit higher M for age 5–8+ estimates for the 97th percentile.
3. Retrospective analyses were not run for Gadget during WGSAM.

Concerns with model stability were raised at the meeting, and were confirmed by additional tests. Further work is necessary to evaluate different initial conditions, parameter estimation phases, and adjustments to the simulated annealing algorithm to ensure convergence to a global minimum. Sensitivity to initial conditions and other assumptions is difficult to evaluate while model stability remains a concern.

4.1.6 Previous peer review

This is the first time Baltic Gadget has been reviewed by WGSAM. The implementation of multispecies Gadget for the Baltic Sea was peer-reviewed for its ability to predict cod diets in the Baltic (Kulatska *et al.*, 2019). The Baltic Gadget model was further reviewed as part of a successful doctoral thesis defence in September 2019. The Gadget framework and other assessments implemented in Gadget have been peer reviewed as noted in the section above describing the scientific basis for the model.

4.2 Review recommendations

WGSAM appreciated the visual overview of data sources and the conceptual model provided in the model documentation during the meeting; these aspects of the Gadget model were exemplary and should be emulated in future key-runs for any system. Similarly, visualizations of fits to index and compositional data were very useful. A minor suggestion would be to ensure that all figures include a key (e.g. red lines = Gadget output, black lines = reference time-series).

However, difficulties with the model prevented review of full Gadget key-run results until the second to last day of the meeting, and precluded comparison of results with the SMS key-run until the last morning of the meeting. Some delays related to the relatively late delivery of length and age-length input data for herring and sprat from acoustic surveys, which was requested in July 2019 but not delivered from all nations until mid-September 2019. Streamlining processes for updating data would be helpful to facilitate future key-runs.

For all meetings after 2019, WGSAM will require draft key-run results and documentation 1 month to 2 weeks prior to the meeting so that a more thorough review can be completed prior to the meeting, reserving meeting time for model comparisons, ensemble modelling, and coming to agreement on recommendations. This means that data updates must be requested and provided in a timely manner. If the full results and documentation are not available prior to the meeting, no key-run review will be conducted by WGSAM.

Baltic herring and sprat M time-series estimated by Gadget are overall similar in both scale and pattern to those estimated by Baltic SMS (see section 5, Figure 5.1). This similarity suggests that M time-series estimated by these models are driven by the common input data rather than the particular multispecies model configuration, and lends confidence that use of these M estimates in single species assessment provides a good representation of time-varying predation mortality.

However, due to the short time for review and comparison with SMS (the framework for the previously reviewed 2012 Baltic key-run), and most importantly due to remaining issues with model stability which influence the historical part of the time-series, WGSAM does not endorse the Baltic Gadget key-run for providing M time-series to herring and sprat stock assessments at this time.

WGSAM encourages continued work with the Baltic Gadget model as it is a promising framework for providing future key-run results. In particular, concerns with model stability should be addressed, and methods for estimating uncertainty in M outputs explored. Further work to evaluate differences between Gadget and SS3 growth will also be useful to evaluate why some cod results differ between these frameworks, which might be influential on estimates of herring and sprat M.

If WGSAM had been able to complete a full review and endorse both Gadget and SMS Baltic key-runs, the recommendation would have been to use results of both models to provide an ensemble M input to stock assessments. WGSAM will work towards documenting ensemble

procedures in future years where multiple key-runs for the same system and purpose are reviewed.

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5 Comparison of Gadget and SMS models for the Baltic Sea

Two multispecies models, Gadget and SMS, for the Central Baltic Sea, were developed to estimate cod predation mortalities on herring and sprat in 1974–2018. Most relevant similarities and differences between the models are outlined in the Table 5–1. The major differences are, though, that SMS is a stochastic while Gadget is a deterministic model and that SMS is an age-based model, where predator-prey selection is length based (Lewy and Vinther, 2004), while Gadget is a full age-length based model, as it tracks number and characteristics of fish in a population cell with both age and length attributes (Begley and Howell, 2004).

Table 5–1. Comparison in the use of key dataset, implementation of model components and assumptions of SMS.

Data, model assumption and implementation	SMS	Gadget
Model type	Stochastic age-length structured multispecies model. Fisheries model and survey sub-models are by age, while predation model is by size .	Deterministic full age-length statistical model
Temporal coverage and resolution	1974–2018, quarterly	1974–2018, quarterly
Spatial resolution	Single area	Single area
Stocks included	cod (cod.27.24–32) herring (her.27.25–2932) sprat (spr.27.22–32)	cod (cod.27.24–32) herring (her.27.25–2932) sprat (spr.27.22–32)
Fish population dynamics	herring: dynamic sprat: dynamic cod: fixed, stock size from input	herring: dynamic sprat: dynamic cod: dynamic estimated in a separate single-species phase
Fisheries	No split into fisheries. Total catch at age numbers by species are used.	Two pelagic fleets harvesting herring and sprat, and two fleets (active and passive) harvesting cod
Trophic interactions	Predation of cod on sprat, herring and other food	Predation of cod on sprat, herring and other food
Other food	Fixed (constant biomass)	Fixed (constant biomass)
Gastric evacuation model	Evacuation rate specific per prey was calculated for each stomach using Andersen and Beyer (2005)	Evacuation rate specific per prey was calculated for each stomach using Andersen and Beyer (2005)
Consumption by prey	Size specific total consumption rates (food Ration, R) are estimated outside the model separately by decade and accounting for a seasonal (quarterly) effect. The consumption of an individual prey (p) at size l by cod at length L is derived from the total biomass eaten ($N_L \cdot R_L$), the available	$C_{p,l,L} = \frac{N_L \cdot C_{max,L} \cdot \bar{\varphi} \cdot F_{p,l,L}}{\sum_{p=1}^n F_{p,l,L}}$ <p>where: $\langle N_l \rangle$ is the number of cod of length L $\langle C_{max,L} \rangle$ is the maximum consumption of cod of length L $\langle \bar{\varphi} \rangle$ is the average feeding level by 5 years</p>

	<p>biomass ($B_{p,l} \cdot S_{p,l,L}$) of the individual prey and the total available biomass of all preys ($\sum_{p=1}^n B_{p,l} \cdot S_{p,l,L}$), as suggested by Andersen and Ursin (1977) and Gislason and Helgason (1985)</p> $C_{p,l,L} = \frac{N_L \cdot R_L \cdot B_{p,l} \cdot S_{p,l,L}}{\sum_{p=1}^n B_{p,l} \cdot S_{p,l,L}}$ <p>Where: B is the biomass of a given prey and S is the food suitability of a given prey and size for a given predator and size</p>	<p>$\langle F_{p,l,L} / \sum_{p=1}^n F_{p,l,L} \rangle$ is the relative contribution of the prey p of length l to the realised consumption of cod of length L</p>
Maximum consumption	Food ration is given as input (average consumption)	97 th quantile of the empirical consumption distribution based on the stomach data
Feeding Level	Assumed constant (1)	$\varphi_{i,L} = C_{i,L} / C_{max,L}$ <p>where: $\langle C_{i,L} \rangle$ is the consumption of fish i and length L estimated using evacuation model $\langle C_{max,L} \rangle$ is maximum consumption of cod of length L</p>
Extent of stomachs data used in the model	1974–2014, quarter 1 to 4	1974–2014, quarter 1 and 4
Data components fitted by the model and based on stomach data	<p>Catch at age numbers (log-normal distribution).</p> <p>Survey CPUE at age (log-normal distribution).</p> <p>Relative stomach contents (weight ratio) by cod length group and prey and prey size groups (Dirichlet distribution)</p>	<p>Data are aggregated into five cod size groups (16–25, 25–35, 35–60, 60–80 and 80–112 cm) and used to represent two data components:</p> <ul style="list-style-type: none"> •prey species composition (weight ratio; from 1974–2014) •prey length composition (presence ratio; from 1977, 1978, 1980–2014)
Prey suitability	<p>The suitability (S) of prey at size for a predator at size is defined as the product of predator dependent size preference coefficient, a predator prey species dependent vulnerability coefficient and a seasonal predator prey overlap index coefficient.</p> <p>A lognormal size preference is used, as suggested by Anderson and Ursin (1977), with the preferred size ratio and its variance estimated in the model.</p>	<p>Prey-specific size selection. Simplified size selection from Andersen and Ursin (1977):</p> $S_{i,L} = p_2 \cdot e^{-\frac{(\ln \frac{L}{l} - p_1)^2}{p_3}}$ <p>where: $\langle L \rangle$ predator size $\langle l \rangle$ prey size $\langle p_1 \rangle$ describes the optimal predator-prey size ratio $\langle p_3 \rangle$ determines the deviation of the selection curve (i.e., the length range of preys selected) $\langle p_2 \rangle$ is a half-year specific prey preference</p>
Background mortality	herring: 0.1 sprat: 0.2	herring: 0.1 sprat: 0.2

Despite the differences in the structure of Gadget and SMS models, the predation mortalities estimated by the two models are rather similar (Figure 5.1). The SMS estimated herring M values for age 0 and age 1 are generally higher than the Gadget estimates, while Gadget generally estimate a higher M for ages 2+ . The same pattern with a higher Gadget M for age 2+ is also seen for sprat.

Recruitment is consistent between the two models (Figure 5.2) and also with the single species assessment, with the exception of larger herring recruitments estimated by Gadget during the first years 1974–1982 and for sprat in the early 1990s.

The SSB of herring are similar between the two models (Figure 5.2) and the ICES assessment from the end of the 1980s, while Gadget estimates are considerably larger during the 1970s and most of the 1980s. The sprat SSB estimates are also quite consistent between the two multispecies models and overall they tend to be larger than in the single species assessment.

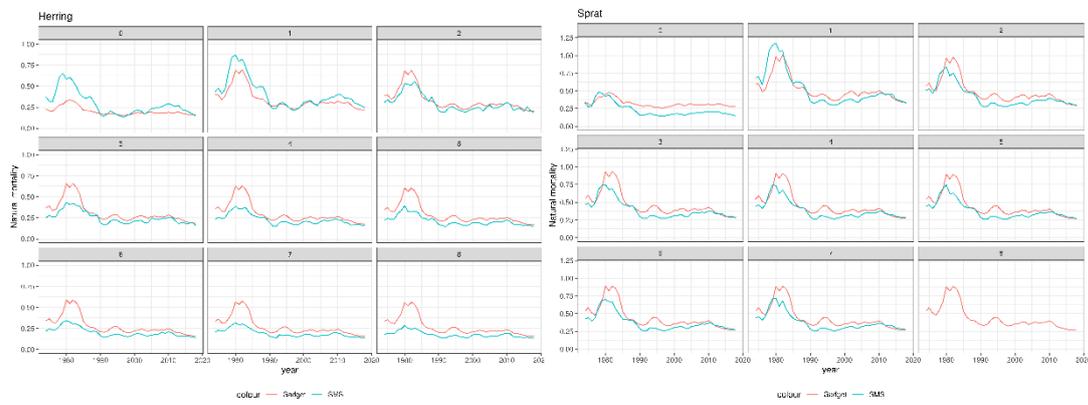


Figure 5.1. Comparison of Gadget (red) and SMS (green) M time-series at age for Baltic herring (left) and sprat (right).

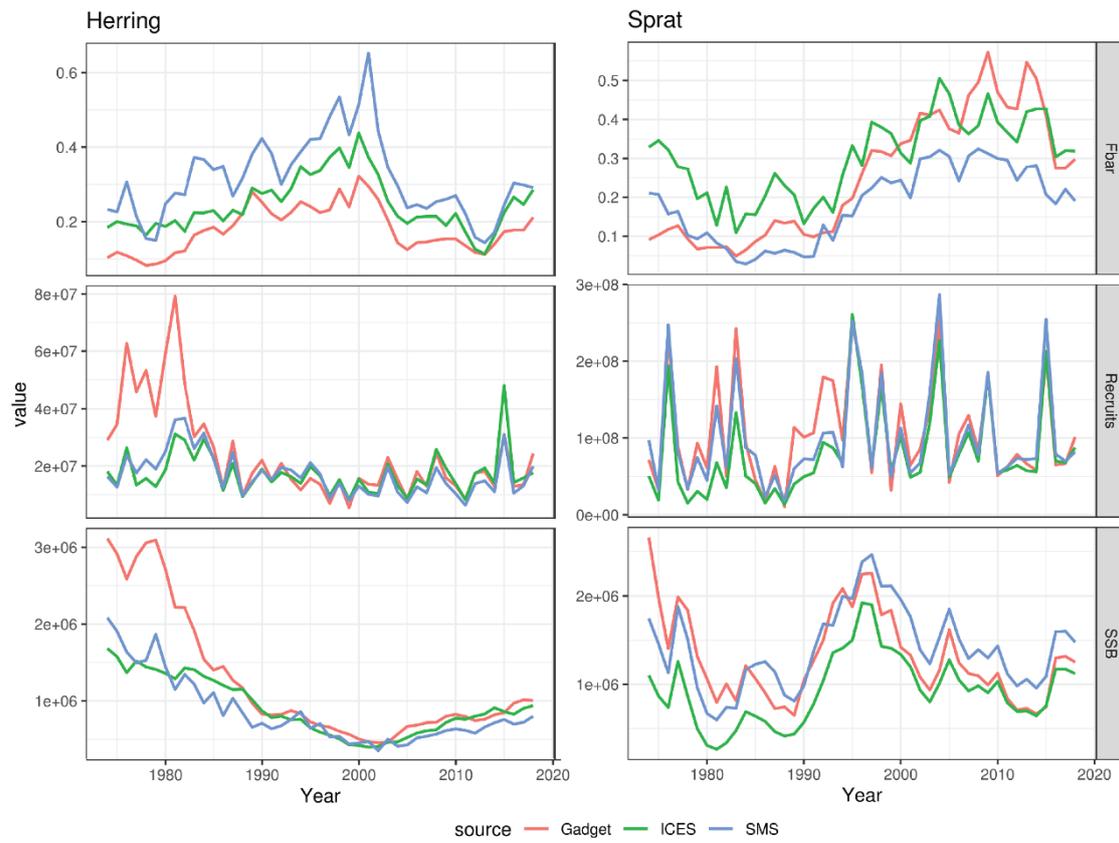


Figure 5.2 Comparison of Gadget (red), SMS (blue) and stock assessment by ICES (green) time-series of F_{bar} , number of recruits (age1) and SSB for Baltic herring (left) and sprat (right).

References

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Annex 1: List of participants

Name	Institute	Country (of institute)	Email
Sarah Gaichas (co-chair)	NOAA Northeast Fisheries Science Center, Woods Hole	USA	Sarah.Gaichas@noaa.gov
Alexander Kempf (CO-CHAIR)	Thuenen Institute of Sea Fisheries Palmaille 9 22767 HAMBURG	Germany	alexander.kempf@thuenen.de
Alan Baudron	Marine Scotland Science 375 Victoria Rd, Aberdeen AB11 9DB	United Kingdom	Alan.Baudron@gov.scot
Valerio Bartolino	Swedish University of Agricultural Sciences, Department of Aquatic Resources, Institute of Marine Research, Turistgatan 5, SE-453 30 Lysekil	Sweden	valerio.bartolino@slu.se
Andrea Belgrano	Swedish University of Agricultural Sciences, Department of Aquatic Resources, Institute of Marine Research, Turistgatan 5, SE-453 30 Lysekil, and Swedish Institute for the Ma- rine Environment (SIME), Box 260, SE-405 30 Göteborg	Sweden	andrea.belgrano@slu.se
Jacob Bentley	Scottish Association for Marine Science Oban, Argyll, PA37 1QA	United Kingdom	Jacob.Bentley@sams.ac.uk
Chloe Bracis	French Institut of Research for the Exploitation of the Sea (Ifremer), 150 Quai Gam- betta, 62200 Boulogne-sur- Mer	France	Chloe.Bracis@ifremer.fr
Francisco DeCastro	Fisheries & Aquatic Ecosystems. AFBI 18a Newforge Lane, Belfast, BT9 5PX	United Kingdom	Francisco.DeCastro@afbini.gov.uk
Thomas Del Santo O'Neill	Queen Mary, University of London	United Kingdom	delsantooneillthomas@gmail.com
Nataliia Kulatska	Swedish University of Agricultural Sciences, Department of Aquatic Resources, Institute of Marine Research, Turistgatan 5, SE-453 30 Lysekil	Sweden	nataliia.kulatska@slu.se
Sigrid Lehuta	French Institut of Research for the Exploitation of the Sea (Ifremer), rue de l'île d'Yeu, 44300 Nantes	France	sigrid.lehuta@ifremer.fr
Sean Lucey	NOAA Northeast Fisheries Science Center, Woods Hole	USA	Sean.Lucey@noaa.gov
Vidette McGregor	National Institute of Water & Atmospheric Research Ltd (NIWA)	New Zealand	Vidette.McGregor@niwa.co.nz

	301 Evans Bay Parade, Greta Point, Wellington		
Stefan Neuenfeldt	DTU-Aqua Kemitorvet 2800 Kgs. Lyngby	Denmark	stn@aqua.dtu.dk
Diego Panzeri	Istituto Nazionale di Oceanografia e di Geofisica Sperimentale - OGS Division of Oceanography ECHO Group Ecology and Computational Hydrodynamics in Oceanography Via Beirut 2/4 (Ex-Sissa building), 34151, Trieste	Italy	dpanzeri@inogs.it
Floor Soudijn	Wageningen Marine Research Haringkade 1, IJmuiden	Netherlands	floor.soudijn@wur.nl
Michael Spence	Centre for Environment, Fisheries and Aquaculture Science (CEFAS) Pakefield Road NR33 0HT Lowestoft Suffolk	United Kingdom	michael.spence@cefas.co.uk
Vanessa Trijoulet	DTU-Aqua Kemitorvet 2800 Kgs. Lyngby	Denmark	vttri@aqua.dtu.dk
Morten Vinther	DTU-Aqua Kemitorvet 2800 Kgs. Lyngby	Denmark	mv@aqua.dtu.dk

Annex 2: Resolutions

The **Working Group on Multispecies Assessment Methods** (WGSAM), chaired by Alexander Kempf, Germany, and Sarah Gaichas, USA, will work on ToRs and generate deliverables as listed in the Table below.

	MEETING DATES	VENUE	REPORTING DETAILS	COMMENTS (CHANGE IN CHAIR, ETC.)
Year 2019	14–18 October	Rome, Italy	Interim report by 1 December	
Year 2020			Interim report by DATE	
Year 2021			Final report by DATE	Change in Chair <u>Incoming co-chair</u> : Valerio Bartolino <u>Outgoing co-chair</u> : Alexander Kempf

ToR descriptors

ToR	Description	Background	Science Plan codes	Duration	Expected Deliverables
a	Review further progress and deliver key updates on multispecies modelling and ecosystem data analysis contributing to modeling throughout the ICES region	This ToR acts to increase the speed of communication of new results across the ICES area	5.1; 5.2; 6.1,	3 years	Report on further progress and key updates.
b	Update of key-runs (standardized model runs updated with recent data) of multispecies and ecosystem models for different ICES regions	The key runs provide information on natural mortality for inclusion in various single species assessments	5.1; 5.2; 6.1	3 years	Report on output of multispecies models including stock biomass and numbers and natural mortalities for use by single species assessment groups and external users.
c	Establish and apply methods to assess the skill of multispecies models intended for operational advice	This work is aimed at assessing the performance of models intended for strategic or tactical management advice.	5.1; 6.1; 6.3	Establish methods 2019, apply 2020-2021	Manuscript for methods, report on success of methods for different examples.
d	Evaluate methods for generating advice by comparing and/or combining multiple models	This work is aimed at addressing structural uncertainty in advice arising from multiple models, as applied for example management questions	5.1; 6.1; 6.3	3 years	Report on methods for comparing models and for constructing model ensembles.
e	Management Strategy	Adapting existing	5.3; 6.1; 6.3	3 years	Review of MSE

Evaluation (MSE) methods and applications for multispecies and ecosystem advice, including evaluating management procedures and estimating biological reference points	multispecies/ecosystem models for MSE (operating models, assessment models), visualizing tradeoffs and uncertainty for managers and stakeholders	modeling approaches. Review of visualization methods. Review of applications throughout the ICES area with lessons learned.
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Summary of the Work Plan

Year 1	All ToRs, Key run Baltic, multiple models
Year 2	All ToRs, Key Run North Sea SMS (maybe others)
Year 3	All ToRs, Key Run US Northeast Shelf, multiple models

Supporting information

Priority	The current activities of this Group will lead ICES into issues related to the ecosystem effects of fisheries, especially with regard to the application of the MSY Approach. The activities will provide information (e.g., natural mortality estimates, performance of indicators) and tools (e.g., multi-model ensembles, keyrun models) valuable for the implementation of an integrated advice in several North Atlantic ecosystems. Consequently, these activities are considered to have a very high priority.
Resource requirements	The research programmes which provide the main input to this group are already underway, and resources are already committed. The additional resource required to undertake additional activities in the framework of this group is negligible.
Participants	Approx 20. Expertise in ecosystem, modelling and fish stock assessment from across the whole ICES region.
Secretariat facilities	None.
Financial	No financial implications.
Linkages to ACOM and groups under ACOM	ACOM, most assessment Expert Groups
Linkages to other committees or groups	WGMIXFISH, WGDIM, WGBIFS, IBTSWG, WGEKO, WGINOSE, WGIAB, WGNARS, WGIPEM.
Linkages to other organizations	None

Annex 3: Irish Sea EwE documentation

A key-run for the Irish Sea EwE model covering 1973–2016 was produced. The Irish Sea EwE model was co-created by researchers and stakeholders as part of ICES WKIrish. The aim with the Irish Sea EwE key-run is to use the model to “fine tune” the quota advice within the predefined EU F_{MSY} ranges. In “good” conditions you could fish at the top of the range, in “poor” conditions you should fish lower in the range. The range has already been evaluated as giving good yield while still being precautionary, so this should be fine for ICES to use in advice. The model was also developed with the aim to (1) better understand the drivers underpinning the slow recovery of commercial stocks and (2) provide a medium for stakeholder input and engagement.

1.1. Ecopath parameterization

The Irish Sea EwE model comprises 41 functional groups including two detrital groups (detritus, discards), two primary producers (phytoplankton, seaweed), ten invertebrate groups, 22 finfish groups, two seabird groups (low discard diet and high discard diet), and three marine mammal groups (Figure 2.1). A detailed description of functional group design can be found in (Bentley *et al.*, 2018). Table 0.1 summarises the basic input parameters for functional groups.

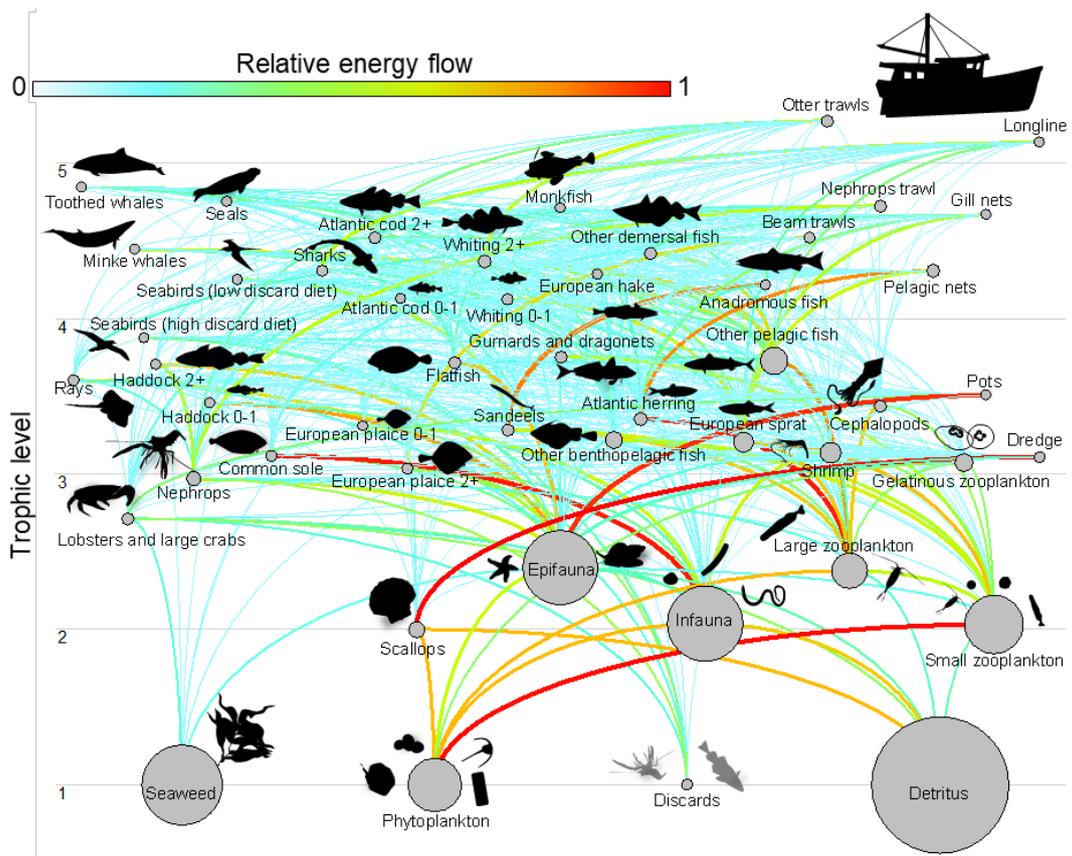


Figure 2.1. Energy flow and biomass diagram for the Irish Sea Ecopath food web model. Functional groups and fleets are represented by nodes, the relative size of functional group nodes denote their biomass whilst the size of fleet nodes denote the size of their catch. Lines represent the flow of energy and the y-axis denotes group trophic level.

Table 0.1. Irish Sea functional group information. Trophic level (TL), biomass t.km⁻² (B), production/biomass year⁻¹ (PB), consumption/biomass year⁻¹ (QB), production /consumption (PQ), ecotrophic efficiency (EE), landings t.km⁻² (L), discards t.km⁻² (D). Parameters estimated by the model are placed in brackets.

	Functional group	TL	B	PB	QB	PQ	EE	L	D
	1 Toothed whales	4.85	0.005	0.02	15.52	(0.001)	(0.64)	0.00	0.00007
	2 Minke whales	4.45	0.07	0.02	6.58	(0.003)	(0.14)	0.00	0.0002
	3 Seals	4.75	0.002	0.06	14.43	(0.004)	(0.12)	0.00	0.00002
	4 Seabirds (high discard diet)	3.87	0.002	0.40	66.02	(0.006)	(0.00)	0.00	0.00
	5 Seabirds (low discard diet)	4.25	0.002	0.40	69.21	(0.006)	(0.00)	0.00	0.00
	6 Sharks	4.31	0.29	0.40	4.01	(0.10)	(0.34)	0.01	0.02
	7 Rays	3.60	(0.25)	0.85	3.28	(0.26)	0.50	0.05	0.02
	8 Atlantic cod 2+	4.53	0.34	0.82	3.12	(0.26)	(0.92)	0.19	0.02
	9 Atlantic cod 0-1	(4.13)	0.07	1.01	(7.64)	(0.13)	(0.94)	0.02	0.001
	10 Whiting 2+	4.37	0.56	0.76	5.39	(0.14)	(0.97)	0.24	0.06
	11 Whiting 0-1	(4.12)	0.24	1.52	(11.88)	(0.13)	(1.00)	0.03	0.02
	12 Haddock 2+	3.70	0.09	0.89	4.42	(0.20)	(0.99)	0.03	0.007
	13 Haddock 0-1	(3.46)	0.05	1.78	(10.28)	(0.17)	(0.99)	0.0001	0.003
	14 European plaice 2+	3.03	0.16	0.79	3.75	(0.21)	(0.99)	0.07	0.02
	15 European plaice 0-1	(3.31)	0.03	1.38	(10.30)	(0.13)	(0.90)	0.00004	0.0007
	16 Common sole	3.12	0.11	0.81	5.61	(0.14)	(0.96)	0.03	0.0004
	17 Flatfish	3.72	0.47	(1.52)	6.07	0.25	(0.96)	0.01	0.002
	18 Monkfish	4.71	0.03	0.49	2.75	(0.18)	(0.69)	0.01	0.002
	19 European hake	4.28	(0.09)	(0.98)	3.92	0.25	0.95	0.02	0.003
	20 Sandeels	3.29	(0.35)	(2.05)	8.21	0.25	0.95	0.00002	0.00
	21 Gurnards	3.76	0.34	(1.40)	5.61	0.25	(1.00)	0.001	0.001
	22 Other demersal fish	4.42	(0.36)	0.96	4.32	(0.22)	0.95	0.05	0.004
	23 Other benthopelagic fish	3.22	(1.57)	(1.85)	7.38	0.25	0.95	0.002	0.0005
	24 Atlantic herring	3.35	0.72	1.35	6.59	(0.21)	(0.95)	0.40	0.00004
	25 European sprat	3.21	(2.30)	(2.43)	9.70	0.25	0.95	0.27	0.000001
	26 Other pelagic fish	3.73	(4.18)	(1.28)	5.11	0.25	0.95	0.02	0.0009
	27 Anadromous fish	4.22	0.03	0.64	3.17	(0.20)	(0.34)	0.002	0.00
	28 Lobsters and large crabs	2.71	(0.51)	0.62	(4.13)	0.15	0.95	0.007	0.0003
	29 <i>Nephrops</i>	2.97	(0.91)	1.27	(8.47)	0.15	0.95	0.12	0.03
	30 Shrimp	3.14	(2.32)	2.67	(17.80)	0.15	0.95	0.007	0.00
	31 Cephalopods	3.44	(0.32)	1.98	15.00	(0.13)	0.95	0.002	0.0001
	32 Scallops	2.00	(1.24)	1.15	(7.64)	0.15	0.95	0.23	0.002
	33 Epifauna	2.39	(25.45)	1.01	(4.03)	0.25	0.95	0.07	0.00
	34 Infauna	2.04	(25.76)	1.70	(6.80)	0.25	0.95	0.00001	0.00
	35 Gelatinous zooplankton	3.07	1.70	(0.76)	2.54	0.30	(0.69)	0.00	0.00
	36 Large zooplankton	2.38	6.81	10.0	(33.33)	0.30	(0.68)	0.00	0.00
	37 Small zooplankton	2.03	16.18	18.0	(60.00)	0.30	(0.52)	0.00	0.00
	38 Seaweed	1.00	29.30	1.00	-	-	(0.39)	0.00	0.00
	39 Phytoplankton	1.00	13.83	226	-	-	(0.33)	0.00	0.00
	40 Discards	1.00	0.22	-	-	-	(0.54)	-	-
	41 Detritus	1.00	100.00	-	-	-	(0.12)	-	-

Ecopath input parameters, references and assumptions are documented in Table 0.2. All biomass units (**B**) are in units of $t.km^{-2}$ (area covered = 58,000 km^2) whilst production/biomass (**PB**) and consumption/biomass (**QB**) are annual ratios ($year^{-1}$). Where necessary, assumptions were made regarding the ecotrophic efficiency (**EE**) or production/consumption (**PQ**; $year^{-1}$) parameters in order to estimate missing parameters (B, PB, and/or QB). We also provide references for diet composition (**DC**). Parameters which have been updated since the publication of the 2018 technical report have been denoted with '*’.

Table 0.2. Irish Sea Ecopath parameter origins and assumptions.

Functional group	Parameter	Value	Source	Comment
1: Toothed whales	B	0.00526	(Hammond <i>et al.</i> , 2013, Bjorge and Tolley, 2009)	Estimate from the Celtic Sea population and knowledge from Dr Hernández-Milián.
	PB	0.02	(Trites <i>et al.</i> , 1999, Mackinson and Daskalov, 2008)	Parameter reflects half of the maximum rate for annual whale population increase (4%)
	QB	15.52	(Trites <i>et al.</i> , 1999)	Mean daily ration calculated as a function of individual weight.
	EE	0.642	Calculated by EwE	-
	PQ	0.001	Calculated by EwE	-
	DC	See Table 0.4	(Santos <i>et al.</i> , 2001, Hernandez-Milian <i>et al.</i> , 2015, Rogan and Hernández-Milián, 2011)	The parameterisation of marine mammal diets were guided by marine mammal expert Dr Hernández-Milián.
2: Minke whales	B	0.0664	(Wall, 2013, Hammond <i>et al.</i> , 2013)	Estimate from the Celtic Sea population and knowledge from Dr Hernández-Milián.
	PB	0.02	(Trites <i>et al.</i> , 1999)	Parameter reflects half of the maximum rate for annual whale population increase (4%)
	QB	6.58	(Trites <i>et al.</i> , 1999)	Mean daily ration calculated as a function of individual weight.
	EE	0.136	Calculated by EwE	-
	PQ	0.003	Calculated by EwE	-
	DC	See Table 0.4	(Pierce <i>et al.</i> , 2004, Ryan <i>et al.</i> , 2013)	The parameterisation of marine mammal diets were guided by marine mammal expert Dr Hernández-Milián.
3: Seals	B	0.00225	(Bonner, 1981, Bonner, 1972, Summers <i>et al.</i> , 1980, Lyons,	Biomass estimated with guidance from Dr Hernández-Milián.

			2004, Ó'Cadhla and Strong, 2007)	
	PB	0.06	(Trites <i>et al.</i> , 1999, Small and DeMaster, 1995)	Parameter reflects half of the maximum rate for annual seal population increase (12%)
	QB	14.43	(Trites <i>et al.</i> , 1999)	Mean daily ration calculated as a function of individual weight.
	EE	0.117	Calculated by EwE	-
	PQ	0.004	Calculated by EwE	-
	DC	See Table 0.4	(Kierly <i>et al.</i> , 2000, Philpott, 2001, Kavanagh <i>et al.</i> , 2010, Gosch, 2017, Gosch <i>et al.</i> , 2014)	The parameterisation of marine mammal diets were guided by marine mammal expert Dr Hernández-Milián.
4: Seabirds (high discard diets) <i>Includes species for which discards constitutes >10% of their diet.</i>	B	0.0018	(ICES, 2002)	Value based on report from the ICES Seabird Ecology Working Group. This estimate reflects population sizes in 2001 and was used in the absence of data for earlier years.
	PB	0.4	(Trites <i>et al.</i> , 1999, Serpetti <i>et al.</i> , 2017)	Based on the estimate of Trites <i>et al.</i> (1999) for the mortality rate of piscivorous birds as adopted by the West Coast of Scotland EwE model (Serpetti <i>et al.</i> , 2017)
	QB	66.02	(Nilsson and Nilsson, 1976)	Calculated from daily ration and body weight (equation from Nilsson and Nilsson (1976)).
	EE	0	Calculated by EwE	Group neither consumed by other groups nor caught by fisheries in the model.
	PQ	0.006	Calculated by EwE	-
	DC	See Table 0.4	See Table 5 in Bentley <i>et al.</i> (2018) for an extensive list of diet references.	-
5: Seabirds (low discard diets) <i>Includes species for which discards constitutes <10% of their diet.</i>	B	0.0015	(ICES, 2002)	Value based on report from the ICES Seabird Ecology Working Group. This estimate reflects population sizes in 2001 and was used in the absence of data for earlier years.
	PB	0.4	(Trites <i>et al.</i> , 1999, Serpetti <i>et al.</i> , 2017)	Based on the estimate of Trites <i>et al.</i> (1999) for the mortality rate of piscivorous

				birds as adopted by the West Coast of Scotland EwE model (Serpetti <i>et al.</i> , 2017)
	QB	69.21	(Nilsson and Nilsson, 1976)	Calculated from daily ration and body weight (equation from Nilsson and Nilsson (1976)).
	EE	0	Calculated by EwE	Group neither consumed by other groups nor caught by fisheries in the model.
	PQ	0.006	Calculated by EwE	-
	DC	See Table 0.4	See Table 5 in Bentley <i>et al.</i> (2018) for an extensive list of diet references.	-
6: Sharks	B	0.29	(ICES, 2017a, ICES, 2017b)	Estimate based on the BTS-VIIa and NIGFS surveys for the Irish Sea (VIIa).
	PB	0.4	(Allen, 1971, Pauly <i>et al.</i> , 1990)	Equivalent to the instantaneous rate of total mortality (Allen, 1971) which is calculated as fishing mortality (F ; catch/biomass) plus natural mortality (M ; Pauly <i>et al.</i> (1990)).
	QB	4.01	(Pauly <i>et al.</i> , 1990, Christensen and Pauly, 1992)	Calculated using an empirical model which incorporates water temperature and feeding characteristics.
	EE	0.344	Calculated by EwE	-
	PQ	0.1	Calculated by EwE	-
	DC	See Table 0.4	(Pinnegar, 2014, ICES, 2018e, Bentley <i>et al.</i> , In press)	Diet designed using CEFAS fish stomach records (DAP-STOM) and fishers' knowledge.
7: Rays	B	0.254	Calculated by EwE	Survey estimates (1993-2016) were too low to balance production with mortality (F and M).
	PB	0.845	(Allen, 1971, Pauly <i>et al.</i> , 1990)	Equivalent to the instantaneous rate of total mortality (Allen, 1971) which is calculated as fishing mortality (F ; catch/biomass) plus natural mortality (M ; Pauly <i>et al.</i> (1990)).
	QB	3.28	(Pauly <i>et al.</i> , 1990, Christensen and Pauly, 1992)	Calculated using an empirical model which incorporates water temperature and feeding characteristics.

	EE	0.5	-	Assumption applied to estimate biomass and provide realistic responses to changes in F .
	PQ	0.258	Calculated by EwE	-
	DC	See Table 0.4	(Pinnegar, 2014, ICES, 2018e, Bentley <i>et al.</i> , In press)	Diet designed using CEFAS fish stomach records (DAP-STOM) and fishers' knowledge.
8: Adult cod (2+)	B	0.339	(ICES, 2017c, ICES, 2018c)	Estimated Age 2+ biomass for the year 1973 from ASAP model output for the Irish Sea (VIIa).
<i>Multi-stanza group; linked to Juvenile cod (0-1)</i>	PB	0.82	(Allen, 1971, Pauly <i>et al.</i> , 1990)	Equivalent to the instantaneous rate of total mortality (Allen, 1971) which is calculated as fishing mortality (F ; catch/biomass) plus natural mortality (M ; Pauly <i>et al.</i> (1990)).
	QB	3.12	(Pauly <i>et al.</i> , 1990, Christensen and Pauly, 1992)	Calculated using an empirical model which incorporates water temperature and feeding characteristics.
	EE	0.92	Calculated by EwE	-
	PQ	0.263	Calculated by EwE	-
	DC	See Table 0.4	(Pinnegar, 2014)	Diet designed using CEFAS fish stomach records (DAP-STOM) from cod with length greater than 57.8 cm (L_{mat}).
9: Juvenile cod (0-1)	B	0.0662	Calculated by EwE	Estimate based on adult cod parameters (leading group)
<i>Multi-stanza group; linked to Adult cod (2+)</i>	PB	1.01	(Allen, 1971, Pauly <i>et al.</i> , 1990)	Equivalent to the instantaneous rate of total mortality (Allen, 1971) which is calculated as fishing mortality (F ; catch/biomass) plus natural mortality (M ; Pauly <i>et al.</i> (1990)).
	QB	7.641	Calculated by EwE	Estimate based on adult cod parameters (leading group)
	EE	0.92	Calculated by EwE	-
	PQ	0.263	Calculated by EwE	-
	DC	See Table 0.4	(Pinnegar, 2014)	Diet designed using CEFAS fish stomach records (DAP-STOM) from cod with length less than 57.8 cm (L_{mat}).
	B	0.56	(ICES, 2017c, ICES, 2018c)	Estimated Age 2+ biomass for the year 1980 from ASAP

<p>10: Adult whiting (2+)</p> <p><i>Multi-stanza group; linked to Juvenile whiting (0-1)</i></p>				model output for the Irish Sea (VIIa).
	PB	0.762	(Allen, 1971, Pauly <i>et al.</i> , 1990)	Equivalent to the instantaneous rate of total mortality (Allen, 1971) which is calculated as fishing mortality (<i>F</i> ; catch/biomass) plus natural mortality (<i>M</i> ; Pauly <i>et al.</i> (1990)).
	QB	5.39	(Pauly <i>et al.</i> , 1990, Christensen and Pauly, 1992)	Calculated using an empirical model which incorporates water temperature and feeding characteristics.
	EE	0.948	Calculated by EwE	-
	PQ	0.141	Calculated by EwE	-
	DC	See Table 0.4	(Pinnegar, 2014, ICES, 2018e, Bentley <i>et al.</i> , In press)	Diet designed using CEFAS fish stomach records (DAP-STOM) from whiting with length greater than 25.1 cm (<i>L_{mat}</i>) and fishers' knowledge.
<p>11: Juvenile whiting (0-1)</p> <p><i>Multi-stanza group; linked to Adult whiting (2+)</i></p>	B	0.236	Calculated by EwE	Estimate based on adult whiting parameters (leading group)
	PB	1.524	(Lees and Mackinson, 2007, Mackinson and Daskalov, 2008, Serpetti <i>et al.</i> , 2017)	Assumed to be 2 times adult PB
	QB	11.88	Calculated by EwE	Estimate based on adult whiting parameters (leading group)
	EE	0.994	Calculated by EwE	-
	PQ	0.128	Calculated by EwE	-
	DC	See Table 0.4	(Pinnegar, 2014)	Diet designed using CEFAS fish stomach records (DAP-STOM) from whiting with length less than 25.1 cm (<i>L_{mat}</i>).
<p>12: Adult haddock (2+)</p> <p><i>Multi-stanza group; linked to Juvenile haddock (0-1)</i></p>	B	0.086	(ICES, 2017c, ICES, 2018c)	Assessment data prior to 1993 is unavailable, therefore an initial biomass was estimated as the average biomass from the period 1993-2000 from ASAP model output for the Irish Sea (VIIa).
	PB	0.89	(Allen, 1971, Pauly <i>et al.</i> , 1990)	Equivalent to the instantaneous rate of total mortality (Allen, 1971) which is calculated as fishing mortality (<i>F</i> ; catch/biomass) plus natural

				mortality (M ; Pauly <i>et al.</i> (1990)).
	QB	4.42	(Pauly <i>et al.</i> , 1990, Christensen and Pauly, 1992)	Calculated using an empirical model which incorporates water temperature and feeding characteristics.
	EE	0.962	Calculated by EwE	-
	PQ	0.201	Calculated by EwE	-
	DC	See Table 0.4	(Pinnegar, 2014)	Diet designed using CEFAS fish stomach records (DAP-STOM) from haddock with length greater than 37.1 cm (L_{mat}).
13: Juvenile haddock (0-1)	B	0.0484	Calculated by EwE	Estimate based on adult whiting parameters (leading group)
<i>Multi-stanza group; linked to Adult haddock (2+)</i>	PB	1.789	(Lees and Mackinson, 2007, Mackinson and Daskalov, 2008, Serpetti <i>et al.</i> , 2017)	Assumed to be 2 times adult PB
	QB	10.28	Calculated by EwE	Estimate based on adult whiting parameters (leading group)
	EE	0.999	Calculated by EwE	-
	PQ	0.128	Calculated by EwE	-
	DC	See Table 0.4	(Pinnegar, 2014)	Diet designed using CEFAS fish stomach records (DAP-STOM) from haddock with length less than 37.1 cm (L_{mat}).
14: Adult plaice (2+)	B	0.155	(ICES, 2017c, ICES, 2018c)	Estimated Age 2+ biomass for the year 1973 from SAM model output for the Irish Sea (VIIa).
<i>Multi-stanza group; linked to Juvenile plaice (0-1)</i>	PB	0.79	(Allen, 1971, Pauly <i>et al.</i> , 1990)	Equivalent to the instantaneous rate of total mortality (Allen, 1971) which is calculated as fishing mortality (F ; catch/biomass) plus natural mortality (M ; Pauly <i>et al.</i> (1990)).
	QB	3.75	(Pauly <i>et al.</i> , 1990, Christensen and Pauly, 1992)	Calculated using an empirical model which incorporates water temperature and feeding characteristics.
	EE	0.997	Calculated by EwE	-
	PQ	0.211	Calculated by EwE	-

	DC	See Table 0.4	(Pinnegar, 2014, ICES, 2018e, Bentley <i>et al.</i> , In press)	Diet designed using CEFAS fish stomach records (DAP-STOM) from plaice with length greater than 36.1 cm (<i>L_{mat}</i>) and fishers' knowledge.
15: Juvenile haddock (0-1) <i>Multi-stanza group; linked to Adult haddock (2+)</i>	B	0.0315	Calculated by EwE	Estimate based on adult plaice parameters (leading group)
	PB	1.38	(Lees and Mackinson, 2007, Mackinson and Daskalov, 2008, Serpetti <i>et al.</i> , 2017)	Assumed to be 2 times adult PB
	QB	10.3	Calculated by EwE	Estimate based on adult plaice parameters (leading group)
	EE	0.934	Calculated by EwE	-
	PQ	0.134	Calculated by EwE	-
	DC	See Table 0.4	(Pinnegar, 2014, ICES, 2018e, Bentley <i>et al.</i> , In press)	Diet designed using CEFAS fish stomach records (DAP-STOM) from plaice with length less than 36.1 cm (<i>L_{mat}</i>) and fishers' knowledge.
16: Common sole	B	0.113	(ICES, 2018c)	Estimated biomass for the year 1973 from XSA model output for the Irish Sea (VIIa).
	PB	0.81	(Allen, 1971, Pauly <i>et al.</i> , 1990)	Equivalent to the instantaneous rate of total mortality (Allen, 1971) which is calculated as fishing mortality (<i>F</i> ; catch/biomass) plus natural mortality (<i>M</i> ; Pauly <i>et al.</i> (1990)).
	QB	5.61	(Pauly <i>et al.</i> , 1990, Christensen and Pauly, 1992)	Calculated using an empirical model which incorporates water temperature and feeding characteristics.
	EE	0.958	Calculated by EwE	-
	PQ	0.144	Calculated by EwE	-
	DC	See Table 0.4	(Pinnegar, 2014)	Diet designed using CEFAS fish stomach records (DAP-STOM).
17: Flatfish	B	0.47	(ICES, 2017a, ICES, 2017b)	Estimate based on the BTS-VIIa and NIGFS surveys for the Irish Sea (VIIa).
	PB	1.518	Calculated by EwE	

	QB	6.07	(Pauly <i>et al.</i> , 1990, Christensen and Pauly, 1992)	Calculated using an empirical model which incorporates water temperature and feeding characteristics.
	EE	0.956	Calculated by EwE	-
	PQ	0.25	-	We estimate a PQ of 0.25 to facilitate the calculation of a PB parameter
	DC	See Table 0.4	(Pinnegar, 2014)	Diet designed using CEFAS fish stomach records (DAP-STOM).
18: Monkfish	B	0.033	(ICES, 2017a, ICES, 2017b)	Estimate based on the BTS-VIIa and NIGFS surveys for the Irish Sea (VIIa).
	PB	0.49	(Allen, 1971, Pauly <i>et al.</i> , 1990)	Equivalent to the instantaneous rate of total mortality (Allen, 1971) which is calculated as fishing mortality (F ; catch/biomass) plus natural mortality (M ; Pauly <i>et al.</i> (1990)).
	QB	2.746	(Pauly <i>et al.</i> , 1990, Christensen and Pauly, 1992)	Calculated using an empirical model which incorporates water temperature and feeding characteristics.
	EE	0.687	Calculated by EwE	-
	PQ	0.178	Calculated by EwE	-
	DC	See Table 0.4	(Pinnegar, 2014, ICES, 2018e, Bentley <i>et al.</i> , In press)	Diet designed using CEFAS fish stomach records (DAP-STOM) and fishers' knowledge.
19: European hake	B	0.093	Calculated by EwE	Biomass from trawl surveys suggest hake may be under-represented (potentially due to catchability).
	PB	0.981	Calculated by EwE	-
	QB	3.924	(Pauly <i>et al.</i> , 1990, Christensen and Pauly, 1992)	Calculated using an empirical model which incorporates water temperature and feeding characteristics.
	EE	0.95	-	We estimate an EE of 0.95 to facilitate the calculation of a B parameter
	PQ	0.25	-	We estimate a PQ of 0.25 to facilitate the calculation of a PB parameter

	DC	See Table 0.4	(Pinnegar, 2014, ICES, 2018e, Bentley <i>et al.</i> , In press)	Diet designed using CEFAS fish stomach records (DAP-STOM) and fishers' knowledge.
20: Sandeels	B*	0.354	Calculated by EwE	Biomass from trawl surveys suggest sandeels may be under-represented (potentially due to catchability).
	PB	2.053	Calculated by EwE	-
	QB	8.21	(Pauly <i>et al.</i> , 1990, Christensen and Pauly, 1992)	Calculated using an empirical model which incorporates water temperature and feeding characteristics.
	EE	0.95	-	We estimate an EE of 0.95 to facilitate the calculation of a B parameter
	PQ	0.25	-	We estimate a PQ of 0.25 to facilitate the calculation of a PB parameter
	DC	See Table 0.4	(Pinnegar, 2014)	Diet designed using CEFAS fish stomach records (DAP-STOM).
21: Gurnards and dragonets	B	0.34	(ICES, 2017a, ICES, 2017b)	Estimate based on the BTS-VIIa and NIGFS surveys for the Irish Sea (VIIa).
	PB	1.403	Calculated by EwE	When compared to other models through PREBAL analysis, the initial PB was very low. We therefore estimate PQ in order to balance the group and achieve a PB more consistent with other models (West Coast of Scotland, North Sea).
	QB	5.61	(Pauly <i>et al.</i> , 1990, Christensen and Pauly, 1992)	Calculated using an empirical model which incorporates water temperature and feeding characteristics.
	EE	0.976	Calculated by EwE	
	PQ	0.25	-	We estimate a PQ of 0.25 to facilitate the calculation of a PB parameter
	DC	See Table 0.4	(Pinnegar, 2014)	Diet designed using CEFAS fish stomach records (DAP-STOM).
22: Other demersal fish	B	0.359	Calculated by EwE	Diet structures placed too much predation pressure on the survey biomass estimate,

				therefor a biomass was estimated for the 'other demersal fish' group.
	PB	0.96	(Allen, 1971, Pauly <i>et al.</i> , 1990)	Equivalent to the instantaneous rate of total mortality (Allen, 1971) which is calculated as fishing mortality (F ; catch/biomass) plus natural mortality (M ; Pauly <i>et al.</i> (1990)).
	QB	4.32	(Pauly <i>et al.</i> , 1990, Christensen and Pauly, 1992)	Calculated using an empirical model which incorporates water temperature and feeding characteristics.
	EE	0.95	-	We estimate an EE of 0.95 to facilitate the calculation of a B parameter
	PQ	0.22	Calculated by EwE	-
	DC	See Table 0.4	(Pinnegar, 2014)	Diet designed using CEFAS fish stomach records (DAP-STOM).
23: Other benthopelagic fish	B	1.435	Calculated by EwE	-
	PB	1.845	Calculated by EwE	-
	QB	7.38	(Pauly <i>et al.</i> , 1990, Christensen and Pauly, 1992)	Calculated using an empirical model which incorporates water temperature and feeding characteristics.
	EE	0.95	-	We estimate an EE of 0.95 to facilitate the calculation of a B parameter
	PQ	0.25	-	We estimate a PQ of 0.25 to facilitate the calculation of a PB parameter
	DC	See Table 0.4	(Pinnegar, 2014)	Diet designed using CEFAS fish stomach records (DAP-STOM).
24: Atlantic herring	B*	0.72	(Molloy, 2006, ICES, 2016a)	TSB for 1973 from 2016 ICES age based analytical assessment (ICES, 2016a). Subsequent assessments only hindcast to 1980.
	PB*	1.35	(Allen, 1971, Pauly <i>et al.</i> , 1990)	Equivalent to the instantaneous rate of total mortality (Allen, 1971) which is calculated as fishing mortality (F ; catch/biomass) plus natural mortality (M ; Pauly <i>et al.</i> (1990)).

	QB	6.59	(Pauly <i>et al.</i> , 1990, Christensen and Pauly, 1992)	Calculated using an empirical model which incorporates water temperature and feeding characteristics.
	EE	0.95	Calculated by EwE	-
	PQ	0.205	Calculated by EwE	-
	DC	See Table 0.4	(Pinnegar, 2014)	Diet designed using CEFAS fish stomach records (DAP-STOM).
25: European sprat	B	2.294	Calculated by EwE	-
	PB	2.425	Calculated by EwE	-
	QB	9.7	(Pauly <i>et al.</i> , 1990, Christensen and Pauly, 1992)	Calculated using an empirical model which incorporates water temperature and feeding characteristics.
	EE	0.95	-	We estimate an EE of 0.95 to facilitate the calculation of a B parameter
	PQ	0.25	-	We estimate a PQ of 0.25 to facilitate the calculation of a PB parameter
	DC	See Table 0.4	(Pinnegar, 2014)	Diet designed using CEFAS fish stomach records (DAP-STOM).
26: Other pelagic fish	B	4.147	Calculated by EwE	-
	PB	1.278	Calculated by EwE	-
	QB	5.11	(Pauly <i>et al.</i> , 1990, Christensen and Pauly, 1992)	Calculated using an empirical model which incorporates water temperature and feeding characteristics.
	EE	0.95	-	We estimate an EE of 0.95 to facilitate the calculation of a B parameter
	PQ	0.25	-	We estimate a PQ of 0.25 to facilitate the calculation of a PB parameter
	DC	See Table 0.4	(Pinnegar, 2014)	Diet designed using CEFAS fish stomach records (DAP-STOM).
27: Anadromous fish	B	0.03	(Lees and Mackinson, 2007)	Estimate from Lees and Mackinson (2007) Irish Sea model which derived its biomass estimate from expert advice.
	PB	0.644	(Allen, 1971, Pauly <i>et al.</i> , 1990)	Equivalent to the instantaneous rate of total mortality (Allen, 1971) which is calculated as fishing mortality (F ;

				catch/biomass) plus natural mortality (M ; Pauly <i>et al.</i> (1990)).
	QB	3.17	(Pauly <i>et al.</i> , 1990, Christensen and Pauly, 1992)	Calculated using an empirical model which incorporates water temperature and feeding characteristics.
	EE	0.336	Calculated by EwE	-
	PQ	0.203	Calculated by EwE	-
	DC	See Table 0.4	(Pinnegar, 2014)	Diet designed using CEFAS fish stomach records (DAP-STOM).
28: Lobsters and large crabs	B	0.5	Calculated by EwE	-
	PB	0.62	(Tumbiolo and Downing, 1994)	Empirical model for the production rate of marine invertebrates
	QB	4.133	Calculated by EwE	-
	EE	0.95	-	We estimate an EE of 0.95 to facilitate the calculation of a B parameter
	PQ	0.15	(Christensen, 1995)	We estimate a PQ of 0.15 to facilitate the calculation of a QB parameter
	DC	See Table 0.4	(Barker and Gibson, 1977, Bernárdez <i>et al.</i> , 2000, Brey, 2001)	-
29: <i>Nephrops</i>	B	0.916	Calculated by EwE	-
	PB	1.27	(Tumbiolo and Downing, 1994)	Empirical model for the production rate of marine invertebrates
	QB	8.467	Calculated by EwE	-
	EE	0.95	-	We estimate an EE of 0.95 to facilitate the calculation of a B parameter
	PQ	0.15	(Christensen, 1995)	We estimate a PQ of 0.15 to facilitate the calculation of a QB parameter
	DC	See Table 0.4	(Cristo and Cartes, 1998)	-
30: Shrimp	B	2.249	Calculated by EwE	-
	PB	2.67	(Tumbiolo and Downing, 1994)	Empirical model for the production rate of marine invertebrates
	QB	17.8	Calculated by EwE	-

	EE	0.95	-	We estimate an EE of 0.95 to facilitate the calculation of a B parameter
	PQ	0.15	(Christensen, 1995)	We estimate a PQ of 0.15 to facilitate the calculation of a QB parameter
	DC	See Table 0.4	(Simpson <i>et al.</i> , 1970, Oh <i>et al.</i> , 2001)	-
31: Cephalopods	B	0.315	Calculated by EwE	-
	PB	1.981	(Tumbiolo and Downing, 1994)	Empirical model for the production rate of marine invertebrates
	QB	15	(Lees and Mackinson, 2007, Mackinson and Daskalov, 2008, Serpetti <i>et al.</i> , 2017)	Little information was available regarding cephalopod consumption rates in the Irish Sea, therefore an estimate was taken from other local models.
	EE	0.95	-	We estimate an EE of 0.95 to facilitate the calculation of a B parameter
	PQ	0.132	Calculated by EwE	-
	DC	See Table 0.4	(Pierce <i>et al.</i> , 1994, Collins and Pierce, 1996)	-
	32: Scallops	B	1.214	Calculated by EwE
PB		1.146	(Tumbiolo and Downing, 1994)	Empirical model for the production rate of marine invertebrates
QB		7.643	Calculated by EwE	-
EE		0.95	-	We estimate an EE of 0.95 to facilitate the calculation of a B parameter
PQ		0.15	(Christensen, 1995)	We estimate a PQ of 0.15 to facilitate the calculation of a QB parameter
DC		See Table 0.4	(Serpetti <i>et al.</i> , 2017)	-
33: Epifauna	B*	24.648	Calculated by EwE	-
	PB*	1.7	(Tumbiolo and Downing, 1994)	Empirical model for the production rate of marine invertebrates
	QB*	4.028	Calculated by EwE	-
	EE	0.95	-	We estimate an EE of 0.95 to facilitate the calculation of a B parameter

	PQ	0.25	(Mackinson and Daskalov, 2008, Serpetti <i>et al.</i> , 2017)	We estimate a PQ of 0.25 to facilitate the calculation of a QB parameter
	DC	See Table 0.4	(Serpetti <i>et al.</i> , 2017)	-
34: Infauna	B*	25.005	Calculated by EwE	-
	PB*	1.7	(Tumbiolo and Downing, 1994)	Empirical model for the production rate of marine invertebrates
	QB*	6.8	Calculated by EwE	-
	EE	0.95	-	We estimate an EE of 0.95 to facilitate the calculation of a B parameter
	PQ	0.25	(Mackinson and Daskalov, 2008, Serpetti <i>et al.</i> , 2017)	We estimate a PQ of 0.25 to facilitate the calculation of a QB parameter
	DC	See Table 0.4	(Serpetti <i>et al.</i> , 2017)	-
35: Gelatinous zooplankton	B	1.7	(Stephen Beggs, per.comms)	Estimate based on AFBI jellyfish surveys between May and June. Value taken from earliest survey date (1994).
	PB	0.762	Calculated by EwE	-
	QB	2.54	(Martinussen and Båmstedt, 1995, Brey, 2001)	Calculated using carbon food rations (Martinussen and Båmstedt, 1995) converted into wet weight (Brey, 2001).
	EE	0.938	Calculated by EwE	-
	PQ	0.3	(Lees and Mackinson, 2007, Mackinson and Daskalov, 2008)	We estimate a PQ of 0.3 to facilitate the calculation of a PB parameter
	DC	See Table 0.4	(Martinussen and Båmstedt, 1995)	-
36: Large zooplankton	B*	6.81	(Pitois and Fox, 2006, Richardson <i>et al.</i> , 2006)	Plankton abundances from the SAHFOS continuous plankton recorder (Richardson <i>et al.</i> , 2006) were converted into biomass (Pitois and Fox, 2006).
	PB	10	(Lees and Mackinson, 2007, Serpetti <i>et al.</i> , 2017)	-
	QB	33.3	Calculated by EwE	-
	EE	0.682	Calculated by EwE	-
	PQ	0.3	(Lees and Mackinson, 2007, Mackinson and Daskalov, 2008)	We estimate a PQ of 0.3 to facilitate the calculation of a QB parameter

	DC	See Table 0.4	(Lees and Mackinson, 2007, Serpetti <i>et al.</i> , 2017)	-
37: Small zooplankton	B*	16.18	(Pitois and Fox, 2006, Richardson <i>et al.</i> , 2006)	Plankton abundances from the SAHFOS continuous plankton recorder (Richardson <i>et al.</i> , 2006) were converted into biomass (Pitois and Fox, 2006).
	PB	18	(Serpetti <i>et al.</i> , 2017)	-
	QB	60	Calculated by EwE	-
	EE	0.521	Calculated by EwE	-
	PQ	0.3	(Lees and Mackinson, 2007, Mackinson and Daskalov, 2008)	We estimate a PQ of 0.3 to facilitate the calculation of a QB parameter
	DC	See Table 0.4	(Lees and Mackinson, 2007, Serpetti <i>et al.</i> , 2017)	-
38: Seaweed	B	29.3	(Burrows <i>et al.</i> , 2018)	Estimated biomass of seaweed in the Irish Sea extracted from a UK wide model of seaweed biomass.
	PB	1	(Mike Burrows, per.comms)	-
	EE	0.393	Calculated by EwE	-
39: Phytoplankton	B	13.83	(Gowen <i>et al.</i> , 2000)	Gowen <i>et al.</i> (2000) provide a production estimate of 97 g.C.m ⁻² .yr for the Irish Sea,
	PB*	226.3	(Heymans, 2001)	The conversion ratio for C to wet weight was taken from Heymans (2001), bringing the PB close to those in the North Sea and Baltic Sea models.
	EE	0.327	Calculated by EwE	-
40: Discards	B*	0.219	(STECF, 2018, ICES, 2019)	Total discards were estimated using discard data from the STECF database and ICES stock assessments.
	EE	0.127	Calculated by EwE	-
41: Detritus	B	100	(Lees and Mackinson, 2007, Mackinson and Daskalov, 2008, Serpetti <i>et al.</i> , 2017)	Includes dissolved and particulate organic matter.
	EE	0.115	Calculated by EwE	-

1.2. Multi-stanzas

Cod, whiting, haddock, and plaice functional groups were represented with two life stages, adult and juvenile (Table 0.3). Multi-stanza representation of life stages enables the model to account for ontogenetic changes in diet preference and fishing mortality. When multi-stanza groups are

included in Ecopath, the ‘usual’ Ecosim differential equations to model biomass change are replaced by a set of difference equations that track monthly changes in the number and mean body weight of animals of all monthly cohorts. Production of juveniles does not occur in a yearly pulse, as in reality, but spread evenly across the annual cycle. Thus, juvenile biomass estimated by EwE models is considerably lower (approximately 1/12th) of real biomass and can only be considered a proxy variable (Walters *et al.*, 2010, ICES, 2011, ICES, 2016d).

Table 0.3. Multi-stanza parameters based on reported values for the Irish Sea.

Multi-stanza	Parameter	Value	Source
Cod	VBGF K	0.16	(Froese and Pauly, 2017)
	Recruit power	1	-
	BA/B	0	-
	Adult stanza start month	24	(ICES, 2016b)
	Wmat/Winf	0.137	(Bentley <i>et al.</i> , 2018)
Whiting	VBGF K	0.34	(Froese and Pauly, 2017)
	Recruit power	1	-
	BA/B	0	-
	Adult stanza start month	24	(ICES, 2016b)
	Wmat/Winf	0.221	(Bentley <i>et al.</i> , 2018)
Haddock	VBGF K	0.29	(Froese and Pauly, 2017)
	Recruit power	1	-
	BA/B	0	-
	Adult stanza start month	24	(ICES, 2016b)
	Wmat/Winf	0.173	(Bentley <i>et al.</i> , 2018)
Plaice	VBGF K	0.13	(Froese and Pauly, 2017)
	Recruit power	1	-
	BA/B	0	-
	Adult stanza start month	24	(ICES, 2016b)
	Wmat/Winf	0.165	(Bentley <i>et al.</i> , 2018)

It is difficult to compare the stock-recruitment (SR) relationships from the EwE model with single species predictions because in addition to fishing effects, the dynamics of the adult juvenile groups are affected by the environmental forcing function. Key-run models for the North Sea (ICES, 2016e) and Baltic Sea (ICES, 2017e) suggest that the closest we can get to demonstrating these emergent patterns is to switch off environmental forcing functions and apply a ‘V’-shaped fishing pattern to drive stock biomasses through high and low values. The emergent SR trends are dependent upon the effects of the fishing pattern and the resulting multi-species interactions, providing an indication of how recruitment changes as adult biomass changes in the model. Even though this test has been applied before, it should be noted that it is not entirely robust as the emergent SR patterns are sensitive to how fishing mortality is applied. However, this check does help to reaffirm whether the links between adult biomass and recruitment are sensible by ensuring SR patterns are not unrealistically erratic. The parameterisation of the key-run (under a ‘V’-shaped fishing pattern) leads to stock trajectories for cod and plaice that are relatively flat over a large range of biomass, with steep recruitment declines below a low biomass threshold (Figure 0.2). Whiting and haddock SR trends are more dome-shaped (Figure 0.2).

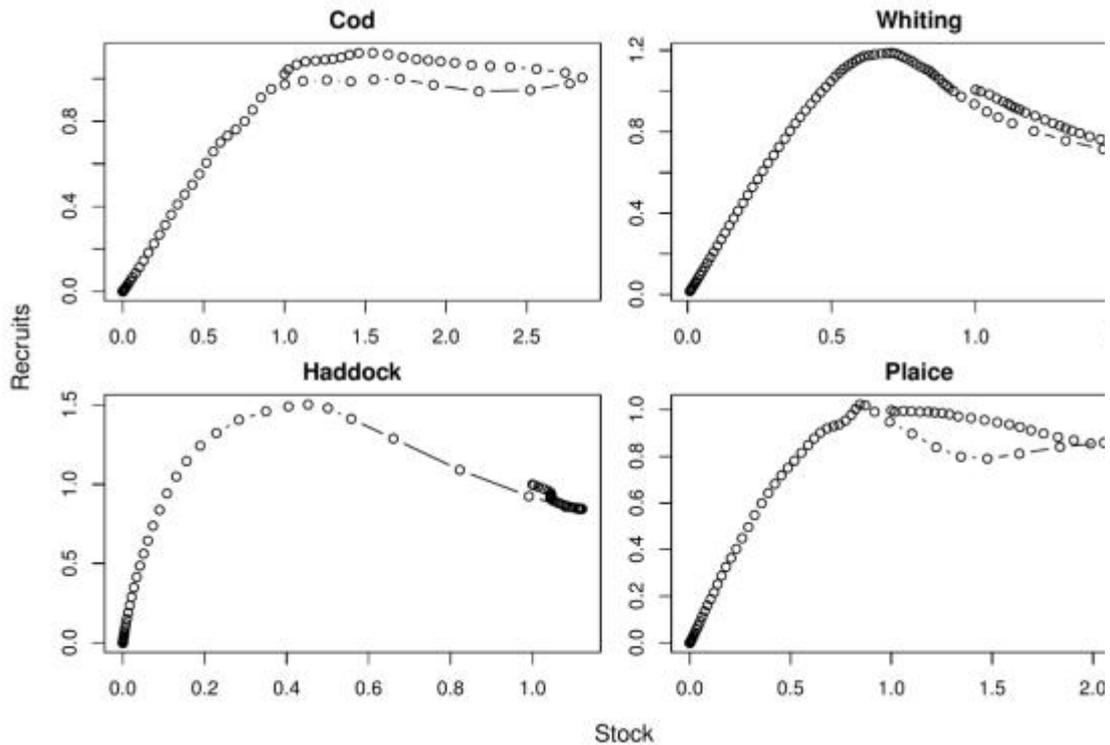


Figure 0.2. Stock recruitment trajectories under a 'V' shaped fishing regime for all multi-stanza groups.

1.3. Ecopath diet matrix

The models initial diet matrix for finfish was built using information held in the Cefas integrated DAtabase and Portal for STOMach records (DAPSTOM) (Pinnegar, 2014, Bentley *et al.*, 2019a). DAPSTOM contains 26 765 records from 38 295 stomachs covering 96 predator species from the Irish Sea. Records date back as far as 1836 but for the purpose of the present model only data from 1960-2016 were used (23 331 records). The default format for data entry is as counts of prey item found per predator. In order to convert count data to weight (kg) data, weights were assigned to each prey item. For fish, these weights were obtained by converting length to weight. Length information was obtained from the BTS-VIIa in order to generate an average length and weight relative to the Irish Sea. For invertebrates, average weight data was acquired from SeaLifeBase (Palomares and Pauly, 2017). Weighted diets were then transformed into proportion diets, as is required by Ecopath. The diet extracted for each predator included the mean proportion of prey items consumed based on all the data available from 1960-present day. In addition, minimum, maximum, standard deviation and percentile values were extracted, providing a range of plausible diet proportions each prey may contribute towards a predator's diet (Figure 0.3). Diets of functional groups comprising multiple species were prorated by the biomass proportion each species contributes towards the functional group. When balancing Ecopath models diet preferences are often the first biological parameters revisited and adjusted in order to fix model imbalances (Heymans *et al.*, 2016). This is often done using 'ad hoc' tuning but with the diet preference ranges (min, max, percentiles) produced using DAPSTOM records we were able to take a systematic approach to diet tuning, reducing the need for 'ad hoc' adjustments.

Diets for mammals, seabirds and invertebrates were taken from literature sources as described in Bentley *et al.* (2018) and Table 0.2 of this key-run annex.

Fishers' knowledge regarding the diets of commercially important species was shared during a WKIrish workshop (WKIrish4) held in Dun Laoghaire, Ireland, on the 23-27 October 2017 (ICES,

2018e). The aim of the workshop was to update the Irish Sea model so that it used both scientific knowledge and fishers' knowledge of predator-prey interactions for the species they commonly encountered in their operations, and where they would have observed stomach contents whilst processing catches. During the workshop, cod, whiting, haddock, plaice, rays (*Raja spp.*), and Norway lobster were identified as the species for which fishers' felt they had substantial knowledge.

Fishers' diet links were quantified in the model on a case-by-case basis. New interactions were added to the model diet matrix whilst ensuring that the combined predation and fishing mortality placed on each functional group did not exceed production, as for an Ecopath model to be mass balanced total consumption cannot exceed the production of the species (Figure 0.3). To ensure diets remained balanced, additions of new prey proportions were counterbalanced by adjusting other prey proportions within the range of plausible values. Due to the inherent uncertainty in quantifying qualitative information, the diets of functional groups which were altered by fishers' knowledge were assigned large confidence intervals ($\pm 80\%$) in the models 'pedigree' routine (Christensen and Walters, 2004). The large confidence intervals assigned to diets altered by fishers ensured, when later applying Monte Carlo simulations, that a large range of parameters could be tested to reflect data uncertainty in model outputs. The Irish Sea key-run diet matrix is shown in Table 0.4.

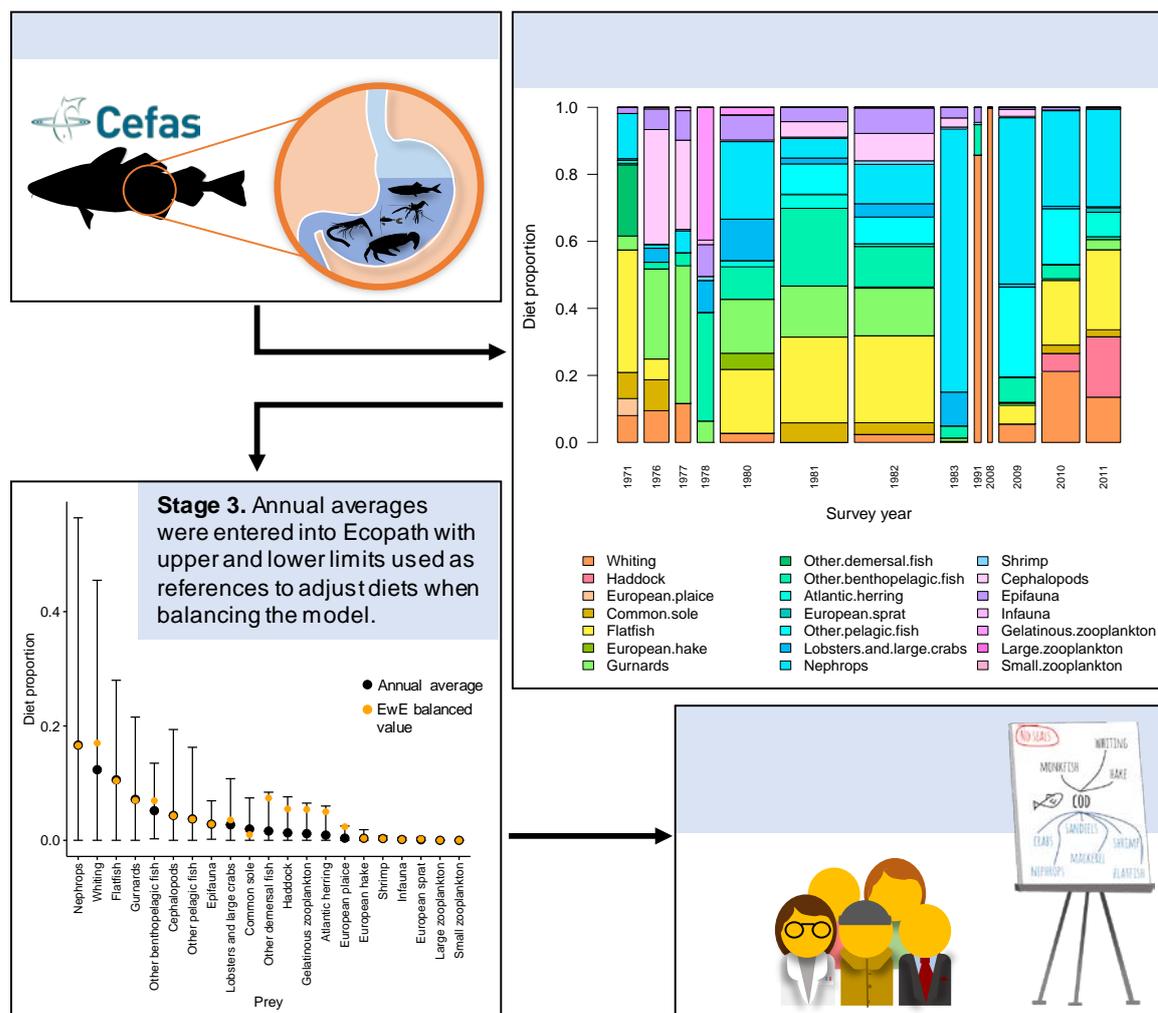


Figure 0.3. Conceptual figure for the parameterisation of finfish diets in the Irish Sea Ecopath model.

Table 1.4. (part 4/5) Irish Sea Ecopath diet matrix.

Predator/Prey	25	26	27	28	29	30	31	32
1 Toothed whales	-	-	-	-	-	-	-	-
2 Minke whales	-	-	-	-	-	-	-	-
3 Seals	-	-	-	-	-	-	-	-
4 Seabirds (high discard diet)	-	-	-	-	-	-	-	-
5 Seabirds (low discard diet)	-	-	-	-	-	-	-	-
6 Sharks	-	-	-	-	-	-	-	-
7 Rays	-	-	-	-	-	-	-	-
8 Atlantic cod 2+	-	-	-	-	-	-	-	-
9 Atlantic cod 0-1	-	-	-	-	-	-	-	-
10 Whiting 2+	-	-	-	-	-	-	0.001	-
11 Whiting 0-1	-	-	-	-	-	-	0.002	-
12 Haddock 2+	-	-	-	-	-	-	-	-
13 Haddock 0-1	-	-	-	-	-	-	-	-
14 European plaice 2+	-	-	-	-	-	-	-	-
15 European plaice 0-1	-	-	-	-	-	-	-	-
16 Common sole	-	-	-	-	-	-	-	-
17 Flatfish	-	-	-	-	-	-	-	-
18 Monkfish	-	-	-	-	-	-	-	-
19 European hake	-	-	-	-	-	-	-	-
20 Sandeels	-	-	0.600	-	-	-	0.020	-
21 Gurnards	-	-	-	-	-	-	0.004	-
22 Other demersal fish	-	-	-	-	-	-	-	-
23 Other benthopelagic fish	-	0.010	0.076	0.011	-	-	0.050	-
24 Atlantic herring	-	-	0.133	-	-	-	0.020	-
25 European sprat	-	0.130	0.130	-	-	-	-	-
26 Other pelagic fish	-	0.050	-	-	-	-	0.029	-
27 Anadromous fish	-	-	-	-	-	-	-	-
28 Lobsters and large crabs	-	-	-	0.019	-	-	0.010	-
29 <i>Nephrops</i>	-	-	-	-	-	-	-	-
30 Shrimp	-	0.223	0.003	0.095	0.014	-	-	-
31 Cephalopods	-	-	-	-	0.020	-	0.010	-
32 Scallops	-	-	-	-	-	-	-	-
33 Epifauna	0.017	0.003	-	0.222	0.400	0.111	0.080	-
34 Infauna	0.002	-	0.033	0.139	0.069	0.404	0.002	-
35 Gelatinous zooplankton	0.005	-	-	-	-	-	0.020	-
36 Large zooplankton	0.476	0.584	0.026	-	0.120	0.185	0.471	-
37 Small zooplankton	0.500	-	-	-	0.092	0.300	0.281	-
38 Seaweed	-	-	-	0.122	-	-	-	-
39 Phytoplankton	-	-	-	-	-	-	-	0.500
40 Discards	-	-	-	0.126	0.286	0.0004	-	-
41 Detritus	-	-	-	0.266	-	-	-	0.500

Table 1.4. (part 5/5) Irish Sea Ecopath diet matrix.

Predator/Prey	33	34	35	36	37
1 Toothed whales	-	-	-	-	-
2 Minke whales	-	-	-	-	-
3 Seals	-	-	-	-	-
4 Seabirds (high discard diet)	-	-	-	-	-
5 Seabirds (low discard diet)	-	-	-	-	-
6 Sharks	-	-	-	-	-
7 Rays	-	-	-	-	-
8 Atlantic cod 2+	-	-	-	-	-
9 Atlantic cod 0-1	-	-	-	-	-
10 Whiting 2+	-	-	-	-	-
11 Whiting 0-1	-	-	-	-	-
12 Haddock 2+	-	-	-	-	-
13 Haddock 0-1	-	-	-	-	-
14 European plaice 2+	-	-	-	-	-
15 European plaice 0-1	-	-	-	-	-
16 Common sole	-	-	-	-	-
17 Flatfish	-	-	-	-	-
18 Monkfish	-	-	-	-	-
19 European hake	-	-	-	-	-
20 Sandeels	-	-	-	-	-
21 Gurnards	-	-	-	-	-
22 Other demersal fish	-	-	-	-	-
23 Other benthopelagic fish	-	-	0.100	-	-
24 Atlantic herring	-	-	-	-	-
25 European sprat	-	-	-	-	-
26 Other pelagic fish	-	-	-	-	-
27 Anadromous fish	-	-	-	-	-
28 Lobsters and large crabs	-	-	-	-	-
29 <i>Nephrops</i>	-	-	-	-	-
30 Shrimp	-	-	0.050	-	-
31 Cephalopods	-	-	-	-	-
32 Scallops	0.010	-	-	-	-
33 Epifauna	0.090	-	0.100	-	-
34 Infauna	0.150	0.035	-	-	-
35 Gelatinous zooplankton	-	-	-	-	-
36 Large zooplankton	-	-	0.250	0.012	-
37 Small zooplankton	0.100	-	0.250	0.350	0.030
38 Seaweed	0.100	-	-	-	-
39 Phytoplankton	0.375	0.500	0.250	0.500	0.800
40 Discards	-	-	-	-	-
41 Detritus	0.175	0.465	-	0.138	0.170

1.4. Fishing fleet structure

The Irish Sea model contains 8 fleets which are based on the aggregation of gear categories used in the STECF (Scientific, Technical and Economic Committee for Fisheries) reports (STECF, 2018) (Table 0.5).

Table 0.5. Irish Sea Ecopath model fleet groups and their corresponding equivalents in STECF data.

Ecopath fleet	STECF gears	STECF description
Beam trawl	BT2	Beam trawls > 80 mm and < 120 mm
	BEAM	Beam trawl
Otter trawl	TR1	Bottom trawls and seines > 100 mm
	TR3	Beam trawls > 16 mm and < 32 mm
	OTTER	Otter trawl
Nephrops trawl	TR2	Bottom trawls and seines > 70 mm and < 100 mm
Pelagic nets	PEL_TRAWL	Pelagic trawl
	PEL_SEINE	Pelagic seine
Gill nets	GN1	Gillnets and entangling nets
Pots	POTS	Pots and creel
Dredge	DREDGE	Dredge
Longline	LL1	Longlines

Total landings for functional groups in 1973 were taken from ICES landing statistics (ICES, 2018a) and working group reports (ICES, 2017d, ICES, 2018c). In the absence of fleet based data prior to 2003, landings were proportioned amongst Ecopath fleets based on the proportions landed by STECF gears in 2003. Total discards for cod, whiting, haddock, plaice, whiting, and *Nephrops* were taken from ICES stock assessments (ICES, 2019) and distributed amongst gear types based on STECF proportions. For functional groups without ICES discards estimates, total discards were calculated using the discard/landings ratio from STECF using ICES landings from 1973. Bycatch of marine mammals were included in the parameterisation of discards based on literature and records from the Irish and Celtic Seas (Bentley *et al.*, 2018).

1.5. Pre-balance diagnostics

Pre-balance (PreBal) diagnostics described by Link (2010) provide a means to judge the ecological quality of Ecopath models. Below, in Table 0.6, we list the PreBal criteria and our models performance against each. PreBal results are displayed in Figure 0.4.

Table 0.6. PreBal diagnostics for the Irish Sea EwE key-run.

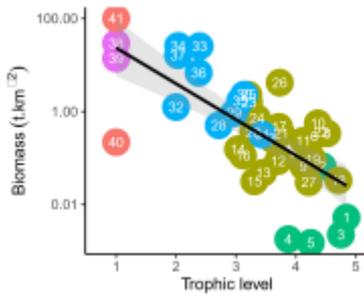
Criteria	Irish Sea model results	Comment
Biomasses should span 5-7 orders of magnitude.	Spans 5 orders of magnitude	-
Biomass slope (on log scale) around 5-10% decline with increasing TL.	8.9%	-

<p>Are any functional group biomasses notably above/below the line?</p>	<p>See Figure 0.4.</p>	<p>Seabirds, seals, whales, and discards below line: anthropogenic impacts. Epifauna, infauna, and other pelagic fish above line. These groups have high model estimated biomasses due to their importance as prey groups.</p>
<p>Compared across taxa, the ratio between predator and prey biomass should be < 1 and ~ 1-2 decimal places, depending on TL.</p>	<p>66.14 % > 0.009 & < 1 18.86 % < 0.009 15 % > 1</p>	<p>Ratios below 2 decimal places are prominent for the relationships between seals, seabirds, and their prey and for predators of epifauna and infauna. Top predators have low relative biomasses whilst epifauna and infauna have high biomasses. Ratios greater than 1 are most commonly seen between high level trophic levels which predate upon each-other and also when comparing predator biomass to discard biomass.</p>
<p>PB should decline with increasing TL (excluding homeotherms).</p>	<p>Criteria met; See Figure 0.4.</p>	<p>When excluding homeotherms, benthic invertebrates and seaweed fall below the line whilst small & large zooplankton and phytoplankton are above.</p>
<p>QB should decline with increasing TL (excluding homeotherms).</p>	<p>Criteria met; See Figure 0.4.</p>	<p>When excluding homeotherms, benthic invertebrates, gellatinous zooplankton, adult plaice, and rays fall below the line whilst small & large zooplankton, shrimp, cephalopods, and juvenile whiting are above.</p>
<p>No taxa should have a PB greater than phytoplankton</p>	<p>Criteria met; See Figure 0.4.</p>	<p>-</p>
<p>PQ should fall below 1 for all functional groups and between 0.1 and 0.3 for finfish.</p>	<p>Criteria met; See Figure 0.4.</p>	<p>-</p>

PR should fall below 1 for all functional groups	Criteria met; See Figure 0.4.	-
EE should fall below 1 for all functional groups	Criteria met; See Figure 0.4.	-
Total production and consumption should decrease with increasing TL.	Criteria met; See Figure 0.4.	-

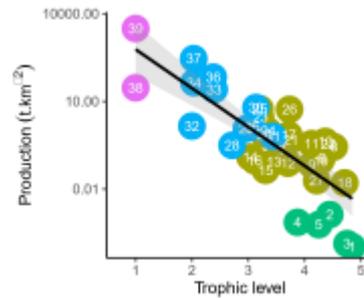
Test 1.

“Biomass should span 5-7 orders of magnitude and decline by 5-10%”.
Spans 5 orders of magnitude, declines by 8.9%.



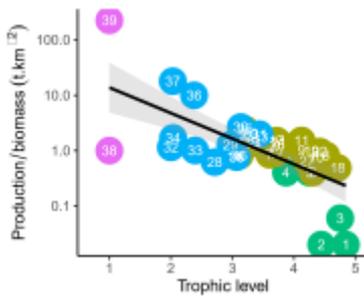
Test 5.

“Total production should decline with increasing trophic level”.
Criteria met



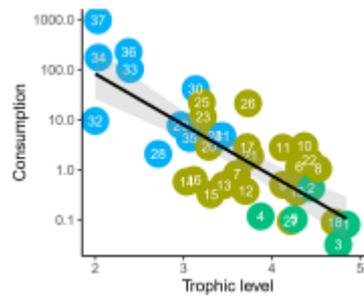
Test 2.

“PB should decline with increasing trophic level & no PB should exceed that of phytoplankton”.
Criteria met



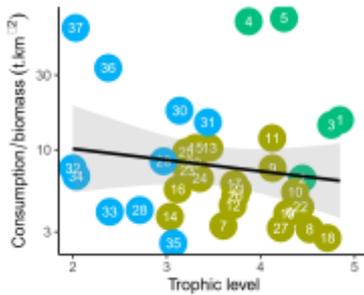
Test 6.

“Total consumption should decline with increasing trophic level”.
Criteria met



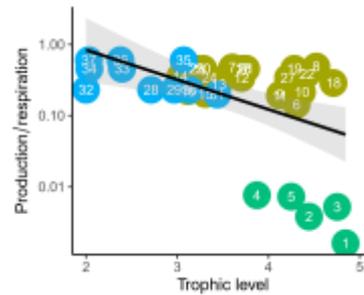
Test 3.

“QB should decline with increasing trophic level”.
Criteria met; the decline is greater when excluding homeotherms.



Test 7.

“PR should fall below 1 for all functional groups”.
Criteria met



Test 4.

“PQ should fall below 1 for all functional groups and between 0.1 and 0.3 for finfish”.
Criteria met

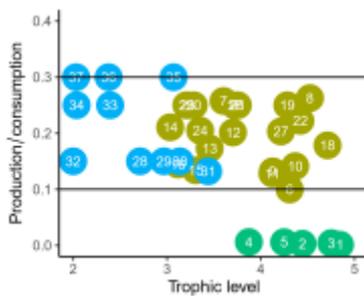


Figure 0.4. Pre-balance (PREBAL) diagnostics for the Irish Sea Ecopath model following the ecological rules of thumb outlined by (Link, 2010a). The number in each point refers to the represented functional group as ordered within the Ecopath model (see Table 0.1).

1.6. Basic input pedigree

Confidence intervals were assigned to the model's basic input parameters using the EwE pedigree routine (Table 0.7.) (Christensen and Walters, 2004). Confidence intervals are assigned based on the quality of the data origin. These confidence intervals provide the basis for parameter uncertainty when using Monte Carlo simulations to generate 95% confidence intervals in model output.

Table 0.7. Input data pedigree indicating data origin and confidence intervals.

Functional group	B	PB	QB	Diet	Catch
1 Toothed whales	0.5	0.5	0.5	0.5	0.5
2 Minke whales	0.5	0.5	0.5	0.5	0.5
3 Seals	0.5	0.5	0.5	0.8	0.3
4 Seabirds (high discard diet)	0.3	0.5	0.5	0.8	-
5 Seabirds (low discard diet)	0.3	0.5	0.5	0.8	-
6 Sharks	0.3	0.5	0.5	0.8	0.3
7 Rays	0.8	0.5	0.5	0.8	0.3
8 Atlantic cod 2+	0.1	0.5	0.5	0.1	0.3
9 Atlantic cod 0-1	0.8	0.7	0.8	0.1	0.3
10 Whiting 2+	0.3	0.5	0.5	0.8	0.3
11 Whiting 0-1	0.8	0.7	0.8	0.1	0.3
12 Haddock 2+	0.3	0.5	0.5	0.1	0.3
13 Haddock 0-1	0.8	0.7	0.8	0.1	0.3
14 European plaice 2+	0.1	0.5	0.5	0.8	0.3
15 European plaice 0-1	0.8	0.7	0.8	0.8	0.3
16 Common sole	0.1	0.5	0.5	0.1	0.3
17 Flatfish	0.3	0.8	0.5	0.1	0.3
18 Monkfish	0.3	0.5	0.5	0.8	0.3
19 European hake	0.8	0.8	0.5	0.8	0.3
20 Sandeels	0.8	0.8	0.5	0.1	0.3
21 Gurnards and dragonets	0.3	0.8	0.5	0.1	0.3
22 Other demersal fish	0.8	0.5	0.5	0.1	0.3
23 Other benthopelagic fish	0.8	0.8	0.5	0.1	0.3
24 Atlantic herring	0.1	0.5	0.5	0.1	0.3
25 European sprat	0.8	0.8	0.5	0.1	0.3
26 Other pelagic fish	0.8	0.8	0.5	0.1	0.3
27 Anadromous fish	0.8	0.5	0.5	0.1	0.3
28 Lobsters and large crabs	0.8	0.5	0.8	0.1	0.3
29 Nephrops	0.8	0.5	0.8	0.8	0.3
30 Shrimp	0.8	0.5	0.8	0.1	0.3
31 Cephalopods	0.8	0.5	0.6	0.1	0.3
32 Scallops	0.8	0.5	0.8	0.8	0.3
33 Epifauna	0.8	0.5	0.8	0.5	0.3
34 Infauna	0.8	0.5	0.8	0.5	0.3
35 Gelatinous zooplankton	0.3	0.8	0.5	0.5	-
36 Large zooplankton	0.5	0.5	0.8	0.8	-
37 Small zooplankton	0.5	0.5	0.8	0.8	-
38 Seaweed	0.3	0.5	-	-	-
39 Phytoplankton	0.3	0.5	-	-	-
40 Discards	0.5	-	-	-	-
41 Detritus	0.8	-	-	-	-

Confidence interval classification

Biomass (B)

0.8: Estimated by Ecopath/from another model/guesstimate
0.5: Approximate or indirect method
0.3: Sampling/locally, low precision
0.1: sampling locally, high precision

Production/biomass (PB)

0.8: Estimated by Ecopath
0.7: Guesstimate
0.5: Empirical relationship

Consumption/biomass (QB)

0.8: Estimated by Ecopath
0.6: From another model
0.5: Empirical relationship

Diet

0.8: Altered by fishers' knowledge/from another model
0.5: General species information/literature
0.1: Stomach records (quantitatively detailed, from Irish Sea: DAPSTON)

Catch

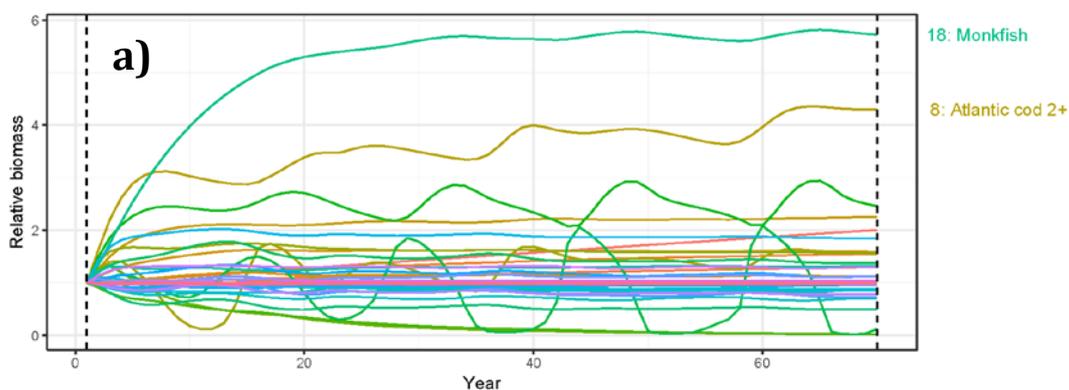
0.5: National statistics
0.3: Local study/ICES catch statistic for Vlla

1.7. Ecosim stability tests

Prior to the application of forcing functions (fishing, environmental drivers), the stability of the model was examined by adjusting baseline fishing effort and examining functional group response and rate of recovery to equilibrium (Figure 0.5). The system was perturbed under three scenarios, (i) the complete cessation of fishing, (ii) a short period of fishing cessation (8 years), and (iii) a short period of increased fishing effort (2x) (8 years).

Before running stability simulations, Ecosim parameters were updated. In Ecosim it is possible to account for the satiation of functional groups and/or a functional groups capacity to alter its foraging behaviour. This is achieved by adjusting the 'Feeding time adjustment rate' of functional groups. Adjustment rates determine how quickly groups can adjust feeding times to stabilise consumption (Q/B) at the Ecopath base rate. Adjustment rates fall between 0 and 1, with larger values representing more rapid adjustments to foraging time. If a functional group has an adjustment rate of 0 it is incapable of altering the time it spends foraging and is assumed to be consistently active in the foraging arena. In general it is recommended that adjustment rates for all groups are initially set to 0, apart from marine mammals where a value of 0.5 is deemed reasonable (Christensen *et al.*, 2008). Adjustment rates of 0.5 were therefore applied to marine mammals whilst the adjustment rates for all other groups were set to 0 (Figure 0.5a). When running the model without fishing we found instabilities in the biomass projections of multi-stanza groups (Figure 0.5a). To fix these instabilities feeding time adjustment rates of 0.2 were applied to all juvenile groups (Figure 0.5b).

The removal of fishing resulted in a relatively large increase in the biomass of Atlantic cod 2+ and monkfish. These groups experience large increases in their biomass as fishing mortality accounts for the majority of their explained mortality. This is reasonable due to their roles as top predators in the ecosystem and the large known fishing mortality in the ecosystem. The removal of fishing effort for a short period led to large relative increases in the biomass of monkfish, Atlantic cod 2+, European plaice 2+, rays, Atlantic herring, whiting 2+, and common sole (Figure 0.5c). These species are the most heavily exploited by the fishing fleets in the base Ecopath model, therefore this response is reasonable. When doubling fishing effort, Atlantic cod 2+, Atlantic cod 0-1, monkfish, European plaice 2+, European plaice 0-1, and rays experience the largest relative biomass declines (Figure 0.5d). The biomasses of haddock 2+ and flatfish increased. The rise in haddock biomass reflects the Irish Sea haddock explosion observed by surveys, fishers', and recent stock assessments (ICES, 2018c).



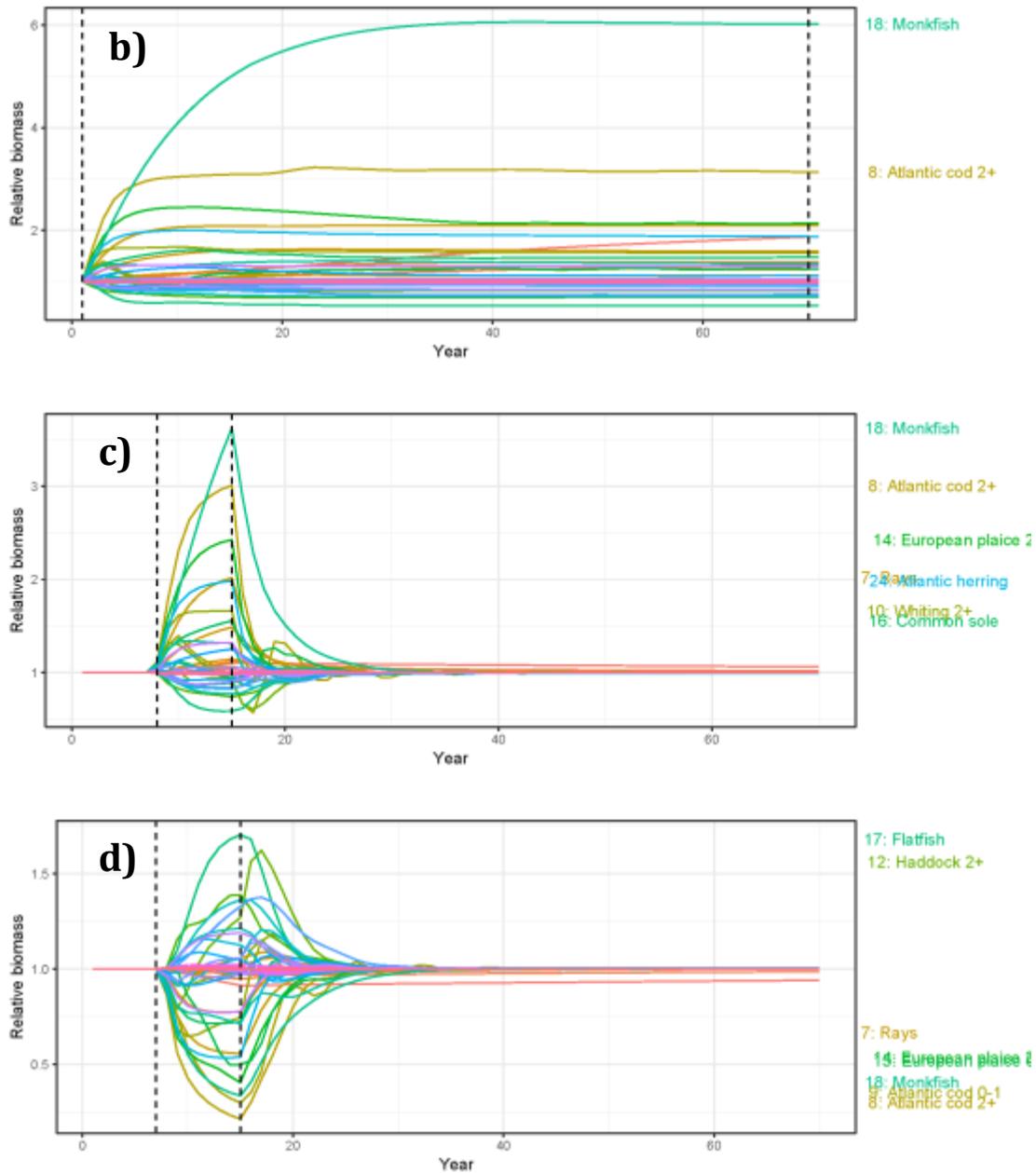


Figure 0.5. Impacts of stopping fishing for all gears (a) without adjusted feeding rates and (b) with adjusted feeding rates. The models ability to recover from a period of fishing adjustment was tested by (c) stopping fishing for a short period and (d) doubling fishing for a short period. Dashed lines indicate the period within which fishing rates were altered. Species with the largest responses are noted on the right of each graph.

1.8. Retrospective trend analysis

To identify which environmental time-series data best accounted for observed changes in recruitment and production in the lower trophic levels of the Irish Sea model we collated environmental time-series data on the Atlantic Multidecadal Oscillation (AMO), North Atlantic Oscillation winter index (NAOw), temperature, phytoplankton colour index, zooplankton abundance (Figure 0.6), and recruitment of multi-stanza functional groups.

Correlations between environmental variables, trends in zooplankton abundance, and fish recruitment were tested using Pearson's product-moment correlation after establishing data normality ($p < 0.05$) using the Shapiro-Wilk test. Recruitment estimates were \log_{10} transformed prior to analysis to stabilise the variance within and between time-series. Recruitment and environmental data are often strongly autocorrelated as values in a given year are closely related to values in previous years (Pyper and Peterman, 1998). Therefore classical correlation tests tend to lead to a greater rate of Type 1 errors, where there is an increased chance of concluding that a correlation is statistically significant when in fact no correlation is present (Jenkins and Watts, 1968). We therefore adjust the degrees of freedom in the statistical tests to compensate for autocorrelation using the equation proposed by Chelton (1984) and modified by Pyper and Peterman (1998):

$$\frac{1}{N^*} = \frac{1}{N} + \frac{2}{N} \sum_j r_{XX}(j) r_{YY}(j) \quad \text{Eq. 1}$$

where N^* is the number of independent joint observations on the time-series X and Y , N is the sample size and $r_{XX}(j)$ and $r_{YY}(j)$ are the autocorrelation of X and Y at lag j . Estimates of r were calculated using the Box-Jenkins' equation (Box *et al.*, 1976) modified by Chatfield (1989):

$$r_{XX}(j) = \frac{N}{N-j} \frac{\sum_{t=1}^{N-j} (X_{t+j} - \bar{X})(X_t - \bar{X})}{\sum_{t=1}^N (X_t - \bar{X})^2} \quad \text{Eq. 2}$$

where \bar{X} is the overall mean. In the present analysis, most time-series comprised 43 common observations for which we applied nine lags (approximately $N/5$) following Pyper and Peterman (1998). Lags were adjusted for time-series with fewer common observations.

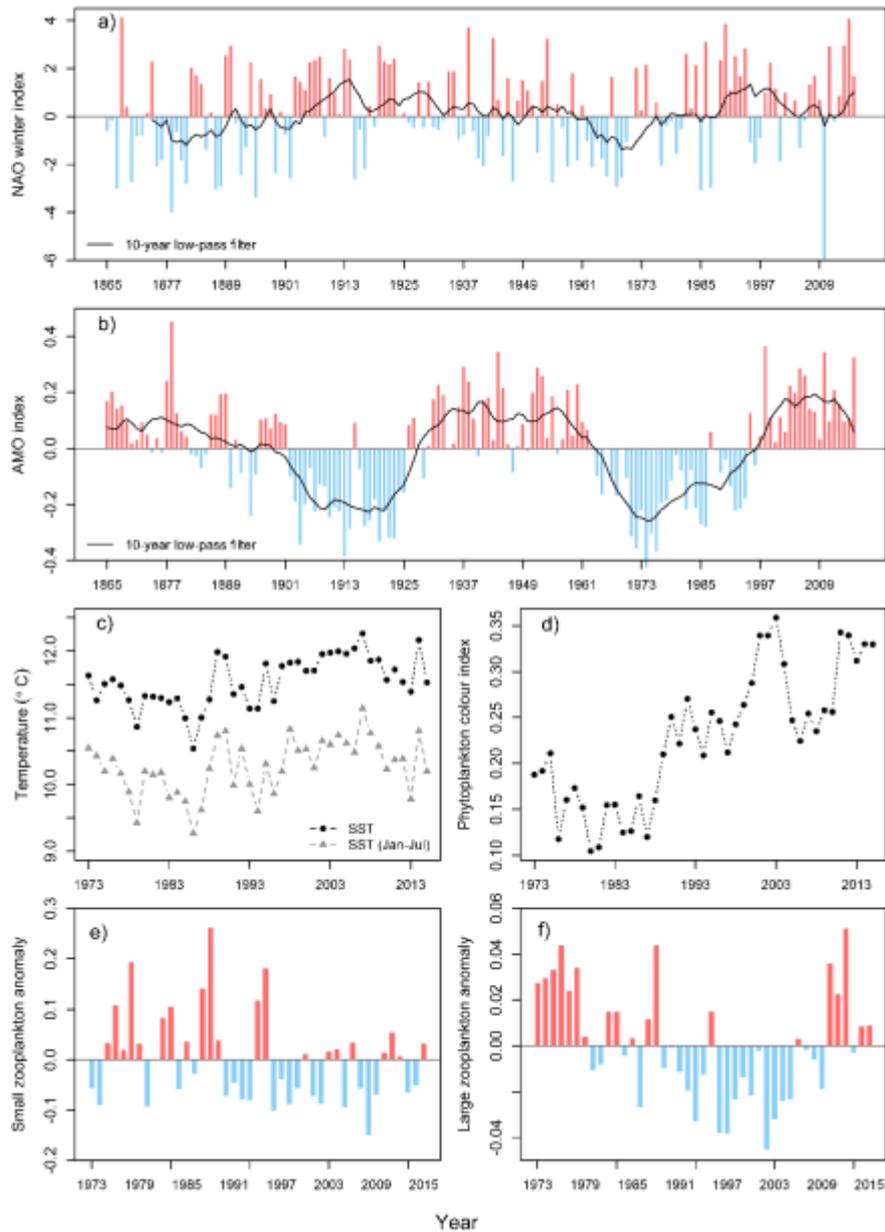


Figure 0.6. Annual time-series for environmental and plankton trends in the Irish; (a) Winter North Atlantic Oscillation (NAO) index, (b) Atlantic Multidecadal Oscillation (AMO) index, (c) annual averaged sea surface temperature ($^{\circ}\text{C}$) (SST) and winter-spring (Jan-Jul) SST, (d) phytoplankton colour index, (e) small zooplankton (< 2mm) abundance, and (f) large zooplankton (> 2mm) abundance.

The time-series trend for large zooplankton was best explained by a 10 year running average of the NAOw. Recruitment of cod and whiting were best explained by a 10 year running average of the AMO. The smoothed NAOw was incorporated as a driver of the ‘other mortality’ of large zooplankton to replicate a direct negative effect. The inverse AMO trend was used to drive cod and whiting recruitment in the model. Here it is assumed that the inverse AMO drives the mortality of larvae, given the adults biomass, to vary on an annual basis. Figure 0.7 shows the results of the correlation analysis supporting the choice of environmental time-series used in fitting the model.

SST (annual)	*** 0.91	SST (Jan-Jul)																	
	0.18	0.21	NAOw																
	0.23	0.11	*	NAOw 10yr															
	0.60	**	0.43	-0.23	0.23	AMO													
	0.61	**	0.44	0.01	0.32	*	***	AMO 10yr											
	0.63	**	0.48	0.23	0.33	*	***	***	***	PCI									
	-0.13	-0.07	-0.17	-0.17	***	-0.56	-0.20	*	-0.35	-0.24	Large Zoop.								
	-0.24	-0.33	-0.17	-0.15	-0.15	-0.13	-0.13	-0.31	-0.29	-0.29	***	0.54	Small Zoop.						
	***	***	-0.70	-0.03	-0.11	***	***	***	***	***	***	0.14	0.29	Cod					
	-0.13	-0.30	0.05	-0.25	0.10	0.10	0.17	-0.02	-0.21	0.07	Haddock								
	0.10	0.05	-0.16	-0.30	0.28	0.35	0.29	0.12	-0.18	-0.39	*	0.02	Plaice						
	**	**	-0.51	0.07	-0.07	***	***	***	0.11	0.26	***	0.85	0.01	-0.28	Whiting				

Figure 0.7. Correlation matrix for environmental variables, plankton trends, and fish recruitment in the Irish Sea using Pearson’s cross product-moment correlation. Variables include sea surface temperature (SST; °C), phytoplankton colour index (PCI), North Atlantic Oscillation winter index with a 10-year low-pass filter (NAO), Atlantic Multidecadal Oscillation with a 10-year low-pass filter (AMO), large zooplankton abundance (L.zoop.), and small zooplankton abundance (S.zoop.). Fish recruitment time-series were taken from ICES stock assessments for cod, haddock, plaice, and whiting. The correlation matrix is shaded to signify the strength of positive (blue) and negative (red) correlations in relation to their r values. Statistically significant correlations are denoted: *p<0.05; **p<0.01; ***p<0.001.

1.9. Time-series data

In order to accurately simulate biomass and catch trends, Ecosim requires the incorporation of time-series data to both calibrate and drive simulations. The Irish Sea model uses 52 calibration time-series (biomass and catch) for functional groups. Calibration time-series are shown in Figure 0.8 and Figure 0.9. Data sources for calibration time-series are listed in Table 0.8. Four types of forcing time-series were used in the model: fishing effort, fishing mortality, forced catch, and abiotic forcing. Fishing fleet catch rates were driven by fishing effort time-series. Effort trends for otter trawl, beam trawl, and *Nephrops* trawl were taken from scientific data, whereas trends for pelagic nets, gillnets, pots, dredge, and longline from 1973-2003 were reconstructed by fishers’ during WKIrish workshops (Figure 0.10, see Table 0.9 for sources). From 2003-2016 STECF effort data was used for these fleets (STECF, 2018). The landings of sharks, whiting, anadromous fish, and infauna could not be simulated using the effort time-series and were therefore driven by fishing mortality (sharks and whiting) or forced catch (anadromous fish, infauna). Abiotic forcing time-series were assigned using Pearson’s correlation analysis.

