INTER-BENCHMARK PROTOCOL ON NORTH SEA HERRING (IBPNSHERRING 2021)

VOLUME 3 | ISSUE 98

ICES SCIENTIFIC REPORTS

RAPPORTS SCIENTIFIQUES DU CIEM

ICES INTERNATIONAL COUNCIL FOR THE EXPLORATION OF THE SEA
CIEM CONSEIL INTERNATIONAL POUR L'EXPLORATION DE LA MER

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

ISSN number: 2618-1371

ICES Scientific Reports

Volume 3 | Issue 98

INTER-BENCHMARK PROTOCOL ON NORTH SEA HERRING (IBPNSHERRING 2021)

Recommended format for purpose of citation:

ICES. 2021. Inter-Benchmark Protocol on North Sea Herring (IBPNSHerring 2021). ICES Scientific Reports. 3:98. 168 pp. https://doi.org/10.17895/ices.pub.8398

Editors

Ciaran Kelly

Authors

Jonathan Ball • Valerio Bartolino • Florian Berg • Benoit Berges • Kirsten Birch Håkansson • Neil Campbell • Afra Egan • Niels Hintzen • Jim Ianelli • Ciaran Kelly • Alexander Kempf • Cecilie Kvamme Steve Mackinson • Henrik Mosegaard • Richard Nash • Martin Pastoors • Campbell Pert • Claus Reedtz Sparrevohn • Norbert Rohlf • Vanessa Trijoulet • Cindy van Damme

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

Contents

i Executive summary

A single-stock was included in this inter-benchmark: North Sea Autumn Spawning (NSAS) herring (her.27.3a47d). This inter-benchmark process was put forward because of: 1) newly available natural mortality values and 2) a discrepancy in the handling of natural mortality (M).

For the NSAS assessment, natural mortality is provided every 3–4 years by WGSAM. This is often associated with a rescaling of the assessment. At WKPELA 2018, a profiling method was developed to handle the introduction of new natural mortalities and in turn, alleviate the potential rescaling of the assessment. The method consists of the testing of the fit of the assessment model for a range of additive rescaling (fixed across years and ages) for M. The optimal fit of the assessment model is then taken as the additive level of rescaling to be applied to M. However, for the profiling performed during WKPELA 2018, a benchmark interim model specification was used. In practice, the assessment profiling should have been performed using the WKPELA 2018 final model configuration to ensure consistency in the derivation of additive rescaling. This discrepancy was only discovered at HAWG 2021 and has a consequence in the scaling of the assessment. In that context, this inter-benchmark process had the objectives of 1) updating the natural mortality for the NSAS assessment and 2) evaluate the methodology for handling newly introduced natural mortality vectors. These tasks subsequently led to the update of the assessment model and associated reference points.

First, the newly available natural mortality values from WGSAM were found to be similar to the previous run and did not affect the assessment significantly. Second, the investigation of the profiling method showed that it brought consistency in the introduction of different natural mortality vectors. Its use was maintained with the intent to run such an assessment profiling at subsequent benchmarks. However, the method was also found to be sensitive to the introduction of new data points and model specification, particularly the introduction of a correlation structure in fishing mortality. This aspect together with better model diagnostics warranted the introduction of such a correlation structure. The new model yields a smaller SSB and higher fishing pressure. With this change in model configuration, new reference points were derived with an updated approach compared to WKPELA 2018. B_{lim} and F_{MSY} have been revised upward whilst MSY $B_{trigger}$ is now smaller. With these reference points, fishing opportunities are overall increased.

ii Expert group information

Expert group name	Inter-benchmark Protocol on North Sea Herring (IBPNSHerring 2021)
Expert group cycle	Annual
Year cycle started	2021
Reporting year in cycle	1/1
Chair	Ciaran Kelly, Ireland
Meeting venue and dates	8–10 June and 25 June, 2021, online meeting (21 participants)

1 Introduction

1.1 NSAS assessment

The assessment for North Sea Autumn Spawner (NSAS) Herring is using commercial and survey data and span the 1947–2020 period. The assessment is conducted yearly at the Herring Assessment Working Group (HAWG). The model used is the SAM stock assessment model (Nielsen and Berg, 2014) in a single fleet configuration. In parallel with the single fleet assessment, a SAM multifleet assessment (Nielsen *et al*., 2021) is also conducted yearly to inform the short term forecast on fleet-wise fishing selectivity. The NSAS stock assessment was benchmarked in 2018 (ICES, 2018) and underwent a management strategy evaluation in 2019 (ICES, 2019). Despite the latter, there is no agreed management strategy to date for this stock and under the ICES framework, the F_{msy} advice rule takes precedence for the advice since 2018.