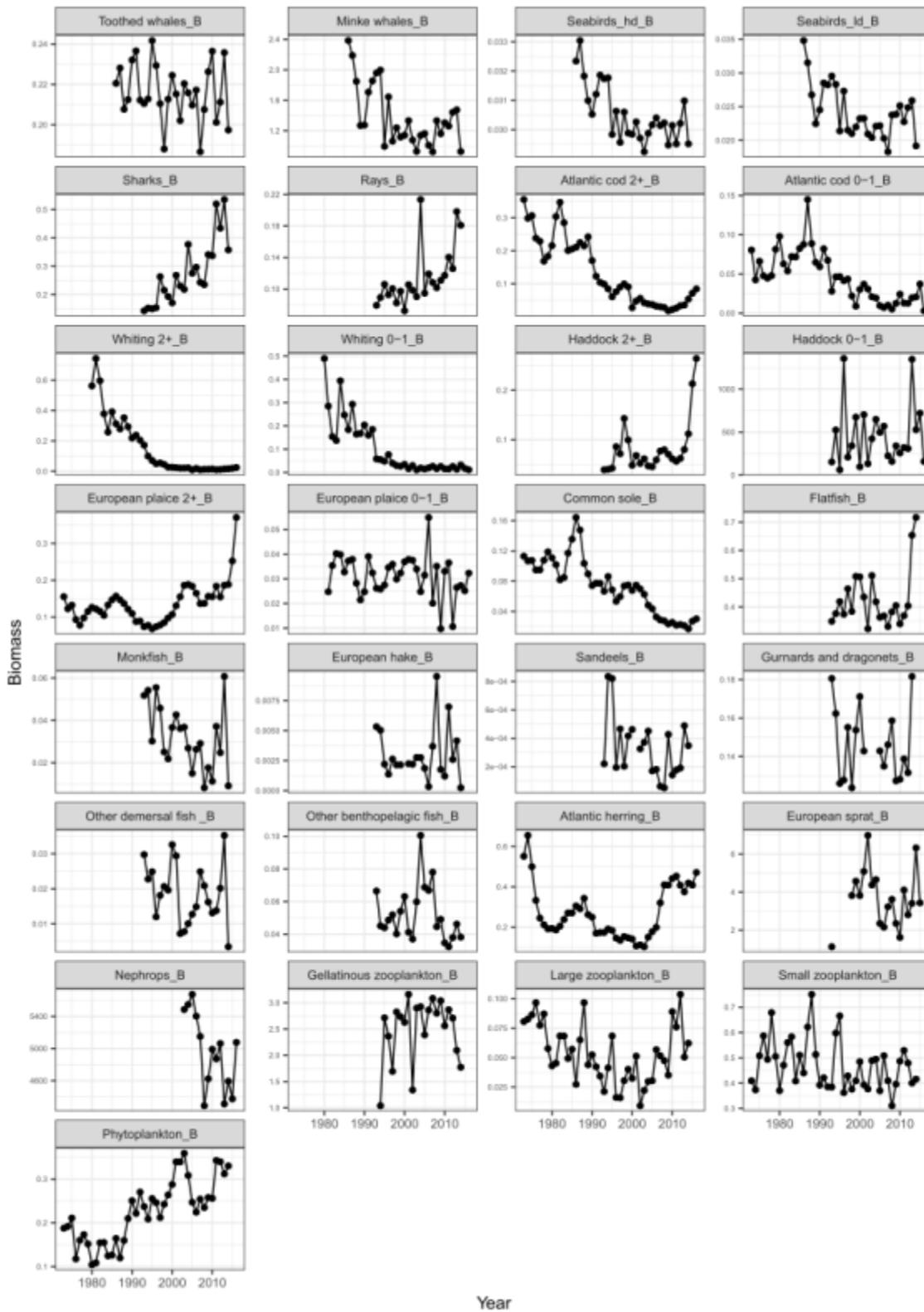


Figure 0.8. Biomass calibration time-series used for fitting the Irish Sea Ecosim model (1973-2016).

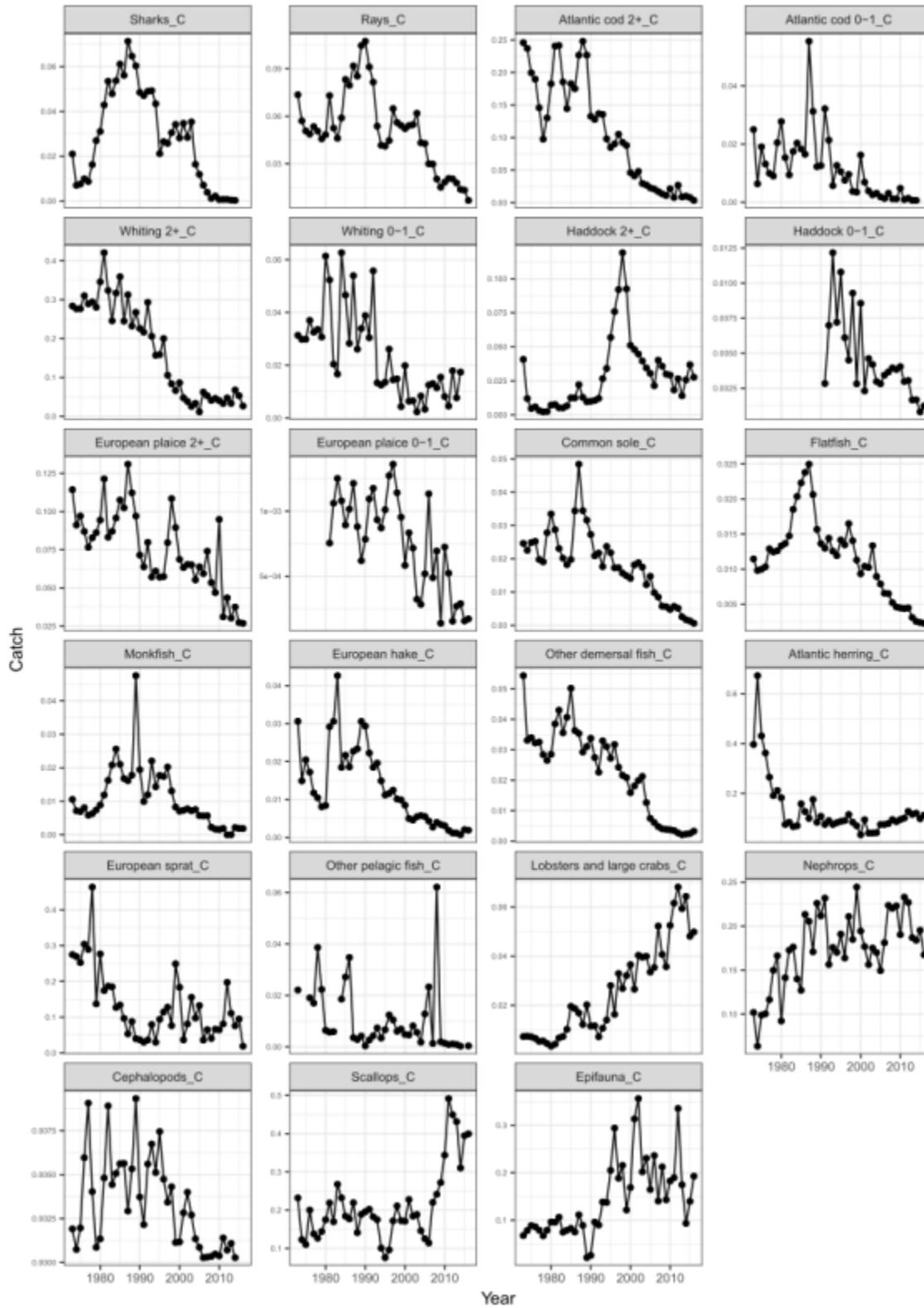


Figure 0.9. Catch calibration time-series used for fitting the Irish Sea Ecosim model (1973-2016).

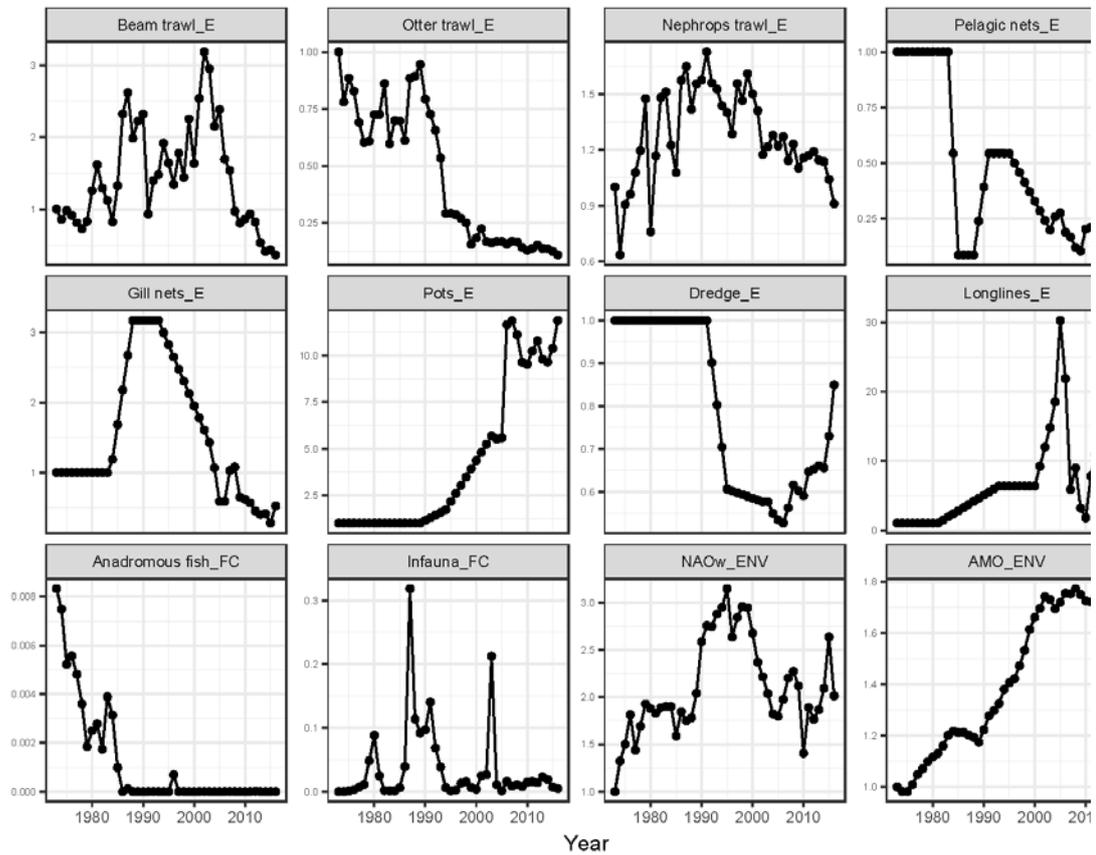


Figure 0.10. Forcing time-series used in the Irish Sea Ecosim model (1973-2016), including fishing fleet effort drivers (E), forced catch (FC), and environmental drivers (ENV).

Table 0.8. Irish Sea EwE key-run calibration time-series sources.

Functional group	Time-series type	Source
Toothed whales	Biomass-model	GAM model, VIIa, (Waggitt <i>et al.</i> , In prep.)
Minke whales	Biomass-model	GAM model, VIIa, (Waggitt <i>et al.</i> , In prep.)
Seabirds (high discard diet)	Biomass-model	GAM model, VIIa, (Waggitt <i>et al.</i> , In prep.)
Seabirds (low discard diet)	Biomass-model	GAM model, VIIa, (Waggitt <i>et al.</i> , In prep.)
Sharks	Biomass-survey	BTS-VIIa (ICES, 2017b)
	Catches	ICES catch statistics (ICES, 2018a)
Rays	Biomass-survey	BTS-VIIa (ICES, 2017b)
	Catches	ICES catch statistics (ICES, 2018a)
Atlantic cod 2+	Biomass-assessment	SAM Age2+, WKIrish (ICES, 2017c, ICES, 2018c)
	Catches	WKIrish/WGCSE, catch in tonnes (landings + discards) (ICES, 2017c, ICES, 2018c)
Atlantic cod 0-1	Biomass-assessment	SAM Age 0-1, WKIrish (ICES, 2017c, ICES, 2018c)

	Catches	WKIrish/WGCSE, catch in tonnes (landings + discards) (ICES, 2017c, ICES, 2018c)
Whiting 2+	Biomass-assessment	ASAP Age2+, WKIrish (ICES, 2017c, ICES, 2018c)
	Catches	WKIrish/WGCSE, catch in tonnes (landings + discards) (ICES, 2017c, ICES, 2018c)
Whiting 0-1	Biomass-assessment	ASAP Age 0-1, WKIrish (ICES, 2017c, ICES, 2018c)
	Catches	WKIrish/WGCSE, catch in tonnes (landings + discards) (ICES, 2017c, ICES, 2018c)
Haddock 2+	Biomass-assessment	ASAP Age2+, WKIrish (ICES, 2017c, ICES, 2018c)
	Catches	WKIrish/WGCSE, catch in tonnes (landings + discards) (ICES, 2017c, ICES, 2018c)
Haddock 0-1	Biomass-assessment	ASAP Age 0-1, WKIrish (ICES, 2017c, ICES, 2018c)
	Catches	WKIrish/WGCSE, catch in tonnes (landings + discards) (ICES, 2017c, ICES, 2018c)
European plaice 2+	Biomass-assessment	SAM Age2+, WKIrish (ICES, 2017c, ICES, 2018c)
	Catches	WKIrish/WGCSE, catch in tonnes (landings + discards) (ICES, 2017c, ICES, 2018c)
European plaice 0-1	Biomass-assessment	SAM Age 0-1, WKIrish (ICES, 2017c, ICES, 2018c)
	Catches	WKIrish/WGCSE, catch in tonnes (landings + discards) (ICES, 2017c, ICES, 2018c)
Common sole	Biomass-assessment	XSA (ICES, 2018c)
	Catches	Landings data from WGCSE (ICES, 2018c)
Flatfish	Biomass-survey	BTS-VIIa (ICES, 2017b)
	Catches	ICES catch statistics (ICES, 2018a)
Monkfish	Biomass-survey	BTS-VIIa (ICES, 2017b)
	Catches	ICES catch statistics (ICES, 2018a)
European hake	Biomass-survey	BTS-VIIa (ICES, 2017b)
	Catches	ICES catch statistics (ICES, 2018a)
Sandeels	Biomass-survey	BTS-VIIa (ICES, 2017b)
Gurnards and dragonets	Biomass-survey	BTS-VIIa (ICES, 2017b)
Other demersal fish	Biomass-survey	BTS-VIIa (ICES, 2017b)
	Catches	ICES catch statistics (ICES, 2018a)
Other benthopelagic fish	Biomass-survey	BTS-VIIa (ICES, 2017b)
Atlantic herring	Biomass-assessment	SAM, HAWG, (ICES, 2018b)

	Catches	Landings data from HAWG (ICES, 2018b)
European sprat	Biomass-survey	AFBI annual herring acoustic survey, HAWG, (ICES, 2018b)
	Catches	ICES catch statistics (ICES, 2018a)
Other pelagic fish	Catches	ICES catch statistics (ICES, 2018a)
Lobsters and large crabs	Catches	ICES catch statistics (ICES, 2018a)
Nephrops	Biomass-assessment	UWTV index for Irish Sea West (FU15) (ICES, 2018c)
	Catches	WGCSE, catch in tonnes (landings + discards) (ICES, 2018c) and info from ICES catch statistics from 1973-2003 (ICES, 2018a)
Cephalopods	Catches	ICES catch statistics (ICES, 2018a)
Epifauna	Catches	ICES catch statistics (ICES, 2018a)
Scallops	Catches	ICES catch statistics (ICES, 2018a)
Gelatinous zooplankton	Biomass-survey	Annual average weight from 1994-2016 from S. Beggs, as calculated in Lynam <i>et al.</i> (2011).
Large zooplankton	Biomass-survey	SAHFOS CPR, > 2 mm, VIIa
Small zooplankton	Biomass-survey	SAHFOS CPR, < 2 mm, VIIa
Phytoplankton	Biomass-survey	SAHFOS CPR, PCI, VIIa

Table 0.9. Irish Sea EwE key-run forcing time-series sources.

Forcing Series	Group(s)	Target variable	Source
Fishing effort	Beam trawl, otter trawl, Nephrops trawl	Effort	Beam and otter trawl effort from WGCSE (ICES, 2018c). Nephrops trawl effort taken from Coughlan <i>et al.</i> (2015) who reconstructed the trend based on catch per unit effort (CPUE).
Fishing effort	Pelagic nets, gill nets, pots, dredge, longline	Effort	Fishers' knowledge effort trends (ICES, 2018e, Bentley <i>et al.</i> , 2019b)
Fishing mortalities (yield/biomass)	Sharks, whiting 2+, whiting 0-1	Fishing mortality (F)	Group catch/biomass
Forced catch	Anadromous fish, in-fauna	Catch	ICES catch statistics (ICES, 2018a). EwE fleet structure could not simulate the landings of these groups.
Winter North Atlantic Oscillation index (NAOw)	Large zooplankton	Other mortality	Winter (December through March) index of the NAO is based on the difference of normalised sea level pressure between Lisbon, Portugal and Reykjavik, Iceland (NCAR,

			2019b). Assigned to large zooplankton mortality based on Pearson’s correlation analysis.
Atlantic Multidecadal Oscillation (AMO)	Cod, whiting	Larval recruitment success	The AMO is defined here as the annual mean area averaged sea surface temperature (SST) anomalies over the North Atlantic basin (NCAR, 2019a). Assigned to cod and whiting based on Pearson’s correlation analysis.

1.10. Time-series fitting

Ecosim uses the foraging arena theory (Ahrens *et al.*, 2012) to quantify “vulnerabilities”, which represent the degree to which a change in predator biomass will impact predation mortality for a given prey. Vulnerabilities are adjusted to statistically fit model simulations to observed data. This is done by applying multipliers to the rate with which a prey moves between being vulnerable and not vulnerable (Christensen and Walters, 2004). Multipliers can range from one to infinity with two as the default. Vulnerabilities with multipliers greater than two indicate top-down control, where predator biomass drives prey mortality, whereas vulnerabilities with multipliers between one and two suggest bottom-up control, where even large increases in predator biomass cause only a limited increase in the consumption rate of that predator on the given prey, therefore the biomass of the prey regulates predator consumption (Christensen *et al.*, 2008).

Vulnerability multipliers can be estimated for predator-prey interactions or for whole predator diets. The automated fitting routine (Scott *et al.*, 2016) facilitates the estimation of one or the other, however it is ecologically probable that, whilst species may exert a general top-down or bottom-up forcing on the majority of their prey due to their behaviour or morphology, some interactions may be unique as a result of prey behaviour, habitat, or morphology. Estimating predator-prey vulnerabilities alone accounts for these unique interactions, however the number of vulnerabilities that can be estimated this way is largely limited by the available degrees of freedom. As 52 calibration time-series were used we were able to estimate a maximum of 51 predator/prey vulnerabilities before the model could be considered as ‘overfitted’, thus leaving the majority of the vulnerability matrix at its default setting of two. However, estimating predator vulnerabilities alone homogenises the impact of a group’s biomass on its prey, meaning potentially important dynamics may be overlooked.

We therefore propose a new approach for the ecological optimisation of vulnerability multipliers which has the potential to improve model performance whilst remaining within the given degrees of freedom. Firstly, the automated stepwise fitting routine was used to find the model of best fit with predator vulnerabilities (first stage best fit, Figure 0.11). The best fit model was determined by the minimum difference between model simulations and time-series observations using the weighted sum of squared differences (SS) and the Akaike Information Criterion for small sample sizes (AICc) (Akaike, 1974, Burnham and Anderson, 2003). Secondly, using the best fit model and the remaining degrees of freedom, we systematically searched for the most sensitive predator-prey vulnerabilities which would improve the statistical fit of model simulations to observed data (second stage best fit). The AICc was manually calculated for each iteration to consider the predator vulnerabilities already estimated during the stepwise fitting procedure. The model iteration with the lowest AICc was used as the best fit model.

Once environmental drivers were applied to the model the automated stepwise fitting routine was used to generate a set of model iterations with altered predator vulnerability multiplies.

Here we identified the first stage best fit model to include fishing and 26 estimated predator vulnerabilities (Figure 0.11, Table 0.10). At this stage the models SS was reduced from 1251 to 754 and the AICc was reduced from -829 to -1753. As 26 parameters were estimated we were still capable to estimate a maximum of 25 additional predator/prey vulnerabilities to optimise model fit whilst retaining statistical integrity. Using a stepwise approach, the most sensitive predator/prey vulnerabilities were altered incrementally from the addition of 1 to 25 parameter changes. The second stage best fit model included the 26 predator vulnerabilities from the first stage best fit with the alteration of 14 predator/prey vulnerability multipliers (Figure 0.11, Table 0.11) The second stage best fit and final model had an improved SS of 656 and an AICc of -1984.

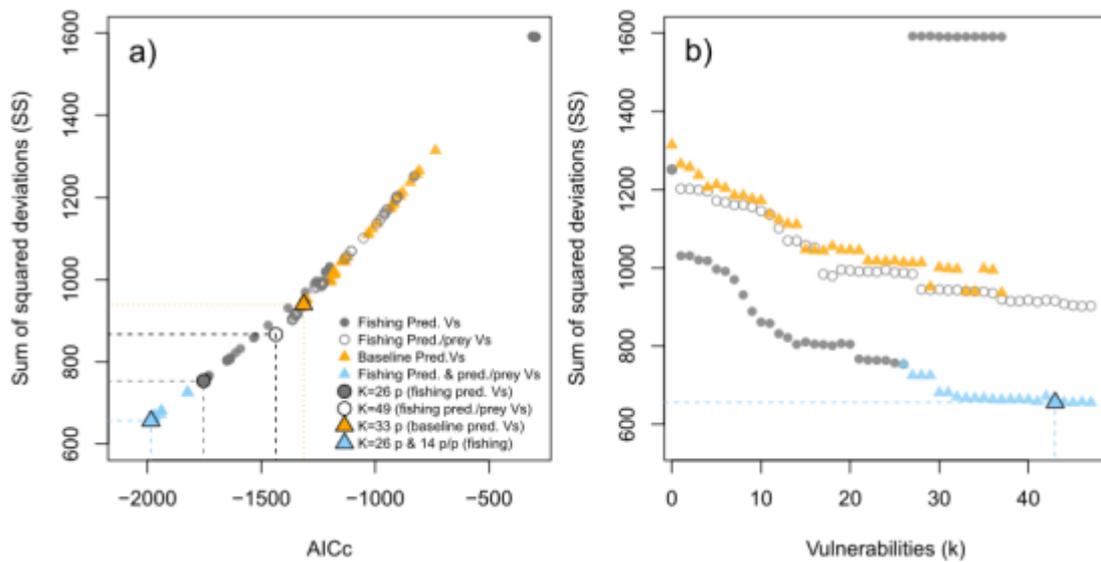


Figure 0.11. Ecosim fitting. (a) Sensitivity of the sum of squared deviations (SS) and Akaike's information criterion (AICc) to fitting predator (p) and predator/prey (p/p) vulnerabilities (Vs). Best fit models are highlighted by larger points and reference lines, with the legend indicating the number of parameters (K) estimated. (b) Change in SS as a function of vulnerability parameters estimated.

Table 0.10. Fitted predator vulnerabilities applied to specific groups in the key-run during the first stage of model fitting.

Functional group	Vulnerability
Sharks	2.17
Rays	2.42
Atlantic cod 2+	>100
Atlantic cod 0-1	>100
Whiting 2+	1.53
Whiting 0-1	>100
Haddock 2+	2.63
Haddock 0-1	1.00
European plaice 2+	1.10
European plaice 0-1	1.67
Common sole	4.31
Flatfish	1.00
Monkfish	1.00
European hake	1.00
Gurnards	>100
Atlantic herring	1.30
European sprat	2.54
Other pelagic fish	1.00
Nephrops	>100
Shrimp	1.00
Cephalopods	1.00
Scallops	16.10
Infauna	1.00
Gelatinous zooplankton	1.00
Large zooplankton	3.63
Small zooplankton	1.77

Table 0.11. Fitted predator/prey vulnerabilities applied to predator/prey pairs in the key-run during the second stage of model fitting. These 14 pairs were the most sensitive to altered vulnerabilities.

Functional group		Vulnerability
Predator	Prey	
	Atlantic cod 0-1	>100
	European hake	1.00
Whiting 2+	Other benthopelagic fish	>100
	Other pelagic fish	1.10
	European sprat	>100
Haddock 2+	Nephrops	2.64
Common sole	Epifauna	1.59
	Infauna	>100
Atlantic herring	Large zooplankton	1.45
European sprat	Small zooplankton	1.00
	Small zooplankton	1.85
Large zooplankton	Phytoplankton	>100
	Detritus	>100
Small zooplankton	Phytoplankton	2.66

1.11. Fitting diagnostics and performance

Plots of sum of squares residuals of model predictions to observation data are given in Figure 0.12 and Figure 0.13 for functional groups with calibration time-series. The rank order of SS values contributing to the total SS (Figure 0.14) shows that the largest contributions generally come from key-run catch simulations, particularly for ‘Other pelagic fish’, which is most likely due to the models use of fishing effort to drive catch simulations rather than using group specific fishing mortality which is often capable of capturing the impact of additional variables such as changes in catchability over time. Biomass and catch simulations for all functional groups are shown in Figure 0.15 and Figure 0.16 with 95% confidence intervals derived from 1000 Monte Carlo model permutations varying Ecopath basic input parameters using data pedigree information.

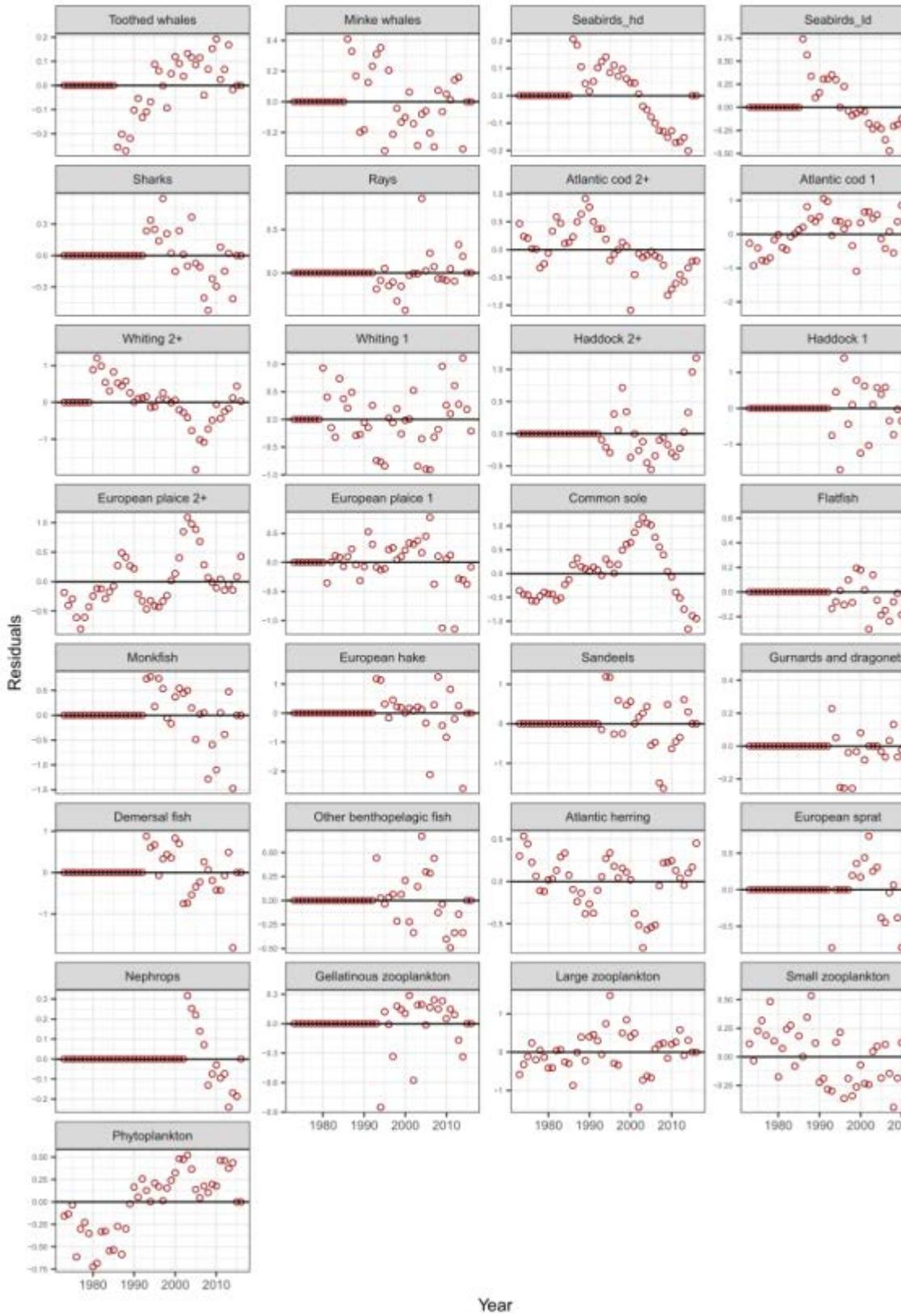


Figure 0.12. Residuals for relative biomass simulations vs observed data.

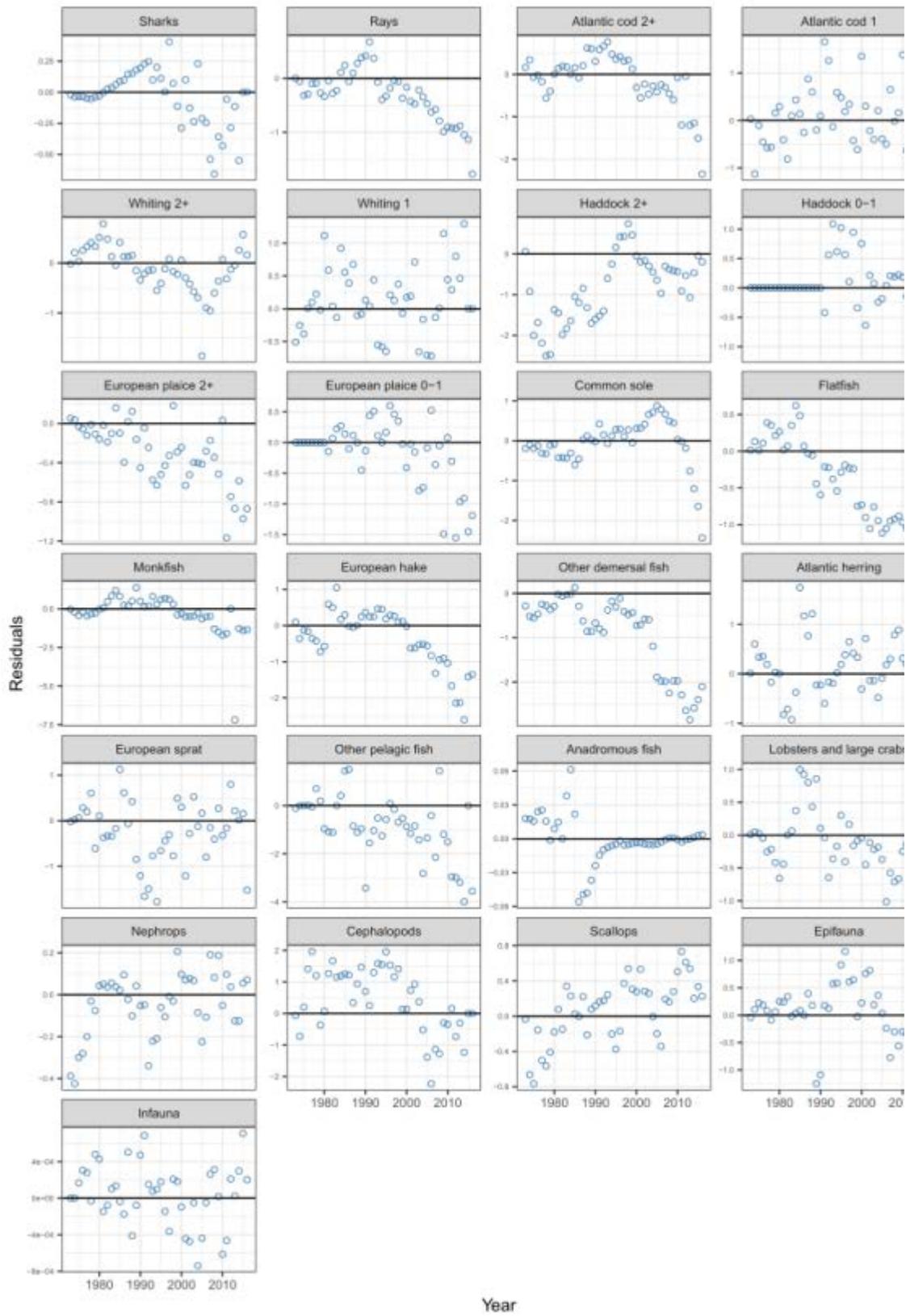


Figure 0.13. Residuals for catch simulations vs observed data.

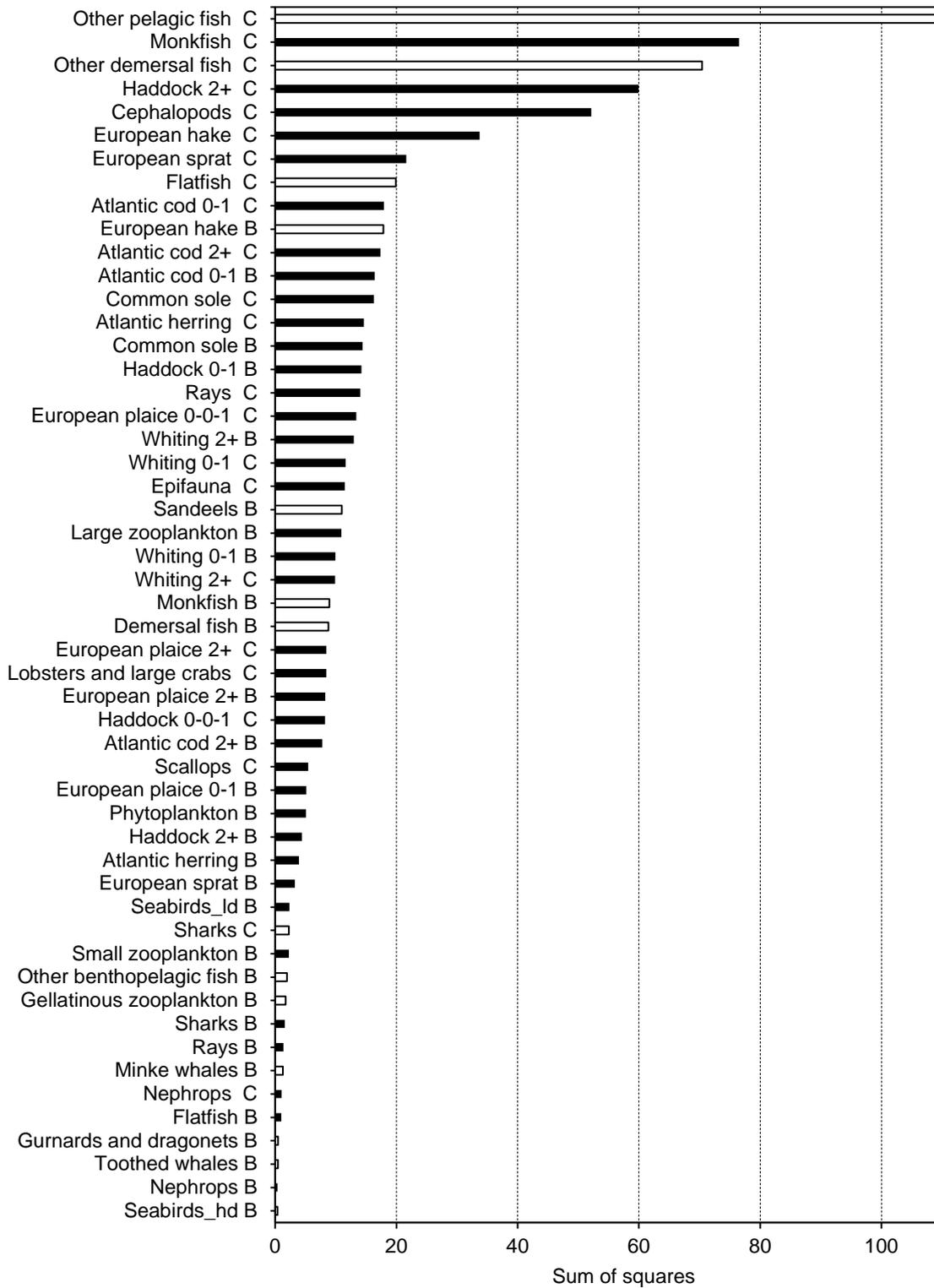


Figure 0.14. Sum of squares contributions from all biomass (B) and catch (C) simulations in the fitted key-run. Time-series with low weightings (0.5) based on data reliability and relevance are hollow. All others use the default weighting of 1.

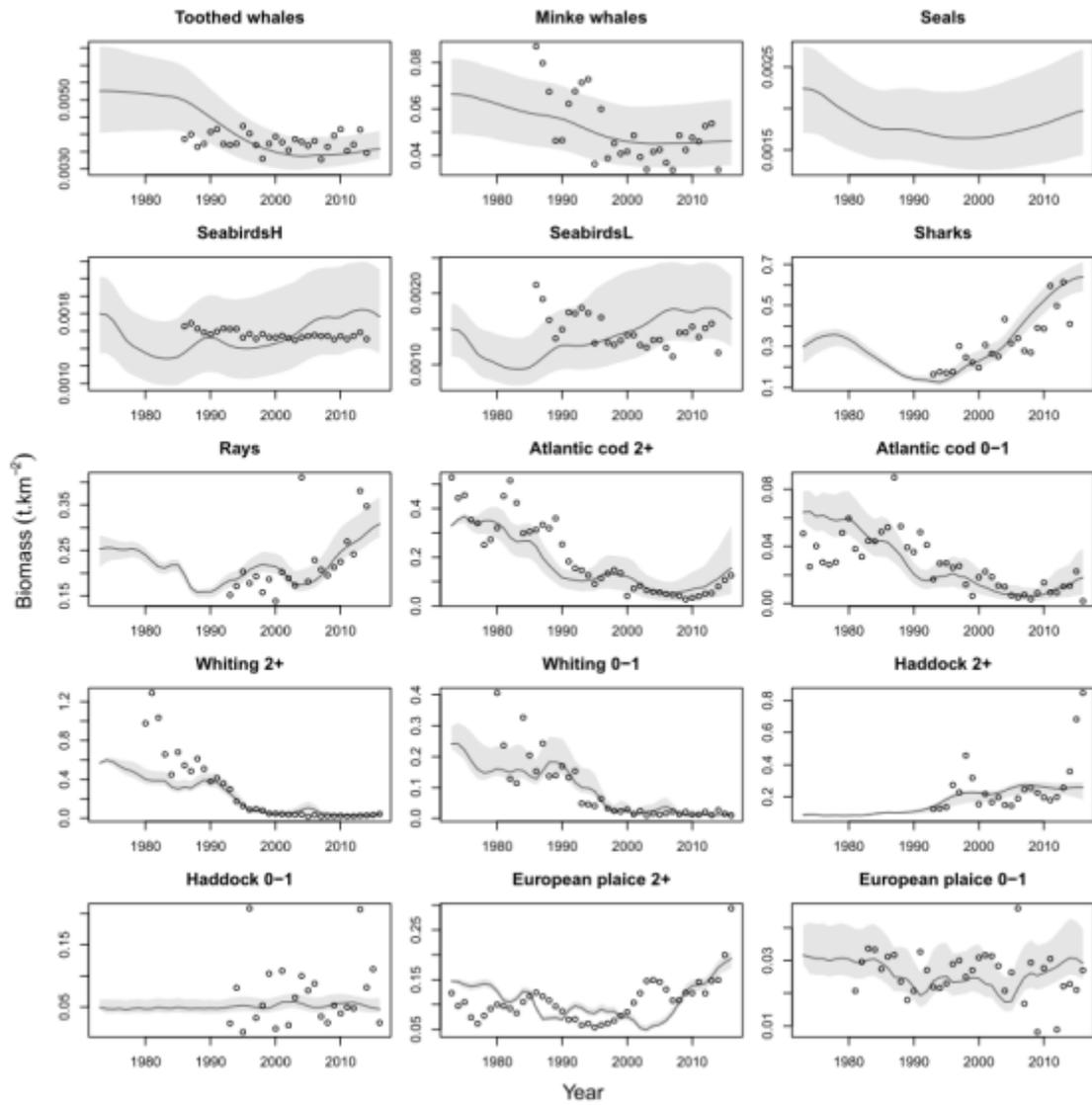


Figure 0.15. Ecosim predicted biomass trends (1/3) for functional groups in the Irish Sea Ecopath with Ecosim model (page 1 of 3). Black lines indicate model simulations against observed data (points). The shaded area indicates 95% confidence intervals based on Monte Carlo simulations varying Ecopath basic input parameters (B, PB, QB, diet).

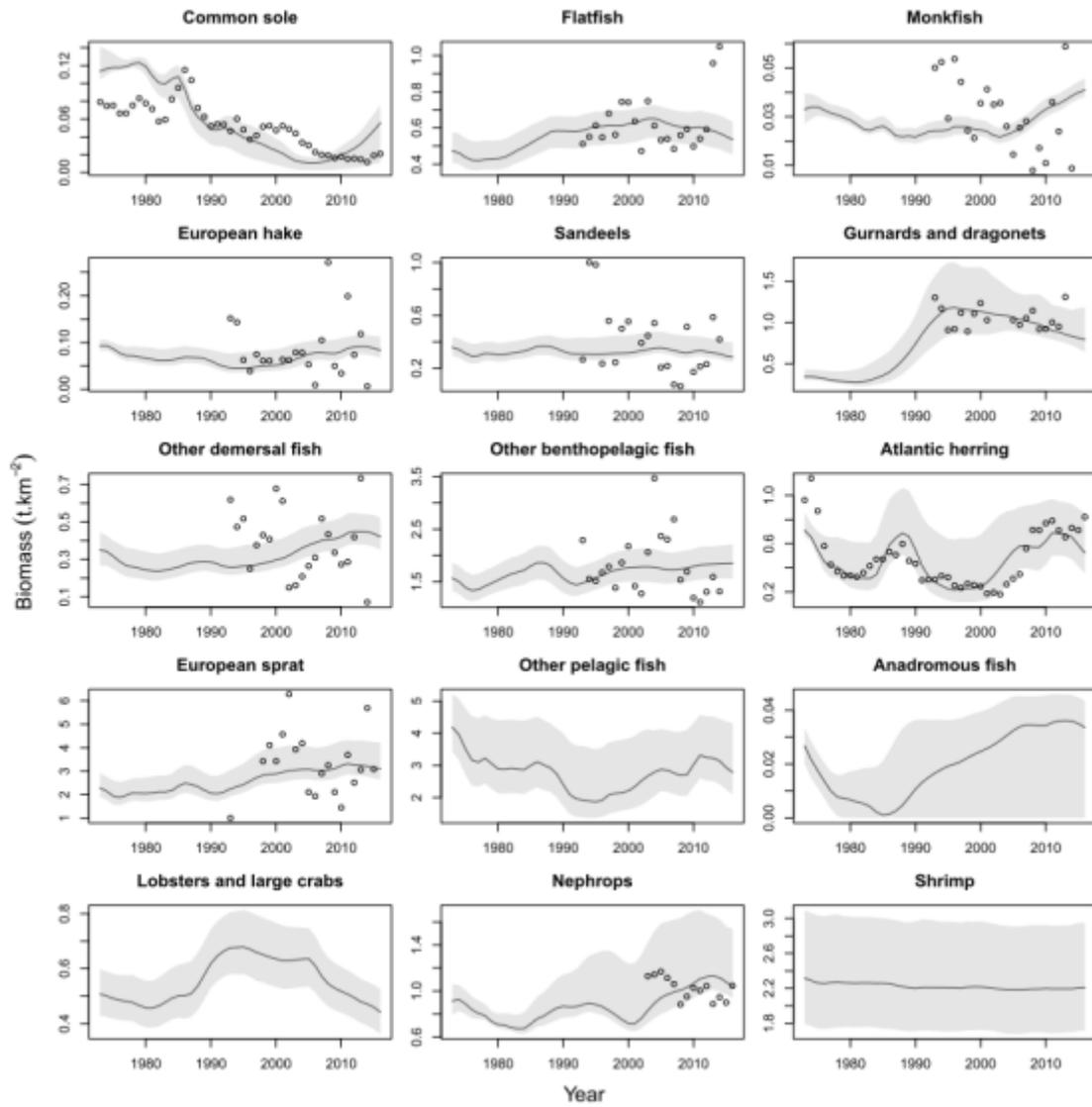


Figure 0.15. continued. Ecosim predicted biomass trends for functional groups in the Irish Sea Ecopath with Ecosim model (page 2 of 3). Black lines indicate model simulations against observed data (points). The shaded area indicates 95% confidence intervals based on Monte Carlo simulations varying Ecopath basic input parameters (B, PB, QB, diet).

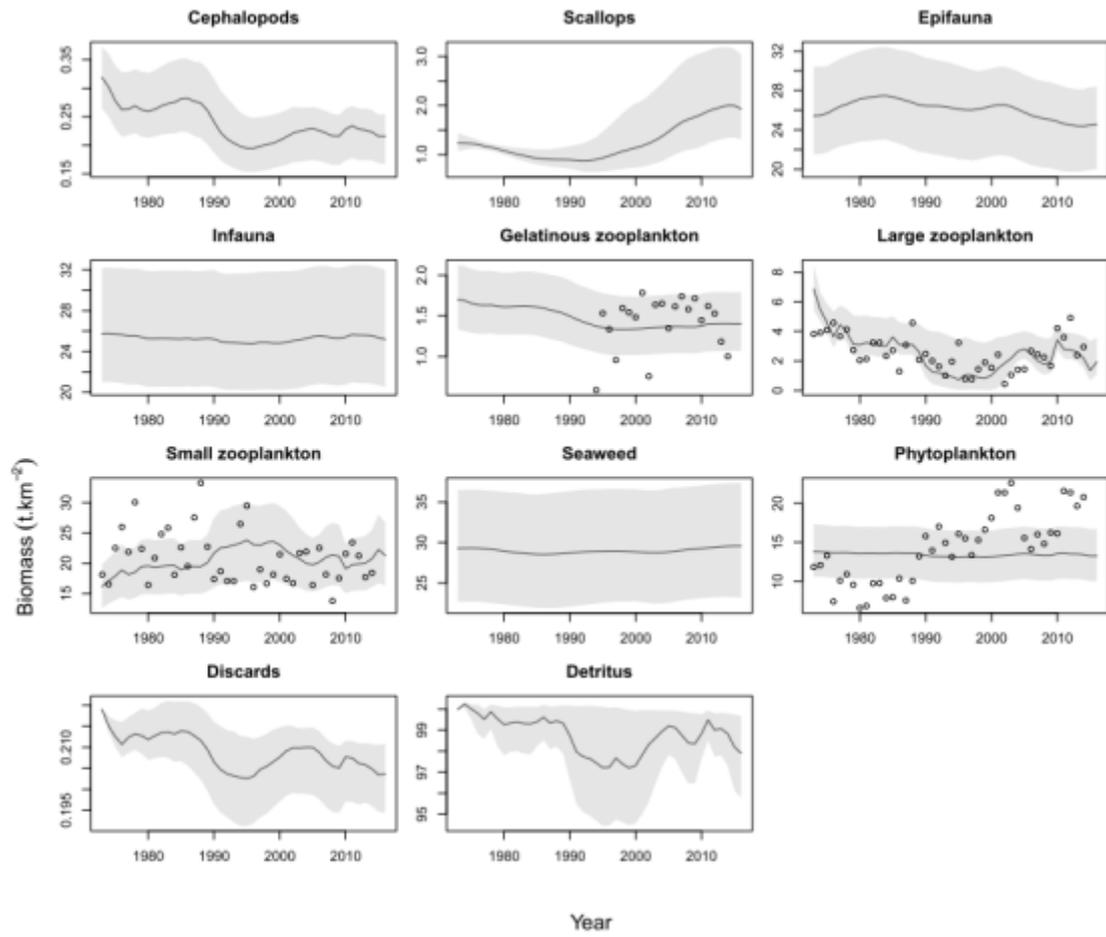


Figure 0.15. continued. Ecosim predicted biomass trends for functional groups in the Irish Sea Ecopath with Ecosim model (page 3 of 3). Black lines indicate model simulations against observed data (points). The shaded area indicates 95% confidence intervals based on Monte Carlo simulations varying Ecopath basic input parameters (B, PB, QB, diet).

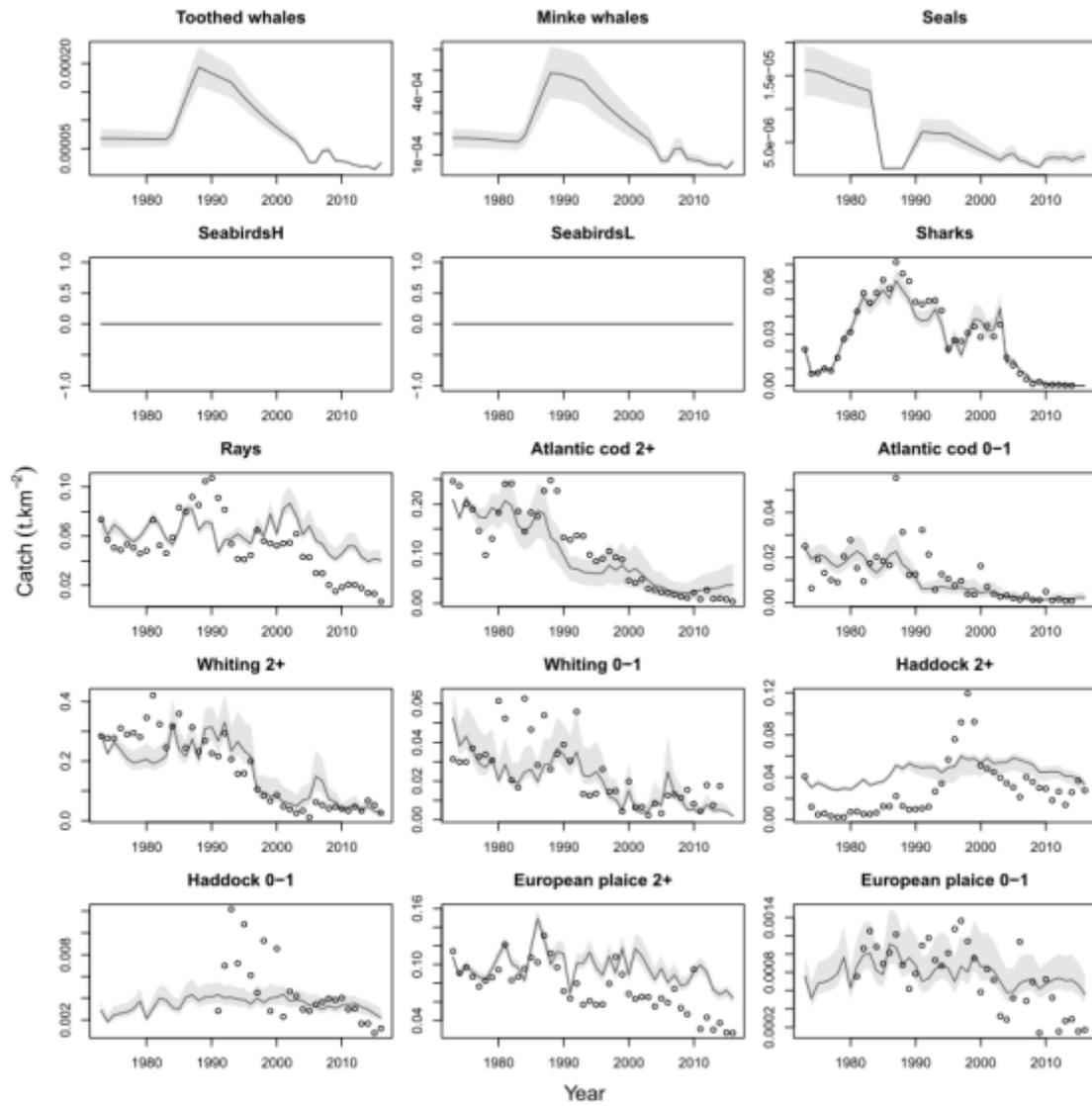


Figure 0.16. Ecosim predicted catch trends for functional groups in the Irish Sea Ecopath with Ecosim model (page 1 of 3). Black lines indicate model simulations against observed data (points). The shaded area indicates 95% confidence intervals based on Monte Carlo simulations varying Ecopath basic input parameters (B, PB, QB, diet).

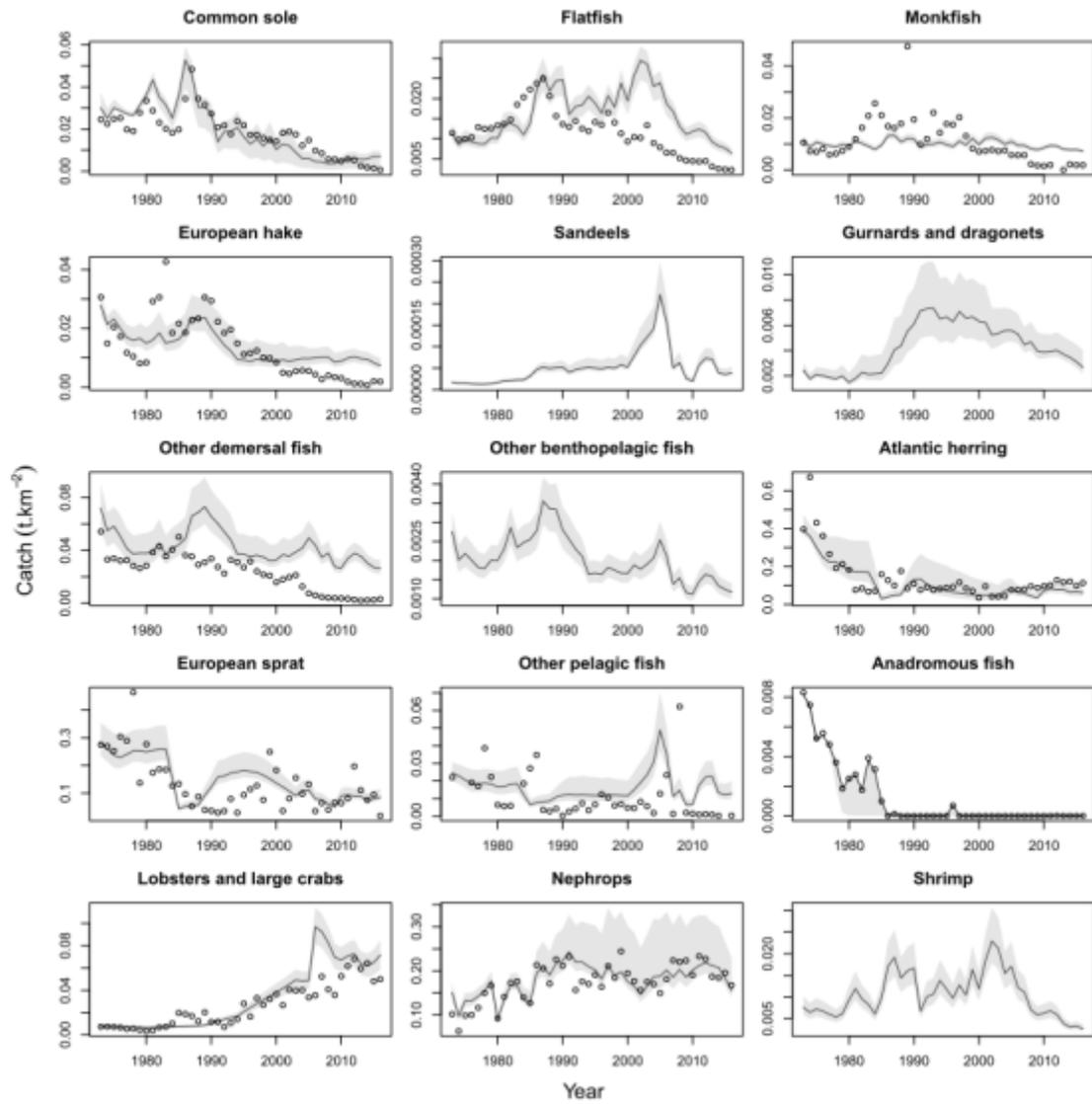


Figure 0.16. continued. Ecosim predicted catch trends for functional groups in the Irish Sea Ecosystem with Ecosim model (page 2 of 3). Black lines indicate model simulations against observed data (points). The shaded area indicates 95% confidence intervals based on Monte Carlo simulations varying Ecosystem basic input parameters (B, PB, QB, diet).

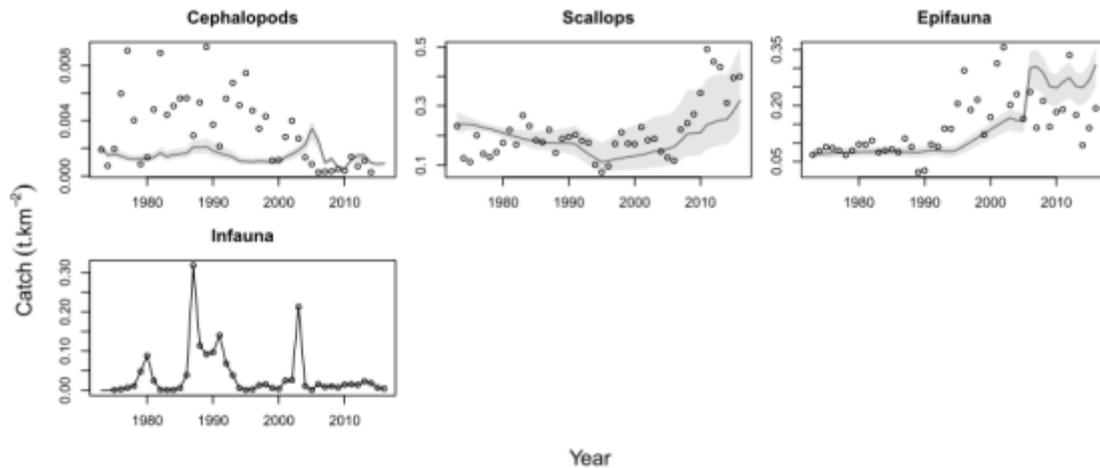


Figure 0.16. continued. Ecosim predicted catch trends for functional groups in the Irish Sea Ecopath with Ecosim model (page 3 of 3). Black lines indicate model simulations against observed data (points). The shaded area indicates 95% confidence intervals based on Monte Carlo simulations varying Ecopath basic input parameters (B, PB, QB, diet).

1.12. Key-run outputs

1.12.1. Model fits and mortality estimates

The fit of model biomass and catch simulations to observed data (relative biomass and catch) along with estimates of total, fishing, and predation mortality for selected key species of interest are shown in Figure 0.17.

1.12.2. Estimates of F_{MSY}

The key-run was used to estimate F_{MSY} ranges for each functional group using two approaches: “Full compensation” and “Stationary system”. The full compensation assessment takes into account the indirect changes in biomass of other species caused through trophic linkages. During this assessment method, the F of the assessed species is incremented across all ranges of F over a long simulation period (100 years) until stock depletion whilst groups that are not being assessed are set to $F=F_{current}$ and allowed to interact. During the Stationary system assessment there are no interactions between species (the biomasses of the groups that are not assessed are kept constant through the simulations). Both methods are well explained by Walters *et al.* (2015). Key-run F_{MSY} estimates for all species are shown in Table 0.12, whilst MSY curves are plotted for key commercial species in Figure 0.18 and compared to ICES reference points in Figure 0.19.

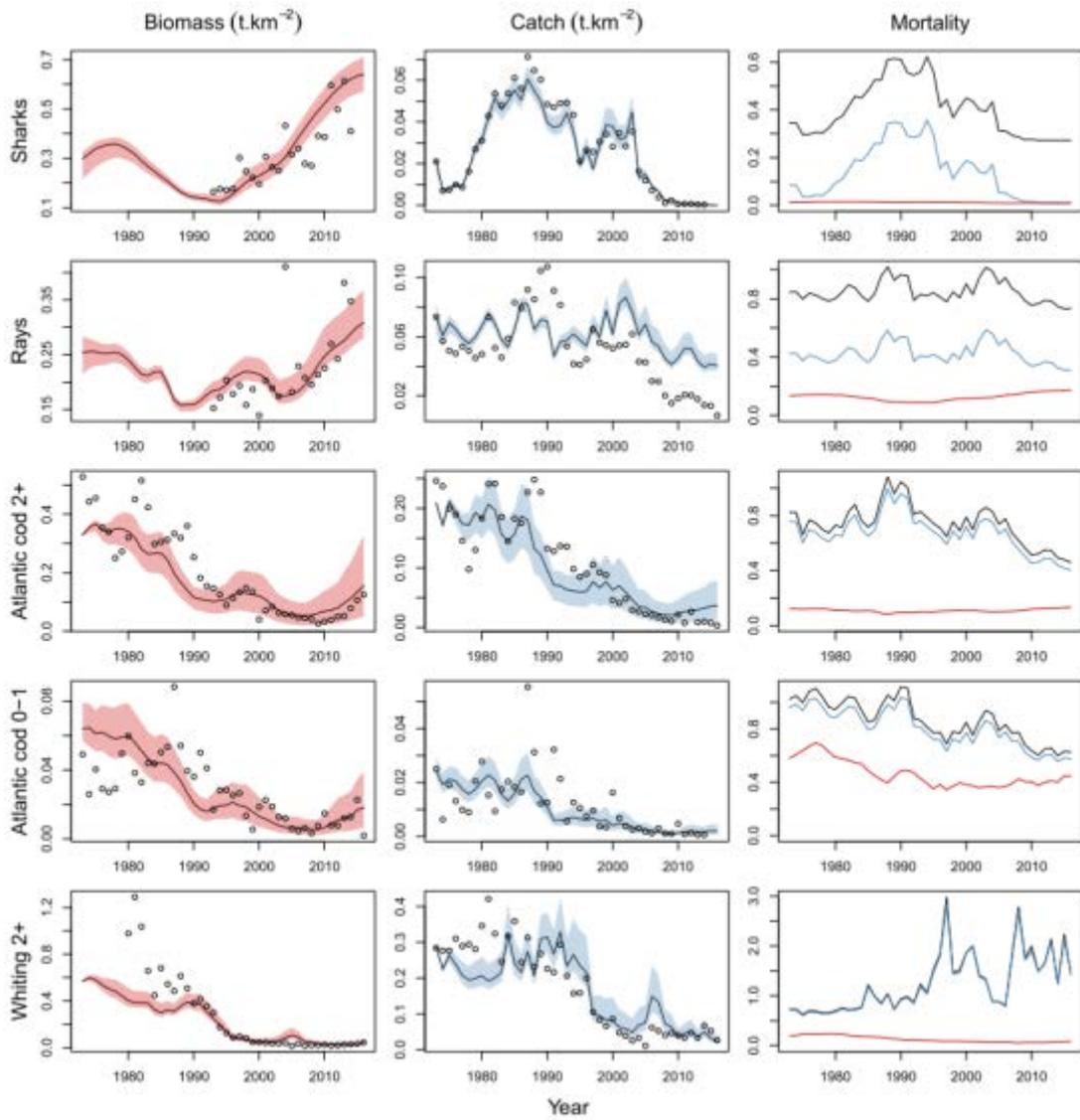


Figure 0.17. Ecosim simulated biomasses, catches, and mortalities for key functional groups in the Irish Sea EwE key-run (page 1 of 3). For biomass and catch simulations, solid lines represent key-run simulations, dots represent observed data, and the shaded areas indicate 95% confidence intervals based on Monte Carlo simulations varying Ecopath input parameters using data pedigree confidence intervals. Mortalities are shown as total mortality (black line), fishing mortality (blue line) and predation mortality (red line).

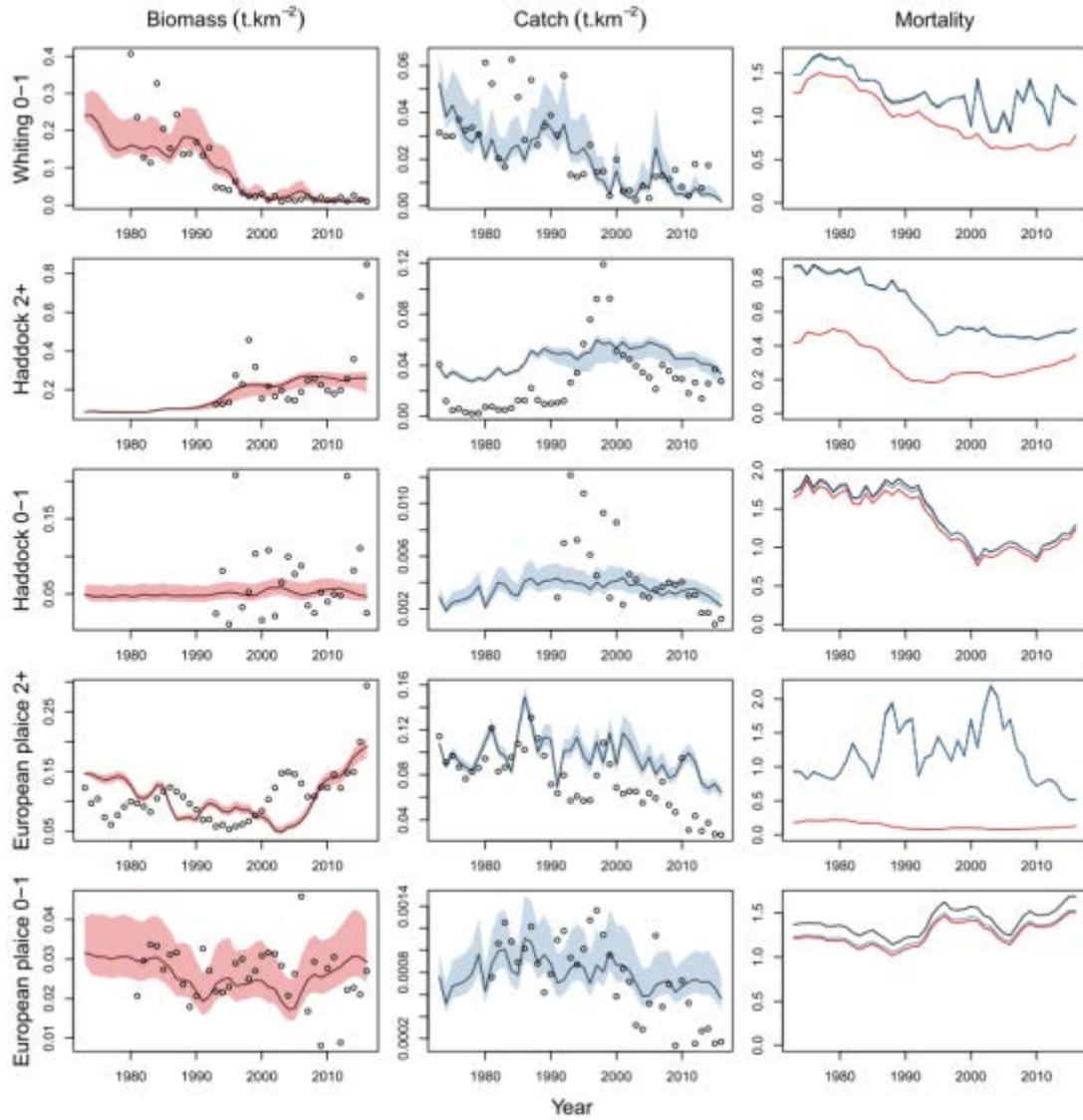


Figure 0.17. continued. Ecosim simulated biomasses, catches, and mortalities for key functional groups in the Irish Sea EwE key-run (page 2 of 3). For biomass and catch simulations, solid lines represent key-run simulations, dots represent observed data, and the shaded areas indicate 95% confidence intervals based on Monte Carlo simulations varying Ecopath input parameters using data pedigree confidence intervals. Mortalities are shown as total mortality (black line), fishing mortality (blue line) and predation mortality (red line).

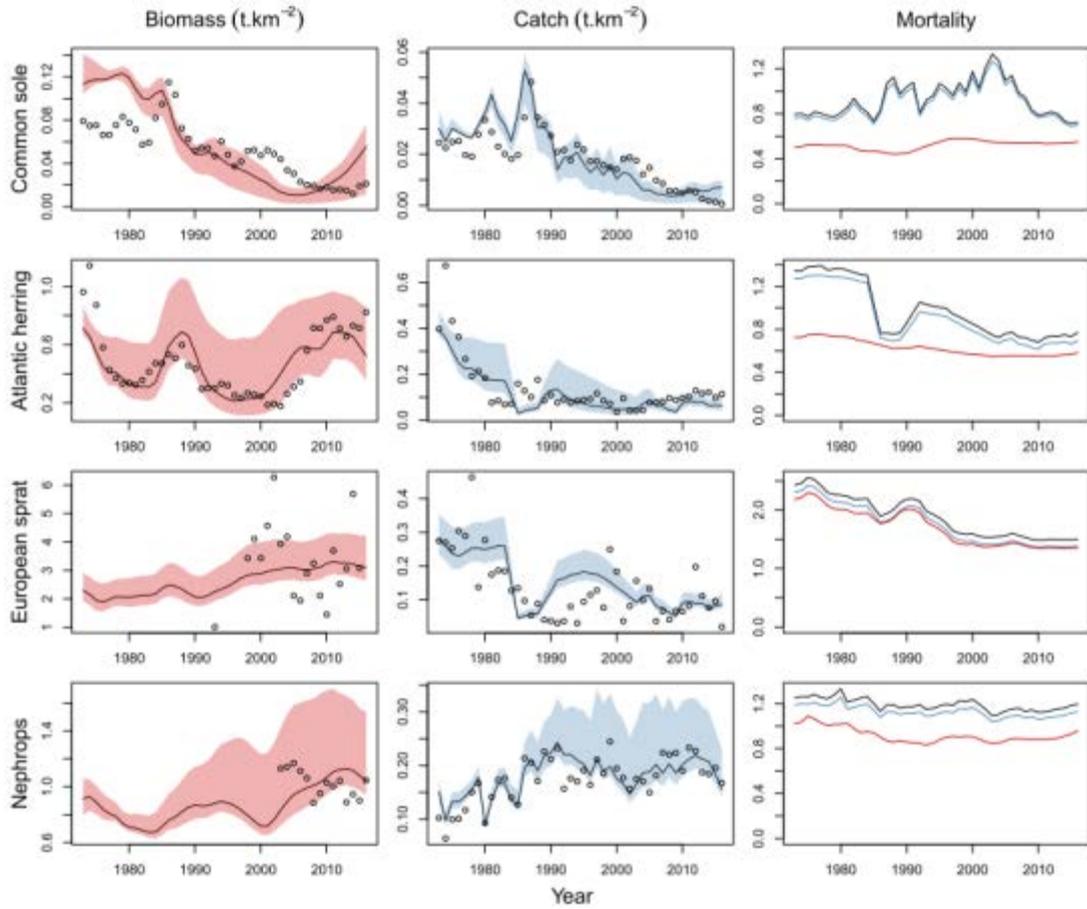


Figure 0.17. continued. Ecosim simulated biomasses, catches, and mortalities for key functional groups in the Irish Sea EwE key-run (page 3 of 3). For biomass and catch simulations, solid lines represent key-run simulations, dots represent observed data, and the shaded areas indicate 95% confidence intervals based on Monte Carlo simulations varying Ecopath input parameters using data pedigree confidence intervals. Mortalities are shown as total mortality (black line), fishing mortality (blue line) and predation mortality (red line).

Table 0.12. Irish Sea EwE estimated Fmsy reference points compared with ICES single species reference points for VIIa stocks.

Functional group	EwE-IS Key-run 2016: Full compensation Fmsy	EwE-IS Key-run 2016: Station- ary system Fmsy	ICES				
			Fmsy	Fmsy _{upper}	Fmsy _{lower}	Fli m	Fpa
Toothed whales	0.01	0.01	-	-	-	-	-
Minke whales	0.01	0.01	-	-	-	-	-
Seals	0.01	0.01	-	-	-	-	-
Rays	0.29	0.27	-	-	-	-	-
Atlantic cod 2+	0.24	0.24	0.44	0.46	0.34	0.81	0.58
Atlantic cod 0-1	0.36	0.30	-	-	-	-	-
Whiting 2+	0.46	0.38	0.22	0.29	0.16	0.37	0.22
Whiting 0-1	0.33	0.27	-	-	-	-	-
Haddock 2+	0.42	0.36	0.28	0.35	0.2	0.53	0.38
Haddock 0-1	0.00	0.00	-	-	-	-	-
European plaice 2+	0.28	0.28	0.2	0.29	0.13	0.48	0.35
European plaice 0-1	0.01	0.01	-	-	-	-	-
Common sole	0.22	0.20	0.2	0.24	0.16	0.29	0.21
Flatfish	0.06	0.06	-	-	-	-	-
Monkfish	0.18	0.18	-	-	-	-	-
European hake	0.25	0.24	-	-	-	-	-
Sandeels	0.00	0.00	-	-	-	-	-
Gurnards and dragonets	0.02	0.02	-	-	-	-	-
Other demersal fish	0.31	0.31	-	-	-	-	-
Other benthope- lagic fish	0.00	0.00	-	-	-	-	-
Atlantic herring	0.26	0.23	0.27	0.35	0.2	0.4	0.29
European sprat	0.14	0.14	-	-	-	-	-
Other pelagic fish	0.02	0.02	-	-	-	-	-
Anadromous fish	0.00	0.00	-	-	-	-	-
Lobsters and large crabs	0.26	0.26	-	-	-	-	-
Nephrops	0.42	0.38	0.18	0.18	0.12	-	-
Shrimp	0.01	0.01	-	-	-	-	-
Cephalopods	0.02	0.02	-	-	-	-	-
Scallops	0.34	0.34	-	-	-	-	-
Epifauna	0.06	0.06	-	-	-	-	-
Infauna	0.00	0.00	-	-	-	-	-

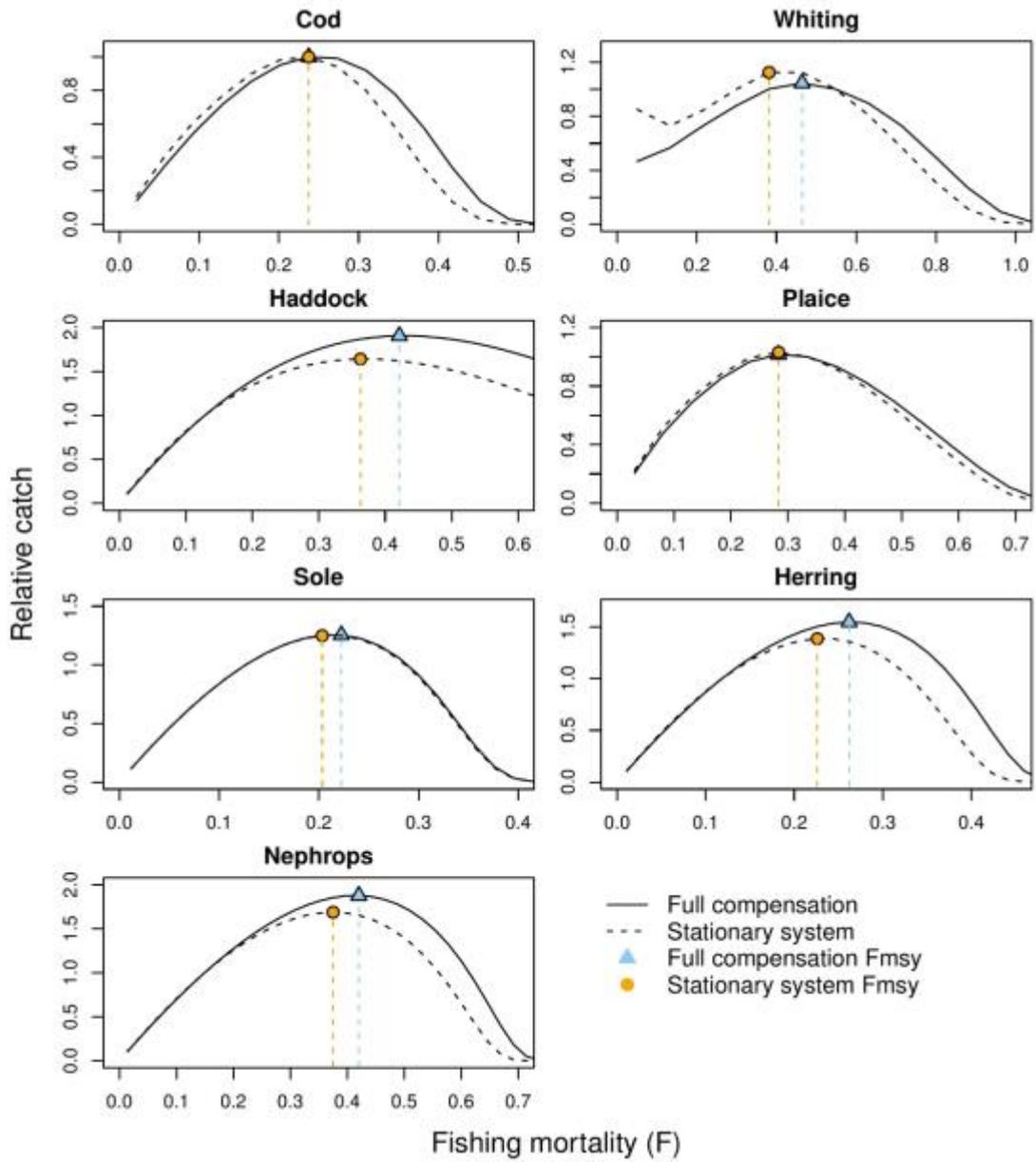


Figure 0.18. Relative catch as a function of F and F_{msy} reference points for commercial important species as simulated under “stationary” and “full compensation” system dynamics.

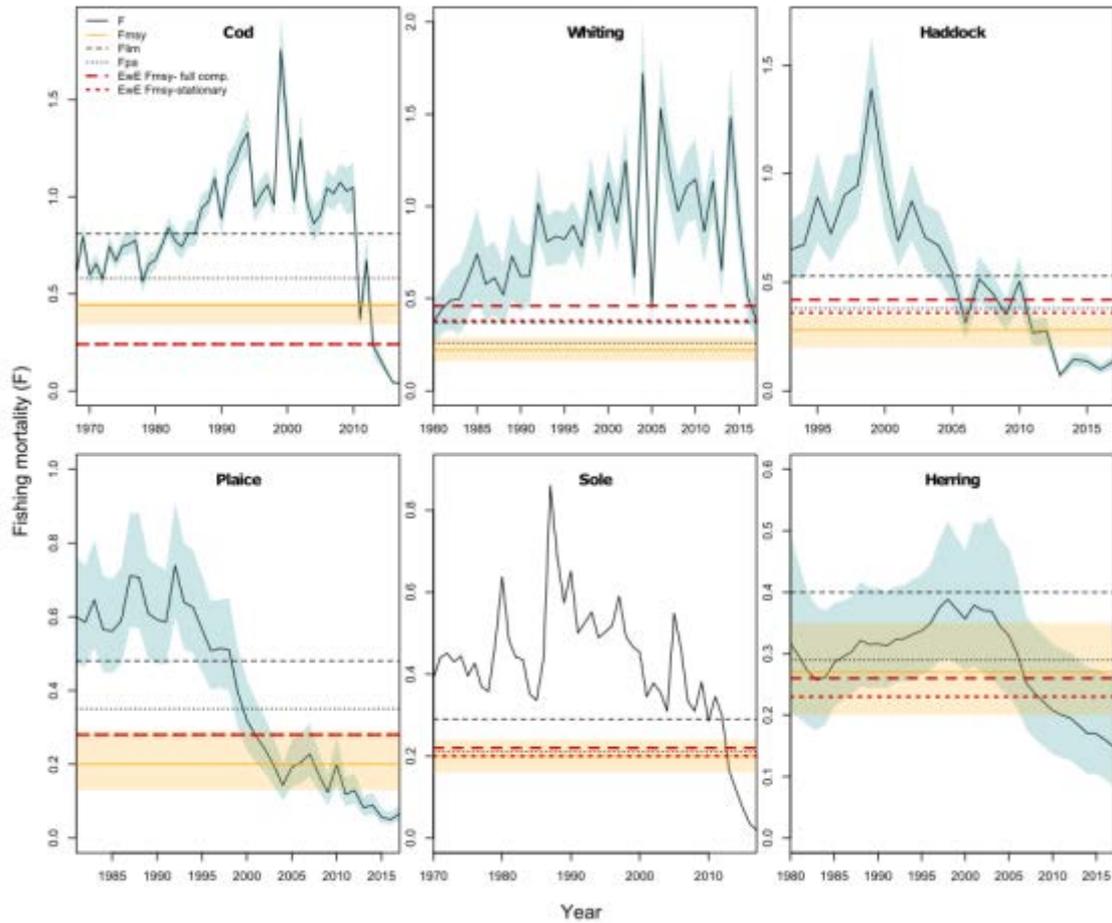


Figure 0.19. Multi-species fishing mortality estimates from the Irish Sea EwE key-run in comparison to ICES fishing mortality trends and reference points for assessed stocks. Blue shading: fishing mortality high and low limits; Orange shading: ICES Fmsy range ($F_{msy_{lower}}-F_{msy_{upper}}$).

1.12.3. Ecosystem indicator trends

Changes in selected system and community indicators are shown in Figure 0.20. Referring to the figure, these include:

- Trends in total system biomass and catch and the biomass and catch of finfish, invertebrates, and mammals.
- Changes to the trophic level of the community and catch.
- Total system production
- Measure of food web diversity (Shannon diversity index)

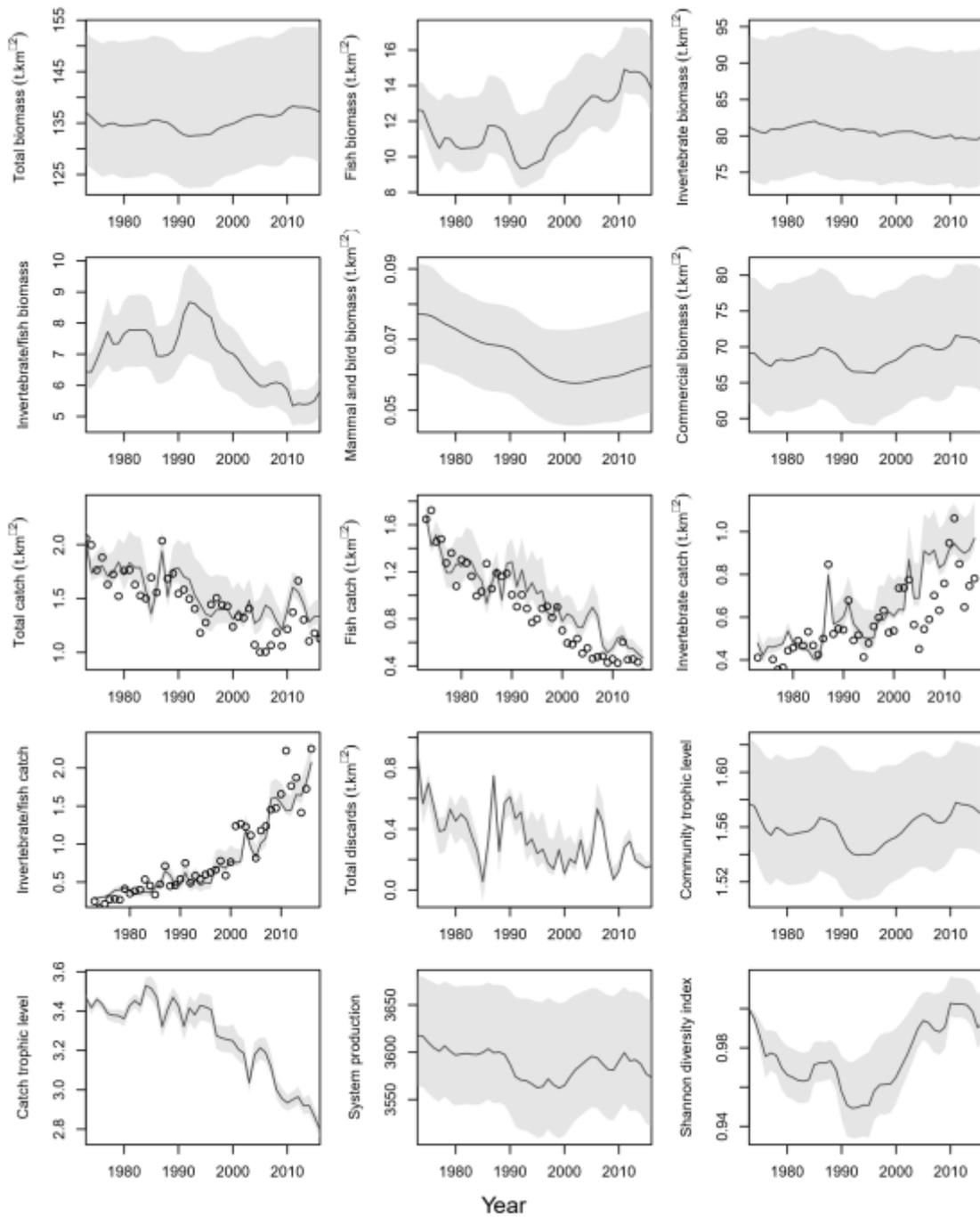


Figure 0.20. Ecosystem indicators derived from the Irish Sea EwE key-run. Shaded areas indicate 95% confidence intervals based on Monte Carlo simulations varying Ecopath input parameters using data pedigree confidence intervals. Model estimated indicators of catch are accompanied by observed data from ICES catch statistics (points).

1.12.4. Changes made to the model following WGSAM workshop

During the review of the Key-run by ICES WGSAM several important issues were discussed in relation to confidence in the interpretation of the key-run outputs and the application of the model for evaluating research and management questions and are worth taking note of here.

- One of the models intended purposes was to try and determine the drivers underpinning the slow recovery of cod in response to management changes. The key-run suggests

that cod's recovery may have been dampened by the negative impact of the AMO on cod recruitment. When removing environmental drivers from the model, cod recovers in response to the reduced fishing mortality. The issue was raised that a high P/B value for cod may have led to an overly productive stock in the model, and that a lower P/B may produce a slower response to changes in fishing mortality. This brings into question whether the environment did play a role in reducing cods recovery rate or whether the productivity of cod in the model is too high that it needed an environmental signal in order to match the observed biomass trend. Sensitivity analyses were carried out to test the impact of a lower P/B on the recovery rate of cod, with and without the AMO driving recruitment over time. Monte Carlo simulations were run wherein cod P/B was permeated between 0.820 (Ecopath value) and 0.1, with and without the AMO driving the recruitment rate of juveniles to the adult stage (Figure 0.21). Results suggest that a reduced P/B would indeed reduce the recovery rate of cod, however without the inclusion of the AMO as a driver of cod recruitment rate all simulations overestimated the recovery response to reduced fishing effort. This is not necessarily surprising as previous studies have recognised the negative relationship between the AMO and Irish Sea cod recruitment (Planque and Fox, 1998; Beggs *et al.*, 2014).

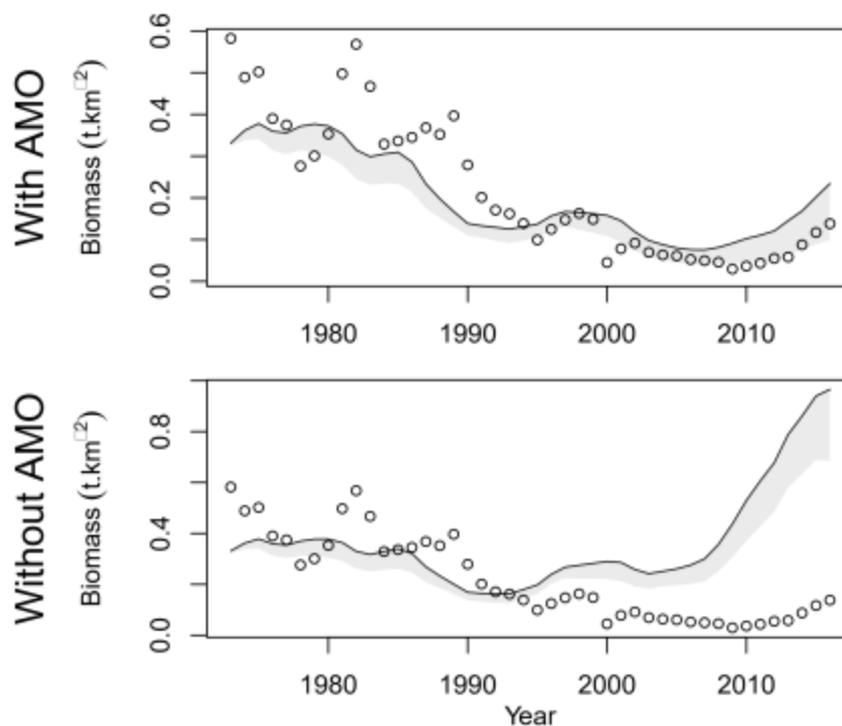


Figure 0.21. Sensitivity analysis of cod biomass simulations in the Irish Sea with PB permeated between 0.82 and 0.1. Black lines indicate initial model simulations (PB = 0.82), grey areas indicate the range of possible projections with a reduced PB, and dots refer to the 2018 stock assessment trend.

- It was noted that the Irish Sea key-run overestimated catches of plaice in the latter half of model simulations. A quick analysis of catch by fleet highlighted that catches were high due to the increasing effort of the *Nephrops* trawl fleet. Plaice in the Irish Sea is predominantly caught by beam, otter, and *Nephrops* trawls. Beam and otter trawl effort has dramatically declined over the last two decades whereas *Nephrops* effort remained

high. The initial distribution of 1973 catches of plaice were distributed amongst these fleets based on catch-by-fleet data from the year 2000, suggesting the initial distribution of catch may have been weighted too high in favour of the *Nephrops* trawl. Initial catches were redistributed using data from 1989 (Casey, 1996), which suggested a larger proportion of the catch should be attributed to the otter trawl fleet. Redistributing initial catches led to a much better model fit for plaice catches (Figure 0.22).

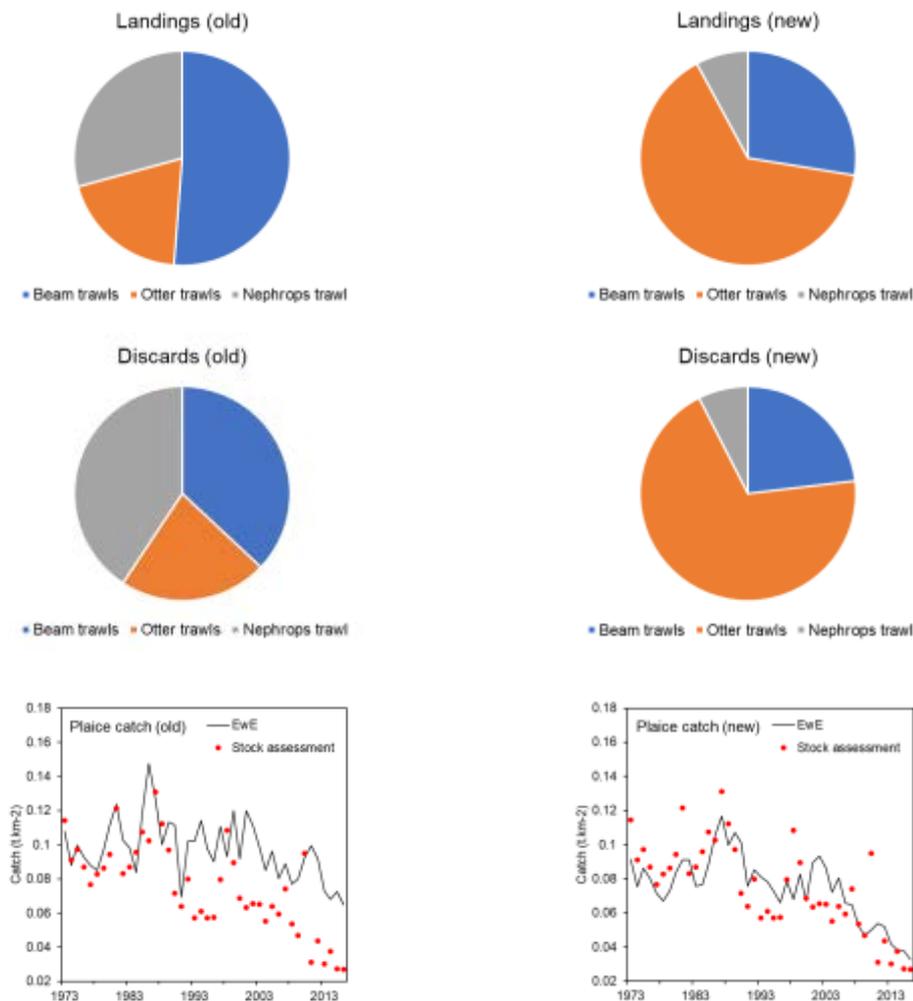


Figure 0.22. Plaice catch simulated by the EwE key-run. Catch fit was improved by correcting the initial distribution of landings and discards between fleets. The plots on the left show the old distributions and simulation, plots on the right show the new distributions and simulation.

The key-run model was refit after adjusting plaice catch distributions. Updated vulnerability parameters are provided in Table 0.13 and Table 0.14. Overall, the general direction vulnerabilities (top-down vs bottom up) and the vulnerabilities adjusted remain very similar to those adjusted by the automated fitting routine prior to plaice catch adjustment.

Table 0.13. Predator vulnerabilities in the key-run pre and post changes made during WGSAM.

Functional group	Vulnerability	
	Pre-WGSAM	Post-WGSAM
Sharks	2.17	2.18
Rays	2.42	2.00
Atlantic cod 2+	>100	>100
Atlantic cod 0-1	>100	>100
Whiting 2+	1.53	1.55
Whiting 0-1	>100	>100
Haddock 2+	2.63	1.48
Haddock 0-1	1.00	1.63
European plaice 2+	1.10	1.00
European plaice 0-1	1.67	3.09
Common sole	4.31	2.76
Flatfish	1.00	-
Monkfish	1.00	1.00
European hake	1.00	1.00
Gurnards	>100	>100
Atlantic herring	1.30	1.29
European sprat	2.54	1.81
Other pelagic fish	1.00	1.00
Nephrops	>100	>100
Shrimp	1.00	1.00
Cephalopods	1.00	1.00
Scallops	16.10	-
Infauna	1.00	-
Gelatinous zooplanton	1.00	-
Large zooplankton	3.63	3.12
Small zooplankton	1.77	4.41

Table 0.14. Predator/prey vulnerabilities in the key-run pre and post changes made during WGSAM.

Predator	Prey	Vulnerability	
		Pre_WGSAM	Post-WGSAM
Sharks	Common sole	-	>100
	Gurnards	-	1.00
Whiting 2+	Atlantic cod 0-1	>100	-
	European hake	1.00	1.00
	Other benthopelagic fish	>100	>100
	Other pelagic fish	1.10	-
	European sprat	>100	1.696
Haddock 2+	Nephrops	2.64	2.335
Common sole	Epifauna	1.59	-
	Infauna	>100	2.853
Flatfish	Epifauna	-	1.00
Atlantic herring	Large zooplankton	1.45	-
European sprat	Large zooplankton	-	>100
	Small zooplankton	1.00	1.00
Large zooplankton	Small zooplankton	1.85	2.50
	Phytoplankton	>100	1.673
	Detritus	>100	-
Small zooplankton	Phytoplankton	2.66	-

The sum of squared deviations of the updated Irish Sea key-run was reduced from 660 to 627 (Table 0.15 and Table 0.16), and the number of vulnerabilities estimated was reduced from 40 (26

predator, 14 predator/prey) to 34 (22 predator, 12 predator/prey). Biomass and catch simulation trajectories and uncertainty bounds remain very similar across all functional groups, however plaice biomass and catch show an increased fit to calibration time-series (Figure 0.23 and Figure 0.24).

Table 0.15. Biomass sum of squared deviations between key-run simulations and calibration time-series pre- and post-WGSAM.

Biomass	Sum of squared deviations	
	Pre-WGSAM	Post-WGSAM
Toothed whales	0.24	0.20
Minke whales	0.64	0.74
Seabirds_hd	0.16	0.23
Seabirds_ld	1.19	1.36
Sharks	1.59	1.32
Rays	1.40	1.52
Atlantic cod 2+	8.14	7.39
Atlantic cod 0-1	15.65	17.61
Whiting 2+	12.64	14.15
Whiting 0-1	9.98	12.42
Haddock 2+	4.63	5.18
Haddock 0-1	14.28	14.21
European plaice 2+	8.31	4.36
European plaice 0-1	5.11	3.78
Common sole	15.17	9.04
Flatfish	0.99	1.02
Monkfish	4.48	4.67
European hake	8.94	8.58
Sandeels	5.19	5.59
Gurnards	0.48	0.63
Other demersal fish	4.42	4.10
Other benthopelagic fish	0.98	0.91
Atlantic herring	3.79	5.20
European sprat	3.26	3.30
Nephrops	0.18	0.15
Gelatinous zoo-plankton	0.89	1.18
Large zooplankton	11.53	8.48
Small zooplankton	2.29	2.13
Phytoplankton	5.11	5.23
Sum	151.65	144.66

Table 0.16. Biomass sum of squared deviations between key-run simulations and calibration time-series pre- and post-WGSAM.

Catch	Sum of squared deviations	
	Pre-WGSAM	Post-WGSAM
Sharks	2.27	2.57
Rays	14.81	13.34
Atlantic cod 2+	18.29	18.86
Atlantic cod 0-1	17.51	18.80
Whiting 2+	9.52	13.92
Whiting 0-1	12.00	12.74
Haddock 2+	60.29	57.68
Haddock 0-1	8.25	8.55
European plaice 2+	8.66	2.71
European plaice 0-1	13.47	13.25
Common sole	16.67	16.82
Flatfish	9.65	6.02
Monkfish	76.35	79.67
European hake	33.44	21.37
Other demersal fish	34.73	19.19
Atlantic herring	15.11	14.42
European sprat	21.70	21.59
Other pelagic fish	54.96	62.65
Lobsters and large crabs	8.32	8.01
Nephrops	1.82	1.56
Cephalopods	53.99	47.25
Epifauna	11.84	12.17
Scallops	4.60	8.87
Sum	508.24	482.01

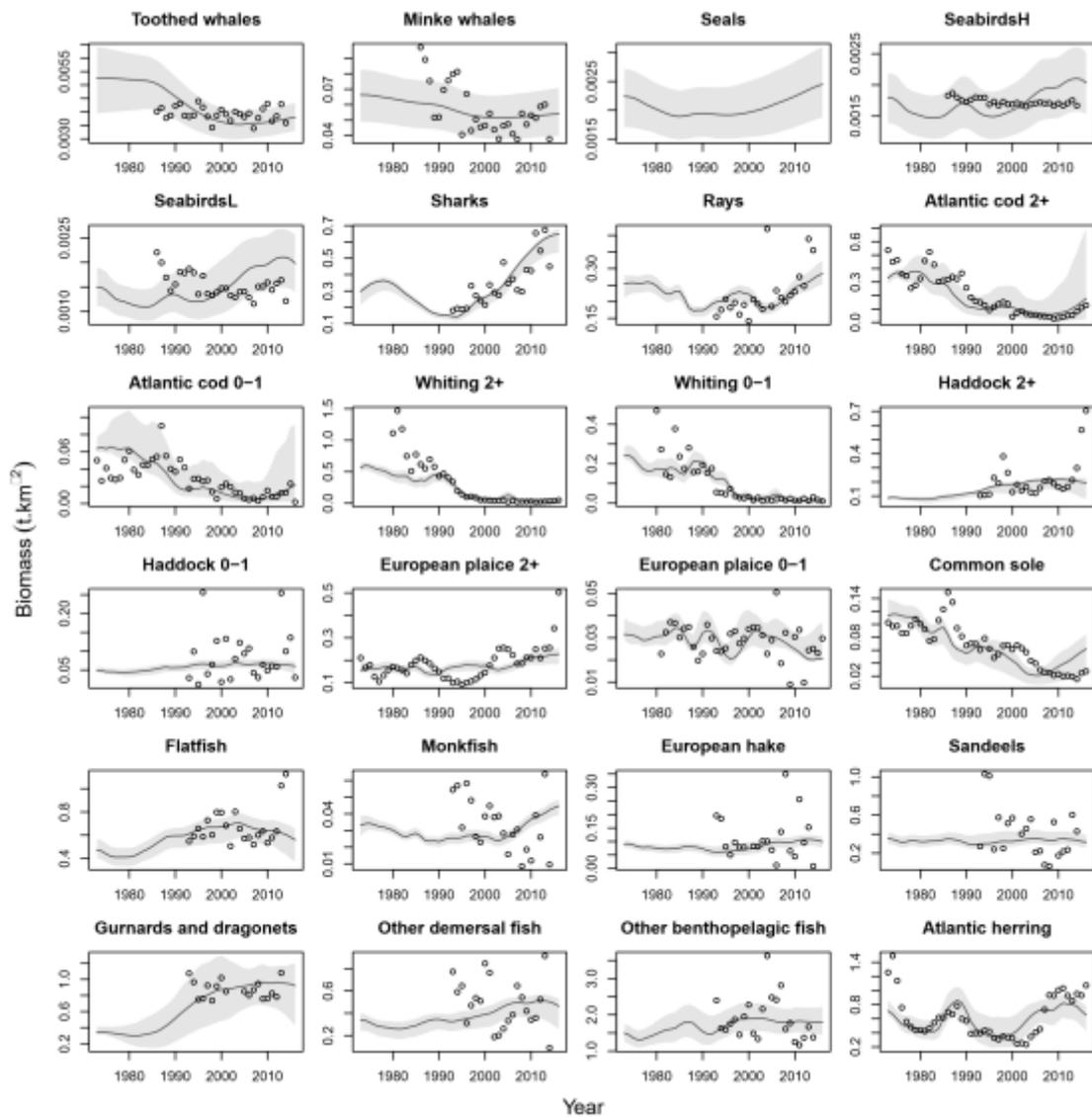


Figure 0.23. Ecosim predicted biomass trends (1/2) post WGSAM for functional groups in the Irish Sea Ecopath with Ecosim model. Black lines indicate model simulations against observed data (points). The shaded area indicates 95% confidence intervals based on Monte Carlo simulations varying Ecopath basic input parameters (B, PB, QB, diet).

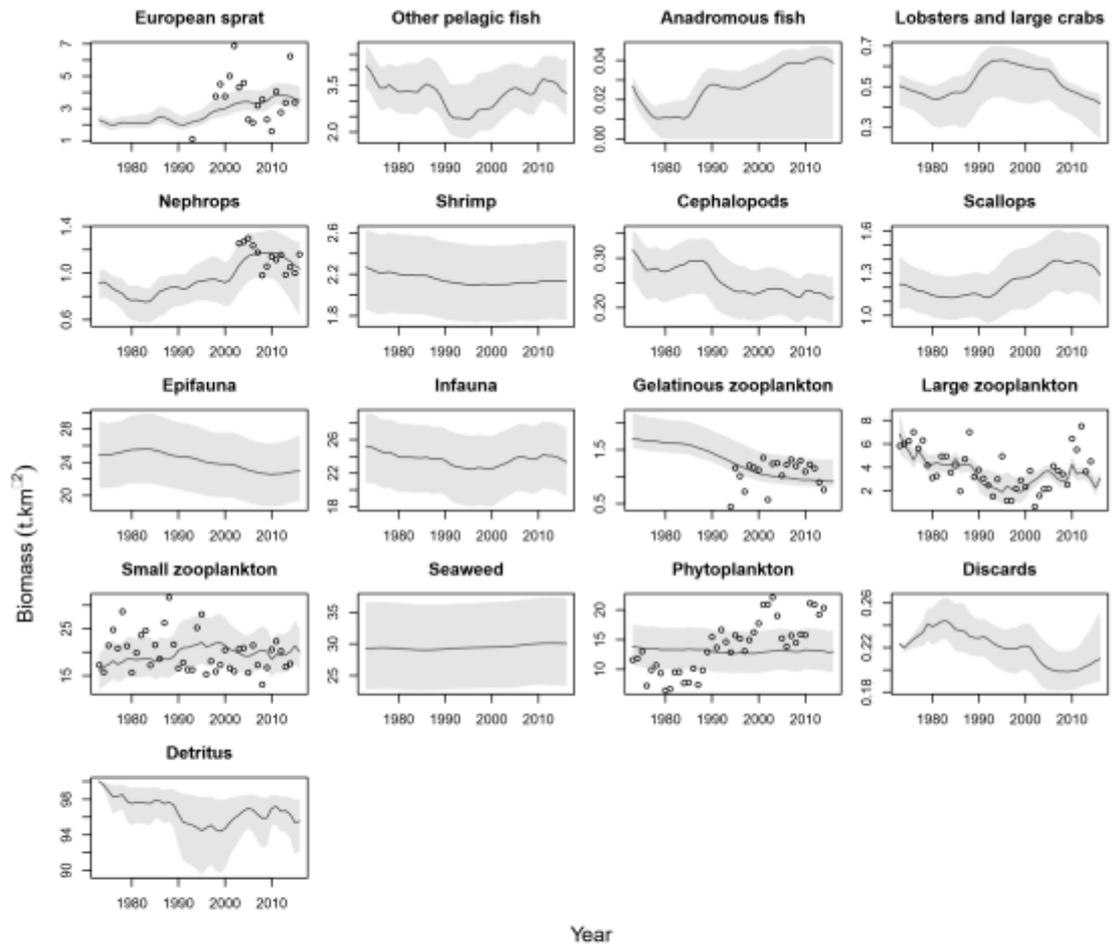


Figure 0.23. Ecosim predicted biomass trends (2/2) post WGSAM for functional groups in the Irish Sea Ecopath with Ecosim model. Black lines indicate model simulations against observed data (points). The shaded area indicates 95% confidence intervals based on Monte Carlo simulations varying Ecopath basic input parameters (B, PB, QB, diet).

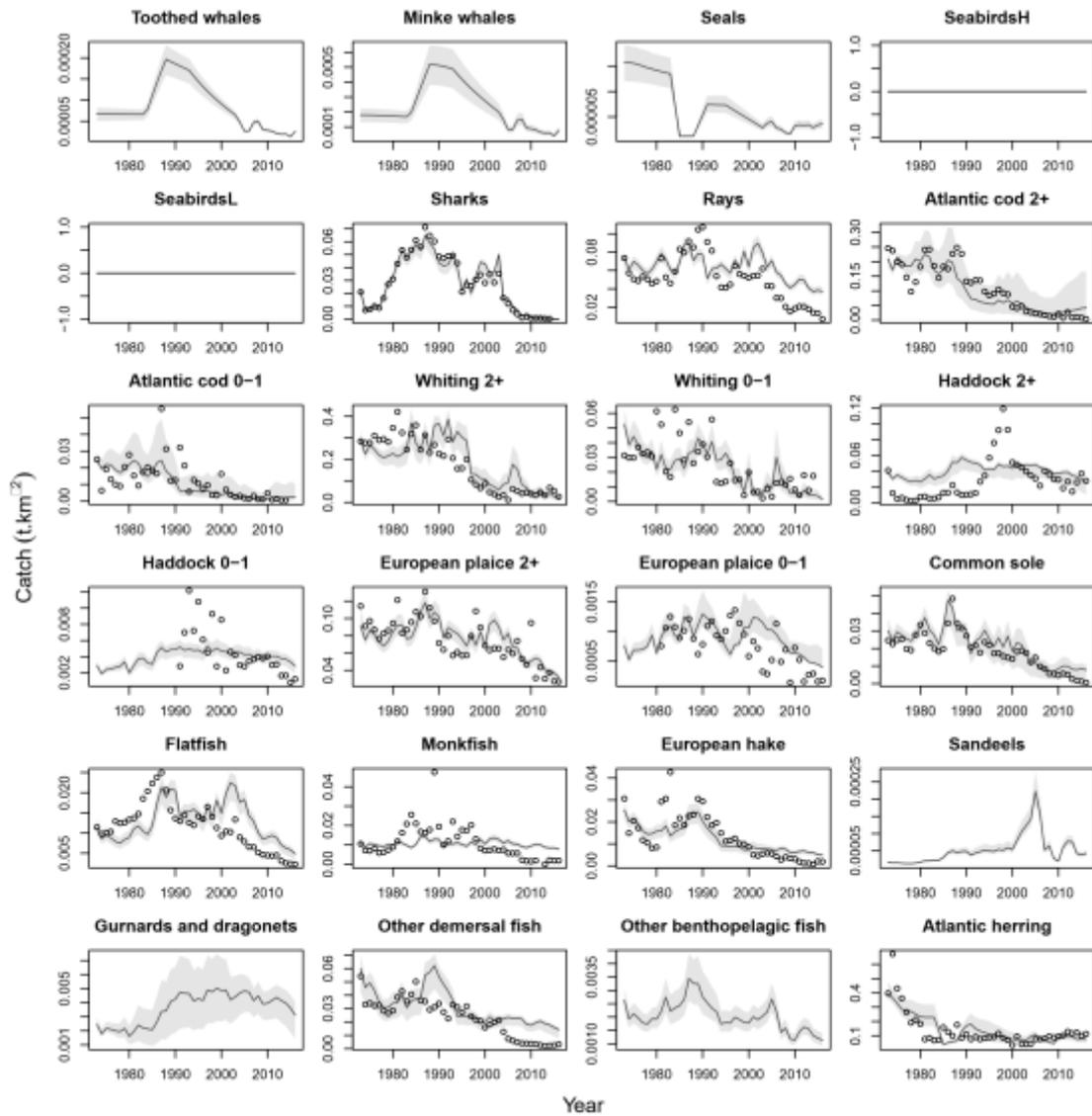


Figure 0.24. Ecosim predicted catch trends (1/2) post WGSAM for functional groups in the Irish Sea Ecopath with Ecosim model. Black lines indicate model simulations against observed data (points). The shaded area indicates 95% confidence intervals based on Monte Carlo simulations varying Ecopath basic input parameters (B, PB, QB, diet).

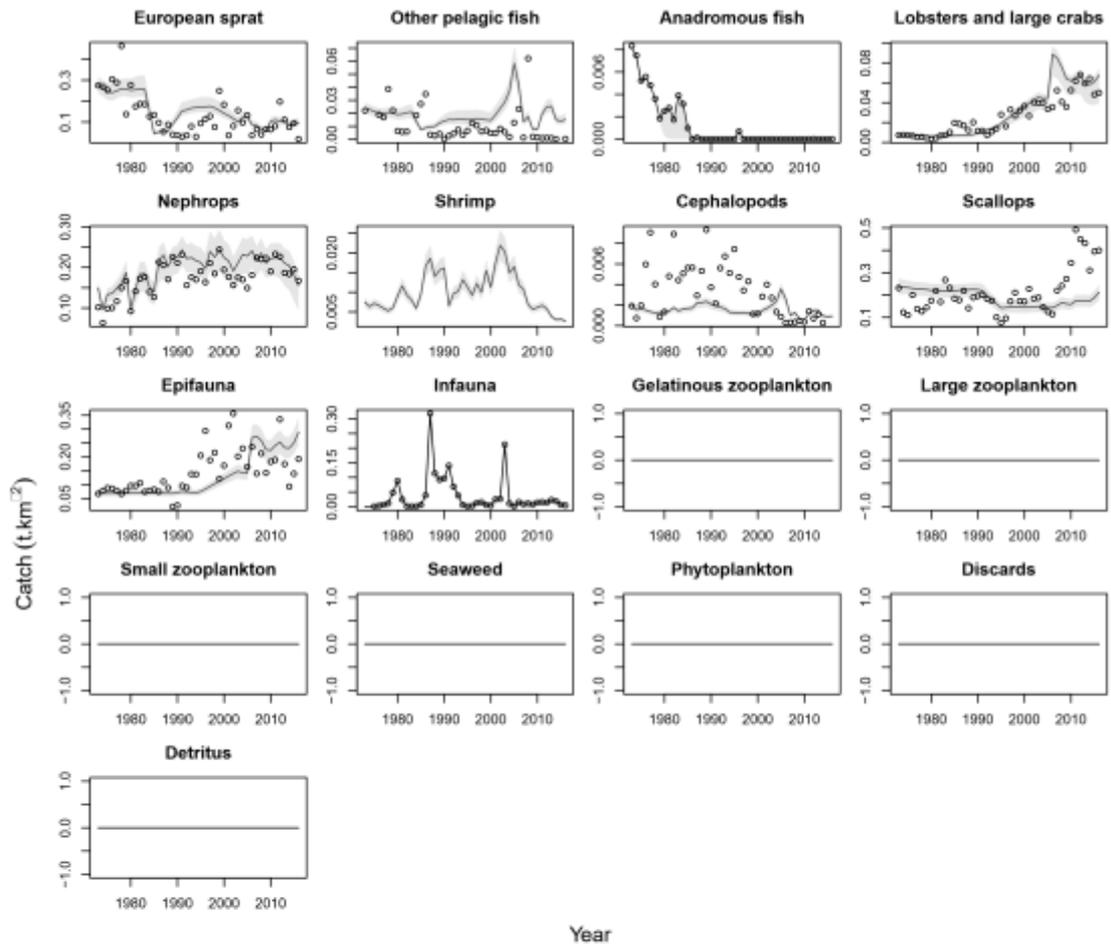


Figure 0.24. Ecosim predicted catch trends (2/2) post WGSAM for functional groups in the Irish Sea Ecopath with Ecosim model. Black lines indicate model simulations against observed data (points). The shaded area indicates 95% confidence intervals based on Monte Carlo simulations varying Ecopath basic input parameters (B, PB, QB, diet).

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Annex 4: Stock Annex for the ICES Eastern Baltic Sea SMS configuration

Working Group: Working Group on Multispecies Assessment Methods (WGSAM)

Date: November 2019 (after the WGSAM 2019 meeting)

Predatory species: Cod (given as input population size)

Prey species: Assessed species: Herring, Sprat

Stock Assessor: Morten Vinther

Summary

SMS (Lewy and Vinther, 2004) is a stock assessment model including biological interaction estimated from a parameterised size-dependent food selection function. The model is formulated and fitted to observations of total catches, survey cpue and stomach contents for the Eastern Baltic Sea (ICES Sub-divisions 25-32, excluding the Gulf of Riga). Parameters are estimated by maximum likelihood and the variance/covariance matrix is obtained from the Hessian matrix.

In the present SMS analysis, cod is a predator, and herring and sprat are preys. The population dynamics of cod were estimated outside the model, such that the population number and size distribution is assumed known without errors. For this reason and in contrast to earlier key runs for the Eastern Baltic Sea, this key run does not include predation mortality estimates on cod due to cannibalism.

Substantial changes of input data to the 2019 keyrun have been made since the last keyrun in 2012. However, the new estimated predation mortalities (M2) are consistent with the M2 values from the previous key run.

2019 key run

A key run for the Eastern Baltic Sea SMS model, including data for the period 1974–2018 was produced at the 2019 WGSAM. This key run replaces the key 2012 key run. The new key run includes revision and updates to the input data. A major modification is that cod is treated as external predator and the use of newly available data on cod stomach contents sampled mainly by the Latvian Institute.

SMS was updated with the most recent data from WGBFAS 2019, i.e. data for Herring in subdivisions 25–29 and 32, excluding the Gulf of Riga (central Baltic Sea) and for Sprat in subdivisions 22–32.

Due to age reading problems for cod in the eastern Baltic, ICES now applies an age-length based analytical assessment with the Stock Synthesis model (SS3). Natural mortality of cod is estimated within the SS3 model. Without input data by ages data, and with estimated high and time variable natural mortality SMS is no longer able to estimate cod stock numbers and predation mortality estimates on cod due to cannibalism. Instead, cod is now considered as an “other predator” where stock number and size distribution are assumed to be known without errors. Population numbers and size distributions were extracted from the SS3 output.

Consumption (food ration) of cod was revised to reflect the most recent knowledge of evacuation rates and temporal trends in cod consumption rates.

Diet data for cod were substantially extended by including the stomach content data from the EU Stomach Tender. This addition of data did not change predation rates on herring and sprat substantially, but increased the weight of the stomach data in the model likelihood, indicating a higher quality of stomach data compared to the previously used data.

1. Model description

The SMS model (Lewy and Vinther, 2004) is a stock assessment model including biological interaction estimated from a parameterised size-dependent food selection function. The model is formulated and fitted to observations of total catches, survey cpue and stomach contents for the main stocks in the North Sea. Parameters are estimated by maximum likelihood and the variance/covariance matrix is obtained from the Hessian matrix.

The following predator and prey stocks are available:

External predator: cod;

Prey: herring and sprat

The population dynamics of herring and sprat are estimated within the model.

A detailed description of the model can be found in Appendix 1.

2. Input data

The description of input data is divided into four main sections:

Analytical assessment stocks: Stocks for which analytical age-based assessments are done by ICES or can be done from data available from ICES. Data input are similar to those applied by ICES “single-species” assessments used for TAC advice, with some additional data.

External predator stocks: Stocks for which stock numbers are assumed known and given as input to SMS.

Diet and ration data: Diet data and food ration data for all predators (analytical stocks and external predators) derived from observed stomach contents data.

Additional data: Miscellaneous data.

2.1. Analytical assessment stocks

This group of stocks includes:

Herring;

Sprat;

“Single-species” input data, by default given by quarterly time steps, include

Catch-at-age in numbers (SMS input file `canum.in`);

Proportion of the catch-at-age landed, assumed 100% (file `proportion_landed.in`);

Mean weight-at-age in the catch (file `weca.in`);

Mean weight-at-age in the stock (file `west.in`);

Proportion mature-at-age (file `propmat.in`);

Proportion of M and F before spawning (file `proportion_M_and_F_before_spawning.in`);

M, single-species natural mortality-at-age (file `natmor.in`);

Survey catch-at-age and effort (file `fleet_catch.in`).

SMS uses quarterly time steps, so input catch data should preferably also be given by quarter. The ICES assessments for herring and sprat are however done using annual time steps (see table below).

Table 2.1.1. Overview of “dynamic” stocks used in SMS and their basis from ICES single-species advice.

SPECIES	SMS		ICES ASSESSMENT			
	Species code	Max age	Stock area	First year	Age range (data)	time step
Herring	HER	8+	SD 25–29 and 32, excluding the Gulf of Riga (central Baltic Sea)	1947	1–8+	Year
Sprat	SPR	7+	SD 22-32	1974	1–8+	Year

Discarding is considered to be negligible for both stocks.

Quarterly catch-at-age number for herring (2002-2018) and sprat (1998-2018) were provided by ICES WGBFAS.

Herring

Catch data

ICES WGBFAS provided quarterly catch-at-age number and mean weights for herring for the period 2002-2018. The full data series are not presented in the WGBFAS report, but were kindly made available by Tomas Gröhsler. Older quarterly catch at age data were copied from the 2012 SMS key run.

Mean weight at age

WGBFAS assumes that mean weight at age in the sea is the same as mean weight at age in the catch. This assumption is fairly unbiased for older fish even though fisheries may be concentrated in areas (southern part of the EB) with the largest individuals. Mean weight at age in the catch for the youngest fish is higher than the mean weight in the sea as these size classes are not fully selected in the fishery. The mean weight at age as used by WGBFAS (Figure 6.1-1) shows a clear temporal trend with a decreasing mean weight in the period 1974-2000 followed by a modest increase.

The quarterly mean weight at age data from WGBFAS (2002-2018) combined with the 2012 key run data for the period 1974-2001 are presented in Figure 6.1-2 for the youngest ages 0 and 1. It is clearly seen that the mean weights for age 1 in quarter 2 do poorly link to quarter 1 and not at all to quarter 3.

It is assumed that the mean weight in the sea are the same as the observed mean weight in the catch. However, when calculation the mean weight at age in the sea, the observed mean weight at age in the catch for age 1 in quarter 2 was discarded and substituted by the mean of the observed mean weight at age in quarter 1 and 3 (Figure 6.1-3). As the observed mean weights for the ages 0-1 are highly variable, the smoothed values, ages 0 and 1, were finally used as mean weight in the sea.

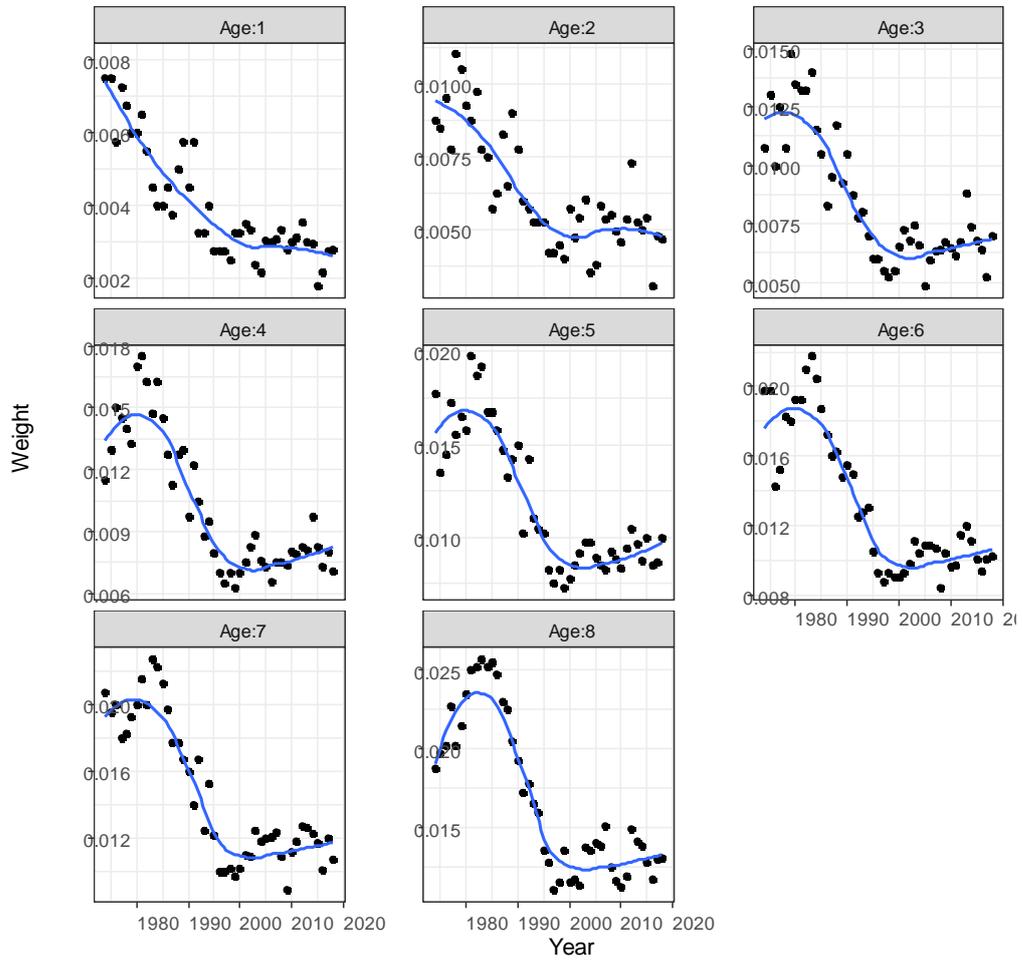


Figure 6.1-25. Herring mean weight at age in the catch (and in the sea) as used by WGBFAS. Dots show data points and the blue line is a loess smoother.

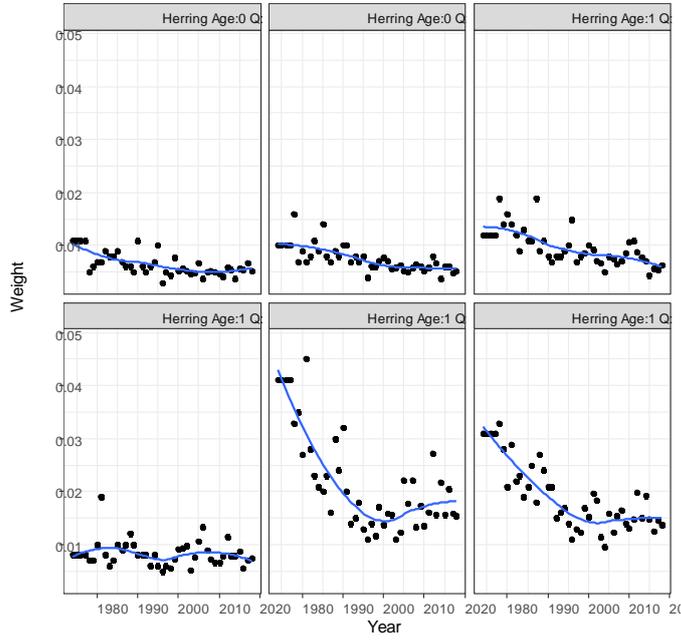


Figure 6.1-26. Quarterly herring mean weight at ages 0 and 1 in the catch as available for SMS. Dots show data points and the blue line is a loess smoother.

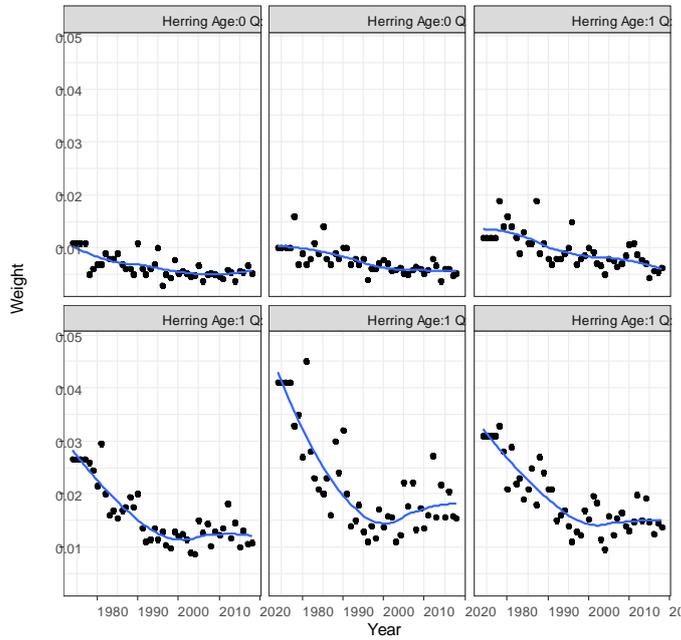


Figure 6.1-27. Quarterly herring mean weight at ages 0 and 1 in the sea as used for SMS. Dots show data points and the blue line is a loess smoother.

Other biological data

Proportion mature and M(used for “single species” SMS) at age data are copied from single-species data. WGSAM 2019 decided to use M1 at 0.025 per quarter for all ages. The 2012 key-run applied 0.05, but for consistency with herring in the North Sea this was changed to 0.025.

Survey data

Survey data are copied from the previous key run and the ICES single-species assessment.

SMS name	Years	Ages	alfa and beta	Source
Herring_Acoustic_May	1982-1996	1-8	0.2-0.7 (Q2)	2012 key run
Herring_BIAS	1998-2018	1-7	0.0-0.3 (Q3)	WGBFAS ,2019

Sprat

Catch data

Quarterly catch-at-age number and mean weights for sprat, 1998-2018, were provided by ICES WGBFAS. The full data series are not presented in the WGBFAS report, but were kindly made available by Tomas Gröhslér. Older quarterly catch at age data were copied from the 2012 SMS key run.

Mean weight at age

WGBFAS assumes that mean weight at age in the sea is the same as mean weight at age in the catch. This assumption is probably unbiased for older fish even though fisheries may be concentrated in areas (south-western part of the EB) with the largest individuals. Mean weight at age in the catch for the youngest fish is probably higher than the mean weight in the sea as these size classes are not fully selected in the fishery. The mean weights at age as used by WGBFAS (Figure 6.1-4) show a clear temporal trend with a peak in mean weight around 1987 followed by a decrease until around 2003.

The quarterly mean weight at age in the catch from WGBFAS (1998-2018) combined with the 2012 key run data for the period 1974-1978 are presented in Figure 6.1-5 for the youngest ages 0 and 1. It is clearly seen that the mean weights for age 0 and age 1 in quarter 1 and 2 are highly variable from one year to the next. The same can be said about age 1 in quarter 3 and 4, but these quarters follow better the overall trend presented for the WGBFAS data (Figure 6.1-4). Due to the high (observation) variation in catch mean weights for ages 0-1, the smoothed values were used as mean weight at age in the sea (Figure 6.1-5).

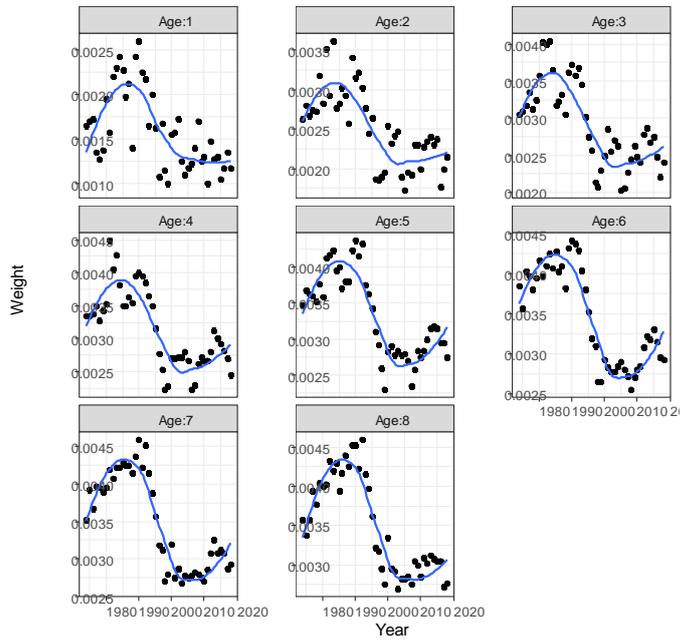


Figure 6.1-28. Sprat mean weight at age in the catch (and in the sea) as used by WGBFAS. Dots show data points and the blue line is a loess smoother.

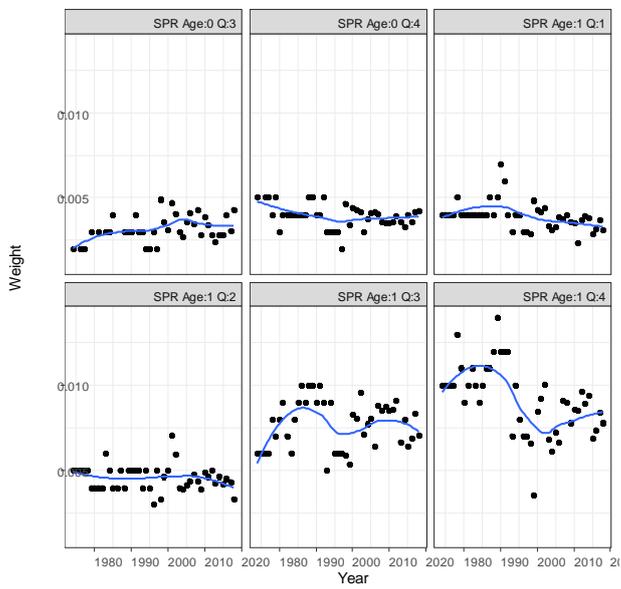


Figure 6.1-29. Quarterly sprat mean weight at ages 0 and 1 in the catch as available for SMS. Dots show data points and the blue line is a loess smoother.

Survey data

Survey data are copied from the single-species assessment (survey 1–3).

	NAME	YEARS	AGES	ALFA AND BETA	SOURCE
1	Int acoustic in Oct.	1991-2018	1-7	0.0–0.1 (Q3)	WGBFAS 2019
2	Int_acoustic_in_May	2001–2018	1–7	0.25–0.50 (Q2)	WGBFAS 2019
3	LAT_RUS_acoustic	2001-2018	1-1	0.0-0.0 (Q1)	WGBFAS 2019

Biological data

Proportion mature and M at age data are copied from single-species data. M1 is assumed to be 0.05 per quarter for all ages.

2.2. External predators

Cod was for the first time in the Baltic SMS treated as an “external predator”. This means that the stock numbers are given by input, extracted from the ICES Stock-Synthesis 3 (SS3) assessment for the stock, using the R-package “r4ss: R code for Stock Synthesis”. The ICES assessment provide cod stock numbers and mean weight by a 2-cm length classes for the main length classes. These data were aggregated into length classes used by SMS (see Table 6.4-2).

The ICES SS3 assessment output is quite different from the previous age-based assessment and from the 2012 key-run (Figure 6.2-1). The SS3 assessment estimates much higher stock numbers for age 1-3 compared to the SMS estimate, and much higher stock numbers for oldest cod when the stock size peaked. SS3 and SMS use different mean weight at age, so the difference in biomass, quarter 1, (Figure 6.2-2) becomes smaller than when stock numbers were compared. Total biomass and biomass of the larger cod are estimated considerable higher in the SS3 assessment (Figure 6.2-3) such that the amount food eaten and predation mortality becomes higher when the cod estimate from SS3 is used.

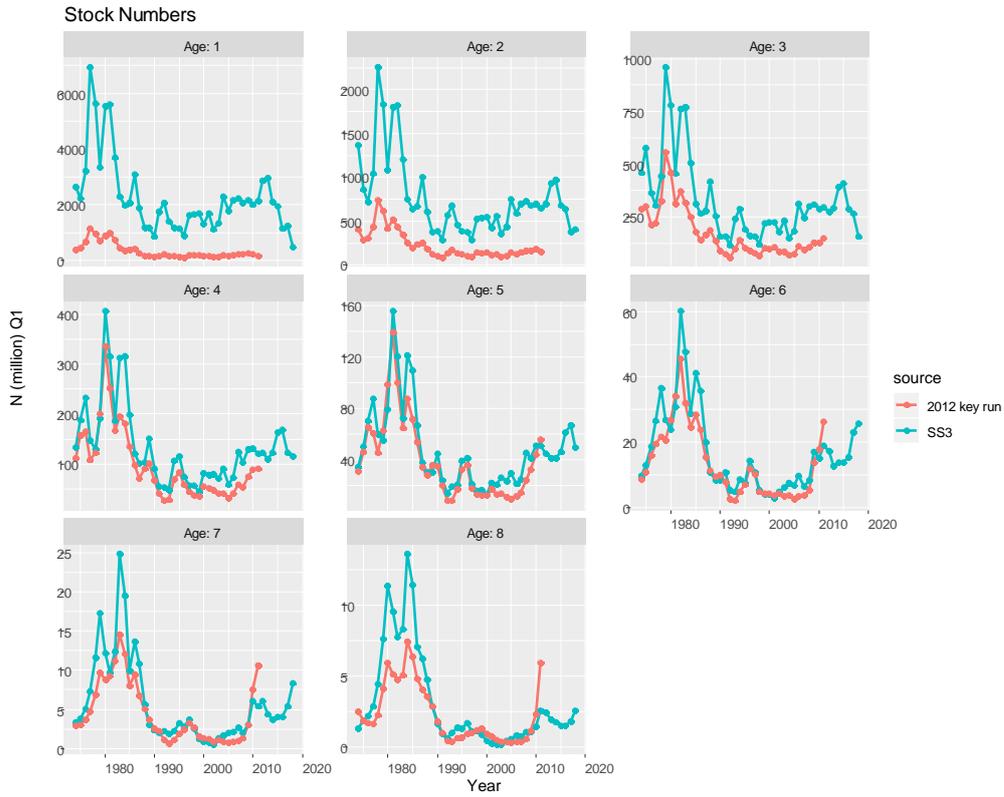


Figure 6.2-30. Comparison of stock numbers at age of cod estimated by the 2012 key-run and by the ICES SS3 assessment.

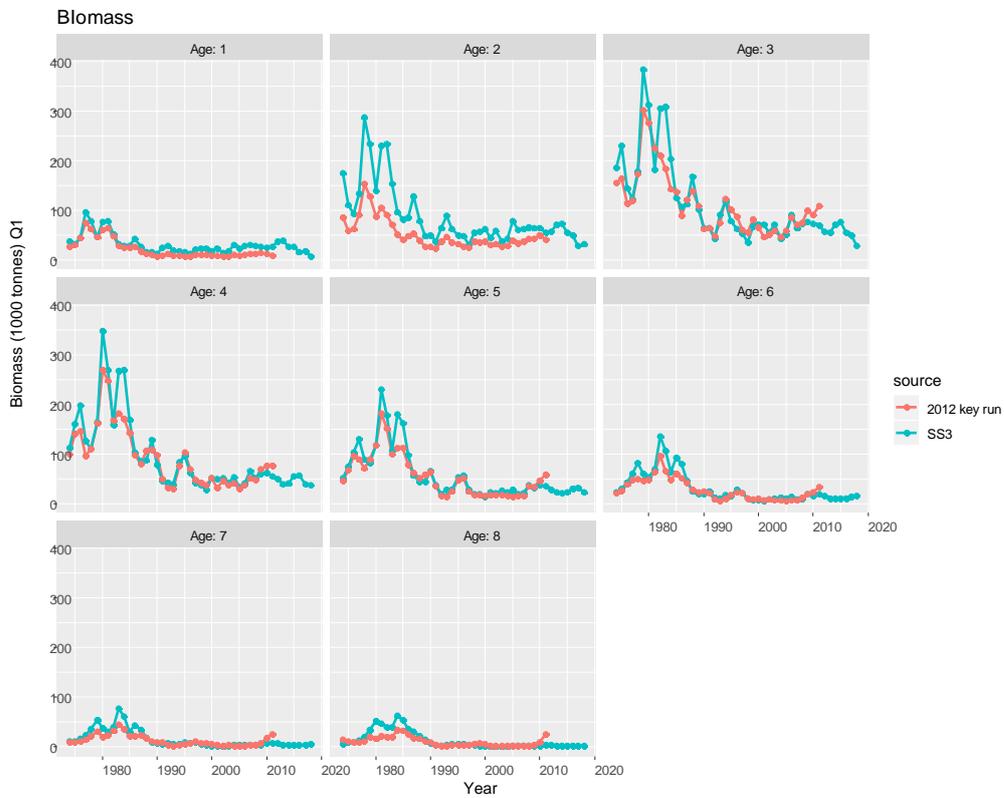


Figure 6.2-31. Comparison of biomass at age of cod estimated by the 2012 key-run and by the ICES SS3 assessment.

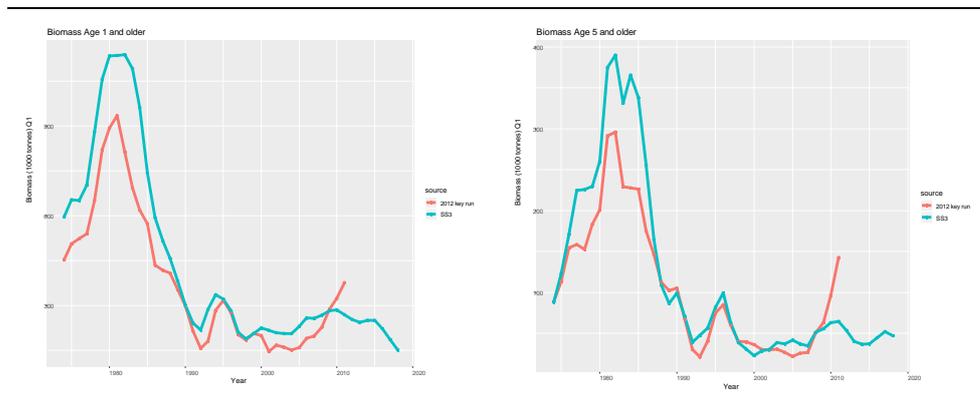


Figure 6.2-32. Comparison of cod biomass for age 1 and older (left panel) and of age 5 and older (right panel) estimated by the 2012 key-run and by the ICES SS3 assessment.

2.3. Diet and ration data

Fish stomach data

Two major cod stomach contents dataset are available:

- “Old”: International sampled stomach content data, 1977-1992, Individual stomachs were pooled by cod size class before analysis. The recorded sizes of both predator and are given by wide size classes, e.g. sprat by the size classes 5-10-15 cm, for the oldest data in the time-series.
- “New”: Individually compiled stomach sampled by mainly Latvia in the period (1963) 1974-2014. Predator and prey sizes are by cm or mm.

“Old” pooled stomach data

An international database of Baltic cod stomach contents contains data from 62 427 cod collected during 1977–1994. The collation of national stomach content data sets into one set for multi-species assessment has mainly been done by DIFRES (now DTU Aqua) and the result published in ICES papers (e.g. ICES 1991/J:30; ICES 1989/J:2; ICES 1990/Assess:25 and ICES 1993/J:11). Stomach content data from 1977-1992 were recompiled during WGSAM 2012 for use in SMS. The stomach contents data are available at “exchange format” from ICES (www.ices.dk).

Compilation of stomach contents data

The “old” data stomach contents data are recorded by year, quarter, predator, predator length, prey and prey length. The compilation of the individual stomach samples from a trawl haul into average diet of the Eastern Baltic Sea follows the technique given by ICES, 1993 and is briefly described below. Most stomachs were pooled within a haul and predator size class before analysis, such that diet data from individual fish are scarce. For part of the time-series, data are only provided (pooled) by country and sub-division.

For each stomach pool, data include the information on the number of a) empty stomachs; b) stomach with skeleton remains only; c) stomach with food and d) stomach with food, but regurgitated. In most cases, stomachs within a haul are pooled at the time of sampling for each predator size class. Only stomach contents from the feeding, non-regurgitated stomachs were recorded and later bulked to save time. In the calculation of the average stomach content, it was assumed that the regurgitated stomachs had similar stomach content as the (valid) feeding fish.

First the average stomach content of the individual prey and prey size classes is calculated by ICES sub-division as a simple mean. Partly digested prey items are in some cases not fully identified to species level or size class. In such cases a species or size redistribution of unidentified items was made accordingly to the fully identified diet.

For a given predator the average Eastern Baltic Sea stomach contents by quarter were finally calculated as a mean of the average stomach contents by sub-division.

“New” individually sampled stomach data

More than one hundred thousand stomachs of cod in the Eastern Baltic Sea have been sampled by trawling between 1963 and 2014, by mainly the Latvian institute (Figure 6.3-1). Sampling covered the distributional area of the Eastern Baltic cod population (Bagge, 1994) except in the period 1995 to 2004, where sampling was limited to the north-eastern part. Stomach contents are provided by individual fish. Prey items in the stomachs were recorded at the highest possible taxonomic resolution with total mass, and, where identifiable, number of individuals and lengths per prey taxon. Prey sizes are given by mm or cm. Predator length was also recorded and in later years also predator weight (Huwer *et al.*, 2014;). The stomach data are available at ICES (www.ices.dk).

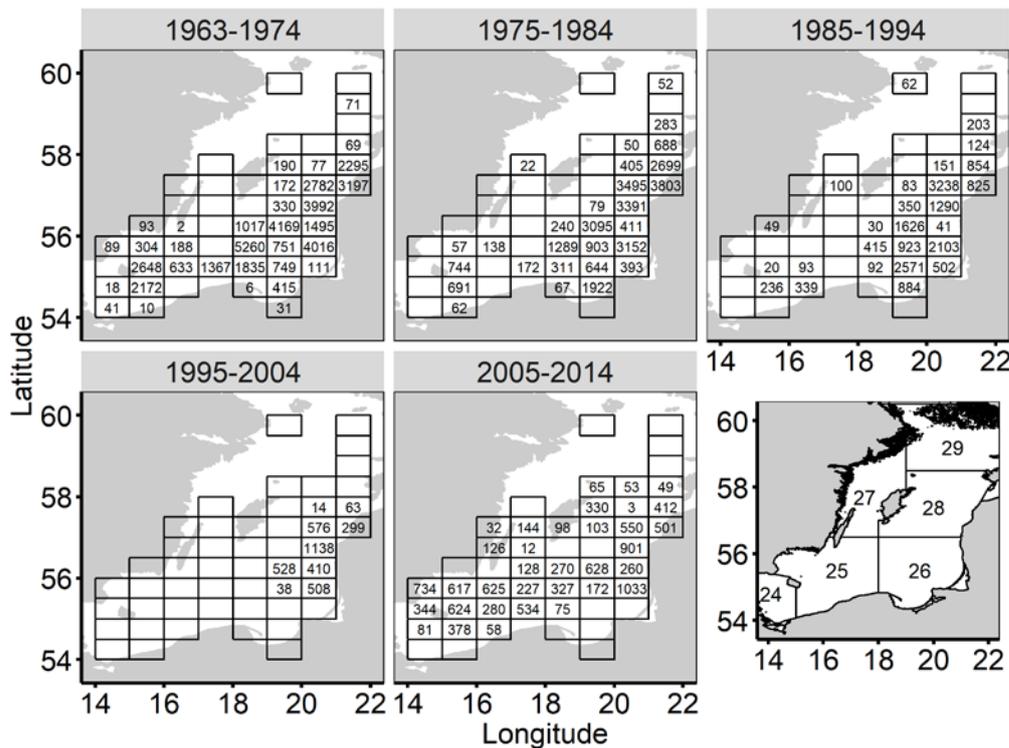


Figure 6.3-33. ICES sub-divisions (bottom right panel) and stomach sampling coverage: number of *Gadus morhua* stomachs by ICES statistical rectangle for each period specified on top of each panel.

Compilation of stomach contents data

The weight of stomach contents are given by prey species, aggregating over all recorded sizes and digestion stages. To assign weight to each prey item, a length weight relation was first made for each prey species and digestion stage, based on stomach data from predators with only one prey item of a given species. Secondly, these length weight relations were used to assign a weight to each prey with size information. The sum of these weights cannot exceed the total recorded prey weight for the individual stomach. If the sum exceeded the total prey weight (of both sizes

and un-sized preys), the mean weight of the sized preys were downscaled and prey items with no size information was removed. If the sum was smaller than the recorded total weight, and the stomach included preys without size information, the difference in weight was assigned to the prey with no size information.

Having done that estimation of weight by recorded prey species and size, the compilation of stomach contents data follows the process outlined above for the “old” stomachs,

Estimation of food ration from stomach contents data

Average daily energy consumption rates C (kJ d⁻¹) were estimated using the cylinder gastric evacuation rate model (Andersen and Beyer, 2005a, b) by year and 1-cm predator length group for cod between 20 and 80 cm total length, amounting to 109 000 stomachs in this size range from the stomach database. Ambient temperature T was assumed constant at 5°C, corresponding roughly to the average temperature experienced by cod in the Baltic Sea (Righton *et al.*, 2010). Although cod experience varying temperature throughout the year, only significant trends in average temperature regime for the cod in their preferred habitat might potentially bias our analyses. Such trends have not been shown for the Baltic Sea. We assumed constant energy densities E_i for benthic prey (3.5 kJ g⁻¹) and consumed fishes (*Clupea harengus* L. (herring) and sprat 5.5 kJ g⁻¹, cod 4.0 kJ g⁻¹; Pedersen and Hislop, 2001). E denotes the average energy densities (kJ g⁻¹) of the individually observed total stomach contents S (g). Using the principle that consumption rate C (kJ d⁻¹) on average over population and time equals evacuation rate (Pennington, 1985), and knowing cod total length L (cm) and the basic evacuation rate parameter $\rho_0 = 2.43 \times 10^{-3}$, we used the parametrization of the cylinder model for cod presented in Andersen (2012):

$$C = 24 \rho_0 L^{1.30} e^{0.083T} E^{0.15} \sqrt{S} \tag{1}$$

In order to consider recent changes in cod consumption rate, the relationship between average quarterly consumption rate and total length (a priori parametrized as $C=aL^b$ with C the average quarterly consumption rate and L total length) was estimated separately for three different periods.

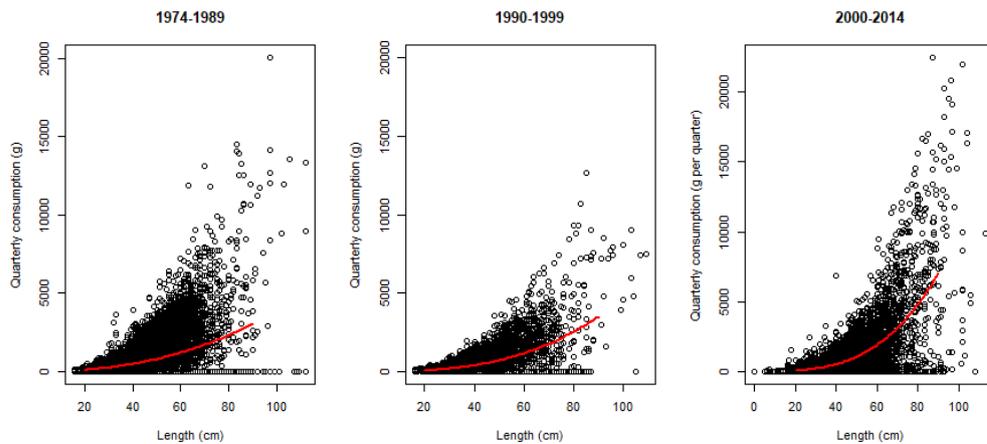


Figure 6.3-34. Scatterplots of cod total length and estimated quarterly consumption rate. The consumption rate has been estimated separately for 1974-1989, 1990-1999 and 2000-2014 in order to account for recent changes in cod consumption (Neuenfeldt *et al.*, in press.

Table 6.3-17. Parameter estimates for the consumption rate model, $C = aL^b$.

PERIOD	PARAMETER	ESTIMATE	STD. ERROR
1974-1989	<i>a</i>	0.10367	0.01184
	<i>b</i>	2.28617	0.02834
1990-1999	<i>a</i>	0.017408	0.003971
	<i>b</i>	2.713702	0.054565
2000-2014	<i>a</i>	0.003230	0.000354
	<i>b</i>	3.243353	0.025560

The stomach data do not include 2015-2018. For this reason, the 2000-2014 estimates were applied for 2015-2018, too.

Subsequently, average quarterly consumption was multiplied by 4 to give average yearly consumption and then distributed over quarters according to the key given in Table 6.3-1.

Table 6.3-18. Distribution of annual consumption rate power the different quarters of the year for different periods and size groups. The key was generated using all years (to account for only few data in the 3rd quarter). l.start and l.stop account for spawners and non-spawners.

year.start	year.stop	l.start	l.stop	q1_prop	q2_prop	q3_prop	q4_prop
1974	1989	15	30	0.27	0.23	0.25	0.25
1974	1989	31	120	0.22	0.16	0.30	0.32
1990	1999	15	30	0.24	0.22	0.27	0.27
1990	1999	31	120	0.21	0.19	0.31	0.29
2000	2019	15	30	0.30	0.16	0.16	0.38
2000	2019	31	120	0.38	0.19	0.11	0.32

Estimation of diet from stomach contents

Due to time limitations, diet of fish species was estimated with the assumption that the observed stomach contents give an unbiased estimate of the diet. This is in contrast to the estimation of food ration as outlined above.

2.4. Age length keys

Age length keys (ALK) are used by SMS to transform stock number at age into stock numbers at length used in the calculation of predation mortality. Length at age is derived from weight at age in the sea using a length-weight relation. The length distribution for each age is derived from the coefficient of variation (CV) of the mean length at age as estimated from age and length observation from the BITS survey, quarter 1 and 4, 2000-2018. A year and quarter independent CV of mean length at age was derived from the estimated values by quarter (Table 6.4-1). These CV's (row "Used" in Table 6.4-1) are afterwards used to produce a length distribution around the mean length for a given age in a given year and quarter, assuming a normal distributed length distribution for each age.

Table 6.4-19. Coefficient of variation of mean length at age derived from survey data

Species	Quarter			Age							
		0	1	2	3	4	5	6	7	8	
Clupea harengus	1	NA	0.14	0.09	0.11	0.13	0.13	0.13	0.13	0.12	
	4	0.12	0.10	0.14	0.16	0.16	0.15	0.13	0.13	0.11	
	Used	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	
Gadus morhua	1	NA	0.32	0.24	0.21	0.18	0.17	0.17	0.16	0.19	
	4	0.34	0.25	0.22	0.18	0.18	0.17	0.18	0.18	0.18	
	Used	0.34	0.25	0.23	0.20	0.18	0.18	0.18	0.18	0.18	
Sprattus sprattus	1	NA	0.12	0.08	0.09	0.08	0.08	0.07	0.08	0.08	
	4	0.10	0.08	0.08	0.08	0.07	0.07	0.06	0.07	0.07	
	Used	0.10	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	

The total number of fish by length classes (Table 6.4-2) are finally calculated as the sum of contributions from each ages. The chosen length classes depends on the length classes used in the stomach data. The “new”, individual sampled stomach data (see section 6.3) have used length classes by cm and mm, however boarder length classes were used due to the low number of stomachs sampled in the individual year and quarter combinations.

The “old” pooled stomach data (see section 6.3) used larger size classes, e.g. 5-10-15 cm for sprat, in the first years of sampling. This mean that the applied length classes used in the SMS configuration depends on the actual used stomach data sets used. As an example, the length classes get wider than outlined in Table 6.4-2, when both the “old” and “new” stomach data are used. When both the “old” and “new” stomach data are used, length classes are defined for each individual year, reflecting the widest length class in the particular year.

Table 6.4-20. Default length classes used for stomach data and ALK.

SPECIES	LOWER LENGTH (MM)	SPECIES	LOWER LENGTH (MM)	SPECIES	LOWER LENGTH (MM)
Gadus morhua	50	Clupea harengus	50	Sprattus sprattus	50
	100		70		60
	150		85		70
	200		100		80
	250		120		90
	300		140		100
	350		160		110
	400		180		120
	500		200		130
	600		220		140
	700		240		
			260		

2.5. Predator–prey overlap

The stock area for predator cod (SD 24-32 + part of SD 23) does not completely overlap with the stock areas for herring (SD 25–29 and 32, excluding the Gulf of Riga) and sprat (SD 22-32). SMS gives the possibility to use input values for stock overlap, however for this key-run it is assumed that there is the discrepancies in stock distribution can be ignored.

Predator–prey species overlap is a quarter dependent parameter used in the calculation of food suitability (see equation 8 in Appendix 1). By default the spatial overlap is set to one, but it is also estimated within SMS for a few combinations, where the “quarter effect” was estimated significantly different from 1.0.

2.6. Length–weight relations

Conversion from length into weight is used for some SMS configurations. The used parameters values are shown below.

Table 6.6-21. Length (mm) weight (kg) relation for herring and sprat ($W=a \cdot l^b$)

SPECIES	A	B
Herring	2.997653e-09	3.136964
Sprat	3.670895e-09	3.107974

The l-w relations were estimated from BITS Q1 & Q4 data, 2000-2018 (minus 2004 data with errors). There is a statistical significant quarter effect in condition (parameter a), however this is ignored for used in SMS, until data for Quarter 2 and 3 data become available.

References

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3. Model configuration

The configuration of the SMS model aims firstly to mimic the results from ICES single-species assessment models when SMS is run in single-species mode (no estimation of predation mortality) using the same annual M values as the single-species assessment, and secondly to configure options for estimation of predation mortality.

Appendix 3 presents the SMS configuration (option files) used for the 2019 key run.

3.1. Fishing mortality

SMS uses a separable F model while the ICES single-species assessments use XSA for herring and sprat. XSA estimate F directly from catch observation in a VPA. Further differences; SMS is using quarterly time steps while XSA is using annual time steps.

A comparison of output from the two assessments shows quite similar results for herring (Figure 7.1-1). Due to the separable F model used in SMS, F is smoother between years than in XSA, where the catch observation at age are translated directly into F. The comparison for sprat (Figure 7.1-2) show that F and SSB have the same trend, but the levels are different. SSB is estimated the 1st January in SMS but at spawning time in the ICES assessment (the proportion of M and F before spawning is set to 40%) which may explain the two levels of SSB estimated. F is however more comparable between models, but there SMS estimates consistently a lower F.

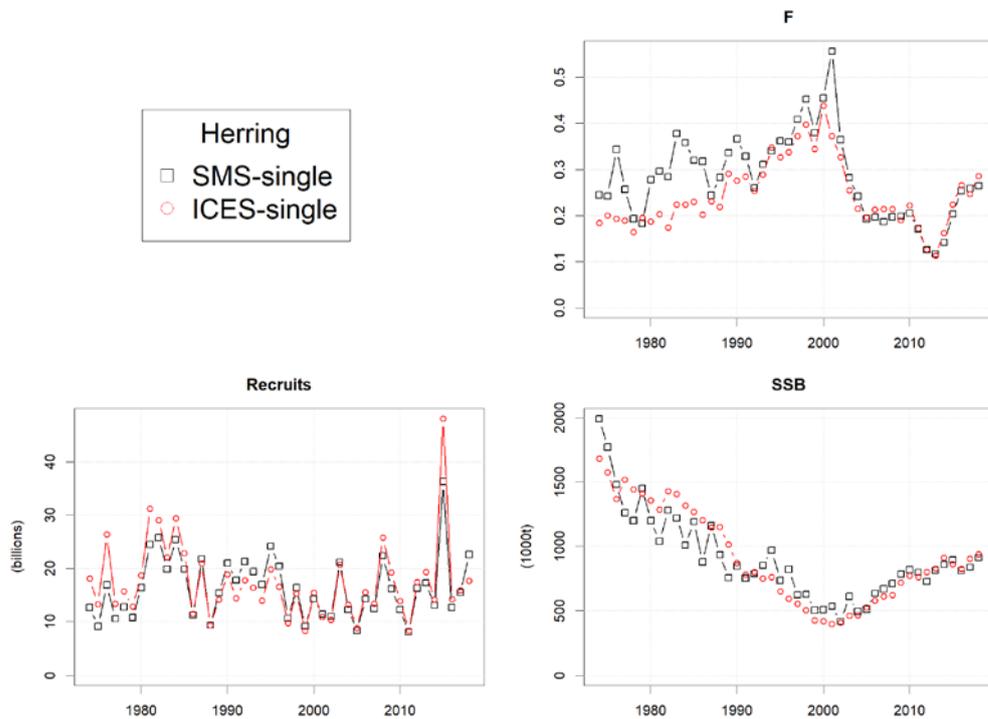


Figure 7.1-35. Comparison of the herring assessment results from SMS assessment using fixed M (from ICES assessment) and the ICES single species XSA assessment. Recruitment is at age 1.

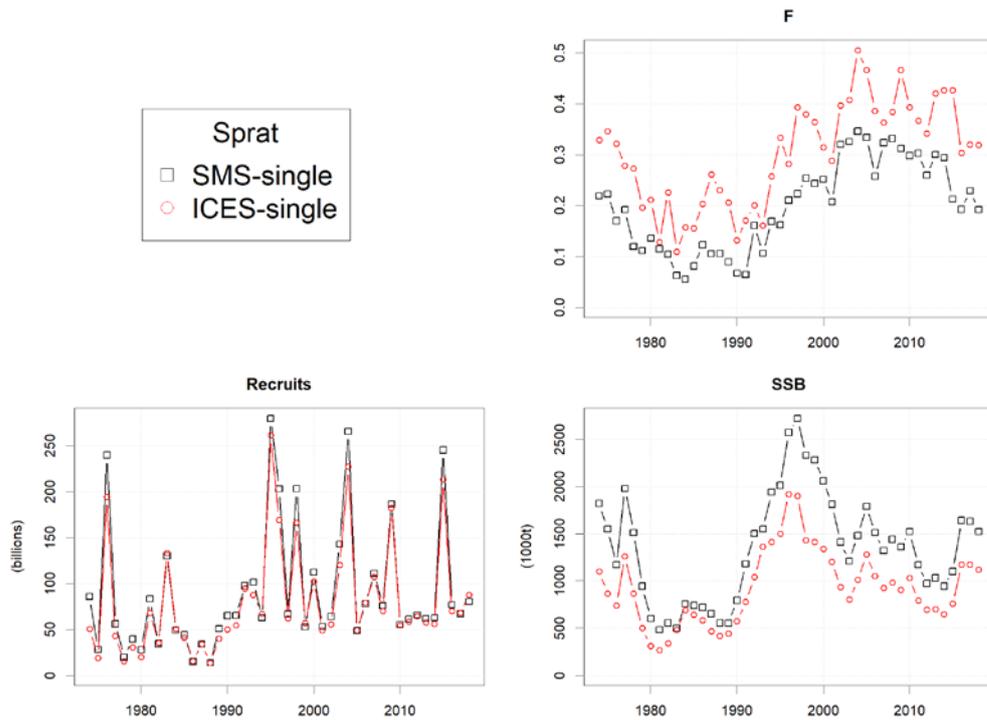


Figure 7.1-36. Comparison of the sprat assessment results from SMS assessment using fixed M (from ICES assessment) and the ICES single species XSA assessment. Recruitment is at age 1.

3.2. Configuring predation mortality options

The SMS model has three main options for size preferences of predators (see equations 11, 12 and 13 in the description of SMS model, Appendix 1) :

1. Log normal size selection: a predator has a preferred prey size ratio and a prey twice as big as the preferred size is as attractive as another half the prey size. The preferred size ratio and its variance are estimated by SMS.
2. Uniform size selection: a size preference at 1 within the range of the observed size ratio and 0 outside that ratio.
3. Constraint uniform size selection: as Uniform size selection, but the size preference ratio is constrained to exclude “outliers” in the observed size ratio.

The “Constraint uniform size selection” option was chosen for the 2012 key-run. The new stomach data available for the 2019 key run include more detailed data (prey length by cm group, while the old data set has prey length by 5 cm for most years) and a SMS run using the “log normal size selection” gave actually a better model fit than both the “Uniform size selection” and “Constraint uniform size selection” the (see section 9.5). Therefore, the “log normal size selection” and was chosen option for the 2019 key-run.

4. Other issues

The SMS model, and input and input can be found at Github https://github.com/ices-eg/wg_WGSAM.

The Github include several directories and files:

EBalticKeyRun_2019: The SMS eastern Baltic North Sea key run made at the 2019 WGSAM, including data for the period 1974–2018.

StockAnnex_ICES_EB_SMS_Configuration.docx: This document.

SMS_ADMB: AD Model Builder source code for the SMS the North Sea and Baltic Sea.

SMS_R_prog: R scripts for preparing, running and presenting results from a SMS run

5. Results of the 2019 Eastern Baltic Sea SMS key run

Substantial changes of input data to the new key run and ICES benchmarks for some of the stocks since the 2012 key run have produced stock summaries (recruitment, mean F and SSB) from the 2019 key run that is somewhat different from the summaries from the 2012 key run. However, the new estimated predation mortalities (M2) are consistent with the M2 values from the previous key run.

Key run summary sheet.

AREA	NORTH SEA
Model name	SMS
Type of model	Age-length structured statistical estimation model
Run year	2019
Predatory species	Assessed species: Herring , Sprat
Prey species	Herrmig, Sprat
Time range	1974–2018.
Time step	Quarterly
Area structure	Eastern Baltic Sea, ICES sub-divisions 25-29 excl Gulf of Riga
Stomach data	Cod: 1974-2014
Purpose of key run	Making historic data on natural mortality available and multispecies dynamics
Model changes since last key run	All time-series updated. More stomach data included. Cod is now an external predator estimated by WGBFAS Stock-synthesis model. Daily food ration of changed for the main fish species.
Output available at	Sharepoint/data/EBaltic_SMS_key_run and https://github.com/ices-eg/wg_WGSAM
Further details in	Report of the Working Group on Multispecies Assessment Methods 2019 (WGSAM, 2019)

5.1. Results of the 2019 key run

Model diagnostics

The population dynamics of all species except ‘external predators’ were estimated within the model. The key-run converged and the uncertainties of parameters and key output variables were obtained from the inverse Hessian matrix. Key diagnostics (Table 9.1-1) show a reasonable fit for catch (“sqrt(catch variance) ~ CV:”) and survey indices (“sqrt(Survey variance) ~ CV:”) data. Catch and survey data fit better for herring than for sprat. The same can be seen from the catch at age residual plots (Figure 9.1-2). Herring has in general smaller residuals than for sprat,

but herring residuals show a more clustered distribution with periods of either positive or negative residuals. The survey residuals show in some cases a “year effect” with all either positive or all negative residuals within a year. This often seen where the survey indices are based on an acoustic measurement.

The residual plot of stomach contents Figure 9.1-4 shows a quite randomly distributed residuals for sprat. Model estimate of the stomach contents of herring seems generally higher than the observed in the period since 1990, while the opposite pattern is seen for “other food”. The same picture is seen in the boxplots of residuals (Figure 9.1-5), where the upper two rows of the plot show generally positive residuals for herring and generally negative residuals for “other food” since 1990. The bias in residuals by quarter seems limited (third row of Figure 9.1-5). The residual pattern is not independent of predator size (fourth row of Figure 9.1-5). The model overestimate the stomach contents of herring for the medium sized cod, and underestimate the stomach contents of sprat for the largest cod. This might be a result of size dependent spatial distribution of cod.

Table 9.1-22. SMS key run model diagnostics.

```

November 06, 2019 18:57:28   run time:40 seconds

objective function (negative log likelihood):  -1232.3
Number of parameters: 292
Number of observations used in likelihood: 14892
Maximum gradient: 5.5994e-007
Akaike information criterion (AIC):  -1880.6
Number of observations used in the likelihood:

Species: 1, Cod           Catch   CPUE   S/R   Stomach   Sum
Species: 2, Herring      1440   251    45    0         3472
Species: 3, Sprat       1260   318    45    0         3246
Sum                     5400   1138   180   3210     14892

objective function weight:

Species: 1, Cod           Catch  CPUE   S/R    Stom.   Stom N.
Species: 2, Herring      1.00  1.00  0.05   0.00    0.00
Species: 3, Sprat       1.00  1.00  0.05   0.00    0.00

unweighted objective function contributions (total):

Species: 1, Cod           Catch  CPUE   S/R    Stom.   Stom N.   Penalty   Sum
Cod                      0.0    0.0    0.0   -256.2   0.0       0.00     -256
Herring                  -660.4 -118.7 -8.6    0.0     0.0       0.00    -788
Sprat                    -92.3  -104.0 -5.6    0.0     0.0       0.00    -202
Sum                      -752.7 -222.7 -14.2  -256.2   0.0       0.00   -1246

unweighted objective function contributions (per observation):

Species: 1, Cod           Catch  CPUE   S/R    Stomachs
Cod                      0.00  0.00  0.00  -0.16
Herring                  -0.46 -0.47 -0.19  0.00
Sprat                    -0.07 -0.33 -0.12  0.00

contribution by fleet:
-----
Species:2, Herring
Herring Acoustic May      total: -41.296   mean:  -0.397
Herring BIAS              total: -77.452   mean:  -0.527

Species:3, Sprat
Sprat Int acoustic in Oct. total: -72.723   mean:  -0.416
Sprat Int acoustic in May. total: -40.115   mean:  -0.337
Sprat LAT RUS acoustic    total:   8.860   mean:   0.369

F, Year effect:
-----
      sp. 2  sp. 3
1974: 1.000  1.000
1975: 0.972  0.982
1976: 1.317  0.747
    
```

```

1977: 0.920 0.777
1978: 0.663 0.486
1979: 0.644 0.442
1980: 1.063 0.516
1981: 1.189 0.392
1982: 1.169 0.324
1983: 1.598 0.167
1984: 1.574 0.137
1985: 1.458 0.195
1986: 1.494 0.294
1987: 1.154 0.267
1988: 1.360 0.304
1989: 1.000 0.278
1990: 1.109 0.223
1991: 1.004 0.229
1992: 0.788 0.611
1993: 0.924 0.424
1994: 1.016 0.728
1995: 1.103 0.721
1996: 1.108 0.971
1997: 1.264 1.061
1998: 1.402 1.190
1999: 1.135 1.124
2000: 1.348 1.000
2001: 1.708 0.813
2002: 1.162 1.228
2003: 0.907 1.249
2004: 0.778 1.319
2005: 0.622 1.253
2006: 0.644 0.992
2007: 0.618 1.258
2008: 0.665 1.333
2009: 0.682 1.283
2010: 0.708 1.231
2011: 0.581 1.215
2012: 0.414 0.999
2013: 0.376 1.140
2014: 0.451 1.156
2015: 0.642 0.849
2016: 0.796 0.751
2017: 0.783 0.905
2018: 0.763 0.782
    
```

F, season effect:

```

Herring
age: 1
  1974-1988: 0.033 0.072 0.118 0.250
  1989-2018: 0.096 0.063 0.057 0.250
age: 2
  1974-1988: 0.111 0.405 0.179 0.250
  1989-2018: 0.216 0.190 0.066 0.250
age: 3 - 8
  1974-1988: 0.137 0.612 0.309 0.250
  1989-2018: 0.296 0.329 0.117 0.250
    
```

```

Sprat
age: 1
  1974-1999: 0.075 0.045 0.036 0.250
  2000-2018: 0.318 0.143 0.051 0.250
age: 2 - 7
  1974-1999: 0.427 0.270 0.069 0.250
  2000-2018: 0.590 0.331 0.060 0.250
    
```

F, age effect:

```

          0      1      2      3      4      5      6      7      8
Herring
1974-1988: 0.000 0.090 0.141 0.148 0.163 0.201 0.201 0.201 0.201
1989-2018: 0.000 0.182 0.241 0.270 0.358 0.455 0.455 0.455 0.455
Sprat
1974-1999: 0.000 0.088 0.144 0.218 0.201 0.201 0.201 0.201
2000-2018: 0.000 0.117 0.147 0.193 0.200 0.200 0.200 0.200
    
```

Exploitation pattern (scaled to mean F=1)

```

-----
                0      1      2      3      4      5      6      7      8
Herring
1974-1988 season 1:    0  0.013  0.067  0.087  0.096  0.118  0.118  0.118  0.118
          season 2:    0  0.028  0.245  0.389  0.429  0.527  0.527  0.527  0.527
          season 3:  0.000  0.045  0.109  0.196  0.216  0.266  0.266  0.266  0.266
          season 4:  0.000  0.096  0.152  0.159  0.175  0.215  0.215  0.215  0.215

1989-2018 season 1:    0  0.046  0.136  0.210  0.278  0.354  0.354  0.354  0.354
          season 2:    0  0.030  0.120  0.233  0.308  0.393  0.393  0.393  0.393
          season 3:  0.000  0.027  0.041  0.083  0.110  0.140  0.140  0.140  0.140
          season 4:  0.000  0.119  0.158  0.177  0.234  0.298  0.298  0.298  0.298

Sprat
1974-1999 season 1:    0  0.031  0.292  0.443  0.409  0.409  0.409  0.409
          season 2:    0  0.019  0.185  0.280  0.258  0.258  0.258  0.258
          season 3:  0.000  0.015  0.047  0.072  0.066  0.066  0.066  0.066
          season 4:  0.000  0.105  0.171  0.259  0.239  0.239  0.239  0.239

2000-2018 season 1:    0  0.153  0.356  0.467  0.485  0.485  0.485  0.485
          season 2:    0  0.069  0.200  0.262  0.273  0.273  0.273  0.273
          season 3:  0.000  0.024  0.036  0.047  0.049  0.049  0.049  0.049
          season 4:  0.000  0.120  0.151  0.198  0.206  0.206  0.206  0.206
    
```

sqrt(catch variance) ~ CV:

```

-----
Herring
1      0.591
2      0.378
3      0.358
4      0.358
5      0.358
6      0.358
7      0.358
8      0.358
    
```

```

Sprat
1      0.772
2      0.487
3      0.391
4      0.592
5      0.592
6      0.592
7      0.592
    
```

Survey catchability:

```

-----
Herring          age 0  age 1  age 2  age 3  age 4  age 5  age 6  age 7  age 8
Herring Acoustic May      0.423  1.040  1.772  2.482  2.482  2.482  2.482  2.482
Herring BIAS              0.613  1.168  2.011  2.841  2.841  2.841  2.841
Sprat
Sprat Int acoustic in Oct. 0.479  0.728  1.034  0.895  0.895  0.895  0.895
Sprat Int acoustic in May. 0.295  0.675  0.996  0.945  0.945  0.945  0.945
Sprat LAT RUS acoustic    0.282
    
```

sqrt(Survey variance) ~ CV:

```

-----
Herring          age 0  age 1  age 2  age 3  age 4  age 5  age 6  age 7  age 8
Herring Acoustic May      0.37  0.37  0.37  0.43  0.43  0.43  0.43  0.43
Herring BIAS              0.45  0.33  0.33  0.33  0.33  0.37  0.37
Sprat
Sprat Int acoustic in Oct. 0.48  0.35  0.35  0.41  0.41  0.41  0.41
Sprat Int acoustic in May. 0.51  0.35  0.35  0.46  0.46  0.46  0.46
Sprat LAT RUS acoustic    0.88
    
```

```

Recruit-SSB          alfa      beta      var      sd
Herring Geometric mean:      16.857      0.251      0.501
Sprat   Geometric mean:      18.552      0.251      0.501
    
```

Multispecies parameters
=====

stomach content variance model: Dirichlet distribution

Vulnerability pred - prey

```

          Other-food      Herring      Sprat
    
```

```

Cod          1.000      8.857      3.529

Size selection parameters:
-----
                                Cod
Size selection model:           log-norm.
Sum prey sizes in likelihood:   yes
Preferred size ratio:           5.434
Variance of size ratio:        2.789

Other food Suitability slope:
Cod          0.4643

Stomach variance:  value  internal  max alfa0
Cod          0.381    0.381    37.083

Predator prey season overlap
-----
Predator:Cod      Other-food  Herring   Sprat
q:1               1           1         1
q:2               0.486       0.354     1
q:3               0.486       0.354     0.356
q:4               1.781       1         0.902
    
```

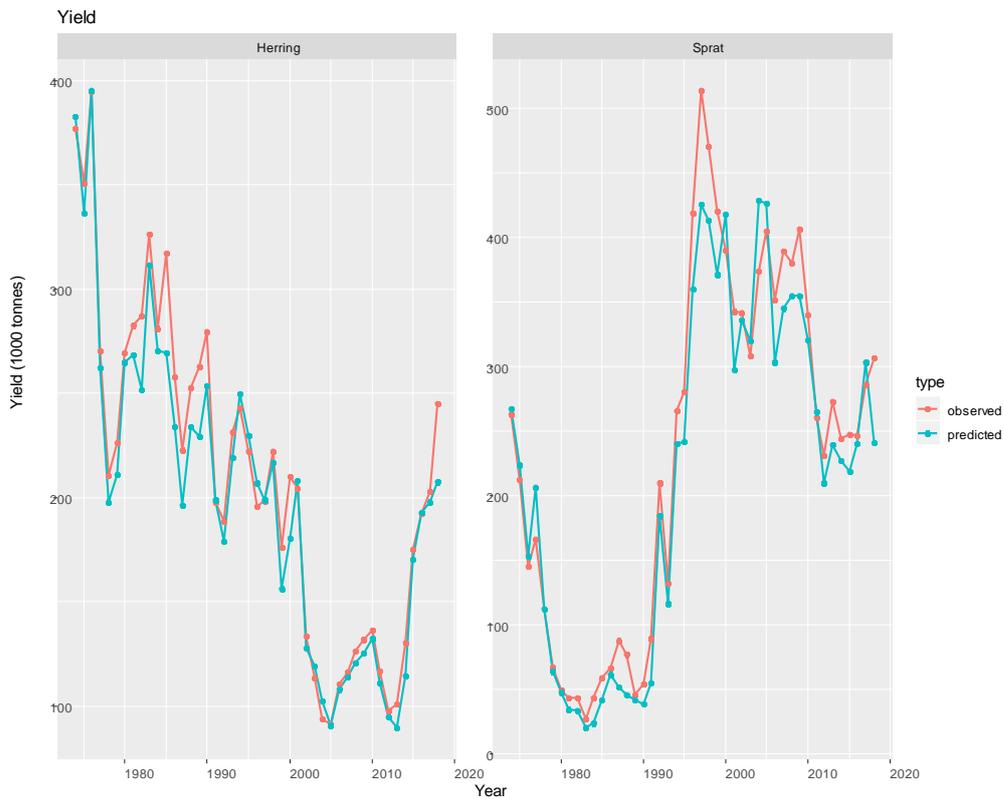


Figure 9.1-37 Observed and model predicted catch.



Figure 9.1-38. Residual plots for catch at age observations by species and quarter. Residuals are not standardised. The red dot shows that the observed catch are larger than the model estimate. The yellow dots show the largest residual value.

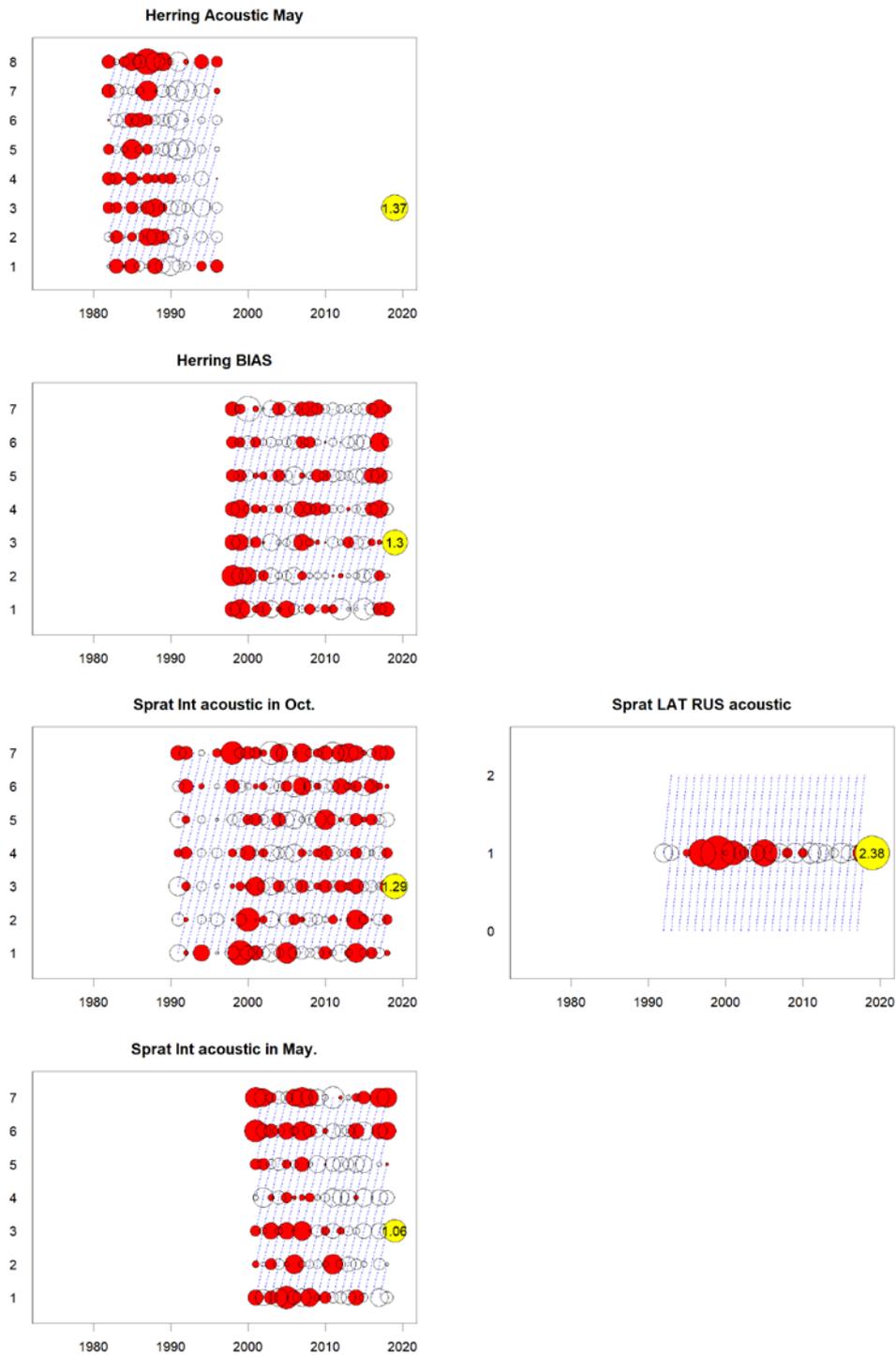


Figure 9.1-39. Residual plots for survey Catch per unit effort at age observations by species and survey. Residuals are not standardised. The red dot shows that the observed catch are larger than the model estimate. The yellow dots show the largest residual value.



Figure 9.1-40. Stomach contents residuals (“Dirichlet residuals”, Peter Lewy, pers. comm.). The y-axis show prey group and predator (cod) size class. The x-axis time period, where the upper panel is sorted by year and quarter, and lower panel sorted by quarter and year. Green dots show that the observed stomach contents are lower than the model estimate.

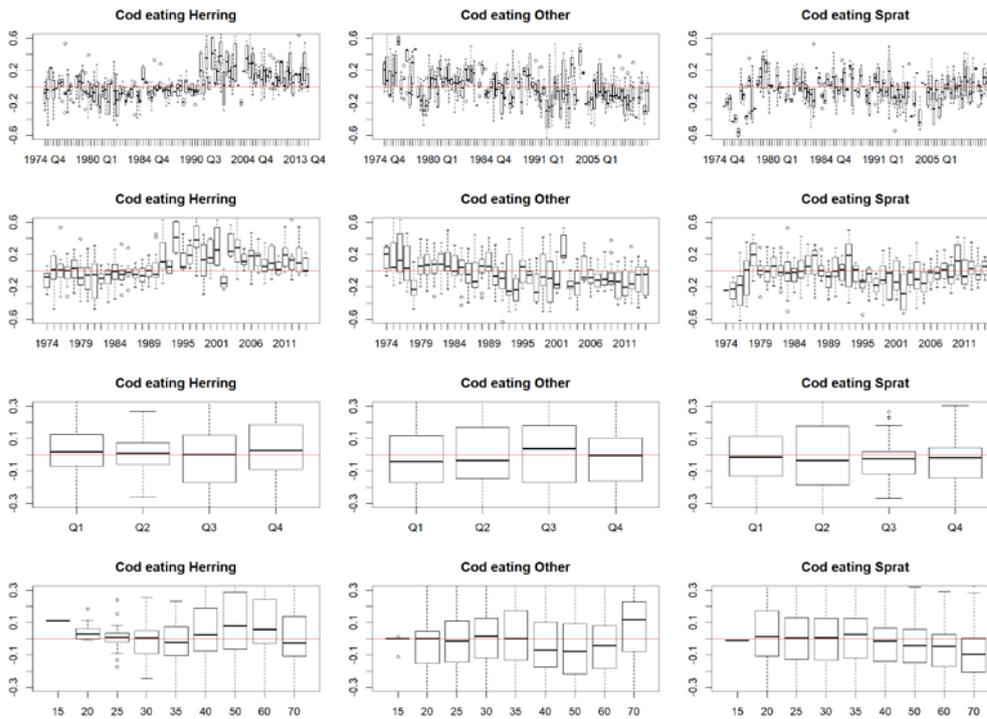


Figure 9.1-41. Box plot of stomach contents residual. Upper (first) row shows the boxplots by individual quarter and years, second row by year (quarters combined), third row by quarter and fourth row by cod size class.

Stock summary results

The stock summaries are presented in Figure 9.1-6 (herring) and Figure 9.1-7 (Sprat).

The estimated predation mortalities (M2) are shown in details in Figure 9.1-8 and Figure 9.1-9. Total natural mortality $M=M1+M2$ are tabulated in Table 9.1-2 and Table 9.1-3 Please note that M1 for herring has been changed from 0.2 in the 2012 key-run to 0.1 in the 2019 key-run. Figure 9.1-10 shows the same data using the same scale on the y-axis and with an added smoother. The smoothed M values are tabulated in Table 9.1-4 and Table 9.1-5.

A comparison of M2 from this key run with M2 from the previous key run show the some substantial changes for herring (Figure 9.1-11) and a more consistent estimate for sprat (Figure 9.1-12), even though sprat M2 is now higher for age 0 and 1. Herring M2 is now estimated considerably higher, but follows the same trend as seen in the 2012 key run. . The main difference between the two key runs is the estimate of the predator (cod) stock. The present estimate of the cod biomass is higher, and especially higher for the larger cod that eats herring. This is probably the main reason for the differences in the estimates of M2, but application of new stomach contents data, a different size selection option and new consumption estimates are also contributing.

Natural mortalities ($M=M1+M2$) estimated by SMS may be used as input to the ICES stock assessment of herring and sprat. If M values are used, WGSAM does recommend to update the full time-series of M.

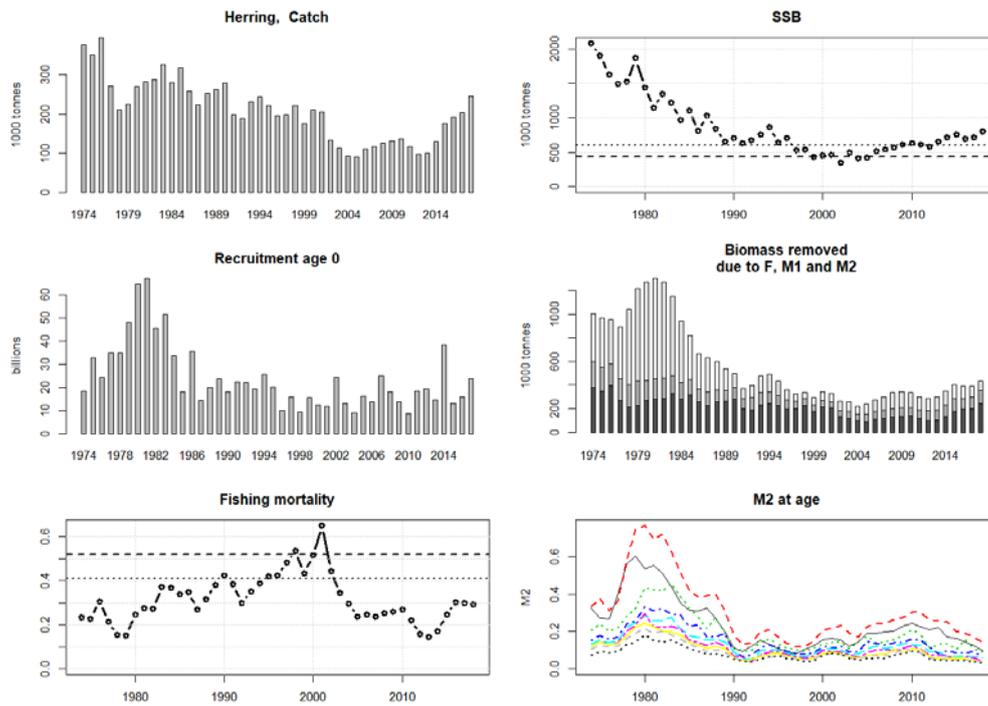


Figure 9.1-42. SMS output for Herring. Catch weight, Recruitment, F, SSB, Biomass removed due to fishery (F), predation by SMS species (M2) and residual natural mortality (M1). The predation mortality (M2) presented by the 0-group (black solid line) is for the second half of the year. The M2 for the rest of the ages are annual values.

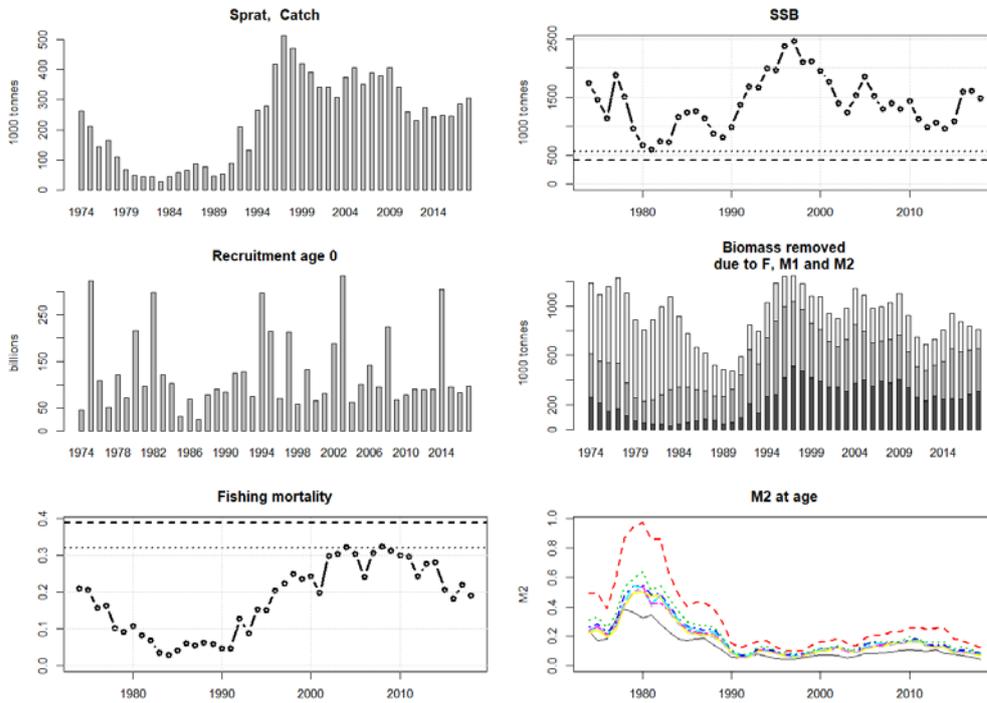


Figure 9.1-43. SMS output for Sprat. Catch weight, Recruitment, F, SSB, Biomass removed due to fishery (F), predation by SMS species (M2) and residual natural mortality (M1). The predation mortality (M2) presented by the 0-group (black solid line) is for the second half of the year. The M2 for the rest of the ages are annual values.

Table 9.1-23. Herring Natural mortality (sum of quarterly M1 (=0.1)+M2)

Year/Age	0	1	2	3	4	5	6	7	8+
1974	0.375	0.433	0.307	0.251	0.233	0.220	0.219	0.205	0.176
1975	0.321	0.476	0.340	0.278	0.257	0.243	0.244	0.229	0.195
1976	0.318	0.412	0.303	0.258	0.240	0.229	0.228	0.216	0.187
1977	0.454	0.465	0.320	0.270	0.251	0.238	0.237	0.222	0.191
1978	0.610	0.676	0.385	0.342	0.322	0.302	0.278	0.262	0.233
1979	0.653	0.848	0.420	0.358	0.350	0.335	0.325	0.291	0.244
1980	0.583	0.869	0.534	0.432	0.386	0.394	0.344	0.317	0.283
1981	0.606	0.793	0.521	0.409	0.356	0.325	0.327	0.290	0.252
1982	0.560	0.821	0.514	0.423	0.358	0.320	0.301	0.301	0.242
1983	0.492	0.731	0.556	0.396	0.375	0.331	0.299	0.283	0.251
1984	0.403	0.616	0.488	0.386	0.313	0.312	0.281	0.258	0.233
1985	0.365	0.519	0.424	0.324	0.280	0.250	0.246	0.232	0.211
1986	0.360	0.483	0.378	0.336	0.267	0.245	0.227	0.213	0.190
1987	0.377	0.491	0.318	0.271	0.256	0.223	0.207	0.195	0.177
1988	0.321	0.498	0.374	0.270	0.259	0.244	0.219	0.202	0.180
1989	0.249	0.415	0.290	0.290	0.243	0.219	0.208	0.190	0.171
1990	0.163	0.281	0.209	0.189	0.195	0.170	0.163	0.157	0.149

1991	0.142	0.229	0.193	0.168	0.152	0.162	0.144	0.147	0.138
1992	0.171	0.240	0.197	0.175	0.149	0.141	0.150	0.137	0.134
1993	0.205	0.298	0.247	0.212	0.196	0.178	0.168	0.176	0.155
1994	0.182	0.308	0.257	0.230	0.201	0.190	0.178	0.164	0.163
1995	0.160	0.271	0.234	0.218	0.201	0.190	0.185	0.173	0.170
1996	0.140	0.235	0.214	0.195	0.186	0.179	0.171	0.166	0.155
1997	0.133	0.215	0.200	0.182	0.173	0.165	0.159	0.155	0.150
1998	0.156	0.222	0.193	0.180	0.166	0.158	0.151	0.150	0.139
1999	0.176	0.253	0.214	0.191	0.182	0.169	0.158	0.155	0.144
2000	0.207	0.306	0.230	0.217	0.207	0.196	0.183	0.174	0.174
2001	0.214	0.318	0.241	0.214	0.208	0.194	0.189	0.181	0.180
2002	0.205	0.331	0.249	0.220	0.199	0.191	0.183	0.177	0.176
2003	0.171	0.291	0.205	0.190	0.179	0.172	0.166	0.159	0.155
2004	0.196	0.270	0.246	0.191	0.180	0.164	0.159	0.154	0.147
2005	0.239	0.323	0.276	0.248	0.207	0.186	0.172	0.165	0.155
2006	0.240	0.342	0.239	0.235	0.224	0.202	0.177	0.169	0.160
2007	0.248	0.344	0.243	0.228	0.210	0.204	0.179	0.169	0.154
2008	0.253	0.364	0.259	0.241	0.221	0.197	0.206	0.183	0.172
2009	0.278	0.374	0.279	0.241	0.232	0.208	0.191	0.204	0.183
2010	0.294	0.403	0.308	0.258	0.229	0.225	0.210	0.195	0.193
2011	0.276	0.400	0.281	0.255	0.224	0.204	0.199	0.185	0.186
2012	0.260	0.363	0.211	0.217	0.195	0.174	0.168	0.159	0.149
2013	0.272	0.355	0.231	0.181	0.188	0.169	0.156	0.153	0.146
2014	0.221	0.353	0.234	0.196	0.165	0.171	0.156	0.150	0.144
2015	0.212	0.298	0.203	0.185	0.167	0.155	0.155	0.148	0.142
2016	0.195	0.288	0.254	0.185	0.174	0.164	0.156	0.151	0.144
2017	0.173	0.268	0.207	0.195	0.164	0.158	0.148	0.139	0.136
2018	0.145	0.244	0.188	0.162	0.160	0.142	0.141	0.139	0.133

Table 9.1-24. Sprat Natural mortality (sum of quarterly M1 (=0.2)+M2)

Year/Age	0	1	2	3	4	5	6	7+
1974	0.335	0.690	0.507	0.462	0.441	0.441	0.420	0.436
1975	0.271	0.695	0.529	0.486	0.464	0.464	0.443	0.459
1976	0.284	0.586	0.462	0.429	0.413	0.413	0.397	0.410
1977	0.414	0.783	0.544	0.491	0.468	0.468	0.439	0.463
1978	0.484	1.067	0.736	0.682	0.631	0.617	0.609	0.610
1979	0.463	1.144	0.789	0.740	0.745	0.690	0.692	0.707
1980	0.422	1.174	0.839	0.749	0.733	0.744	0.699	0.720
1981	0.444	1.061	0.712	0.679	0.622	0.624	0.671	0.603
1982	0.386	1.063	0.751	0.690	0.670	0.627	0.669	0.680
1983	0.332	0.828	0.663	0.611	0.596	0.579	0.566	0.565
1984	0.283	0.688	0.576	0.519	0.516	0.500	0.493	0.487
1985	0.271	0.603	0.498	0.471	0.461	0.444	0.424	0.435

1986	0.281	0.631	0.480	0.456	0.442	0.424	0.415	0.411
1987	0.285	0.626	0.472	0.440	0.422	0.418	0.409	0.398
1988	0.243	0.594	0.465	0.452	0.429	0.413	0.405	0.396
1989	0.205	0.495	0.399	0.376	0.371	0.360	0.354	0.351
1990	0.157	0.354	0.303	0.299	0.293	0.286	0.287	0.282
1991	0.152	0.324	0.272	0.268	0.263	0.258	0.257	0.258
1992	0.168	0.341	0.280	0.270	0.267	0.260	0.259	0.257
1993	0.179	0.369	0.329	0.315	0.308	0.305	0.301	0.297
1994	0.163	0.369	0.328	0.314	0.305	0.303	0.300	0.299
1995	0.152	0.327	0.298	0.296	0.290	0.287	0.285	0.284
1996	0.144	0.299	0.287	0.275	0.273	0.269	0.268	0.269
1997	0.143	0.298	0.277	0.272	0.265	0.260	0.260	0.258
1998	0.155	0.306	0.283	0.278	0.275	0.268	0.266	0.267
1999	0.163	0.336	0.302	0.292	0.292	0.290	0.284	0.281
2000	0.173	0.362	0.309	0.312	0.308	0.305	0.303	0.298
2001	0.176	0.374	0.323	0.312	0.313	0.308	0.310	0.311
2002	0.169	0.385	0.332	0.329	0.323	0.323	0.322	0.322
2003	0.154	0.351	0.308	0.303	0.303	0.299	0.302	0.303
2004	0.167	0.335	0.309	0.293	0.288	0.289	0.288	0.289
2005	0.185	0.385	0.353	0.341	0.321	0.317	0.315	0.318
2006	0.186	0.405	0.362	0.356	0.348	0.332	0.328	0.328
2007	0.191	0.411	0.362	0.348	0.347	0.345	0.334	0.326
2008	0.192	0.431	0.364	0.357	0.348	0.353	0.355	0.341
2009	0.203	0.429	0.364	0.353	0.349	0.346	0.349	0.346
2010	0.210	0.457	0.399	0.376	0.368	0.367	0.365	0.365
2011	0.204	0.463	0.384	0.378	0.369	0.361	0.363	0.358
2012	0.201	0.448	0.358	0.342	0.340	0.333	0.331	0.332
2013	0.208	0.455	0.355	0.336	0.328	0.327	0.326	0.326
2014	0.182	0.453	0.357	0.339	0.327	0.321	0.322	0.328
2015	0.177	0.380	0.315	0.304	0.299	0.294	0.290	0.296
2016	0.169	0.367	0.326	0.304	0.294	0.293	0.290	0.291
2017	0.159	0.350	0.307	0.300	0.288	0.283	0.283	0.284
2018	0.145	0.322	0.288	0.282	0.280	0.273	0.270	0.271

Table 9.1-25. Herring GAM-Smoothed Natural mortality (sum of quarterly M1 (=0.1)+M2).

Year/Age	0	1	2	3	4	5	6	7	8
1974	0.297	0.366	0.281	0.232	0.217	0.206	0.208	0.195	0.170
1975	0.370	0.457	0.312	0.262	0.245	0.234	0.231	0.216	0.187
1976	0.439	0.544	0.343	0.291	0.273	0.261	0.254	0.236	0.204
1977	0.498	0.622	0.374	0.319	0.298	0.285	0.274	0.254	0.219
1978	0.544	0.685	0.406	0.344	0.320	0.305	0.291	0.269	0.232
1979	0.571	0.730	0.437	0.366	0.336	0.319	0.302	0.280	0.241
1980	0.577	0.754	0.469	0.383	0.347	0.327	0.308	0.287	0.247
1981	0.565	0.757	0.495	0.395	0.351	0.329	0.309	0.288	0.249
1982	0.538	0.742	0.512	0.400	0.350	0.325	0.304	0.284	0.246
1983	0.502	0.711	0.514	0.396	0.342	0.315	0.294	0.276	0.240
1984	0.459	0.666	0.497	0.382	0.328	0.300	0.280	0.263	0.230
1985	0.413	0.609	0.459	0.358	0.308	0.281	0.261	0.245	0.217
1986	0.367	0.547	0.409	0.327	0.284	0.259	0.241	0.226	0.202
1987	0.322	0.483	0.354	0.293	0.259	0.237	0.220	0.206	0.186
1988	0.281	0.422	0.303	0.262	0.236	0.216	0.201	0.188	0.172
1989	0.245	0.370	0.263	0.236	0.216	0.199	0.185	0.174	0.162
1990	0.215	0.329	0.239	0.218	0.201	0.187	0.175	0.165	0.155
1991	0.192	0.299	0.227	0.207	0.191	0.178	0.168	0.160	0.151
1992	0.174	0.277	0.223	0.201	0.184	0.173	0.165	0.158	0.149
1993	0.162	0.262	0.223	0.198	0.181	0.171	0.164	0.158	0.150
1994	0.156	0.253	0.223	0.197	0.180	0.170	0.164	0.159	0.151
1995	0.155	0.249	0.222	0.197	0.180	0.171	0.165	0.161	0.153
1996	0.157	0.248	0.220	0.197	0.182	0.173	0.167	0.162	0.155
1997	0.161	0.251	0.217	0.197	0.184	0.175	0.168	0.164	0.156
1998	0.167	0.256	0.216	0.198	0.187	0.177	0.169	0.164	0.158
1999	0.173	0.263	0.216	0.199	0.188	0.178	0.170	0.164	0.159
2000	0.180	0.272	0.219	0.200	0.189	0.179	0.170	0.164	0.159
2001	0.186	0.282	0.223	0.202	0.190	0.179	0.169	0.163	0.159
2002	0.194	0.293	0.229	0.205	0.192	0.180	0.170	0.163	0.159
2003	0.204	0.305	0.236	0.210	0.195	0.183	0.172	0.164	0.160
2004	0.215	0.318	0.244	0.217	0.201	0.187	0.175	0.167	0.162
2005	0.229	0.331	0.253	0.226	0.207	0.192	0.180	0.172	0.165
2006	0.242	0.344	0.260	0.234	0.214	0.197	0.185	0.177	0.168
2007	0.254	0.356	0.266	0.241	0.220	0.201	0.189	0.181	0.170
2008	0.264	0.366	0.269	0.244	0.222	0.203	0.192	0.183	0.172
2009	0.270	0.372	0.268	0.243	0.221	0.203	0.191	0.183	0.171
2010	0.273	0.375	0.265	0.237	0.216	0.199	0.188	0.180	0.169
2011	0.271	0.374	0.259	0.229	0.209	0.194	0.183	0.175	0.166
2012	0.264	0.368	0.251	0.219	0.200	0.187	0.177	0.169	0.162
2013	0.253	0.357	0.242	0.209	0.191	0.180	0.170	0.162	0.157
2014	0.238	0.341	0.233	0.200	0.183	0.172	0.164	0.157	0.152
2015	0.218	0.320	0.225	0.192	0.176	0.165	0.158	0.151	0.147

2016	0.196	0.296	0.216	0.184	0.169	0.158	0.152	0.146	0.141
2017	0.172	0.269	0.207	0.177	0.162	0.151	0.146	0.141	0.136
2018	0.147	0.242	0.198	0.170	0.156	0.145	0.140	0.136	0.130

Table 9.1-26. Sprat GAM-Smoothed Natural mortality (sum of quarterly M1 (=0.1)+M2).

Year/Age	0	1	2	3	4	5	6	7+
1974	0.276	0.567	0.448	0.408	0.390	0.392	0.365	0.386
1975	0.323	0.698	0.520	0.477	0.456	0.454	0.432	0.450
1976	0.367	0.819	0.589	0.541	0.518	0.512	0.496	0.509
1977	0.403	0.923	0.648	0.597	0.572	0.563	0.551	0.560
1978	0.428	1.000	0.694	0.640	0.614	0.602	0.595	0.600
1979	0.438	1.041	0.723	0.667	0.641	0.627	0.622	0.625
1980	0.431	1.042	0.732	0.675	0.650	0.634	0.632	0.632
1981	0.412	1.010	0.722	0.666	0.643	0.625	0.626	0.623
1982	0.384	0.952	0.697	0.644	0.623	0.604	0.606	0.601
1983	0.352	0.880	0.661	0.611	0.592	0.574	0.575	0.570
1984	0.320	0.801	0.615	0.570	0.554	0.536	0.536	0.530
1985	0.292	0.722	0.564	0.525	0.511	0.494	0.493	0.487
1986	0.267	0.646	0.511	0.479	0.466	0.451	0.447	0.441
1987	0.245	0.576	0.458	0.434	0.422	0.408	0.403	0.398
1988	0.226	0.513	0.411	0.392	0.381	0.370	0.363	0.358
1989	0.207	0.459	0.372	0.357	0.348	0.338	0.330	0.327
1990	0.191	0.415	0.342	0.330	0.322	0.314	0.307	0.304
1991	0.177	0.380	0.321	0.311	0.303	0.297	0.291	0.289
1992	0.165	0.354	0.307	0.297	0.290	0.285	0.281	0.279
1993	0.156	0.336	0.298	0.289	0.283	0.278	0.276	0.275
1994	0.152	0.325	0.293	0.284	0.279	0.275	0.274	0.273
1995	0.151	0.320	0.290	0.283	0.278	0.275	0.274	0.272
1996	0.152	0.320	0.290	0.283	0.280	0.276	0.276	0.274
1997	0.155	0.323	0.292	0.286	0.283	0.280	0.278	0.277
1998	0.158	0.328	0.295	0.290	0.287	0.283	0.282	0.280
1999	0.161	0.334	0.299	0.294	0.291	0.287	0.285	0.284
2000	0.163	0.340	0.304	0.298	0.295	0.291	0.289	0.289
2001	0.164	0.347	0.310	0.303	0.299	0.296	0.294	0.294
2002	0.166	0.356	0.316	0.309	0.305	0.301	0.300	0.300
2003	0.169	0.365	0.324	0.316	0.311	0.308	0.306	0.307
2004	0.174	0.376	0.334	0.325	0.319	0.316	0.315	0.314
2005	0.179	0.389	0.344	0.335	0.329	0.325	0.324	0.322
2006	0.186	0.402	0.354	0.344	0.338	0.334	0.333	0.330
2007	0.192	0.415	0.363	0.352	0.346	0.342	0.341	0.336
2008	0.197	0.427	0.370	0.358	0.351	0.348	0.346	0.341
2009	0.201	0.438	0.374	0.361	0.354	0.350	0.349	0.344

2010	0.204	0.446	0.374	0.360	0.353	0.349	0.348	0.345
2011	0.204	0.451	0.372	0.356	0.349	0.345	0.344	0.343
2012	0.202	0.451	0.366	0.350	0.343	0.339	0.338	0.338
2013	0.197	0.443	0.358	0.342	0.334	0.330	0.329	0.331
2014	0.190	0.428	0.348	0.332	0.324	0.320	0.319	0.321
2015	0.181	0.407	0.335	0.320	0.313	0.308	0.307	0.310
2016	0.170	0.380	0.321	0.308	0.300	0.295	0.294	0.297
2017	0.158	0.350	0.305	0.294	0.287	0.282	0.280	0.282
2018	0.145	0.318	0.290	0.281	0.274	0.268	0.266	0.268

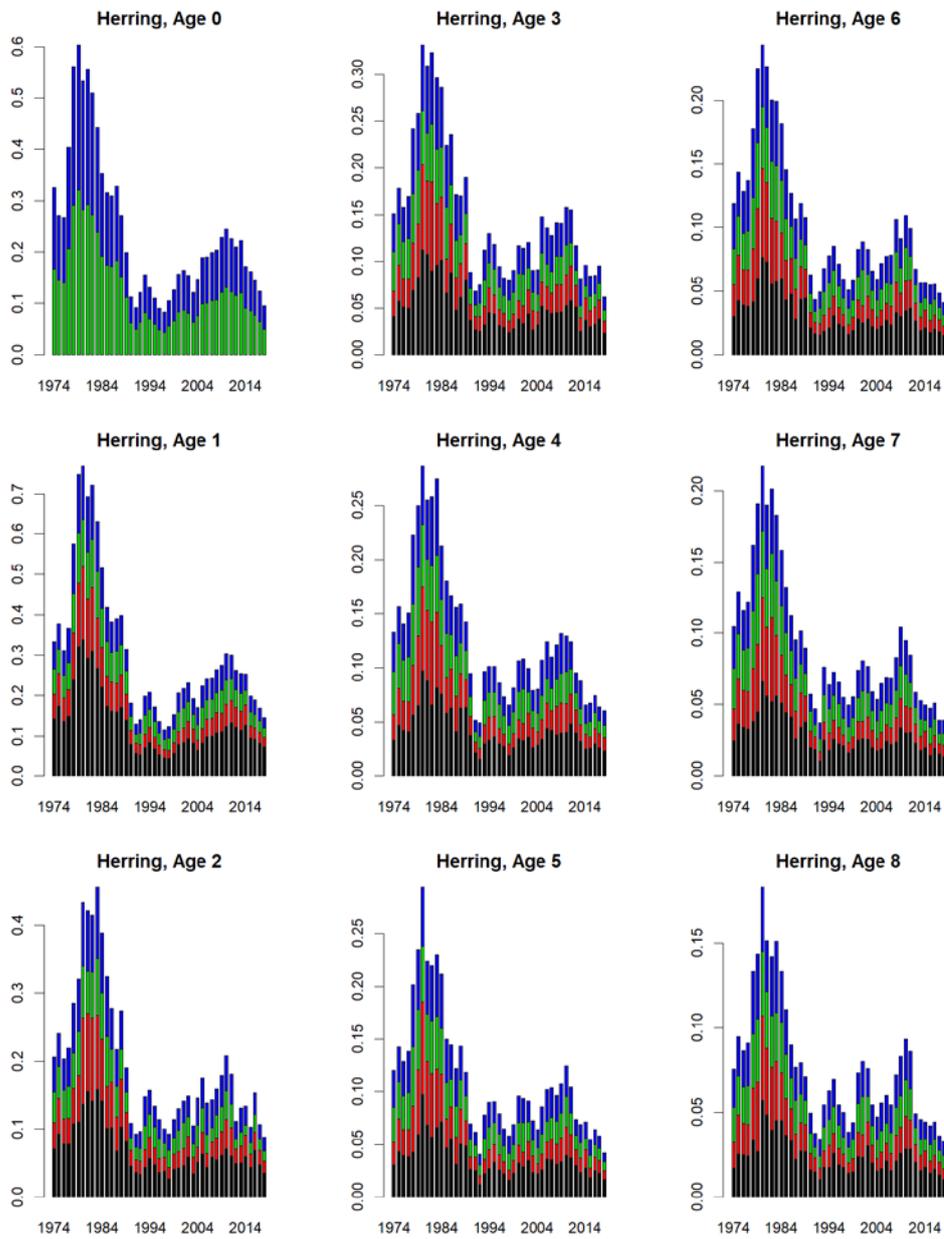


Figure 9.1-44. Annual predation mortality (M2) of herring the colours show M2 by quarter (green Q3, blue Q4, black Q1 and red Q2).

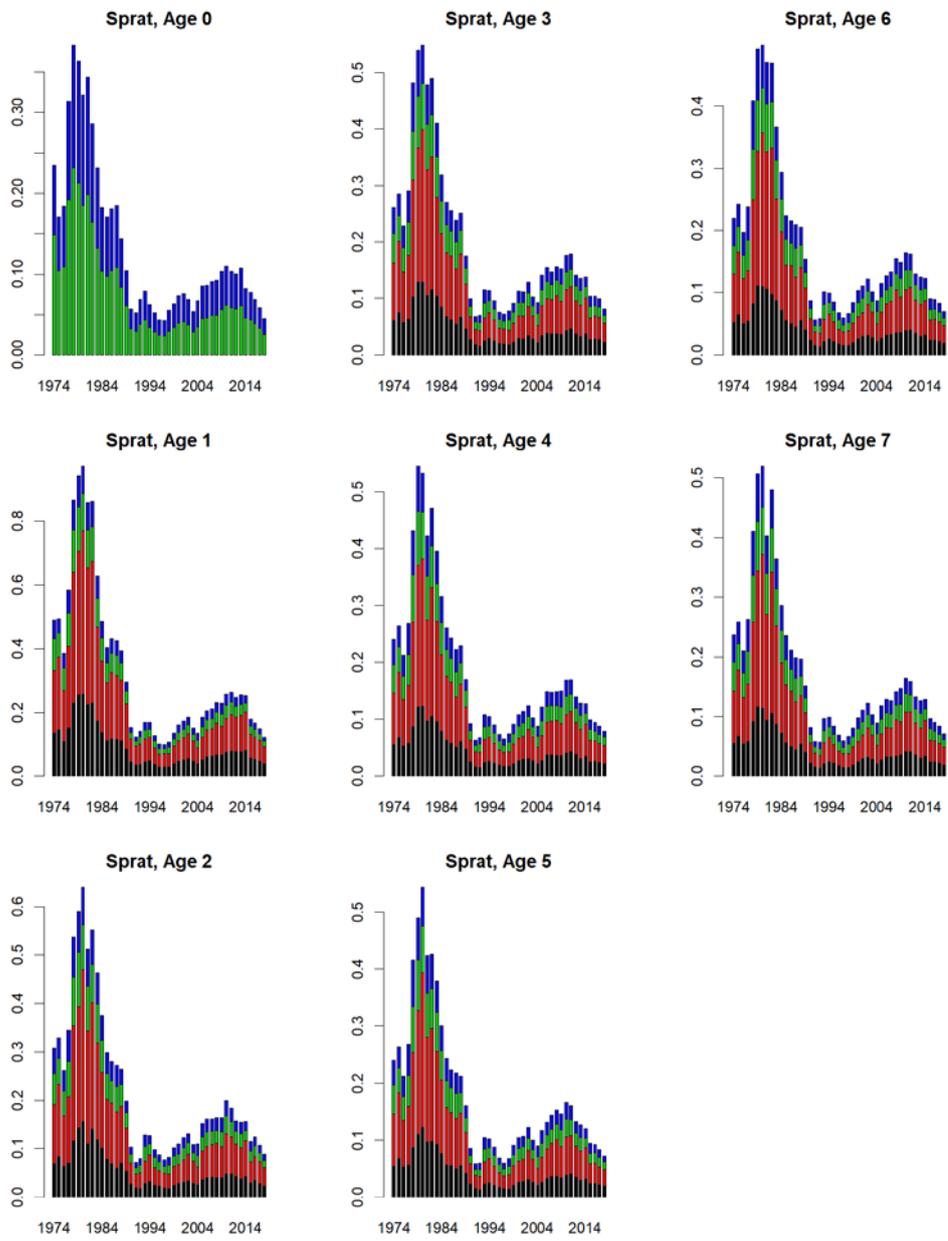


Figure 9.1-45. Annual predation mortality (M2) of herring the colours show M2 by quarter (green Q3, blue Q4, black Q1 and red Q4).