The NSAS stock is harvested by 4 fleets:

- A fleet: human consumption in the North Sea and Eastern Channel
- B fleet: bycatch of herring (in the sprat fishery) in the North Sea
- C fleet: human consumption in 3.a
- D fleet: bycatch of herring (in the sprat fishery) in the 3.a

The corresponding data for catches-at-age are available from 1947 but are only disaggregated by fleet from 1997. While most of the catches are from the A-fleet, other fleets are of importance because of the mixing with the Western Baltic spring (WBSS) spawning stock. Also of importance is the selectivity between the different fleets. Whilst the A fleet harvests ages 2+, the fishing pressure from other fleets (B, C and D) is significant for ages 0–1.

In terms of surveys, the assessment model is informed by 5 surveys:

- IHLS (larvae abundance index, LAI): survey focuses on the early larvae life stage of NSAS and covers the four different stock components: Orkney/Shetland, Buchan, Central North Sea (CNS), Southern North Sea (SNS). The influence of this survey is limited but remain important as it provides information on stock components
- IBTS-Q1 (age 0): late larvae survey (MIK net) taking place Q1 of each year on all stock components except Downs. This is usually a good indicator of recruitment
- IBTS-Q1 (age 1): bottom-trawl survey taking place Q1 of each year which provides clear information on the survivors to the fishery
- IBTS-Q3 (age 0–5): bottom-trawl survey taking place Q3 of each year
- HERAS (age 2–9+): acoustic survey covering the full extent of the NSAS and WBSS stocks and is conducted yearly in June/July. The derived indices cover age 2+ and are very influential to the stock assessment model

1.2 Issues leading to the IBP

Natural mortality is an important input to the NSAS assessment and is taken from the most up to date Stochastic Multi-Species model (SMS) key run provided by WGSAM[1]. However, it has been shown that updating the stock assessment to use the most recent SMS key run natural mortality estimates is associated with large changes in the perception of the NSAS stock. This is

[1] https://www.ices.dk/community/groups/Pages/WGSAM.aspx

mainly due to the varying absolute levels of the M vectors at age between the different SMS key runs. This is exemplified in Figure 1.1 where the absolute level of the four different natural mortality vectors (2010, 2013, 2016, 2019) are compared per decade. Whilst the 2016 and 2019 SMS key runs yield similar levels, there was a significant change from 2013 to 2016. Figure 1.2 shows the SSB estimated by the NSAS assessment model as of 2010 (with WKPELA 2018 final model configuration) with the different natural mortality SMS vectors. One can observe a scaling induced by the use of different SMS key runs.

The external information available on appropriate absolute levels of M are lacking and are limited to estimates of biomass by the HERAS acoustic survey and life history based empirical estimates of M. Given the limited ability to use this information to prevent rescaling in between SMS key run updates, a profiling method was developed and applied during WKPELA 2018 (ICES 2018). The method consists of the testing of the fit of the assessment model for a range of additive rescaling (fixed across years and ages, i.e. adding a single value, identical by age and year, to all Ms at age/year) for M. The optimal fit (AIC and negative log-likelihood) of the assessment model is then taken as the additive level of rescaling to be applied to M.

However, for the profiling performed during WKPELA 2018 (associated with the 2016 SMS key run), a benchmark interim model specification was used yielding an absolute level of rescaling of 0.11 in M. In other words, the interim model on which the profiling was based and the final selected model from the benchmark were different in model configuration. This resulting additive M of 0.11 was deemed plausible by the benchmark group and reviewers, especially in light of the resulting catchability of the HERAS survey which was estimated to be close to 1. The profiling method was not rerun with the final assessment setup that was agreed during the benchmark which caused a discrepancy.

This difference in setup was discovered at HAWG 2021 when rerunning the profiling of the assessment as this was the first time a new SMS key run (2019) had become available. Recalculation of the profiling method applied to the final WKPELA 2018 assessment model suggested a different additive M. Moreover, the investigation also revealed that changing the absolute level of the M vectors based on the profiling of the assessment model is sensitive to specific model configuration parameters. It was unclear why these changes in data and model settings during the benchmark had such a large effect on the profiling results. These aspects were not explored at WKPELA 2018. IBPNSHerring 2021 comes in this context, focusing on the strategy for handling new SMS natural mortality vectors. Moreover, changing the correction factor on M also lead to a change in the perception of the stock and the need to re-evaluate reference points.