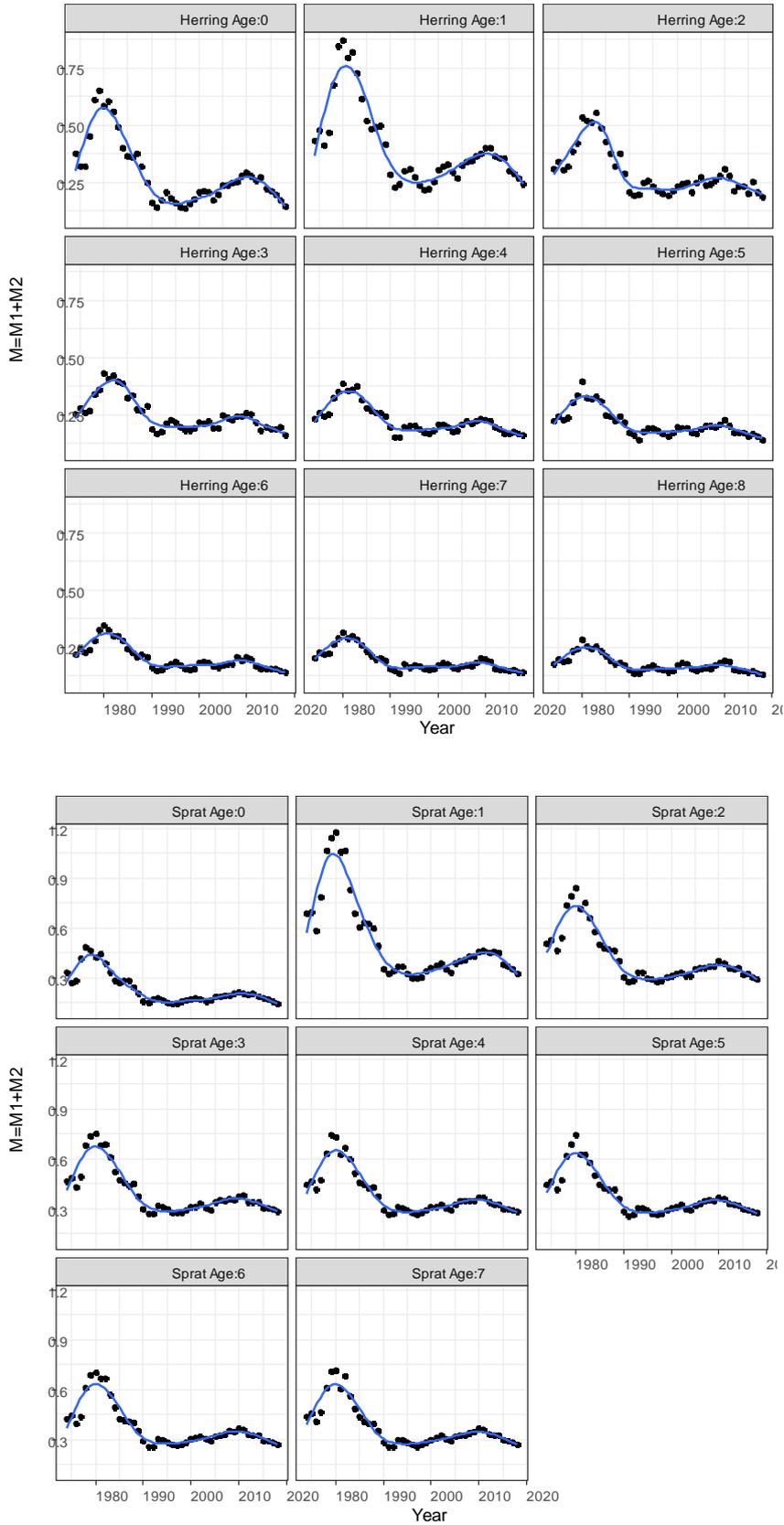


Figure 9.1-46. Annual natural mortalities ($M=M1+M2$) by species and age. Black dots are the sum of quarterly $M1$ and $M2$; the blue line is a gam spline estimate.

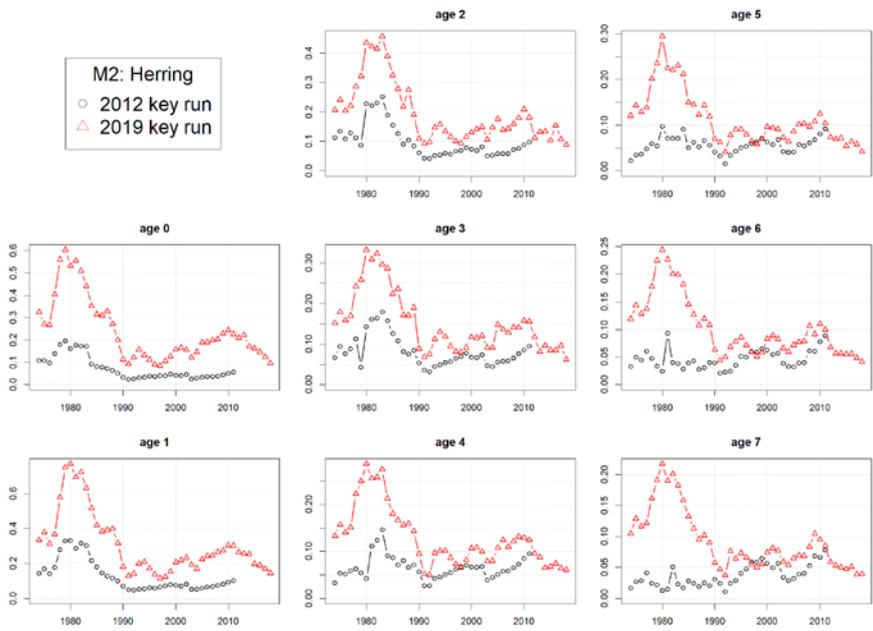


Figure 9.1-47. Herring. Comparison of predation mortality (M2) estimated by the 2012 key-run and by the 2019 key run.

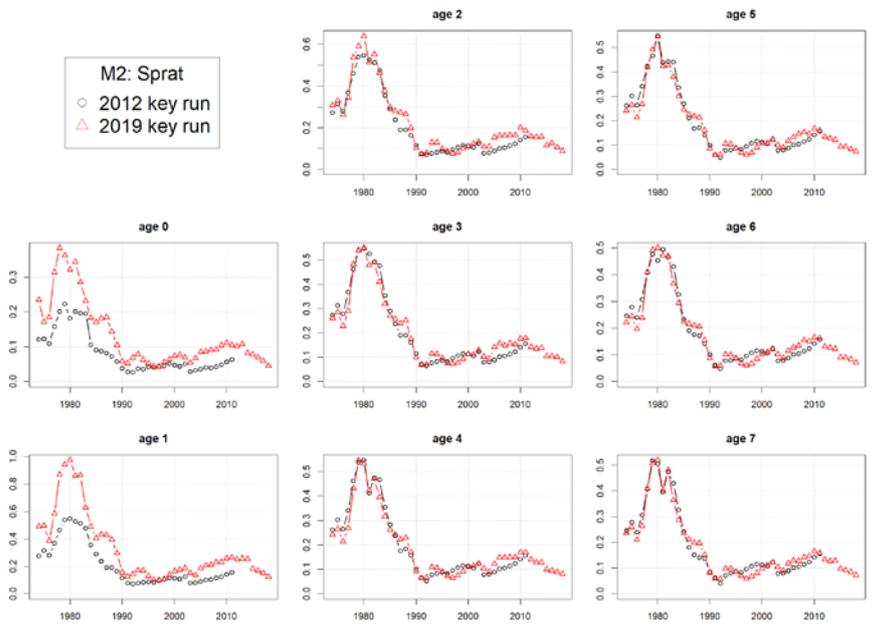


Figure 9.1-48. Sprat. Comparison of predation mortality (M2) estimated by the 2012 key-run and by the 2019 key run.

Uncertainties of parameters and output

SMS estimate the uncertainties of selected output variables using the Hessian matrix and the delta-method approximation. Most variables like stock number and F for dynamic species are estimated within the model, while other variables like the stock numbers of the “external predators” cod are assumed known without errors. With cod as the only predator, this combination of estimated and assumed “known” variables will certainly lead to an underestimate of the uncertainties of e.g. predation mortality. Therefore, the uncertainties estimated from the Hessian matrix are not presented in details.

An example of estimated uncertainties is presented in Figure 9.1-13. The confidence interval seems too tight!

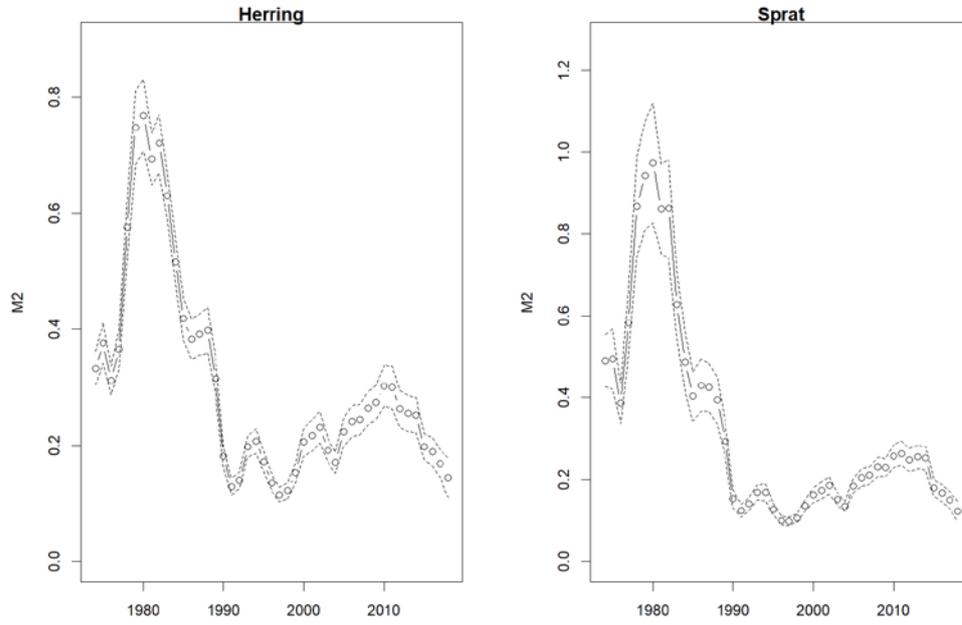


Figure 9.1-49. Values of M2 and 95% confidence interval (+- 2*standard deviation) for age 1 of herring and sprat

5.2. Sensitivity test

To get a better idea on true uncertainties several sensitivity runs were carried out:

1. Retrospective analysis (5 year peel of all input data)
2. Sensitivity to stomach data (old vs. new stomach data set)
3. Sensitivity to stomach data (aggregation stomach data over a 5 or 10 years period)
4. Sensitivity towards using different assumptions for size selection
5. Sensitivity towards using or not using an overlap index for Other Food
6. Sensitivity towards consumption rates
7. Comparison with the old 2012 keyrun
8. Comparison with the Gadget model run.

5.3. Retrospective analysis (5 year peel of all input data)

The retrospective analysis shows variable estimates of recruitment, SSB and F for the terminal years in the time-series, (Figure 9.3-1). Comparison with the same kind of output for the ICES assessment (WGBFAS, 2019) reveals however a similar variability in the ICES single species assessment output.

The retrospective analysis show a consistent estimate of predation mortalities (Figure 9.3-2). This consistent estimate is probably also because all runs use the same stomach contents data; the last year with stomach data is 2014. As for all other retrospective assessment analysis, values (M2) in the terminal year of the time-series have larger uncertainties.

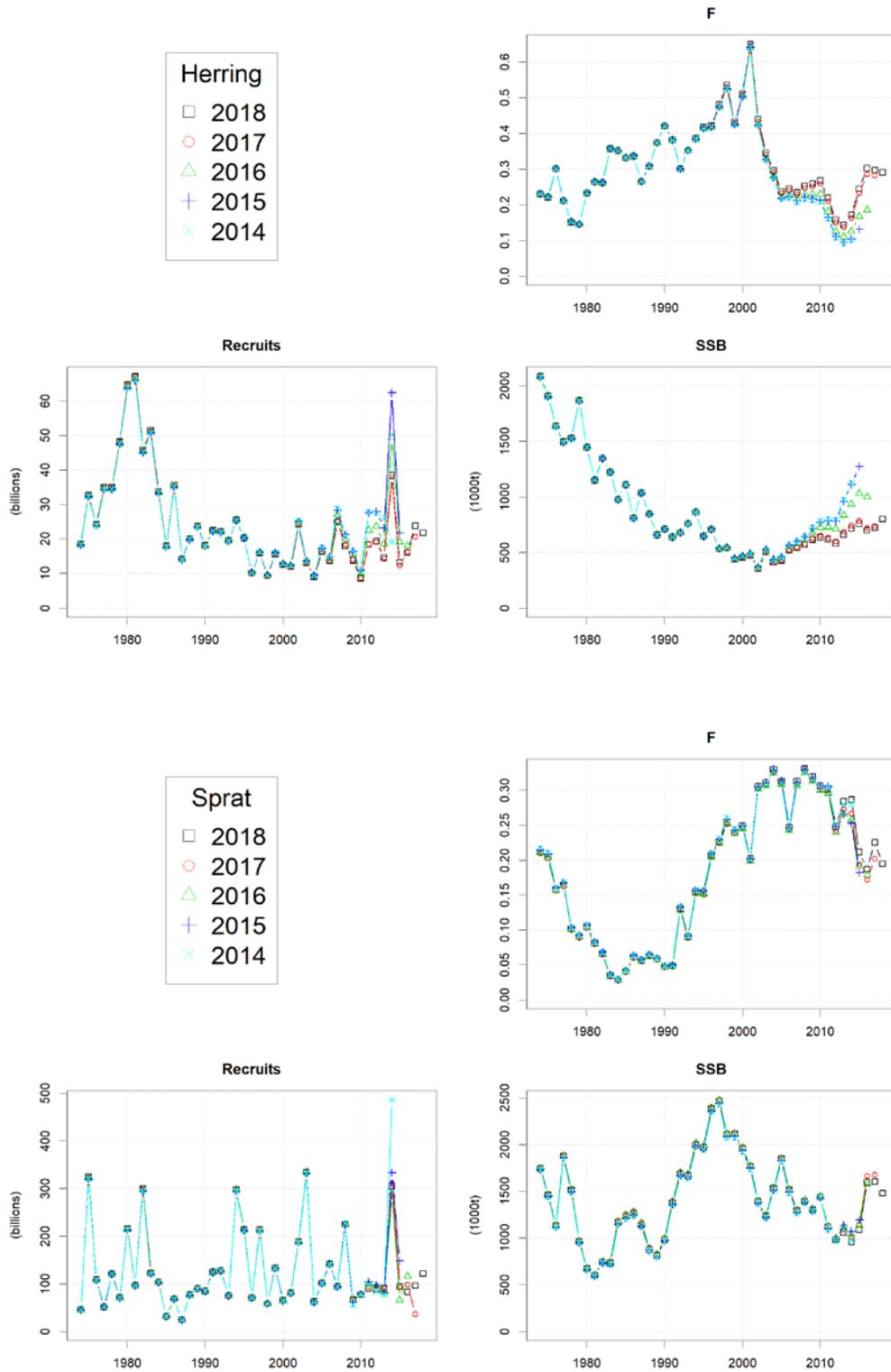


Figure 9.3-50. Retrospective analysis for herring and sprat. Summary output.

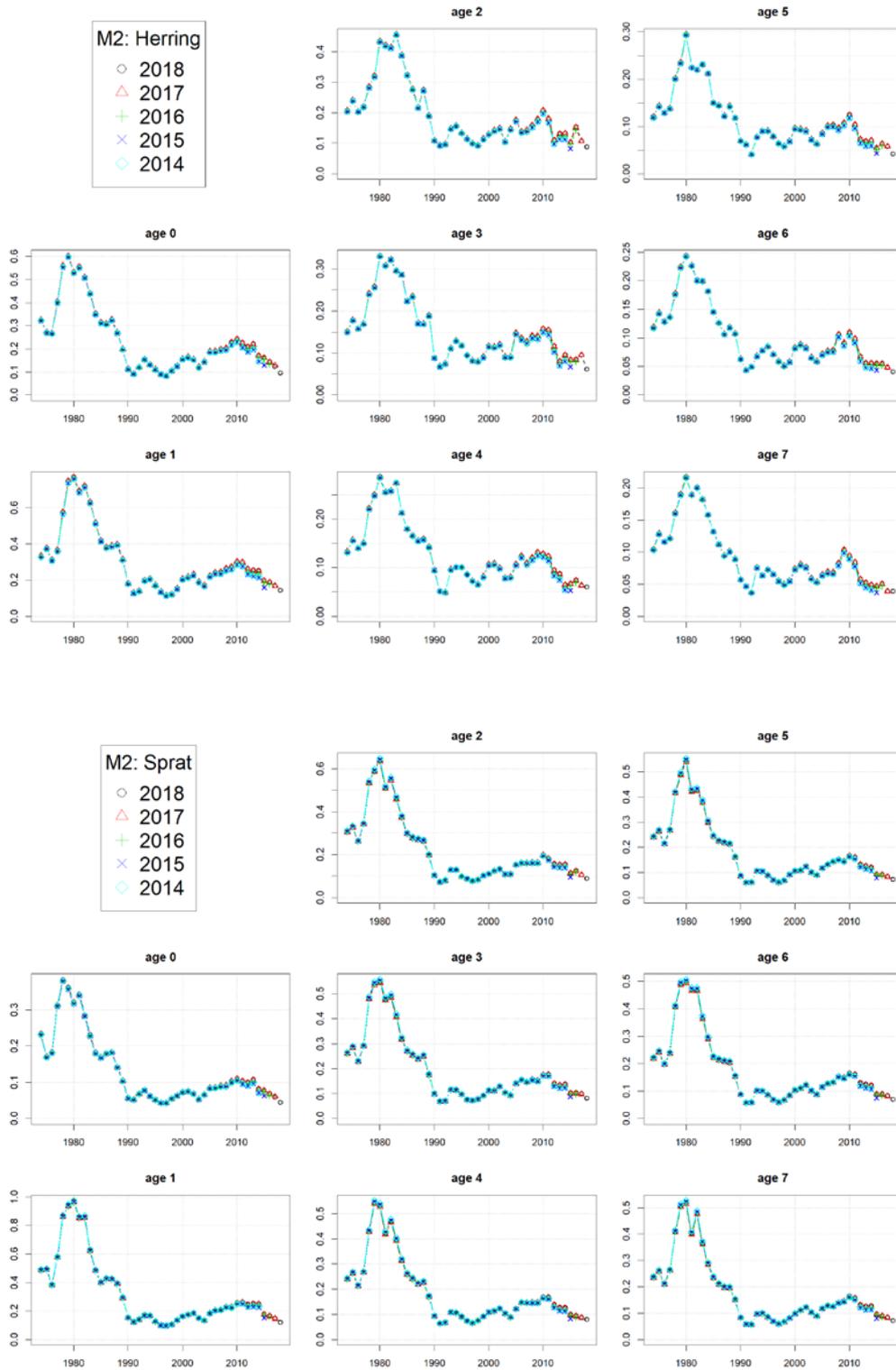


Figure 9.3-51. Retrospective analysis for herring and sprat, M2 at age

5.4. Sensitivity to stomach data (old vs. new stomach data set)

The choice of stomach contents data, “old”, “new” and combined has limited effect on the SMS stock summary output (Figure 9.4-2) or predation mortalities (Figure 9.4-2)

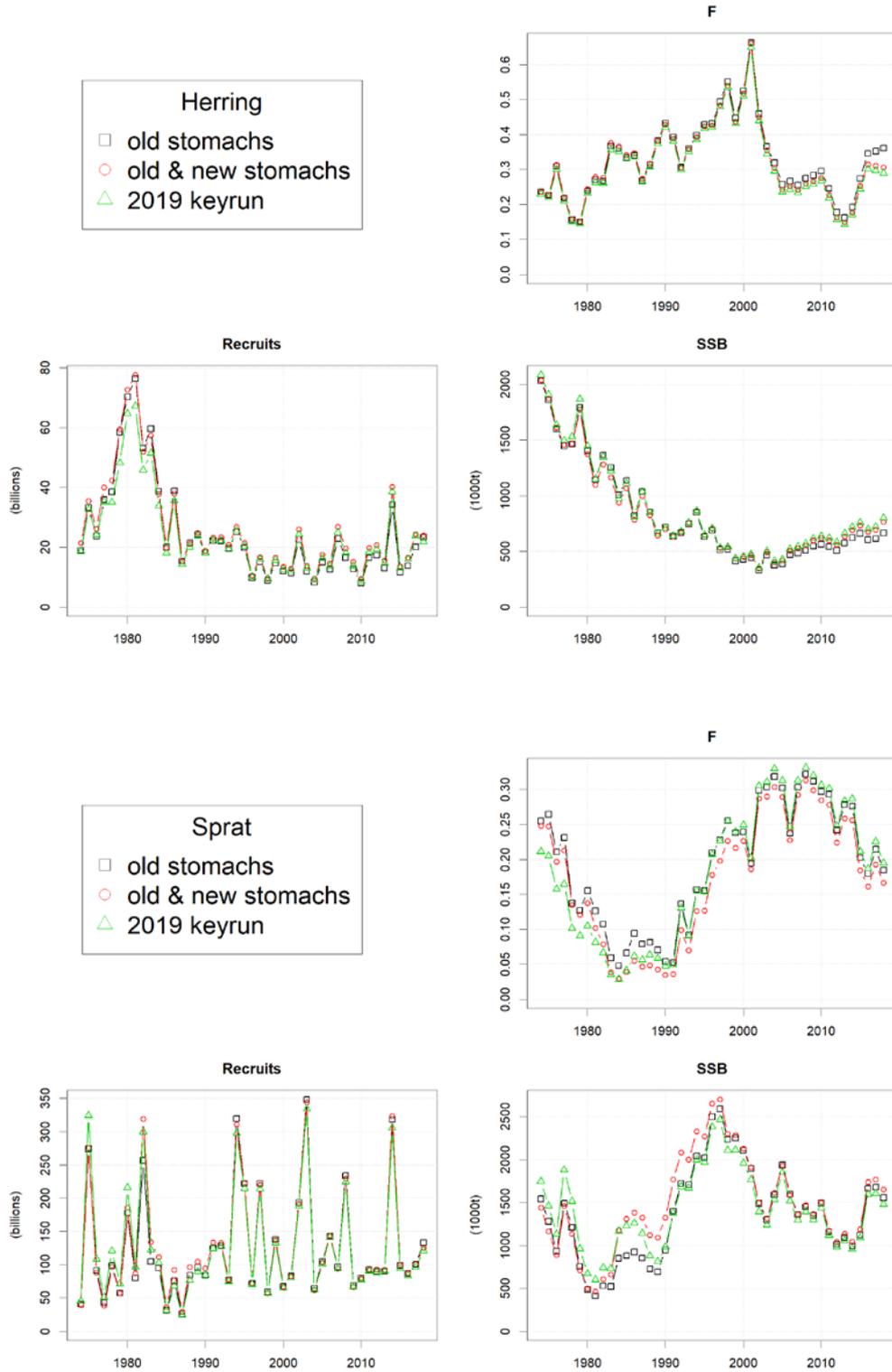


Figure 9.4-52. Comparison of output from SMS runs with combinations of contents data: “old” pooled stomach data, “new” individually sample stomachs. The key run uses only the “new” data.

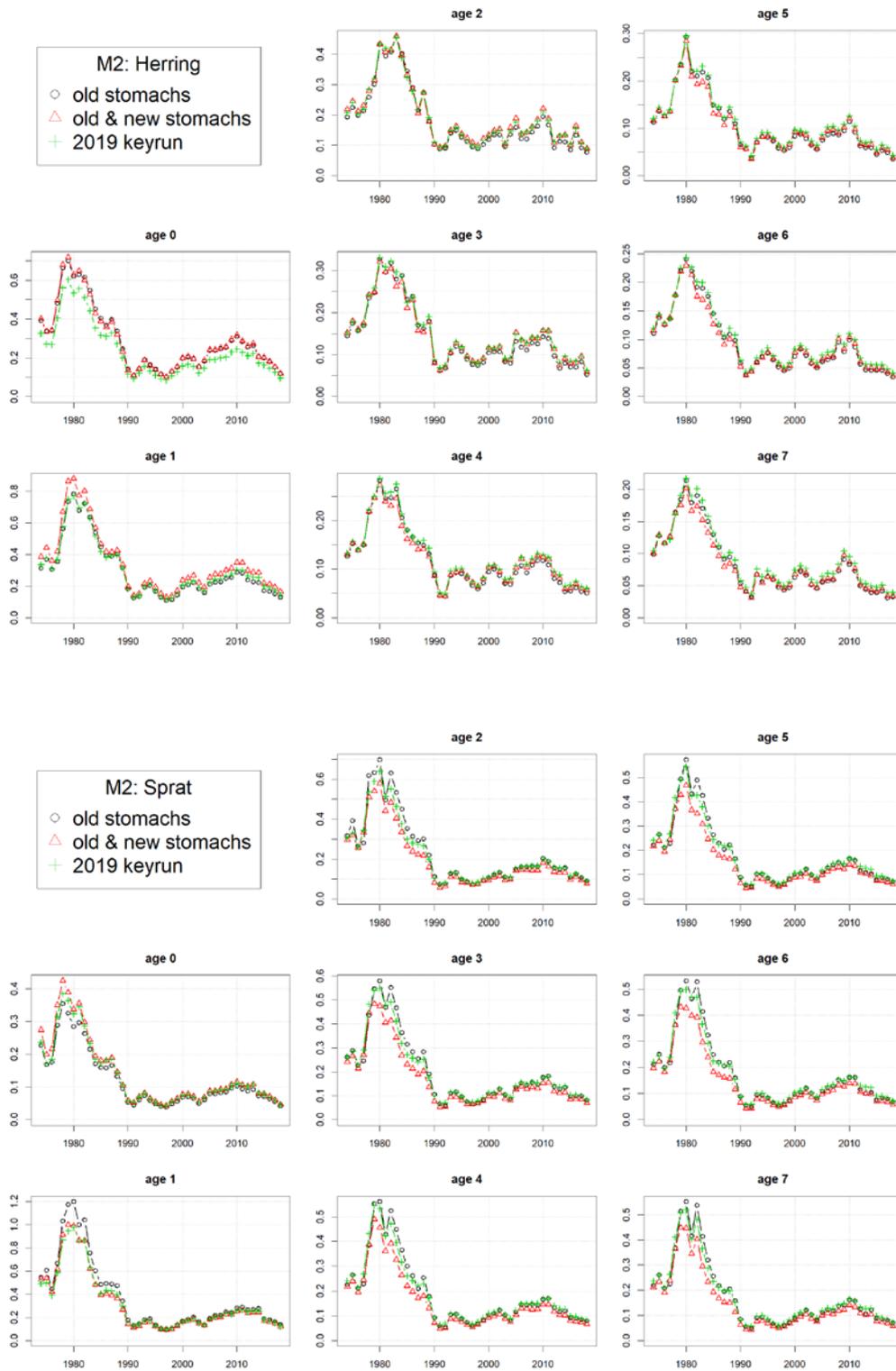


Figure 9.4-53. Comparison of M2 values from SMS runs with combinations of contents data: “old” pooled stomach data, “new” individually sampled stomachs. The key run uses only the “new” data.

5.5. Sensitivity towards using different assumptions for size selection

Three options for predator prey size selection were tried:

1. Log normal size selection (key run): a predator has a preferred prey size ratio and a prey twice as big as the preferred size is as attractive as another half the prey size. The preferred size ratio and its variance are estimated by SMS.
2. Uniform size selection: a size preference at 1 within the range of the observed size ratio and 0 outside that ratio.
3. Constraint uniform size selection: as Uniform size selection, but the size preference ratio is constrained to exclude “outliers” from the observed size ratio, estimated from a quantile regression (Figure 9.5-1).

The main performance statistics of a SMS run for the three size selection models (Table 9.5-1) show the best model likelihood and AIC for the keyrun.

Stock summary output (Figure 9.5-2) and M2 (Figure 9.5-3) are quite sensitive to the choice of size selection option. It seems as if the “constraint uniform” option excludes interactions from medium sized cod on larger herring (Figure 9.5-1) such that M2 on herring ages 4-8 becomes very low. The (unconstraint) “uniform” options includes the full observed predator/prey size ratio which results in a higher M2 for the older herring than for the “constraint uniform” option.

The “constraint uniform” option performed well in the 2012 key run, however there is difference in the quality of stomach contents data used in the old and the new 2019 key run. The old key runs made use of stomach contents data with large size classes for predator preys, e.g. sprat 5-10-15 cm, while the new stomach data uses a much smaller size classes, e.g. by cm group for sprat. With wider size classes, the in predator/prey size ratio becomes imprecise, such that the cutting of “outliers” by the “constraint uniform” options had a limited effect. With the new data, the full range of observations should probably be used, if a uniform size selection option is used.

Table 9.5-27. SMS main performance statistics from a SMS run with the “uniform size selection”, “constraint uniform size selection” and the keyrun.**uniform size selection**

objective function (negative log likelihood): -1166.15
 Number of parameters: 289
 Number of observations used in likelihood: 14892
 Maximum gradient: 0.000624719
 Akaike information criterion (AIC): -1754.31

Number of observations used in the likelihood:

unweighted objective function contributions (total):

	Catch	CPUE	S/R	Stom.	Stom N.	Penalty	Sum
Cod	0.0	0.0	0.0	-173.4	0.0	0.00	-173
Herring	-667.6	-117.3	-12.5	0.0	0.0	0.00	-797
Sprat	-100.9	-106.0	-5.5	0.0	0.0	0.00	-212
Sum	-768.6	-223.3	-18.0	-173.4	0.0	0.00	-1183

constraint uniform size selection

objective function (negative log likelihood): -1110.12
 Number of parameters: 289
 Number of observations used in likelihood: 14892
 Maximum gradient: 3.75233e-005
 Akaike information criterion (AIC): -1642.24

unweighted objective function contributions (total):

	Catch	CPUE	S/R	Stom.	Stom N.	Penalty	Sum
Cod	0.0	0.0	0.0	-182.5	0.0	0.00	-183
Herring	-645.5	-121.1	-8.2	0.0	0.0	0.00	-775
Sprat	-56.8	-103.5	-5.2	0.0	0.0	0.00	-166
Sum	-702.4	-224.7	-13.4	-182.5	0.0	0.00	-1123

Log-normal size selection (key run)

objective function (negative log likelihood): -1232.3
 Number of parameters: 292
 Number of observations used in likelihood: 14892
 Maximum gradient: 5.5994e-007
 Akaike information criterion (AIC): -1880.6

unweighted objective function contributions (total):

	Catch	CPUE	S/R	Stom.	Stom N.	Penalty	Sum
Cod	0.0	0.0	0.0	-256.2	0.0	0.00	-256
Herring	-660.4	-118.7	-8.6	0.0	0.0	0.00	-788
Sprat	-92.3	-104.0	-5.6	0.0	0.0	0.00	-202
Sum	-752.7	-222.7	-14.2	-256.2	0.0	0.00	-1246

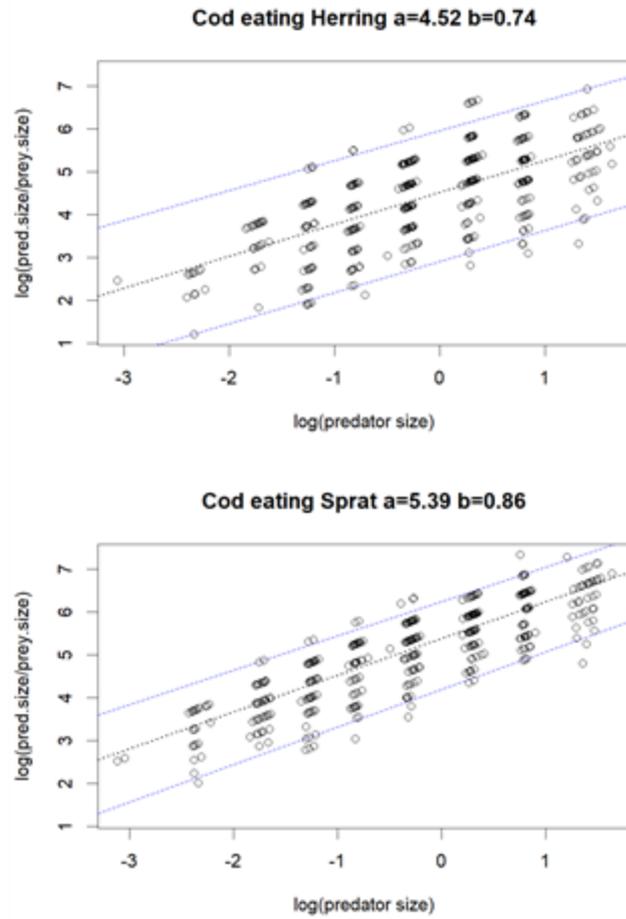


Figure 9.5-54. Quantile regression with observations of predator and predator/prey sizes. The blue lines shows the 2.5% and 97.5 % percentile lines, which defines the “size selection window”.

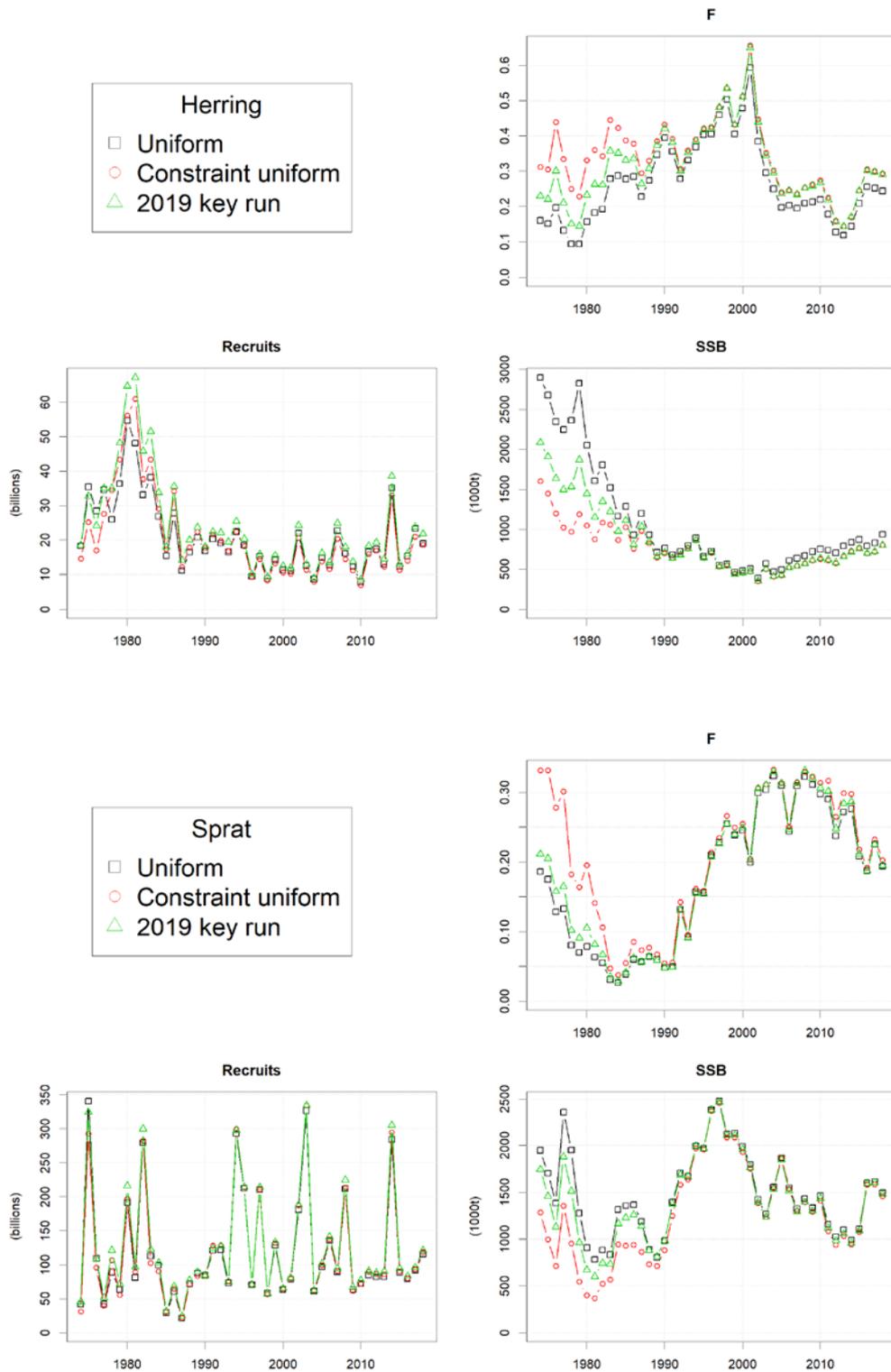


Figure 9.5-55. Comparison of output from SMS runs with three options for predator prey size selection.

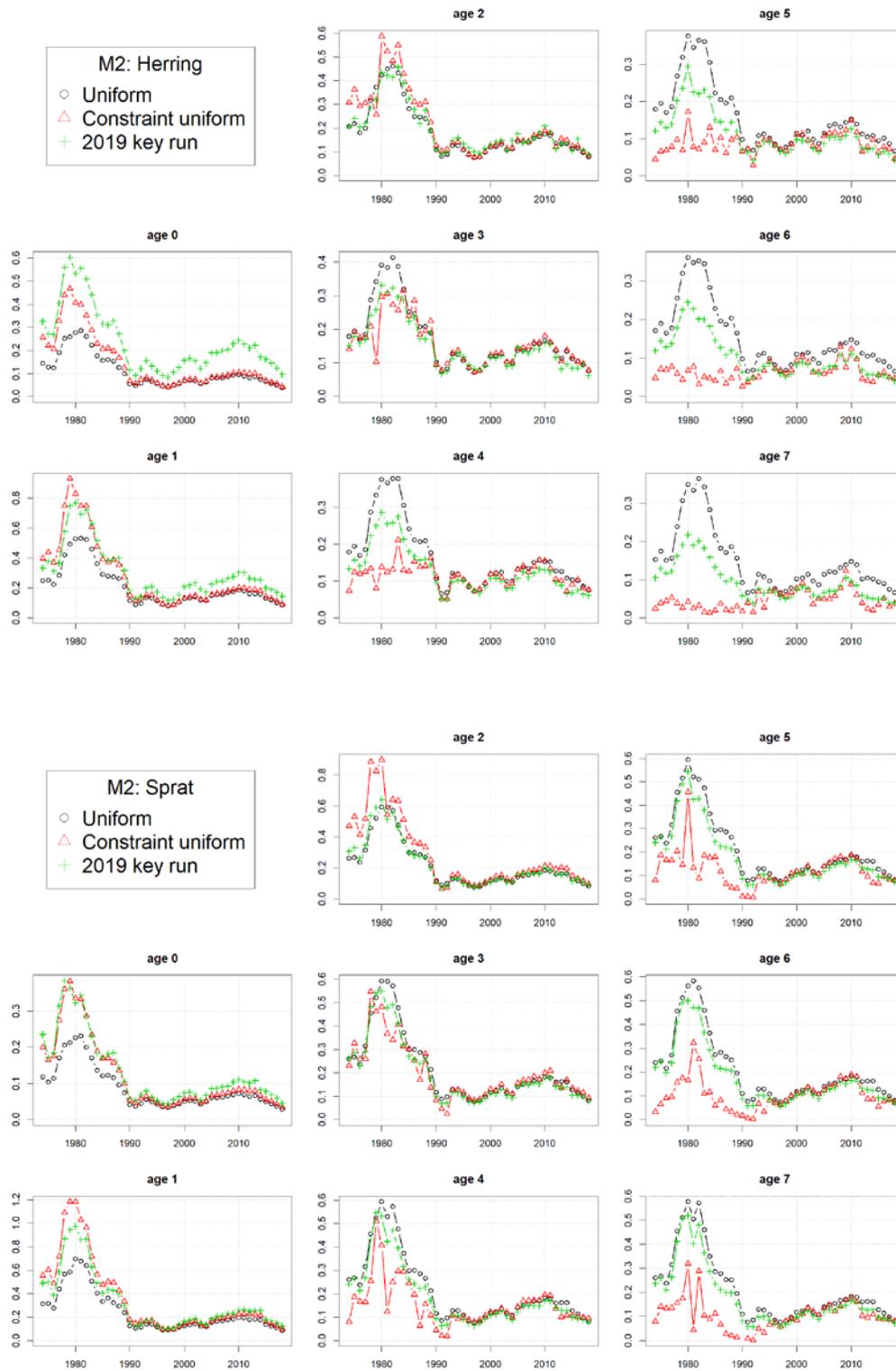


Figure 9.5-56. Comparison of M2 values from SMS runs with three options for predator prey size selection.

5.6. Sensitivity to stomach data (aggregation over a 5 or 10 years period)

Stomachs data are by default aggregated for each combination of year and quarter of the year. For most cases this leads to a rather few stomachs for some of the predator length classes and uncertainties on how partly identified prey items should be assigned. Aggregating stomach data over more years, e.g. 5 or 10 years, provides a larger sample size and a smaller observation uncertainties, but an e.g. "10 years diet" will not reflect the variability in available food for the individual years.

The average likelihood contribution (Table 9.6-1) show that likelihood per stomach contents observation becomes better (more negative) when data are aggregated over some years compared to the keyrun which uses data by year. The best average likelihood for stomach data is obtained using a 5-years aggregation. This may be interpreted that pooling stomach data between year gives a higher precision (more stomachs) of data used by SMS. However, using a very wide year range may negatively affect the fit between "observed" stomach contents and the model estimate of stomach contents calculated for the midpoint of the years used in the data aggregation. Likelihood contributions from For Catch, CPUE and S/R observations are quite the same for the three configurations.

M2 values for the three configurations are differ mainly for age 0 and 1 of herring and sprat (Figure 9.6-1).

Table 9.6-28. Objective function contributions (per observation) from SMS models using stomach contents data aggregated over 5, 10 years and from the keyrun.

5 years aggregation:

	Catch	CPUE	S/R	Stomachs
Cod	0.00	0.00	0.00	-0.28
Herring	-0.46	-0.46	-0.18	0.00
Sprat	-0.08	-0.33	-0.12	0.00

10 years aggregation:

	Catch	CPUE	S/R	Stomachs
Cod	0.00	0.00	0.00	-0.26
Herring	-0.47	-0.45	-0.18	0.00
Sprat	-0.09	-0.33	-0.11	0.00

Keyrun:

	Catch	CPUE	S/R	Stomachs
Cod	0.00	0.00	0.00	-0.16
Herring	-0.46	-0.47	-0.19	0.00
Sprat	-0.07	-0.33	-0.12	0.00

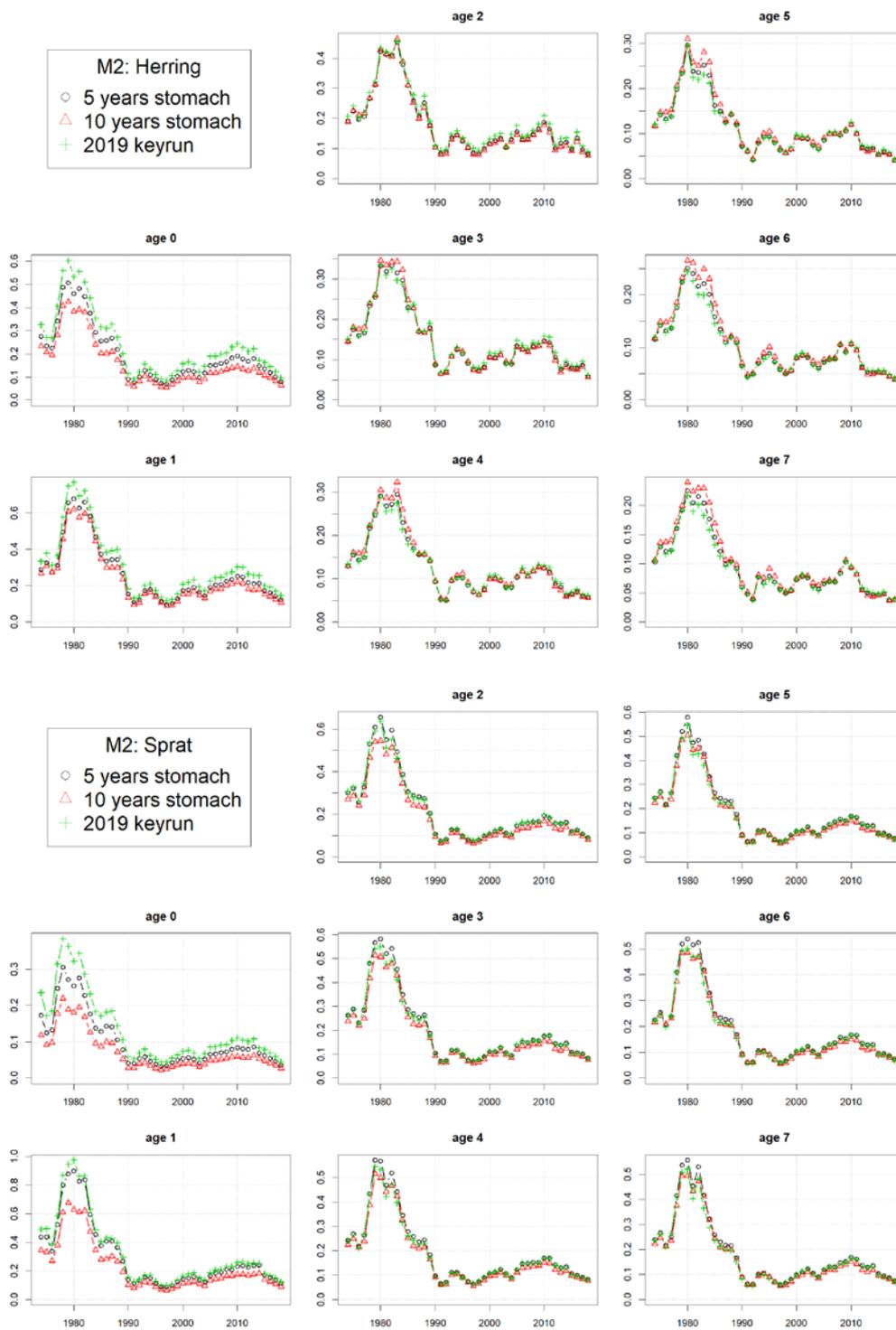


Figure 9.6-57. M2 estimated from SMS runs using stomach contents data aggregated over 5, 10 years and from the keyrun.

5.7. Sensitivity towards using an overlap index for Other Food

The “other food” prey *Saduria entomon* is an important benthic prey item for cod. The occurrence of this prey depends on the oxygen level at the bottom, which have changed considerably in the model timespan.

A time-series of total area (km²) of hypoxic bottoms (between 20 and 100 m depth) was used to develop an index for overlap with *Saduria entomon* and other benthic components, assuming ≤ 1 ml l⁻¹ (approx. 1.4 mg l⁻¹) as threshold for oxygen concentration to indicate failure in benthic productivity. With A_h indicating the hypoxic bottom area, the index was defined as $(A_h / \max A_h)^{-1}$, yielding higher values the smaller the hypoxic area was in a given year. We applied a 5-yr running mean. Weighting the areas with the sub-division specific cod distribution did not change the index time-series except for the last two years with data, 2013 and 2014.

The overlap index between cod and the prey species herring and sprat was left unchanged (assumed 1 throughout the period)

The performance statistics (Table 9.7-1) for the runs with input overlap index and the keyrun are almost the same, even though the key run has a better total model likelihood. The likelihood contributions from stomach observations are the same for the two models.

Stomach contents residuals (Figure 9.7-1) are similar to the keyrun residuals (Figure 9.1-4) but residuals are actually less clustered in positive and negative residuals when the input overlap index is applied.

Table 9.7-29. SMS main performance statistics from a SMS run with input overlap index for Other Food and the keyrun.

Log-normal size selection (key run)

objective function (negative log likelihood): -1232.3

Number of parameters: 292

Number of observations used in likelihood: 14892

Maximum gradient: 5.5994e-007

Akaike information criterion (AIC): -1880.6

unweighted objective function contributions (total):

	Catch	CPUE	S/R	Stom.	Stom N.	Penalty	Sum
Cod	0.0	0.0	0.0	-256.2	0.0	0.00	-256
Herring	-660.4	-118.7	-8.6	0.0	0.0	0.00	-788
Sprat	-92.3	-104.0	-5.6	0.0	0.0	0.00	-202
Sum	-752.7	-222.7	-14.2	-256.2	0.0	0.00	-1246

With input overlap index for Other Food

Objective function (negative log likelihood): -1210.41

Number of parameters: 292

Number of observations used in likelihood: 14892

Maximum gradient: 1.62572e-006

Akaike information criterion (AIC): -1836.83

unweighted objective function contributions (total):

	Catch	CPUE	S/R	Stom.	Stom N.	Penalty	Sum
Cod	0.0	0.0	0.0	-256.3	0.0	0.00	-256
Herring	-662.2	-116.4	-20.4	0.0	0.0	0.00	-799
Sprat	-71.9	-102.3	-5.9	0.0	0.0	0.00	-180
Sum	-734.1	-218.7	-26.3	-256.3	0.0	0.00	-1235



Figure 9.7-58. Stomach contents residuals (“Dirichlet residuals”, Peter Lewy, pers. comm.). The y-axis show prey group and predator (cod) size class. The x-axis is time period sorted by year and quarter. Green dots show that the observed stomach contents are lower than the model estimate.

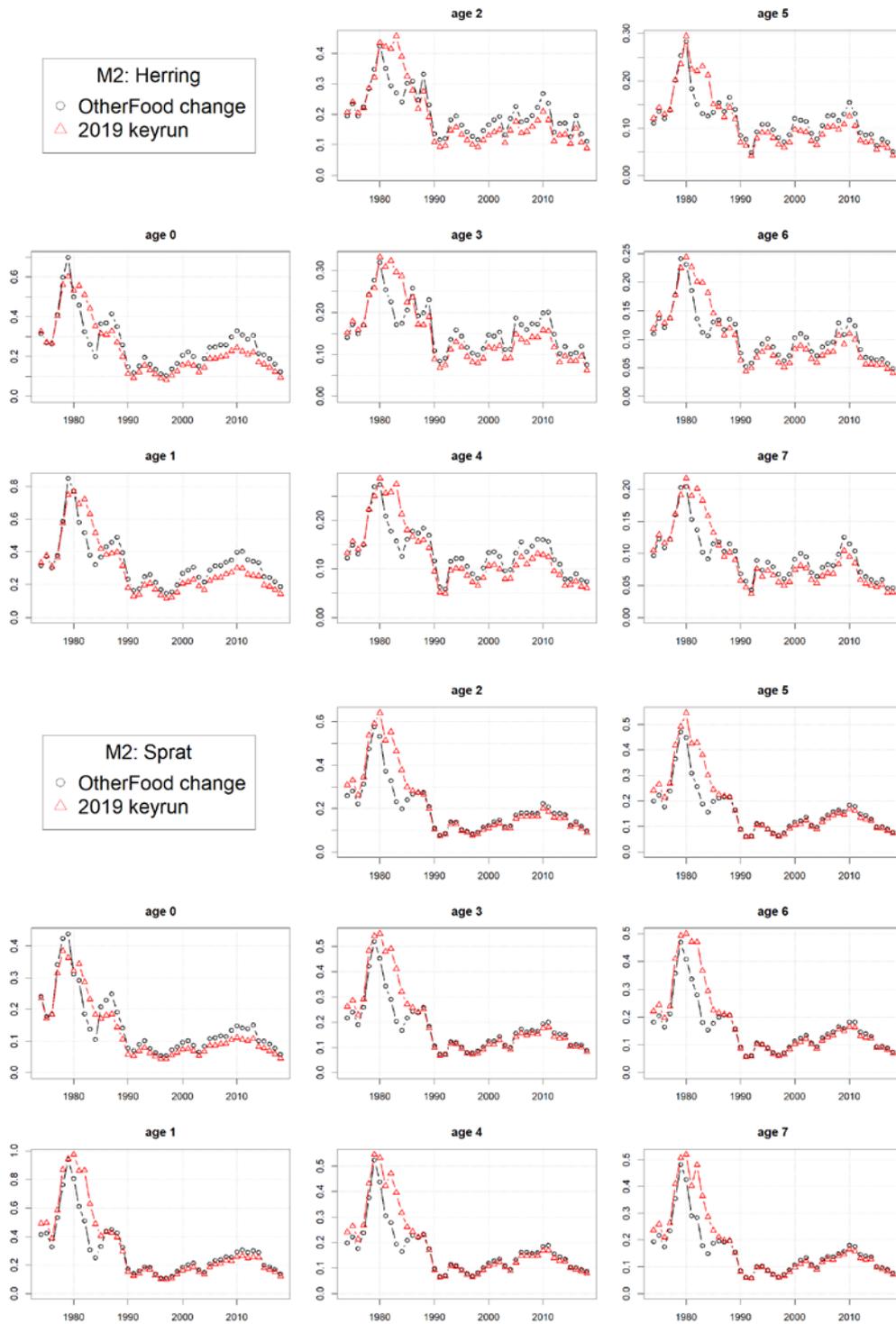


Figure 9.7-59. M2 estimated from a SMS run with input overlap index for Other Food and from the keyrun.

5.8. Sensitivity towards consumption rates

SMS can estimate a scaling factor for the input consumption rate by species. For cod this was estimated to 0.47, with a standard deviation at 0.07. This run was used to illustrate the sensitivity of M2 to consumption rates.

The performance statistics (Table 9.8-1 and Table 6.4-1) show a slightly better fit, when the factor to the input consumption rate is applied. Likelihood contribution from stomach becomes better on the cost of the likelihood for catch at age.

M2 values are lower when a considerably lower consumption rate are applied, but the reduction is not linear to the reduction in consumption, as expected (Figure 9.8-1). The reduction in M2 is larger for herring than for sprat.

Table 9.8-30 SMS main performance statistics from a SMS run with input overlap index for Other Food and the keyrun.

Log-normal size selection (key run)

objective function (negative log likelihood): -1232.3
 Number of parameters: 292
 Number of observations used in likelihood: 14892
 Maximum gradient: 5.5994e-007
 Akaike information criterion (AIC): -1880.6

unweighted objective function contributions (total):

	Catch	CPUE	S/R	Stom.	Stom N.	Penalty	Sum
Cod	0.0	0.0	0.0	-256.2	0.0	0.00	-256
Herring	-660.4	-118.7	-8.6	0.0	0.0	0.00	-788
Sprat	-92.3	-104.0	-5.6	0.0	0.0	0.00	-202
Sum	-752.7	-222.7	-14.2	-256.2	0.0	0.00	-1246

With input consumption rates *0.47

objective function (negative log likelihood): -1244.78
 Number of parameters: 293
 Number of observations used in likelihood: 14892
 Maximum gradient: 6.23567e-005
 Akaike information criterion (AIC): -1903.57

unweighted objective function contributions (total):

	Catch	CPUE	S/R	Stom.	Stom N.	Penalty	Sum
Cod	0.0	0.0	0.0	-273.5	0.0	0.00	-273
Herring	-659.6	-119.9	-16.1	0.0	0.0	0.00	-796
Sprat	-87.2	-103.6	-5.4	0.0	0.0	0.00	-196
Sum	-746.7	-223.5	-21.5	-273.5	0.0	0.00	-1265

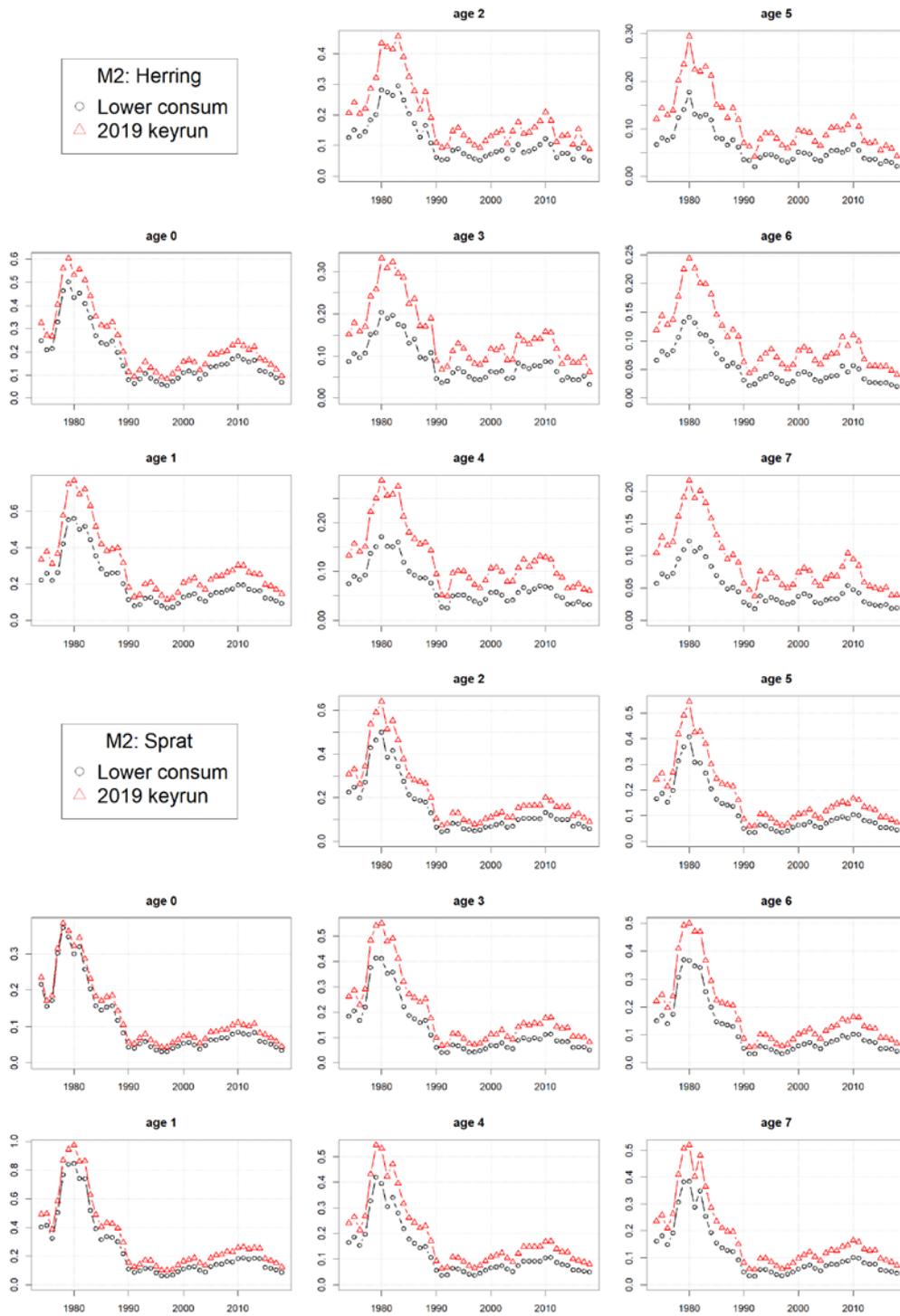


Figure 9.8-60. M2 estimated from a SMS run with lower (47%) consumption rates the keyrun.

5.9. Comparison with the old 2012 keyrun

Even though the 2012 and the 2019 key run are based on different stomach data, different assumption about the only predator species and different M1, the two key runs shows quite similar results for the summary output recruitment, SSB and mean F (Figure 9.9-1). Herring F and SSB are similar, while recruitment is considerably higher in the beginning of the time-series in the 2019 key run, probably as an effect of the assumed larger cod stock. For Sprat, the trend in SSB and F is the same in the two runs, but F in the 2019 keyrun is consistently estimated lower and SSB higher.

The difference in M2 for the two runs is more pronounced, especially for herring (Figure 9.9-2). Herring M2 is now estimated higher for all ages, and much higher for the first part of the time-series. The difference is probably due to the assumption of a larger cod stock (especially of larger cod) in the 2019 key run, and the application of the predator-prey size selection model in the new keyrun, whereas the old version used a “constrained uniform” size selection. Herring M2 follows better the stock size of cod in the new run which may indicate that the uniform size selection option was not the best choice for the 2012 key run.

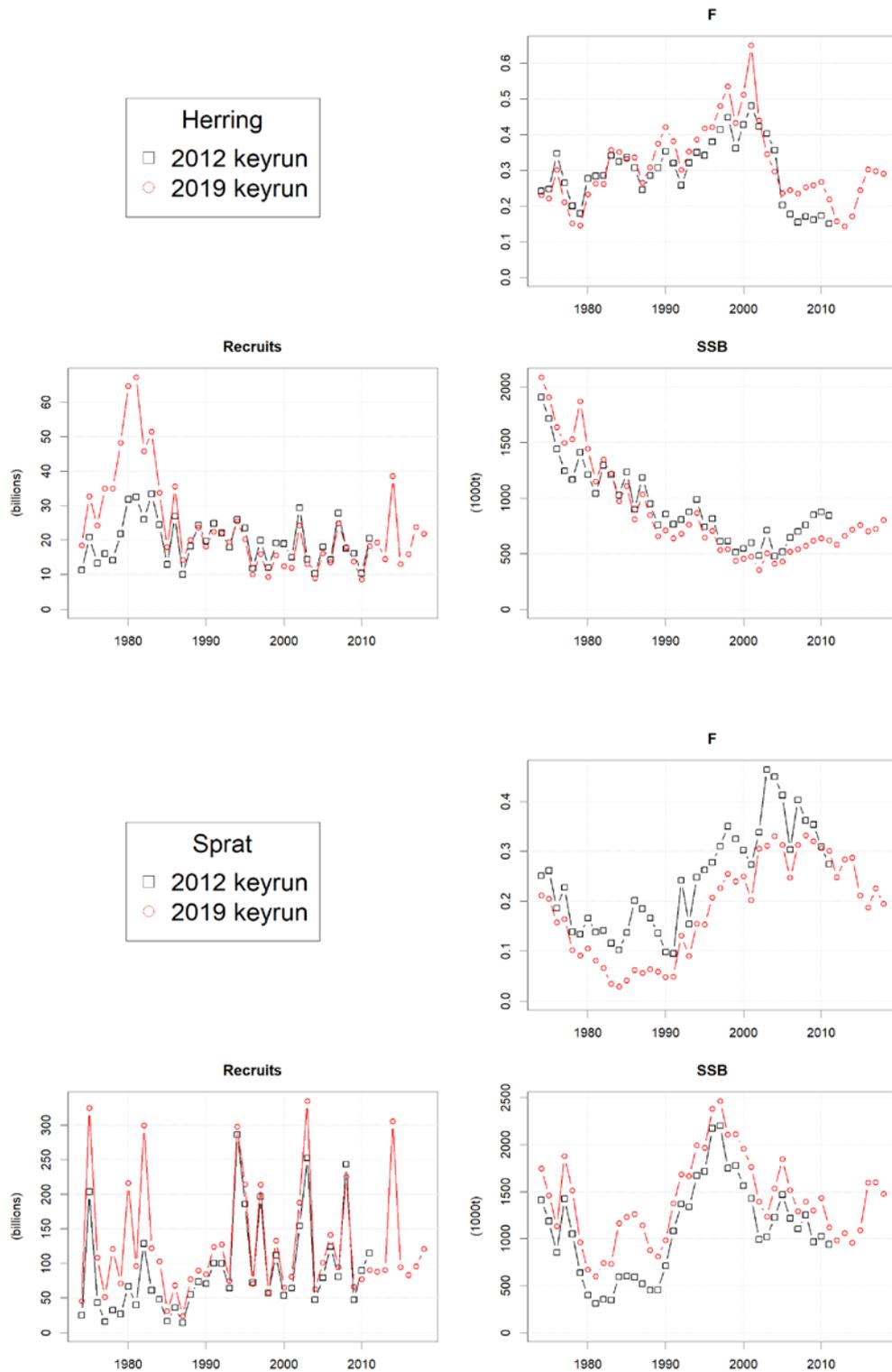


Figure 9.9-61. Comparison of the 2012 key run and the new 2019 key run. Summary output.

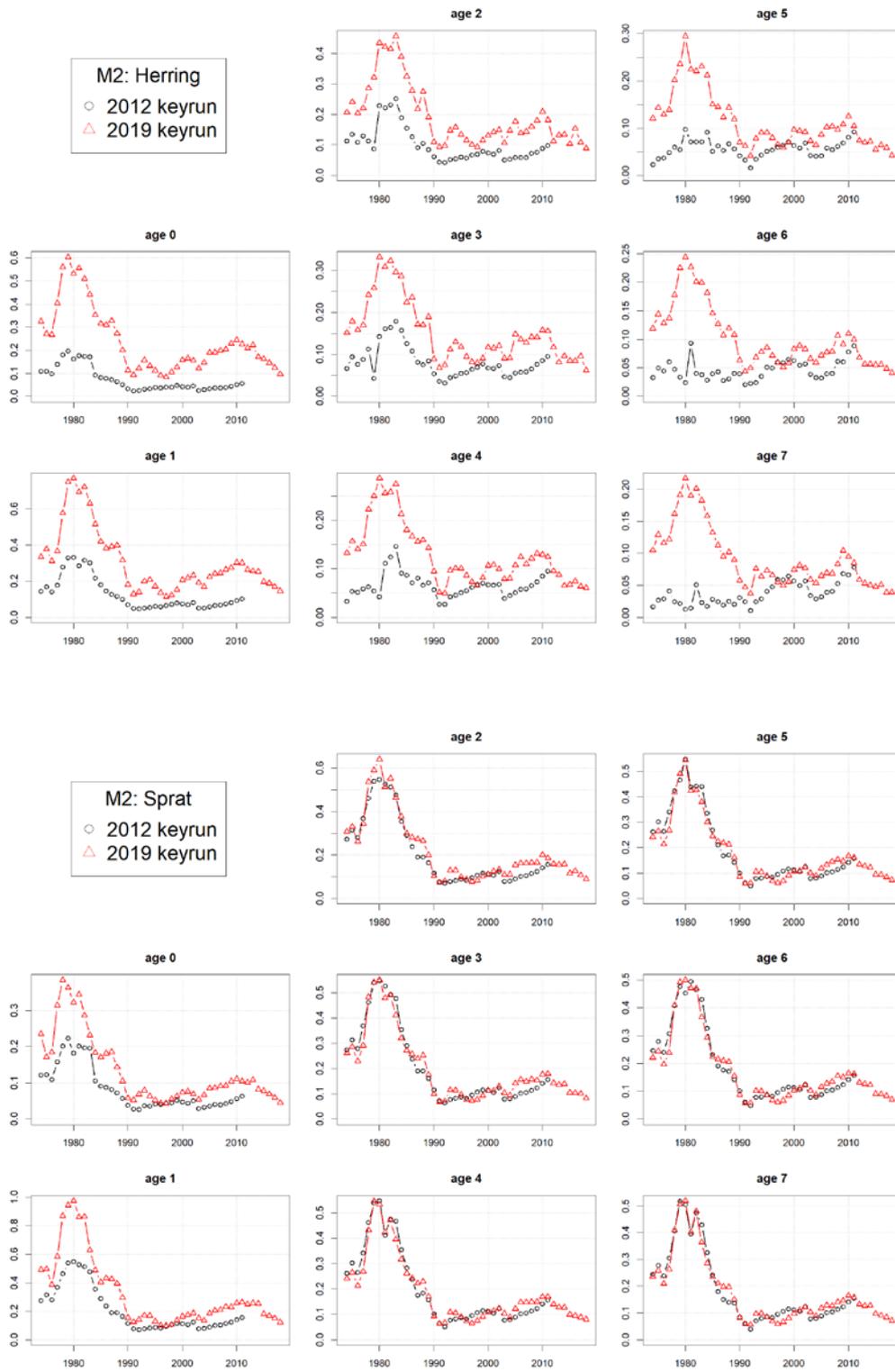


Figure 9.9-62. Comparison of the 2012 key run and the new 2019 key run. Predation mortality (M2).

5.10. Comparison with the Gadget model run

A comparison of the SMS results and the results from the Gadget model presented the last day of WGSAM is presented for herring (Figure 9.10-1) and for sprat (Figure 9.10-2). The estimated M values are quite similar.

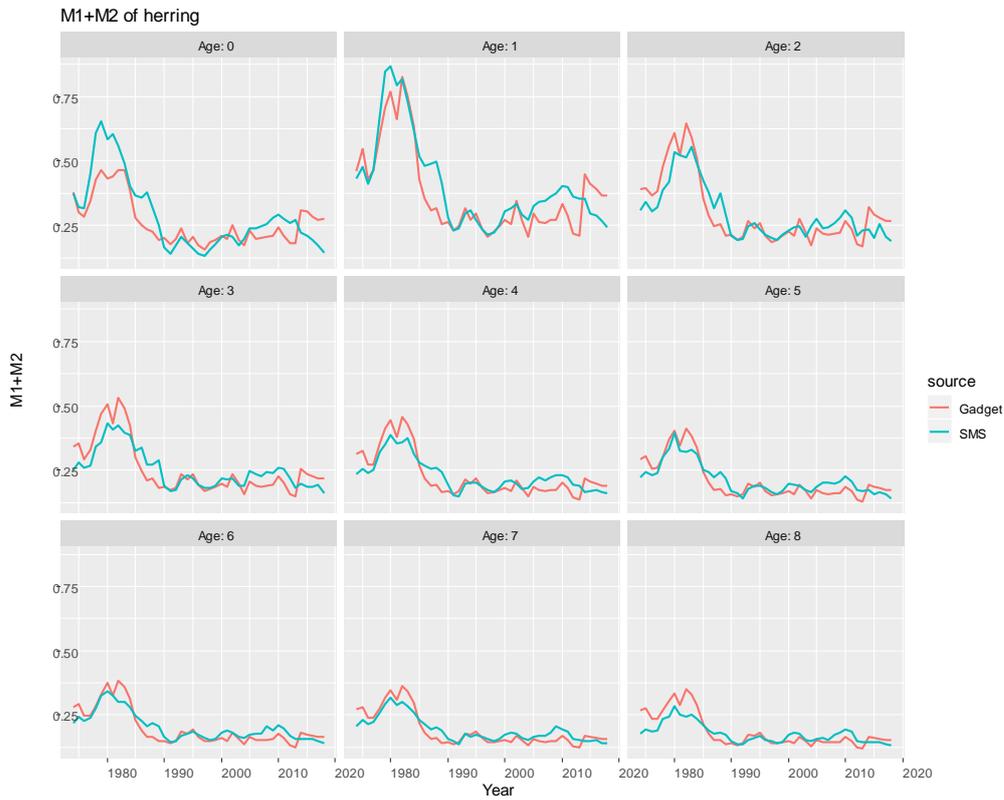


Figure 9.10-63. Comparison of M ($M=M1+M2$) values for herring from the SMS keyrun and the Gadget configuration.

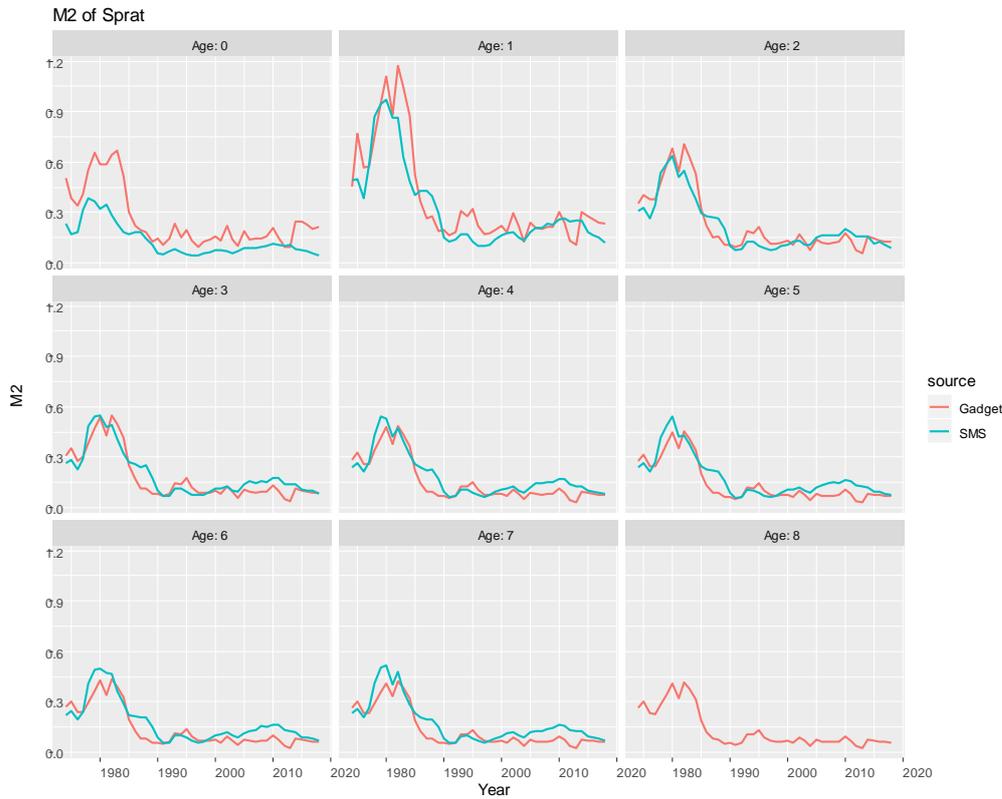


Figure 9.10-64. Comparison of M ($M=M1+M2$) values for sprat from the SMS keyrun and the Gadget configuration.

5.11. Conclusion, 2019 key run

WGSAM 2019 discussed and reviewed the changes in input data and the results in detail and concluded that:

The key-run as currently best possible run with SMS to provide natural mortality estimates. WGSAM recommends to use these values as input to single species stock assessments. The full time-series should be used and not only an update for the years after the last key-run in 2012.

However, there are also clear limitations with the approach and results have been shown to be sensitive to e.g., consumption rates, assumptions regarding M1 and treatment of “Other Food” as well as the size selectivity of cod. In addition, the results depend to a large extent on the outcome of the ICES Eastern Baltic cod assessment. Any bias in this assessment directly influences the predation mortality estimates. Assumptions around other food and constant vulnerabilities may also bias the natural mortality estimates to some extent. Contrarily, the very similar results from the Gadget model run are encouraging and increase the credibility of the provided M time-series.

WGSAM does not recommend using the uncertainty estimates around M as these are underestimated due to the assumption that the cod population is known without error.

5.12. Identified areas of priority research

The WGSAM 2019 recommended

1. More analyses on stomach data to get a better process understanding what is driving the systematic changes in relative stomach contents.

2. A split of Other Food in parts where the time dynamic can be taken into account (e.g., flatfish and *Saduria entomon*) and a part that still needs to be assumed constant in time may be beneficial.
3. The inclusion of spatial dynamics (either directly or via overlap coefficients) may improve the fit to data sources.
4. A run with age 1 as recruits could be tried because input for the 0 group is highly uncertain.
5. Account for the uncertainty in cod numbers in the model.

APPENDIX 1: SMS, a stochastic age–length structured multispecies model applied to North Sea and Baltic Sea stocks

Working document to ICES WKMULTBAL, March 2012

By Morten Vinther and Peter Lewy,

DTU Aqua. Technical University of Denmark, National Institute of Aquatic Resources, Charlottenlund Castle, DK-2920 Charlottenlund, Denmark.

Overview

SMS (Stochastic Multi Species model) is a fish stock assessment model in which includes estimation of predation mortalities from observation of catches, survey indices and stomach contents. Estimation of predation mortality is based on the theory for predation mortality as defined by Andersen and Ursin (1977) and Gislason and Helgason (1985). SMS is a “forward running” model that operates with a chosen number of time steps (e.g. quarters of the year). The default SMS is a one-area model, but the model has options for spatial explicit predation mortality given a known stock distribution.

Model parameters are estimated using maximum likelihood (ML) technique. Uncertainties of the model parameters are estimated from the Hessian matrix and confidence limits of derived quantities like historical fishing mortalities and stock abundances are estimated from the parameter estimates and the delta-method. SMS can be used to for forecast scenarios and Management Strategy Evaluations, where fishing mortalities are estimated dynamically from Harvest Control Rules.

This document describes the model structure and the statistical models used for parameter estimation.

Model Structure

Survival of the stocks

The survival of the stocks is described by the standard exponential decay equation of stock numbers (N).

$$N_{s,a,y,q+1} = N_{s,a,y,q} e^{-Z_{s,a,y,q}} \quad \text{Eq. 1}$$

or

$$\begin{aligned} N_{s,a+1,y,+1,q=1} \\ = N_{s,a,y,q=\text{last season}} e^{-Z_{s,a,y,q=\text{last season}}} \end{aligned} \quad \text{Eq. 2}$$

The instantaneous rate of total mortality, $Z_{s,a,y,q}$ by species s , age group a , year y and season q , is divided into three components; predation mortality (M2), fixed residual natural mortality (M1) and fishing mortality (F):

$$Z_{s,a,y,q} = M1_{s,a,q} + M2_{s,a,y,q} + F_{s,a,y,q}$$

For non-assessment species which act as predators (e.g. grey seal and horse mackerel) stock numbers are assumed known and must be given as input.

Fishing mortality

Fishing mortality, $F_{s,a,y,q}$ is modelled from an extended separable model including age, year and season effects. However, as these effects may change over time a more flexible structure is assumed, allowing for such changes for specified periods. For convenience, the species index is left out in the following:

$$F_{a,y,q} = F_{Y,A1}^1 F_y^2 F_{Y,A2,q}^3 \tag{Eq. 3}$$

where indices $A1$ and $A2$ are grouping of ages, (e.g. ages 1–3, 4–7 and 8–9) and Y is grouping of years (e.g. 1975–1989, 1990–2011).

Eq. 3 defines that the years included in the model can be grouped into a number of period clusters (Y), in which the age selection (F^1) and seasonal selection (F^3) are assumed constant. F^2 is the year effect, specifying the overall level of F for a particular year. The grouping of ages for age selection, $A1$, and season selection, $A2$, can be defined independently.

2.2.1 Options for year effect

Given a good relationship between F and effort the fishing mortality can be calculated from the observed effort.

$$F_{a,y,q} = F_{Y,A1}^1 EFFORT_y F_{Y,A2,q}^1$$

Natural Mortality

Natural mortality is divided into two components, predation mortality (M2) caused by the predators included in the model and a residual natural mortality (M1), which is assumed to be known and is given as input.

M2 of a prey species, $prey$, with size group l_{prey} due to a predator species, $pred$, with size group l_{pred} is calculated as suggested by Andersen and Ursin (1977) and Gislason and Helgason (1985).

$$M2_{prey,l_{prey},y,q} = \sum_{pred} \sum_{l_{pred}} \frac{\bar{N}_{pred,l_{pred},y,a} RA_{pred,l_{pred},y,q} S_{prey,pred,q}(l_{prey}, l_{pred})}{AB_{pred,l_{pred},y,a}} \tag{Eq. 4}$$

where RA denotes the total food ration (weight) of one individual predator per time unit, where S denotes the food suitability defined in section 10.2.3.2 and where AB is the total available (suitable) biomass. AB is defined as the sum of the biomass of preys weighted by their suitability. This total prey biomass includes also the so-called “other food” (OF) which includes all prey items not explicitly modelled, e.g. species of invertebrates and non-commercial fish species. Other food species are combined into one group, such that the total available prey biomass becomes:

$$AB_{pred,l_{pred},y,q} = \sum_{prey} \sum_{l_{prey}} \left(\bar{N}_{prey,l_{prey},y,q} W_{prey,l_{prey},y,q} S_{prey,pred,q}(l_{prey},l_{pred}) \right) + OF_{pred}, S_{OF,pred,q}(l_{pred}) \quad \text{Eq. 5}$$

M2 cannot directly be calculated from Eq. 4 because M2 also is included in the right hand term in Eq. 6 to calculate \bar{N} .

$$\bar{N} = \frac{N(1 - e^{-(M1+M2+F)})}{M1 + M2 + F} \quad \text{Eq. 6}$$

As no analytical solution for $M2$ exists, $M2$ has to be found numerically. If the time step considered is sufficiently small, for instance a quarter, $M2$ becomes small and can optionally be approximated by replacing the average number during the season, \bar{N} , on the right hand side of Eq. 4 by the stock at the beginning of the season, N . As the right hand side of equation now is independent of $M2$ this quantity can be calculated directly from Eq. 4 where AB (Eq. 5) is modified correspondingly.

Use of size distribution by age

The equations outlined in the section above provide $M2$ at-size groups. However, predation mortality by age is needed as well because F and catches are age-structured. If just one size group per age group of predators and preys is assumed Eq. 4 can be used directly where the age index substitutes the size group index in stock numbers ($\bar{N}_{prey,a,y,q} = \bar{N}_{prey,l_{prey},y,q}$)

Given more size groups per age, the calculation of $M2$ at-age requires age-length-keys to split N at age to N at size group.

$$N_{s,l_s,y,q} = \sum_a N_{s,a,y,q} ALK_{s,a,l_s,y,q} \quad \text{Eq. 7}$$

where $ALK_{s,l_s,a,y,q}$ denotes the observed proportion of size group l_s for a given species and age group, i.e. $\sum_{l_s} ALK_{s,l_s,a,y,q} = 1$

Assuming that F and $M1$ depends only of the age and that $M2$ only depends of the length, $M2$ at-age is estimated by: (leaving out the species, year and quarter indices).

$$M2_a = Z_a \frac{\sum_l \bar{N}_{a,l} M2_{a,l}}{D_a} = \log\left(\frac{N_a}{N_a - D_a}\right) \frac{\sum_l \bar{N}_{a,l} M2_l}{D_a}$$

where

$$\bar{N}_{a,l} = N_{a,l} \frac{1 - e^{-(F_{a,l} + M1_{a,l} + M2_{a,l})}}{F_{a,l} + M1_{a,l} + M2_{a,l}} = N_{a,l} \frac{1 - e^{-(F_a + M1_a + M2_l)}}{F_a + M1_a + M2_l}$$

and where

$$D_a = \sum_l \bar{N}_{a,l} (F_a + M1_a + M2_l)$$

denotes the number of individuals at-age died within a season.

Food suitability

As suggested by Andersen and Ursin (1977) and Gislason and Helgason (1985) the size-dependent food suitability of prey entity j for predator entity i is defined as the product of a species dependent vulnerability coefficient, $\rho_{i,j}$, a size preference coefficient $q_{i,j}(l_i, l_j)$, and an overlap index $o_{i,j,q}$. Suitability is then defined as:

$$S_{pred,prey,q}(l_{pred}, l_{prey}) = \rho_{pred,prey} q_{pred,prey}(l_{pred}, l_{prey}) o_{pred,prey,q} \quad \text{Eq. 8}$$

For the “other food” part suitability is defined as:

$$S_{OF,pred,q}(l_{pred}) = \rho_{OF,pred} o_{OF,pred,q} \exp\left(v_{pred} \log\left(W_{pred,l_{pred,q}}/\bar{W}_{pred}\right)\right) \quad \text{Eq. 9}$$

Where \bar{W}_{pred} is the average size of the predator species. Eq. 9 extends the original equation, to allow size dependent suitability for other food, for values of v_{pred} different from zero. The overlap index may change between seasons, but is assumed independent of year and sizes.

Log-normal distributed size selection

Several functions can be used for size preference of a prey. Andersen and Ursin (1977) assumed that a predator has a preferred prey size ratio and that a prey twice as big as the preferred size is as attractive as another half the prey size. This was formulated as a log-normal distribution:

$$q_{pred,prey}(l_{pred}, l_{prey}) = \exp\left(-\frac{\left(\log\left(\frac{W_{l_{pred}}}{W_{l_{prey}}}\right) - \eta_{PREF\ pred}\right)^2}{2\sigma_{PREF\ pred}^2}\right); 0 < q \leq 1 \quad \text{Eq. 10}$$

Where η_{PREF} is the natural logarithm of the preferred size ratio, σ_{PREF}^2 is the "variance" of relative preferred size ration, expressing how selective a predator is with respect to the size of a prey and where W_s is the mean weight for a species size group.

The basic size selection equation (Eq. 10) has been extended by modifying the preferred size ratio parameter.

$$q_{pred,prey}(l_{pred}, l_{prey}) = \exp\left(-\frac{\left(\log\left(\frac{W_{l_{pred}}}{W_{l_{prey}}}\right) - \left(\eta_{PREF\ pred} + \xi_{prey} + \varpi_{pred} \log(W_{l_{pred}})\right)\right)^2}{2\sigma_{PREF\ pred}^2}\right) \quad \text{Eq. 11}$$

Where ξ_{prey} specify a prey-specific adjustment term for the preferred size ratio, and where ϖ_{pred} specifies how the preferred size range can change by predator size.

Uniform size selection

Alternatively, a uniform size preference can be assumed within the range of the observed size ratio and zero size selection outside that ratio:

$$Q_{pred,prey}(l_{prep}, l_{prey}) = \begin{cases} 1 & \text{for } \eta_{MIN_{pred,prey}} \leq \frac{W_{l_{pred}}}{W_{l_{prey}}} \leq \eta_{MAX_{pred,prey}} \\ 0 & \text{for values outside observed range} \end{cases} \quad \text{Eq. 12}$$

where η_{MIN} and η_{MAX} are the observed minimum and maximum predator/prey size ratios.

Constraint uniform size selection

The uniform size preference does not take into account that the preferred predator/prey size ratio might change by size, such that larger individuals select relatively smaller preys (Floeter and Temming, 2005; Sharft *et al.*, 2000). A way to account for that is to assume that the fixed minimum and maximum constants, η_{MIN} and η_{MAX} , depend on the predator size:

$Q_{pred,prey}(l_{pred}, l_{prey}) = \begin{cases} 1 & \text{for } U1_{pred,prey} + U2_{pred,prey} \log(W_{l_{pred}}) \leq \log\left(\frac{W_{l_{pred}}}{W_{l_{prey}}}\right) \leq U3_{pred,prey} + U4_{pred,prey} \log(W_{l_{pred}}) \\ 0 & \text{for values outside regression range} \end{cases}$	Eq. 13
--	--------

The regression parameters are estimated externally by quantile regression (e.g. Koenker and Bassett, 1978) using e.g. the 2.5% and 97.5% percentiles of stomach content data. Figure 7.1 shows an example of such regression.

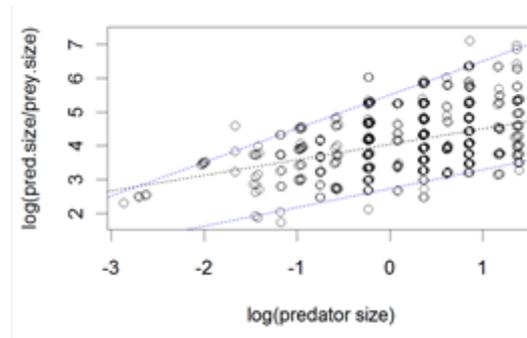


Figure 7.1. Quantile regression of stomach contents observations (Baltic cod eating cod), with 2.5%, 50% and 97.5% lines shown. Predator and prey size in weight.

Adjustment of age–size keys

For the North Sea configuration, age length keys were obtained from the IBTS surveys where the same gear (i.e. the GOV trawl) has been used in the period considered. This allows an adjustment of the observed ALK’s to account for mesh size selection. Using a logistic length-dependent selection function, selection is defined as:

$$SL_s(l) = 1 / (1 + e^{(S1_s - S2_s * l)})$$

Where $S1_s$ and $S2_s$ are species-specific gear selection parameters.

The adjusted ALK can then be derived from the observed ALK by:

$$ALK_{s,l_s,a,y,a} = \text{ObservedALK}_{s,l_s,a,y,q} / SL_{s,l_s}$$

which finally has to be standardised to 1 for each age before used in Eq. 7.

Growth

Not implemented yet!

Food ration

Food ration, RA, pr. time step is given as input or estimated from mean weight by size group assuming an exponential relationship between ration and body weight W.

$$RA_{pred,l_{pred},q} = \gamma_{pred,q} W_{pred,l_{pred}}^{\zeta} \tag{Eq. 2}$$

where the coefficient γ and ζ are assumed to be known.

Body weight at-size group l_{pred} is estimated from mean length within the size group and a length-weight relationship.

Area-based SMS

SMS has three area explicit options:

- 1) Default one area model. Both F and M2 are calculated for the entire stock area; M2 by area. M2 is calculated by subareas, but F is assumed global;
- M2 and F by area. Both M2 and F are calculated by area (forecast only).

Stock distribution

For the area-based models, the stock is assumed redistributed between areas between each seasonal time step.

$$N_{s,a,y,q}^{area} = N_{s,a,y,q} DIST_{s,a,y,q,area}$$

Where

DIST is a stock distribution key that sums up to 1

$$\sum_{area} DIST_{s,a,y,q,area} = 1$$

The

calculation of M2 for Option 1) is provided in the previous section.

The method for option 3) is very similar, but the calculations must be done by each subarea separately.

$$Z_a^{area} = F_a^{area} + M1_a^{area} + M2_a^{area}$$

where $M2^{area}$ is calculated as given in Eq. 4.

Option 2) is the hybrid, where F is global but M is calculated by area.

$$Z_a^{area} = F_a + M1_a^{area} + M2_a^{area}$$

\bar{N} in an area is calculate in the usual way

$$\bar{N}_a^{area} = N_a^{area} \frac{1 - e^{-Z_a^{area}}}{Z_a^{area}}$$

The total number of individuals died due to predation mortality (DM2) then becomes:

$$DM2_a = \sum_{area} M2_a^{area} \bar{N}_a^{area} \quad \text{Eq. 3}$$

M2 for the whole stock can be estimated from:

$$M2_a = \log\left(\frac{N_a}{N_a - D_a}\right) \frac{DM2_a}{D_a}$$

where

$$D_a = \sum_{area} DF_a^{area} + DM1_a^{area} + DM2_a^{area}$$

and DF and DM1 are the number died due to fishery and residual mortality (M1) and are calculated in similar ways as specified for DM2 (Eq. 3).

Area based suitability parameters

For the "one area" SMS suitability is defined by Eq. 8.

The area-based version of suitability uses an area-specific vulnerability and overlap index, while the size preference (ϱ) is assumed independent of area.

$$S_{pred,prey,q}^{area}(l_{pred}, l_{prey}) = \rho_{pred,prey}^{area} \varrho_{pred,prey}(l_{pred}, l_{prey}) \sigma_{pred,prey,q}^{area}$$

Statistical models

Three types of observations are considered: Total international catch-at-age; survey abundance indices and relative stomach content. For each type, a stochastic model is formulated and the likelihood function is calculated. As the three types of observations are independent, the total log likelihood is the sum of the contributions from three types of observations. A stock–recruitment (penalty) function is added as a fourth contribution.

Catch-at-age

Catch-at-age observations are considered stochastic variables subject to sampling and process variation. The probability model for these observations is modelled along the lines described by Lewy and Nielsen (2003):

Catch-at-age is assumed to be lognormal distributed with log mean equal to log of the standard catch equation. The variance is assumed to depend on age and season and to be constant over years. To reduce the number of parameters, ages and seasons can be grouped, e.g. assuming the same variance for age 3 and age 4 in one or all seasons. Thus, the likelihood function, LCATCH, associated with the catches is:

$$L_{CATCH} = \prod_{s,a,y,q} \frac{1}{\sigma_{CATCH\ s,a,q} \sqrt{2\pi}} \exp\left(-\frac{(\log(C_{s,a,y,q}) - E(\log(C_{s,a,y,q})))^2}{2 \sigma_{CATCH\ s,a,q}^2}\right) \quad \text{Eq. 4}$$

Where

$$E(\log(C_{s,a,y,q})) = \log(F_{s,a,y,q} \bar{N}_{s,a,y,q})$$

Leaving out the constant term, the negative log-likelihood of catches then becomes:

$$\begin{aligned}
 l_{CATCH} &= -\log(L_{CATCH}) \\
 &\propto NOY \sum_{s,a,q} \log(\sigma_{CATCH\ s,a,q}) \\
 &+ \sum_{s,a,y,q} (\log(C_{s,a,y,q}) - E(\log(C_{s,a,y,q})))^2 / 2\sigma_{CATCH\ s,a,q}^2
 \end{aligned}
 \tag{Eq. 5}$$

Where *NOY* is the number of years in the time-series.

Annual catches

Catch-at-age numbers by quarter have not been available for some of the demersal North Sea stocks in recent years. For use in the default SMS configuration of the North Sea, where quarterly time step is used, it is assumed that the seasonal distribution (the F^3 parameter in Eq. 3) is known and given as input. The likelihood function is modified to make use of the observed annual catches.

$$\begin{aligned}
 E(\log(C_{s,a,y})) &= \log\left(\sum_q F_{s,a,y,q} \bar{N}_{s,a,y,q}\right) \\
 L_{CATCH} &= \prod_{s,a,y} \frac{1}{\sigma_{CATCH\ s,a} \sqrt{2\pi}} \exp\left(-\frac{(\log(C_{s,a,y}) - E(\log(C_{s,a,y})))^2}{2\sigma_{CATCH\ s,a}^2}\right)
 \end{aligned}
 \tag{Eq. 6}$$

Survey indices

Similarly to the catch observations, survey indices, $CPUE_{survey,s,a,y,q}$ are assumed to be log-normally distributed with mean:

$$E(\log(CPUE_{survey,s,a,y,q})) = \log(Q_{survey,a} \bar{N}_{SURVEY\ s,a,y,q})
 \tag{Eq. 7}$$

where Q denotes catchability by survey and \bar{N}_{SURVEY} is mean stock number during the survey period. Catchability may depend on a single age or groups of ages. Similarly, the variance of log cpue, σ_{SURVEY}^2 may be estimated individually by age or by clusters of age groups. The negative log-likelihood is on the same form as Eq. 4.

$$\begin{aligned}
 l_{SURVEY} &= -\log(L_{SURVEY}) \\
 &\propto NOY_{survey,s} \sum_{survey,s,a} \log(\sigma_{SURVEY\ survey,s,a}) \\
 &+ \sum_{survey,s,a,y} (\log(CPUE_{survey,s,a,y}) - E(\log(CPUE_{survey,s,a,y})))^2 / 2\sigma_{SURVEY\ s,a}^2
 \end{aligned}
 \tag{Eq. 8}$$

Stomach contents

The stomach contents observations, which are the basis for modelling predator food preference, consist of the average proportions by weight of the stomach content averaged over the stomach

samples in the North Sea. The model observations, $STOM_{pred,l_{pred},prey,l_{prey},y,q}$, are given for combinations of prey and predator species and size classes. In the following we use entity i for a combination of predator species and predator size class (e.g. saithe 50–60 cm) and entity j for the combination of prey species and prey size class eaten by entity i . Model observations therefore becomes $STOM_{i,j,y,q}$.

$STOM$ is assumed to be stochastic variables subject to sampling and process variations. For a given predator entity the observations across prey entities i are continuous variables which sum to one. Thus, the probability distribution of the stomach observations for a given predator including all prey/length groups needs to be a multivariate distribution defined on the simplex. As far as the authors know the Dirichlet distribution is the only distribution fulfilling this requirement. Leaving out the year and season index, the Dirichlet density function for a predator entity i with k observed diet proportions $STOM_{i,1}, \dots, STOM_{i,k-1} > 0$ and the parameters $p_1, \dots, p_k > 0$ has the probability density given byS:

$$f_i = f(STOM_{i,1}, \dots, STOM_{i,k-1} | p_{i,1}, \dots, p_{i,k}) = \frac{\Gamma(p_i)}{\prod_{j=1}^k \Gamma(p_{i,j})} \prod_{j=1}^k STOM_{i,j}^{p_{i,j}-1} \quad \text{Eq. 9}$$

Where

$$STOM_{i,k} = 1 - \sum_{j=1}^{k-1} STOM_{i,j}$$

and

$$p_i = \sum_{j=1}^k p_{i,j}$$

The mean and variance of the observations in the Dirichlet distribution are:

$$E(STOM_{i,j}) = \frac{p_{i,j}}{p_i}$$

$$Var(STOM_{i,j}) = \frac{E(STOM_{i,j}) (1 - E(STOM_{i,j}))}{p_i + 1} \quad \text{Eq. 10}$$

The expected value of the stomach contents observations is modelled using the theory developed by Andersen and Ursin (1977):

$$E(STOM_{i,j}) = \frac{\bar{N}_j W_j S_{i,j}(l_i, l_j)}{\sum_j (\bar{N}_j W_j S_{i,j}(l_i, l_j)) + OF_i S_{OF,i}(l_i)} = \frac{p_{i,j}}{p_i} \quad \text{Eq. 11}$$

where the food suitability function, S , is defined by Eq. 8 and Eq. 9. We make the same assumption as made for the calculation of $M2$ (Eq. 4) that the small time steps used in the model, allows a replacement of \bar{N}_j by N_j in Eq. 11.

Regarding the variance of stomach contents observations unpublished analyses of the present authors of data from the North Sea stomach-sampling project 1991 (ICES, 1997) indicate that the relationship between the variance and the mean of the stomach contents may be formulated in the following way:

$$\text{Var}(STOM_{i,j,y,q}) = \frac{E(STOM_{i,j,y,q}) (1 - E(STOM_{i,j,y,q}))}{V_{pred} U_{i,y,q}} \quad \text{Eq. 12}$$

where $U_{i,y,q}$ is a known quantity reflecting the sampling level of a predator entity, e.g. the number of hauls containing with stomach samples of a given predator and size class. V_{pred} is a predator species-dependent parameter linking the sampling level and variance. Equating Eq. 10 and Eq. 12 implies that:

$$P_{i,y,q} = V_{pred} U_{i,y,q} - 1 \quad \text{Eq. 13}$$

Insertion of Eq. 13 into Eq. 11 results in that:

$$P_{i,j,y,q} = (V_{pred} U_{i,y,q} - 1) \frac{\bar{N}_j W_j S_{i,j}(l_i, l_j)}{\sum_j (\bar{N}_j W_j S_{i,j}(l_i, l_j)) + OF_i S_{OF,i}(l_i)}$$

The parameters, $p_{i,j,y,q}$ are uniquely determined through stock numbers, total mortality, suitability parameters and V_{pred} .

Assuming that the diet observations for the predator/length groups are independent the negative log likelihood function including all predators/length groups are derived from Eq. 9:

$$l_{STOM} = -\log(L_{STOM}) = - \sum_{i,j,y,q} \log(f_{i,j,y,q}) \quad \text{Eq. 14}$$

Modification of the stomach contents model

The stomach contents observations, $STOM_{prey,l_{prey},pred,l_{pred},y,q}$ are given for combinations of prey and predator species and size classes. For a diet consisting of a large proportion “other food” and several species and prey size classes, the proportion of the individual combination of species and size becomes small (less than 0.1%) for several prey entities. Very small proportions, in combination with a modest sampling size per stratum, make the estimation of parameters impossible in some cases. To overcome the problem SMS has an option to let the likelihood use proportion summed overall size classes for a given prey species such that the prey entity equals the species.

The same grouping of all sizes from a prey is applied when the uniform size selection option (Eq. 12 and Eq. 1) is used. The likelihood function is the same as used for stomach observations that include prey size.

Stock–recruitment

In order to enable estimation of recruitment in the last year for cases where survey indices catch from the recruitment age is missing (e.g. saithe), and to estimate parameters for forecast use, a stock–recruitment relationship $R_{s,y} = R(SSB_{s,y} | \alpha_s, \beta_s)$ penalty function is included in the likelihood function.

Recruitment to the model takes place in the same season ($recq$) and at the same age (fa) for all species. It is estimated from the Spawning–Stock Biomass (SSB) in the first season (fq) of the year, and a stock–recruitment relation. SSB is calculated from stock numbers, proportion mature (PM) and mean weight in the sea.

$$SSB_{s,y} = \sum_a N_{s,y,a,q=recq} PM_{s,y,a,q=recq} W_{s,y,a,q=recq} \quad \text{Eq. 15}$$

At present the Ricker (Eq. 16), the Beverton and Holt (Eq. 17), segmented regression (Eq. 18) and geometric mean are implemented.

$$R_{s,y} = \alpha_s SSB_{s,y-fa,fq} e^{(\beta_s SSB_{s,y-fa,fq})} \quad \text{Eq. 16}$$

$$R_{s,y} = \frac{\alpha_s SSB_{s,y-fa,fq}}{1 + \beta_s SSB_{s,y-fa,fq}} \quad \text{Eq. 17}$$

$$R_{s,y} = \begin{cases} \alpha_s SSB_{s,y-fa,fq} & \text{for } SSB_{s,y-fa,fq} < \beta_s \\ \alpha_s \beta_s & \text{for } SSB_{s,y-fa,fq} > \beta_s \end{cases} \quad \text{Eq. 18}$$

Assuming that recruitment is lognormal distributed, the negative log likelihood, l_{SR} , equals:

$$l_{SR} = -\log(L_{SR}) \propto NOY \sum_s \log(\sigma_{SRs}) + \sum_{s,a,y} (\log(N_{ss,a=fa,y,q=recq}) - E(\log(R_{s,y})))^2 / 2\sigma_{SRs}^2 \quad \text{Eq. 19}$$

Where NOY gives the number of years selected and where Eq. 20 gives the expected recruitment for the Ricker case.

$$E(\log(R_s)) = \log(\alpha_s SSB_{s,y-fa,fq} e^{(\beta_s SSB_{s,y-fa,fq})}) \quad \text{Eq. 20}$$

Total likelihood function and parameterisation

The total negative log likelihood function, l_{TOTAL} , is found as the sum of the four terms:

$$l_{TOTAL} = l_{CATCH} + l_{SURVEY} + l_{STOM} + l_{SR}$$

To ensure uniquely determined parameters it is necessary to fix part of them. For the F at-age model (Eq. 3) the year selection in the beginning of each year range (Y) has been fixed to one ($F_{y=\text{first year in each group of years}}^2 = 1$). The season effect in the last season of all years and ages is also fixed ($F_{y,a,q=\text{last season}}^3 = 1/\text{number of seasons}$).

Eq. 4 and Eq. 8 indicate that it is only possible to determine relative vulnerability parameters, $\rho_{pred,prey}$. We have chosen to fix the vulnerability of other food for all predators to 1.0. Similarly the biomass of other food OF_{pred} has arbitrarily been set (e.g. at 1 million tonnes) for each predators. The actual value by predator was chosen to obtain estimates of vulnerability parameters for the fish prey at around 1. Other parameters than suitability are practically unaffected of the actual choice of biomass of other food.

In the food suitability function (Eq. 8 and Eq. 9) vulnerability and overlap effects cannot be distinguished. Hence the overlap parameters were must be fixed for at least one season. In practice, several combinations of overlap have however to be fixed (at e.g. 1).

Initial stock size, i.e. the stock numbers in the first year and recruitment over years are used as parameters in the model while the remaining stock sizes are considered as functions of the parameters determined by Eq. 1 and Eq. 2.

The year effect ($F_{y,s}^2$) in the separable model for fishery mortality (Eq. 3) takes one parameter per species for each year in the time-series which sum up to a considerable number of parameters. To reduce this high number of parameters, the year effect can optionally be model from a cubic spline function which requires fewer parameters. The number of knots must be specified if this option is used.

Another way to reduce the number of parameters is to substitute the parameters σ_{CATCH} , σ_{SURVEY} and σ_{SR} used in the likelihood functions by their empirical estimates. This optional substitution has practically no effect on the model output and the associated uncertainty.

Appendage 1 gives an overview of parameters and variables in the model.

The parameters are estimated using maximum likelihood (ML) i.e. by minimizing the negative log likelihood, l_{TOTAL} . The variance/covariance matrix is approximated by the inverse Hessian matrix. Uncertainties of functions of the estimated parameters (such as biomass and mean fishing mortality) are calculated using the delta method.

SMS forecast

SMS is a forward-running model and can as such easily be used for forecast scenarios and Management Strategy Evaluation (MSE). SMS used the estimated parameters to calculate the initial stock numbers and exploitation pattern used in the forecast. Exploitation pattern are assumed constant in the forecast period, but is scaled to a specified average F, derived dynamically from Harvest Control Rules (HCR). Recruits are produced from the stock–recruitment relation, input parameters and a noise term.

Recruitment

Recruitment is estimated from the available stock–recruitment relationships, $f(SSB)$, (see Section 10.3.4) and optionally a lognormal distributed noise term with standard deviation std .

$$R = f(SSB) e^{(std \text{ NORM}(0,1))} \quad \text{Eq. 21}$$

Where $\text{NORM}(0,1)$ is a random number drawn from a normal distribution with mean=0 and standard deviation 1. A default value for std can be obtained from the estimated variance of stock–recruitment relationship, $\sigma_{SR_s}^2$ (Eq. 19)

Application of the noise function for the lognormal distributed recruitment gives on average a median recruitment as specified by $f(SSB)$. Optionally, recruitment can be adjusted with half of the variance, to obtain, on average, a mean recruitment given by $f(SSB)$.

$$R = f(SSB) e^{(std \text{ NORM}(0,1))} e^{-(std^2/2)} \quad \text{Eq. 22}$$

Harvest Control Rules

Several HCR have been implemented, e.g. constant F and the ICES interpretation of management according to MSY for both short- and long-lived species. Selected, more complex management plans in force for the North Sea and Baltic Sea species have also been implemented.

Model validation

Model validation (in the years 2004–2009) was focused on the performance of the model using simulated data from an independent model and simulated data produced by the SMS model itself. The independent model was implemented using the R-package (R Development Core Team, 2011) and include a medium complex North Sea configuration (nine species, of which four are predators and eight species preys). The simulation model follows the SMS model specification with an addition of von Bertalanffy growth curves to model mean length-at-age. Variance around mean length-at-age was assumed to increase by increasing age. This combined age-length approach made it possible to simulate all the data needed for model verification. Test dataset from the simulation model included 20 years of catch data, one survey time-series per species covering all years and ages, and four quarterly stomach samples in year ten including stomach observations for all predator length groups. Data from the independent simulation model was used to verify that the SMS model actually works as intended and to investigate model sensitivity with respect to observation errors on catch, survey cpue and stomach data.

To test if model parameters were identifiable when uncertainties estimated from real data were applied, the SMS model was modified to produce observations with the estimated observation noise of catch, survey and stomach data. The experiment consists of the following steps:

- 1) Estimate model parameters using the SMS model and available North Sea data.
- 2) Generate 100 set of input data from SMS output (expected catch numbers, survey indices and stomach observations) and their associated variance of these values).
- 3) Let SMS estimate 100 sets of parameters from the 100 sets of input data.

This procedure results in one set of “true parameters”, $\theta = (\theta_1, \dots, \theta_k)$ and 100 sets of estimated parameters, $\hat{\theta}_j = (\hat{\theta}_{1,j}, \dots, \hat{\theta}_{k,j})$, $j = 1, \dots, k$. Based on the 100 repetitions and for each of the k parameters the mean and the standard deviation of the mean $\bar{\theta}_i$ and σ_i and hence the 95% confidence limits, was calculated. Finally the proportion of the parameters was calculated for which θ_i lies in the 95% confidence interval of $\bar{\theta}_i$.

The test showed that parameters are identifiable for most “real” North Sea configurations. For some species with relatively few diet observations, size selection parameters (Eq. 11) and the variance parameter (V) linking the stomach sampling level to the variance of Dirichlet distribution (Eq. 12 and Eq. 13), were outside the 95% confidence interval of $\bar{\theta}_i$.

A more informal testing of the model has been done by simply using the model. SMS has been applied to produce the so called key run for both the species rich North Sea system (ten species with stock number estimation including seven prey species, and 16 species of “other predators”) (ICES, WGSAM 2011) and the species poor Baltic Sea (cod, herring and sprat, one predator and three prey species) (WGSAM 2008; WKMAMPEL 2009). In addition the model has been used in single-species mode for the ICES advice of blue whiting in the North East Atlantic (WGWIDE 2011) since 2005 and several sandeel stocks in the North Sea since 2009 (WGNSSK 2011). For MSE purposes, the model has been applied for sandeel and Norway pout in the North Sea (AGSAN-NOP 2007), blue whiting and pelagic stocks in the Baltic (WKMAMPEL 2009) in both single and multispecies mode.

SMS is essentially an extension of the statistical models normally used for single-species stock assessment. This allows the use the long list of available diagnostics tools, e.g. residuals plots, and retrospective analysis, developed for model testing of submodels for catch-at-age and survey indices. For stomach observations however, fewer established methods are available. To apply reliable residual plots for stomach observations residuals need to be independent, which are not the case for the stomach contents model as the observations with respect to prey entity sum

to one. Instead, we do the following: Let the predator entity, year and quarter be given and consider the stomach contents observations following the Dirichlet distribution:

$$STOM_r = (STOM_{r,1}, \dots, STOM_{r,k-1}) \sim Dir(p_{r,1}, \dots, p_{r,k})$$

Where r is the combined entity of predator entity, year and quarter and where $p_{r,j}, j = 1, \dots, k$ are the Dirichlet parameters estimated. Instead of considering the weight proportions, $STOM$, we consider absolute weight in the stomachs, $W_{r,j}, j = 1, \dots, k$, where

$$STOM_{r,j} = \frac{W_{r,j}}{\sum_j W_{r,j}}$$

If we assume that $W_{r,j}, j = 1, \dots, k$ are independent and follow gamma distributions with the same scale parameter, θ_r , i.e.

$$W_{r,j} \sim \Gamma(p_{r,j}, \theta_r) \quad j = 1, \dots, k$$

it is well known that $STOM_r$ follows the Dirichlet distribution. We now assume that opposite is the case (we have to prove that!) and hence assume that the absolute weights, $W_{r,j}$ are independent gamma distributed variables. We then transform these observations to obtain normal distributed residuals: Leaving out the indices, we get that $U = p\gamma(W, p, \theta)$, where $p\gamma$ is the distribution function of the gamma distribution, is uniform distributed. To obtain normal distributed variables U is finally transformed to $V = qnorm(U)$, where $qnorm$ is the inverse of the distribution function of the standardized normal distribution. This mean that V is our new residuals for stomach contents observations.

To obtain the absolute weight of the prey entities form the relative stomach content, $STOM$, we have to know the total stomach weight for the predator entity. We have not extracted those from the basic observations, but simply assumed that the total weight in the stomach is proportional to the number of stomachs sampled for a given predator entity.

Implementation

The SMS has been implemented using the AD Model Builder (Fournier *et al.*, 2011), which is freely available from ADMB Foundation (www.admb-project.org). ADMB is an efficient tool including automatic differentiation for Maximum likelihood estimation of many parameters in nonlinear models.

SMS configurations may contain more than 1000 parameters of which less than 5% are related to predation mortality. It is not possible to estimate all parameters simultaneously without sensible initial parameter values. Such values are obtained in three phases:

- 1) Estimate “single-species” stock numbers, fishing mortality and survey catchability parameters assuming that natural mortality ($M1+M2$) are fixed and known (i.e. as used by the ICES single-species assessments).
- 2) Fix all the “single-species” parameters estimated in step 1 and use the fixed stock numbers to estimate initial parameter values for the predation parameters.
- 3) Use the parameter values from step 1 and 2 as initial parameter values and re-estimate all parameters simultaneously in the full model including estimation of predation mortality $M2$.

Optimisation might potentially be dependent on the initial parameter values, however the same final result was obtained using the three steps above or using a configuration where step two is

omitted. Using step two however in general makes the estimation process more robust as extreme values and system crash are avoided.

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Appendage 1. Notation, parameters and variables

Indices

<i>a</i>	age
<i>area</i>	area with specific predation mortality
<i>A1, A2</i>	group of ages
<i>Fa</i>	first age group in the model
<i>i</i>	prey entity, combination of prey species and prey size group
<i>j</i>	predator entity, combination of predator group and predator size group
<i>l</i>	species size class
<i>lpred</i>	predator size class
<i>lprey</i>	prey size class
<i>other</i>	other food “species”

<i>pred</i>	predator species
<i>prey</i>	prey species
<i>q</i>	season of the year, e.g. quarter
<i>recq</i>	recruitment season
<i>s</i>	species
<i>survey</i>	survey identifier
<i>y</i>	year
<i>Y</i>	group of years

Parameters and variables

<i>AB</i>	available (suitable) prey biomass for a predator
<i>ALK</i>	proportion at-size for a given age group. Input
<i>C</i>	catch in numbers. Observations
<i>Cpue</i>	catch in numbers per unit of effort. Observations
<i>D</i>	number died
<i>DM1</i>	number died due to M1
<i>DM2</i>	number died due to M2
<i>DF</i>	number died due to F
<i>F</i>	instantaneous rate of fishing mortality
<i>F¹</i>	age effect in separable model for fishing mortality. Estimated parameter
<i>F²</i>	year effect in separable model for fishing mortality. Estimated parameter
<i>F³</i>	season effect in separable model for fishing mortality. Estimated parameter
<i>M1</i>	instantaneous rate of residual natural mortality. Input
<i>M2</i>	instantaneous rate of predation mortality estimated in the model
<i>N</i>	stock number
<i>N_{s,a,y=first year,q=1}</i>	Stock number in the first year of the model. Estimated parameters
<i>N_{s,a=fa,q=recq}</i>	Stock numbers at youngest age (recruitment). Estimated parameter
<i>OF</i>	Biomass of other food for a predator. Input
<i>Q</i>	catchability, proportion of the population caught by one effort unit. Estimated
<i>Rs,y</i>	recruitment calculated from stock–recruitment model
<i>RA</i>	food ration, biomass consumed by a predator. Input
<i>S</i>	suitability of a prey entity as food for a predator entity
<i>S1, S2</i>	mesh selection parameters. Estimated
<i>SSB</i>	spawning–stock biomass
<i>STOM</i>	weight proportion of prey <i>i</i> found in the stomach of predator <i>j</i> . Observations
<i>U</i>	sampling intensity of stomachs. Observation
<i>V</i>	variance of diet observations in relation to sampling intensity. Estimated Parameter
<i>W</i>	body weight. Input
<i>Z</i>	instantaneous rate of total mortality
<i>α</i>	stock–recruitment parameter. Estimated
<i>β</i>	stock–recruitment parameter. Estimated
<i>ρ</i>	prey size preference of a predator. Estimated parameter
<i>γ</i>	food ration coefficients. Input
<i>ς</i>	food ration exponent. Input
<i>v</i>	parameter for size dependent preference for other food. Estimated parameter
<i>η^{PREF}</i>	natural logarithm of the preferred predator prey size ratio. Estimated parameter
<i>η^{MIN}</i>	observed minimum relative prey size for a predator species. Input
<i>η^{MAX}</i>	observed maximum relative prey size for a predator species. Input
<i>o</i>	spatial overlap between predator and prey species. Estimated parameter

ρ	coefficient of species vulnerability. Estimated parameter
σ_{CATCH}	standard deviation of catch observations. Estimated parameter
σ_{PREF}	parameter expressing how particular a predator is about the size of its prey. Parameter
σ_{SR}	standard deviation of stock–recruitment estimate. Estimated parameter
σ_{STOM}	standard deviation of stomach content observations (used with lognormal distribution)
σ_{SURVEY}	standard deviation of survey cpue observations. Estimated parameter

APPENDIX 2: Diet composition used in the model

The following figures show the relative stomach content composition of herring, sprat and “Other food”. For each predator the stomach contents are shown by observed predator size classes (showing the lower length in mm for the size class). The number on top of each bar is the number of stomachs sampled within the length class. On the figures, all length classes of preys are merged, however the darkness of each main colour indicate the sizes of the preys, with darkest colour for the largest preys. Stomach contents have been aggregated over 10 years and only the “new” stomachs are presented here. Figures by year for both the “old” and the “new” data set can be found on the Github.

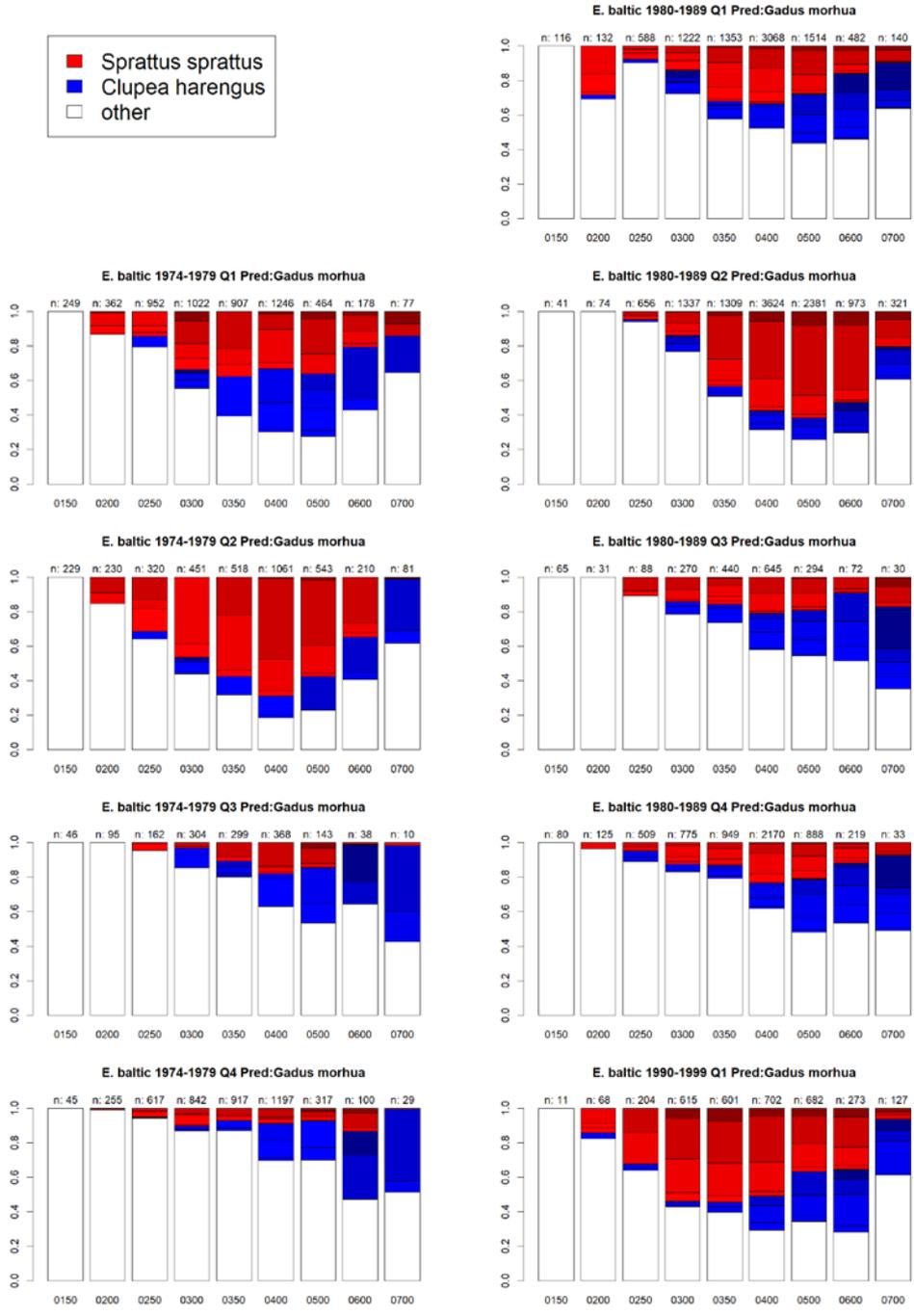


Figure 1, Appendix 2. Relative stomach contents weight of cod by decade, quarter and cod size class for the “new” stomachs. For each prey, the darkness of the prey colour indicates the size of the prey. The number on top of each bar shows the number of stomachs sampled.

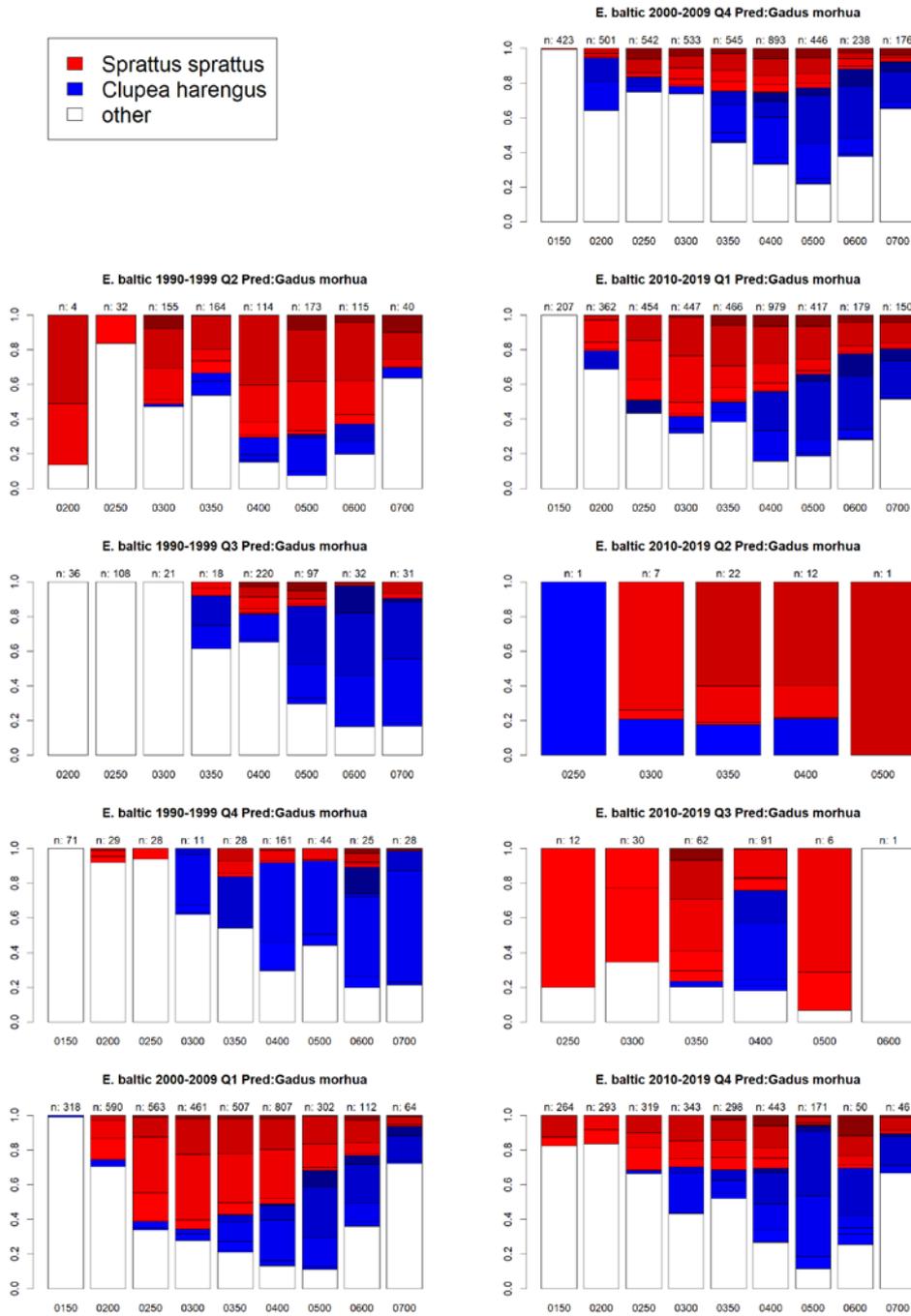


Figure 2, Appendix 2. Relative stomach contents weight of cod by decade, quarter and cod size class for the "new" stomachs. For each prey, the darkness of the prey colour indicates the size of the prey. The number on top of each bar shows the number of stomachs sampled.

APPENDIX 3: Option file for SMS-key-runs

Key-run 2019

```

# sms.dat option file
# the character "#" is used as comment character, such that all text and numbers
# after # are skipped by the SMS program
#
#####
# Produce test output (option test.output)
# 0 no test output
# 1 output file sms.dat and file fleet.info.dat as read in
# 2 output all single species input files as read in
# 3 output all multi species input files as read in
# 4 output option overview
#
# 11 output between phases output
# 12 output iteration (obj function) output
# 13 output stomach parameters
# 19 Both 11, 12 and 13
#
# Forecast options
# 51 output hcr_option.dat file as read in
# 52 output prediction output summary
# 53 output prediction output detailed
0
#####
# Produce output for SMS-OP program. 0=no, 1=yes
1
#####
# Single/Multispecies mode (option VPA.mode)
# 0=single species mode
# 1=multi species mode, but Z=F+M (used for initial food suitability parm. est.)
# 2=multi species mode, Z=F+M1+M2
0
#####
# Number of areas for multispecies run (default=1)
1
#
# single species parameters
#
## first year of input data (option first.year)
1974
#####
## first year used in the model (option first.year.model)
1974
#####
## last year of input data (option last.year)
2018
#####
## last year used in the model (option last.year.model)
2018
#####
## number of seasons (option last.season). Use 1 for annual data
4
#####
## last season last year (option last.season.last.year). Use 1 for annual data
4
#####
## number of species (option no.species)
3
#####
# Species names, for information only. See file species_names.in
# Cod Herring Sprat
#####

```

```

## first age all species (option first.age)
0
#####
## recruitment season (option rec.season). Use 1 for annual data
3
#####
## maximum age for any species(max.age.all)
11
#####
## various information by species
# 1. last age
# 2. first age where catch data are used (else F=0 assumed)
# 3. last age with age dependent fishing selection
# 4. Estimate F year effect from effort data. 0=no, 1=yes
# 5. Last age included in the catch at age likelihood (normally last age)
# 6. plus group, 0=no plus group, 1=plus group
# 7. predator species, 0=no, 1=VPA predator, 2=Other predator
# 8. prey species, 0=no, 1=yes
# 9. Stock Recruit relation
# 1=Ricker, 2=Beverton & Holt, 3=Geom mean,
# 4= Hockey stick, 5=hockey stick with smoother,
# 51=Ricker with estimated temp effect,
# 52=Ricker with known temp effect,
# 61=STN Ricker for sprat. Input from file Sprat_rec_61.in
# 71=STN special SSB/R for cod. Input from file Cod_rec_71.in
# >100= hockey stick with known breakpoint (given as input)
# 10. Spawning season (not used yet, but set to 1)
# 11. Additional data for Stock Recruit relation
11 0 0 0 0 2 0 0 0 0 # 1 Cod as other predator
8 1 5 0 8 1 0 1 3 0 0 # 2 Herring
7 1 4 0 7 0 0 1 3 0 0 # 3 Sprat
#####
## use input recruitment estimate (option use.known.rec)
# 0=estimate all recruitments
# 1=yes use input recruitment from file known_recruitment.in
0
#####
## adjustment factor to bring the beta parameter close to one (option beta.cor)
1e+06 # Herring
1e+06 # Sprat
#####
## year range for data included to fit the R-SSB relation (option SSB.R.year.range)
# first (option SSB.R.year.first) and last (option SSB.R.year.last) year to consider.
# the value -1 indicates the use of the first (and last) available year in time-series
# first year by species
-1 # Herring
1990 # Sprat
# last year by species
-1 # Herring
-1 # Sprat
#####
## Objective function weighting by species (option objective.function.weight)
# first=catch observations,
# second=CPUE observations,
# third=SSB/R relations
# fourth=stomach observations, weight proportions
# fifth=stomach observations, number at length
##
0 0 0 1 0 # 1 Cod
1 1 0.05 0 0 # 2 Herring
1 1 0.05 0 0 # 3 Sprat
#####
## parameter estimation phases for single species parameters
# phase.rec (stock numbers, first age) (default=1)

```

```

1
# phase.rec.older (stock numbers, first year and all ages) (default=1)
1
# phase.F.y (year effect in F model) (default=1)
1
# phase.F.y.spline (year effect in F model, implemented as spline function)
-1
# phase.F.q (season effect in F model) (default=1)
1
# phase.F.a (age effect in F model) (default=1)
1
# phase.catchability (survey catchability) (default=1)
1
# phase.SSB.R.alfa (alfa parameter in SSB-recruitment relation) (default=1)
1
# phase.SSB.R.beta (beta parameter in SSB-recruitment relation) (default=1)
1
#####
## minimum CV of catch observation used in ML-estimation (option min.catch.CV)
0.1
#####
## minimum CV of catch SSB-recruitment relation used in ML-estimation (option min.SR.CV)
0.1
#####
## Use proportion landed information in calculation of yield (option calc.discard)
# 0=all catches are included in yield
# 1=yield is calculated from proportion landed (file proportion_landed.in)
    0 # Herring
    0 # Sprat
#####
## use seasonal or annual catches in the objective function (option combined.catches)
# do not change this options from default=0, without looking in the manual
# 0=annual catches with annual time steps or seasonal catches with seasonal time steps
# 1=annual catches with seasonal time steps, read seasonal relative F from file F_q_ini.in (default=0)
    0 # Herring
    0 # Sprat
#####
## use seasonal or common combined variances for catch observation
# seasonal=0, common=1 (use 1 for annual data)
    1 # Herring
    1 # Sprat
#####
##
# catch observations: number of separate catch variance groups by species
    3 # Herring
    4 # Sprat

# first age group in each catch variance group
1 2 3 # Herring
1 2 3 4 # Sprat
#####
##
# catch observations: number of separate catch seasonal component groups by species
    3 # Herring
    2 # Sprat
# first ages in each seasonal component group by species
1 2 3 # Herring
1 2 # Sprat
#####
## first and last age in calculation of average F by species (option avg.F.ages)
3 6 # Herring
3 5 # Sprat
#####
## minimum 'observed' catch, (option min.catch). You cannot log zero catch at age!

```

```

#
# 0 ignore observation in likelihood
#
# negative value gives percentage (e.g. -10 ~ 10%) of average catch in age-group for input catch=0
# negative value less than -100 substitute all catches by the option/100 /100 *average catch in the age group for catches
less than (average catch*-option/10000
#
# if option>0 then will zero catches be replaced by catch=option
#
# else if option<0 and option >-100 and catch=0 then catches will be replaced by catch=average(catch at age)*(-option)/100
# else if option<-100 and catch < average(catch at age)*(-option)/10000 then catches will be replaced by catch=aver-
age(catch at age)*(-option)/10000
    0 # Herring
    0 # Sprat
#####
##
# catch observations: number of year groups with the same age and seasonal selection
    2 # Herring
    2 # Sprat
# first year in each group (please note #1 will always be changed to first model year)
1974 1989 # Herring
1974 2000 # Sprat
#####
##
# number of nodes for year effect Fishing mortality spline
# 1=no spline (use one Fy for each year), >1 number of nodes
    1 # Herring
    1 # Sprat
# first year in each group
1976 # Herring
1976 # Sprat
#####
## year season combinations with zero catch (F=0) (option zero.catch.year.season)
# 0=no, all year-seasons have catches,
# 1=yes there are year-season combinations with no catch.
# Read from file zero_catch_seasons_ages.in
# default=0
0
#####
## season age combinations with zero catch (F=0) (option zero.catch.season.ages)
# 0=no, all seasons have catches,
# 1=yes there are seasons with no catch. Read from file zero_catch_season_ages.in
# default=0
0
#####
## Factor for fixing last season effect in F-model (default=1) (fix.F.factor)
    1 # Herring
    1 # Sprat
#####
## Uncertainties for catch, CPUE and SSB-R observations (option calc.est.sigma)
# values: 0=estimate sigma as a parameter (the right way of doing it)
# 1=Calculate sigma and truncate if lower limit is reached
# 2=Calculate sigma and use a penalty function to avoid lower limit
# catch-observation, CPUE-obs, Stock/recruit
    0    0    0
#####
# Read HCR_option file (option=read.HCR) default=0
# 0=no 1=yes
0
#####
# multispecies parameters
#
# Exclude year, season and predator combinations where stomach data are not incl.(option incl.stom.all)
# 0=no, all stomach data are used in likelihood

```

```

# 1=yes there are combinations for which data are not included in the likelihood.
# Read from file: incl_stom.in
# default(0)
1
#####
## N in the beginning of the period or N bar for calculation of M2 (option use.Nbar)
# 0=use N in the beginning of the time step (default)
# 1=use N bar
0
#####
## Maximum M2 iterations (option M2.iterations) in case of use.Nbar=1
5
#####
## convergence criteria (option max.M2.sum2) in case of use.Nbar=1
# use max.M2.sum2=0.0 and M2.iterations=7 (or another high number) to make Hessian
0
#####
## likelihood model for stomach content observations (option stom.likelihood)
# 1=likelihood from prey weight proportions only (see option below)
# 2=likelihood from prey weight proportions and from prey numbers to estimate size selection
# 3=Gamma distribution for prey absolute weight and size selection from prey numbers
1
#####
# Variance used in likelihood model for stomach contents as prey weight proportion (option stomach.variance)
# 0 =not relevant,
# 1 =log normal distribution,
# 2 =normal distribution,
# 3 =Dirichlet distribution
3
#####
## Usage of age-length-keys for calc of M2 (option simple.ALK)
# 0=Use only one size group per age (file lsea.in or west.in)
# 1=Use size distribution per age (file ALK_all.in)
0
#####
## Usage of food-rations from input values or from size and regression parameters (option consum)
# 0=Use input values by age (file consum.in)
# 1=use weight at age (file west.in) and regression parameters (file consum_ab.in)
# 2=use length at age (file lsea.in), l-w relation and regression parameters (file consum_ab.in)
0
#####
## Size selection model based on (option size.select.model)
# 1=length:
# M2 calculation:
# Size preference:
# Predator length at age from file: lsea.in
# Prey length at age from file: lsea.in
# Prey mean weight is weight in the sea from file: west.in
# Likelihood:
# Size preference:
# Predator mean length per length group (file: stom_pred_length_at_sizecl.in)
# Prey mean length per length group (file stomlen_at_length.in)
# Prey mean weight from mean weight per prey length group (file: stomweight_at_length.in)
# 2=weight:
# M2 calculation:
# Size preference:
# Predator weight at age from file: west.in
# Prey weight at age from file: west.in
# Prey mean weight is weight in the sea from file: west.in
# Likelihood:
# Size preference
# Predator mean weight is based on mean length per predator length group (file: stom_pred_length_at_sizecl.in)
# and l-w relation (file: length_weight_relations.in),
# Prey mean weight per prey length group (file: stomweight_at_length.in)

```

```

#   Prey mean weight from mean weight per prey length group (file: stomweight_at_length.in
# 3=weight:
#   M2 calculation: Same as option 2
#   Likelihood:
#   Size preference:
#   Predator mean weight is based on mean length per predator length group (file: stom_pred_length_at_sizecl.in)
#     and l-w relation (file: length_weight_relations.in),
#   Prey mean weight per prey length group (file: stomlen_at_length.in) and l-w relation (file:length_weight_rela-
tions.in)
#   Prey mean weight from prey mean length per prey length group (file: stomlen_at_length.in) and l-w relation (file:
length_weight_relations.in)
# 4=weight:
#   M2 calculation:
#   Size preference:
#   Predator mean weight from file lsea.in (length in the sea) and l-w relation (file: length_weight_relations.in)
#   Prey mean weight from file lsea.in (length in the sea) and l-w relation (file: length_weight_relations.in)
#   Likelihood: Same as option 3
# 5=weight in combination with simple.ALK=1:
#   M2 calculation:
#   Size preference:
#   Predator weight based on length from file ALK_all.in (length distribution at age) and l-w relation (file:
length_weight_relations.in)
#   Prey weight based on length from file ALK_all.in (length distribution at age) and l-w relation (file:
length_weight_relations.in)
#   Prey mean weight based on length from file ALK_all.in (length distribution at age) and l-w relation (file:
length_weight_relations.in)
#   Likelihood: Same as for option 2
# 6=weight in combination with simple.ALK=1:
#   M2 calculation: Same as option 5
#   Likelihood: Same as option 3
2
#####
# Adjust Length at Age distribution by a mesh selection function (option L50.mesh)
# Please note that options simple.ALK should be 1 and option size.select.model should be 5
# L50 (mm) is optional given as input. Selection Range is estimated by the model
# L50= -1 do not adjust
# L50=0, estimate L50 and selection range
# L50>0, input L50 (mm) and estimate selection range
# by VPA species
  -1 #   Herring
  -1 #   Sprat
#####
## spread of size selection (option size.selection)
# 0=no size selection, predator/preys size range defined from observations
# 1=normal distribution size selection
# 3=Gamma distribution size distribution
# 4=no size selection, but range defined by input min and max regression parameters (file
pred_prej_size_range_param.in)
# 5=Beta distributed size distribution, within observed size range
# 6=log-Beta size distributed, within observed size range
#
# by predator
  1 #   Cod
#####
## sum stomach contents over prey size for use in likelihood for prey weight proportions (option sum.stom.like)
# 0=no, use observations as they are; 1=yes, sum observed and predicted stomach contents before used in likelihood for
prey weight proportions
#
# by predator
  1 #   Cod
#####
## # Use estimated scaling factor to link number of observation to variance for stomach observation likelihood (option
stom_obs_var)
# 0=no, do not estimate factor (assumed=1); 1=yes, estimate the factor; 2=equal weight (1) for all samples

```

```

#
# by predator
1 # Cod
#####
## # Upper limit for Dirichlet sumP. A low value (e.g. 10) limits the risk of overfitting. A high value (e.g. 100) allows a
full fit. (option stom_max_sumP)
# by predator
1000 # Cod
#####
## Scaling factor (to bring parameters close to one) for relation between no of stomachs sampling and variance
# value=0: use default values i.e. 1.00 for no size selection and otherwise 0.1 (option var.scale.stom)
0 # Cod
#####
## other food suitability size dependency (option size.other.food.suit)
# 0=no size dependency
# 1=yes, other food suitability is different for different size classes
1 # Cod
#####
## Minimum observed relative stomach contents weight for inclusion in ML estimation (option min.stom.cont)
0.001 # Cod
#####
## Upper limit for no of samples used for calculation of stomach observation variance (option max.stom.sampl)
500 # 1e+06 # Cod
#####
## Max prey size/ pred size factor for inclusion in M2 calc (option max.prey.pred.size.fac)
0.3 # Cod
#####
## inclusion of individual stomach contents observations in ML for weight proportions (option stom.type.include)
# 1=Observed data
# 2=+ (not observed) data within the observed size range (=fill in)
# 3=+ (not observed) data outside an observed size range. One obs below and one above (=tails)
# 4=+ (not observed) data for the full size range of a prey species irrespective of predator size (=expansion)
1 # Cod
#####
## use overlap input values by year and season (use.overlap)
# 0: overlap assumed constant or estimated within the model
# 1: overlap index from file overlap.in (assessment only, use overlap from last year in forecast)
# 2: overlap index from file overlap.in (assessment and forecast)
0
#####
## parameter estimation phases for predation parameters
# the number gives the phase, -1 means no estimation
#
# vulnerability (default=2) (phase phase.vulnera)
2
# other food suitability slope (default=-1) (option phase.other.suit.slope)
2
# preferred size ratio (default=2) (option phase.pref.size.ratio)
2
# predator size ratio adjustment factor (default=-1) (option phase.pref.size.ratio.correction)
-1
# prey species size adjustment factor (default=-1) (option phase.prey.size.adjustment)
-1
# variance of preferred size ratio (default=2) (option phase.var.size.ratio)
2
# season overlap (default=-1) (option phase.season.overlap)
3
# Stomach variance parameter (default=2) (option phase.Stom.var)
2
# Mesh size selection of stomach age length key (default=-1) (option phase.mesh.adjust)
-1

```

Annex 5: Central Baltic Sea Gadget multispecies model

Working Group: Working Group on Multispecies Assessment Methods (WGSAM)

Date: 27 November 2019

Model: Gadget - Globally applicable Area Disaggregated General Ecosystem Toolbox, <https://github.com/hafro/gadget>

Species/Stocks: Eastern Baltic cod (cod.27.24-32)

Baltic sprat (spr.27.22-32)

Central Baltic herring (her.27.25-2932)

Contacts: Nataliia Kulatska & Valerio Bartolino

Summary

A Multispecies age-length based model for the Central Baltic system (cod, herring and sprat) is developed using Gadget in order to estimate predation mortality caused by cod on herring and sprat for the period 1974-2018. All three species are dynamically represented in the model, with cod preying on herring and sprat. The model is quarterly based, single area and multifleet, with an active (bottom trawlers) and a passive (guilnetters) fleet targeting cod, and a pelagic fleet targeting herring and sprat. The model is informed and fitted to various data sources (i.e. commercial catches, numerous survey indices of abundance, compositional and biological data from both commercial and scientific surveys), most of which are coherent with data sources used by official stock assessments. Cod predation is informed by consumption rates, prey species and prey length composition from an extensive dataset of cod stomach content covering 1974-2014. The model can estimate cod predation mortalities by age groups for herring and sprat for 1974-2018. The estimated abundances of all the three species are generally consistent with the official assessments, and main differences consist in Gadget estimating slightly higher SSB of cod throughout the time-series, and higher SSB for both herring and sprat at the beginning of time-series. The model, however, suffers from some degree of instability which affects the estimates in the first part of the time period until the end of the 1980s. Estimates are more consistent from the early 1990s, but due to the initial instability it is not considered as a keyrun for the purpose to produce a vector of predation mortalities for the entire time period 1974-2018. Good agreement in the estimated predation mortalities between the Gadget model and the SMS keyrun are considered an additional support for the SMS-based estimates provided by WGSAM to the single species stock assessments of clupeids.

Introduction

The model presented at WGSAM 2019 further extend the model implemented in the MareFrame project and recently presented by Kulatska *et al.* (2019). The model is built in the statistical multispecies modelling framework Gadget that can be used to assess individual fish stocks and to create multispecies, multi-fleet and multi-area models (www.hafro.is/gadget, Begley, 2017).

The model reconstructs the population dynamics of the Eastern Baltic cod (cod.27.24-32; SD 24-32 on *Figure 1-1*(left)), Baltic sprat (spr.27.22-32; SD 22-32 on *Figure 1-1*(left)) and Central Baltic herring (her.27.25-2932; SD 25-27,28.2,29,32 on *Figure 1-1*(left)) stocks (hereafter referred as cod, herring and sprat), with a particular attention to include the predation of cod on the two clupeids. The model is here presented to evaluate its suitability as a keyrun with the scope to provide

annual estimates of the cod predation mortality on herring and sprat by age during the last 4 decades (1974-2018) to inform the single species stock assessment of the two clupeids.

In the Central Baltic Sea ecosystem cod predares on herring and sprat, which compete over zooplankton (Figure 1-1 (right)). Other major sources of mortalities for cod, herring and sprat are fisheries and seals. The model described here focuses on the impact of cod and fisheries on herring and sprat and does not account for other links.

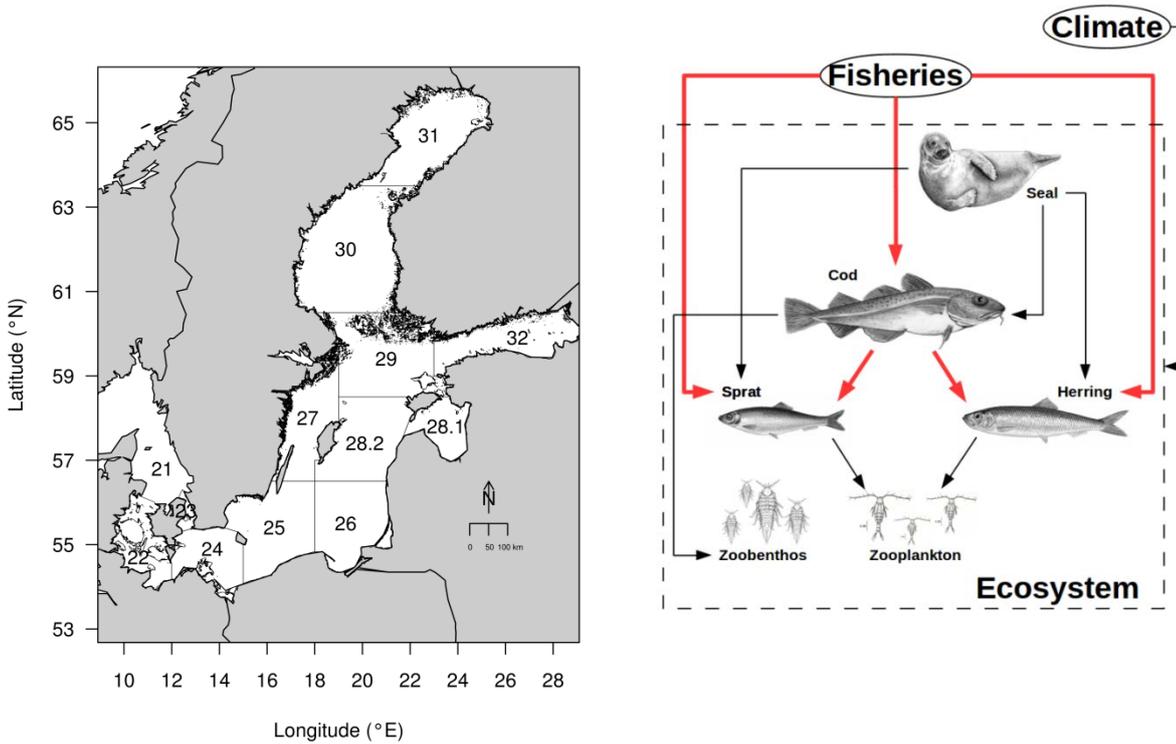


Figure 1-65. (Left) Map of the Baltic Sea with the ICES Subdivisions. (Right) Schematic representation of the central Baltic Sea foodweb including the fisheries. Trophic and fishing interactions are represented by arrows, in red those included in this model.

Conceptual model

The three stocks are built around a similar quarterly based conceptual model (Figure 1-2) starting in January 1974. Fishing and natural mortality occur in all time steps, recruits enter the model once a year in a specified quarter and one or more scientific surveys sample the stocks in different times of the year. Given the order of calculation, both recruitment and surveys occur after fishing in their respective timesteps. The modelled life cycles takes place in one area and no environmental forcing is considered in this model.

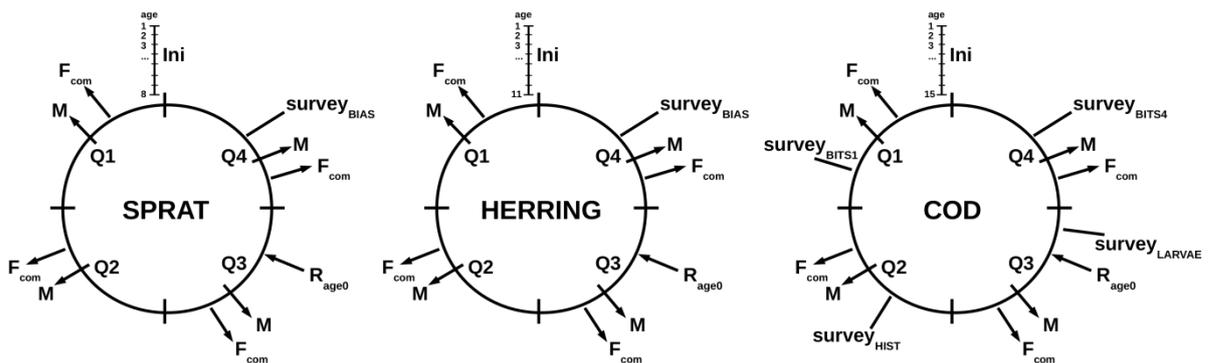


Figure 1-66. Schematic of the sprat, herring and cod conceptual models with the order of calculation of the main events in stock during one year. Q1-4 are the four quarters, Ini is the age composition at initial condition, F_{com} represent removal of fish by commercial fishing, M is the loss of fish due to natural mortality, R_{age0} is recruitment, $survey_x$ are the different surveys. Within each quarter, the order of calculation of the model is respected. The arrows represent outcome and income of fish from the modelled population due to different processes.

Input data

The model is parametrised using multiple data on the cod, herring and sprat stocks. Datasets include information on catch biomasses harvested by the fisheries involved in the exploitation of the three stocks, information on the age and size composition of the commercial catches, indices of abundance derived from scientific surveys, information on the age and size composition of the stocks from the surveys, biological data (mainly from surveys) and stomach data. All the data used for the model are compiled based on publicly available data retrieved from the ICES database or provided by dedicated ICES working groups. Wherever possible data match the exact datasets used for the ICES stock assessment and only in few cases specific compilation of input data, traditionally not shared by the assessment working group, was necessary. An overview of the data applied in the model is provided in table 1-1 and documentation included in the following sections.

Commercial catches

Catches of cod, herring and sprat are retrieved for the period 1974-2018 from the WGBFAS reports (ICES, 2019a). Quarterly catches of cod are also divided for the active and passive gears from 1987 and onward. Before 1987, all the cod catches are assumed to come from the active fleet which is considered a reasonable assumption given that the trawlers dominated the catch of the Baltic cod fisheries during the 1970s and 1980s (pers. comm. WGBFAS). The catches include discards estimates and since 2015, they are also comprehensive of BMS landings (Below Minimum Size) as imposed by the landing obligation. BMS represent approx. 1% of the total catch in 2017-2018. Catches also include estimates of eastern Baltic cod fished in SD24 (13% of total stock landings in 2018), which is the management area of the Western Baltic stock, based on otolith shape analysis combined with genetics (ICES, 2019b).

Quarterly catches of herring and sprat were available from 1995. Prior 1995 quarterly catches of clupeids were derived from the annual catches used in the assessment partitioned among the quarters according to the last accepted multispecies SMS keyrun for the Baltic (ICES, 2012) (ICES 2012).

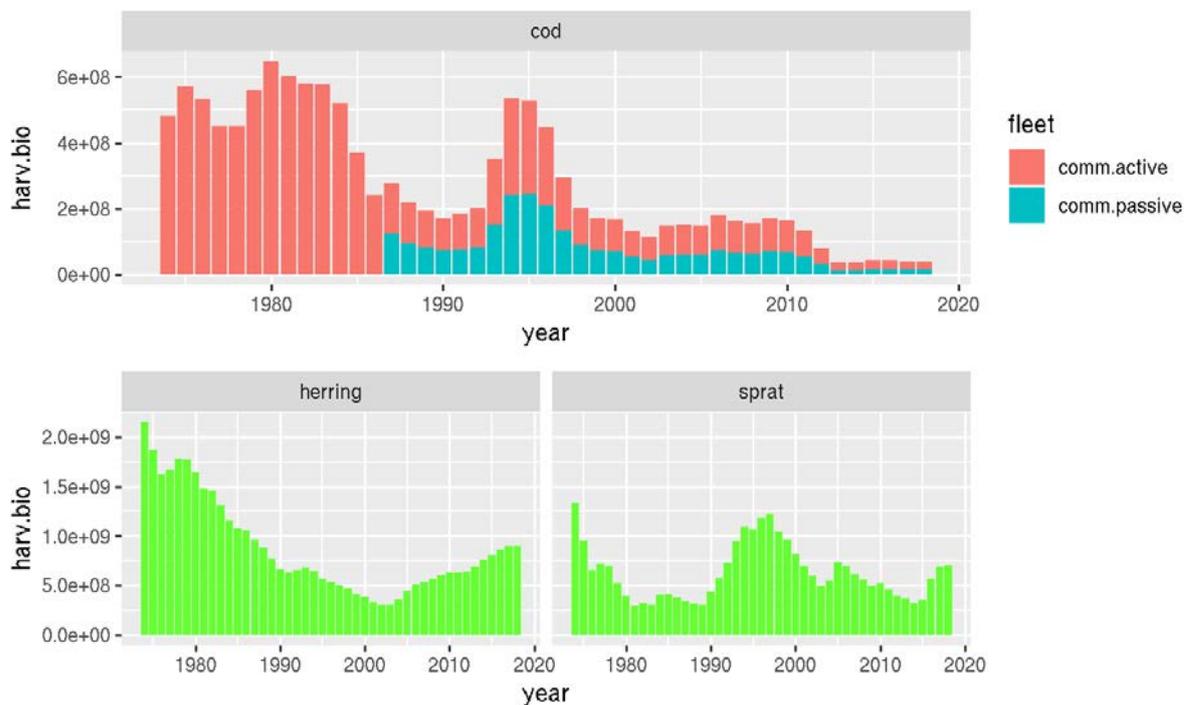


Figure 1-67. Time-series (1974-2018) of commercial catches of cod, herring and sprat by the fleet represented in the model.

Compositional data from commercial catches

Length distributions catch (cod)

Age reading has always been challenging for Eastern Baltic cod. However, this was found to be a major cause of biases in assessments only from the mid 2000s (ICES, 2018a) with increasing discrepancies between different countries' age readings. For this reason length distribution of

the catches by quarter and separately for the active and passive fleets are used from 2000. The Eastern Baltic cod catches in SD24 are assumed to have the same length distribution as in SD25.

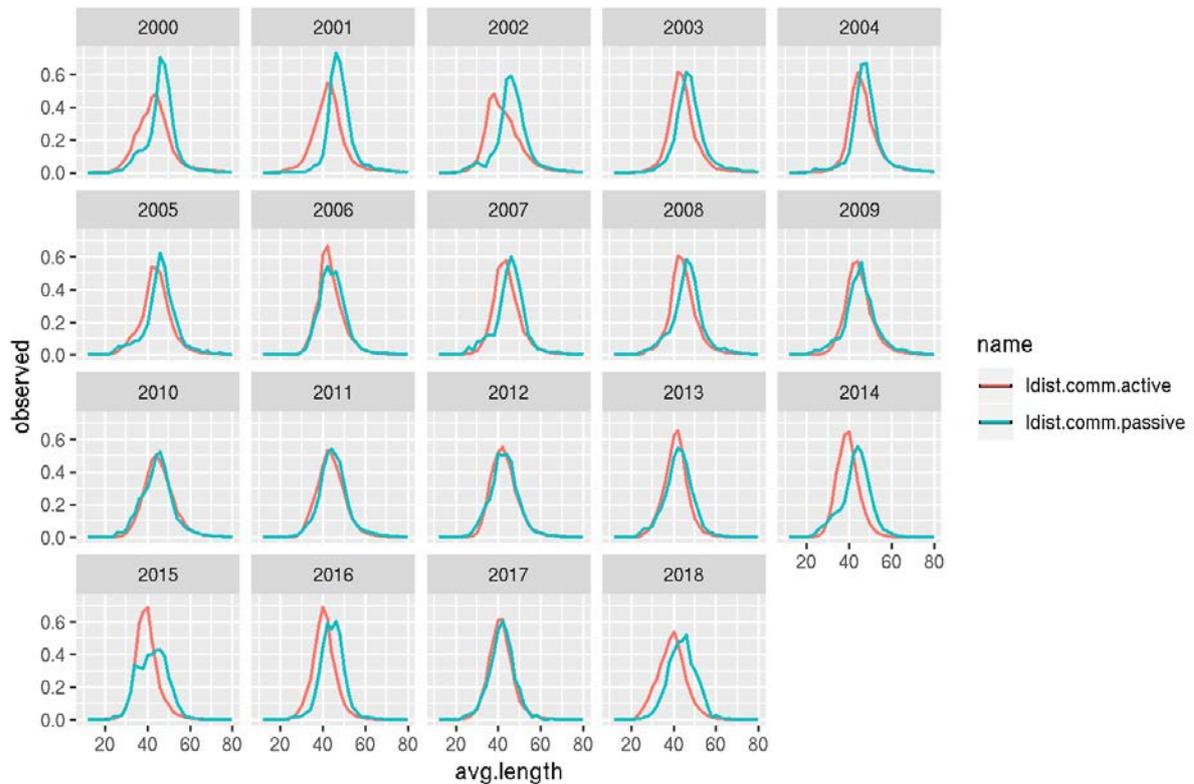


Figure 1-68. Length distributions of cod from the active and passive fleets in 2000-2018.

Age distributions catch (cod, herring, sprat)

Because age reading was not found to cause major biases in assessments at the last cod benchmark it was decided to use age compositions of the catches covering the first time period of the model (1974-1999, *Figure 1-5*). Data are available for this entire period for the active gears, while they cover the period 1987-1999 for the passive gears, which is consistent with assumption on the catches (section 1.2.1).

Age distributions of both herring and sprat commercial catches were available from WGBFAS by quarter from 1995 and aggregated over the entire year for the period 1974-1994 (*Figure 1-6*).

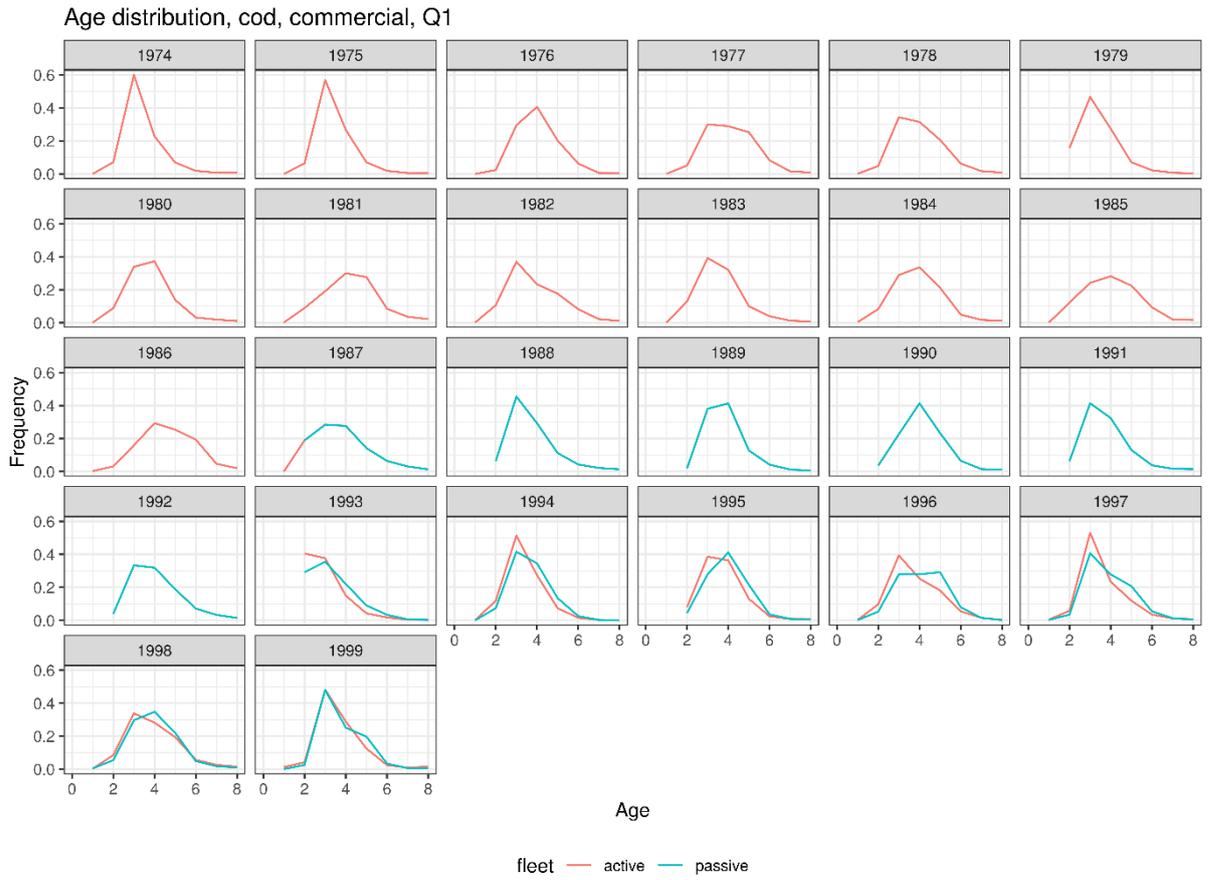


Figure 1-69. Age distributions of cod from the active and passive fleets in 1974-1999.

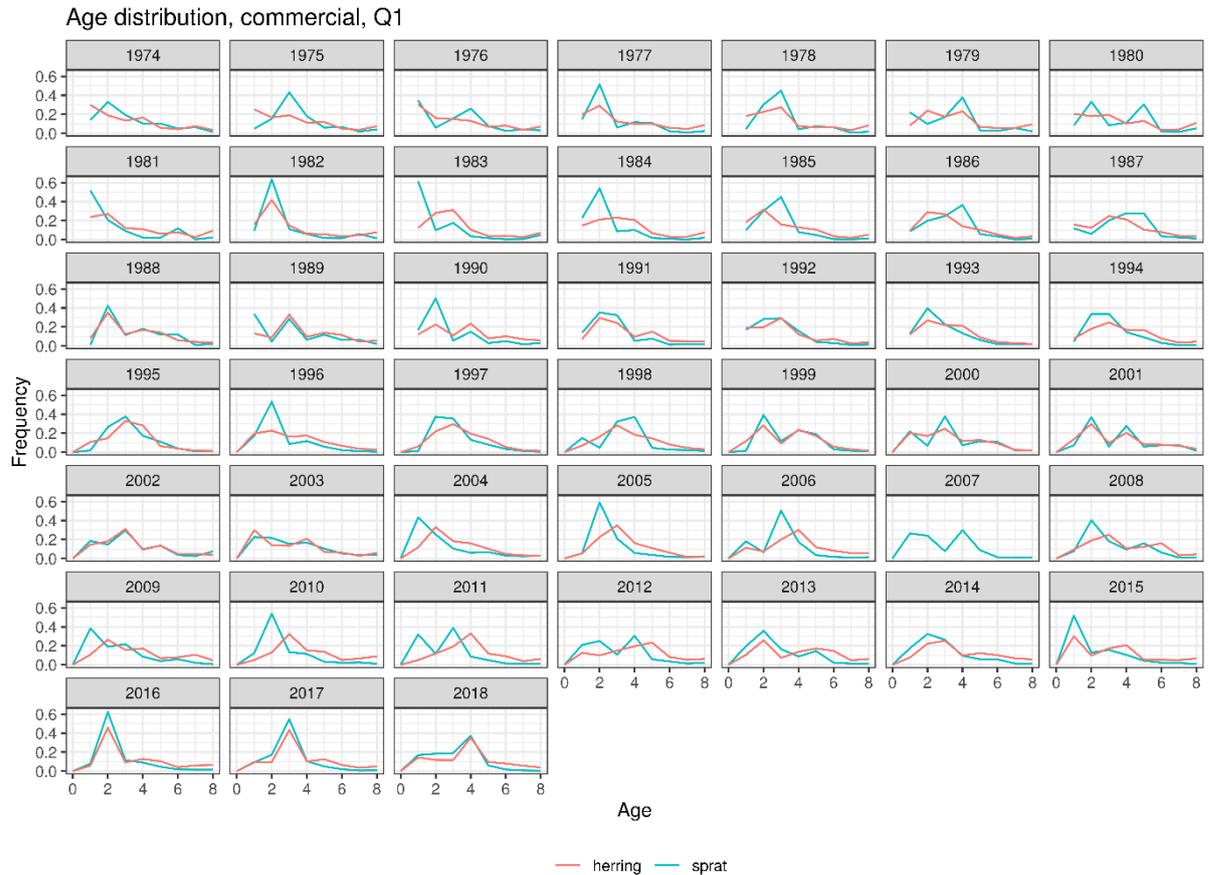


Figure 1-70. Age distributions of herring and sprat from commercial catches. Annual in 1974-1994, Q1 in 1995-2018.

Indices of abundance

BIAS (herring,sprat)

The Baltic Sea International Acoustic Survey (BIAS) has been conducted from the beginning of the 1990s to present with the specific purpose to provide indices of abundance of herring and sprat. The Baltic International Fish Survey Working Group (WGBIFS) calculates the indices of abundance by age for the stock assessment, which are also used in this model (ICES, 2019a, Figure 1-7, Figure 1-8).

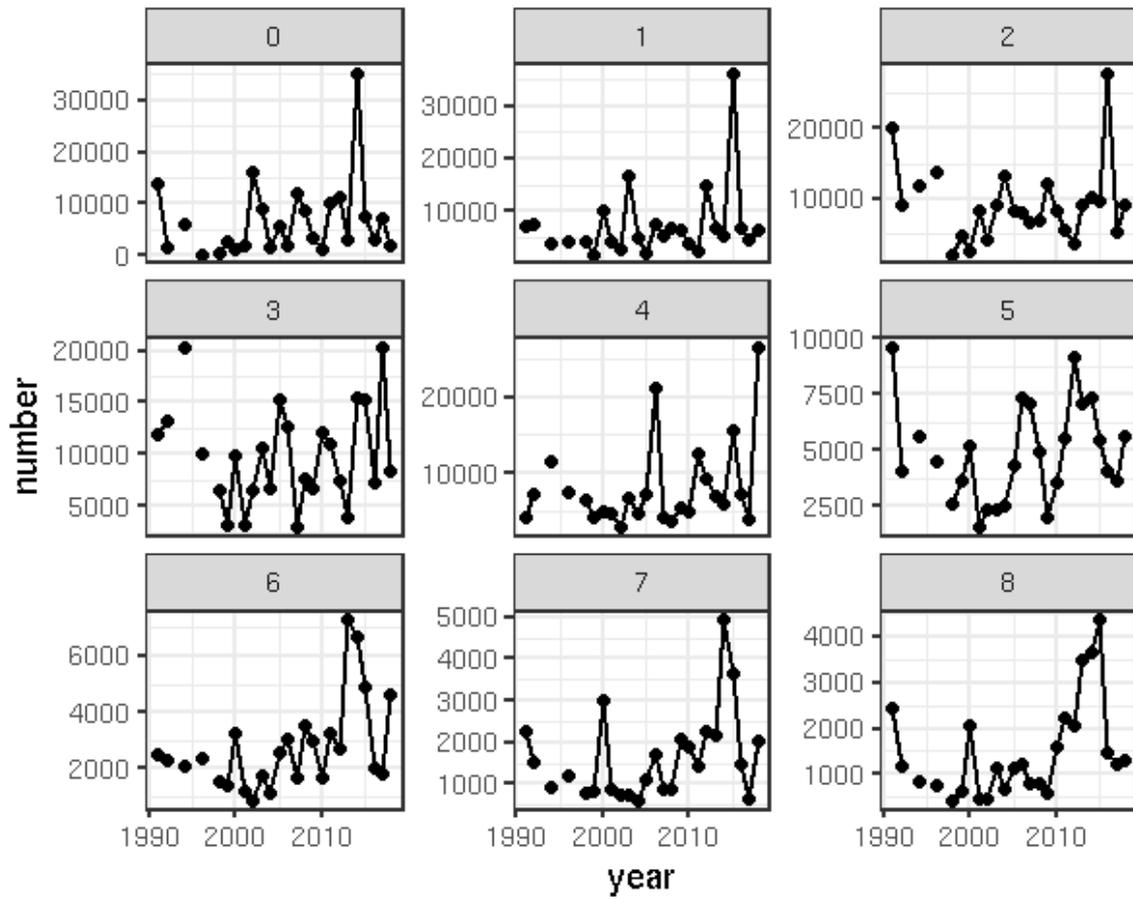


Figure 1-71. Indices of abundance of herring by age (8 is a plus group) from the BIAS

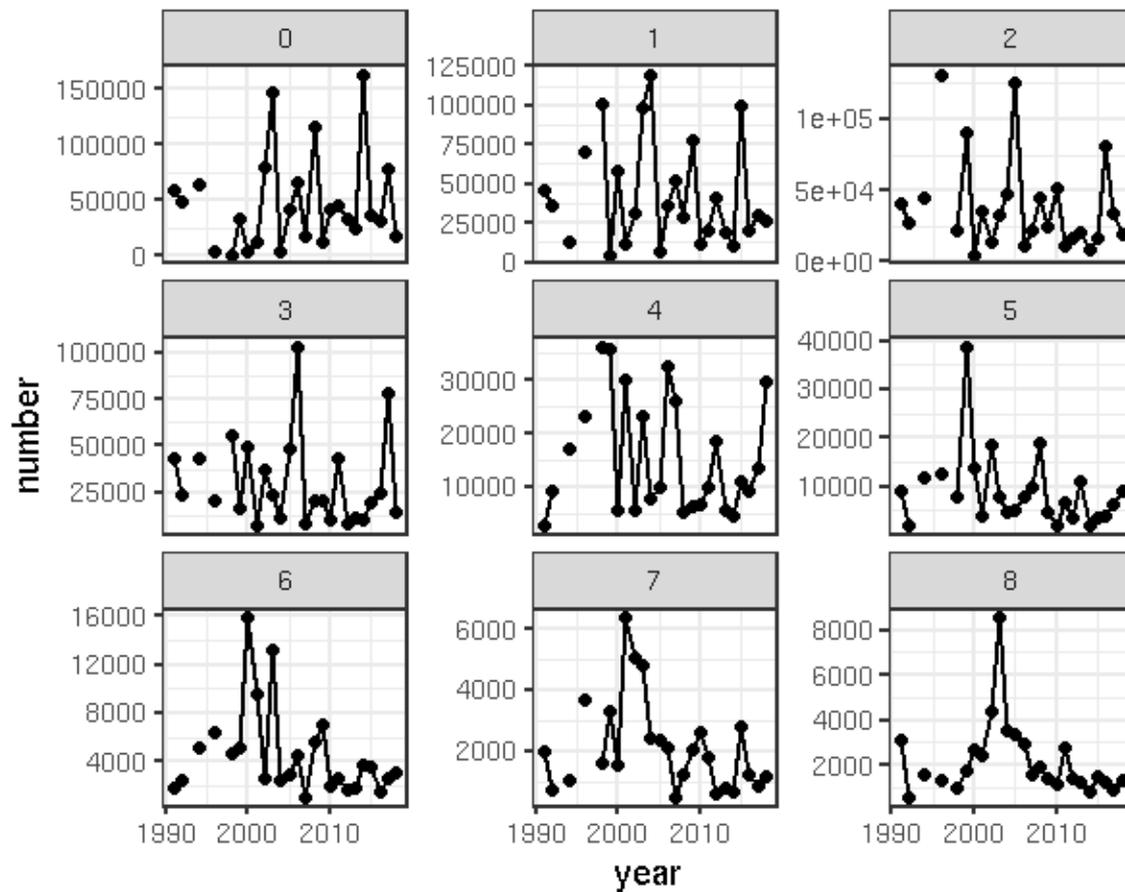


Figure 1-72. Indices of abundance of sprat by age (8 is a plus group) from the BIAS

BITS (cod)

Several survey indices are used to tune the cod assessment (ICES, 2019a) and accordingly this model (*Figure 1-9*). From the early 1990s model-based indices of total biomass are available for Q1 (from 1991) and Q4 (from 1993) from the Baltic International Bottom Trawl Surveys. The indices cover the SD25-32, and include the area east of 13 degrees latitude in SD24.

Prior the 1990s, standardised annual average CPUE (g/hour) from bottom trawl surveys carried on by the Swedish Board of Fisheries and the Baltic Fisheries Research institute in SD25-28 are used (Orio *et al.*, 2017).

In addition, the abundance of larvae during peak spawning from ichthyoplankton surveys, is used to inform about cod recruitment (ICES, 2019a).

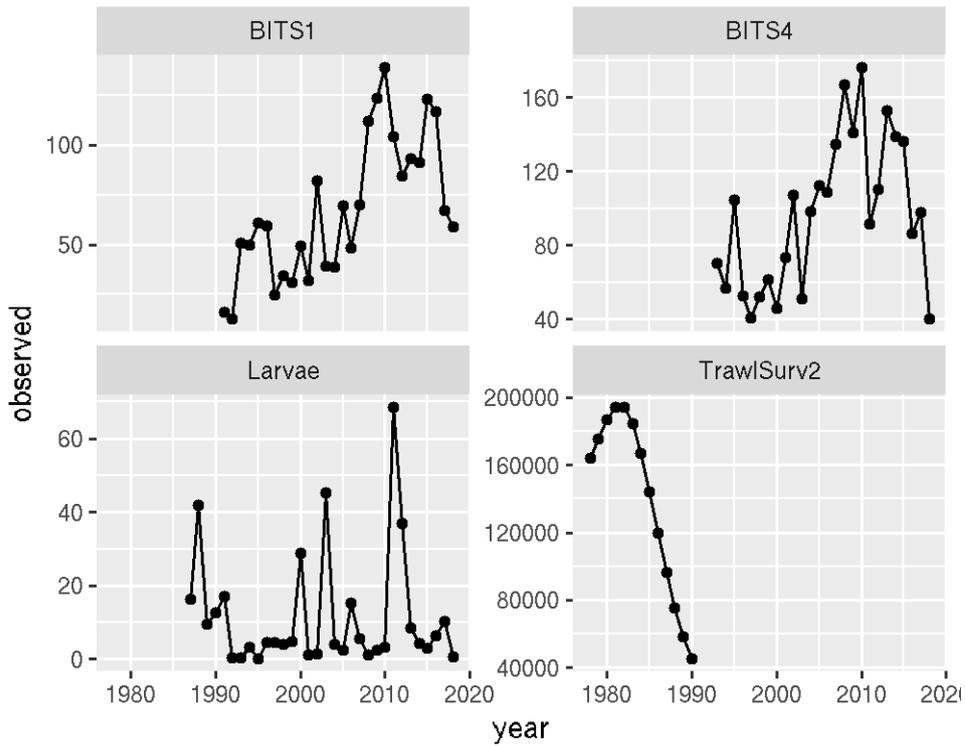


Figure 1-73. Indices of abundance of cod from the BITS Q1 (1991-2018) and Q4 (1993-2018), from the historical part of the trawl survey (TrawlSurv2, 1978-1990) and the index of recruitment from the ichthyoplankton surveys (1987-2018).

Compositional data from scientific surveys

Length distributions BIAS (herring, sprat)

Length distribution data from the BIAS survey were provided from individual countries at the haul level (see *Table 1-2*).

Table 1-32. Number of pelagic trawl hauls associated to the BIAS survey, and countries providing data for the period 1991-2018.

Year	Countries	Number of hauls
1991	SWE, GER	49
1992	SWE, GER	103
1993	GER	41
1994	LAT, SWE, GER	93
1995	LAT, POL, SWE, GER	58
1996	LAT, POL, SWE, GER	100
1997	LAT, POL, GER	44
1998	LAT, POL, SWE, GER	91
1999	FIN, LAT, POL, SWE, GER	77
2000	FIN, LAT, POL, SWE, GER	89
2001	EST, LAT, POL, SWE, GER	83

2002	EST, POL, SWE, GER	69
2003	EST, LAT, POL, SWE, GER	94
2004	EST, LAT, POL, SWE, GER	92
2005	EST, LAT, POL, SWE, GER	89
2006	FIN, LAT, POL, SWE, GER	134
2007	FIN, LAT, POL, SWE, GER	141
2008	FIN, LAT, POL, SWE, GER	130
2009	FIN, LAT, POL, SWE, GER	129
2010	FIN, LAT, POL, SWE, GER	136
2011	FIN, LAT, POL, SWE, GER	131
2012	FIN, LAT, POL, SWE, GER	92
2013	EST, FIN, LAT, POL, SWE, GER	106
2014	GER, EST, FIN, LIT, LAT, POL, SWE	73
2015	GER, EST, FIN, LAT, POL, SWE	73
2016	GER, EST, FIN, LIT, LAT, POL, RUS, SWE	74
2017	GER, EST, FIN, LIT, LAT, POL, RUS, SWE	54
2018	GER, EST, FIN, LIT, LAT, POL, SWE	53

According to the survey design, two (and in some cases more) pelagic trawl hauls are performed in each ICES rectangle to provide information on species composition and size structure. Length distributions representative for the entire stocks of herring and sprat were calculated according to the following steps:

- Number of fish at were pooled for each survey year within each ICES rectangle (*Figure 1-10*)
- Proportion of fish at length were calculated for each survey year by ICES rectangle
- A weighted average of the proportion of fish at length was calculated for each year using the acoustic index of abundance from the survey by rectangle. The estimates were restricted over a predefined area which has been more consistently sampled on the core distribution of each stock

Species	Subdivisions	Rectangles used for the estimation
Herring	25,26,27,28.2,29	39G6,39G7,39G8,39G9,40G6,40G7,40G8,40G9,40G5,40H0,41G7,41G8,41G9,42G7,42G9,43G9,43H0,42H0,44G7,44H0,41H0,45G8,45H0,42G8,38G6,46G9,46H0,45G9,46H1,47H0,47H1,38G9,43G7,45G7,46G8,39H0,44G9,47G9,45H1,44H1,47H2,41G6,40G4,38G8,38G7,44G8,46G7,43H1,43G8,43G6,42G6,47G8,46H2,44G6,41G5,37G9,37G6,37G8,42H1,45G6,41G4,40H1,48G8,46G6,38H0,41H1,39H1

Sprat	24,25,26,27,28.2,29	38G5,38G4,39G6,39G7,39G8,39G9,40G6,40G7,40G8,40G9,40G5,40H0,41G7,41G8,41G9,42G7,42G9,39G5,43G9,43H0,42H0,44G7,44H0,41H0,45G8,45H0,42G8,38G6,46G9,46H0,45G9,46H1,47H0,47H1,38G9,43G7,45G7,46G8,39H0,44G9,47G9,37G4,38G3,38G2,45H1,44H1,47H2,48G9,39G3,41G6,48H0,40G4,37G5,38G8,48H2,49G9,48H1,39G4,38G7,44G8,46G7,43H1,39G2,43G8,43G6,42G6,47G8,46H2,44G6,49G8,37G2,41G5,37G3,37G9,37G6,37G8,49H0,42H1,45G6,49H1,41G4,40H1,48G8,46G6,38H0,49H2,41H1,46H3,39H1
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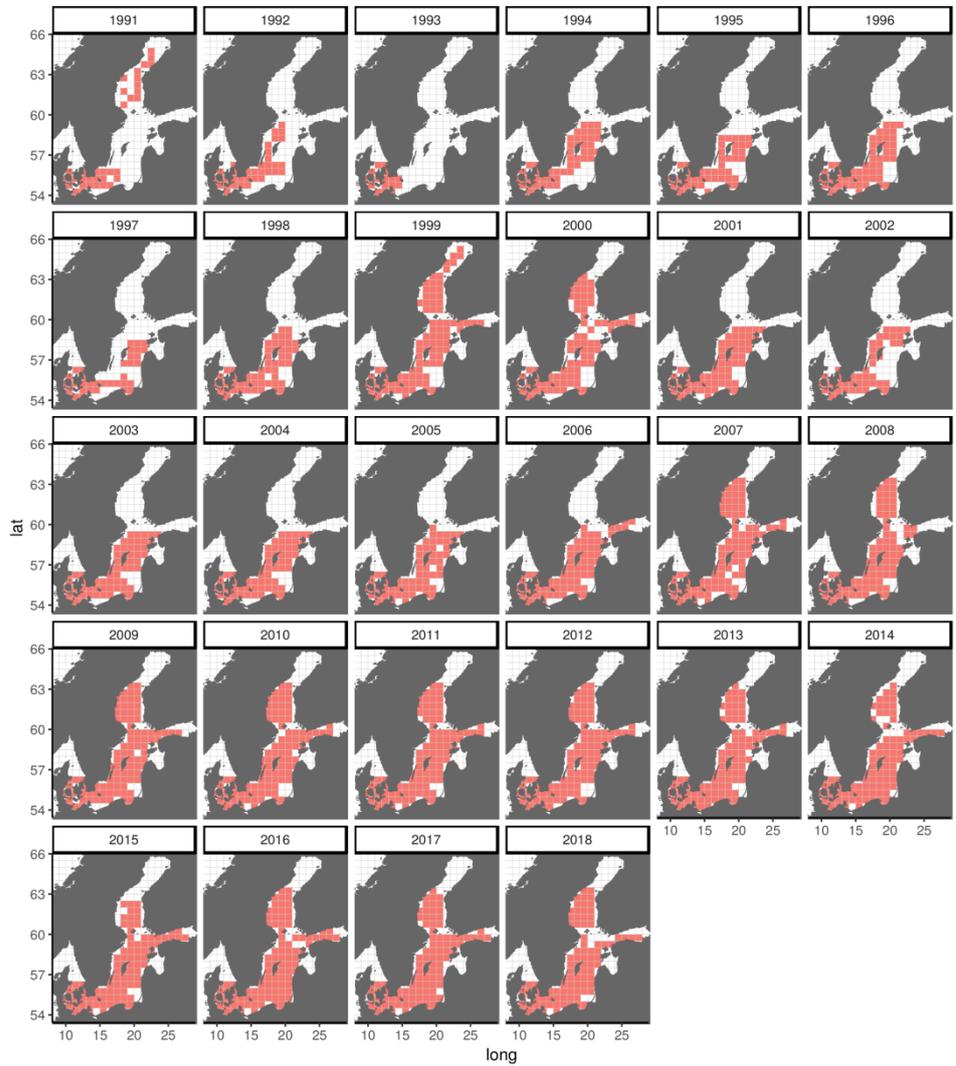


Figure 1-74. Maps with the annual distribution by ICES rectangle of the length samples from the BIAS survey over the period 1991-2018.

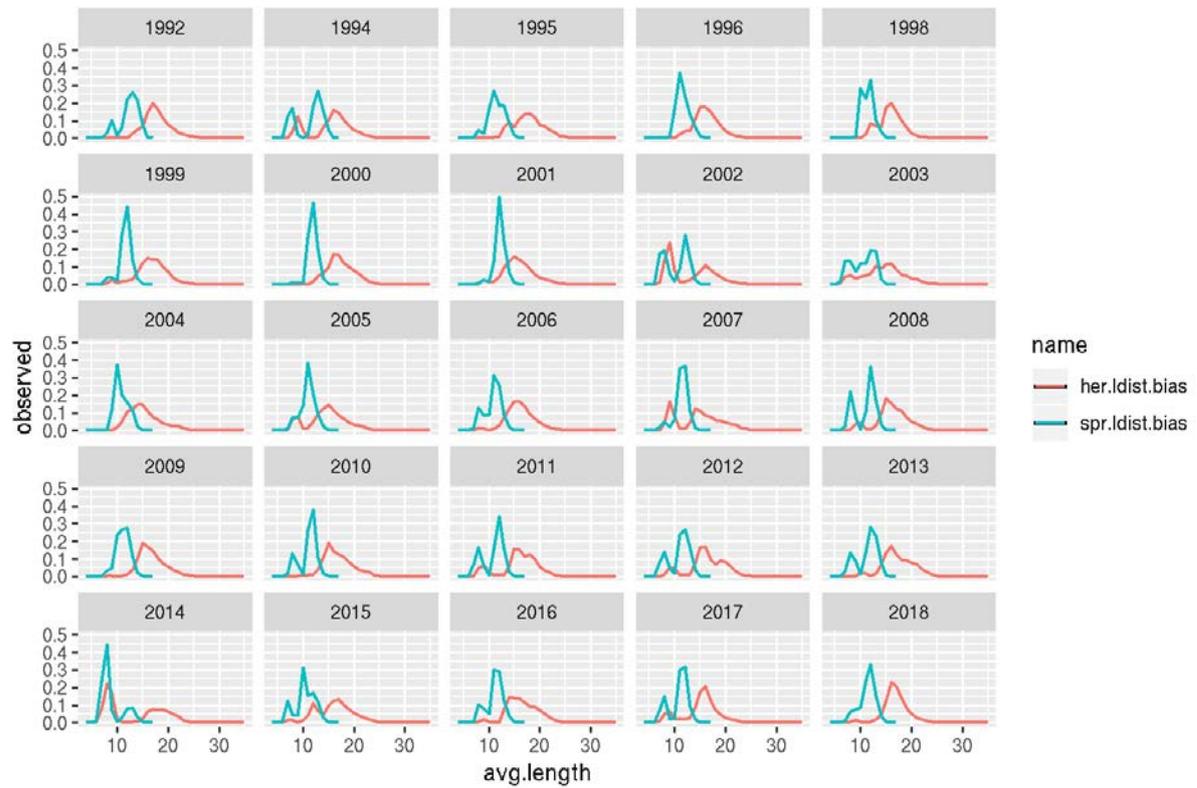


Figure 1-75. Length distributions of herring and sprat from the BIAS survey.

Length distributions BITS (cod)

From the early 1990s, the BITS surveys in Q1 and Q4 provide also information on the size composition of the stock. Also in this case, the dataset on length distributions is retrieved from the last ICES assessment (ICES, 2019a).

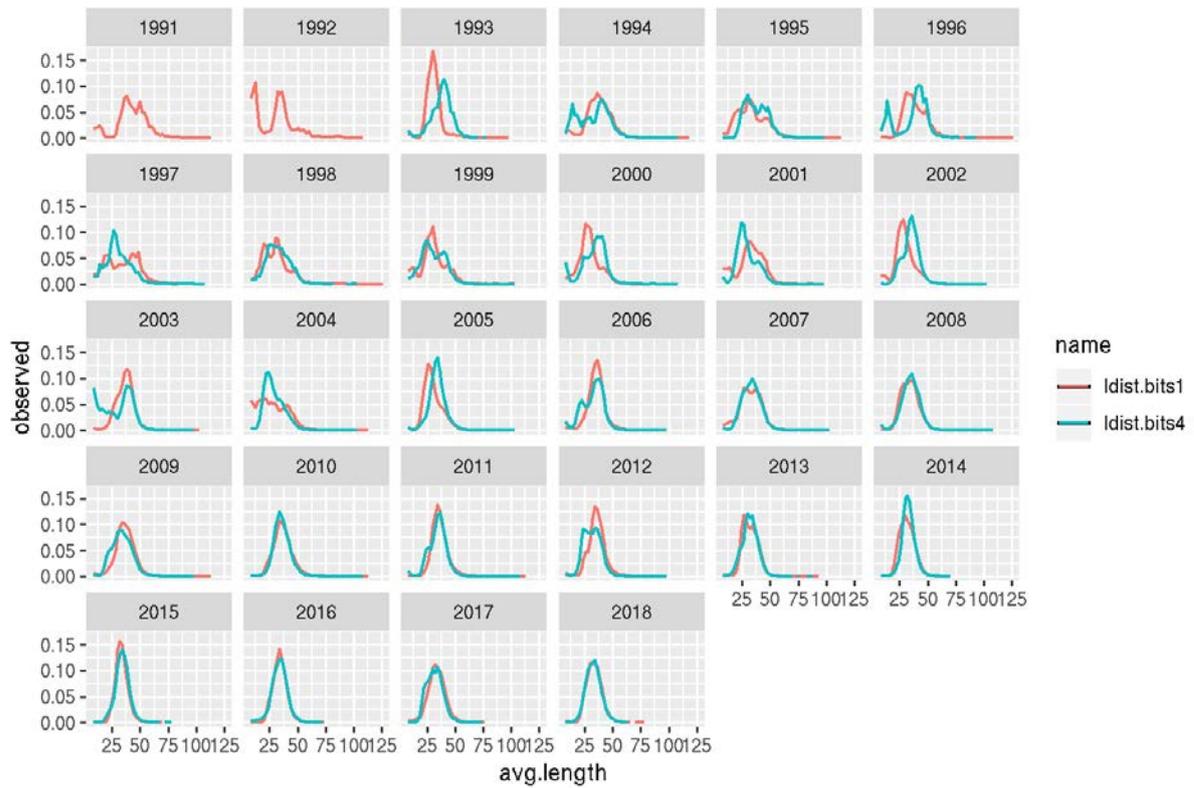


Figure 1-76. Length distributions of cod from the BITS in Q1 and Q4

Biological data

Age-length keys BIAS (herring, sprat)

Age-length keys (ALK) were constructed from individual biological data (age, length) obtained from pelagic trawl samples taken during the BIAS survey were provided by individual countries (Figure 1-14, Figure 1-15). ALKs were estimated as a number of fish in a sample for every length-age combination, this number is further used by the model to estimate probability of fish in each length group to have a specific age.

Table 1-33. Number of herring and sprat sampled for both length and age in the pelagic trawl hauls associated to the BIAS survey, and countries providing data for the period 1991-2018.

Year	Countries	Number of herring sampled	Number of sprat sampled
1991	SWE, GER	3435	595
1992	SWE, GER	6787	1956
1993	GER	1017	683
1994	LAT, SWE, GER	4154	2164
1995	LAT, POL, SWE, GER	5467	2933
1996	LAT, POL, SWE, GER	4954	3297
1997	LAT, POL, GER	2127	1955
1998	LAT, POL, SWE, GER	4459	6154
1999	FIN, LAT, POL, SWE, GER	4976	3522

2000	FIN, LAT, POL, SWE, GER	4761	3098
2001	EST, LAT, POL, SWE, GER	5967	3476
2002	EST, POL, SWE, GER	4263	2047
2003	EST, LAT, POL, SWE, GER	7053	2680
2004	EST, LAT, POL, SWE, GER	6356	4325
2005	EST, LAT, POL, SWE, GER	5048	2223
2006	FIN, LAT, POL, SWE, GER	5759	4173
2007	FIN, LAT, POL, SWE, GER	8759	5371
2008	FIN, LAT, POL, SWE, GER	7334	4345
2009	FIN, LAT, POL, SWE, GER	7434	4382
2010	FIN, LAT, POL, SWE, GER	6502	4276
2011	FIN, LAT, POL, SWE, GER	6329	4635
2012	FIN, LAT, POL, SWE, GER	6619	2749
2013	EST, FIN, LAT, POL, SWE, GER	8069	3702
2014	GER, EST, FIN, LIT, LAT, POL, SWE	12911	5456
2015	GER, EST, FIN, LAT, POL, SWE	8936	6117
2016	GER, EST, FIN, LIT, LAT, POL, RUS, SWE	11036	7213
2017	GER, EST, FIN, LIT, LAT, POL, RUS, SWE	10289	6356
2018	GER, EST, FIN, LIT, LAT, POL, SWE	9241	5231

Same rectangle used for the estimation of length distributions were selected for the calculation of ALKs of herring and sprat.

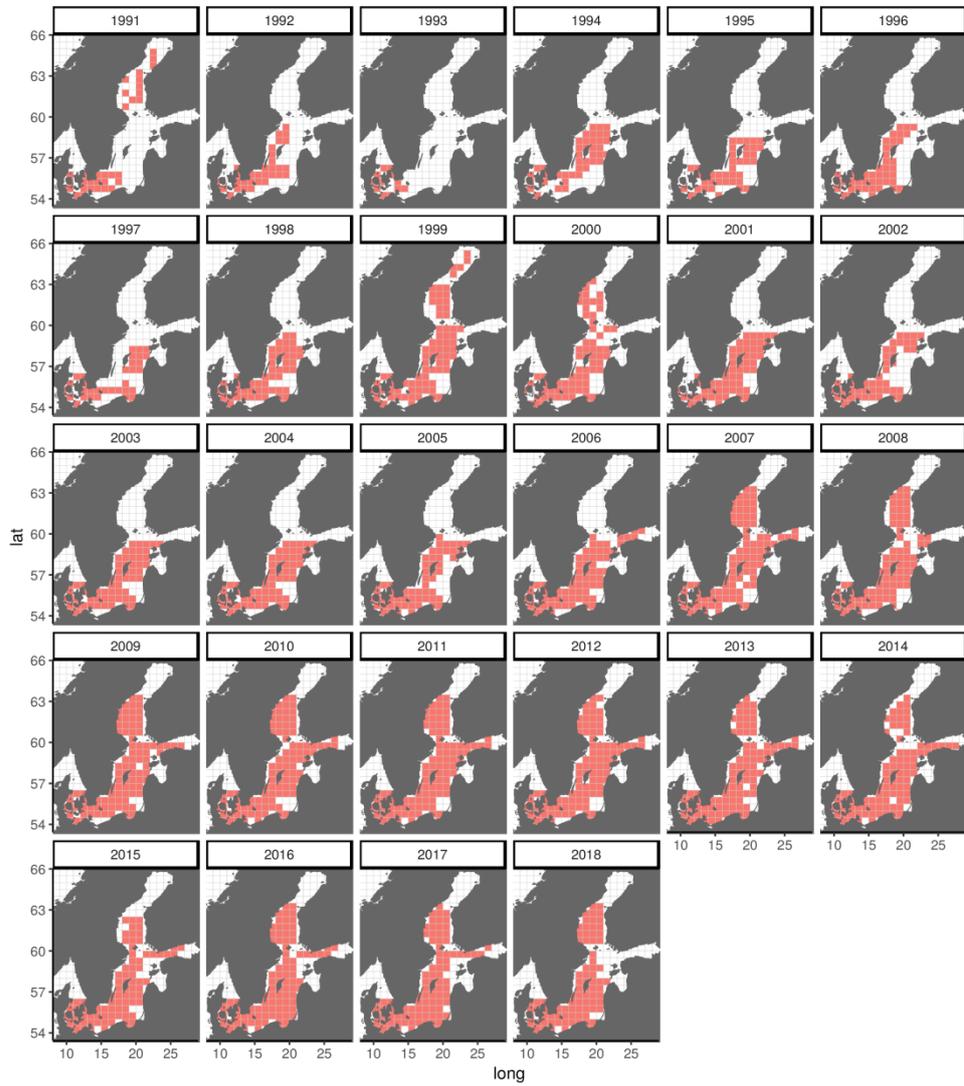


Figure 1-77. Maps with the annual distribution by ICES rectangle of the individual biological samples from the BIAS survey over the period 1991-2018.

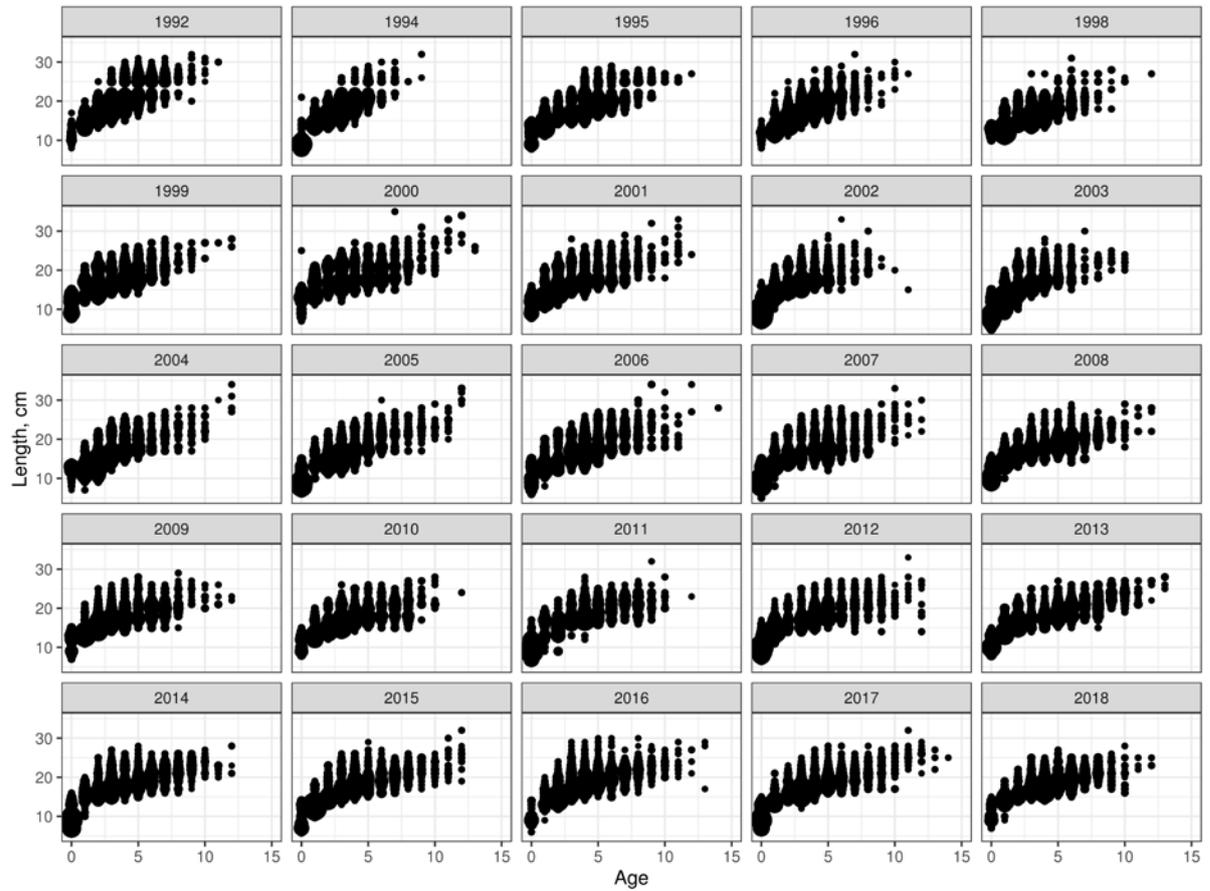


Figure 1-78. Herring age-length key produced from BIAS samples, size of bubbles corresponds to the sample size.

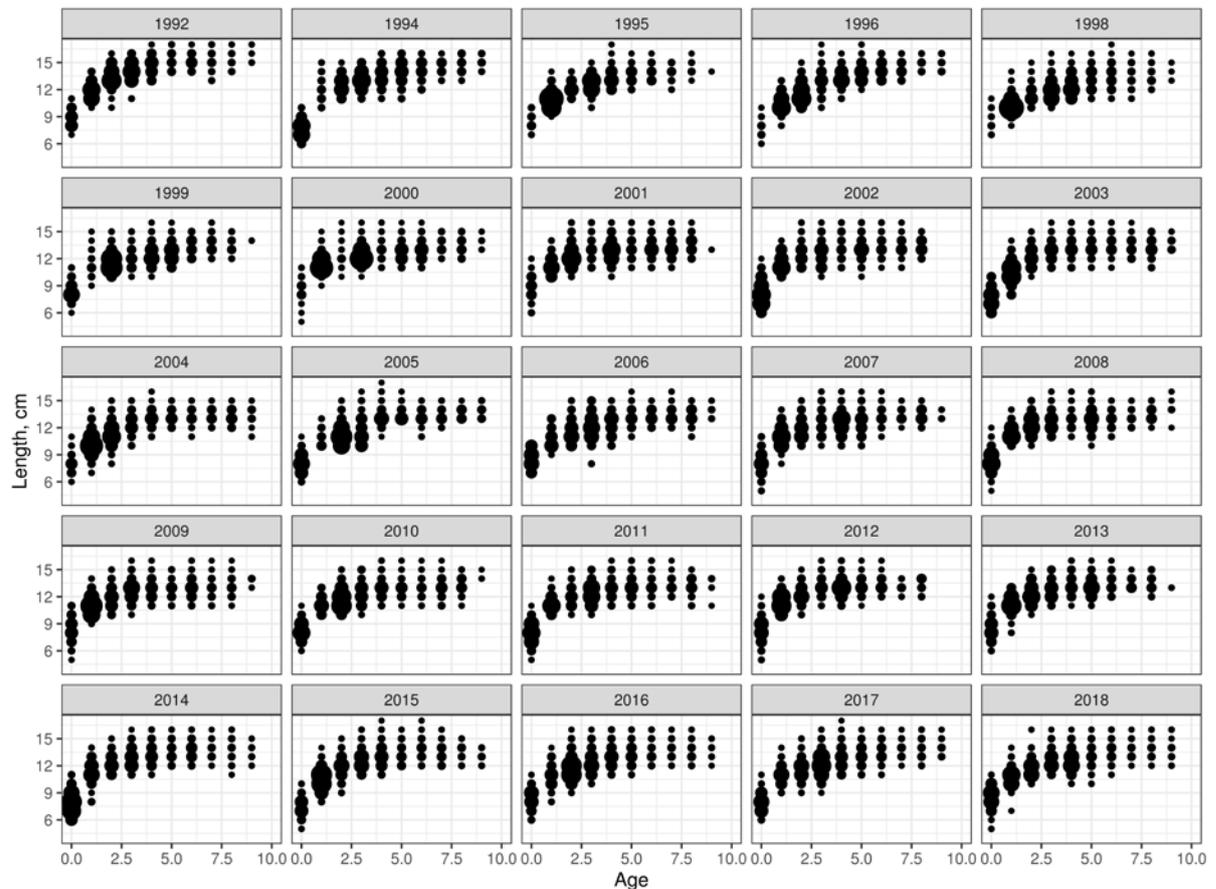


Figure 1-79. Sprat age-length key produced from BIAS samples, size of bubbles corresponds to the sample size.

Maternity data (cod,herring,sprat)

Maturation is not explicitly represented for any of the species included in this model and information on maturity is used a posteriori to calculate the proportions of the modelled stocks that contribute to the mature population. Spawning stock biomass (SSB) is mainly used for comparison with the current single species assessments. The present model includes no index of SSB and no stock-recruitment relationship, which means that no maturity data are used for estimation of the stocks dynamics.

For congruence with the single species assessments, SSB is derived as follows:

- Cod size at maturation has considerably declined between the 1990s and 2000s. Estimates of L50 (50% percent mature) as provided from the last benchmark (ICES, 2019b) suggest that the L50 decreased from 35-40 cm (males and females combined) in the early 1990s to around 20 cm since the late 2000s. Parameters of the corresponding length based maturity ogive were provided from the assessment (ICES, 2019a, *Figure 1-16*)
- Herring maturity is based on a vector of proportion of mature fish at age (age0-1: 0, age2: 0.7, age3: 0.9, age4+: 1, *Figure 1-17*)
- Sprat maturity is based on a vector of proportion of mature fish at age (age0: 0, age1: 0.17, age2: 0.93, age3+: 1, *Figure 1-18*)

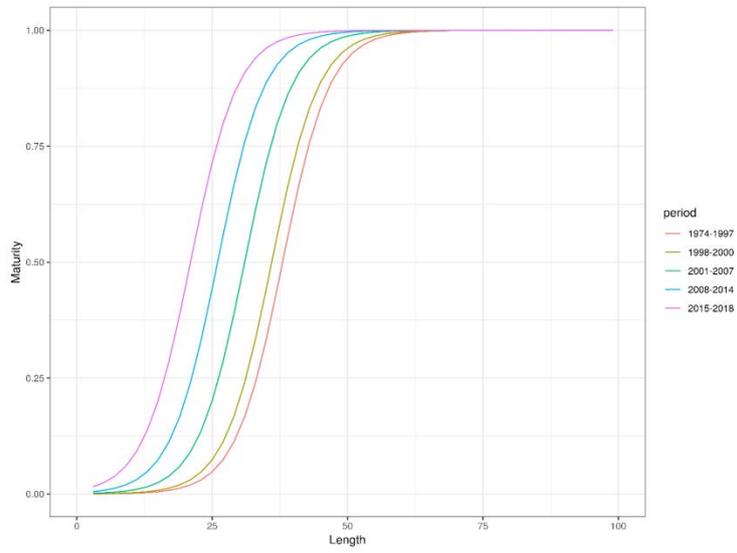


Figure 1-80. Cod maturity ogive.

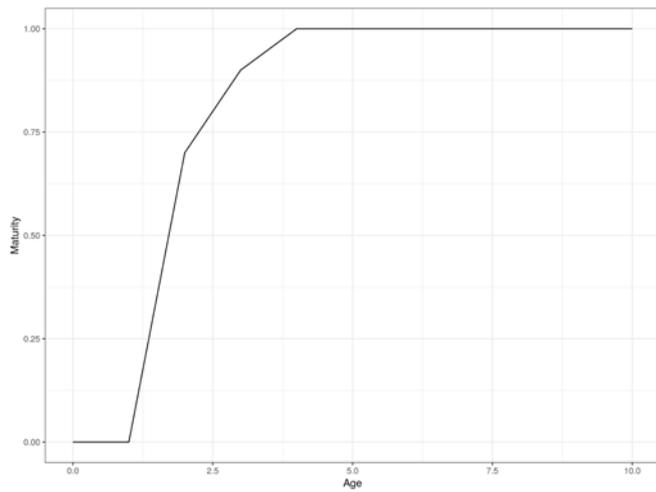


Figure 1-81. Herring maturity ogive

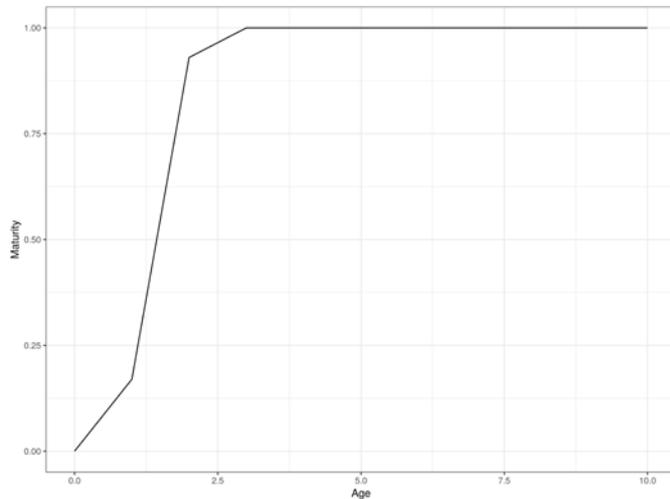


Figure 1-82. Sprat maturity ogive.

Cod stomach data

A unique dataset of >100,000 cod stomachs collected during five decades (1963-2014) in the Baltic Sea was recently digitalised under the EU tender No MARE/2012/02 “Study on stomach content of fish to support the assessment of good environmental status of marine foodwebs and the prediction of MSY after stock restoration” and made available through the ICES database. For the period 1974-2014, we were able to retrieve >45,000 cod stomachs with associated information on predator length and prey weight. This is essential information used to model the predation of cod on herring and sprat in this model. Most of the data prior 2007 were collected by Latvia, while in the most recent data other countries were involved, including Sweden, Poland, Denmark. The collection of this large number of stomachs across many decades lack of a coherent sampling design, and samples have been collected in a number of different national and international projects. Only in the last few years the cod stomach have been more consistently collected by several countries during the Baltic International Trawl Survey (BITS) which also provides main information on the abundance and age-length structure of cod in the Baltic.

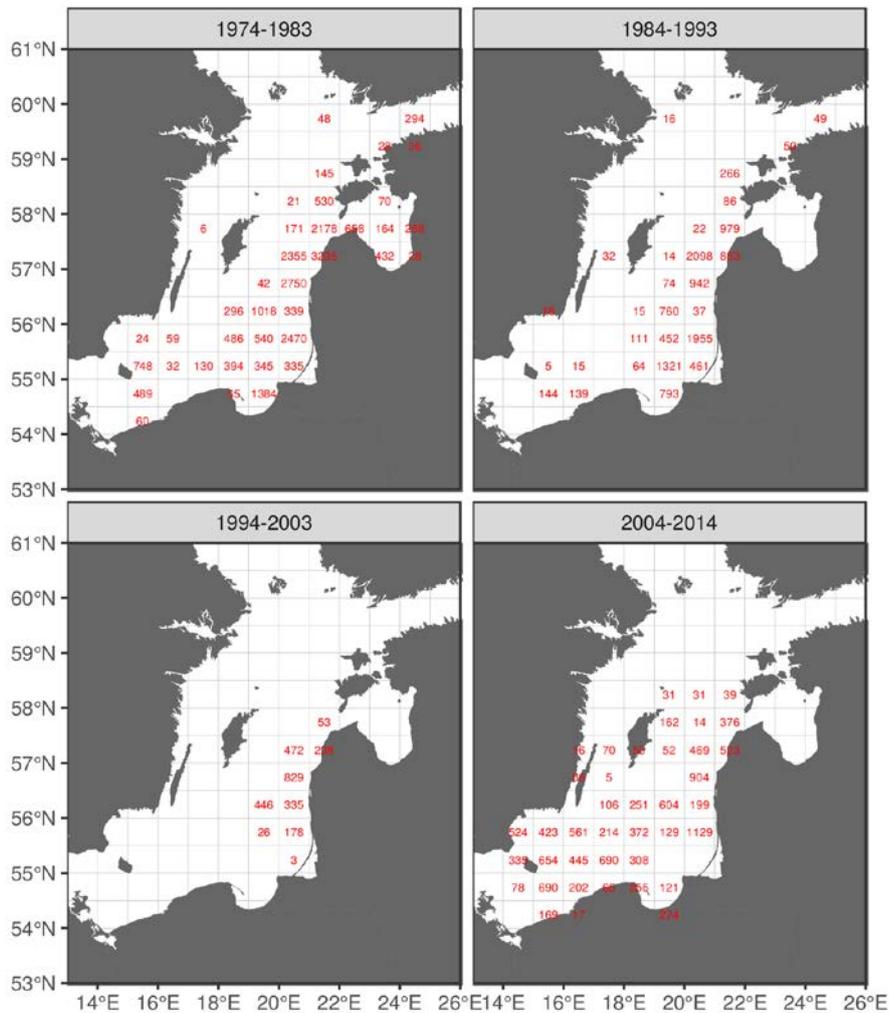


Figure 1-83. Geographical distribution by ICES rectangle of the number of cod stomachs for the periods 1974-1983, 1984-1993, 1994-2003, 2004-2014.

Exploratory data analysis of the historical cod stomachs has been recently presented by the Study Group on Spatial Analyses for the Baltic Sea (ICES, 2014a, 2017). Although more than 100 prey items are reported in the cod stomachs, a handful of species represents >90% of the diet in weight. The data show that mysids (mainly *Mysis mixta*) is the main prey item in weight for small cod (<20 cm). Contribution of the isopod saduria (*Saduria entomon*) has a rapid increase in the diet of small cod until 30 cm, to decrease progressively for larger fish. The importance of sprat has a rapid increase until 45-50 cm when it represents approx. 40% in weight of the cod diet. Herring is progressively more important in the diet of cod with a pick at approx. 60-70 cm. Larger cod above 70 cm show an increasing preference for flounder (*Platichthys flesus*). Similarly, cannibalism becomes more relevant for cod >70 cm. For the purposes of this model, all the preys other than herring and sprat have been grouped into *otherfood*.

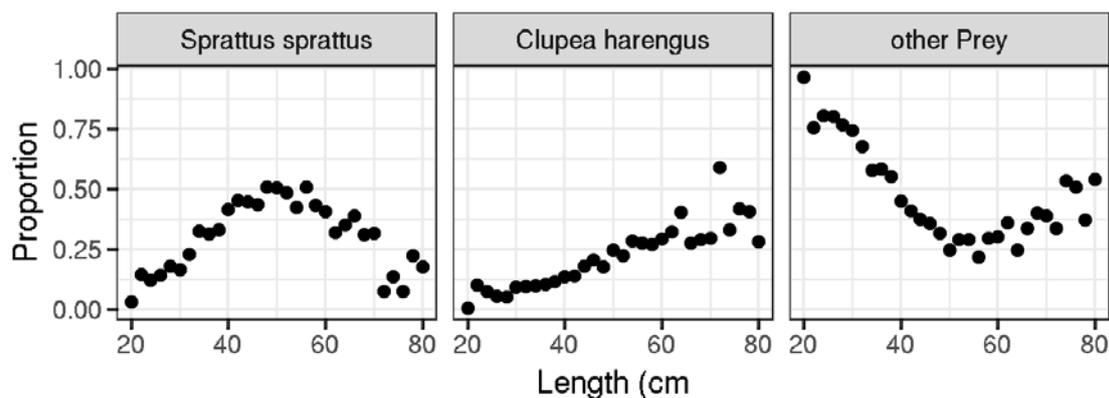


Figure 1-84. Plot of the proportional contribution in weight of sprat, herring and the aggregated all other prey in the stomachs of 20-80 cm cod in relation to cod size (2-cm bin) based on data for the period 1974-2014 and SD25-28.

Overall the stomachs covering the period 1974-2014 are relatively well represented throughout the different seasons (Q1=41%, Q2=28%, Q3=5%, Q4=25%), but Q2 and Q3 are mostly limited to Latvian samples collected before the mid 1990s. For this reason, only stomachs from Q1 and Q4 have been included in this model.

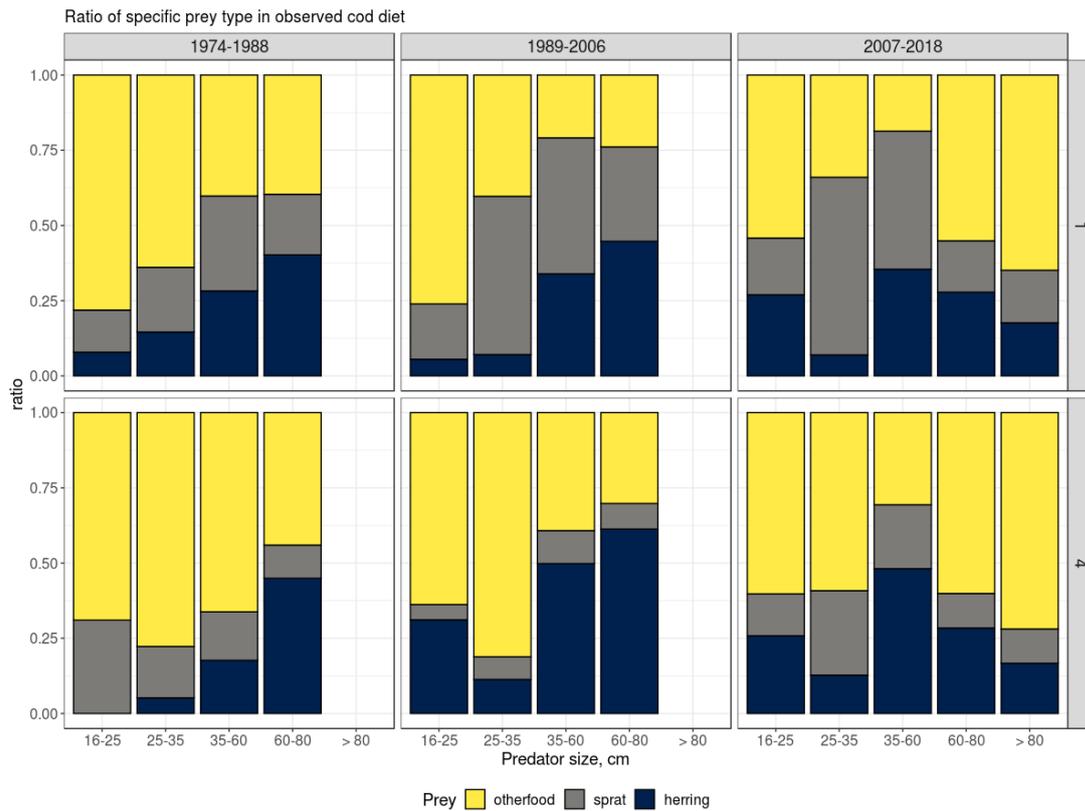


Figure 1-85. Observed species composition in Q1 and Q4 in the stomachs of cod size groups 16-25 cm, 25-35 cm, 35-60 cm, 60-80 cm, >80 cm during the periods 1974-1988, 1989-2006, 2007-2013 (modified from Kulatska *et al.* 2019).

Modelling procedure and implementation

The modelling process to estimate unknown parameters in Gadget can be outlined in three steps. First, provided with initial parameter values, Gadget runs a forward projection model. Then it compares obtained estimates to observed values and calculates likelihood scores (negative log-likelihood) to represent goodness of fit. As the last step, Gadget re-adjusts parameter values and re-runs the model until optimum parameter values are found, which produce the overall best fit of the model to multiple data components (Begley, 2017).

The optimization process in steps two and three uses three algorithms: first, a wide area search simulated annealing (Corana *et al.*, 1987) to reach the general area of a solution, followed by a local search Hooke and Jeeves algorithm (Hooke and Jeeves, 1961) to rapidly find a local solution and then Boyden-Fletcher-Goldfarb-Shanno algorithm (BFGS, Bertsekas, 1999) to fine-tune the optimization. This procedure is repeated several times to prevent converging to a local optimum.