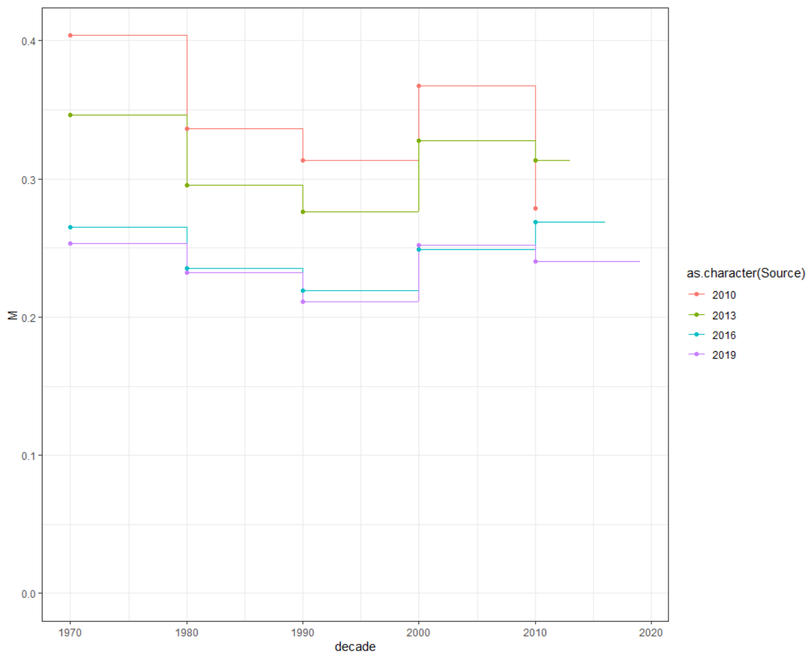


Figure 1.1. M for ages 2–6 WR only, summarized by decade (x-axis) and Key run (colour).

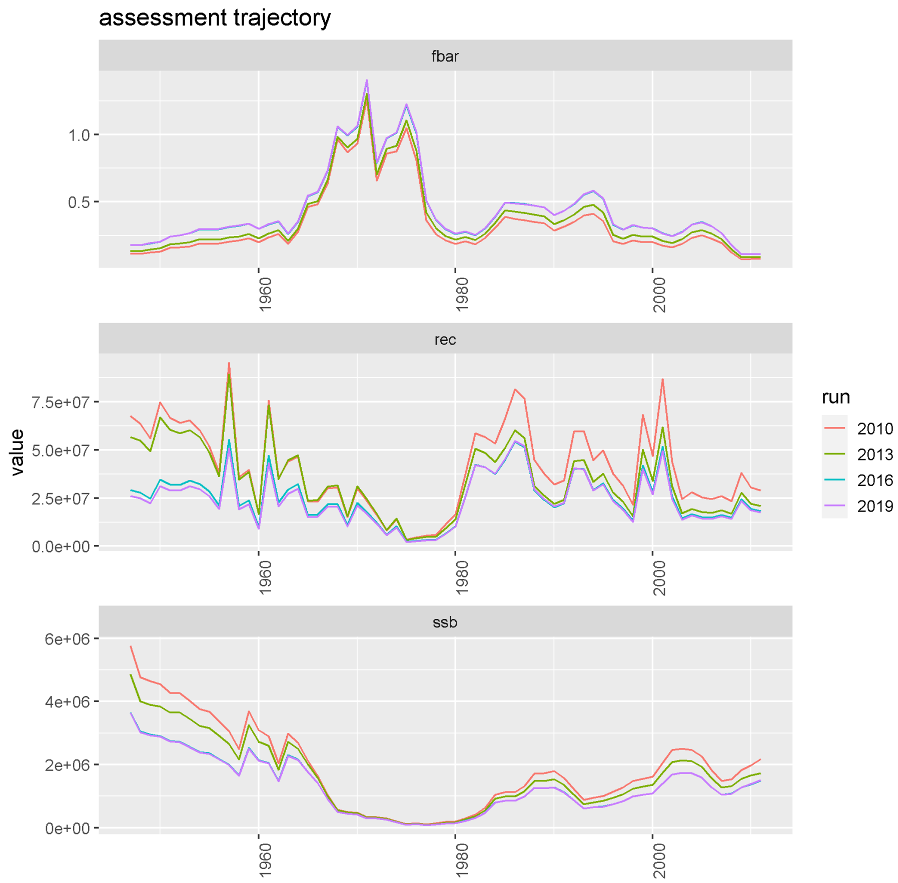


Figure 1.2. NSAS assessment model with 2010 as terminal year with natural mortality taken from the four available SMS keyruns: 2010, 2013, 2016 and 2019.