The multispecies phase of the estimation uses 28 datasets to estimate 124 parameters (see Table 3-2, Table 3-3 and Table 1-1). The nature of these data sets is different (i.e., length distributions, age-length keys, survey indices, etc.), thus, an appropriate function for each data type (called likelihood component) is used to calculate a likelihood score during the optimization. Scores of individual likelihood components are then combined into an overall likelihood score (objective

function; Begley, 2017). In order to prevent some likelihood components from dominating the objective function and reduce the impact of low quality data iterative re-weighting is used (Stefansson, 2003; Taylor *et al.*, 2007; ICES, 2014b):

$$l = \sum_i w_i l_i$$

where l is objective function, l_i and w_i are respectively the likelihood score and weight assigned to a likelihood component i . The iterative re-weighting approach is based on assigning the inverse variance of the fitted residuals as component weights. The variances, and thus the final weights, are calculated as follows:

1. The initial variance (usually sums of squares, SS) are calculated using the initial parametrization for all likelihood components. The inverse SS are assigned as the initial weights for each likelihood component (initial score multiplied by weight will be 1 for each component)
2. For each likelihood component in a sequence, an optimization run is done where the initial weight is multiplied by 10 000 while weights of other components are multiplied by 1 until the minimum negative log-likelihood score is found. The residual variance is then estimated by dividing the resulting SS of that component by the degrees of freedom (df):

$$\sigma^2 = \frac{SS}{df}$$

3. After the series of optimization runs final weight for each component is set as the inverse of the estimated variance from the step above (weight = $1/\sigma^2$).

The time frame for the model was set to 1974–2018, making stepwise calculations for each quarter (year). The model is single area and uses data matching the entire distribution of Eastern Baltic cod (cod.27.24-32), Baltic sprat (spr.27.22-32) and Central Baltic herring (her.27.25-2932).

Implementation of the multispecies model starts with the initial parametrisation of single-species models for cod, herring and sprat. The goodness of fit of each model was evaluated based on visual inspection (where we evaluated whether predicted values had similar magnitude and trends as observed values) and by estimating overall and individual components likelihood scores. When satisfactory single-species models were parametrised, they have been linked into the multispecies implementation.

The current model is entirely implemented in R using functionalities from the *Rgadget* (Elvarsson, 2015) and *mfdB* (Lentin, 2014) libraries. This facilitates part of the modelling process, including: data aggregation and formatting into suitable Gadget likelihood data components, data weighting and fitting, output of graphical diagnostics.

Single-species implementations

Single species sprat model

Biological model

The modelled sprat population spans from age0 to age10 and from 3.5 to 17.5 cm in length with 0.5 cm length resolution. Natural mortality at age is a vector (age0=0.5, age1-3=0.44, age4=0.43, Age5-6=0.42, age7+=0.41) calculated as the average of the natural mortality matrix used in the assessment. This is a one area one stock model with no implementation of sex and sub-population structures. In practice, no difference in any biological parameter is assumed between males and females, or among different stages such as juvenile and adults.

Recruitment is estimated to occur once a year during quarter 3. At this timestep age0 fish enter the model with a fixed mean length of 7.69 cm, estimated during preliminary runs, and standard deviation of 0.9 cm. No stock-recruitment relationship is used to estimate the number of recruits. A year-specific recruitment parameter is estimated for each year of the model.

Mean growth is implemented with a simple von Bertalanffy model where the increase in length for each length group i and the corresponding increase in weight are given by the following two equations:

Equation 2-1

$$\Delta L_i = (L_{inf} - L_i) \cdot (1 - e^{-k\Delta t})$$

Equation 2-2

$$\Delta W_i = a[(L_i + \Delta L_i)^b - L_i^b]$$

where:

< Δt > is the length of the timestep

< L_{inf} > is the asymptotic length at which growth is zero

< k > is the growth rate

< a > is the linear coefficient of the length-weight model

< b > is the exponential coefficient of the length-weight model

L_{inf} (13.26 cm) and k (0.668) were estimated outside the model using individual age-length data from the BIAS survey over the period 1991-2018.

Dispersion around the mean growth in length is implemented with a beta-binomial distribution. Such implementation has the flexibility to produce non-symmetrical distributions with larger right-end tail as the curve dispersion increases (see Taylor *et al.* (2007) and Begley (2006) for more details). Fish were allowed to grow by a maximum of 2 cm within a timestep, and the beta parameter was estimated in the model.

Individual weight-at-age reported in the commercial catches shows a mark change during the study period, with high weights in the 1970s-1980s and low weights from the end of the 1990s. Such pattern could be explained with changes in condition, growth and selectivity of the fishery. In this model it is assumed that changed in the length-weight relationship are responsible for this pattern in the biological data. Accordingly, the length-weight relationship was assumed to change over three time blocks represented by the periods 1974-1989, 1990-1996, 1997-2018. The exponent parameter b of the length-weight relationship was estimated based on the 1991-2018 pooled BIAS survey data, while a parameter a was estimated in Gadget for each of the three time blocks.

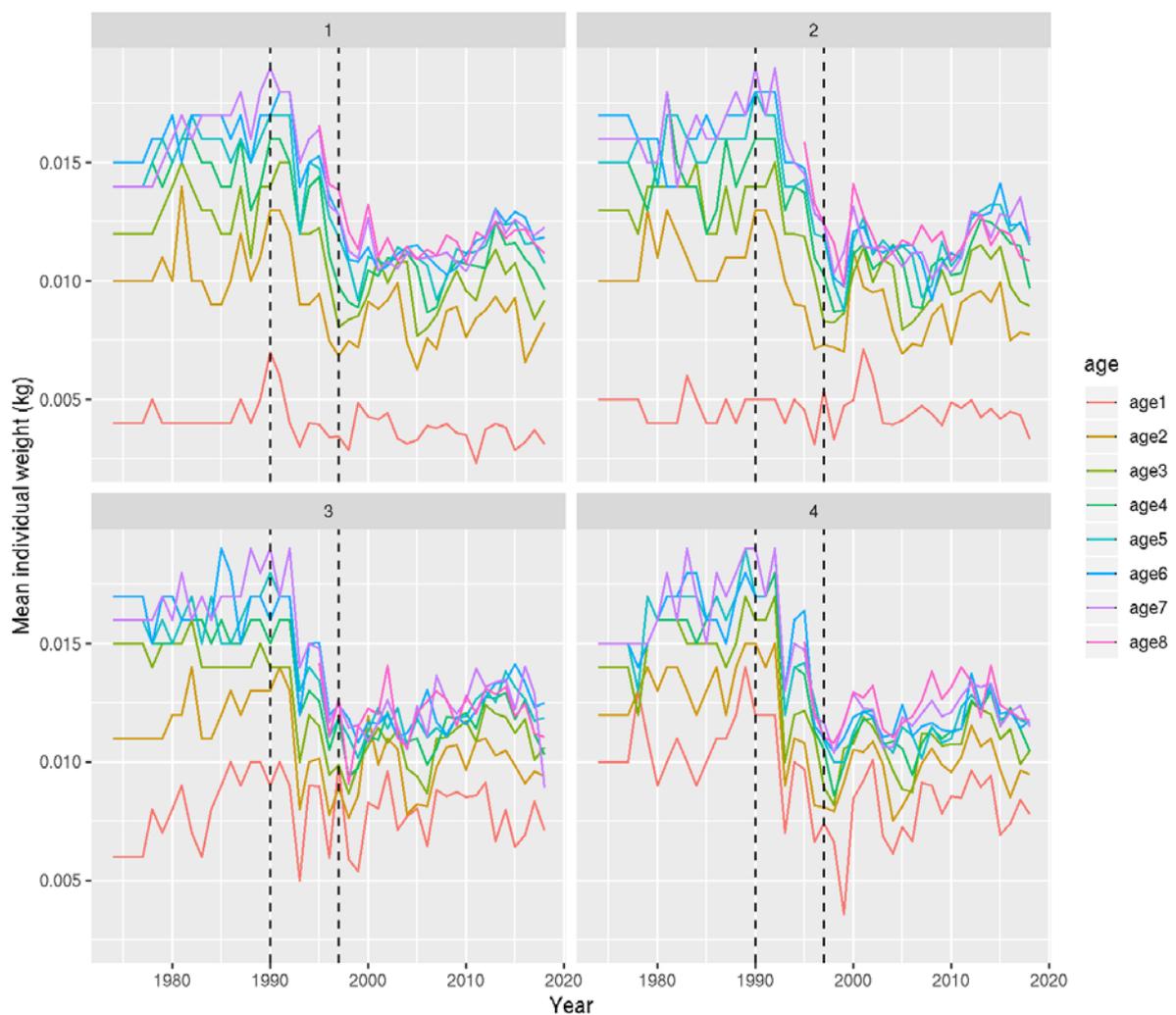


Figure 2-86. Observed weight-at-age of sprat by quarter from commercial catches in 1974-2018. Vertical lines indicate the three time periods selected to represent different length-weight relationships.

The process of maturation is not implemented in the current model. The same constant vector with the proportion of mature fish at age from stock assessment (age0: 0, age1: 0.17, age2: 0.93, age3+: 1) is used to calculate the spawning stock biomass from the estimated number of fish and mean weight-at-age.

Fleets

The model includes one commercial fleet and one survey (BIAS). Sigmoid functions defined by two parameters are assumed for the suitability (i.e., combination of selectivity and availability) of both fishery and survey:

Equation 2-3

$$S_l = \frac{1}{1 + e^{-a(l-l_{50})}}$$

where:

< l_{50} > is the length at which 50% of fish is selected by the gear

< a > is the parameter influencing the steepness

Catch amount as biomass of sprat extracted quarterly from the population is assumed to be exact in the model and correspond to the catches used in the WGBFAS assessment (see section 1.2.1 of this report and ICES, 2019a).

Likelihood components

The Baltic sprat model is parametrised using the following likelihood components:

*** Age distribution commercial fishery**

Number of sprat at age (age1-age8+) caught by all the commercial fisheries are fitted by the model. Data are treated as two likelihood components, one fitting the annually aggregated number-at-age for the period 1974-1994 and the other fitting the quarterly number-at-age for the period 1995-2018. A sum of square likelihood function is used to compare the age distribution from the model with the age distribution from these two datasets as:

Equation 2-4

$$l = \sum_{time} \sum_{ages} (P_{ta} - \pi_{ta})^2$$

where:

< P > is the proportion of the data sample for that time/age combination

< π > is the proportion of the model sample for that time/age combination

*** Length distribution survey**

A length distribution by 1-cm length interval for the stock is derived for each year of the BIAS (see section 1.2.4.1). A sum of square likelihood function is used to compare the length distribution from the model with the length distribution from this dataset as

Equation 2-5

$$l = \sum_{time} \sum_{lengths} (P_{tl} - \pi_{tl})^2$$

where:

$\langle P \rangle$ is the proportion of the data sample for that time/length combination

$\langle \pi \rangle$ is the proportion of the model sample for that time/length combination

* Age-length key survey

Number of sprat by age and length (at 1-cm length interval) is calculated for each year of the BIAS (see section 1.2.5.2). A stratified sum of square likelihood function is used to compare the age-length distribution from the model with the age-length distribution from this dataset as

Equation 2-6

$$l = \sum_{time} \sum_{ages} \sum_{lengths} (P_{tal} - \pi_{tal})^2$$

$\langle P \rangle$ is the proportion of the data sample for that time/area/age/length combination

$\langle \pi \rangle$ is the proportion of the model sample for that time/area/age/length combination

This sum of square is stratified in the sense that the function calculates first the proportion of the different ages in each length class, and then the likelihood component is computed.

* Indices of abundance by age

The rct3 recruitment index and the indices of abundance by age (1-8+) from the BIAS acoustic survey are all fitted by the model. A similar likelihood component is used for all the ages, which is the sum of squares of the log-linear regression of the difference between the modelled index of abundance and the abundance index for that age from the acoustic survey.

Equation 2-7

$$l = \sum_{time} (\log(I_t) - (a + b \cdot \log(N_t)))^2$$

where:

$\langle I \rangle$ is the observed survey index

$\langle N \rangle$ is the corresponding index calculated in the model

The intercept (a) of the log-linear regression is estimated and the slope (b) fixed to 1 for all the ages.

* Weight-at-age

Quarterly weight-at-age from the commercial fishery were used to estimate one of the length-weight parameters. The likelihood function used to compare this data component to the model calculates a sum of squares of the mean weights (no variance estimate is available from the data that could be used to weight the sum of squares) as follows:

Equation 2-8

$$l = \sum_{time} \sum_{ages} (x_{ta} - \mu_{ta})^2 N_{ta}$$

where:

< x > is the mean weight-at-age from the data

< μ > is the mean weight-at-age calculated from the model

< N > is the number-at-age in the commercial fishery

Fitting

The model converges at a minimum overall likelihood of approximately 7134. Estimation is achieved for all the 49 parameters, and none of them is estimated at the lower or upper bound (see *Table 2-2*). Contribution of the different components to the likelihood scores of the model is:

Table 2-34. Summary of likelihood scores and weights assigned to likelihood components, and the respective fraction of their contribution to objective function.

id	score	Weight	wgt_score	fraction	percent
wgtAtAge.comm	2151	0.809	1740.307	0.244	24.390
adist.comm1	0.137	6363.640	868.637	0.122	12.180
adist.comm2	1.644	658.596	1082.732	0.152	15.180
alk.bias	80.930	33.120	2680.385	0.376	37.570
ldist.bias	1.263	323.941	409.137	0.057	5.730
bias.a0.like	16.690	2.036	33.978	0.005	0.480
bias.a1.like	5.394	7.467	40.278	0.006	0.560
bias.a2.like	3.154	13.669	43.111	0.006	0.600
bias.a3.like	2.413	12.742	30.747	0.004	0.430
bias.a4.like	2.893	14.061	40.678	0.006	0.570
bias.a5.like	4.671	5.615	26.230	0.004	0.370
bias.a6.like	6.205	5.664	35.144	0.005	0.490
bias.a7.like	10.370	2.828	29.330	0.004	0.410
bias.a8.like	12.020	6.123	73.598	0.010	1.030

The sprat model was able to fit most of likelihood components (Fig.2-2...2-7). Few exceptions are: overestimated index of abundance of age 8 (*Figure 2-2*) at the beginning of time-series; poor fitting of length distribution from survey in some years (1992, 2000, 2001; *Figure 2-3*); underestimated size of older sprat at the beginning of the survey time-series (*Figure 2-4*); overestimated weight at age1 in commercial catches in q1 (*Figure 2-7*).

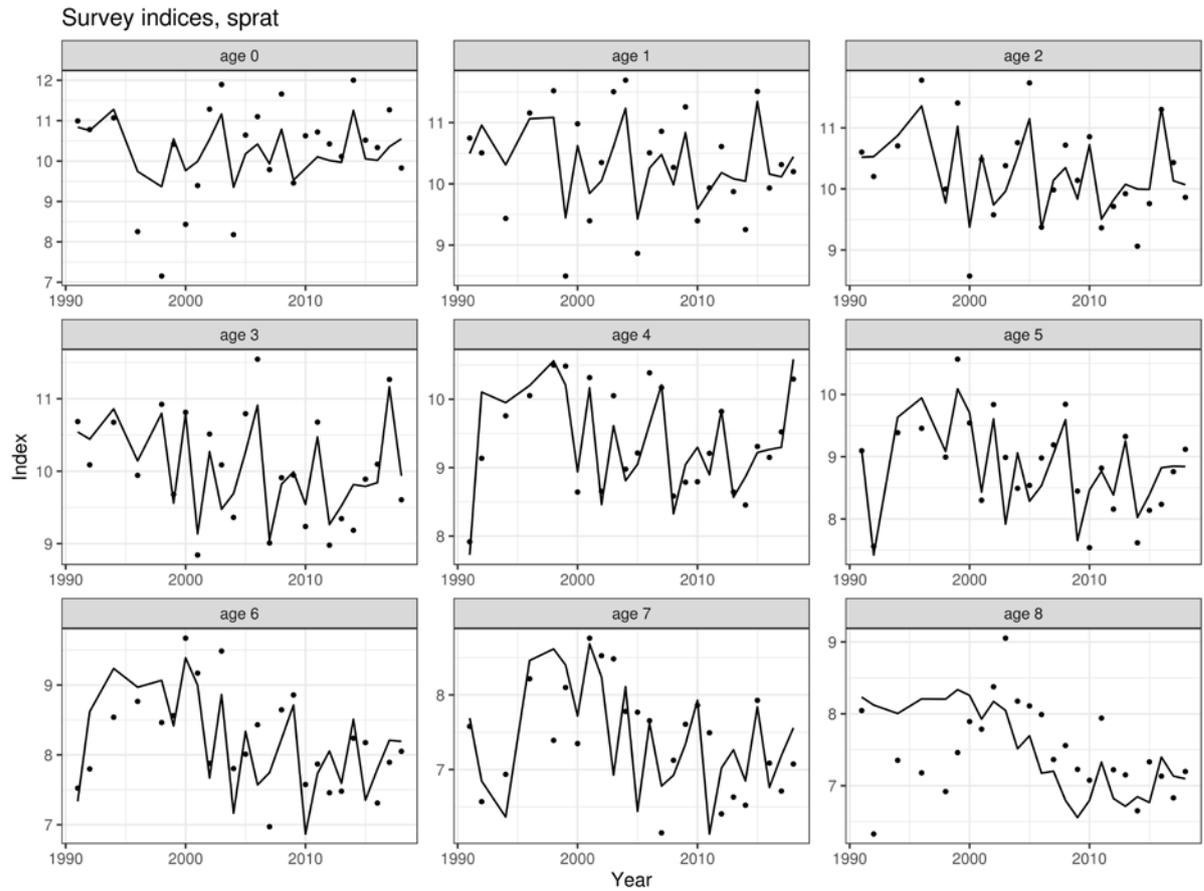


Figure 2-87. Comparison of log-transformed observed (point) and predicted (line) sprat survey abundance indices by age.

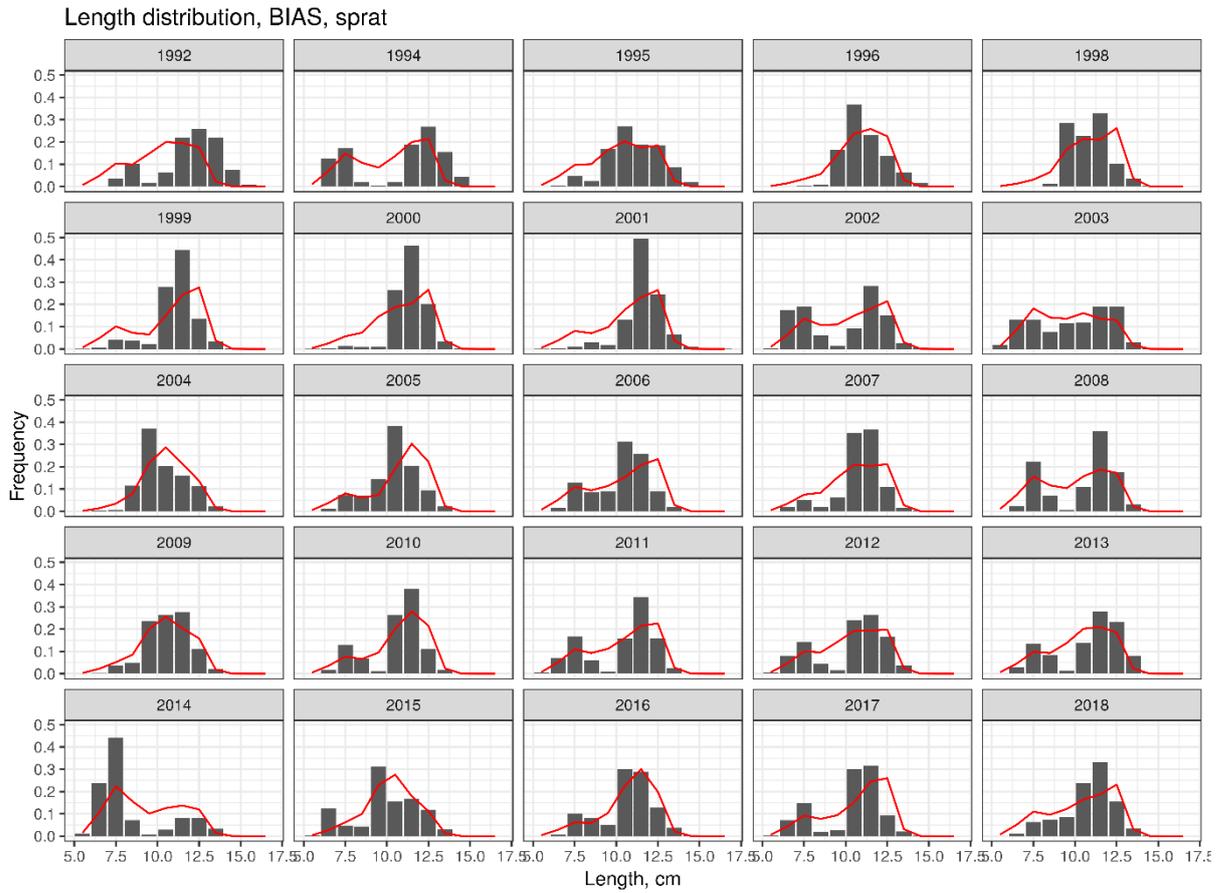


Figure 2-88. Comparison of observed (bars) and predicted (line) sprat length distribution in survey catches.

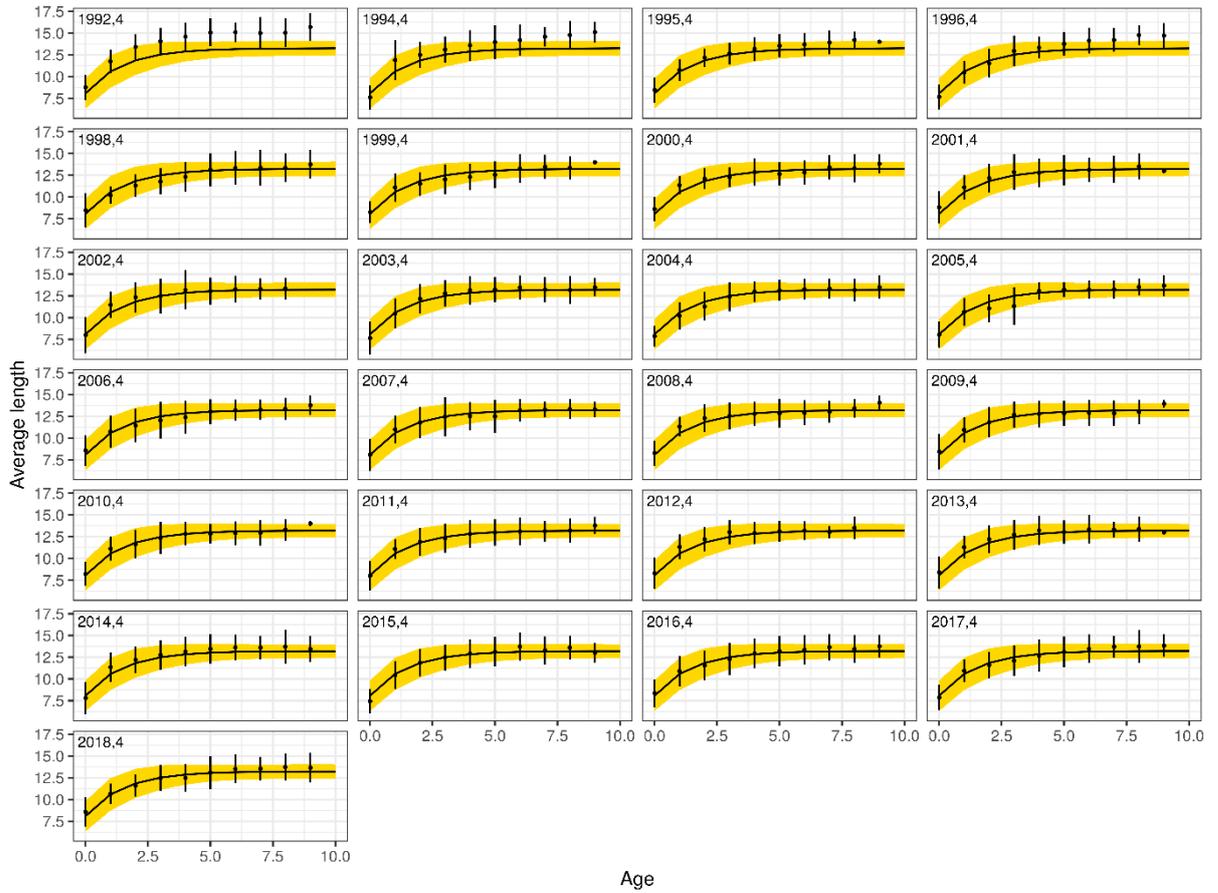


Figure 2-89. Distribution of observed sprat ALK (box-plot) compared with average length at age (line) ± SD (yellow ribbon).

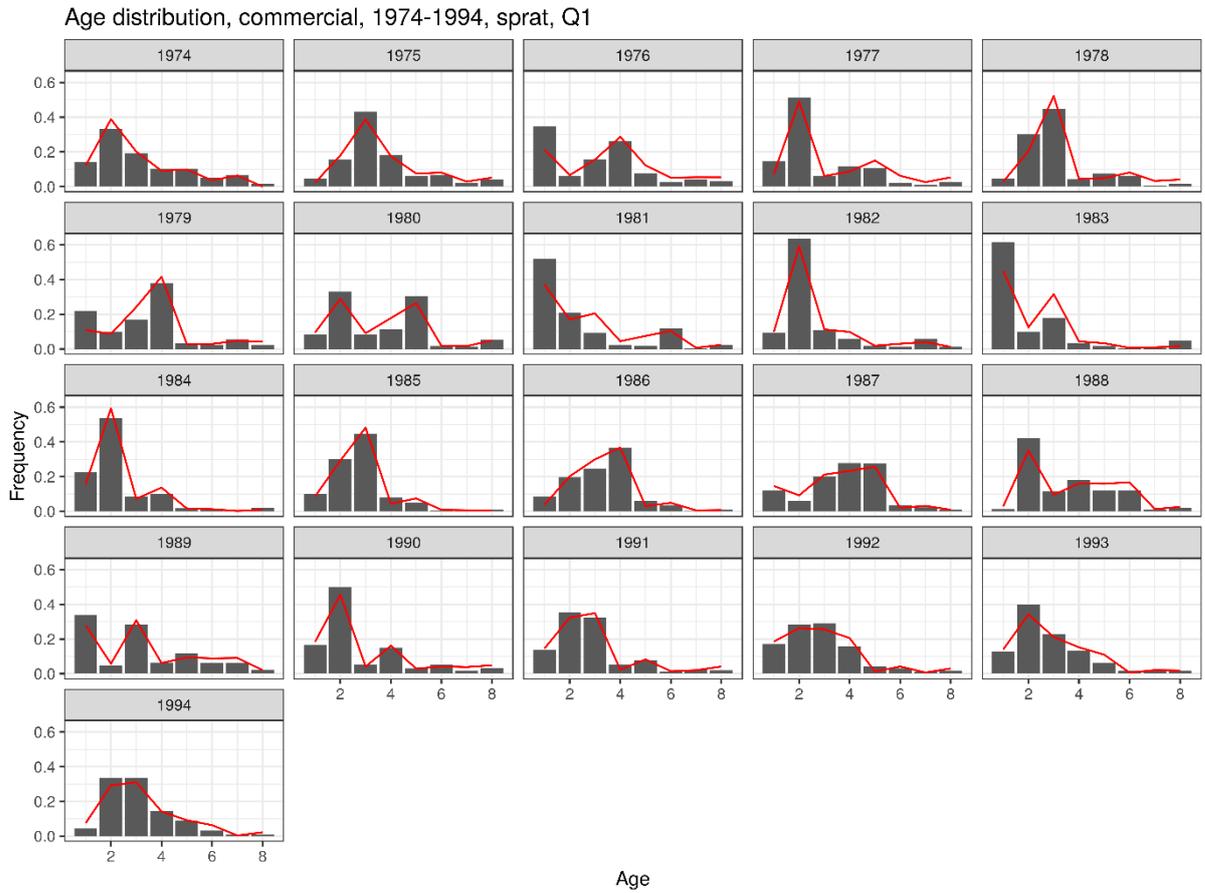


Figure 2-90. Comparison of observed (bars) and predicted (line) sprat age distribution in commercial catches in 1974-1994.

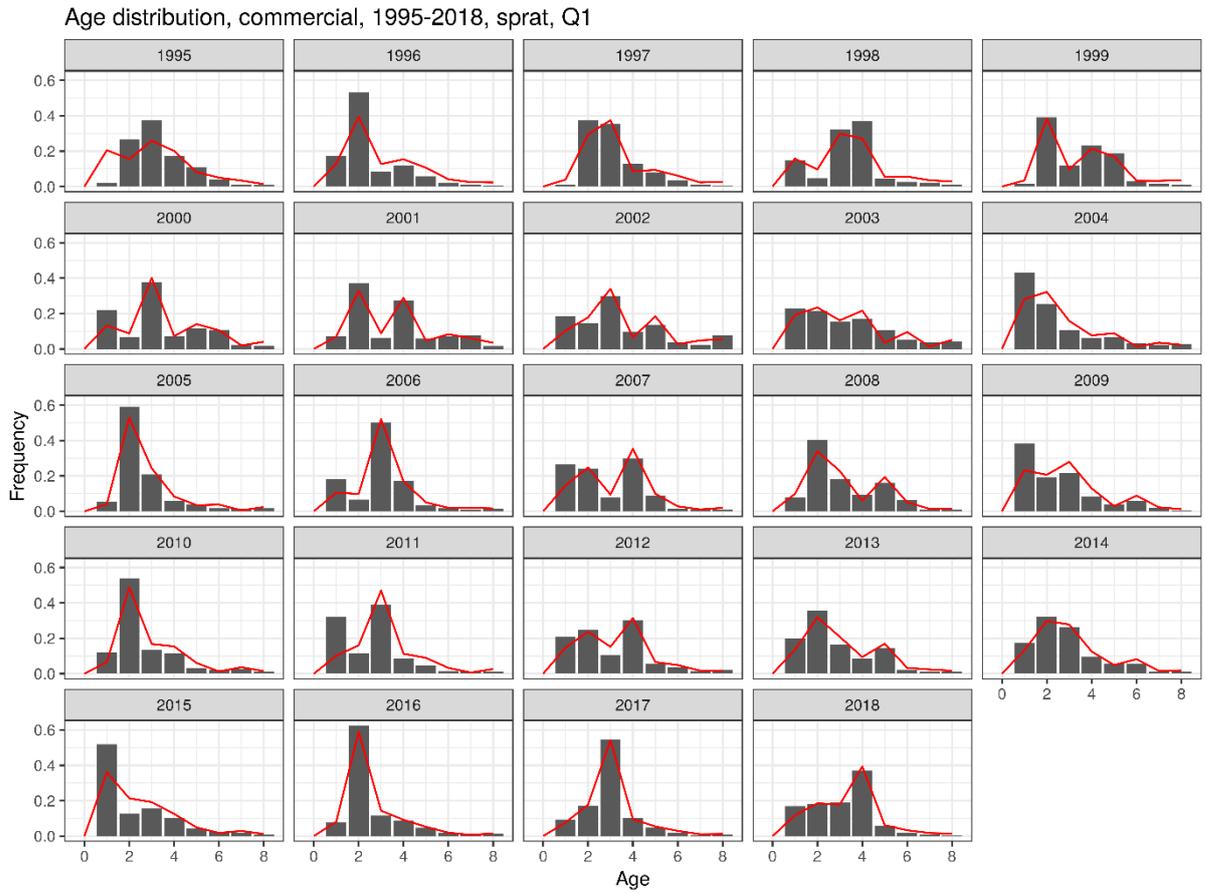


Figure 2-91. Comparison of observed (bars) and predicted (line) sprat age distribution in commercial catches in 1995-2018.

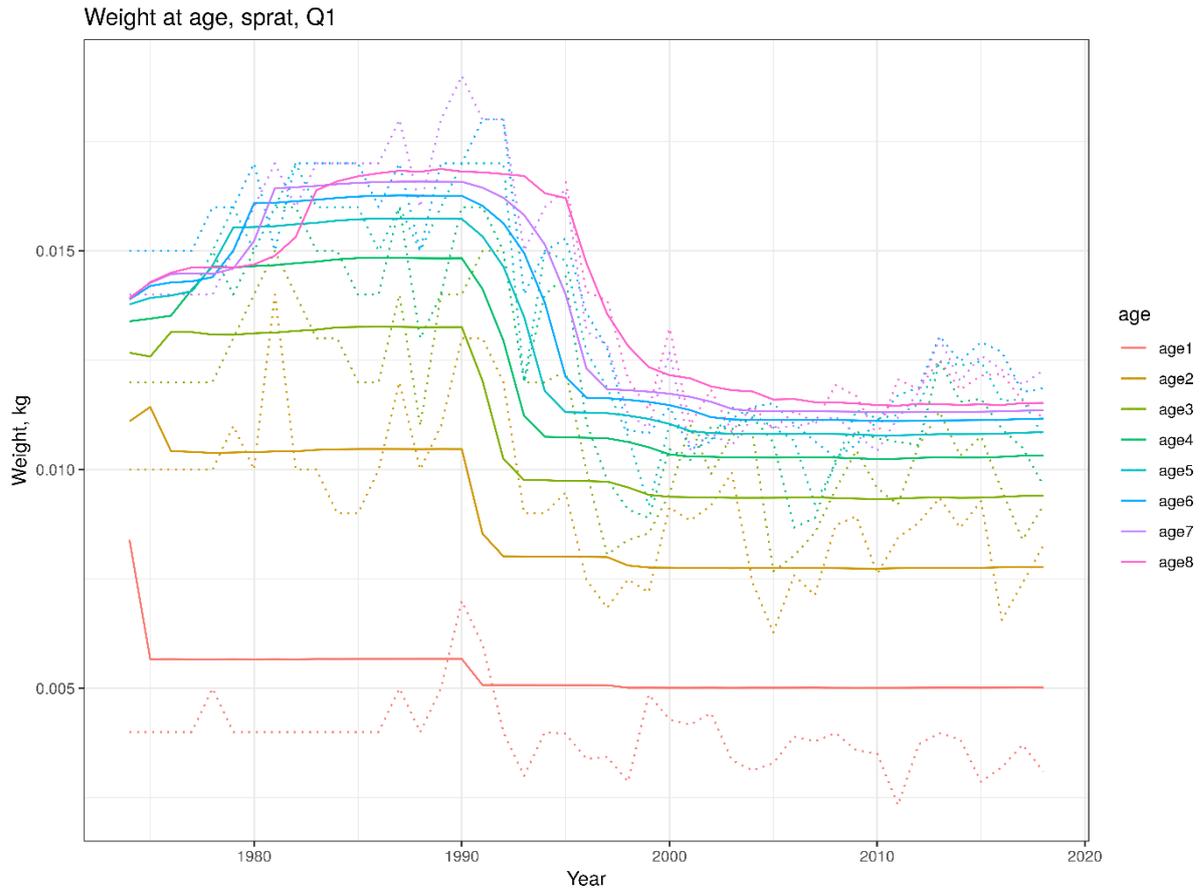


Figure 2-92. Comparison of observed (dashed line) and predicted (solid line) sprat weight at age in commercial catches.

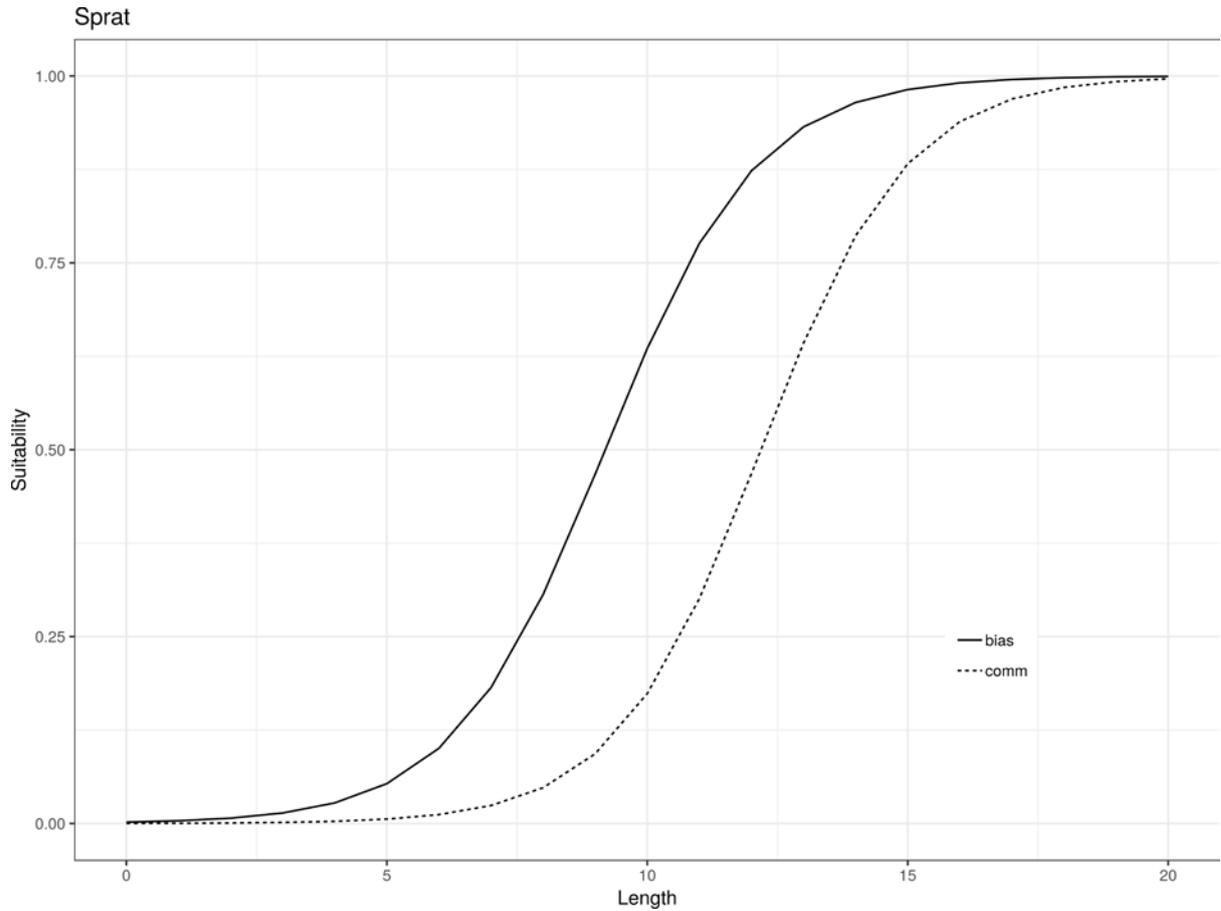


Figure 2-93. Estimated in the model fisheries (comm) and survey (bias) suitabilities.

Table 2-35. List of parameters estimated in the single specie sprat model (optimised = 1) with the lower and upper bound allowed for the search of optimal value.

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; Gadget version 2.2.00-BETA running on ubuntu-ryzen Sun Oct 27 22:01:17 2019
; Simulated Annealing algorithm ran for 40001 function evaluations
; and stopped when the likelihood value was 10617.018
; because the maximum number of function evaluations was reached
; Hooke & Jeeves algorithm ran for 100013 function evaluations
; and stopped when the likelihood value was 7171.9493
; because the maximum number of function evaluations was reached
; BFGS algorithm ran for 3355 function evaluations
; and stopped when the likelihood value was 7134.0931
; because the convergence criteria were met

```

switch	value	lower	upper	optimise
Linf	13.26	10	300	0
k	66.8	0.1	1000	0
lwa1	1.5074218	0.001	50	1
lwa2	0.96635585	0.001	50	1
lwa3	0.91595079	0.001	50	1
lwb	2.72	2.2	3.8	0
bbeta	0.5700208	0.001	50	1
ba01	2.349764	0.001	50	1
ba02	4.3735714	0.001	50	1
ba03	1.8518059	0.001	50	1
ba04	7.634824	0.001	50	1
ba05	7.9236598	0.001	50	1
ba06	2.8129702	0.001	50	1
ba07	4.952717	1e-05	50	1
ba08	1.8217793e-05	1e-05	50	1

rec1974	1.0339741	0.004	100	1
rec1	7.6864673	5	15	0
recsdev	0.9	0.01	15	0
rec1975	7.076579	0.004	100	1
rec1976	2.2002292	0.004	100	1
rec1977	0.60611397	0.004	100	1
rec1978	1.5561005	0.004	100	1
rec1979	1.0592467	0.001	100	1
rec1980	4.8469471	0.001	100	1
rec1981	1.7120903	0.001	100	1
rec1982	13.541029	0.004	100	1
rec1983	8.0839879	0.004	100	1
rec1984	5.3745154	0.004	100	1
rec1985	2.3066278	0.004	100	1
rec1986	8.2571661	0.004	100	1
rec1987	1.5135557	0.004	100	1
rec1988	16.424863	0.004	100	1
rec1989	14.97047	0.004	100	1
rec1990	15.219147	0.004	100	1
rec1991	24.240017	0.004	100	1
rec1992	22.342836	0.004	100	1
rec1993	12.868568	0.004	100	1
rec1994	37.690536	0.004	100	1
rec1995	27.580575	0.004	100	1
rec1996	8.1261226	0.004	100	1
rec1997	28.619623	0.004	100	1
rec1998	5.5762769	0.004	100	1
rec1999	18.214729	0.004	100	1
rec2000	8.335302	0.004	100	1
rec2001	10.423476	0.004	100	1
rec2002	18.086069	0.004	100	1
rec2003	33.712145	0.004	100	1
rec2004	5.5081286	0.004	100	1
rec2005	12.581726	0.004	100	1
rec2006	15.997142	0.004	100	1
rec2007	9.8471237	0.004	100	1
rec2008	23.158569	0.004	100	1
rec2009	6.5714698	0.004	100	1
rec2010	8.7781962	0.004	100	1
rec2011	11.683822	0.004	100	1
rec2012	10.669299	0.004	100	1
rec2013	10.175416	0.004	100	1
rec2014	36.940841	0.004	100	1
rec2015	11.113155	0.004	100	1
rec2016	10.682636	0.004	100	1
rec2017	14.980593	0.004	100	1
rec2018	18.212293	0.004	100	1
L50comm	12.17884	2	30	1
alphacomm	0.71565589	0.001	10	1
L50bias	9.1902228	2	30	1
alphabias	0.68698867	0.001	10	1

Single species herring model

Biological model

The single-area and single stock model for central Baltic herring spans from age0 to age15 and from 4.5 to 35.5 cm in length with 1 cm length resolution. Natural mortality at age calculated as the average of the natural mortality matrix used in the assessment follows the following vector: 0.5, 0.31, 0.29, 0.27, 0.26, 0.25, 0.24, 0.23, 0.23, 0.23.

Fish of age0 recruits to the modelled population once a year in quarter 3 with mean length 10 cm and standard deviation of 2.5. Similarly to sprat, there is no stock-recruitment relationship and the number of recruits is estimated annually.

A von Bertalanffy growth model was adopted to determine the increase in length for each length group (Equation 2-1), where both the parameter k (0.305) and L_{inf} (21.4 cm) are estimated outside the model based on biological data from the BIAS survey over the period 1991-2018. The beta parameter of the beta-binomial distribution around growth was estimated.

Inspection of weight-at-age from commercial data shows marked changes in the condition of herring, with an overall decrease in weight, which is more pronounced in the end of the 1970s and 1980s and in the older age groups. For some age groups the observed decrease in weight was >60% over the time period of interest for the model. Seasonal differences characterise this general pattern with a progressive decrease in quarter 1 and 2, while weights are relatively stable and drop only at the end of the 1980s and early 1990s during quarter 3 and 4. The general decrease in the weight-at-age might be explained by density-dependency, in particular competition with sprat (Casini *et al.*, 2010). On the contrary, seasonal differences could be the result of changes in the fleet catchability (i.e., due to spatial variability related to changes in the contribution of different countries), but also mixing of central Baltic herring with adjacent herring stocks (ie, western Baltic, Gulf of Riga, Bothnian Sea).

Similarly to sprat, changes in weight-at-age of herring are modelled with a variable length-weight relationship over the following three time blocks: 1974-1985, 1986-1995, 1996-2018 (Figure 2-14).

Fleets

Herring is harvested in the model by one commercial fleet corresponding to the pelagic fishery. Suitability is defined with a sigmoid functional form with parameters estimated in the model. Catches expressed as biomass of herring are extracted quarterly from the modelled population.

Similarly to sprat, the BIAS survey is used to tune the herring model.

Likelihood components

Herring and sprat dominate the same pelagic environment in the Baltic and they mostly occur as a mixed catch in the same commercial fisheries and scientific surveys. Despite the mixed nature of the associated samples, for simplification the data and likelihood for the two species are treated independently in the present single and multispecies models. Similar type of data and likelihood functions used for the sprat model are also adopted in the herring model.

*** Age distribution commercial fishery**

Number of herring at age (age0-age8+) caught by all the commercial fisheries cover the entire time extent of the model 1974-2018. Age distributions are annually aggregated before fitting prior 1995, while they are fitted at a quarterly resolution for the period 1995-2018. The likelihood function followed Equation 2-4.

*** Length distribution survey**

Length distributions of herring by 1-cm length interval are calculated from the BIAS survey. The likelihood function followed Equation 2-5.

*** Age-length key**

Number of herring by age and length (at 1-cm length interval) is calculated from the biological samples of the BIAS survey. The likelihood function followed Equation 2-6.

*** Survey indices by age**

Survey indices by age for age0 to age8+ are available from the BIAS survey. A likelihood function from Equation 2-7 is used to fit the time-series for each age group.

*** Weight-at-age**

Quarterly weight-at-age from the commercial fishery are fitted with a function from Equation 2-8.

Fitting

The model converged at a minimum overall likelihood of approximately 7235. Estimation was achieved for all the 49 parameters, and none of them is estimated at the lower or upper bound (see *Table 2-3*). Contribution of the different components to the likelihood scores of the model is:

id	score	Weight	wgt_score	fraction	percent
wgtAtAge.comm	16920.000	0.096	1626.648	0.225	22.48
adist.comm1	0.135	3325.090	448.222	0.062	6.2
adist.comm2	1.637	514.305	841.917	0.116	11.64
alk.bias	150.500	21.332	3210.466	0.444	44.38
ldist.bias	0.606	1333.480	808.622	0.112	11.18
bias.a0.like	16.700	2.174	36.304	0.005	0.5
bias.a1.like	4.184	9.164	38.343	0.005	0.53
bias.a2.like	2.884	12.860	37.089	0.005	0.51
bias.a3.like	2.266	19.142	43.377	0.006	0.6
bias.a4.like	3.005	12.107	36.380	0.005	0.5
bias.a5.like	2.783	7.747	21.560	0.003	0.3
bias.a6.like	2.432	11.457	27.864	0.004	0.39
bias.a7.like	5.388	5.733	30.887	0.004	0.43
bias.a8.like	5.661	4.735	26.804	0.004	0.37

Herring model was able to fit most of likelihood components (Fig.2-9...2-14), few exceptions are model was able to pick the recruitment signal observed in 2002 and 2014 in survey catches (Figure 2-10); underestimated size of older herring in most years in survey catches (Figure 2-11); slightly overestimated number at age8+ in commercial catches (Figure 2-12, Figure 2-13); overestimated weight at age1 and underestimated weight at age8+ in commercial catches in q1 (Figure 2-14).

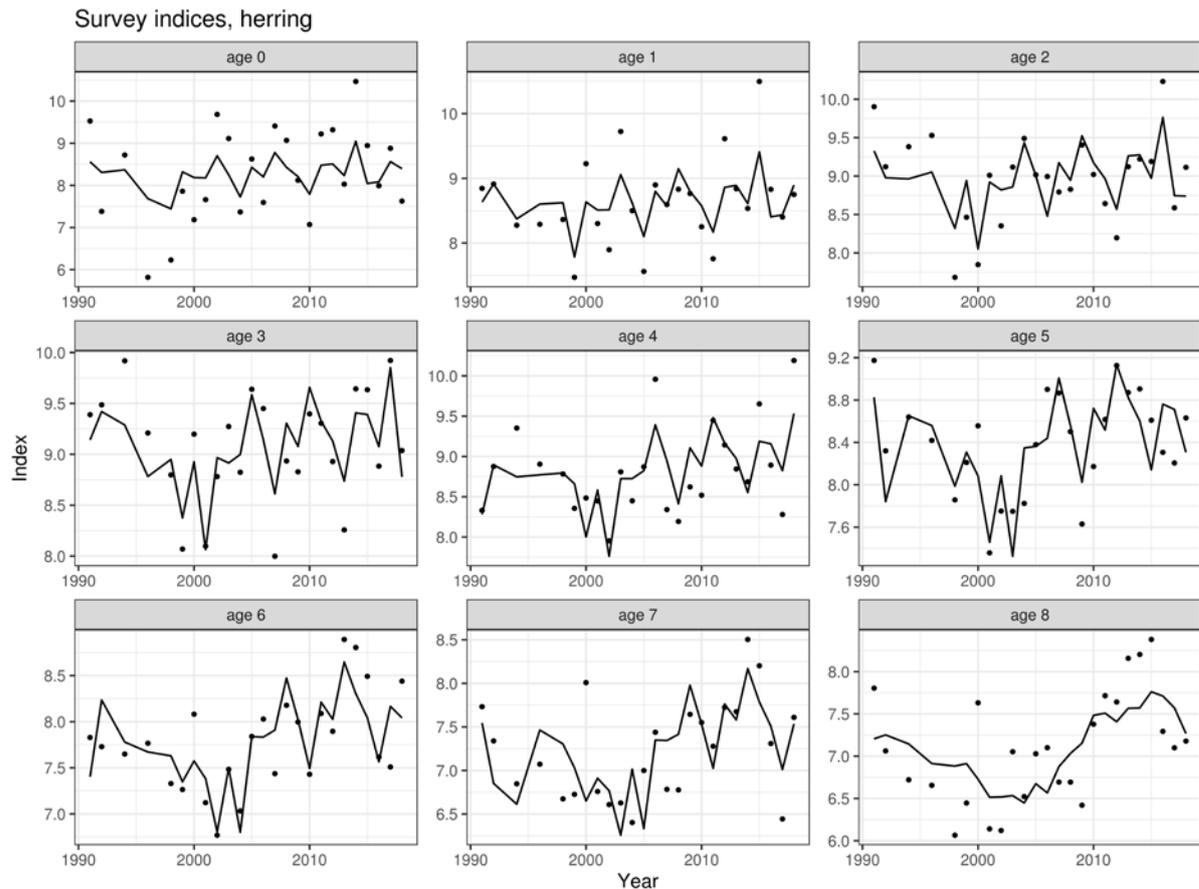


Figure 2-94. Comparison of log-transformed observed (points) and predicted (line) herring survey abundance indices by age.

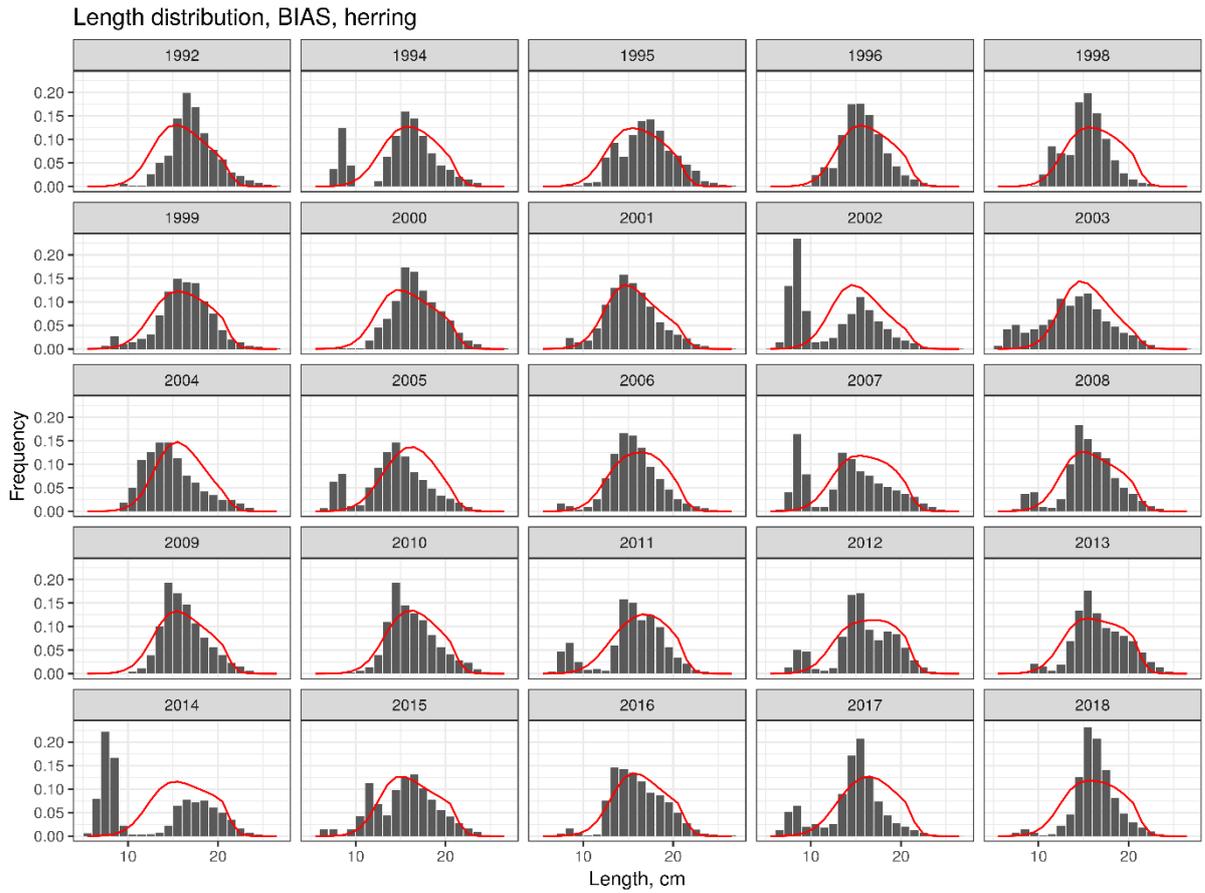


Figure 2-95. Comparison of observed (bars) and predicted (line) herring length distribution in survey catches.

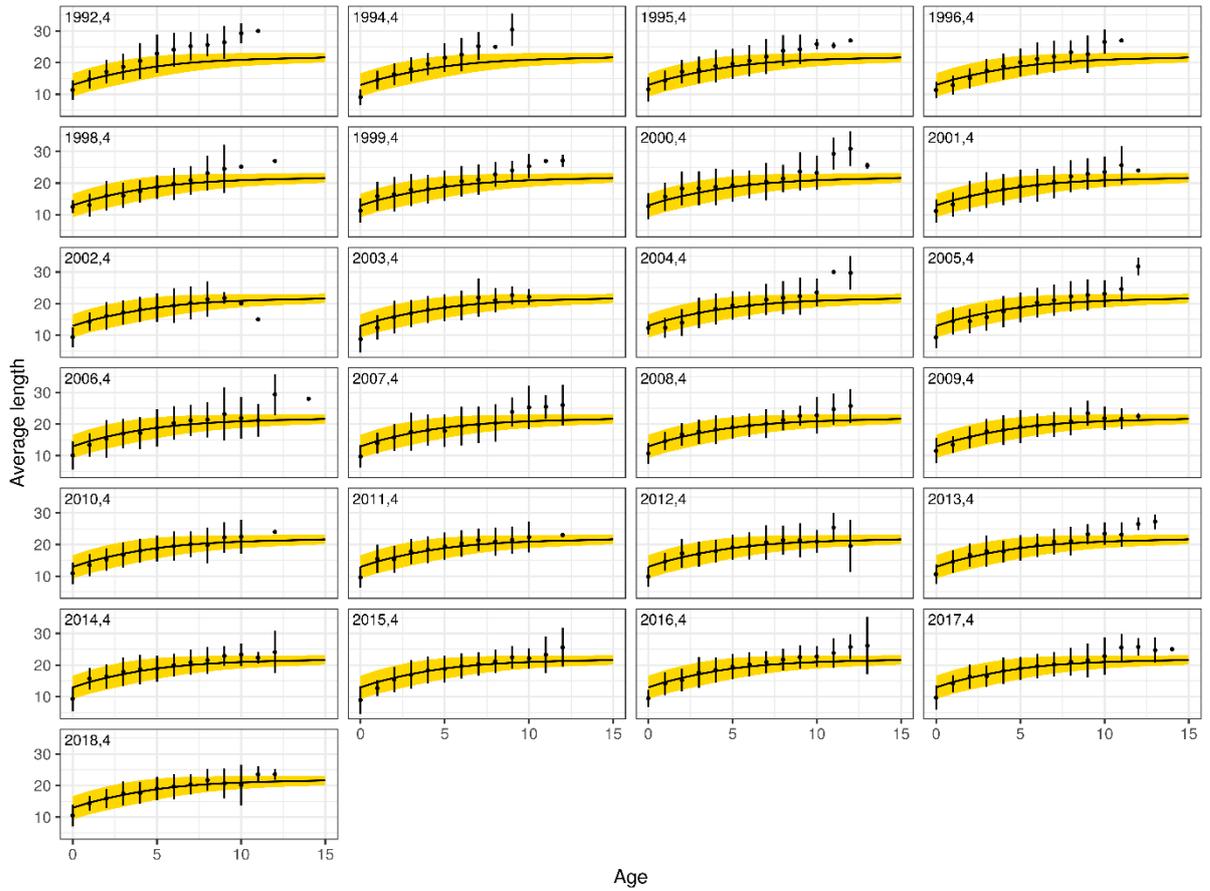


Figure 2-96. Distribution of observed herring ALK (box-plot) compared with average length at age (line) \pm SD (yellow ribbon).

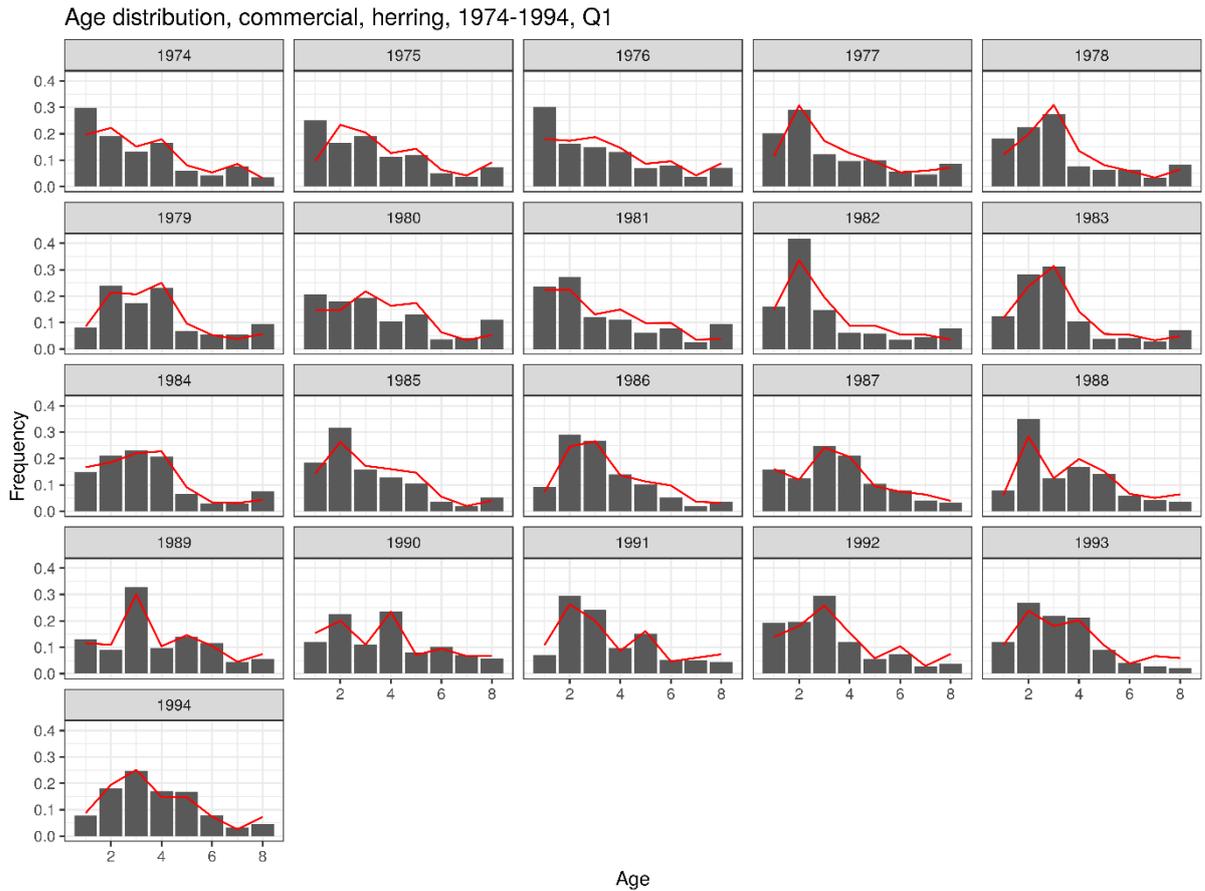


Figure 2-97. Comparison of observed (bars) and predicted (line) herring age distribution in commercial catches in 1974-1994.

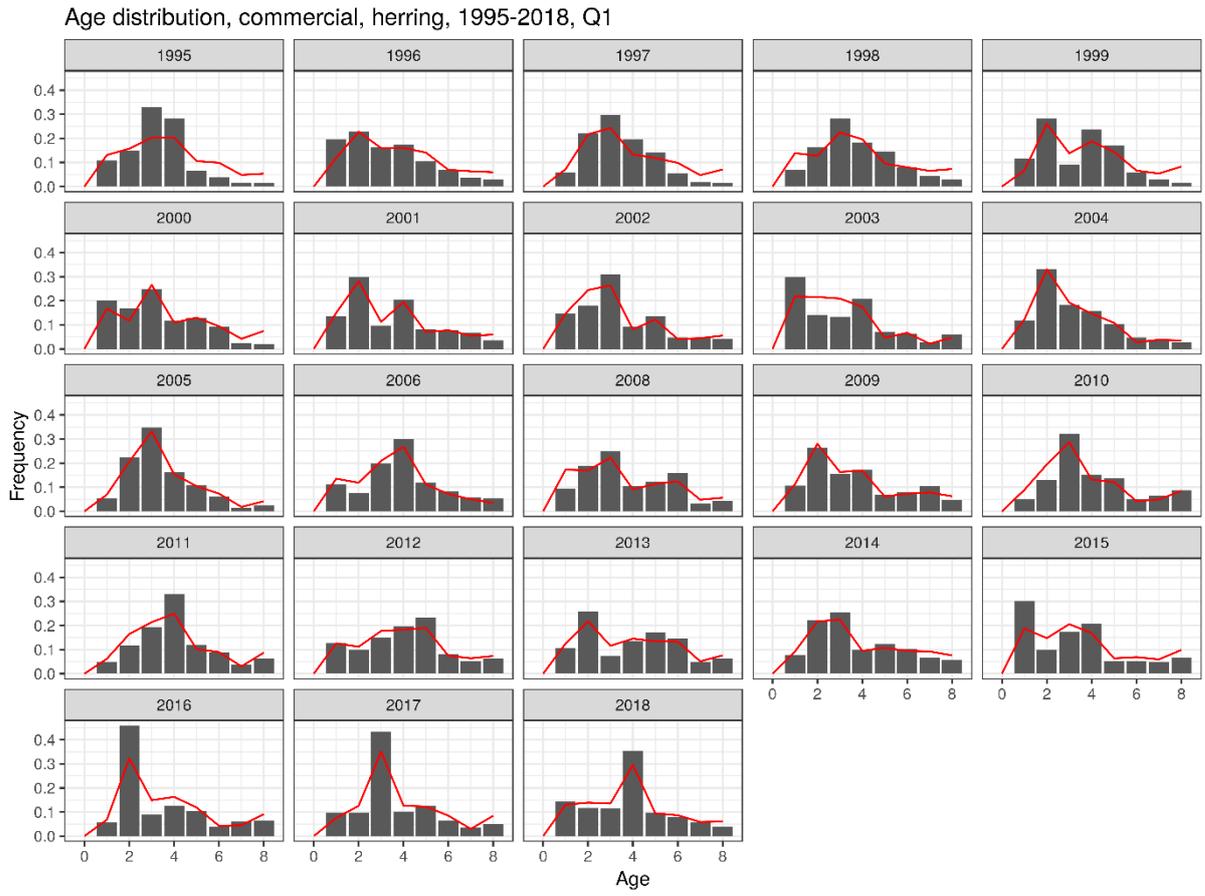


Figure 2-98. Comparison of observed (bars) and predicted (line) herring age distribution in commercial catches in 1995-2018.

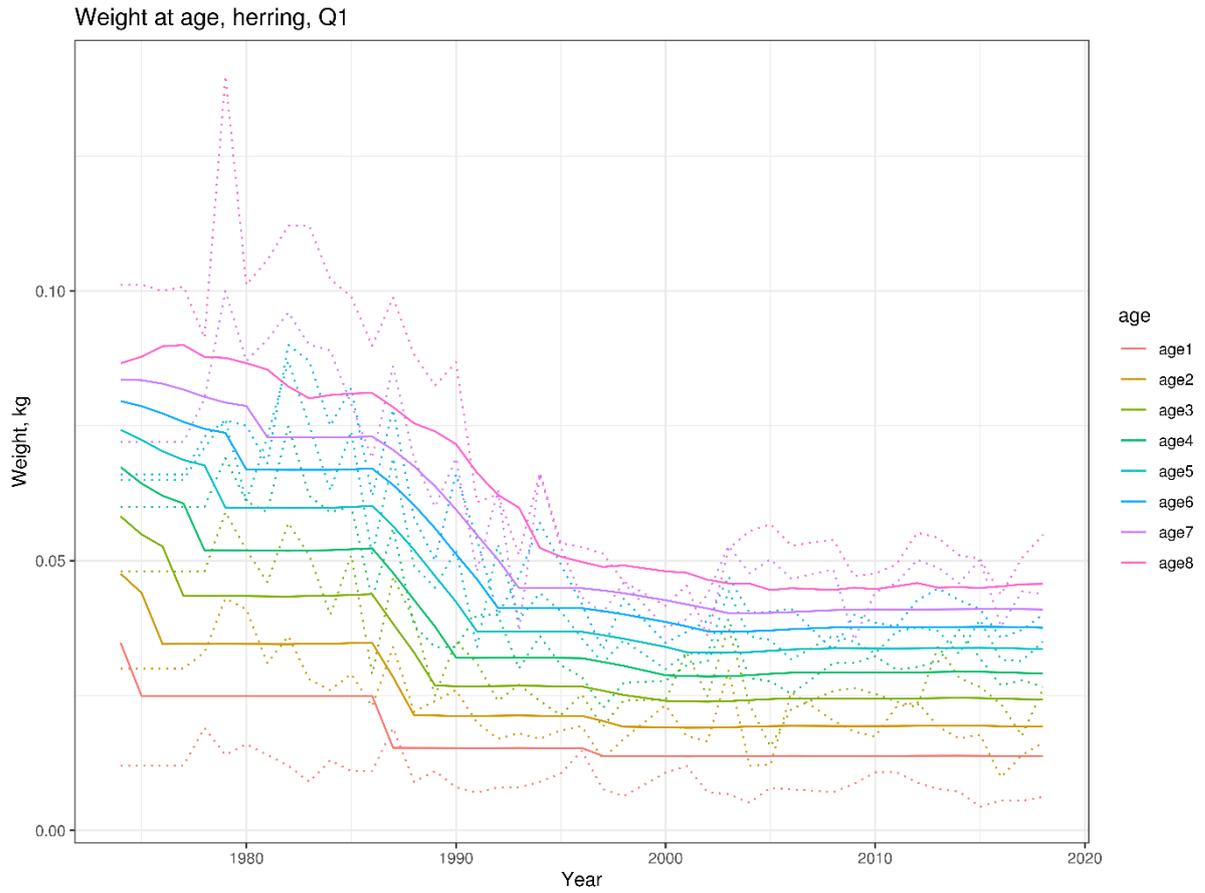


Figure 2-99. Comparison of observed (dashed line) and predicted (solid line) herring weight at age in commercial catches.

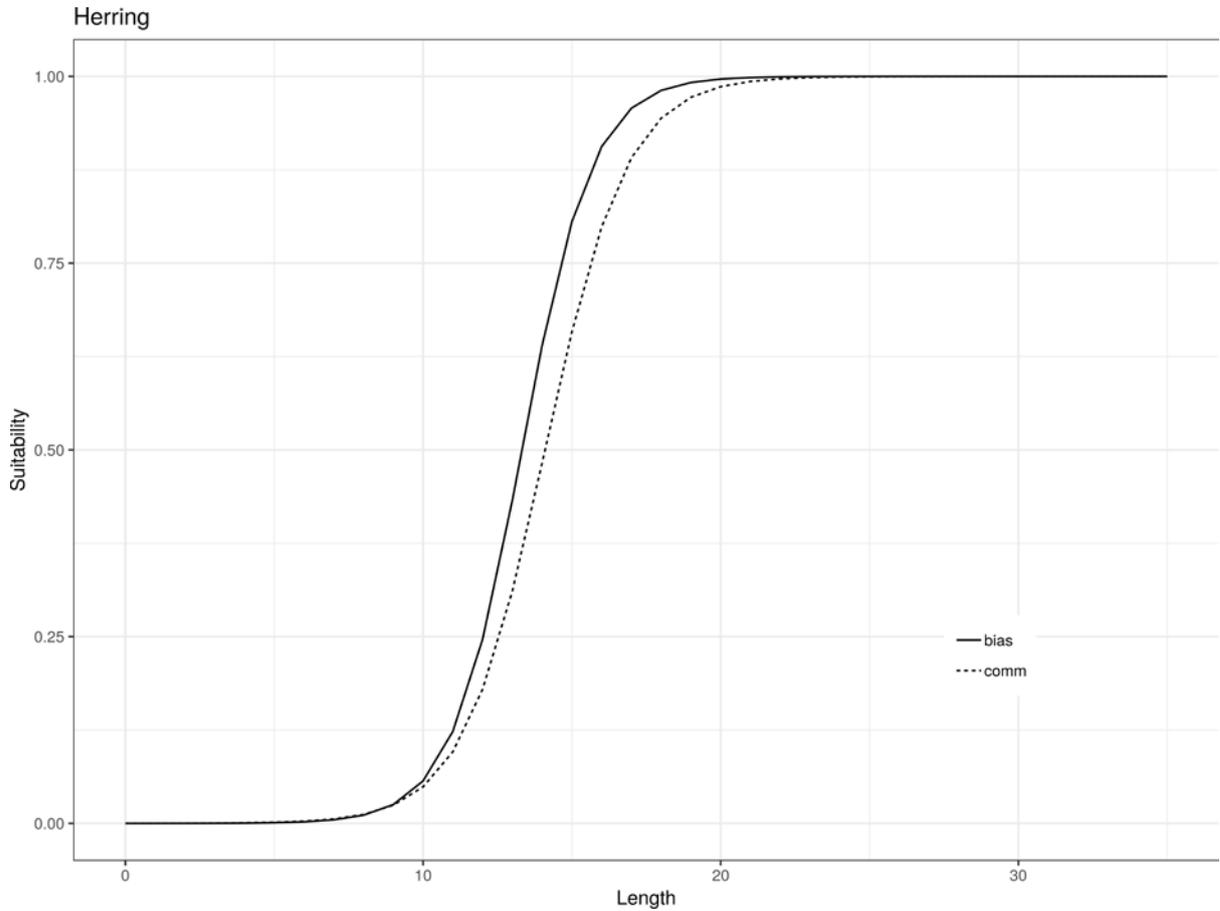


Figure 2-100. Estimated in the model fisheries (comm) and survey (bias) suitabilities of herring of different size.

Table 2-36. List of parameters estimated in the single species herring model (optimised = 1) with the lower and upper bound allowed for the search of optimal value. **cbh_42.2**

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; Gadget version 2.2.00-BETA running on ubuntu-ryzen Sun Oct 27 21:29:08 2019
; Simulated Annealing algorithm ran for 10001 function evaluations
; and stopped when the likelihood value was 15300.515
; because the maximum number of function evaluations was reached
; Hooke & Jeeves algorithm ran for 40080 function evaluations
; and stopped when the likelihood value was 7332.9381
; because the maximum number of function evaluations was reached
; BFGS algorithm ran for 3275 function evaluations
; and stopped when the likelihood value was 7235.6221
; because the convergence criteria were met
switch      value      lower upperoptimise
Linf        21.4        10      300      0
k           30.5        0.1     1000     0
lwa1        0.9796859   0.001   50       1
lwa2        0.60130156  0.001   50       1
lwa3        0.5432413     0.001   50       1
lwb         2.99        2.2     3.8      0
bbeta       4.5569492   0.001   50       1
ba01        1.2906853     0.001   50       1
ba02        0.95973293    0.001   50       1
ba03        5.4702394     0.001   50       1
ba04        5.9490844     0.001   50       1
ba05        2.5605246     0.001   50       1
ba06        1.6557956     0.001   50       1
    
```

ba07	2.6163556	1e-05	50	1
ba08	0.95572976	1e-05	50	1
rec1974	1.4672438	0.004	70	1
recl	10	4	20	0
recsdev	2.5	0.01	15	0
rec1975	2.5522839	0.004	70	1
rec1976	1.6011279	0.004	70	1
rec1977	1.6227149	0.004	70	1
rec1978	1.0777814	0.004	70	1
rec1979	1.7962611	0.001	70	1
rec1980	2.9949012	0.001	70	1
rec1981	2.1989429	0.001	70	1
rec1982	1.8255001	0.004	70	1
rec1983	2.7636687	0.004	70	1
rec1984	2.5743947	0.004	70	1
rec1985	1.308435	0.004	70	1
rec1986	3.0284254	0.004	70	1
rec1987	1.1169968	0.004	70	1
rec1988	2.0140436	0.004	70	1
rec1989	2.6	0.004	70	1
rec1990	1.8048434	0.004	70	1
rec1991	2.3762322	0.004	70	1
rec1992	1.8429172	0.004	70	1
rec1993	1.4090175	0.004	70	1
rec1994	1.9679472	0.004	70	1
rec1995	1.7484562	0.004	70	1
rec1996	0.99134848	0.004	70	1
rec1997	1.8366091	0.004	70	1
rec1998	0.78291309	0.004	70	1
rec1999	1.8767541	0.004	70	1
rec2000	1.6469786	0.004	70	1
rec2001	1.6265884	0.004	70	1
rec2002	2.74933	0.004	70	1
rec2003	1.7424203	0.004	70	1
rec2004	1.0302397	0.004	70	1
rec2005	2.0769474	0.004	70	1
rec2006	1.6575319	0.004	70	1
rec2007	2.9555701	0.004	70	1
rec2008	2.0809612	0.004	70	1
rec2009	1.6659844	0.004	70	1
rec2010	1.1008962	0.004	70	1
rec2011	2.1844943	0.004	70	1
rec2012	2.245358	0.004	70	1
rec2013	1.705252	0.004	70	1
rec2014	3.8480671	0.004	70	1
rec2015	1.4160173	0.004	70	1
rec2016	1.4747819	0.004	70	1
rec2017	2.3908326	0.004	70	1
rec2018	2.0251935	0.004	70	1
L50comm	14.098337	2	30	1
alphacomm	0.72468179	0.001	10	1
L50bias	13.321209	2	30	1
alphabias	0.84645189	0.001	10	1

Single species cod model

Biological model

The single-area and single stock model for eastern Baltic cod spans from age0 to age15 and from 1 to 137 cm in length with 2 cm length resolution. Natural mortality at age is from cod stock assessment (constant in time until 2000, from 2000 has annual variability, WGBFAS, 2019).

Fish of age0 recruits to the modelled population once a year in quarter 3 with mean length 9.05 cm (estimated as length of age0 using von Bertalanffy growth function with parameters used in the model) and standard deviation of 4.12 (estimated using age0 fish caught by BITS in Q4). Similarly to sprat and herring, there is no stock-recruitment relationship and the number of recruits is estimated annually.

A von Bertalanffy growth model was adopted to determine the increase in length for each length group (eq. 2-1), where both the parameters k and L_{inf} come from cod stock assessment (WGBFAS, 2019) and are constant before 1991 and annually variable from 1991. The beta parameter of the beta-binomial distribution around growth was estimated in the model.

Parameters of length-weight relationship are from the cod stock assessment (WGBFAS, 2019) and are constant before 1994 and variable by 3-year period from 1994.

Fleets

Cod is harvested in the model by two commercial fleets: active, representing bottom trawlers, and passive, representing mainly gillnetters. Suitability is defined with a sigmoid functional form with parameters estimated in the model. Catches expressed as biomass of cod are extracted quarterly from the modelled population.

BITS survey from quarters 1 and 4 is used to tune the cod model for 1991-2018. For 1974-1990 national surveys were used as tuning fleets, similarly to what done in the recent assessment of the stock (WGBFAS, 2019).

Likelihood components

* Age distribution commercial, active fishery

Number of cod at age (age0-age8+) caught by the commercial fisheries using active gear cover the first half of the time extent of the model 1974-1999. Age distributions have quarterly resolution. The likelihood function followed Equation 2-4.

* Age distribution commercial, passive fishery

Number of cod at age (age0-age8+) caught by the commercial fisheries using passive gear cover the first half of the time extent of the model 1974-1999. Age distributions have quarterly resolution. The likelihood function followed Equation 2-4.

* Length distribution commercial, active fishery

Number of cod at length (5-115 cm) caught by the commercial fisheries using active gear cover the second half of the time extent of the model 2000-2018. Length distributions have quarterly resolution. The likelihood function followed Equation 2-5.

* Length distribution commercial, passive fishery

Number of cod at length (5-115 cm) caught by the commercial fisheries using active gear cover the second half of the time extent of the model 2000-2018. Length distributions have quarterly resolution. The likelihood function followed Equation 2-5.

* Length distribution survey, Q1

Length distributions of cod by 2-cm length interval (and 5-cm interval starting from 80 cm) are retrieved as in stock assessment from the BITS survey, Q1, 1991-2018. The likelihood function followed Equation 2-5.

* Length distribution survey, Q4

Length distributions of cod by 2-cm length interval (and 5-cm interval starting from 80 cm) are retrieved as in stock assessment from the BITS survey, Q1, 1993-2018. The likelihood function followed Equation 2-5.

* Survey indices, age0

Survey indices for age0 are available from the BITS survey. A likelihood function from Equation 2-7 is used to fit the time-series. Both intercept and slope of the function are estimated.

* Survey indices, historical survey

Survey indices, representing whole stock from the historical survey (1974-1990) are from the stock assessment (WGBFAS, 2019) and assigned to Q2. A likelihood function from Equation 2-7 is used to fit the time-series. Intercept of the function is estimated, while slope is fixed to 1.

* Survey indices, BITS survey, Q1

Survey indices, representing whole stock from the BITS survey Q1 (1991-2018) are from the stock assessment (WGBFAS, 2019). A likelihood function from Equation 2-7 is used to fit the time-series. Intercept of the function is estimated, while slope is fixed to 1.

* Survey indices, BITS survey, Q4

Survey indices, representing whole stock from the BITS survey Q1 (1993-2018) are from the stock assessment (WGBFAS, 2019). A likelihood function from Equation 2-7 is used to fit the time-series. Intercept of the function is estimated, while slope is fixed to 1.

Fitting

The model converged at a minimum overall likelihood of approximately 10761. Estimation was achieved for all the 64 parameters, and none of them is estimated at the lower or upper bound

(see Table 2-4). Contributions of the different components to the likelihood scores of the model were:

id	score	Weight	wgt_score	fraction	percent
adist.comm.act	3.709	223.484	828.902	0.077	7.7
adist.comm.pas	2.128	244.280	519.828	0.048	4.83
ldist.bits1	0.268	5525.800	1479.257	0.137	13.75
ldist.bits4	0.190	6163.640	1173.557	0.109	10.91
ldist.comm.active	0.355	7924.530	2814.001	0.262	26.15
ldist.comm.passive	0.954	2743.550	2618.444	0.243	24.33
age0.like	3.833	100.000	383.300	0.036	3.56
bits1.like	10.670	31.953	340.933	0.032	3.17
bits4.like	5.361	100.000	536.100	0.050	4.98
bits_h.like	0.666	100.000	66.560	0.006	0.62

Cod model in general fitted well to different likelihood components (Fig. 2-16..2-22). Few exemptions are: underestimation in the model indices of abundance in historical national surveys in 1983-1987 (*Figure 2-16*, bits_h.like), poor fitting of length distributions from survey samples in some years (i.e. Q1 in 1991-1993, 1997, *Figure 2-17*, Q4 in 1996, 1999, 2001, 2003-2004 *Figure 2-18*); overestimated number of older fish in the catches of passive fleet (*Figure 2-20*); overestimated size of most abundant cod group in the passive fleet catches (*Figure 2-22*)

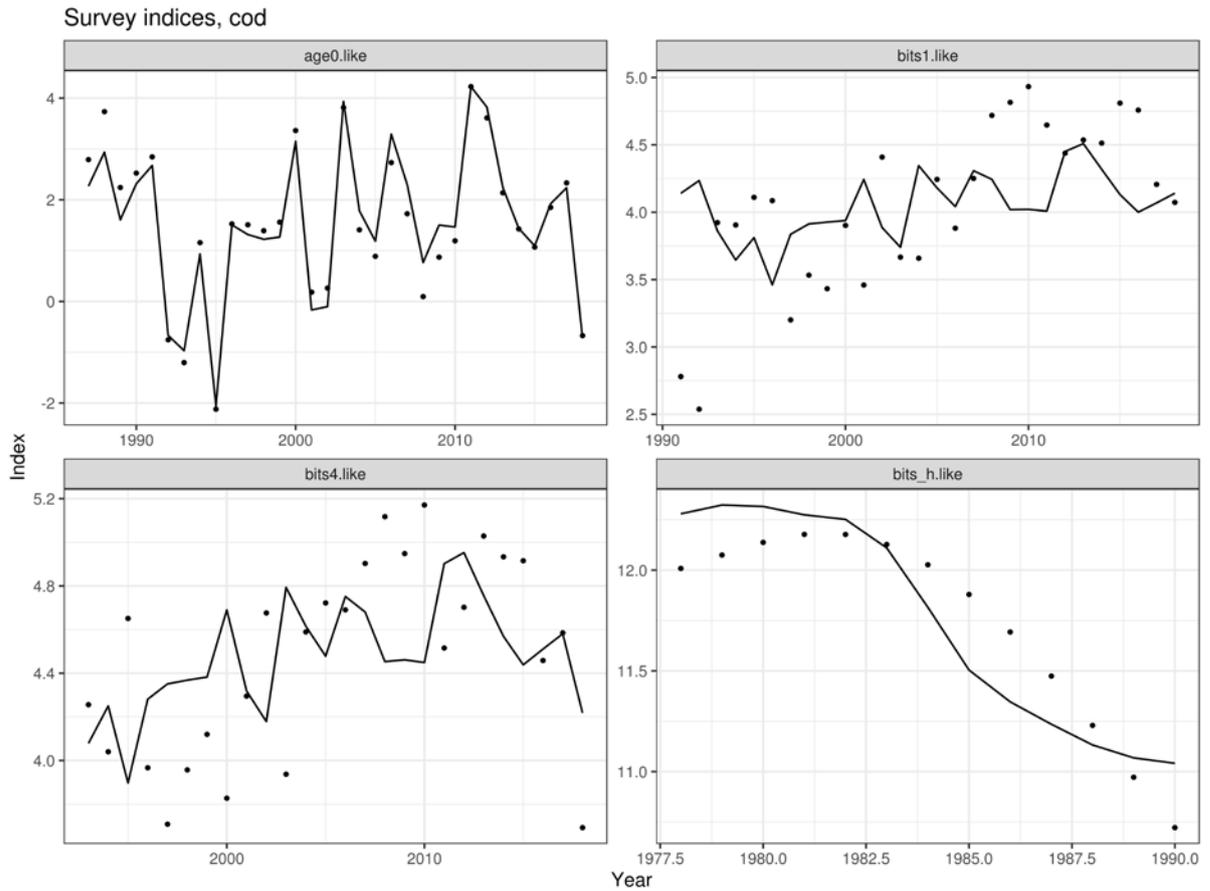


Figure 2-101. Comparison of log-transformed observed (points) and predicted (lines) cod survey abundance indices.

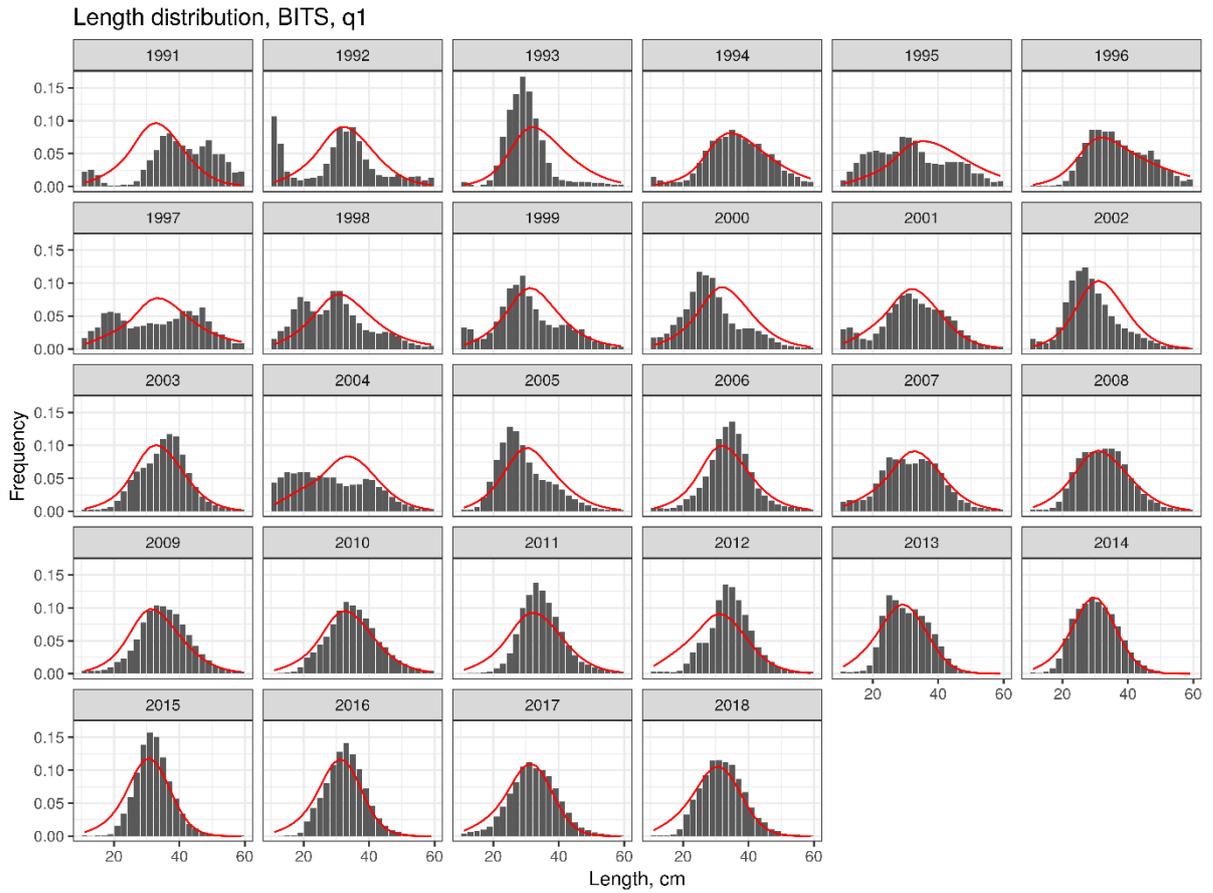


Figure 2-102. Comparison of observed (bars) and predicted (line) cod length distribution in survey catches, BITS Q1.

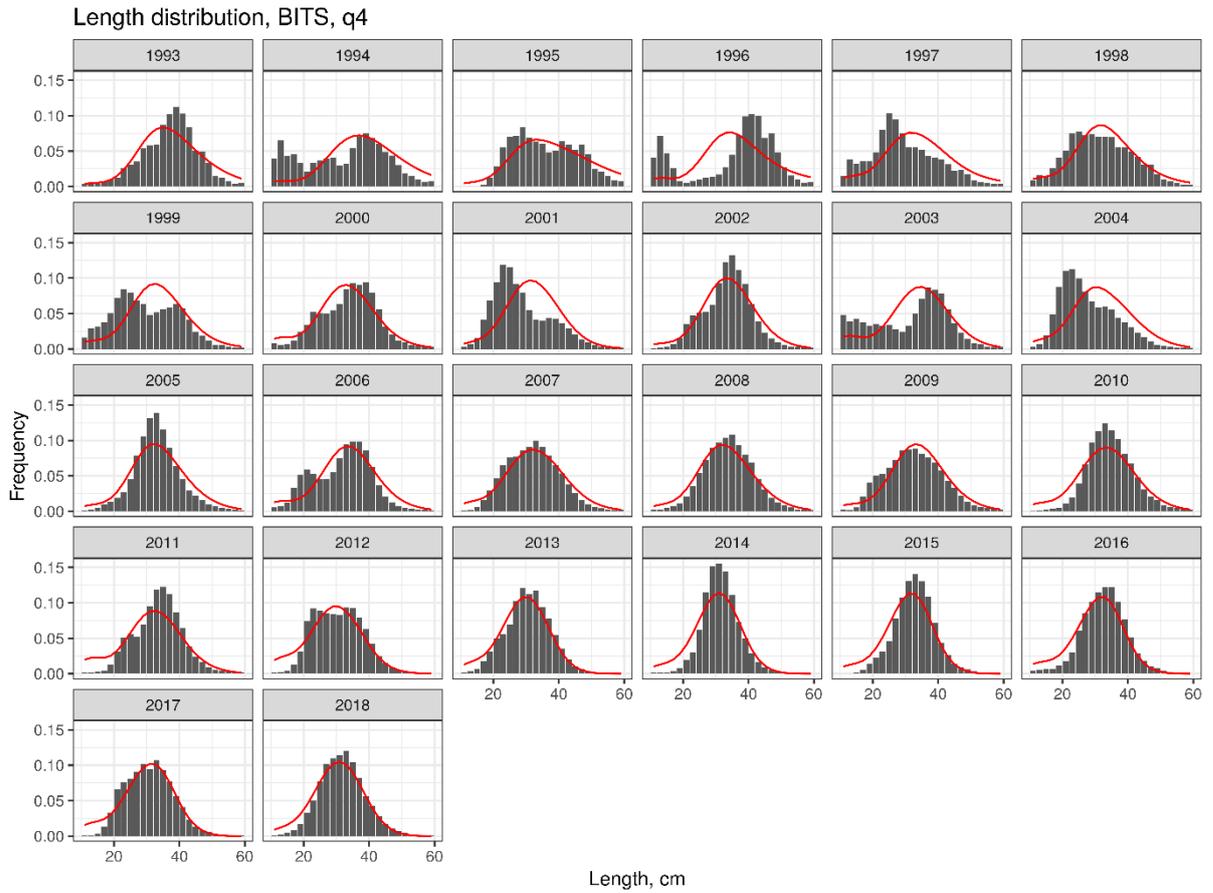


Figure 2-103. Comparison of observed (bars) and predicted (line) cod length distribution in survey catches, BITS Q4.

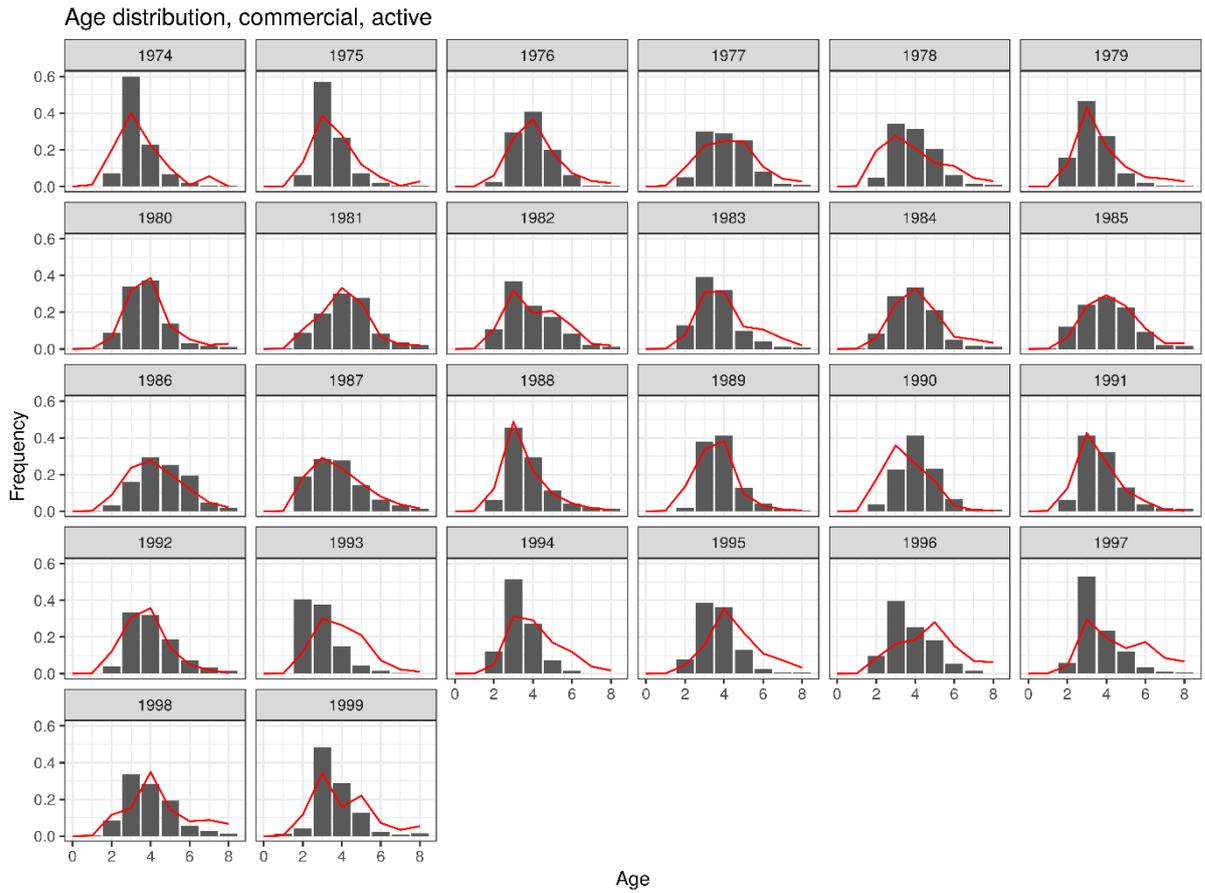


Figure 2-104. Comparison of observed (bars) and predicted (line) cod age distribution in commercial catches, active gear.

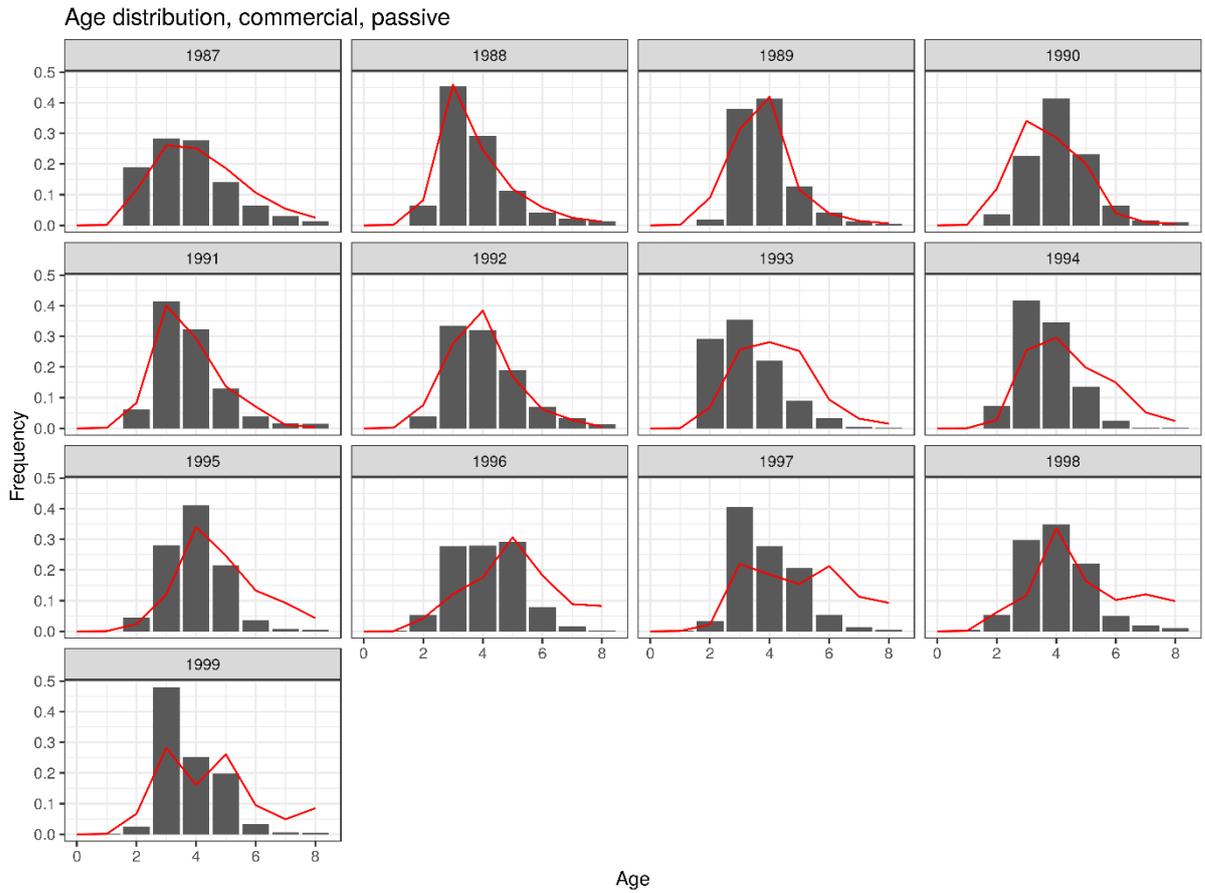


Figure 2-105. Comparison of observed (bars) and predicted (line) cod age distribution in commercial catches, passive gear.

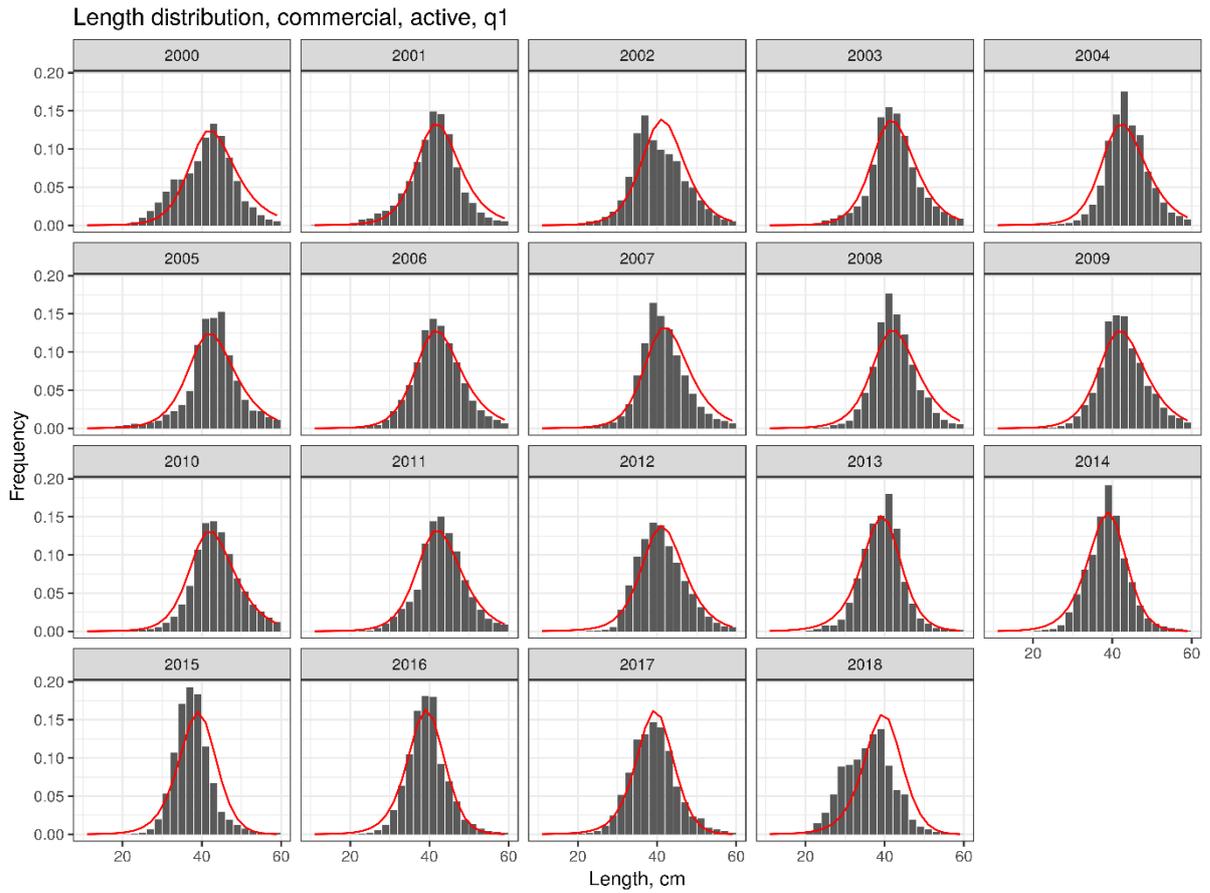


Figure 2-106. Comparison of observed (bars) and predicted (line) cod length distribution in commercial catches, active gear.

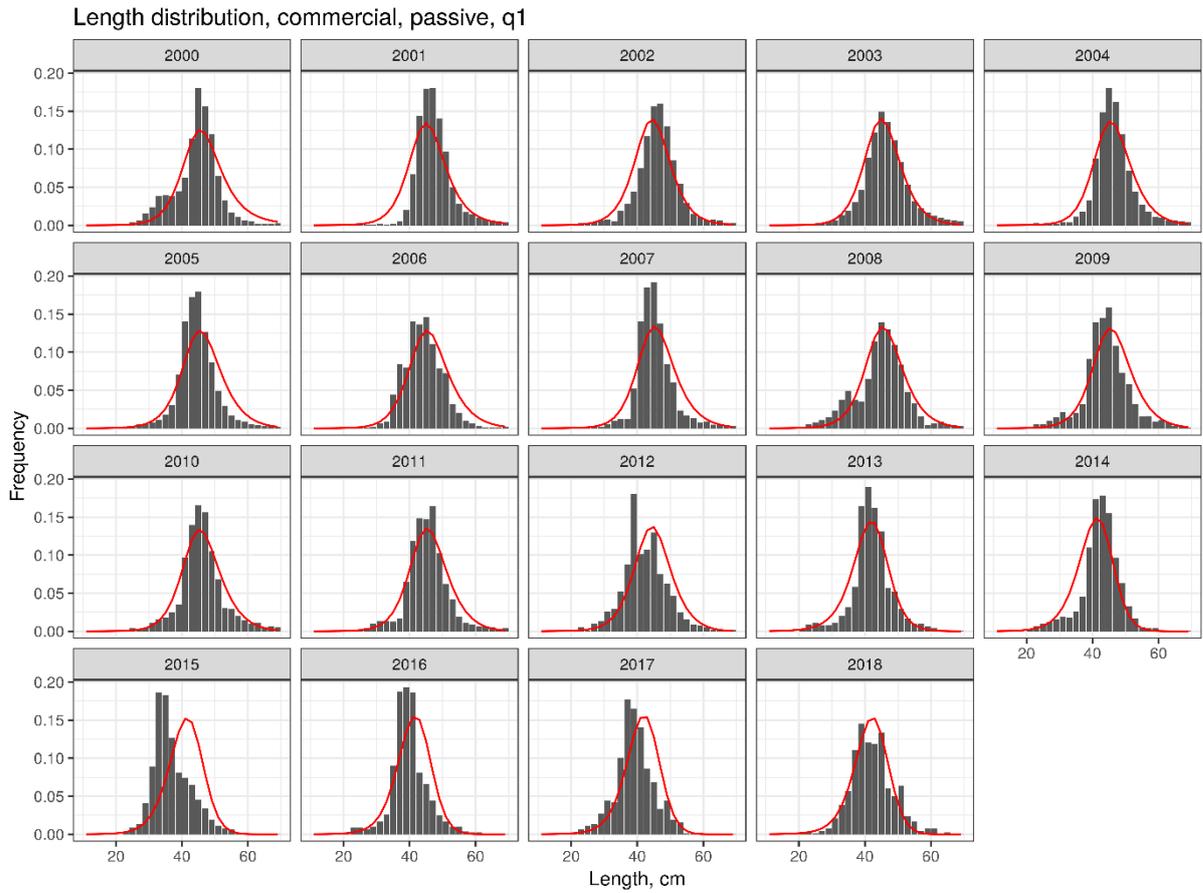


Figure 2-107. Comparison of observed (bars) and predicted (line) cod length distribution in commercial catches, passive gear.

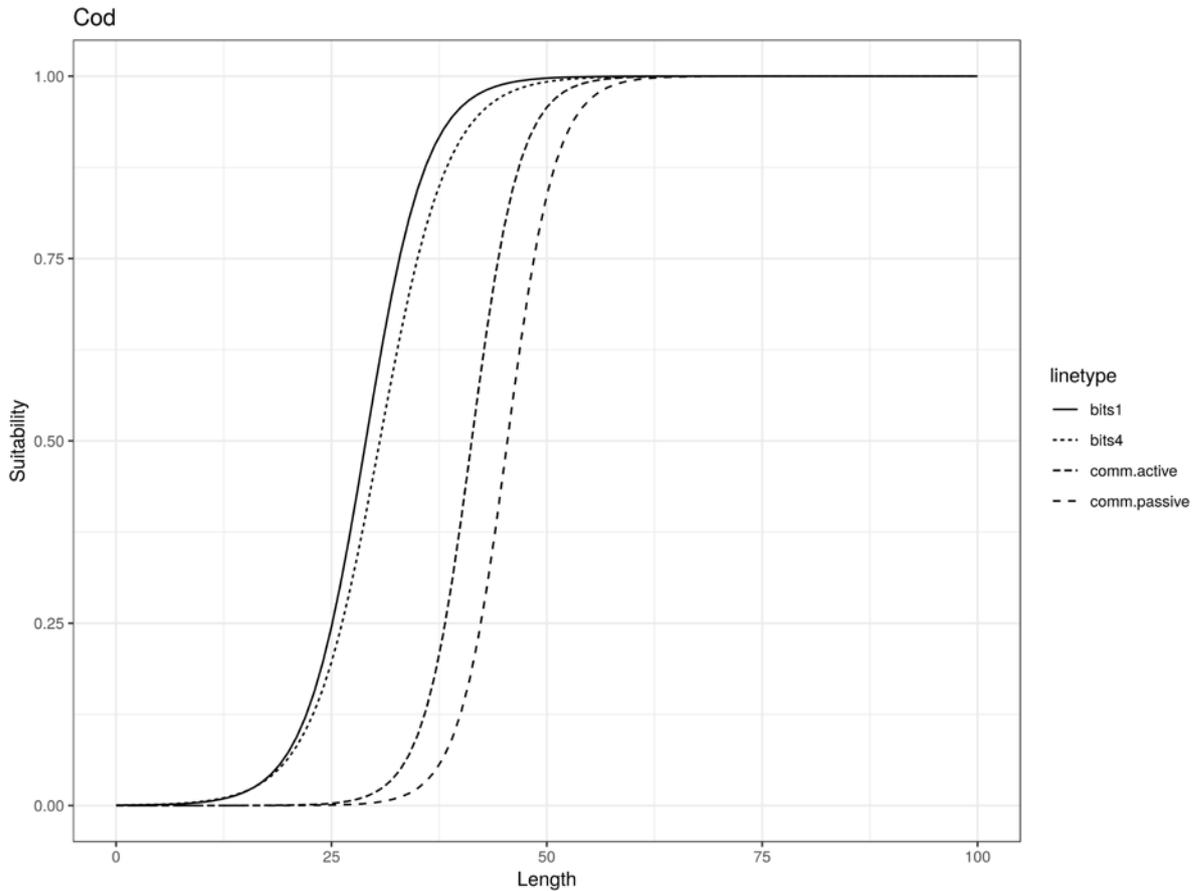


Figure 2-108. Estimated in the model fisheries (comm.actice, comm.passive) and survey (bits1, bits4) suitabilities.