1.3 ToRs

The Inter-Benchmark Protocol on North Sea Herring, chaired by Ciaran Kelly (Ireland), and reviewed by Alexander Kempf (Germany) and Jim Ianelli (USA) will be established and will meet by correspondence from June 8–10 2021 to:

a) Investigate methods to bring consistency in the scaling of the assessment arising from updates in SMS:
    a. Evaluate optimal model configuration;
    b. Investigate the sensitivity of methods and assumptions about M on the assessment of NSAS herring. This includes investigating the assessment profiling method developed at WKPELA 2018.
b) Carry out the 2021 NSAS assessment based on the updated NSAS assessment model.
c) Update reference points based on the updated NSAS assessment model.

The IBP will report by 10 July for the attention of the ACOM.

2 New SMS natural mortality estimates

The NSAS assessment uses mortality input from the North Sea SMS-model provided every 3–4 years by the Working Group on Multispecies Assessment Methods (WGSAM) (ICES, 2021). In 2020 WGSAM carried out new SMS key runs and provided a new natural mortality estimate for NSAS herring. This new natural mortality spans the 1974–2019 period across ages 0–8.

The SMS model provides raw values for the natural mortality-at-age (Figure 2.1). Since 2010, four different natural mortality vectors were provided to HAWG for the NSAS assessment: 2010 key run (WGSAM 2011), .2013 key run (WGSAM 2014), 2016 key run (WGSAM 2017), 2019 key run (WGSAM 2021). The most recent results can be explored through a dedicated app at: http://ono.dtuaqua.dk:8282/SMSapp/. Overall, patterns in M can vary between key runs, especially for ages 0–1 (Figure 2.1). These changes are due to the refining of the SMS model with the inclusion of new predators. Since 2010, the SMS model got fine-tuned and the two most recent SMS key runs are close due to the somewhat smaller modifications in model configuration and account predators. Generally, predation mortality on herring is generally estimated to have decreased between 1975–2000 and increased after 2000. The type of predator that forages on herring is variable between ages. Mackerel and North Sea horse mackerel are the most influential predators on age 0. Whiting and saithe are the main predators on age 1 herring age. Cod and saithe are the main predators on herring from ages 2 and up.

In practice, the input to the assessment is the natural mortality-at-age smoothed using a loess smoother (0.5 in span, order 2). The natural mortality outside the period covered by the key run (1947–1973 and 2019–2021) are extrapolated using a 5-year running average (Figure 2.2).

In the SMS model, two natural mortalities are considered: M1 (background mortality) and M2 (predation mortality). The total mortality is the addition of these two components for each quarter of the year $M=M_1+M_2$. Whilst the SMS model effectively estimates the predation mortality M2, the background mortality M1 is taken as a fixed value. The background mortality or residual mortality is the natural mortality that is not accounted for in M2, either by predators not included in the model or by other natural mortality causes. For NSAS herring, the value of M1=0.1 is taken in the SMS model, an assumption surrounded by uncertainties and a lack of scientific backing. This value likely originates from estimates made during the closure of the fishery in 1978–1979 when the stock was at an ultimate low. However, the absolute level of the total natural mortality estimated by the SMS scales with M1. This is shown in Figure 2.3 with the natural mortality-at-age for a range of values for M1. The subsequent NSAS stock trajectories estimated by the SMS model are also scaled with different values for M1 (Figure 2.4). The absolute level of M should therefore be considered with uncertainties and should be reflected in the input process to the NSAS stock assessment.

Figure 2.1. Raw natural mortality vectors for all SMS keyruns (SMS2010, SMS2013, SMS2016, SMS2019).