Table 2-37. List of parameters estimated in the single species cod model (optimised = 1) with the lower and upper bound allowed for the search of optimal value.

```

; Gadget version 2.2.00-BETA running on ubuntu-ryzen Thu Oct 10 18:14:22 2019
; Simulated Annealing algorithm ran for 100001 function evaluations
; and stopped when the likelihood value was 12090.861
; because the maximum number of function evaluations was reached
; Hooke & Jeeves algorithm ran for 1304 function evaluations
; and stopped when the likelihood value was 11147.287
; because the convergence criteria were met
; BFGS algorithm ran for 7785 function evaluations
; and stopped when the likelihood value was 10761.08
; because the accuracy limit for the gradient calculation was reached
switch      value      lower upperoptimise
bbeta      0.1068525   0.001    50      1
ic01      18.712341   0.001    50      1
ic02      10.899138   0.001    50      1
ic03       3.921619   0.001    50      1
ic04       1.271698   0.001    50      1
ic05       4.4537106   0.001    50      1
ic06       3.1320996   0.001    50      1
ic07      21.724543    1e-05    50      1
ic08     1.0000918e-05  1e-05    50      1
ic09     1.0010731e-05  1e-05    50      1
ic10       1.0573306    1e-05    50      1
rec1974   27.459009    0.004    190     1
recl       9.05         5         40      0
    
```

recsdev	4.12	0	15	0
rec1975	38.184311	0.004	190	1
rec1976	81.283141	0.004	190	1
rec1977	70.014765	0.004	190	1
rec1978	41.006341	0.004	190	1
rec1979	64.82302	0.004	190	1
rec1980	63.115716	0.004	190	1
rec1981	45.144698	0.004	190	1
rec1982	32.969925	0.004	190	1
rec1983	24.311937	0.004	190	1
rec1984	24.514408	0.004	190	1
rec1985	40.623187	0.004	190	1
rec1986	25.770672	0.004	190	1
rec1987	25.33217	0.004	190	1
rec1988	29.761108	0.004	190	1
rec1989	21.605008	0.004	190	1
rec1990	25.616701	0.004	190	1
rec1991	27.939775	0.004	190	1
rec1992	12.50054	0.004	190	1
rec1993	11.627743	0.004	190	1
rec1994	18.38638	0.004	190	1
rec1995	8.9543361	0.004	190	1
rec1996	21.087015	0.004	190	1
rec1997	20.148054	0.004	190	1
rec1998	19.700158	0.004	190	1
rec1999	19.912228	0.004	190	1
rec2000	31.324817	0.004	190	1
rec2001	14.100151	0.004	190	1
rec2002	14.325989	0.004	190	1
rec2003	37.834419	0.004	190	1
rec2004	22.546418	0.004	190	1
rec2005	19.525106	0.004	190	1
rec2006	32.402103	0.004	190	1
rec2007	25.512597	0.004	190	1
rec2008	17.64631	0.004	190	1
rec2009	21.070066	0.004	190	1
rec2010	20.883352	0.004	190	1
rec2011	40.56938	0.004	190	1
rec2012	36.821677	0.004	190	1
rec2013	25.19032	0.004	190	1
rec2014	20.738318	0.004	190	1
rec2015	19.094169	0.004	190	1
rec2016	23.310713	0.004	190	1
rec2017	25.140115	0.004	190	1
rec2018	12.330563	0.004	190	1
alphacomm.a	0.35686682	0.001	10	1
L50comm.a	41.275656	2	100	1
alphacomm.p	0.3574748	0.001	10	1
L50comm.p	45.422039	2	100	1
alphabits1	0.28234399	0.001	10	1
L50bits1	28.989605	2	100	1
alphabits4	0.251169	0.001	10	1
L50bits4	30.610618	2	100	1

Multispecies implementations

Multispecies model

The multispecies model is built on the single species models and essentially, it links the dynamics of herring and sprat to cod via predation (only top-down effect and no feedback on cod). Consequently, cod follows the exact single species implementation (i.e., all parameters influencing the cod dynamic are fixed to the single species estimation), while the clupeids dynamics are reconstructed now accounting for the explicit effect of cod predation. To do so the natural mortality of herring and sprat is now divided in two components:

$$M = M1 + M2$$

where $M1$ correspond to the background mortality and $M2$ to the predation mortality imposed by cod. $M1$ is assumed to be approx. half of the total natural mortality adopted in the single species implementation, hence it was set to 0.1 for herring and 0.2 for sprat.

All the preys other than the two clupeids are pooled into a so called *otherfood* component of the model. According to the stomach data, the otherfood component will include different preys throughout the ontogeny of cod, with a majority of benthic preys as part of the diet of small cod and with a majority of large fish (i.e., flounder and other cod) for the diet of large cod. Such diversity of the otherfood component is not considered in the model presented. Lack of information on the abundance of benthic invertebrates (e.g., mysids and saduria) and lack of cannibalism for this model implementation explain this choice.

The multispecies model includes four distinct fishing fleets: an active fishery on cod (trawlers), a passive fishery on cod (mainly gillnetters), and for simplification two pelagic fisheries operating independently on herring and sprat (i.e., no relationship or mixture is assumed in the harvesting of the two clupeids contrary to the reality).

The predator-prey interaction represented in this cod-herring-sprat model is regulated by three main processes: (1) the consumption, (2) the prey species composition of the diet, and (3) the prey size selection. All the three processes had to be resolved for this multispecies implementation and involve a certain number of assumptions (i.e., constant biomass of otherfood, symmetrical cod-prey size selection curves). Few selected sensitivity tests were performed to evaluate the impact of assumptions on background mortality of clupeids and on maximum consumption (see section 3.2) but a full exploration of structural uncertainty of the model was outside what was feasible for this first Gadget implementation of the Baltic, and consequent limitations are illustrated in section 3.1.9.

Gastric evacuation model and feeding level

Different methods exist for the estimation of energy intake required for different activities in the life of a fish. One of the most established methods is based on the direct use of data on stomach content and weights which are used to derive how much food is eaten by accounting for the rate of evacuation of food from the stomach. Different consumption rates have been proposed for cod using data from different areas and applying different empirically based evacuation rate models. Bogstad and Mehl (1990) investigated the impact of different gastric evacuation models for Barents Sea cod in a multispecies framework (MULTSPEC) and showed

how different models and assumptions could result in largely different estimates of prey consumed.

On average, the rate of elimination of food (R) from the stomach can be considered equivalent to the rate of food entering it, so that gastric evacuation models can be used to approximate consumption (C) from average stomach content weights. The gastric evacuation model proposed by Andersen and Beyer (2005) consists of a simple, geometric representation of the digestive tract as the curved side of a cylinder. The model predicts that the evacuation time is proportional to the square root of meal size in accordance with extensive empirical evidence on cod from the Danish Kattegat coasts and it represents a good general mechanistic model for predatory gadoids. So the evacuation rate of every prey species in the stomach can be written as:

Equation 3-9

$$R_p = 24 \rho_0 L^{1.30} e^{0.083T} E_p^{0.15} \sqrt{S_p}$$

where:

< L > is the cod length

< S_p > is the weight of specific prey type *p* in the stomach

< E_p > is the average energy densities (kJ g⁻¹) of the specific prey type *p* in the stomach

< ρ₀ > is the basic evacuation rate parameter 2.43 x 10⁻³

Experienced temperature *T* was assumed constant at 5°C, corresponding roughly to the average temperature experienced by cod in the Baltic Sea (Righton *et al.*, 2010).

Prey energy was assumed to be constant across seasons and over the whole time period investigated. Being key prey species for a number of gadoids, several energy densities estimates for herring and sprat are available from literature showing considerable variability. Without robust estimates for the specific area and time period covered by the model, we preferred to adopt prey specific values based on average from different sources as shown on Table 3-1.

Table 3-38. Energy density (KJ g⁻¹) of the cod preys represented in the model.

Prey	Energy density (KJ g ⁻¹)	Sources
Herring	5.5	average from Arrhenius and Hansson (1994), dos Santos and Jobling (1995), Temming and Herrmann (2003).
Sprat	6.6	average from Hansson <i>et al.</i> (1996), Arrhenius, (1998), Temming and Herrmann (2003)

Otherfood	3.7	Hansson <i>et al.</i> (1996) uses three energy prey categories for cod in the North Sea, namely fat fish, lean fish and other preys. The latter group has been used here
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Evacuation rate of specific prey (kJ/day) were then converted back into biomass by dividing by prey energy density. The biomasses were then summed for individual stomachs and used to estimate the daily evacuation rate (kg/day). This model was applied to the Baltic cod stomach data. Empty stomachs were included to account for individual variation and to estimate consumption that is representative of the whole population. We discarded the stomachs that were marked as regurgitated, as well as stomachs of cod larger than 80 cm, because their daily rations were too variable as a result of limited sample size.

The maximum consumption (C_{max}) implemented in the model is based on an exponential relationship with the fish length, and for simplicity it is assumed to be independent from environmental temperature:

Equation 3-10

$$C_{max,L} = m_0 \cdot \Delta t \cdot L^{m_3}$$

The parameters m_0 and m_3 were estimated using a quantile regression on consumption rates calculated from the cylinder gastric evacuation model. The distribution of consumption is highly dispersed towards high values and calculation of the maximum consumption is sensitive to the selection of a certain quantile. Based on visual inspection and past experience with alternative gastric evacuation models, the 97th quantile regression was selected as representative of the maximum consumption. It is important to note that the maximum consumption will enter twice into the model: (1) in the calculation of the feeding level and (2) in the calculation of the realised consumption (see implementation of consumption in section 3.1.4). In this way the selection of one quantile versus another will have very little influence on the final average consumption implemented by the model.

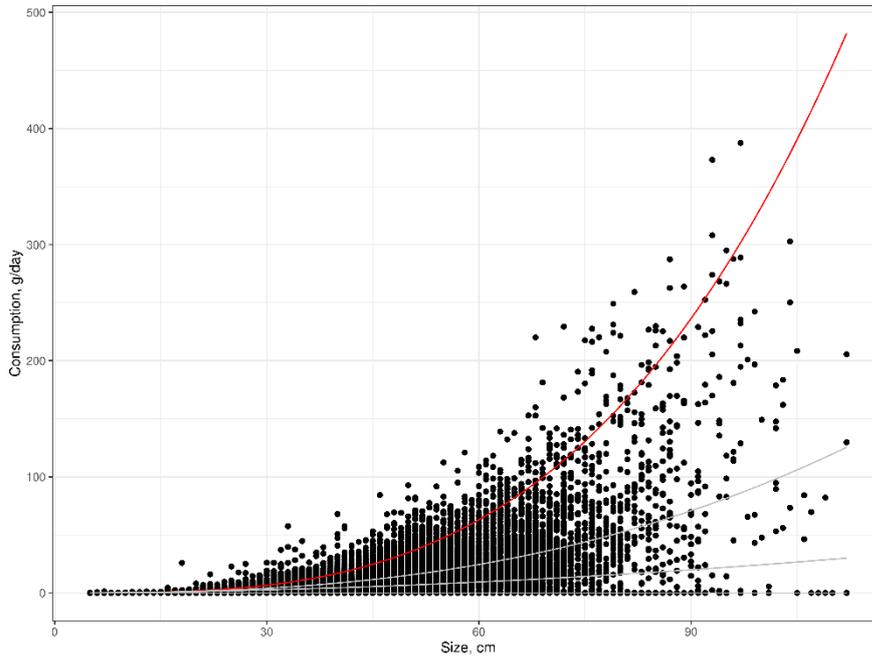


Figure 3-109. Cod consumption in relation to cod size as estimated from the cylinder gastric evacuation model. The grey lines represent the 25th, 50th, 75th quantiles and the red line the 97th quantile used for the maximum consumption.

However as individuals rarely feed on the level of maximum potential, maximum consumption was multiplied by feeding level to obtain the average consumption at the population level scale.

Feeding level φ is the actual level of biomass intake. It was calculated for each individual stomach and it is expressed as the ratio between the consumption estimated from the gastric evacuation model of the stomach (i) and the maximum consumption for that predator length (L):

Equation 3-11

$$\varphi_{i,L} = C_{i,L}/C_{max,L}$$

An average feeding level $\bar{\varphi}$ was calculated from the individual feeding levels φ_i by 5-years time intervals (Figure 3-2). The calculation was restricted to cod of 30-60 cm which account for most of the clupeids predation and the average was weighted by the cod length distribution in that length range.

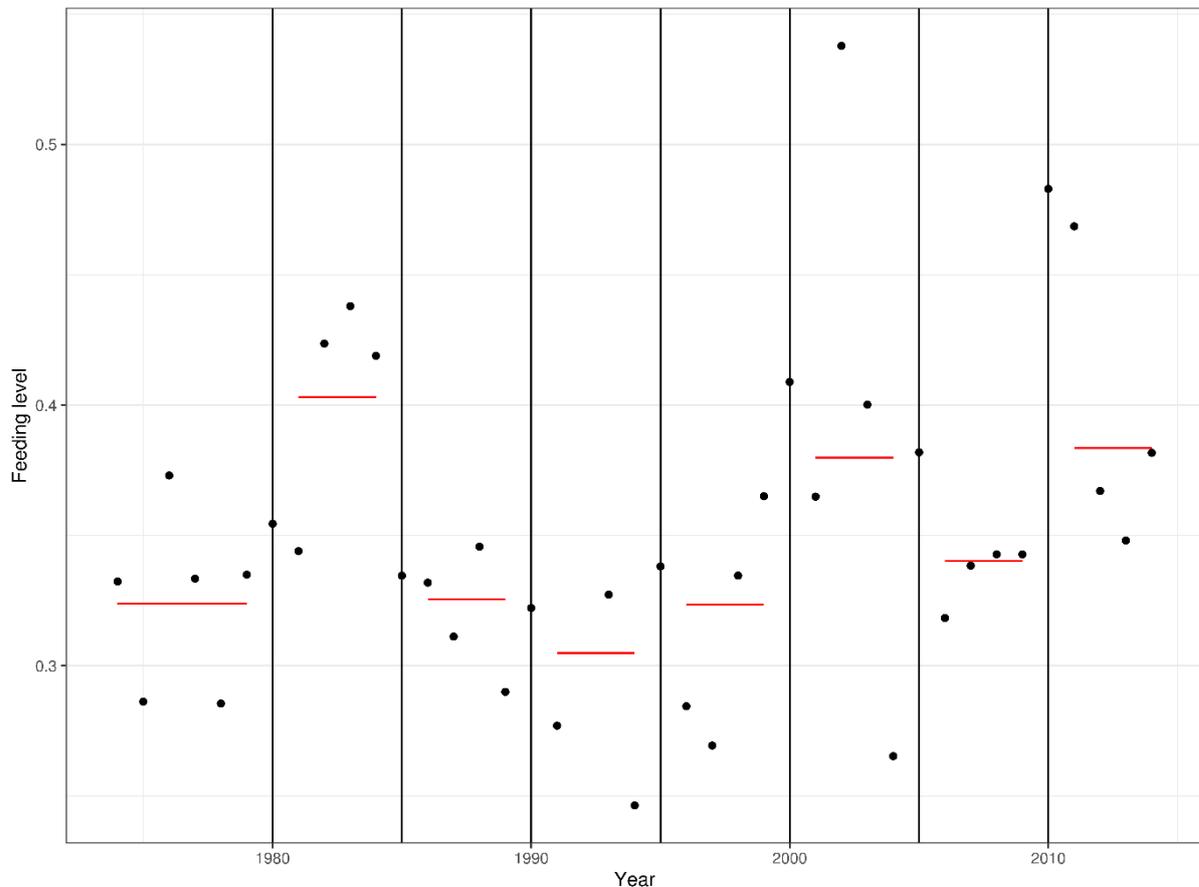


Figure 3-110. Time-series of average feeding levels $\bar{\varphi}$ by 5-year time intervals.

The estimation of the monthly maximum consumption parameters, assuming no effect of temperature resulted in $m_0 = 3.035e-3$ and $m_3 = 3.26$.

Predator-prey size selection

Marked relationships between the size of predator fish and the size of their preys have been documented for many fish species. During their ontogeny, most fish species not only are able to prey on progressively larger preys but also show an increasing prey size range. In practice, rather than simply shifting selectivity towards larger preys, many predators have an increasing size spectrum of preys. This pattern has been reported also among gadoid fish and it is observed in the cod stomach data from the Baltic as well.

The selection applied by the predator for different prey sizes is prey specific and represented in Gadget by the Andersen-Ursin suitability function (Andersen and Ursin, 1977). This function is characterised by the ratio of the predator/prey lengths, which allows for changes in the prey size selection as the predator size increases. Data exploration and preliminary runs showed a symmetric selection curve that resulted in the following simplified version of the Andersen-Ursin function:

Equation 3-12

$$S_{i,L} = p_2 \cdot e^{-\frac{(\ln \frac{L}{l} - p_1)^2}{p_3}}$$

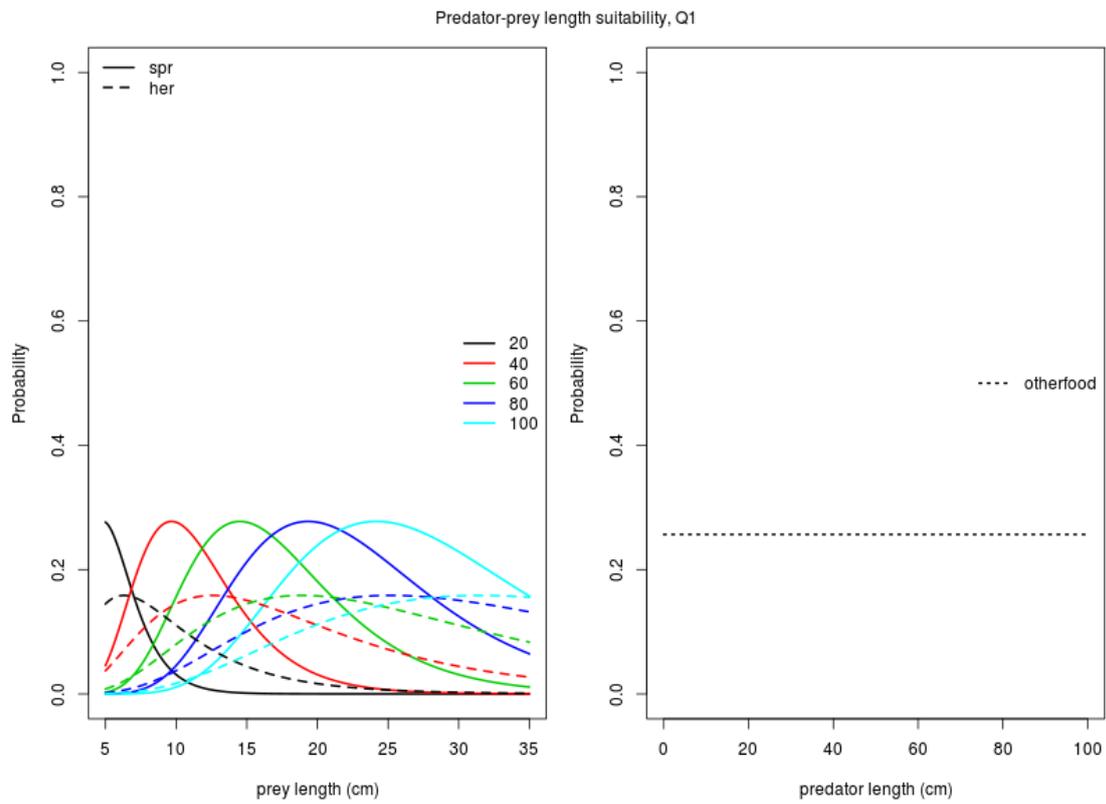
where:

< p_1 > describes the optimal predator-prey size ratio

< p_3 > determines the deviation of the selection curve (i.e., the length range of preys selected)

< p_2 > is a half-year specific prey preference

Initial values of p_1 , p_2 and p_3 were derived from Kulatska, et.al. (2019)



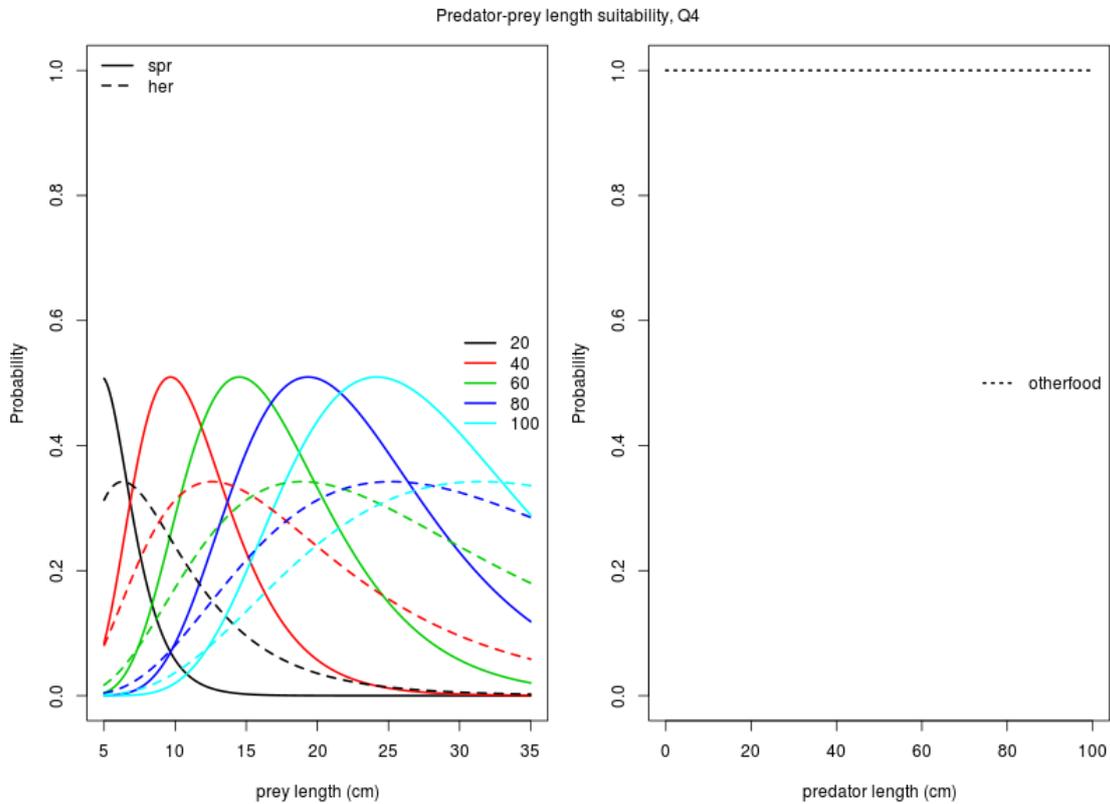


Figure 3-111. Predator-prey (cod-clupeids) size selection estimated in the model. Different colours refer to cod of different size.

Other consumption parameters used in the model

To specify how much sprat and herring is consumed by cod in Gadget several other parameters are required to determine the amount *F* (in energy units) of a given prey which is consumed by cod given the size selection and preference for that prey:

Equation 3-13

$$F_{p,l,L} = (S_{p,l,L} \cdot E_p \cdot N_{p,l} \cdot W_{p,l})^{d_p}$$

where:

- < $S_{p,l,L}$ > is the number of cod in the length cell *L*
- < E_p > is the prey-specific energy density expressed in KJ/kg
- < $N_{p,l}$ > is the number of prey *p* in the length cell *l*
- < $W_{p,l}$ > is the individual mean weight of prey *p* at length *l*
- < d_p > is a preference parameter of cod for each prey

The preference parameter of the predator for the prey (d_p) which controls the form of the functional response has been set to 1 for all preys which in the current implementation of consumption approximates a type II functional response.

Very little is known about other highly correlated parameters of the consumption such as the “half-feeding” value which was fixed to 0 (eq. not shown because irrelevant in the current implementation).

Implementation of consumption in the model

Ultimately, the consumption of each prey p in the model is dependent on the size (L) and abundance of the predator, and size (l) and abundance of preys. For simplicity, the specific configuration of this model (see above) does not allow for the effect of temperature on the consumption and the average feeding intensity $\bar{\varphi}$ is adopted over discrete time periods and it is not the result of a dynamic process dependent on the variability in prey abundance (ie, density of prey in the model does not effect directly the level of consumption). Equation 3-6 come into the consumption model implemented in Gadget as follows:

Equation 3-14

$$C_{p,l,L} = \frac{N_L \cdot C_{max,L} \cdot \bar{\varphi} \cdot F_{p,l,L}}{\sum_{p=1}^n F_{p,l,L}}$$

where:

$\langle N_L \rangle$ is the number of cod in the length cell L

The ratio $F_{p,l,L} / \sum_{p=1}^n F_{p,l,L}$ represents the relative contribution of the prey p of length l to the realised consumption of the predator of length L .

Likelihood components

Given that the cod dynamics are fixed to the single species estimation, data fitting of the multispecies run includes only clupeids likelihood data components (except the weight-at-age likelihood) and two new components related to the stomach data (prey species composition of cod diet and prey length composition of the diet). These two are intended to inform the model about species composition and prey size selection in the diet. Only full stomachs with ≥ 20 stomachs per timestep-length group combination were used for this purpose. Prey species composition of cod diet was estimated as a proportion in weight that specific prey type contributed to a total diet of specific cod length group in specific timestep. Prey length composition of cod diet was estimated as a frequency of occurrence (proportion of stomachs of specific cod length group in specific timestep that included specific prey length) separately for herring and sprat.

A sum of square likelihood function is used to compare the diet composition predicted in the model to observed from stomach content for both components:

Equation 3-15

$$l = \sum_{time} \sum_{predator} \sum_{prey} (P_{tpp} - \pi_{tpp})^2$$

where:

< P > is the ratio of the stomach content data for that time/area/predator/prey combination

< π > is the ratio of the modelled consumption for that time/area/predator/prey combination

Fitting

124 parameters were estimated in the multi-species model (Table 3-3) to fit to 28 likelihood components (Table 3-2), with herring and sprat ALK having highest weighted score and thus contributing in large extent to the objective function:

Table 3-39. Summary of likelihood scores and weights assigned to likelihood components, and the respective fraction of their contribution to objective function.

id	score	Weight	wgt_score	fraction	percent
cod.food.lengths	25,470	46,307	1179,449	0,096	9,64
cod.food.species	84,940	7,883	669,546	0,055	5,47
her.adist.comm1	0,115	6837,610	786,325	0,064	6,43
her.adist.comm2	1,644	400,934	659,135	0,054	5,39
her.alk.bias	150,500	21,042	3166,746	0,259	25,88
her.ldist.bias	0,608	1332,300	809,639	0,066	6,62
spr.adist.comm1	0,126	6787,880	855,952	0,070	6,99
spr.adist.comm2	1,665	622,901	1037,130	0,085	8,47
spr.alk.bias	81,640	25,339	2068,709	0,169	16,9
spr.ldist.bias	1,248	276,777	345,418	0,028	2,82
her.bias.a0.like	15,380	14,124	217,232	0,018	1,78
her.bias.a1.like	4,031	8,235	33,193	0,003	0,27
her.bias.a2.like	2,624	3,519	9,234	0,001	0,08
her.bias.a3.like	1,967	4,498	8,848	0,001	0,07
her.bias.a4.like	3,106	2,987	9,278	0,001	0,08
her.bias.a5.like	3,288	2,139	7,032	0,001	0,06
her.bias.a6.like	2,809	3,274	9,197	0,001	0,08
her.bias.a7.like	6,098	1,922	11,718	0,001	0,1
her.bias.a8.like	5,905	2,406	14,208	0,001	0,12
spr.bias.a0.like	16,430	2,577	42,345	0,003	0,35
spr.bias.a1.like	4,721	15,088	71,228	0,006	0,58
spr.bias.a2.like	2,465	18,532	45,682	0,004	0,37
spr.bias.a3.like	2,429	12,376	30,062	0,002	0,25
spr.bias.a4.like	3,504	6,179	21,651	0,002	0,18
spr.bias.a5.like	5,448	3,546	19,316	0,002	0,16
spr.bias.a6.like	8,489	2,864	24,313	0,002	0,2
spr.bias.a7.like	12,780	1,655	21,145	0,002	0,17
spr.bias.a8.like	19,180	3,327	63,814	0,005	0,52

Model fitted well to most of likelihood components similar to single-species herring and sprat models. For sprat, few exceptions are: overestimated index of abundance of age 8 (*Figure 3-4*) at the beginning of time-series; overestimated number of small sprat and underestimated big sprat in 1992 (initial survey year) in survey catches (*Figure 3-5* vs *Figure 2-3*); underestimated size of older sprat in 1992-1996 in survey catches (*Figure 3-6*).

For herring, few exceptions are model was not able to pick the recruitment signal observed in i.e. 1994, 2002 and 2014 in survey catches (*Figure 3-10* vs *Figure 2-10*); underestimated size of older herring in most years in survey catches (*Figure 3-11*); slightly overestimated number at age8+ in commercial catches (*Figure 3-12*, *Figure 3-13*).

As for components unique to multi-species model: observed prey length composition (points on *Figure 3-14*) suggest that 35-60 cm cod was consuming smaller herring and sprat than estimated by the model (line) in the beginning of time-series. Model estimates became closer to observations from 1991 with available clupeid length information from survey.

As for species composition of the diet: model predict sprat proportions quite well (in q1 *Figure 3-15*, a bit overestimated in q4 *Figure 3-16*), underestimated, compared to observations, proportion of herring in recent years, probably due to decrease in herring abundance (*Figure 3-15*) is compensated with overestimated proportion of otherfood. In q4 proportion of herring is overestimated at the beginning of time-series and underestimated (for 35-60 cm cod) toward the end (*Figure 3-16*)

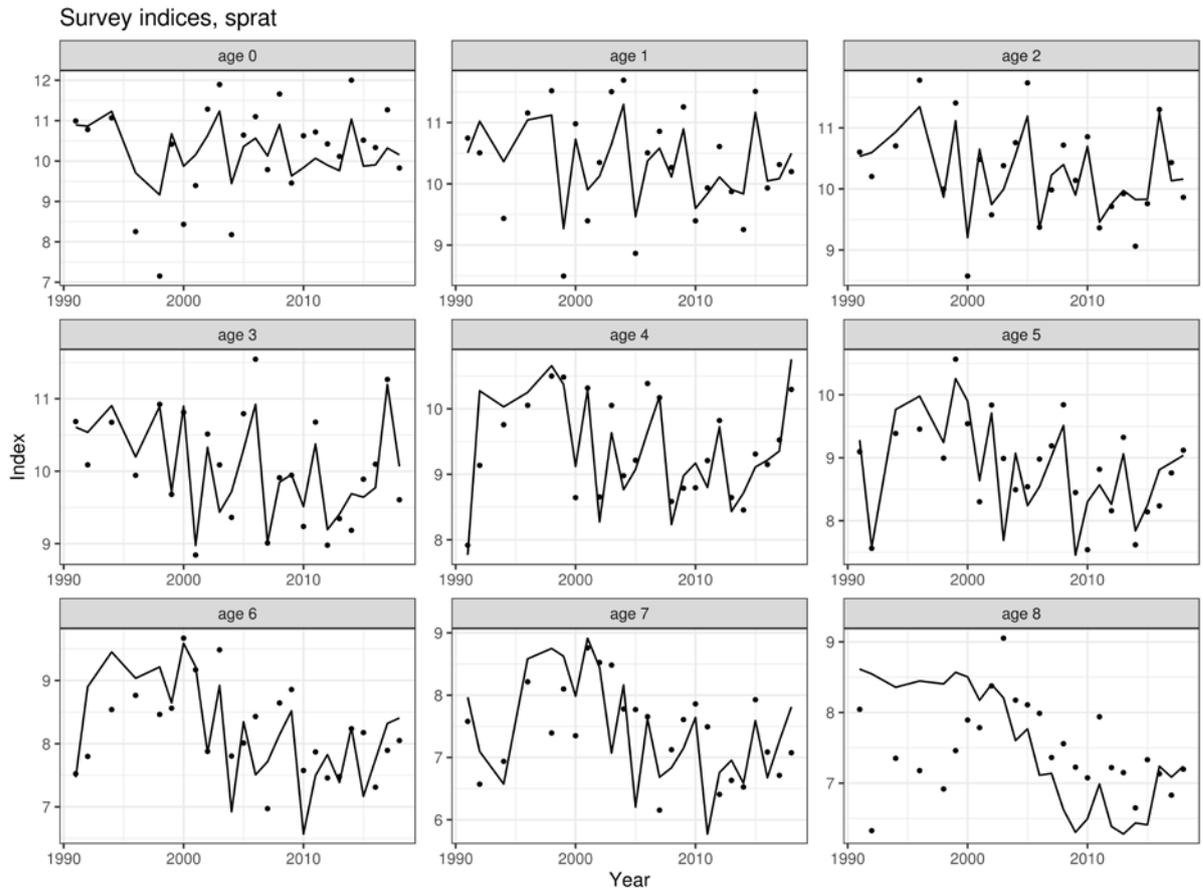


Figure 3-112. Comparison of log-transformed observed (points) and predicted (line) sprat survey abundance indices by age.

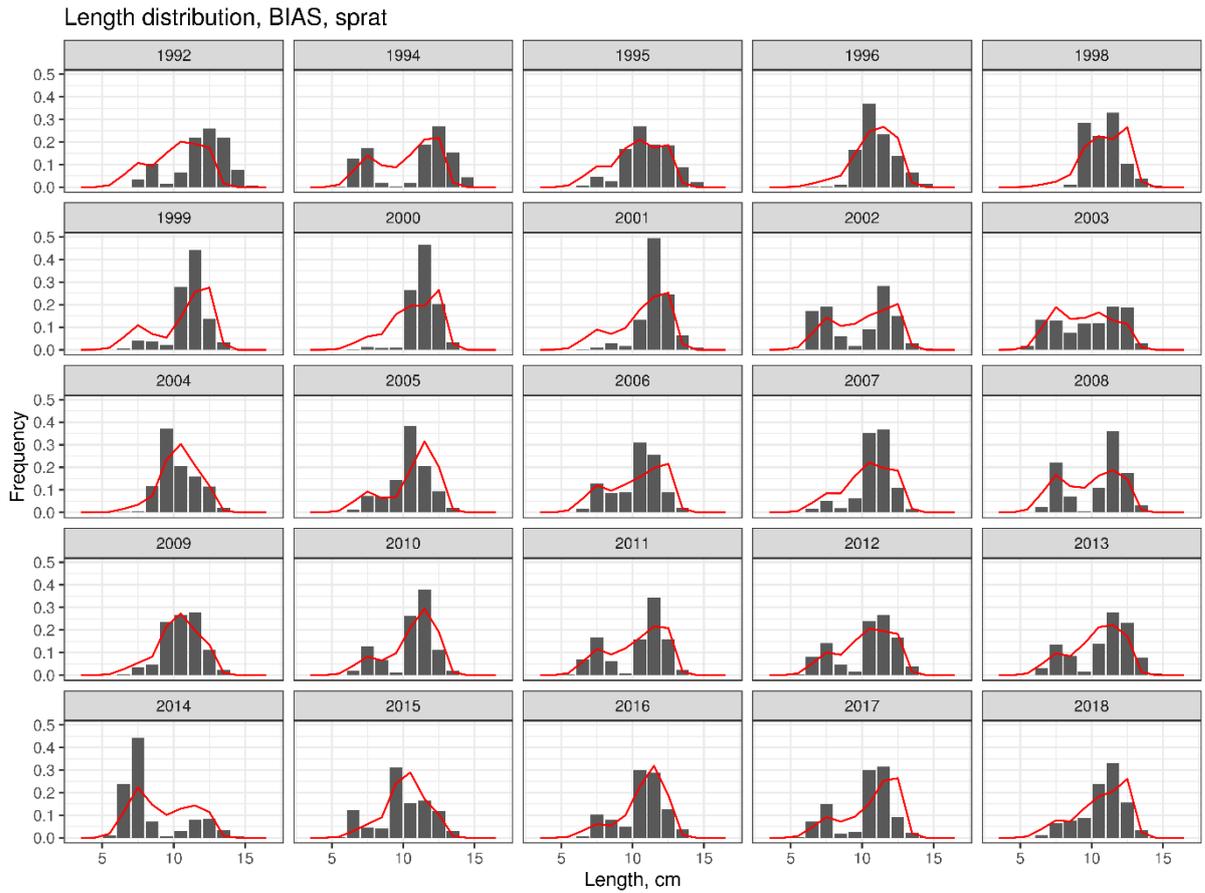


Figure 3-113. Comparison of observed (bars) and predicted (line) sprat length distribution in survey catches.

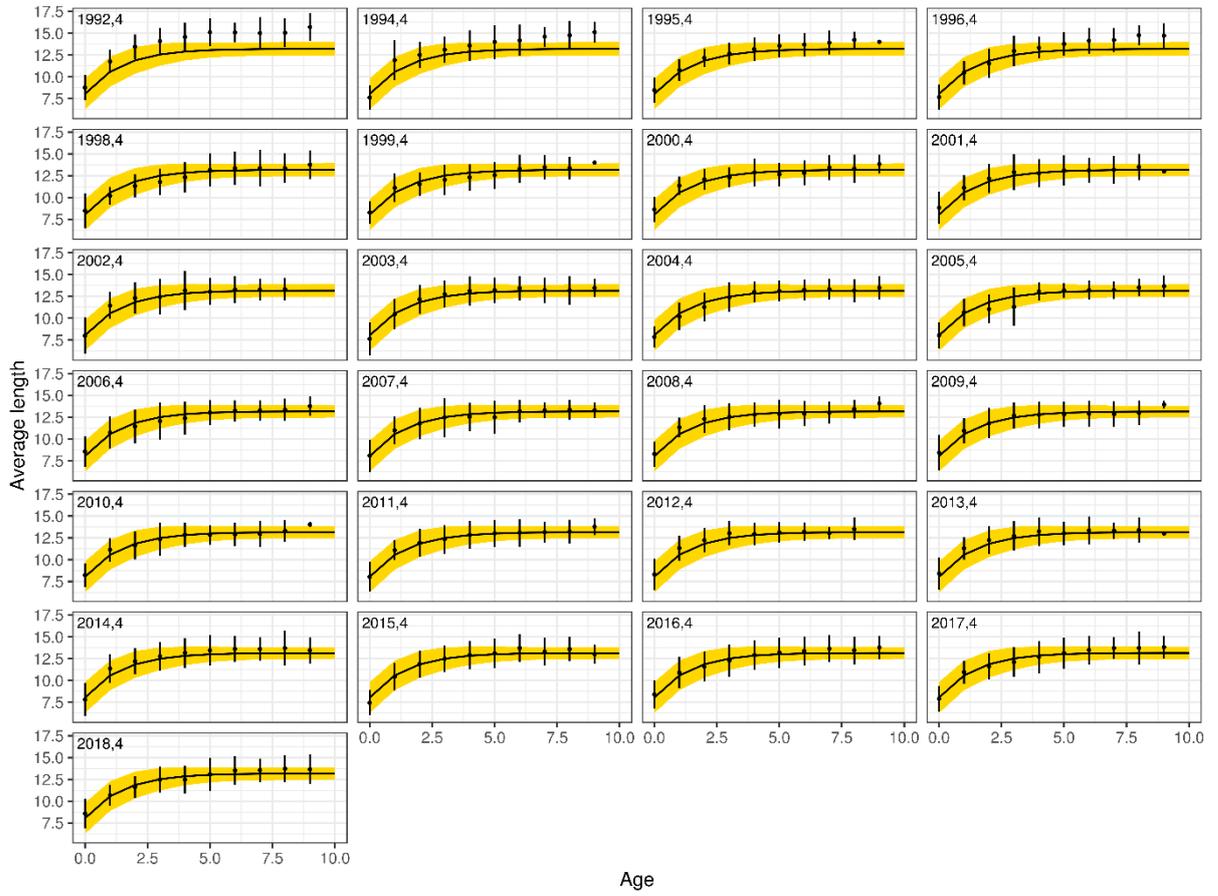


Figure 3-114. Distribution of observed sprat ALK (box-plot) compared with average length at age (line) \pm SD (yellow ribbon).

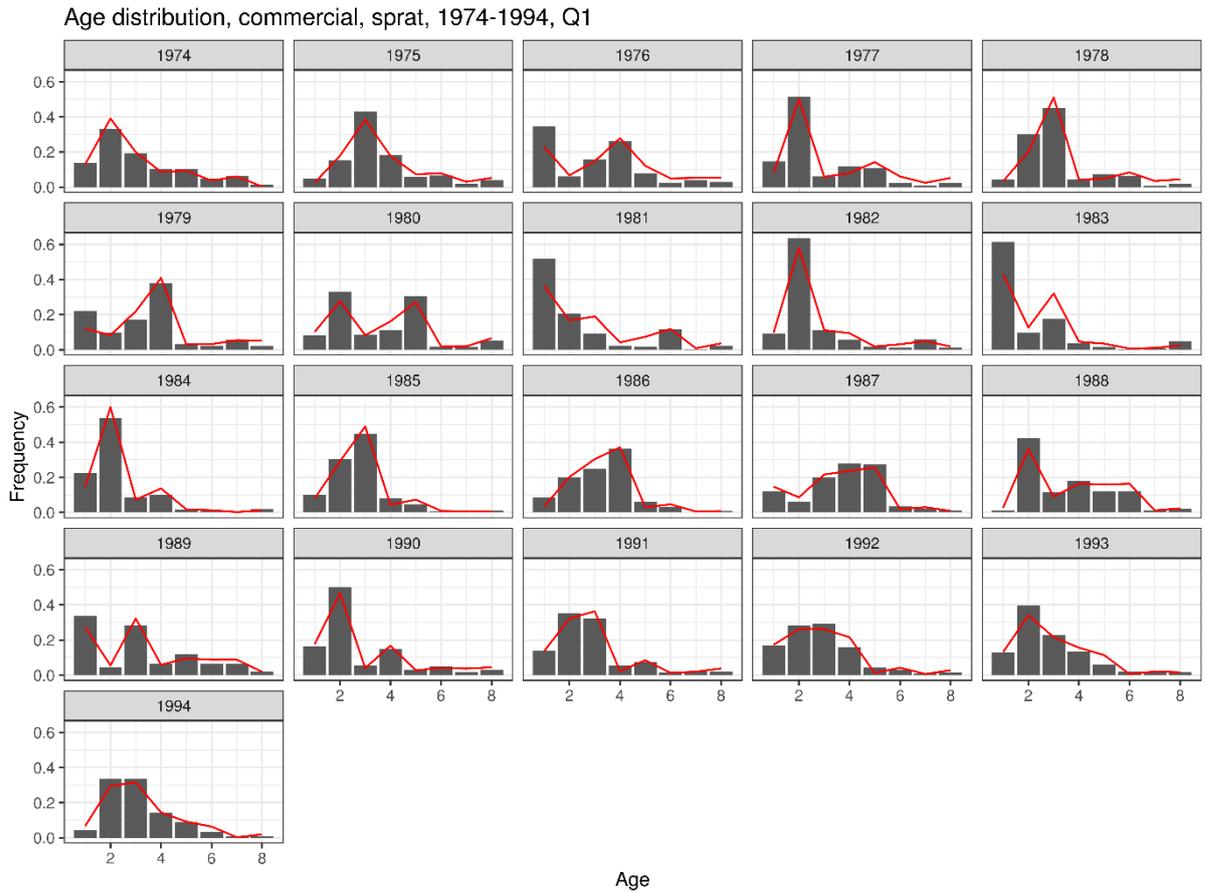


Figure 3-115. Comparison of observed (bars) and predicted (line) sprat age distribution in commercial catches in 1974-1994.

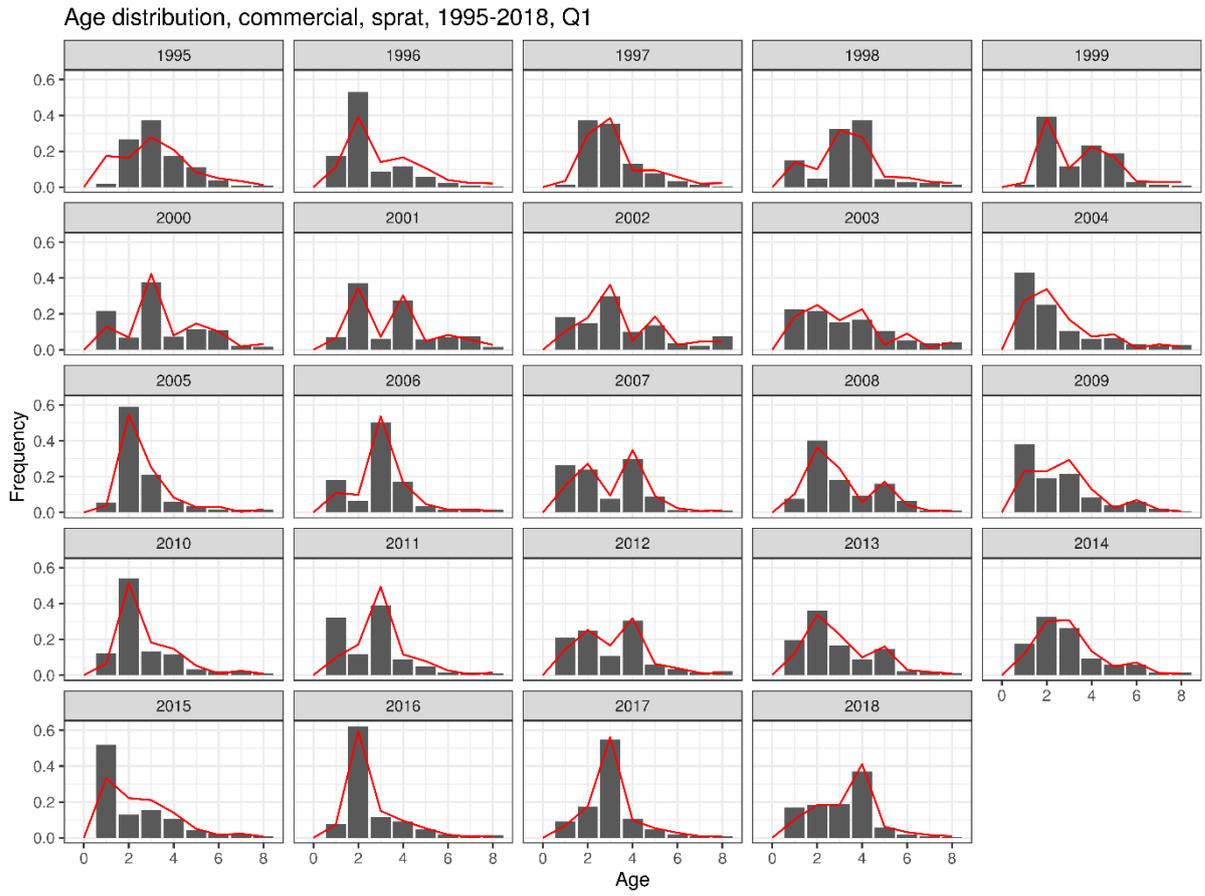


Figure 3-116. Comparison of observed (bars) and predicted (line) sprat age distribution in commercial catches in 1995-2018.

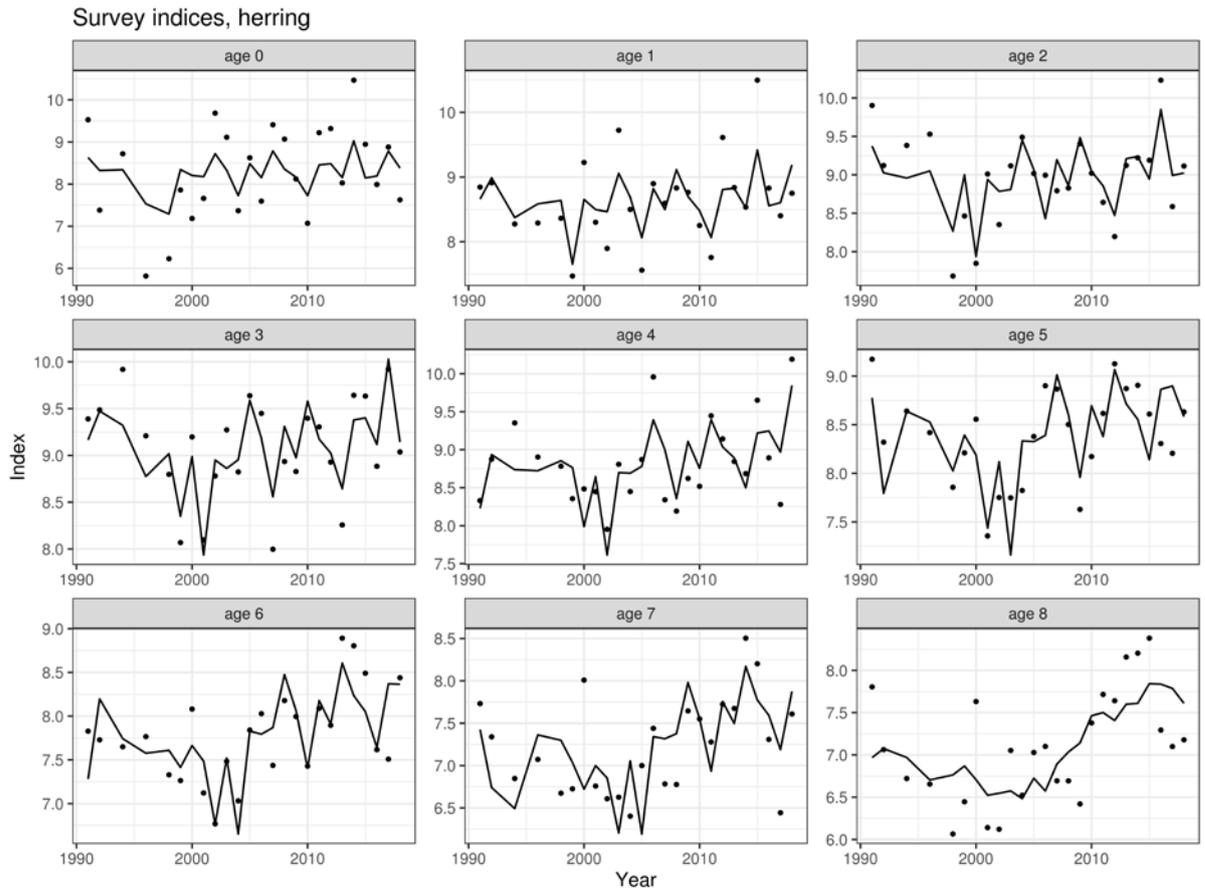


Figure 3-117. Comparison of log-transformed observed (points) and predicted (line) herring survey abundance indices by age.

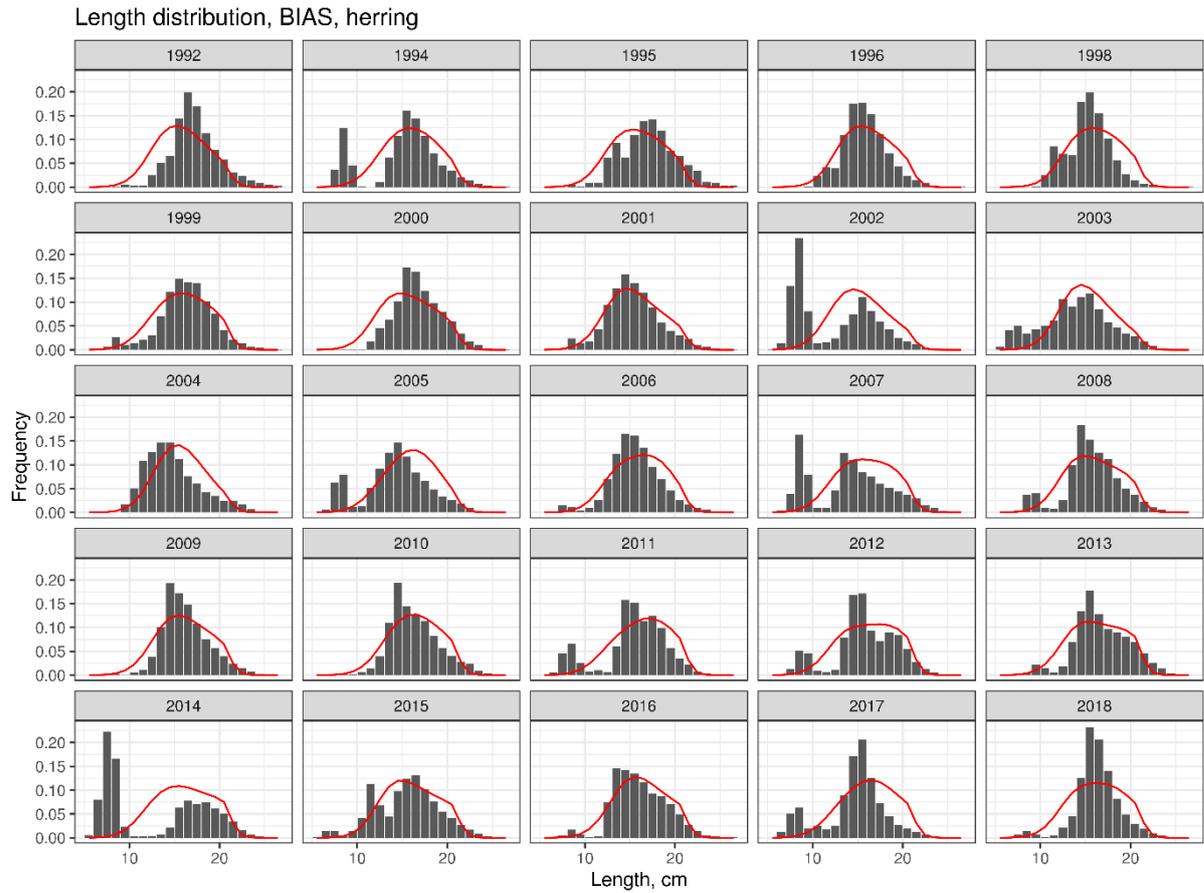


Figure 3-118. Comparison of observed (bars) and predicted (line) herring length distribution in survey catches.

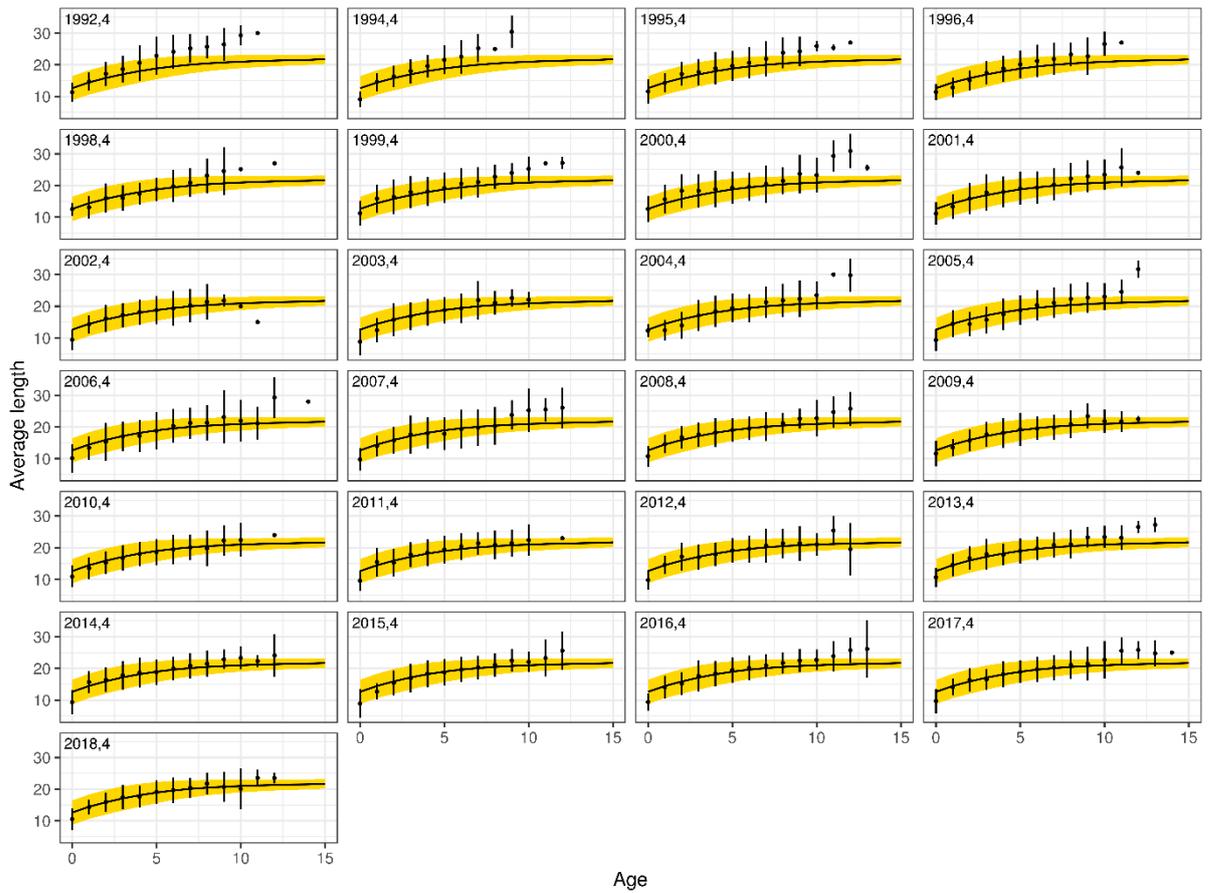


Figure 3-119. Distribution of observed herring ALK (box-plot) compared with average length at age (line) \pm SD (yellow ribbon).

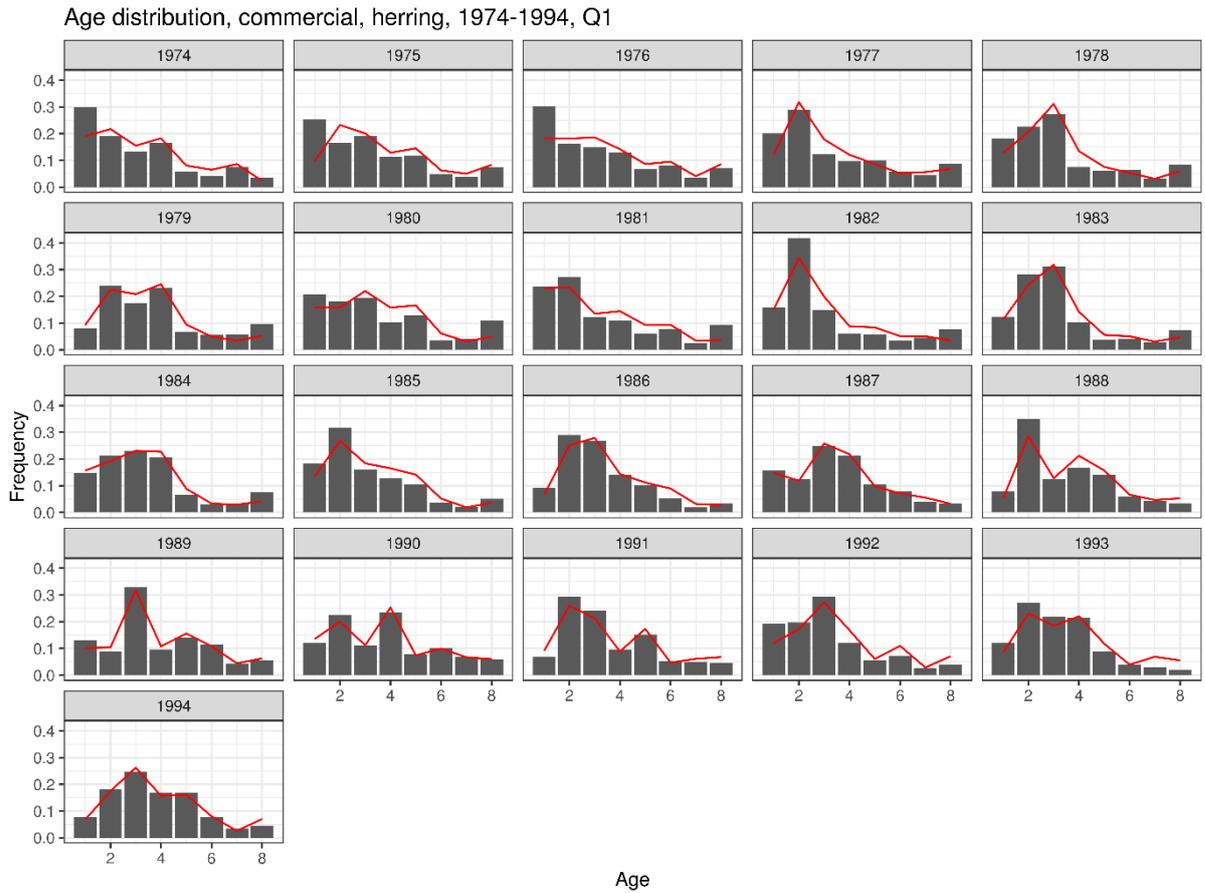


Figure 3-120. Comparison of observed (bars) and predicted (line) herring age distribution in commercial catches in 1974-1994.

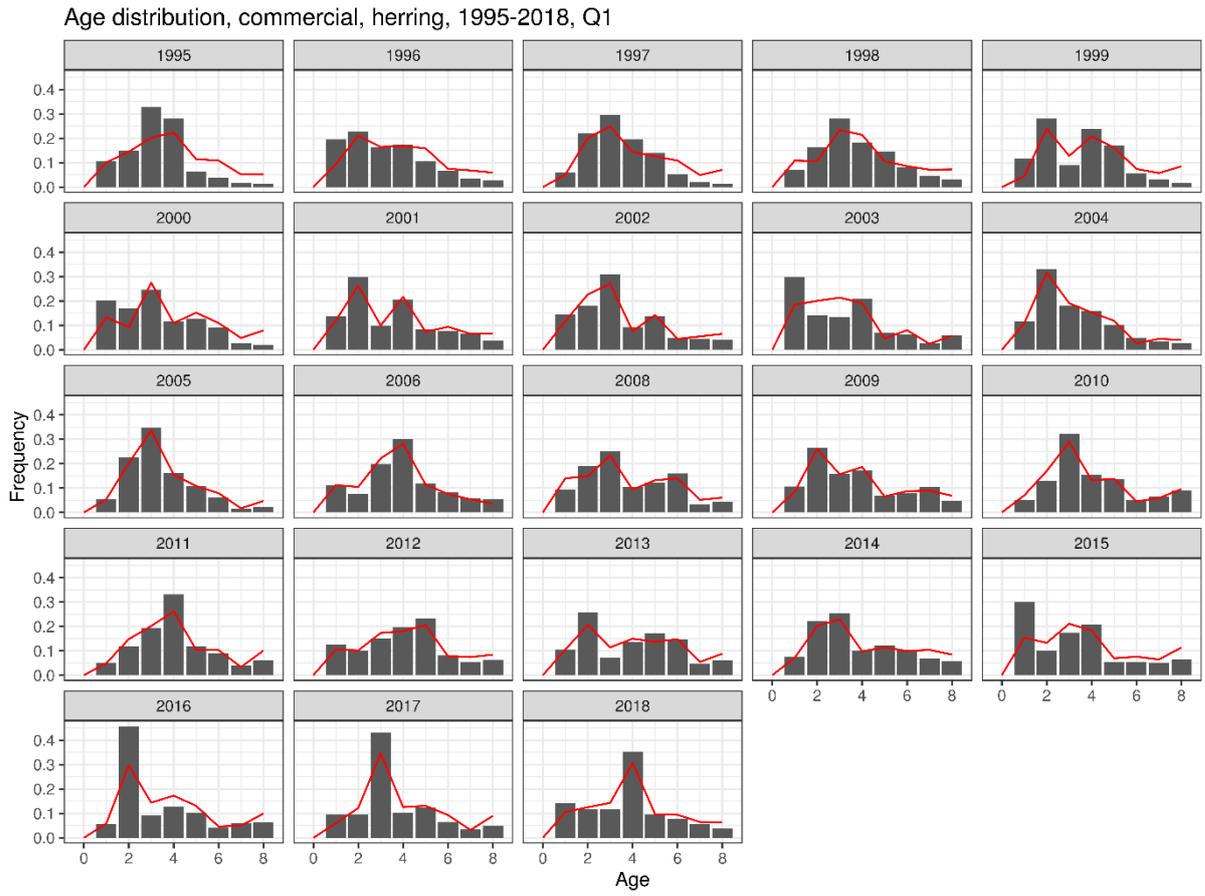


Figure 3-121. Comparison of observed (bars) and predicted (line) herring age distribution in commercial catches in 1995-2018.

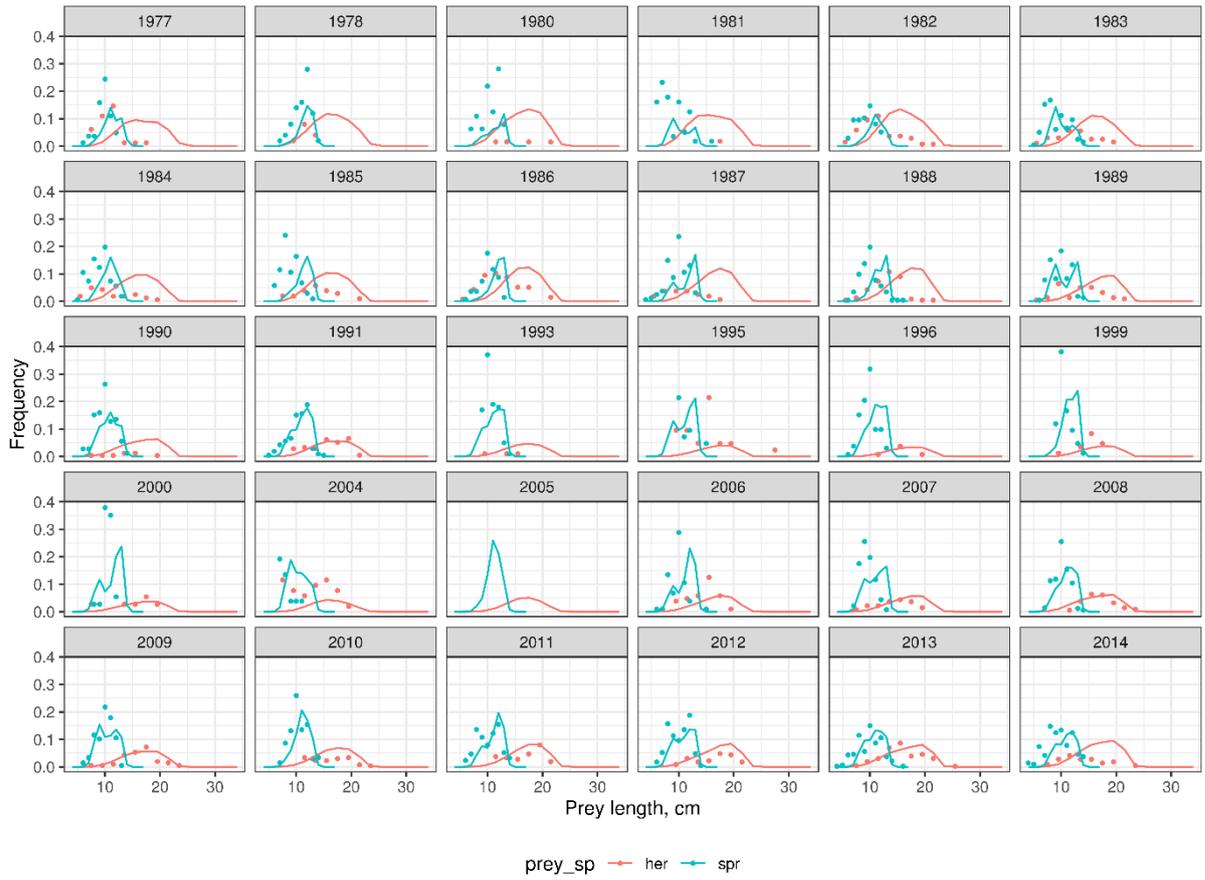


Figure 3-122. Comparison of observed (points) and predicted (line) herring (her) and sprat (spr) length distributions in the diet of 35-60 cm cod.

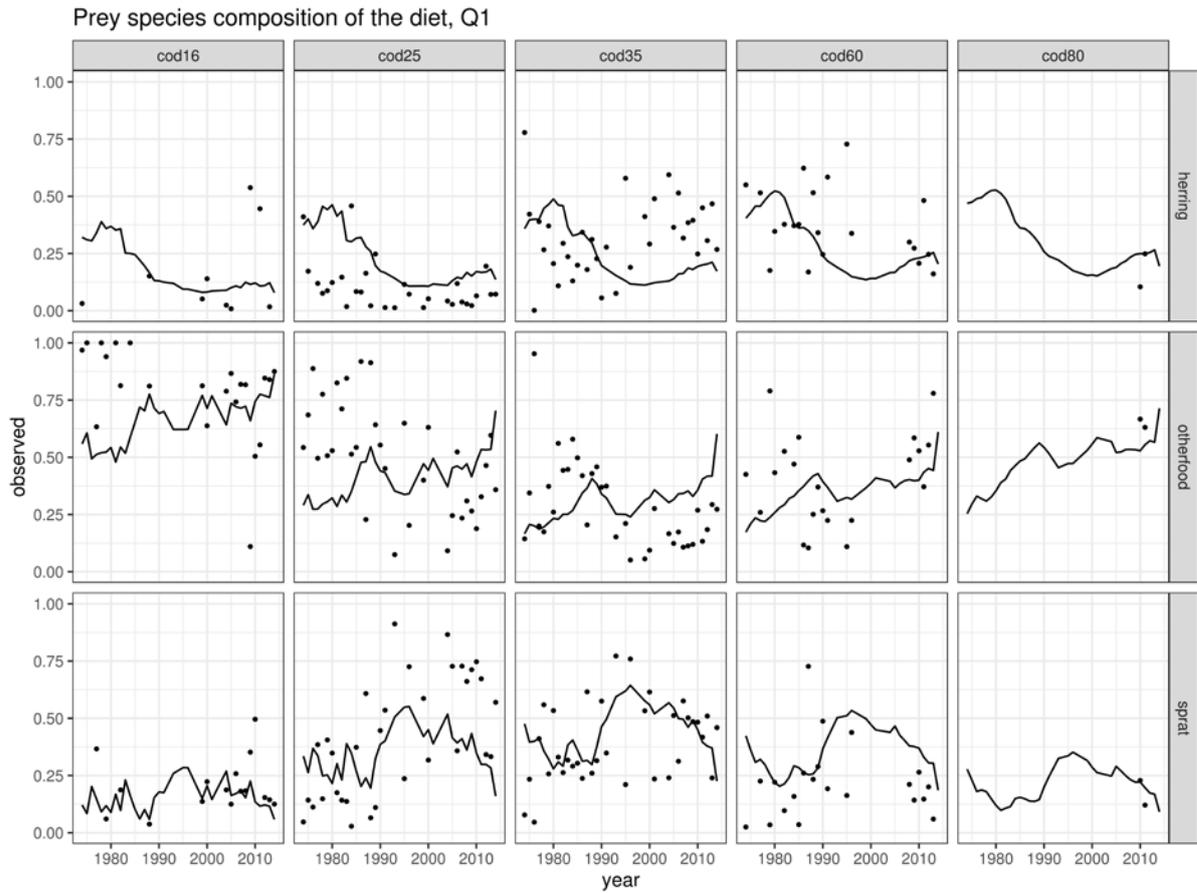


Figure 3-123. Comparison of observed (points) and predicted (line) proportions of different prey types (sprat, herring, otherfood) in the diet of different cod length groups (cod16..80; corresponding to 16-25cm; 25-35cm; 35-60cm, 60-80cm and >80cm, respectively) in Q1.

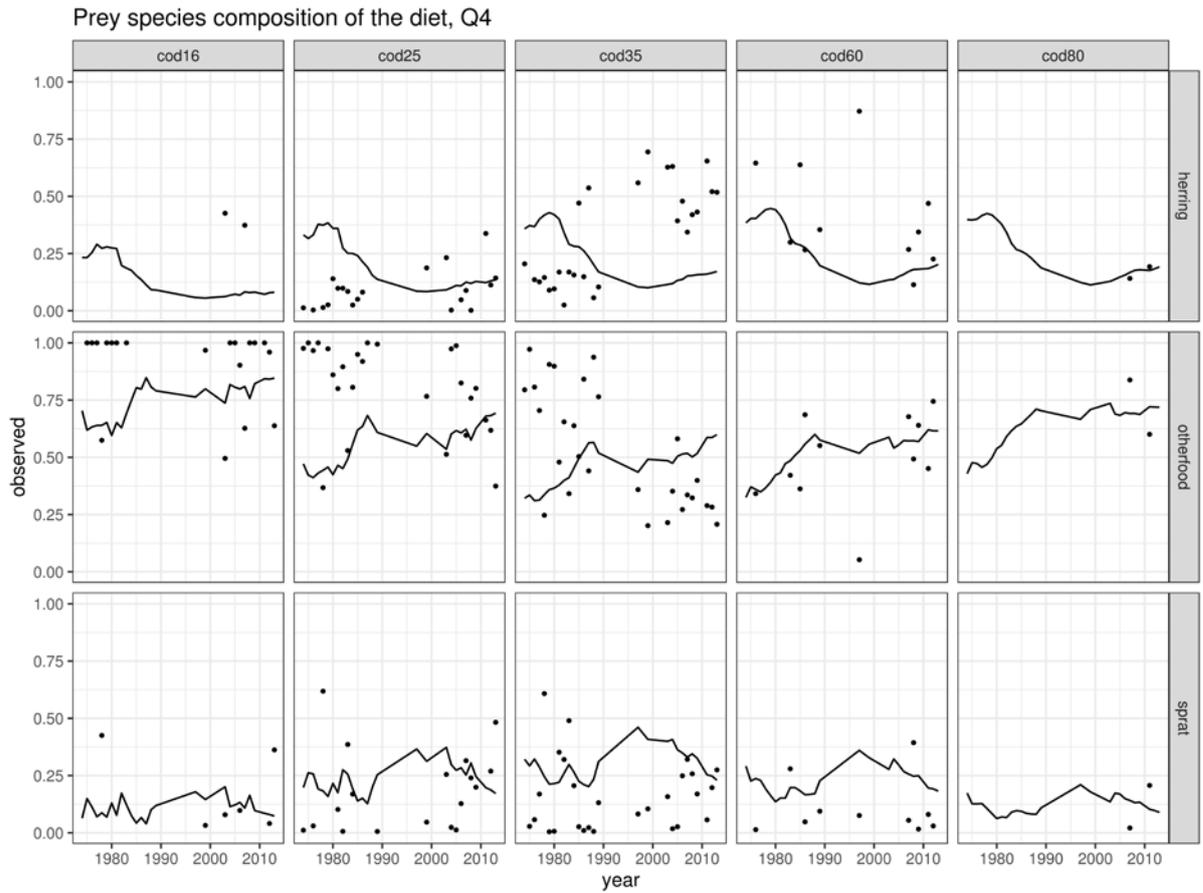


Figure 3-124. Comparison of observed (points) and predicted (line) proportions of different prey types (sprat, herring, otherfood) in the diet of different cod length groups (cod16..80; corresponding to 16-25cm; 25-35cm; 35-60cm, 60-80cm and >80cm, respectively) in Q4.

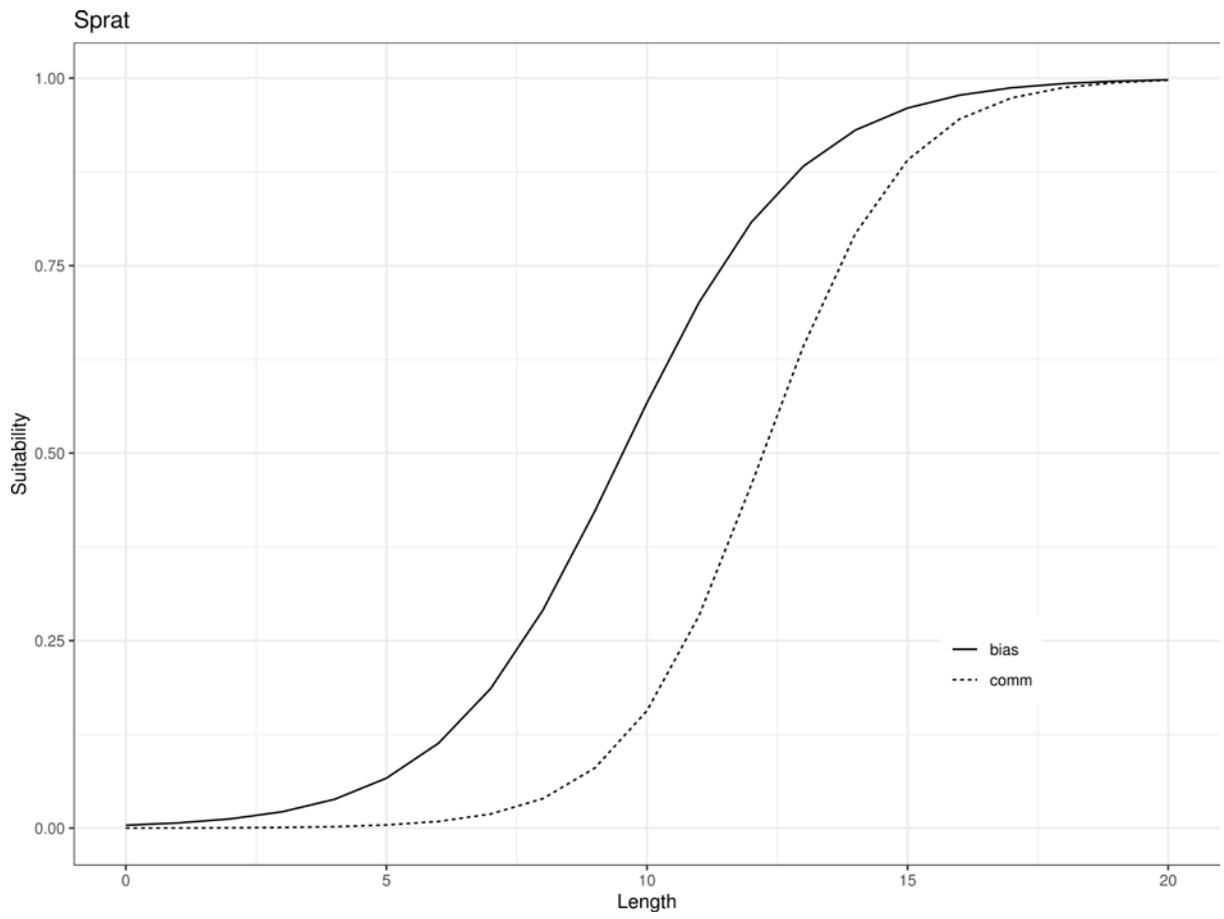


Figure 3-125. Estimated in the model fisheries (comm) and survey (bias) sprat suitabilities.

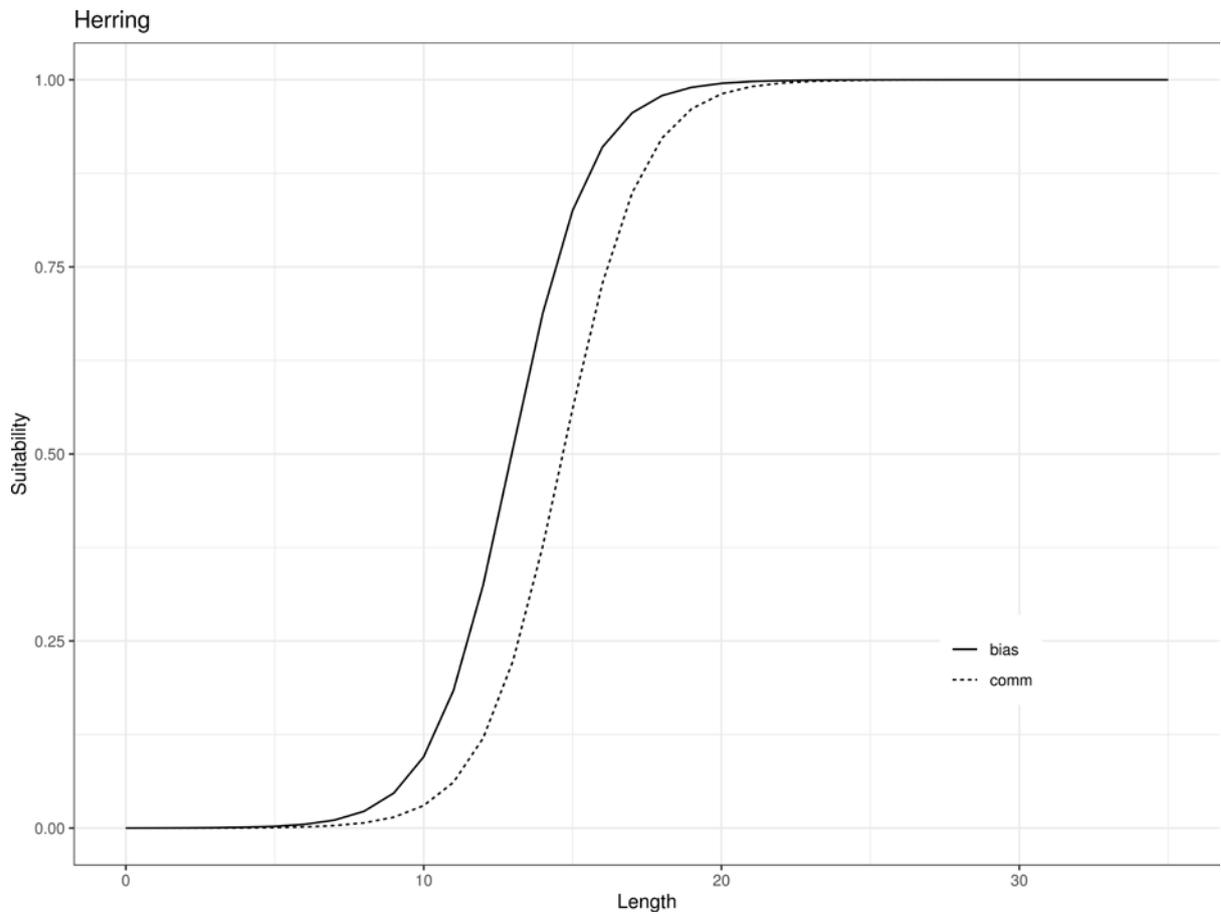


Figure 3-126. Estimated in the model fisheries (comm) and survey (bias) suitabilities of herring of different size.

Table 3-40. List of parameters estimated in the multi-species model (optimised = 1) with the lower and upper bound allowed for the search of optimal value keyrun_13.3

```

; Gadget version 2.2.00-BETA running on ubuntu-ryzen Mon Oct 28 14:27:48 2019
; Simulated Annealing algorithm ran for 10001 function evaluations
; and stopped when the likelihood value was 26931.052
; because the maximum number of function evaluations was reached
; Hooke & Jeeves algorithm ran for 40199 function evaluations
; and stopped when the likelihood value was 12884.901
; because the maximum number of function evaluations was reached
; BFGS algorithm ran for 10047 function evaluations
; and stopped when the likelihood value was 12238.318
; because the maximum number of function evaluations was reached
switch      value      lower upperoptimise
bbeta      0.1068525    0.001    50      0
p0cod2spr  0            0        10      0
p1cod2spr  1.4199118      0.1      10      1
p2cod2spr1 0.2775617      0.1      1        1
p2cod2spr2 0.509645        0.1      1        1
p3cod2spr  0.2412728      0.01     10      1
p0cod2oth1 0.25654624     0.1      1        1
p0cod2oth2 0.99999784     0.1      1        1
p0cod2her  0            0        10      0
p1cod2her  1.1554048      0.1      10      1
p2cod2her1 0.15851777     0.1      1        1
p2cod2her2 0.34234981     0.1      1        1
p3cod2her  0.59096107     0.1      10      1
    
```

prefspr	1	0.1	10	0
prefoth	1	0.1	10	0
prefher	1	0.1	10	0
m0	3.035	1.5	100	0
m1	1	0	5	0
m2	0	0	5	0
m3	3.26	1.5	4	0
Hfeed	0	0	1e+11	0
ic01	18.712341	0.001	50	0
ic02	10.899138	0.001	50	0
ic03	3.921619	0.001	50	0
ic04	1.271698	0.001	50	0
ic05	4.4537106	0.001	50	0
ic06	3.1320996	0.001	50	0
ic07	21.724543	1e-05	50	0
ic08	1.0000918e-05	1e-05	50	0
ic09	1.0010731e-05	1e-05	50	0
ic10	1.0573306	1e-05	50	0
rec1974	27.459009	0.004	190	0
recl	9.05	5	40	0
recsdev	4.12	0	15	0
rec1975	38.184311	0.004	190	0
rec1976	81.283141	0.004	190	0
rec1977	70.014765	0.004	190	0
rec1978	41.006341	0.004	190	0
rec1979	64.82302	0.004	190	0
rec1980	63.115716	0.004	190	0
rec1981	45.144698	0.004	190	0
rec1982	32.969925	0.004	190	0
rec1983	24.311937	0.004	190	0
rec1984	24.514408	0.004	190	0
rec1985	40.623187	0.004	190	0
rec1986	25.770672	0.004	190	0
rec1987	25.33217	0.004	190	0
rec1988	29.761108	0.004	190	0
rec1989	21.605008	0.004	190	0
rec1990	25.616701	0.004	190	0
rec1991	27.939775	0.004	190	0
rec1992	12.50054	0.004	190	0
rec1993	11.627743	0.004	190	0
rec1994	18.38638	0.004	190	0
rec1995	8.9543361	0.004	190	0
rec1996	21.087015	0.004	190	0
rec1997	20.148054	0.004	190	0
rec1998	19.700158	0.004	190	0
rec1999	19.912228	0.004	190	0
rec2000	31.324817	0.004	190	0
rec2001	14.100151	0.004	190	0
rec2002	14.325989	0.004	190	0
rec2003	37.834419	0.004	190	0
rec2004	22.546418	0.004	190	0
rec2005	19.525106	0.004	190	0
rec2006	32.402103	0.004	190	0
rec2007	25.512597	0.004	190	0
rec2008	17.64631	0.004	190	0
rec2009	21.070066	0.004	190	0
rec2010	20.883352	0.004	190	0
rec2011	40.56938	0.004	190	0
rec2012	36.821677	0.004	190	0
rec2013	25.19032	0.004	190	0
rec2014	20.738318	0.004	190	0
rec2015	19.094169	0.004	190	0
rec2016	23.310713	0.004	190	0
rec2017	25.140115	0.004	190	0
rec2018	12.330563	0.004	190	0
spr.Linf	13.26	10	300	0
spr.k	66.8	0.1	1000	0
spr.lwa1	1.5074218	0.001	50	0
spr.lwa2	0.96635585	0.001	50	0

spr.lwa3	0.91595079	0.001	50	0
spr.lwb	2.72	2.2	3.8	0
spr.bbета	0.5700208	0.001	50	0
spr.ba01	7.1497848	0.001	50	1
spr.ba02	12.191592	0.001	50	1
spr.ba03	5.0100675	0.001	50	1
spr.ba04	19.800664	0.001	50	1
spr.ba05	20.50243	0.001	50	1
spr.ba06	7.86421	0.001	50	1
spr.ba07	12.778166	1e-05	50	1
spr.ba08	0.63210629	1e-05	50	1
spr.rec1974	3.6666383	0.004	100	1
spr.recl	7.6864673	5	15	0
spr.recsdev	0.9	0.01	15	0
spr.rec1975	25.736363	0.004	100	1
spr.rec1976	9.8069608	0.004	100	1
spr.rec1977	3.7570506	0.004	100	1
spr.rec1978	10.917968	0.004	100	1
spr.rec1979	7.1307914	0.001	100	1
spr.rec1980	23.040592	0.001	100	1
spr.rec1981	6.074283	0.001	100	1
spr.rec1982	29.086268	0.004	100	1
spr.rec1983	11.028026	0.004	100	1
spr.rec1984	5.2360851	0.004	100	1
spr.rec1985	1.8532766	0.004	100	1
spr.rec1986	7.1019727	0.004	100	1
spr.rec1987	1.1680249	0.004	100	1
spr.rec1988	12.733176	0.004	100	1
spr.rec1989	11.239329	0.004	100	1
spr.rec1990	11.773623	0.004	100	1
spr.rec1991	19.682958	0.004	100	1
spr.rec1992	19.244693	0.004	100	1
spr.rec1993	10.700922	0.004	100	1
spr.rec1994	27.454072	0.004	100	1
spr.rec1995	19.686427	0.004	100	1
spr.rec1996	5.9629063	0.004	100	1
spr.rec1997	21.256471	0.004	100	1
spr.rec1998	3.4888177	0.004	100	1
spr.rec1999	15.901232	0.004	100	1
spr.rec2000	7.192682	0.004	100	1
spr.rec2001	9.6038164	0.004	100	1
spr.rec2002	15.436081	0.004	100	1
spr.rec2003	27.859497	0.004	100	1
spr.rec2004	4.71579	0.004	100	1
spr.rec2005	11.765678	0.004	100	1
spr.rec2006	14.365958	0.004	100	1
spr.rec2007	9.3259657	0.004	100	1
spr.rec2008	20.330038	0.004	100	1
spr.rec2009	5.6777829	0.004	100	1
spr.rec2010	6.9924951	0.004	100	1
spr.rec2011	8.7593251	0.004	100	1
spr.rec2012	7.3967562	0.004	100	1
spr.rec2013	6.518745	0.004	100	1
spr.rec2014	23.14025	0.004	100	1
spr.rec2015	7.174205	0.004	100	1
spr.rec2016	7.3324757	0.004	100	1
spr.rec2017	11.10958	0.004	100	1
spr.rec2018	9.4284145	0.004	100	1
her.Linf	21.4	10	300	0
her.k	30.5	0.1	1000	0
her.lwa1	0.9796859	0.001	50	0
her.lwa2	0.60130156	0.001	50	0
her.lwa3	0.5432413	0.001	50	0
her.lwb	2.99	2.2	3.8	0
her.bbета	4.5569492	0.001	50	0
her.ba01	2.9017406	0.001	50	1
her.ba02	2.0111912	0.001	50	1
her.ba03	11.56018	0.001	50	1
her.ba04	12.332708	0.001	50	1

her.ba05	5.1460206	0.001	50	1
her.ba06	4.0294414	0.001	50	1
her.ba07	5.2362262	1e-05	50	1
her.ba08	1.3716944	1e-05	50	1
her.rec1974	3.7890551	0.004	70	1
her.recl	10	4	20	0
her.recsdev	2.5	0.01	15	0
her.rec1975	6.8129058	0.004	70	1
her.rec1976	4.9609523	0.004	70	1
her.rec1977	5.8759398	0.004	70	1
her.rec1978	4.1918874	0.004	70	1
her.rec1979	6.6598019	0.001	70	1
her.rec1980	9.118778	0.001	70	1
her.rec1981	5.6292111	0.001	70	1
her.rec1982	3.4765122	0.004	70	1
her.rec1983	3.9428588	0.004	70	1
her.rec1984	2.9888339	0.004	70	1
her.rec1985	1.3543599	0.004	70	1
her.rec1986	3.1142181	0.004	70	1
her.rec1987	1.0521417	0.004	70	1
her.rec1988	1.8912475	0.004	70	1
her.rec1989	2.3726688	0.004	70	1
her.rec1990	1.6198884	0.004	70	1
her.rec1991	2.2349804	0.004	70	1
her.rec1992	1.6478306	0.004	70	1
her.rec1993	1.254236	0.004	70	1
her.rec1994	1.6752263	0.004	70	1
her.rec1995	1.4606234	0.004	70	1
her.rec1996	0.74140166	0.004	70	1
her.rec1997	1.5509628	0.004	70	1
her.rec1998	0.58531879	0.004	70	1
her.rec1999	1.6821634	0.004	70	1
her.rec2000	1.4796419	0.004	70	1
her.rec2001	1.4391585	0.004	70	1
her.rec2002	2.4778729	0.004	70	1
her.rec2003	1.6563031	0.004	70	1
her.rec2004	0.91333384	0.004	70	1
her.rec2005	1.9510701	0.004	70	1
her.rec2006	1.3942888	0.004	70	1
her.rec2007	2.6312101	0.004	70	1
her.rec2008	1.7111855	0.004	70	1
her.rec2009	1.4099349	0.004	70	1
her.rec2010	0.91467497	0.004	70	1
her.rec2011	1.8834982	0.004	70	1
her.rec2012	1.9454211	0.004	70	1
her.rec2013	1.4018851	0.004	70	1
her.rec2014	3.3271762	0.004	70	1
her.rec2015	1.3792141	0.004	70	1
her.rec2016	1.4349987	0.004	70	1
her.rec2017	2.5968493	0.004	70	1
her.rec2018	1.7390223	0.004	70	1
alphacomm.a	0.35686682	0.001	10	0
L50comm.a	41.275656	2	100	0
alphacomm.p	0.3574748	0.001	10	0
L50comm.p	45.422039	2	100	0
alphabits1	0.28234399	0.001	10	0
L50bits1	28.989605	2	100	0
alphabits4	0.251169	0.001	10	0
L50bits4	30.610618	2	100	0
spr.L50comm	12.224903	2	30	1
spr.alphacomm	0.75669662	0.001	10	1
spr.L50bias	9.5347894	2	30	1
spr.alphabias	0.58213387	0.001	10	1
her.L50comm	14.676087	2	30	1
her.alphacomm	0.74317813	0.001	10	1
her.L50bias	12.959414	2	30	1
her.alphabias	0.76091148	0.001	10	1

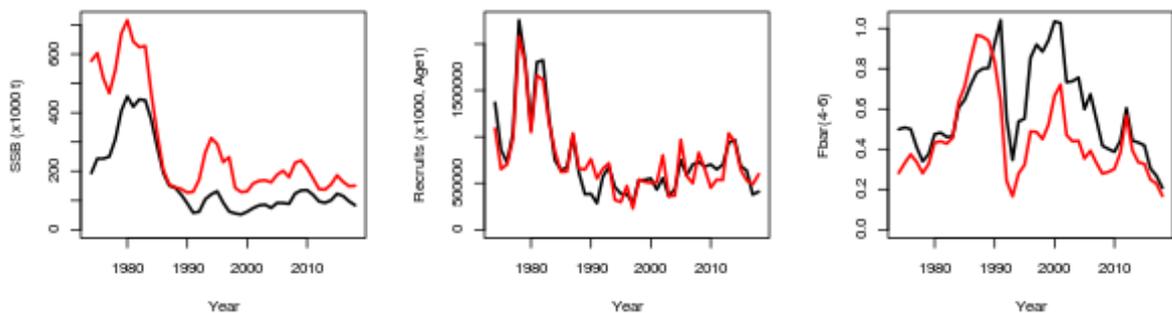
Stock dynamics

Patterns in the SSB of three stocks reconstructed in the model (red line on *Figure 3-19*) are rather similar to those from single-species stock assessments (black line on *Figure 3-19*). However SSB of cod is estimated to be almost double as high (except for 1995-1998, when the two are very close to each other) as in stock assessment (even though numbers at age are rather similar between the models and assumptions on parameters of weight-length relationship and maturity ogive are identical). Herring SSB is higher in the Gadget model in the beginning of time-series. This however has also been observed in the SMS keyrun. A possible explanation is that old version of SMS didn't account for cod size-selection of prey, but both new version and Gadget model do. High number of cod and especially with larger length at the beginning of time-series would have consumed more herring than estimated by previous version of SMS (used to inform natural mortalities in the stock assessment) meaning that the amount of herring to support higher demand of cod should have been higher. Sprat SSB is also higher in the Gadget than in the assessment prior to 1990, after which values get closer. This could be related to the fact that the model is age-length structured and thus heavily relies on both age and length information. The first length information on clupeids enters the model in 1991 with the beginning of survey and prior to that the model has difficulty in reconstructing dynamics of clupeids only based on age information from commercial catches.

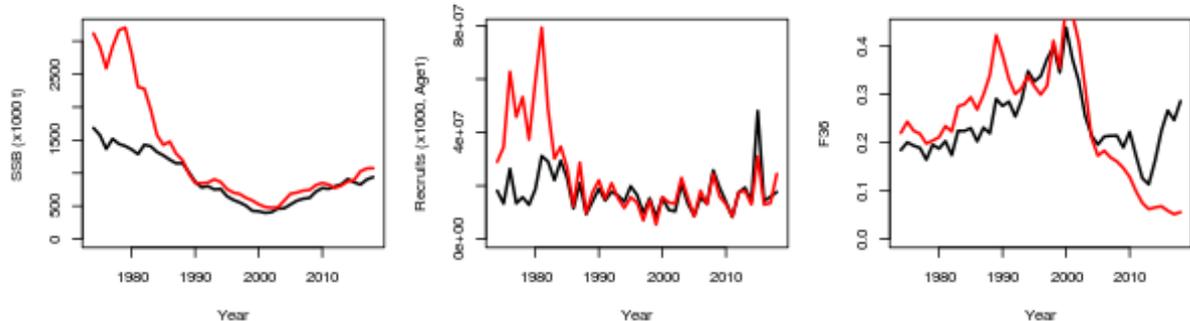
Recruitment of all three stocks was reconstructed quite close to the estimates of stock assessment (except for a higher estimates for herring in the beginning of the time-series).

F_{bar} of all three species have similar trends in Gadget and assessments, but with lower cod F in Gadget in 1992-2010, lower herring F in from 2004 and higher sprat F in 2005-2012.

Cod dynamics: model vs stock assessment



Herring dynamics: model vs stock assessment



Sprat dynamics: model vs stock assessment

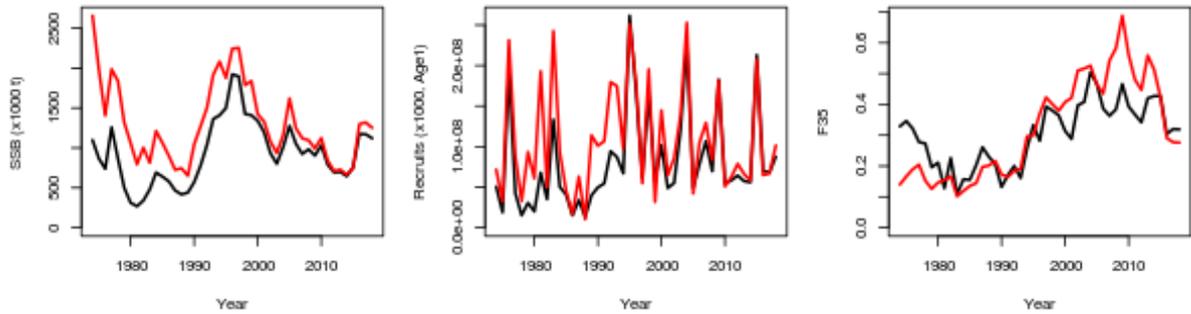


Figure 3-127. Comparison of stock dynamics (SSB, number of recruits, F_{30}) reconstructed in the multispecies model (red) and single species stock assessment (black)

Cod predation mortality of clupeids

Mortality caused by cod to sprat and herring (M2 on Figure 3-20 and Figure 3-21 respectively) was higher for all ages in 1974-1987, when cod abundance was higher. For both clupeids predation mortality is higher for young age (starting from age1) and gradually declines with age.



Figure 3-128. Natural mortality (consisting of background, M1 and predation, M2) of sprat by age estimated in the model.



Figure 3-129. Natural mortality (consisting of background, M1 and predation, M2) of herring by age estimated in the model.

Limitations and caveats

The present model has important limitations and caveats that need to be considered for a correct interpretation of its results.

1. Model instability remains an important issue of the Gadget model for the central Baltic with initial populations of herring and especially sprat (and consequently their SSB prior to 1990, *Figure 3-22*, more details in Supplementary material A1) as well as cod size selectivity toward prey being too variable despite the fact that the model has been seeded to guarantee reproducibility. The main possible reason is that the first information on sprat and herring lengths enters the model in 1991, and prior to that there is only age information from commercial catches. Restriction in the number of estimated parameters, phasing of the estimation (i.e., block of parameters are estimated in turn and some parameters are fixed to estimate from the single species run), adoption of better initial values, excluding seasonality in cod prey selection, adjustments to the global search algorithm (i.e., simulated annealing) by increasing the number of iterations, the initial temperature and the temperature reduction factor, have all been tried in attempts to improve consistency in the estimates. However, none of them was able to fully resolve the issue.

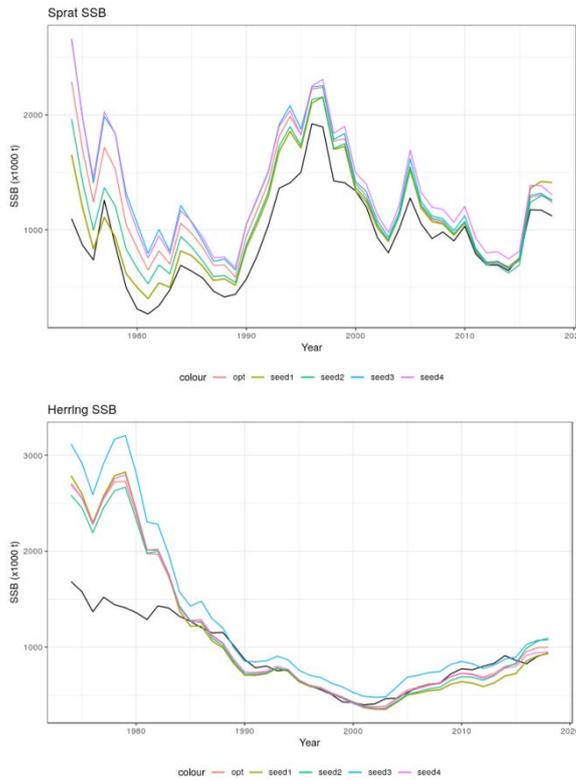


Figure 3-130. Differences in sprat (left) and herring (right) SSB estimated in different runs (different colour) of same model.

2. Estimation of uncertainty similarly to typical stock assessment models remains outside feasibility of the present model and in some respect it can be considered outside its scope. The model has considerable computation time, but the limiting factor here is the availability of a straightforward procedure for estimation of uncertainty (i.e., variance-covariance matrix is not used to calculate uncertainty in Gadget models). A bootstrap approach has been proposed (Elvarsson *et al.*, 2014) and presented on single species implementations of Gadget models, but the extensive use of aggregated catch data as provided by the assessment working group (WGBFAS) would make the approach unfeasible at the moment. Future opportunities may exist in relation to the development of the Regional Database and Estimation System (ICES, 2018b).
3. High uncertainty in key biological processes, such as:
 - Alternative consumption models have been proposed for predatory gadoids. The selection of a certain gastric evacuation models has been shown to have considerable impacts on the estimated consumption of prey (Bogstad and Mehl, 1990). Although more generic models have been presented in recent years (i.e., Andersen and Beier 2005; Temming and Hermann 2009) and one of those has been selected for the model, a consumption model tailored on the eastern Baltic cod is still lacking
 - The functional response relating the level of consumption of cod and the density of its preys remains unclear. A type II response has been adopted in the present model, but it represents more an a priori assumption rather than a data driven choice. The consumption model available in Gadget is highly generic and flexible. Alternative implementations of how the feeding level affect the actual consumption would be possible with more work and additional data and would likely generate differences in the consumption levels especially if the feeding level is linked to the food availability.

Given that the main purpose of the present model is to provide estimates of predation mortality for herring and sprat in the hindcast period this is seen as a limited issue as the feeding level plugged in the model is derived from the stomach data (i.e., field observations).

- Variability in prey encounter probability as a result of changes in horizontal/vertical overlap between cod and clupeids has not been considered in the present model. The spatial distribution of cod and the two clupeids has considerably changed during the last two decades with the cod population contracted in the south-western part of its initial distribution and both sprat and herring shifting towards the north-eastern areas of the Baltic Sea (Eero *et al.*, 2012; Bartolino *et al.*, 2017).
- The quality of the benthic habitat in the central Baltic has been progressively deteriorated with the increasing occurrence and extension of hypoxia and anoxia. A decrease in the abundance of benthos, including important benthic preys of cod (mysids, saduria) has certainly occurred, but the extent and distribution of such decrease are poorly documented. This explains why these two benthic preys are considered together with other preys into the same otherfood category, and why this is set with a constant abundance throughout the entire time period covered by the model.
- The extensive cod stomach dataset used in the model is a unique source of information on cod predation over more than four decades. However, the temporal and spatial coverage of the sampling intensity are highly variable as also reflected in the amount of noise in the data. Certain periods and areas are better represented than others in the stomach dataset which might originate biases. However, the core of the distribution of the cod stock is mostly covered which point towards an overall validity of this important data source. Modelling approaches for future standardisation of the stomach data prior their inclusion in a multispecies model should be considered and might be expected to improve the fitting of the model to this data component
- all issues of the cod assessment underlay also this model which relies on numerous assumption, decisions and estimations of both growth and natural mortality made at the last cod benchmark (ICES, 2019b).
- Limitations in the data exist. For instance, the decreasing weight-at-age observed in the commercial catches of both herring and sprat is the only source of information used to estimate decreasing LW (lack of length information on clupeids prior the survey).

Natural mortality (M), which includes predation mortality, is one of the most elusive parameters to be estimated in fishery science, as it is confounded with fisheries mortality and recruitment variation (Quinn and Deriso, 1999). Stock assessment depends heavily on the prior knowledge or assumptions on natural mortality, as it is impossible to estimate fisheries mortality from commercial and survey data without assumption on M (Gislason *et al.*, 2010). The multispecies model presented here is able to estimate cod predation mortality on herring and sprat, and despite the limitations, the Gadget estimates are rather stable from the early 1990s and onwards. Moreover, good agreement in the estimated predation mortalities between the Gadget model and the SMS keyrun are considered an additional support for the SMS-based estimates provided by WGSAM to the single species stock assessments of clupeids.

Further developments

Model would certainly benefit from the use of additional length information on clupeids prior to 1990, as this may be the reason of instability in estimation of initial clupeid populations. Such information may exist from Swedish national survey data but it is currently unavailable.

In addition, the model might benefit from a burning period prior 1974 that could stabilise estimates of stock size in the mid-1970s.

Additional work on the optimisation procedure should also be pursued.

Multispecies model variants

Few alternative model configurations were checked as most resources were devoted to the attempt of solving instability and to check model sensitivity to parameter values.

Alternative clupeid fisheries selectivity configurations

Multispecies model became unstable when parameters for both fisheries selectivity and cod size selectivity of clupeids were estimated simultaneously. The tests performed suggested that this caused a trade-off between estimates of initial clupeid population and cod size selectivity toward them. To solve the issue we tried fixing parameters of fisheries selectivity to estimates of single-species herring and sprat models. Unfortunately, model instability remained (Figure 3-23,).

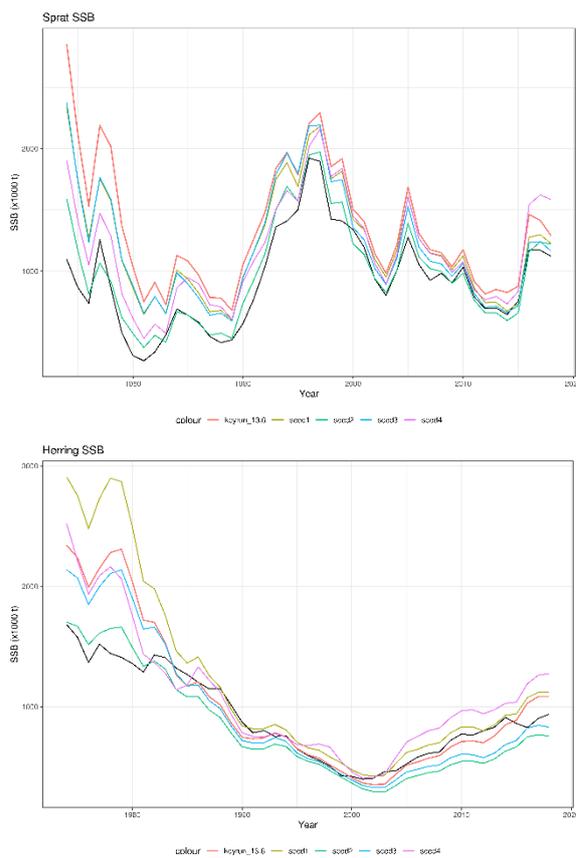


Figure 3-131. Differences in sprat (left) and herring (right) SSB estimated in different runs (different colour) of same model.

Fisheries selectivity parameters were rather consistent in the multispecies runs, thus we fixed fisheries selectivity parameters to estimates of one of these runs. Our expectations is that if the model would be stable all the other parameters should have been estimated very close in values, if not identical, to estimates of these runs. The model estimates were more consistent

under this setting (more details in Appendix) with only one run out of six providing a very different estimate of sprat SSB in the beginning of the time-series (red line on *Figure 3-24* (left) and one run providing a very different estimate of herring SSB (green line on *Figure 3-24* (right)). For a more exhaustive test more runs should be performed.

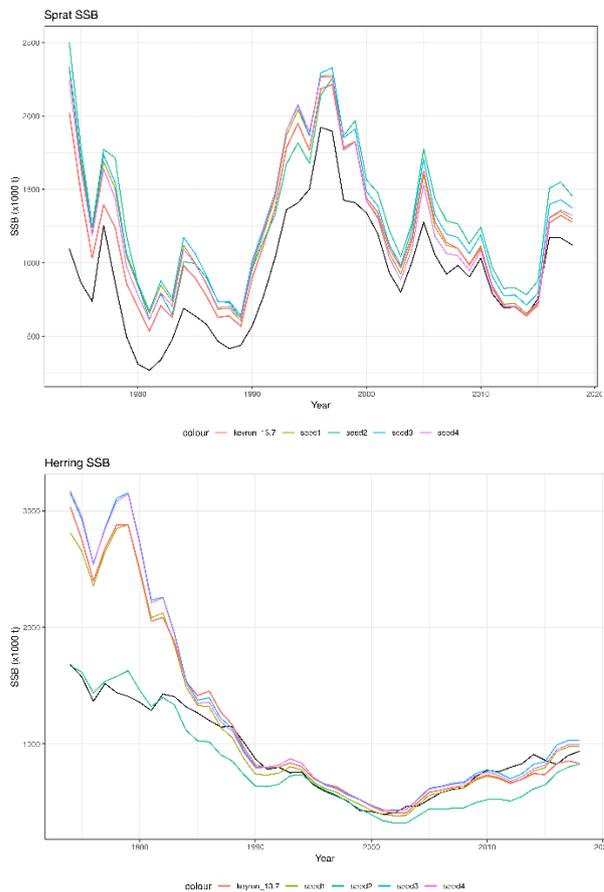


Figure 3-132. Differences in sprat (left) and herring (right) SSB estimated in different runs (different colour) of same model.

Sensitivity background mortality

We tried alternative values of background natural mortality (M_1) by increasing/decreasing initial values (0.1 for herring, 0.2 for sprat) by 30%. The effect of changes of M_1 was generally higher on sprat than on herring (*Figure 3-25*), but for herring the effect was a bit larger at the end of time-series. For this test we used more stable model configuration (*Figure 3-24*), however some degree of instability cannot be excluded.

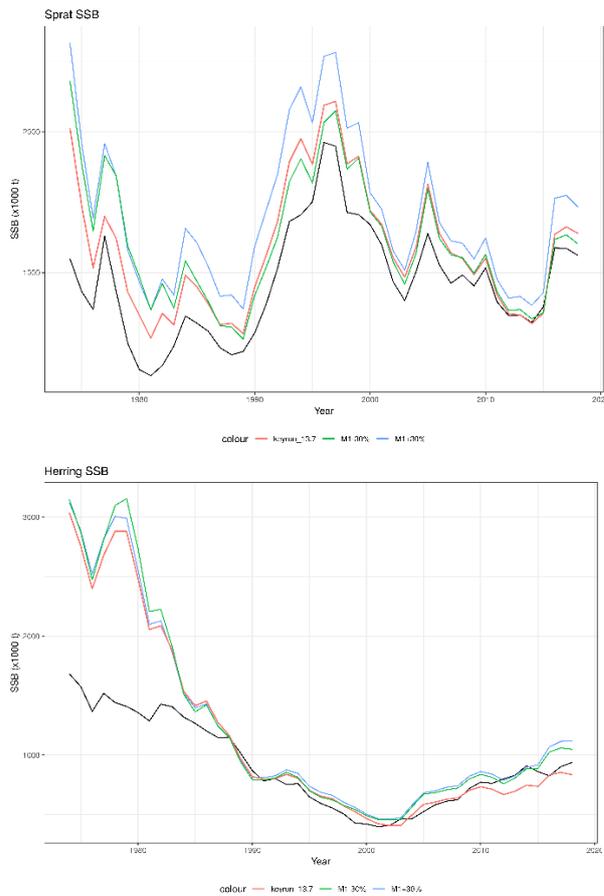


Figure 3-133. Differences in sprat (left) and herring (right) SSB estimated under different background mortality (different colour) setting.

Sensitivity on consumption

In the main model run, the 97% quantile of distribution of daily consumption was used as proxy for the maximum consumption (see section 3.1.1). As a sensitivity test we have tried using 95% and 99% quantiles instead. The effect of consumption alternatives seems to be very small (Figure 3-26). However, as in a previous section SSB from initial model (blue line) is sometimes lower than from the test models, which might be due to instability.

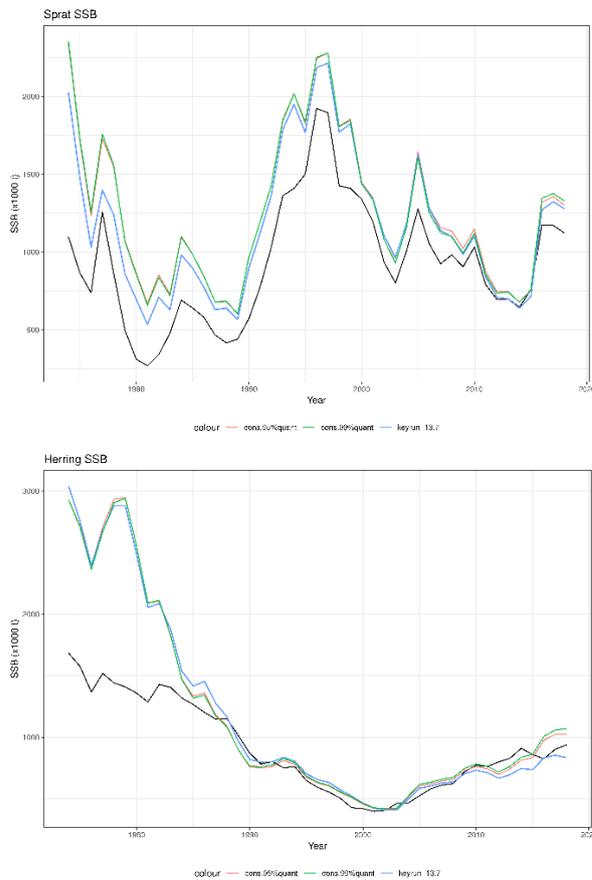


Figure 3-134. Differences in sprat (left) and herring (right) SSB estimated under different consumption (different colour) setting.

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Appendices

A1. Overfitting of recruitment indices

During the meeting, the group expressed concern about possible overfitting of the recruitment index of herring and cod. The issue was quickly fixed for herring, while it was found to be more challenging for cod. We applied several approaches, most of which solved also the overfitting of the cod recruitment index (Figure.A 1. 1), but this came with a price of lost match to numbers at age starting from 1995 (Figure.A 1. 2) in comparison with the results of the cod assessment (WGBFAS, 2019). In some years the numbers got close to record values (from the 80s), which clearly departed from the known dynamics of the cod stock. As a consequence those runs would overestimate the impact of cod on herring and sprat in some years. In contrast to herring, where all survey abundance indices are by age, in the cod model only the recruitment index is age based, while the other three indices represent the total stock abundance. Thus, the model required high flexibility and a relatively close fit of the age0 survey index to reconstruct the stock demography in agreement with the single species assessment.

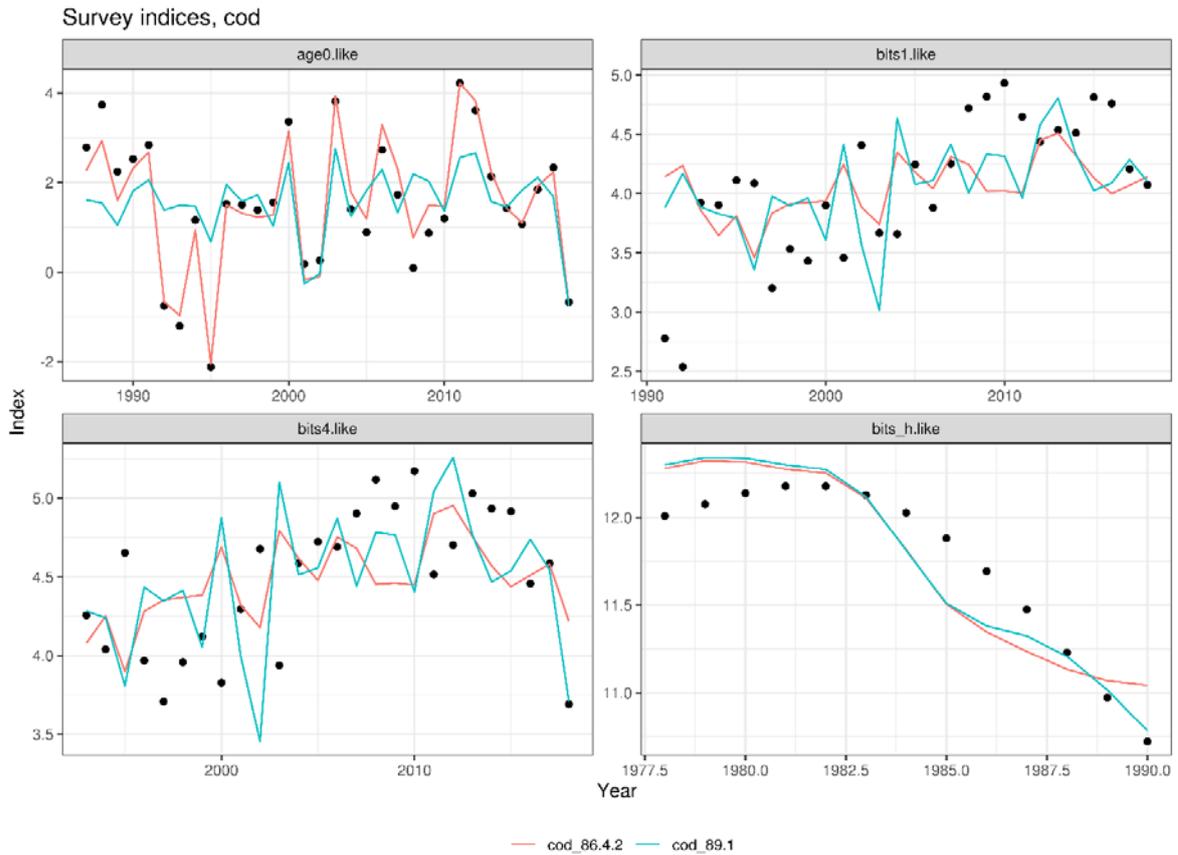


Figure.A 1. 1. Comparison between cod survey indices predicted in different model setting: “cod_86.4.2” is model presented during the meeting, “cod_89.1” is the best model with less overfitting of age0 index

Another issue noticed by the group was a “bump” in number in older age groups in the 1990s (line “cod_86.4.2” on Figure.A 1. 2). Models without overfitting of age0 index (line “cod_89.1” on Figure.A 1. 2) do not have that issue. We, however, see fewer issues with “bump” as it is present only in older cod, which are lower in numbers, and have less impact on herring and sprat compared to increased fluctuations in numbers at age in all age groups (line “cod_89.1” on Figure 2). Thus, the model cod_86.4.2 which was presented during the meeting is considered the best representation of the cod dynamics to be used in the multispecies implementation.

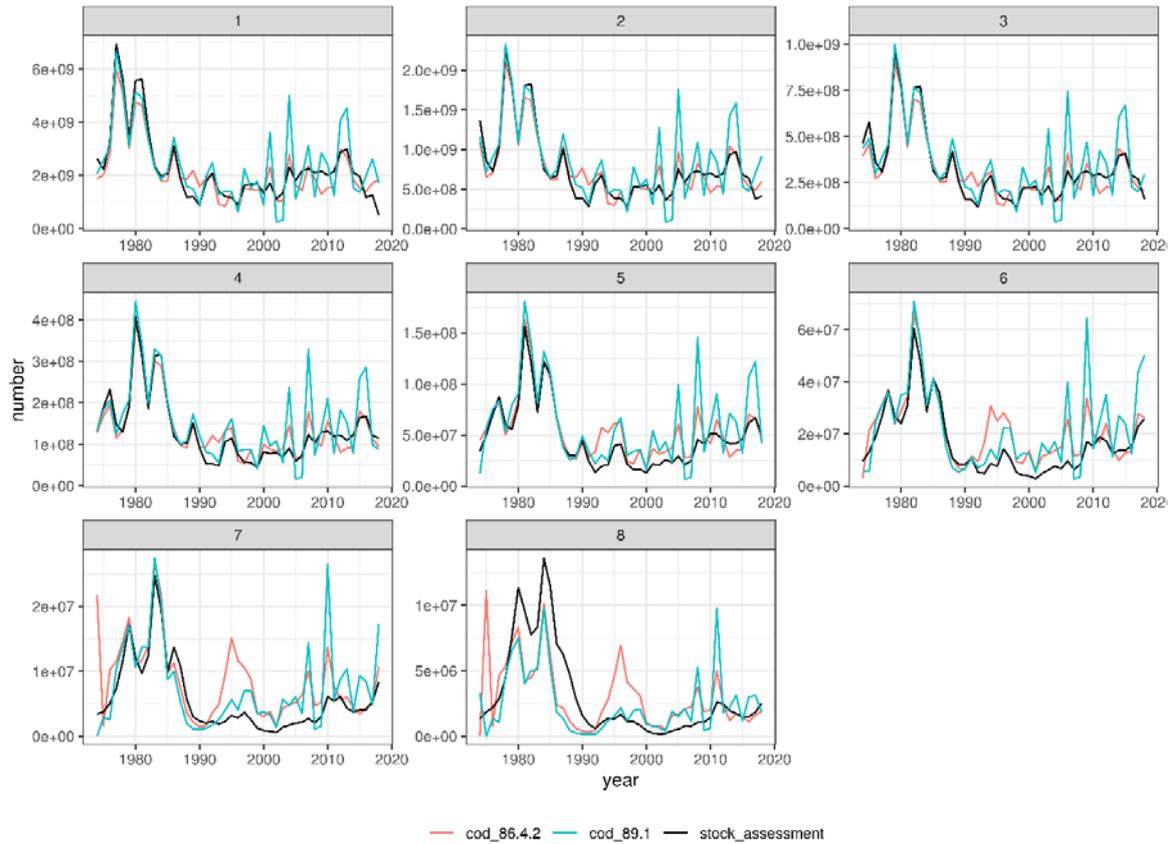


Figure.A 1. 2. Comparison between cod number at age predicted in different model setting and from cod stock assessment (black).

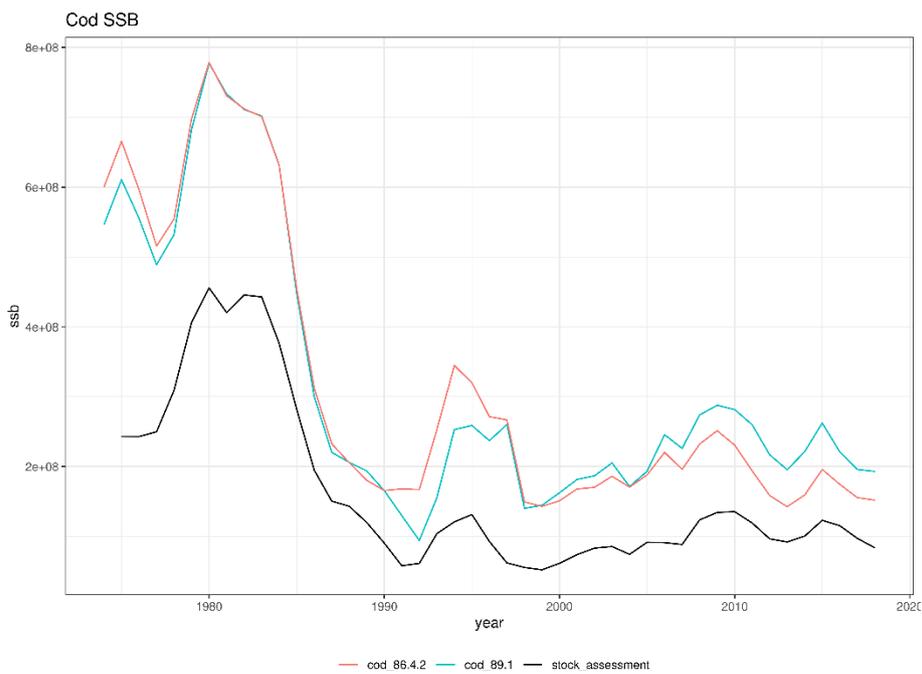


Figure.A 1. 3. Comparison between cod SSB estimated in different model setting and in cod stock assessment (black).

A2. Stability test

We tested model stability by running the same model using different seed values (“seed1...4” on FigureA2.1-A.2.9) and a more advanced optimisation setting (“opt”). Herring SSB was rather stable between the runs (with only “seed3” differing more from others; *Figure.A2.1*). Sprat SSB on the other hand is not stable at the beginning of time-series and gets more stable from 1990 (*Figure.A2.2*)

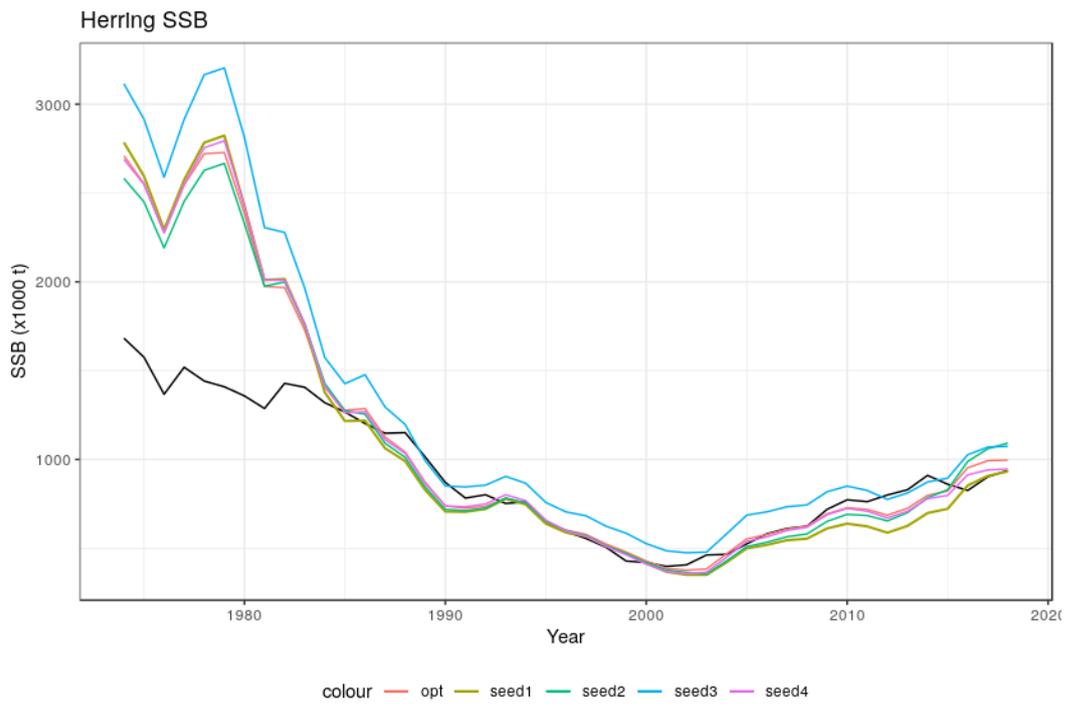


Figure.A2.1. Differences in herring SSB estimated in different runs (different colour) of same model.

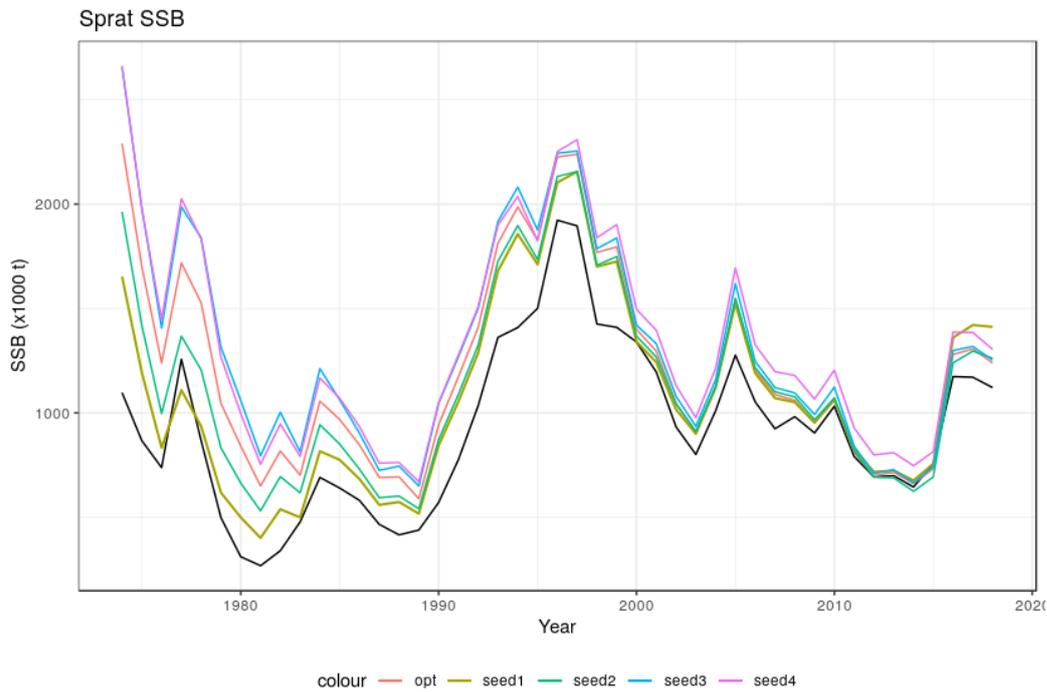


Figure.A2.2. Differences in sprat SSB estimated in different runs (different colour) of same model.

Predicted survey indices of both herring and sprat were rather similar between different runs (Figure.A2.3, Figure.A2.4) except for end of time-series for older herring (age 5+) and beginning of time-series for older sprat (age4+)

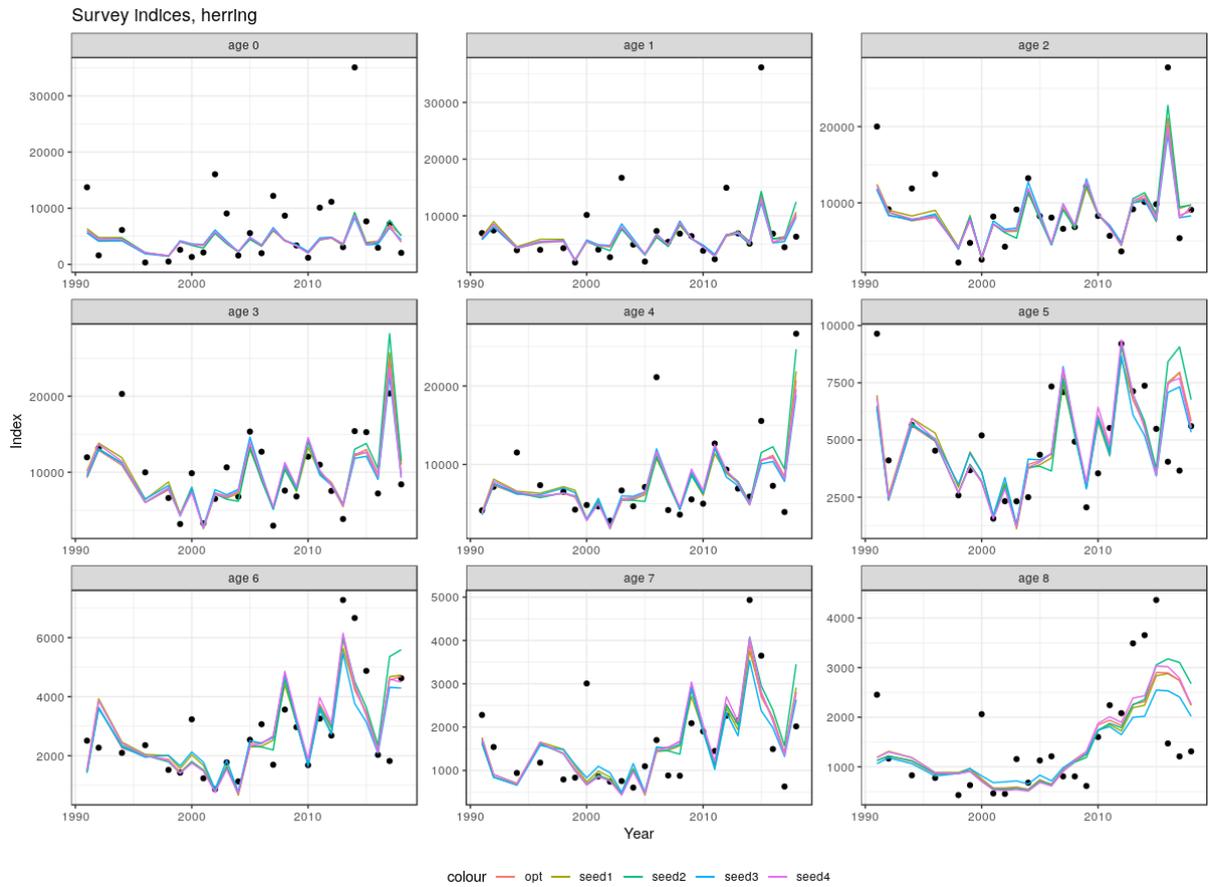


Figure.A2.3. Comparison of observed (points) and predicted (lines) herring survey abundance indices in different runs (different colour) of same model.

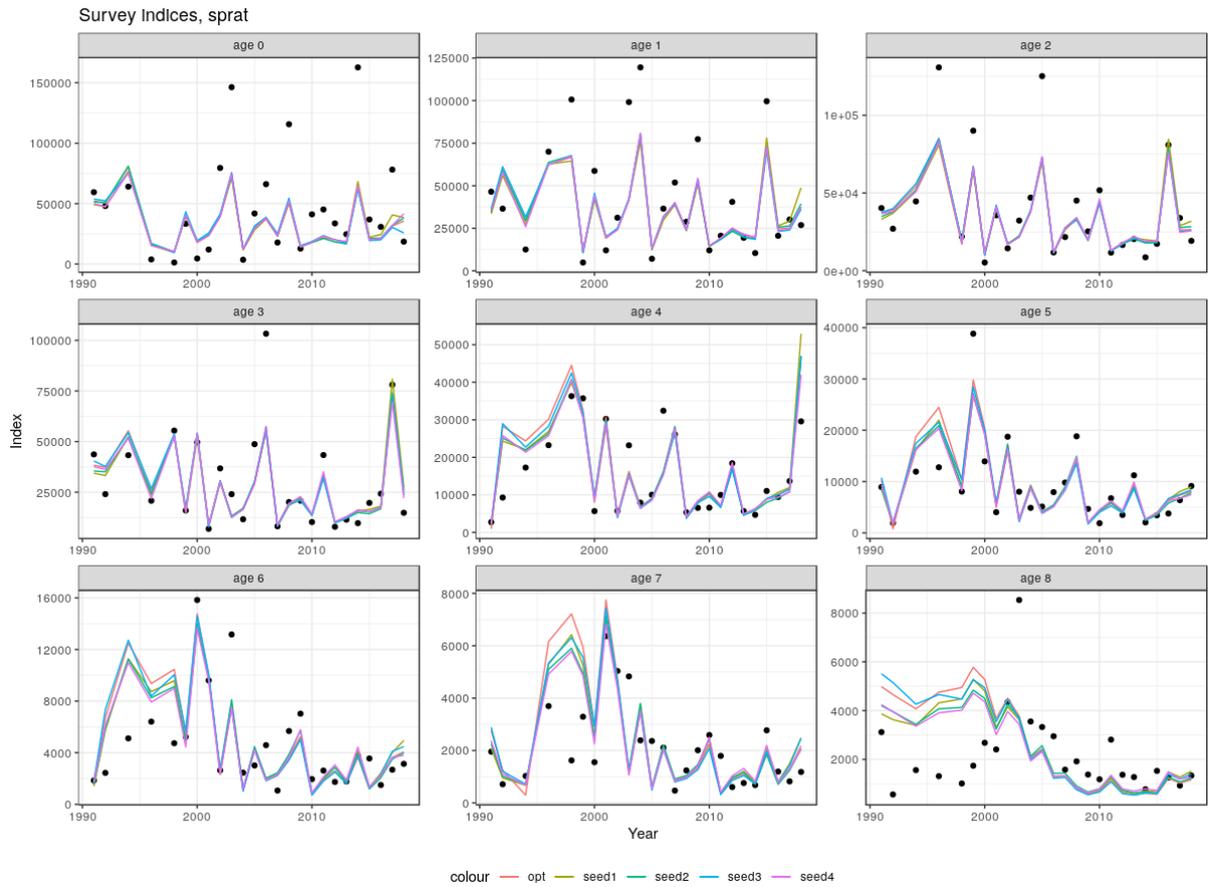


Figure.A2.4. Comparison of observed (points) and predicted (lines) sprat survey abundance indices in different runs (different colour) of same model.

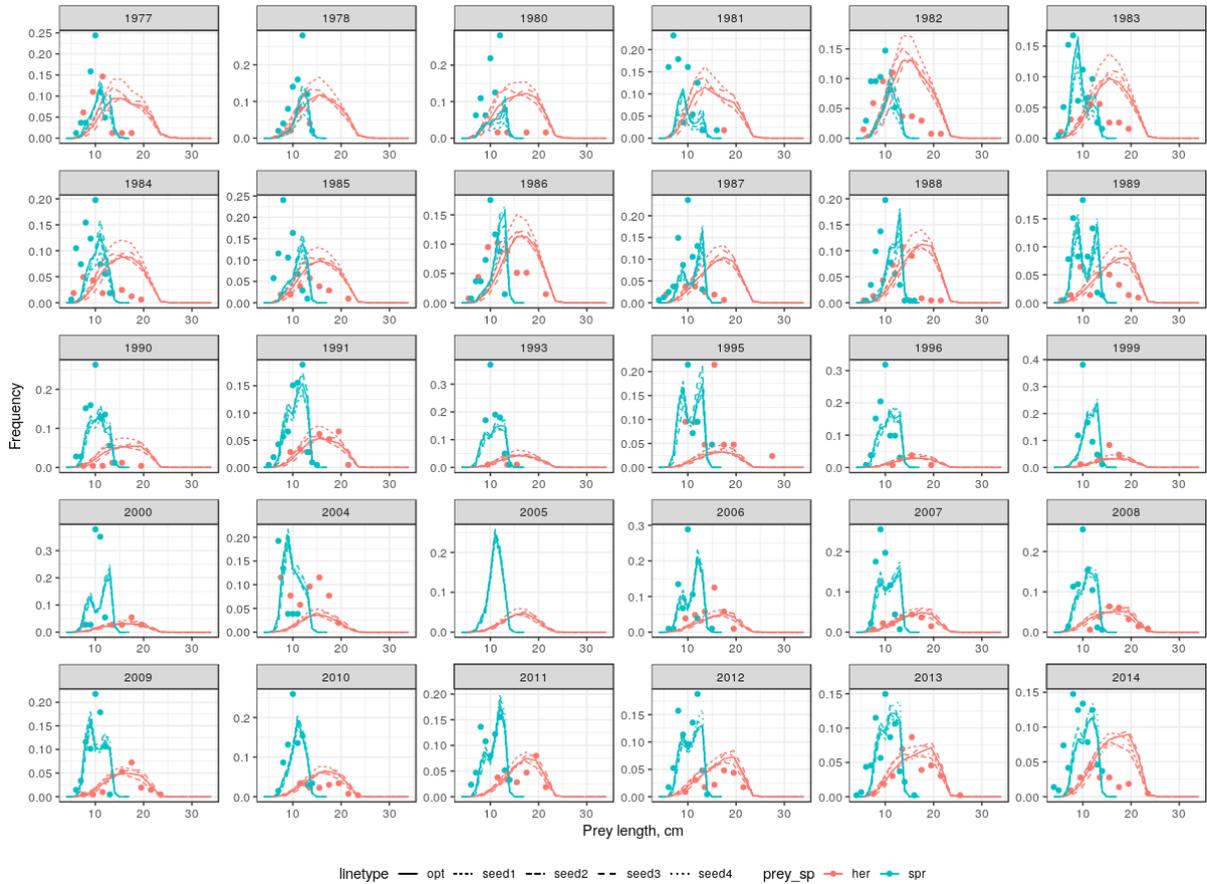


Figure.A2.5. Comparison of observed (points) and predicted (line) herring (her) and sprat (spr) length distributions in the diet of 35-60 cm cod in different runs (different linetype) of same model.

Predicted prey size distributions in 35-60 cm cod diet (Figure.A2.5) were rather similar between different model runs, but differed more for herring than for sprat.

Predation mortalities differed also more for herring than for sprat (Figure.A2.6, Figure.A2.7), but the differences were mainly at the beginning of time-series.

Both fisheries and survey suitabilities (Figure.A2.8, Figure.A2.9) estimated in the model runs for herring and sprat were rather consistent (except for the run labelled "seed1" survey ("BIAS") suitability; Figure.A2.9).

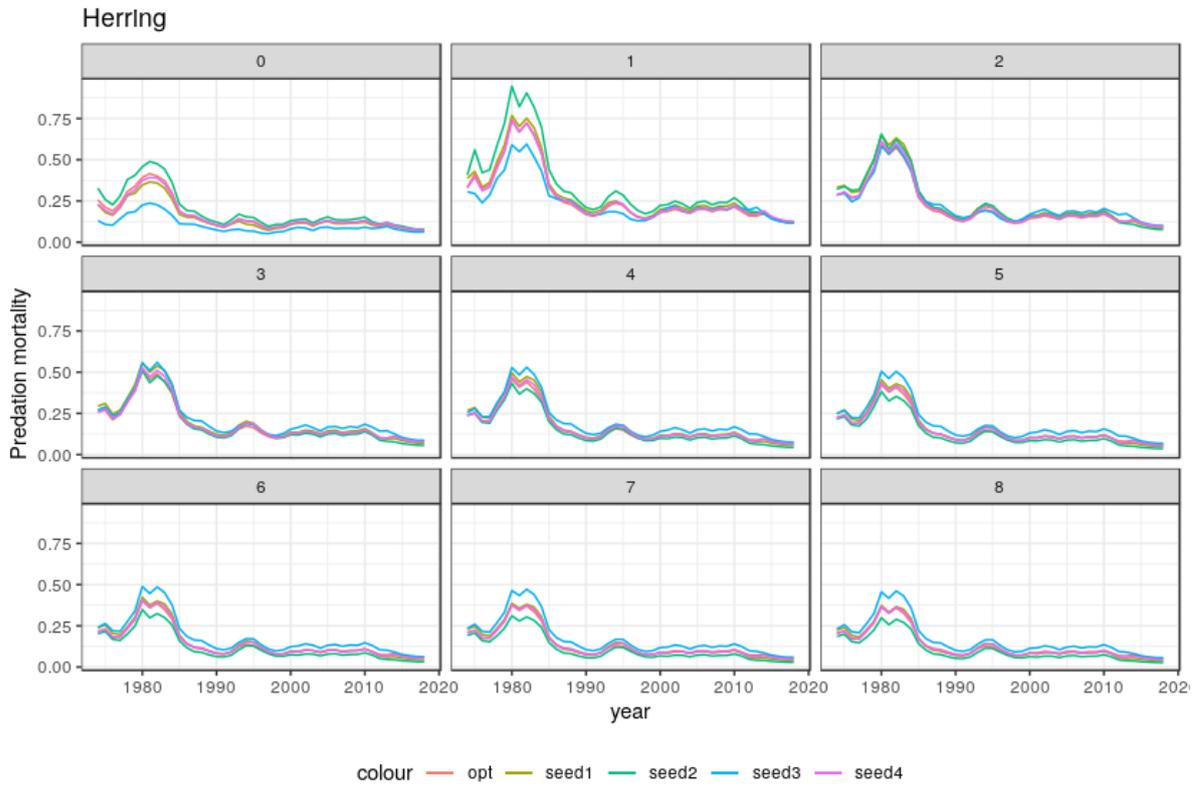


Figure.A2.6. Differences in predation mortality of herring by age estimated in different runs (different colour) of same model.

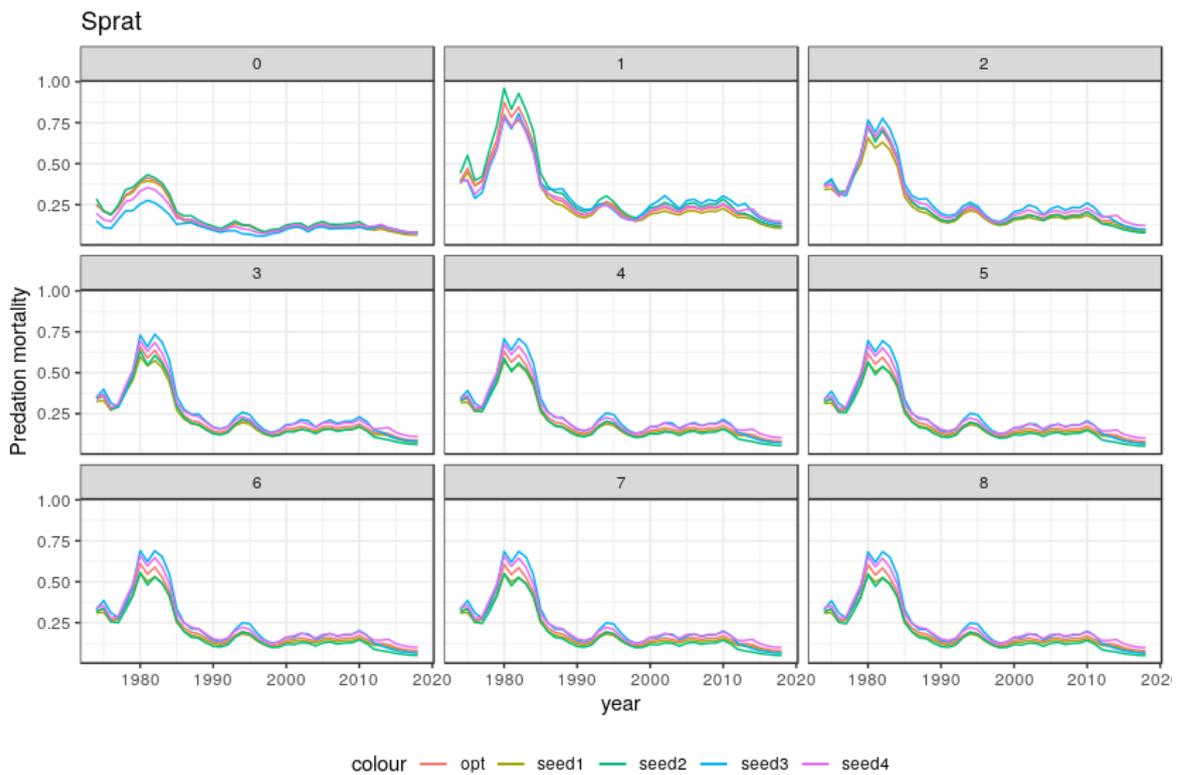


Figure.A2.7. Differences in predation mortality of sprat by age estimated in different runs (different colour) of same model.

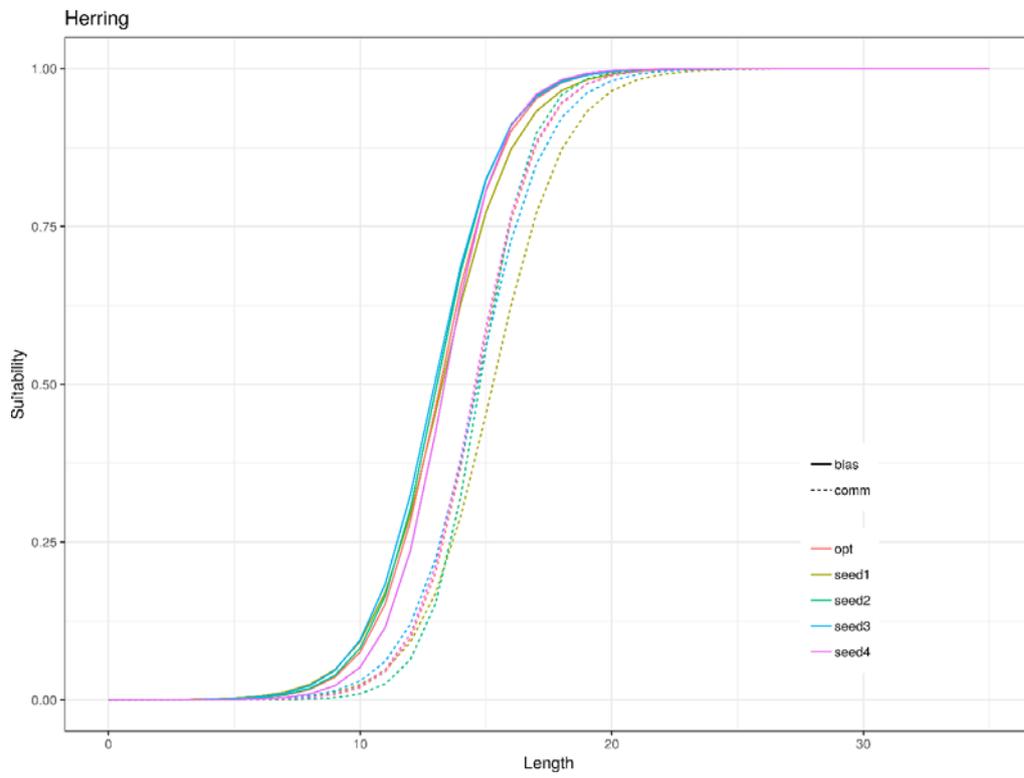


Figure.A2.8. Differences in the fisheries (comm) and survey (bias) suitabilities for herring estimated in different runs (different colour) of same model.

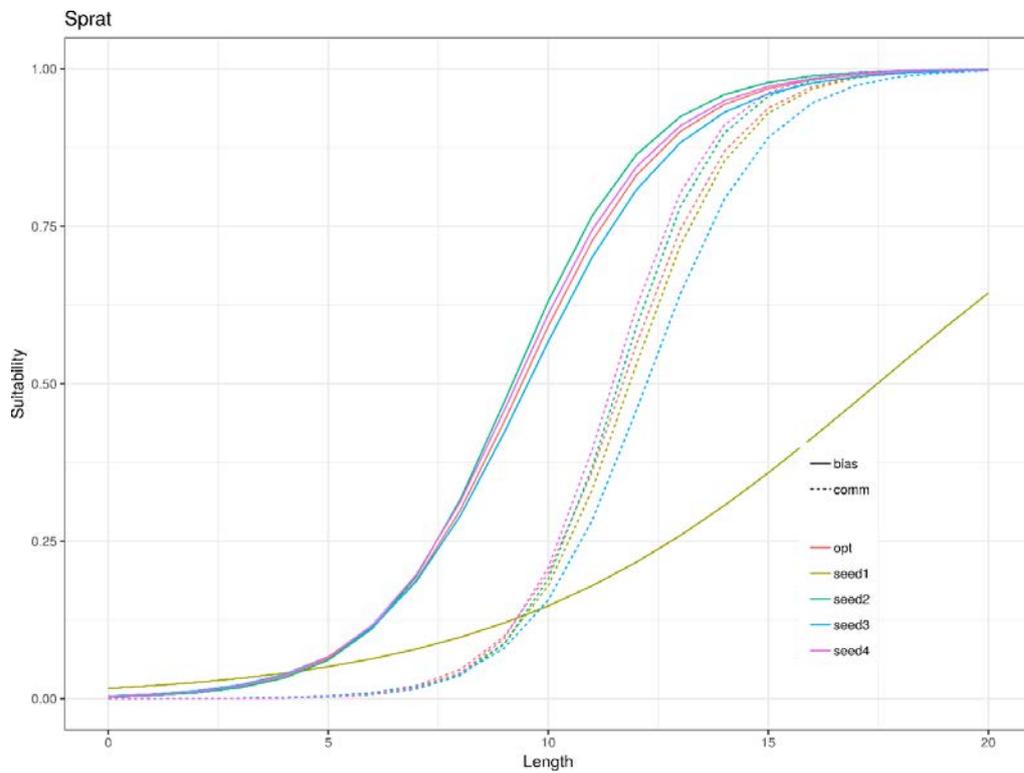


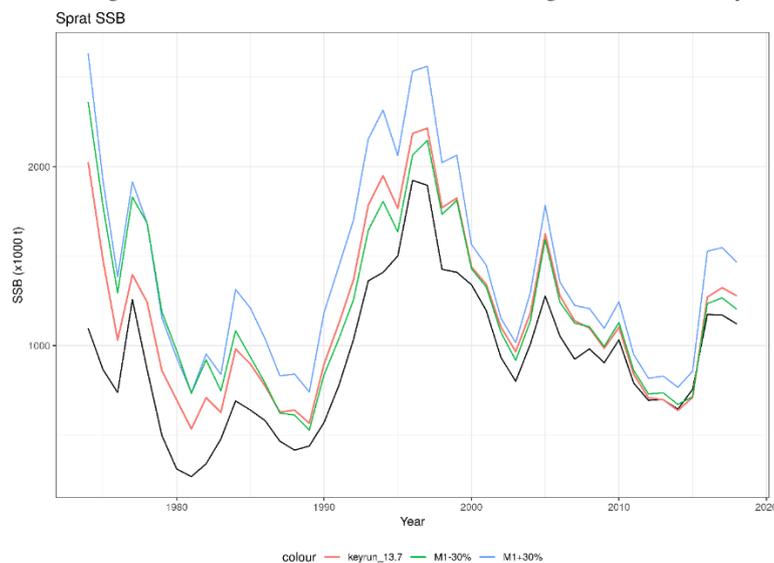
Figure.A2.9. Differences in the fisheries (comm) and survey (bias) suitabilities for sprat estimated in different runs (different colour) of same model.

A3. Sensitivity test: background mortality (M1)

We tested how sensitive the model is to background natural mortality (M1) of clupeids by changing it by 30%. These changes did not have much impact on the herring SSB (*Figure.A3.3*), except for 2000-2018, when the model with initial M1 (red line; *Figure.A3.3*) estimated lower SSB than the models with $\pm 30\%$ M1 (green and blue lines; *Figure.A3.3*). Different mortalities settings had higher impact on sprat SSB (*Figure.A3.4*) than on herring (*Figure.A3.3*). The model with initial M1 (red line; *Figure.A3.4*) estimated lower sprat SSB than the models with $\pm 30\%$ M1 (green and blue lines; *Figure.A3.4*) until 1985, after which it values got closer with the model where M1 was decreased by 30% (green line; *Figure.A3.4*).



Figure.A3.1. Differences in herring SSB estimated under different background mortality



(different colour) setting.

Figure.A3.2. Differences in sprat SSB estimated under different background mortality (different colour) setting.

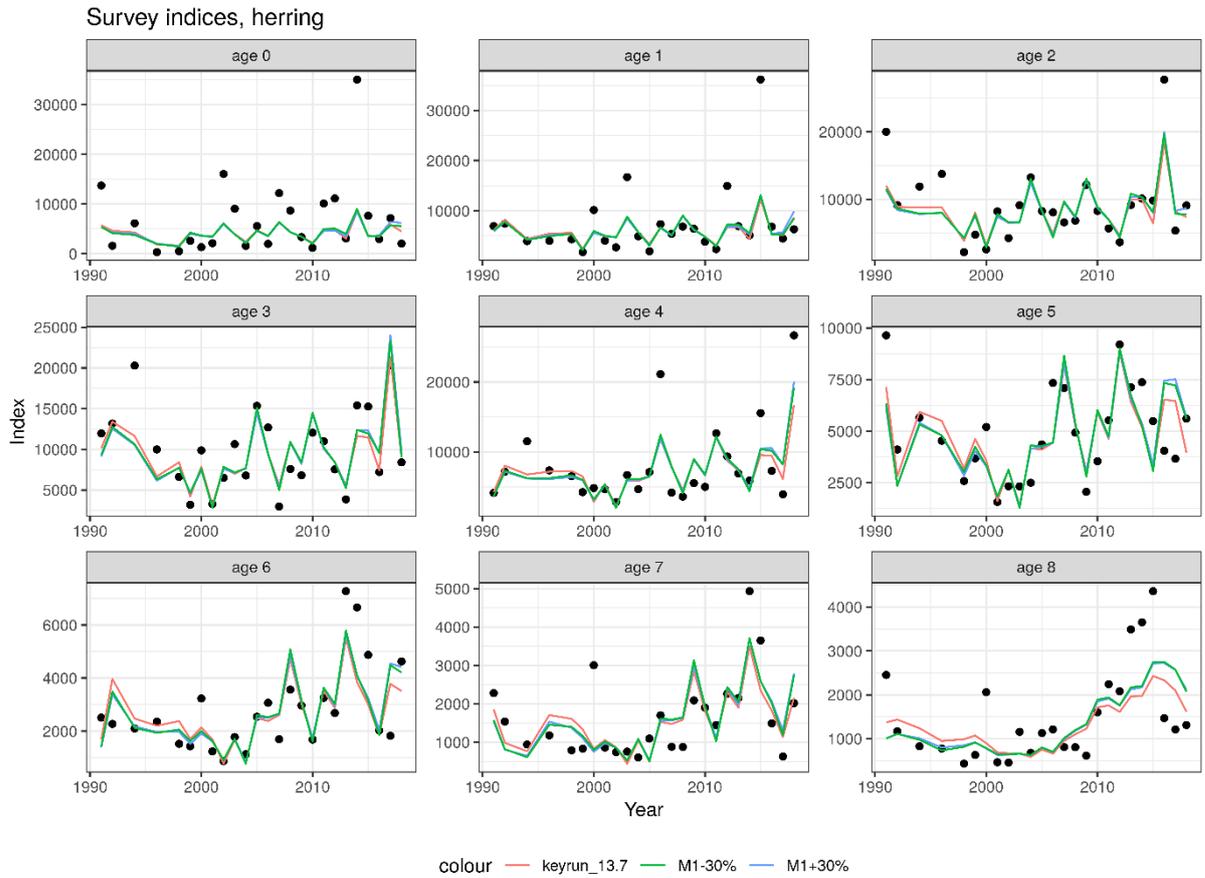


Figure.A3.3. Comparison of observed (points) and predicted (lines) herring survey abundance indices under different background mortality (different colour) setting.

Models with $\pm 30\%$ M1 predicted very similar indices of abundance for herring (blue and green lines on Figure.A3.5), a bit different from the model with initial M1 value in the beginning and end of time-series (red line on Figure.A3.5). Indices of abundance for sprat predicted by the models under different mortalities settings were very similar (Figure.A3.6) except for the beginning of time-series.

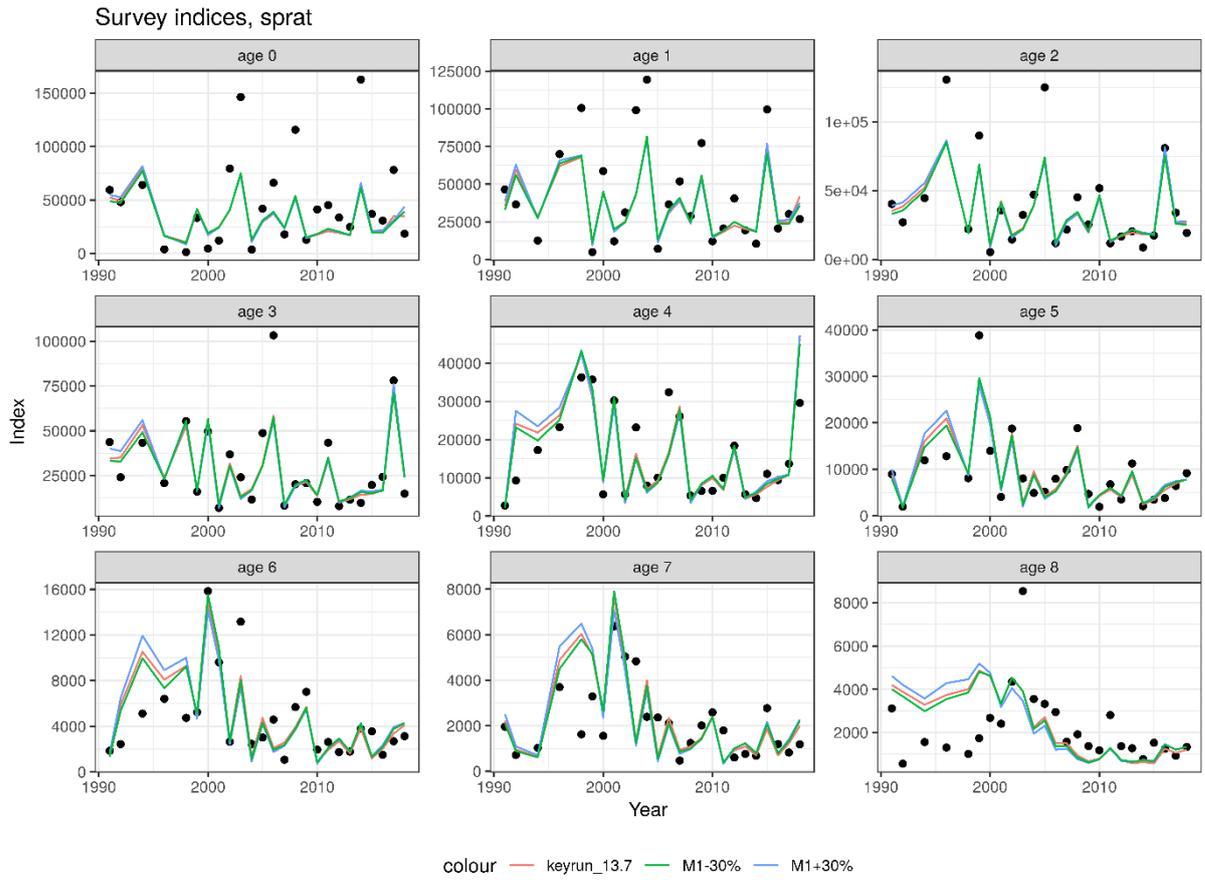


Figure.A3.4. Comparison of observed (points) and predicted (lines) sprat survey abundance indices under different background mortality (different colour) setting.

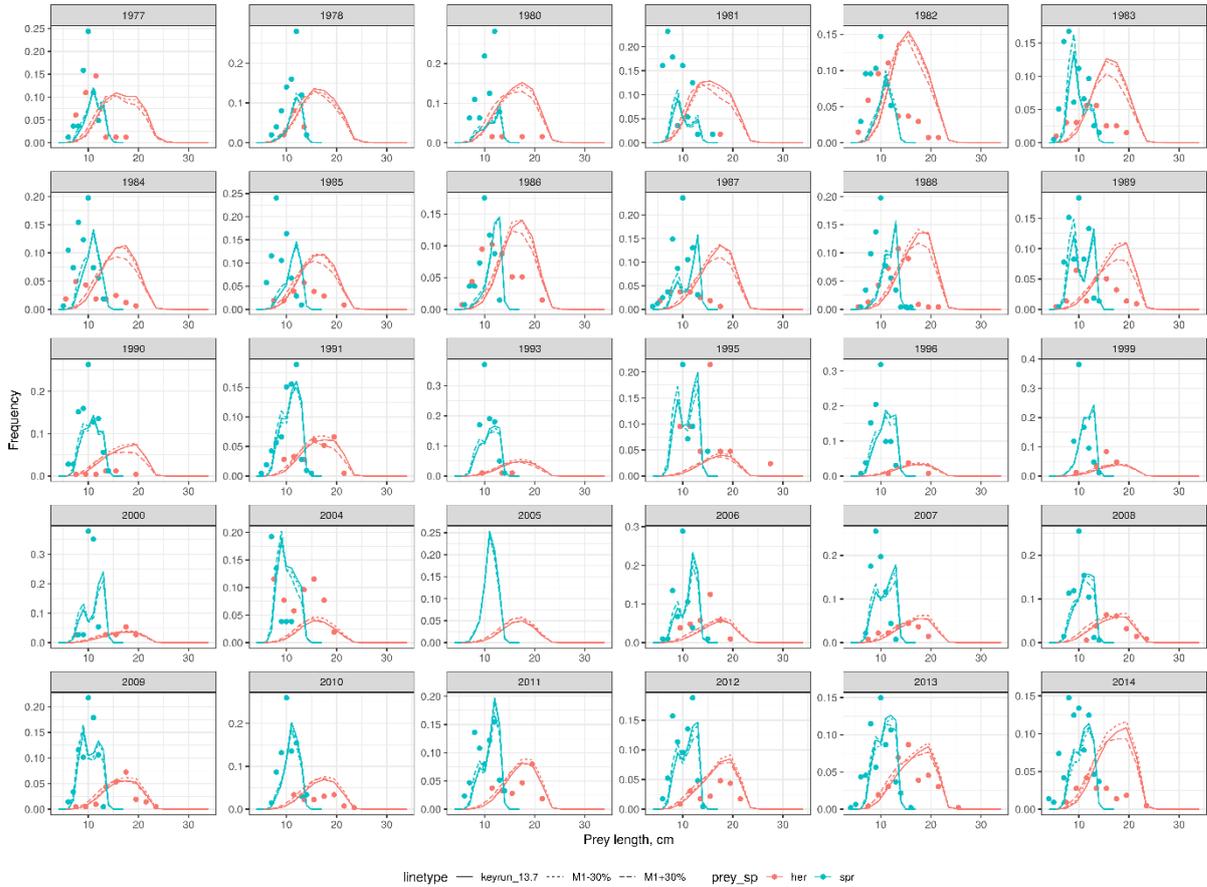


Figure.A3.5. Comparison of observed (points) and predicted (line) herring (her) and sprat (spr) length distributions in the diet of 35-60 cm cod under different background mortality (different linetype) setting.

Different background mortalities had little effect on prey size distribution (Figure.A3.7) and prey species composition (“cod35” on Figure.A3.8) in the diet of 35-60 cm cod in q1. The effect was larger for species composition of the diet of other cod groups in q1 (all groups besides “cod35” on Figure.A3.8) and all cod groups in q4 (Figure.A3.9).

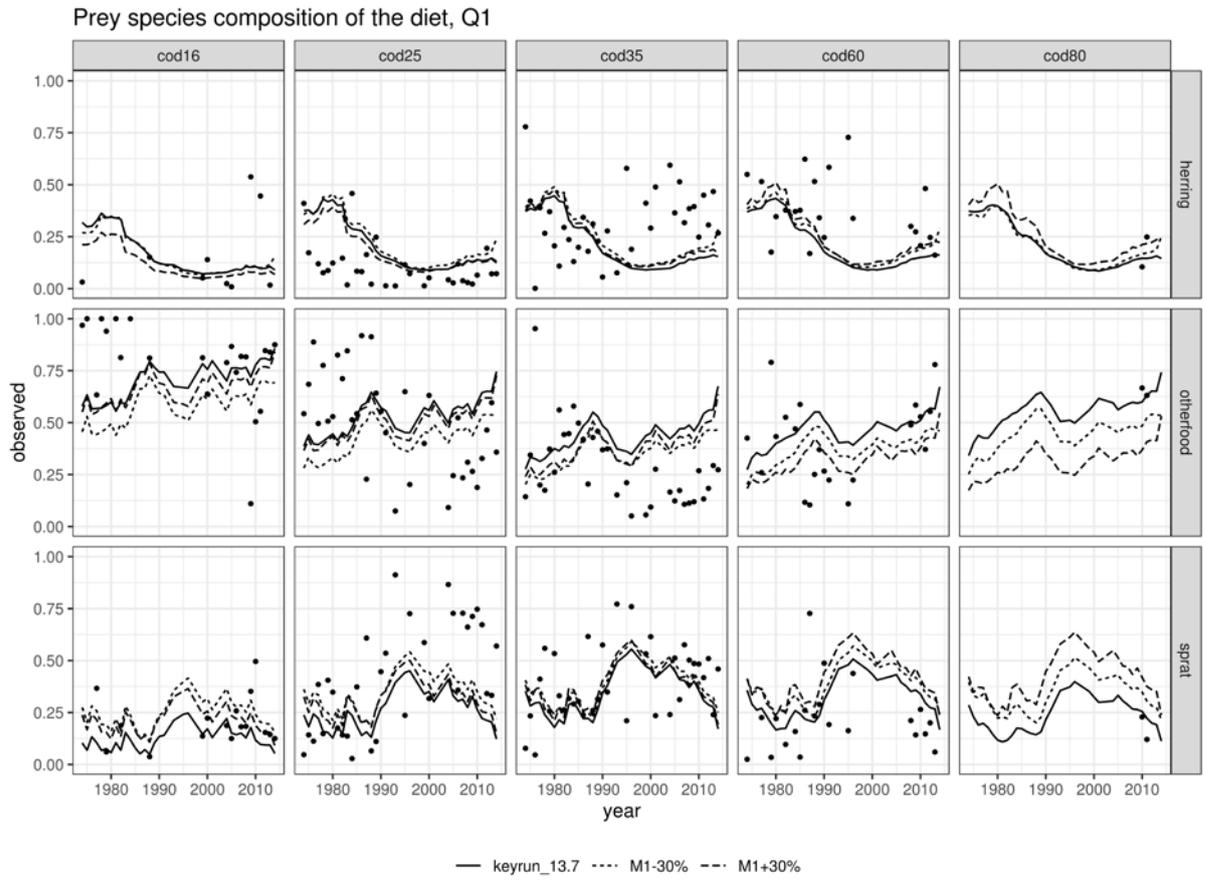


Figure.A3.6. Comparison of observed (points) and predicted (line) proportions of different prey types (sprat, herring, otherfood) in the diet of different cod length groups (cod16..80; corresponding to 16-25cm; 25-35cm; 35-60cm, 60-80cm and >80cm, respectively) in Q1 under different background mortality (different linetype) setting.

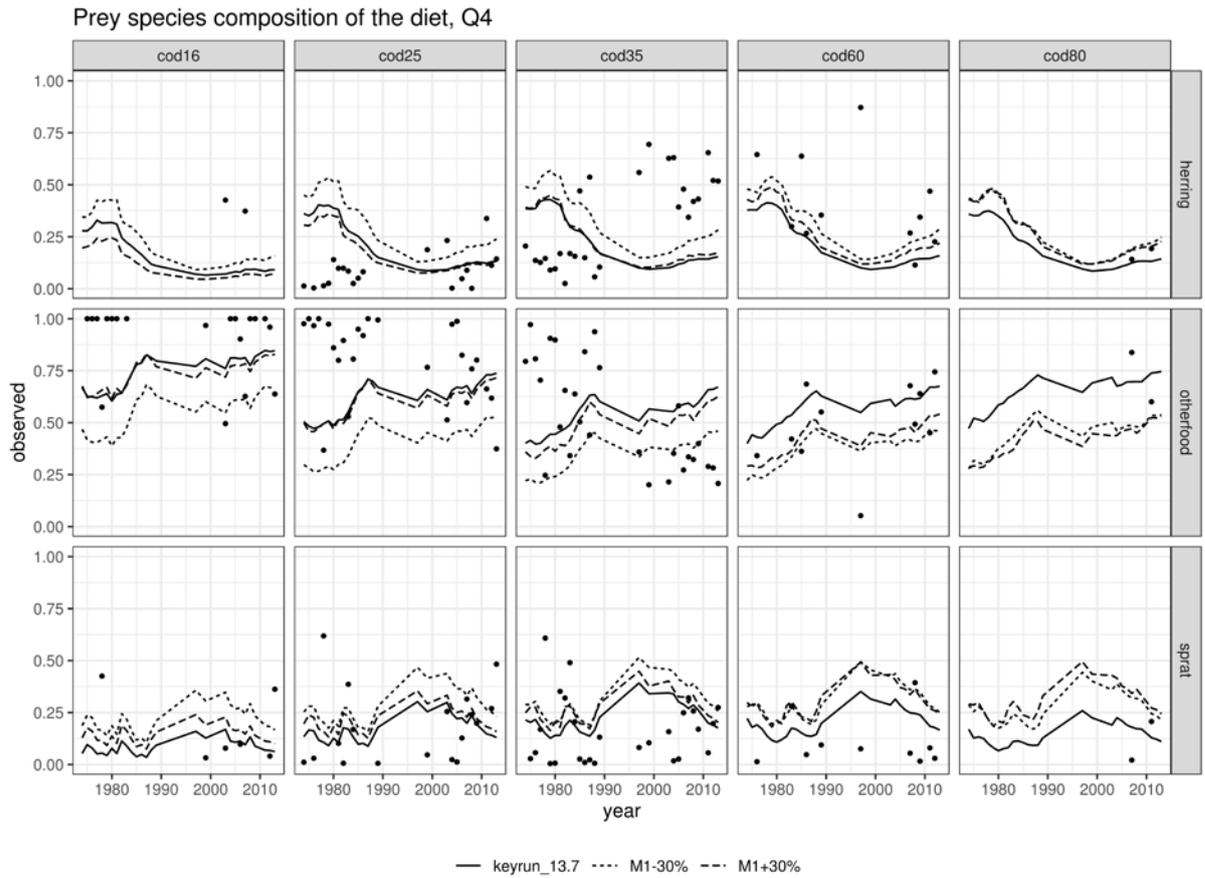


Figure.A3.7. Comparison of observed (points) and predicted (line) proportions of different prey types (sprat, herring, otherfood) in the diet of different cod length groups (cod16..80; corresponding to 16-25cm; 25-35cm; 35-60cm, 60-80cm and >80cm, respectively) in Q4 under different background mortality (different colour) setting.

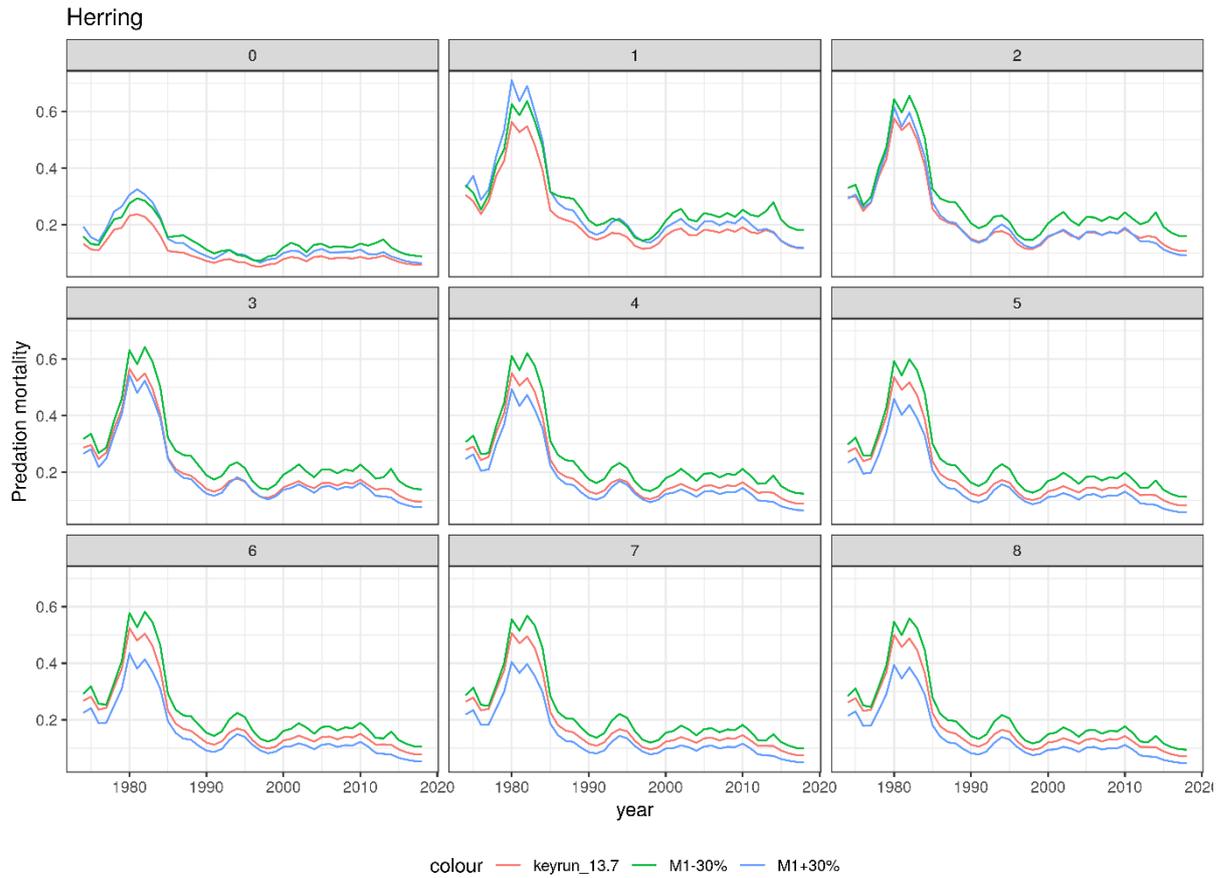


Figure.A3.8. Differences in predation mortality of herring by age estimated under different background mortality (different colour) setting.

Predation mortality estimated under different M1 setting differed more for sprat than for herring, but in both species values were highest under the lowest background mortality (-30% from initial value; green line on Figure.A3.10 and Figure.A3.11).

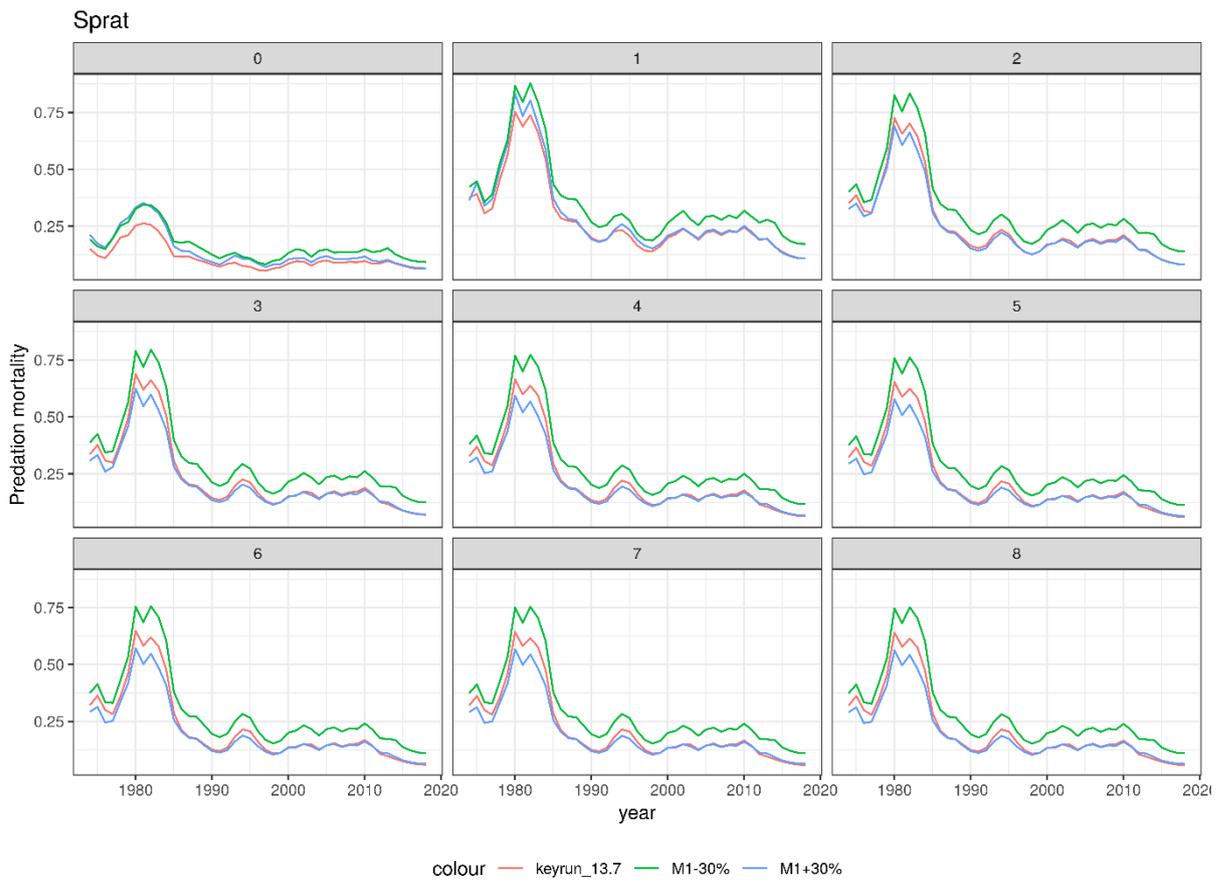


Figure.A3.9. Differences in predation mortality of sprat by age estimated under different background mortality (different colour) setting.

A4. Sensitivity test: consumption

We tested what effect does assumption on maximum consumption has on model output by comparing 97% quantile on the distribution of observed cod consumption (“keyrun_13.7”), to 95% and 99% quantiles. Tested assumptions showed very little effect on herring SSB (except for the end of time-series, *Figure.A4.1*) and rather limited effect on sprat SSB (*Figure.A4.2*). Different consumption assumptions affected herring survey indices (*Figure.A4.3*) a bit more than sprat survey indices (*Figure.A4.4*), however higher differences for herring were at the end of time-series, while for sprat at the beginning.

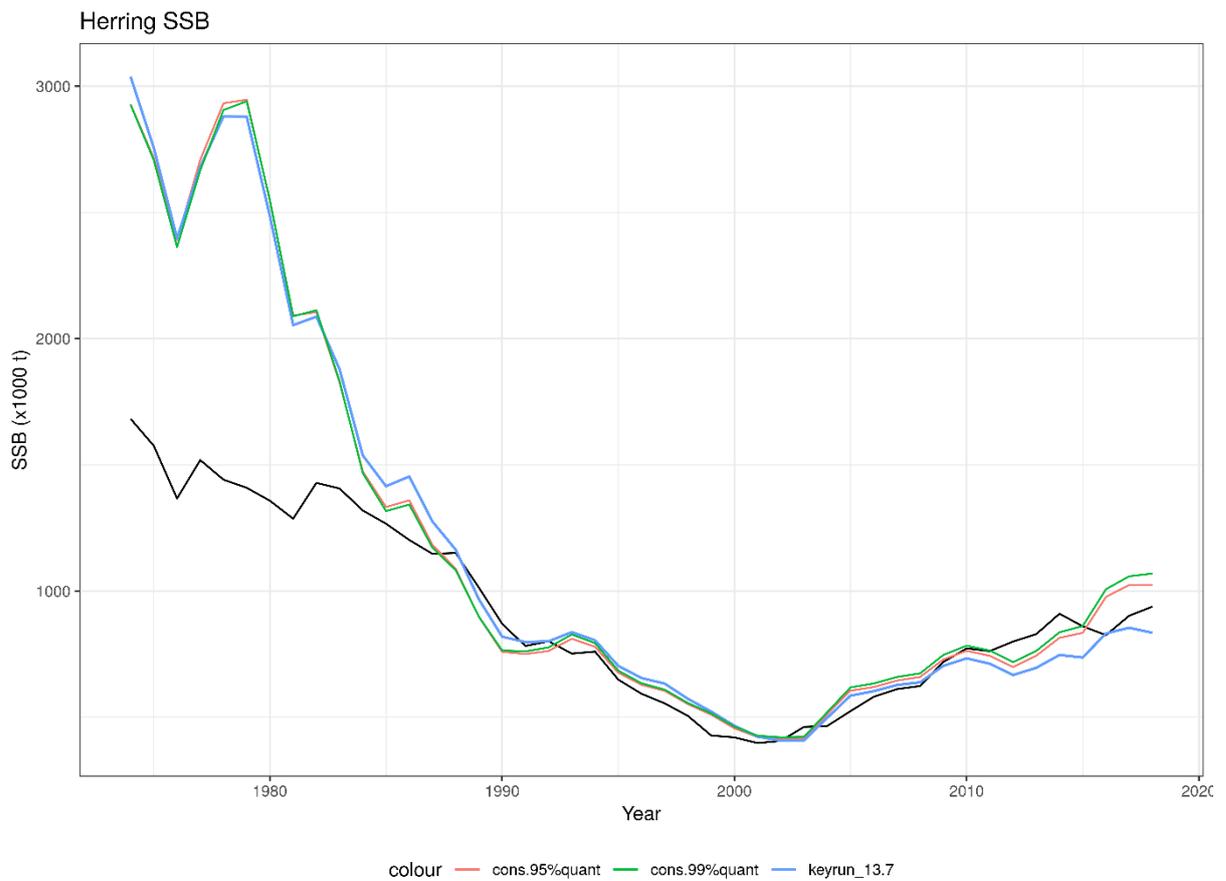


Figure.A4.1. Differences in herring SSB estimated under different consumption (different colour) setting.

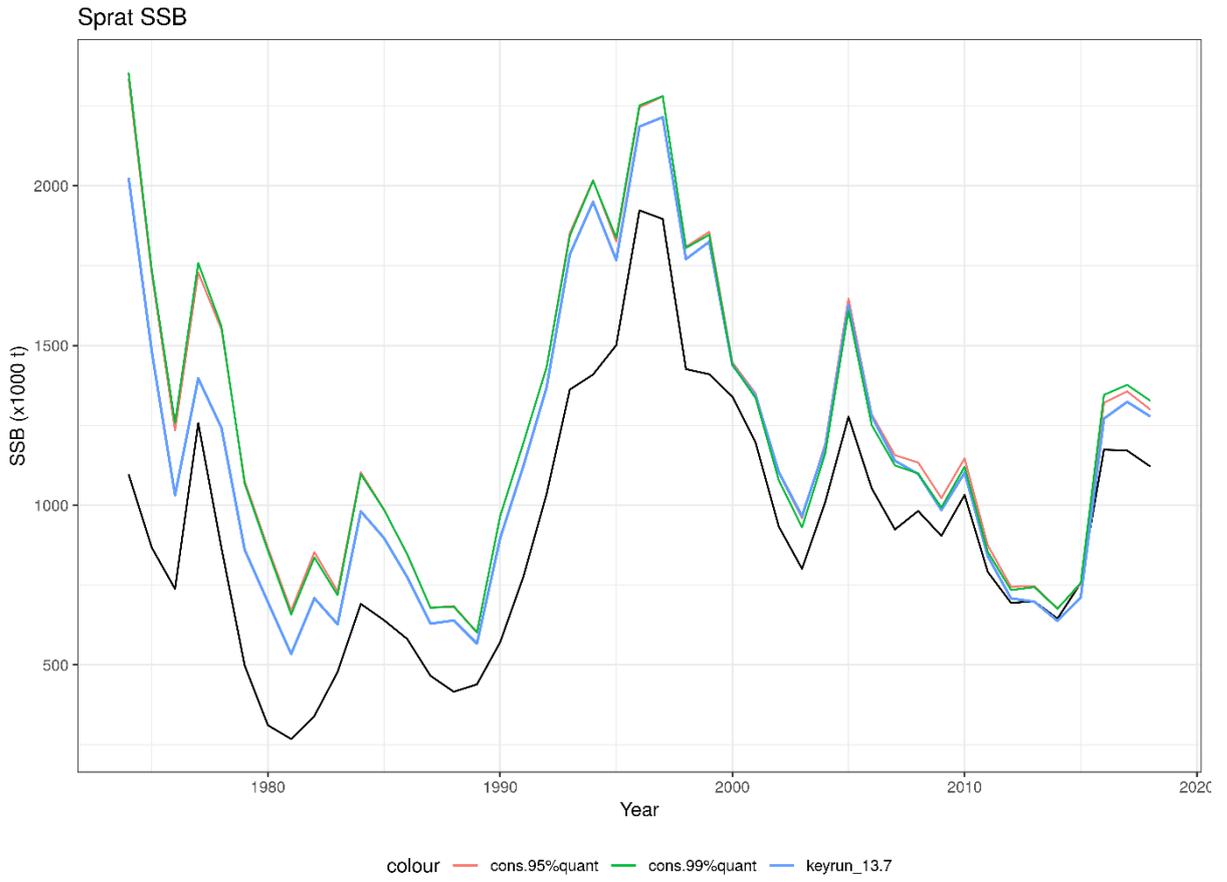


Figure.A4.2. Differences in sprat SSB estimated under different consumption (different colour) setting.

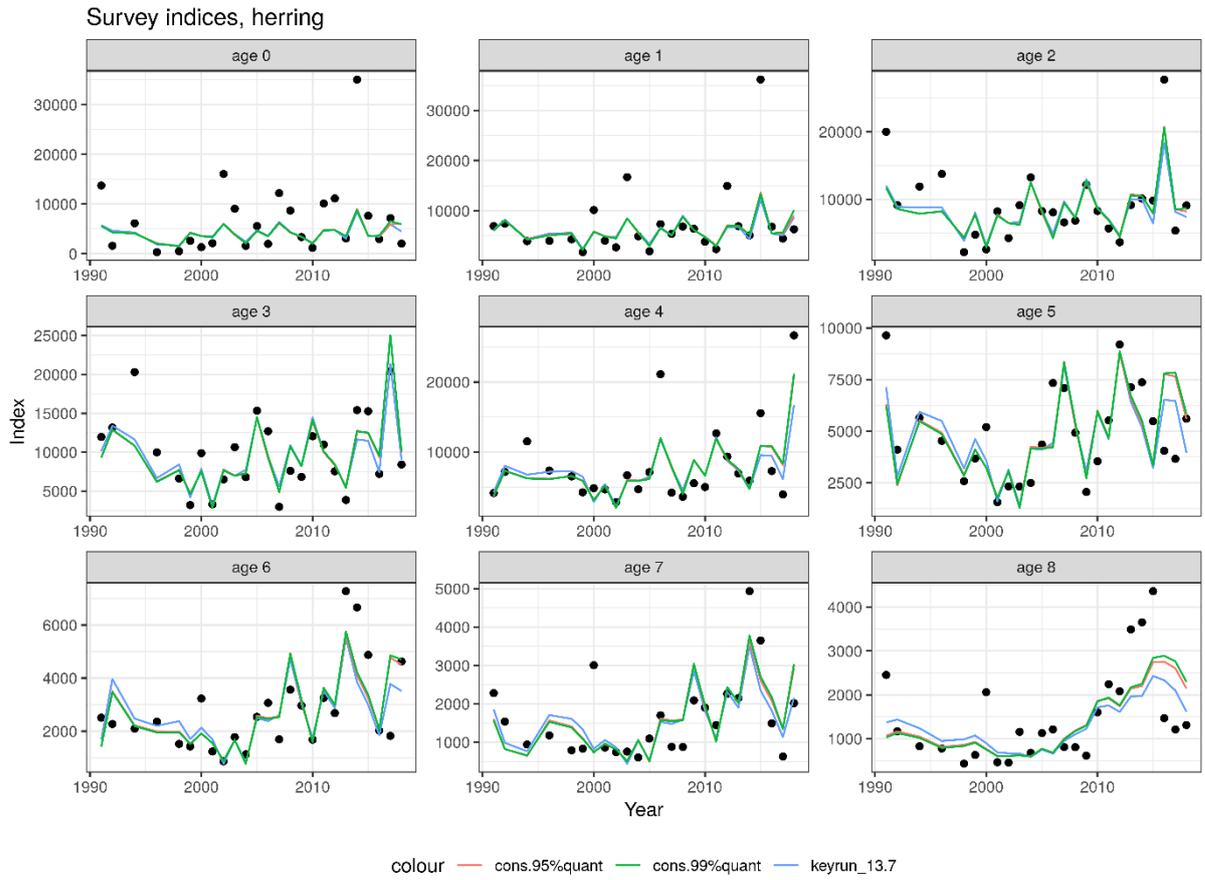


Figure.A4.3. Comparison of observed (points) and predicted (lines) herring survey abundance indices under different consumption (different colour) setting.

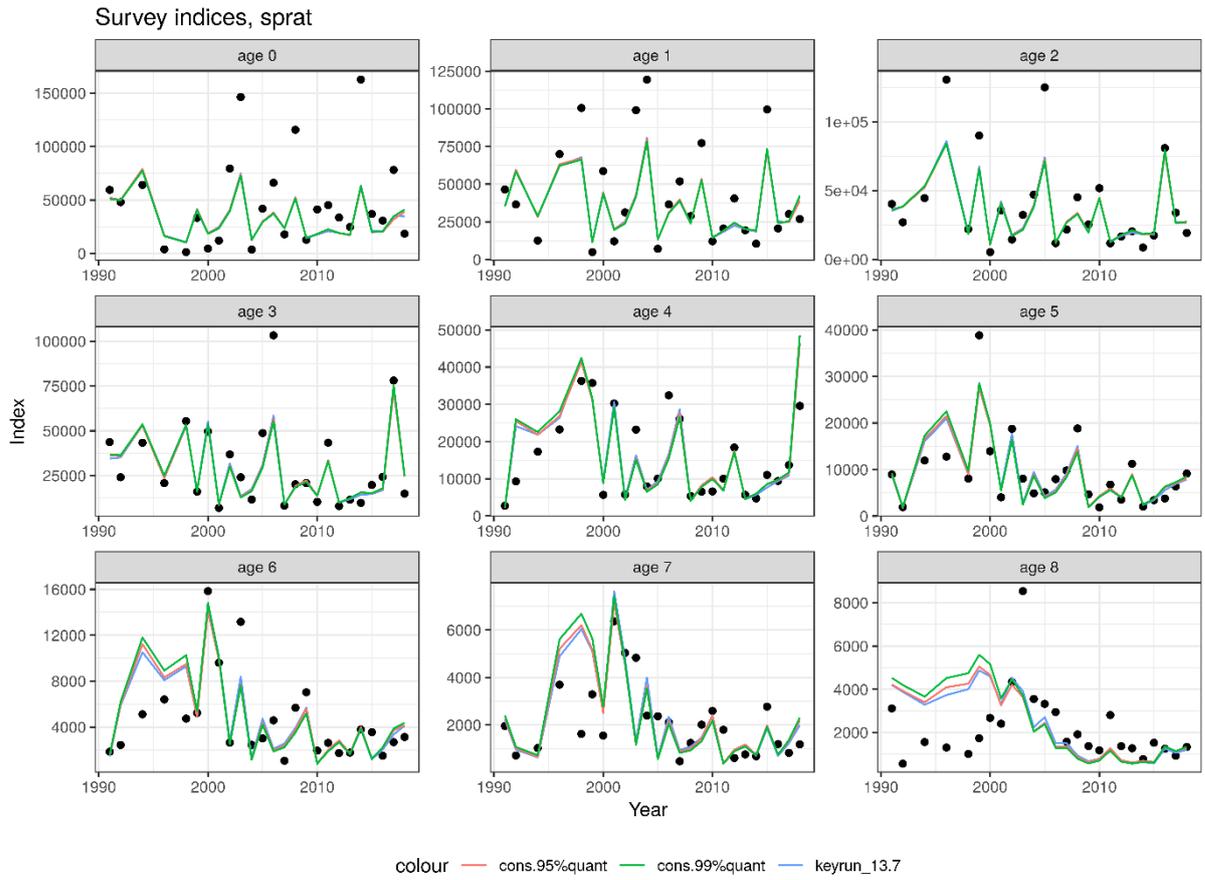


Figure.A4.4. Comparison of observed (points) and predicted (lines) sprat survey abundance indices under different consumption (different colour) setting.

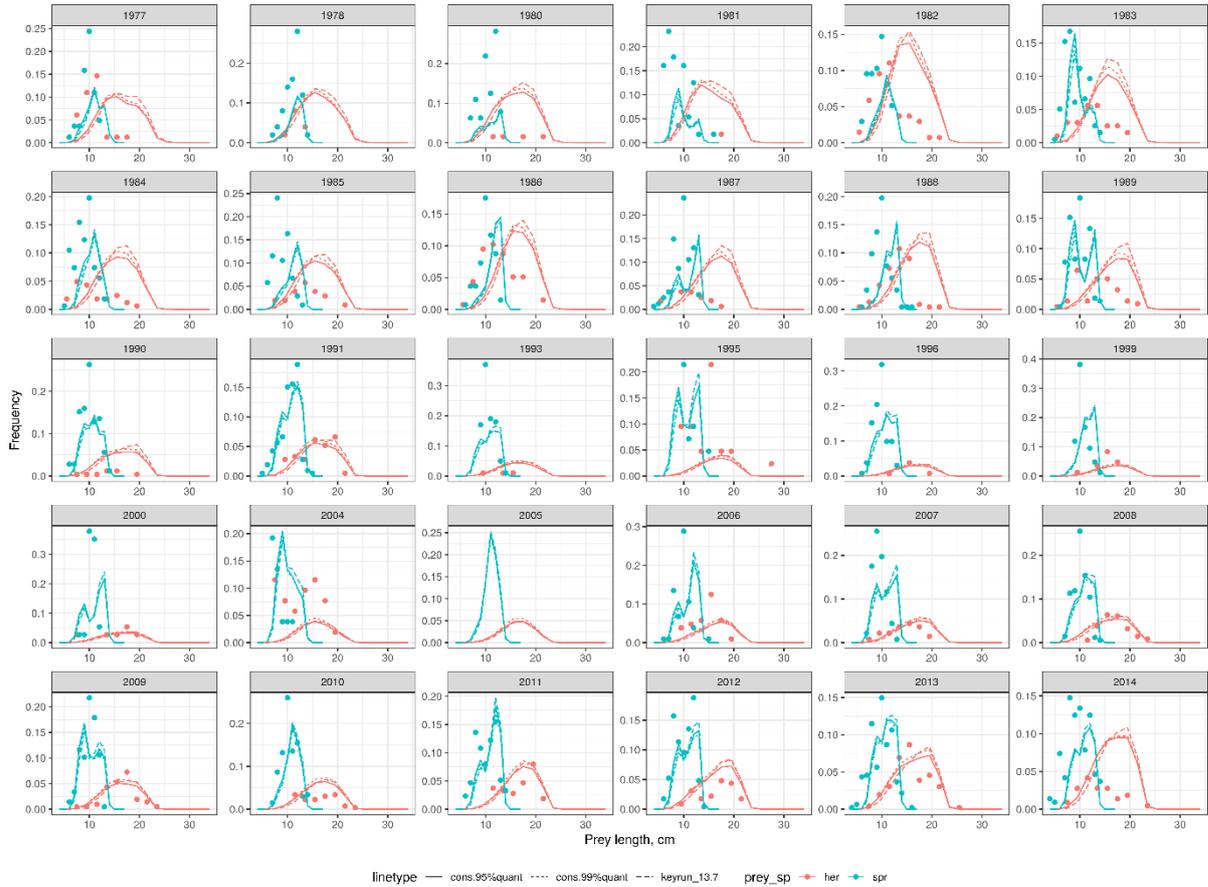


Figure.A4.5. Comparison of observed (points) and predicted (line) herring (her) and sprat (spr) length distributions in the diet of 35-60 cm cod under different consumption (different linetype) setting.

Different cod maximum consumption assumptions had very little effect on prey species distribution in the diet of 35-60 cm cod (Figure.A4.5) as well as species composition in the diet of all cod groups except 60-80 and >80 cm cod (“cod60” and “cod80” respectively on Figure.A4.6 and Figure.A4.7.

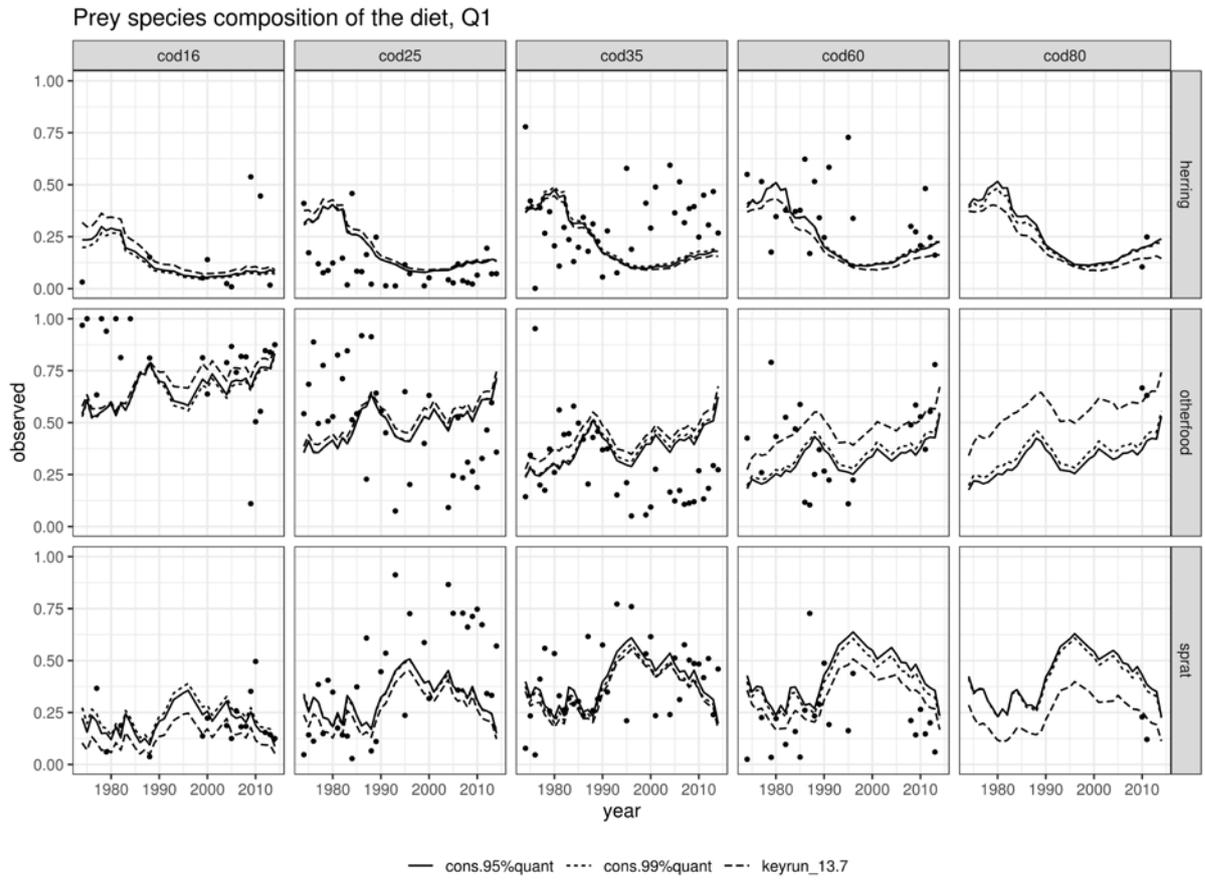


Figure.A4.6. Comparison of observed (points) and predicted (line) proportions of different prey types (sprat, herring, otherfood) in the diet of different cod length groups (cod16..80; corresponding to 16-25cm; 25-35cm; 35-60cm, 60-80cm and >80cm, respectively) in Q1 under different consumption (different linetype) setting.

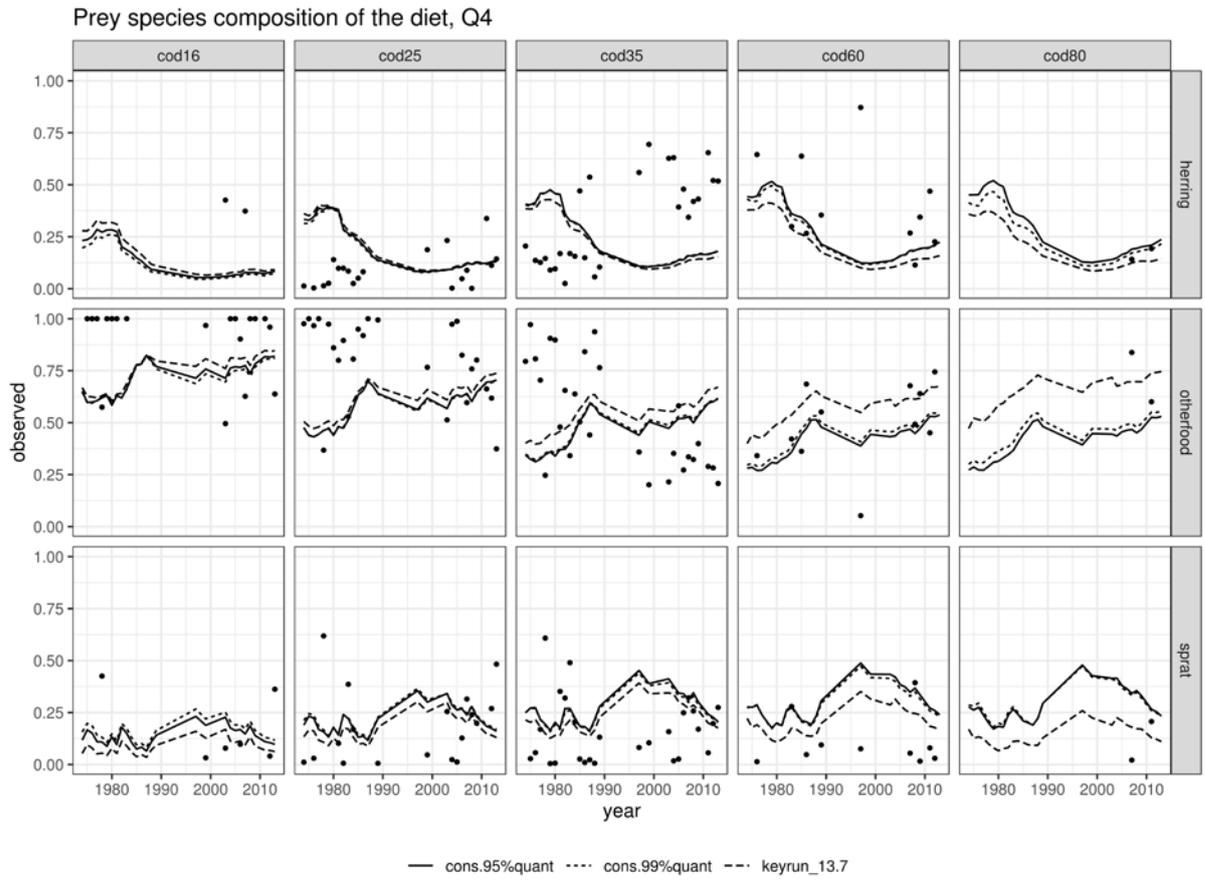


Figure.A4.7. Comparison of observed (points) and predicted (line) proportions of different prey types (sprat, herring, otherfood) in the diet of different cod length groups (cod16..80; corresponding to 16-25cm; 25-35cm; 35-60cm, 60-80cm and >80cm, respectively) in Q4 under different consumption (different linetype) setting.

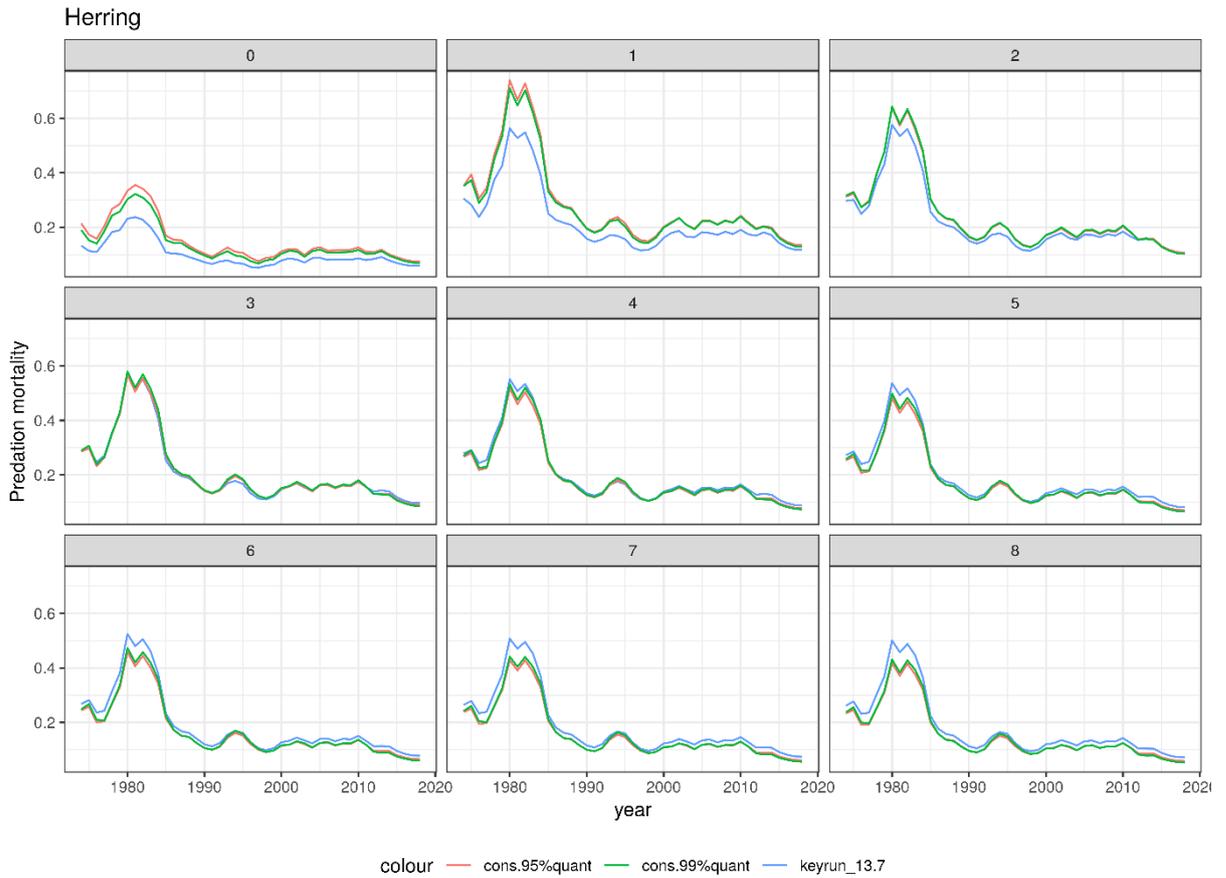


Figure.A4.8. Differences in predation mortality of herring by age estimated under different consumption (different colour) setting.

Different consumption assumption had rather limited effect on predicted predation mortalities (Figure.A4.8 and Figure.A4.9), with 97% quantile (blue line) causing a bit lower mortality for younger herring and all sprat ages and a bit higher mortality for older herring than 95% (red line) or 99% (green line) quantiles.

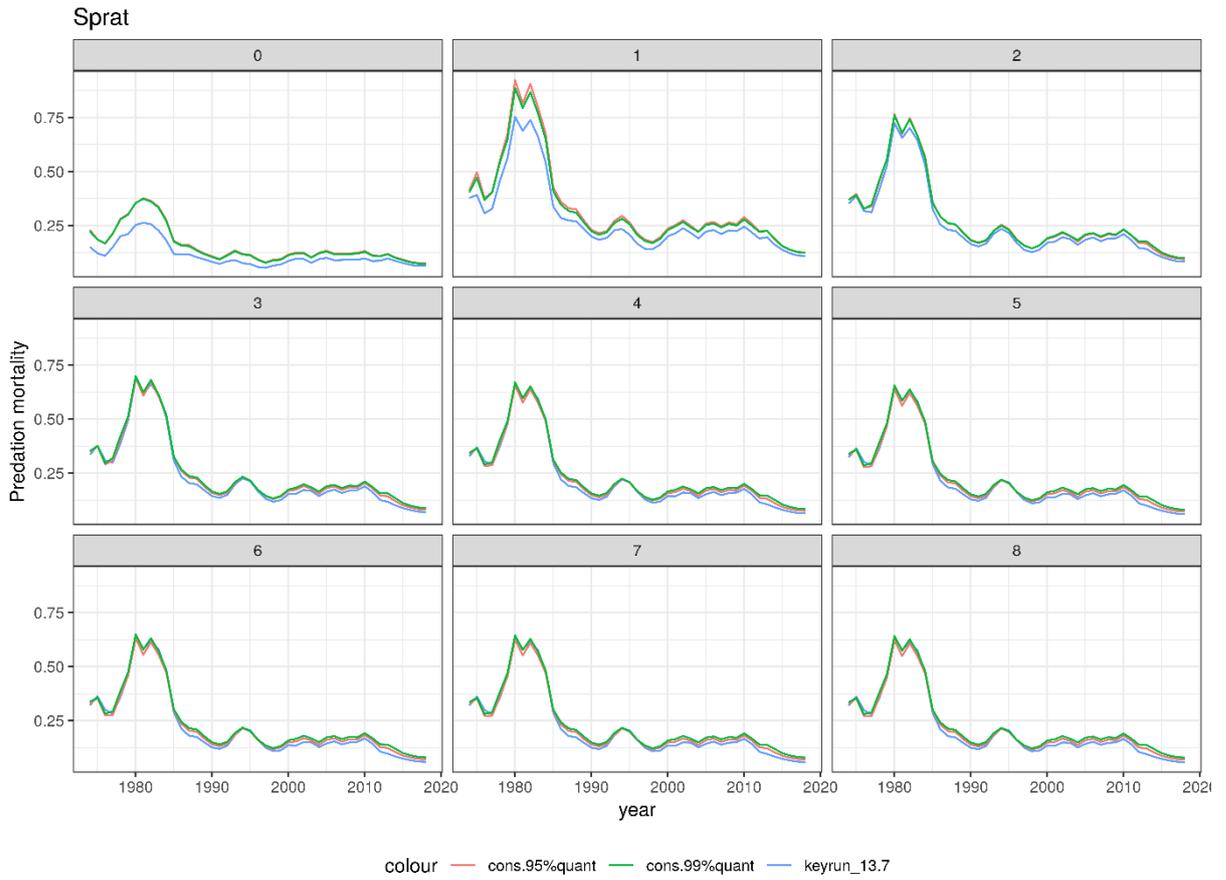


Figure.A4.9. Differences in predation mortality of sprat by age estimated under different consumption (different colour) setting.