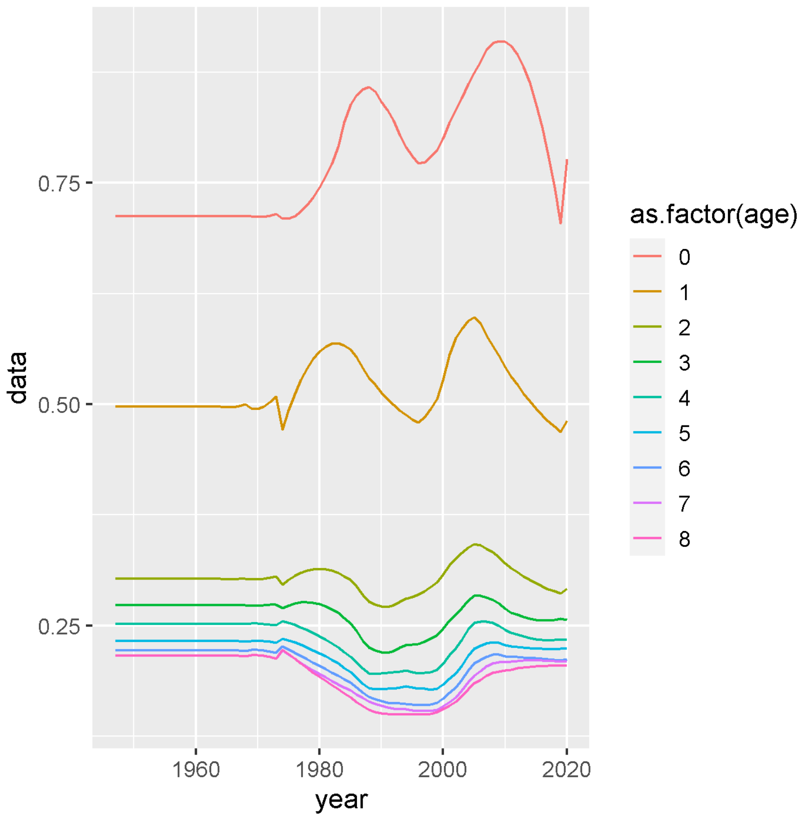


Figure 2.2. Smoothed and extrapolated natural mortality vector for the 2019 key run.

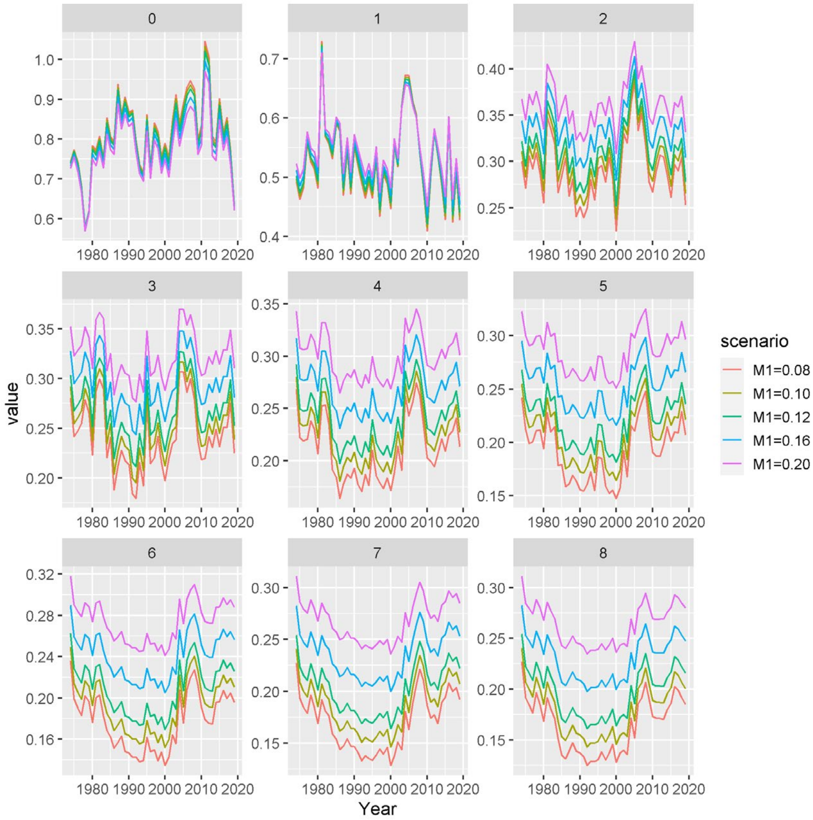


Figure 2.3. Natural mortality-at-age M resulting from the 2019 SMS model with a range of values used for background mortality.

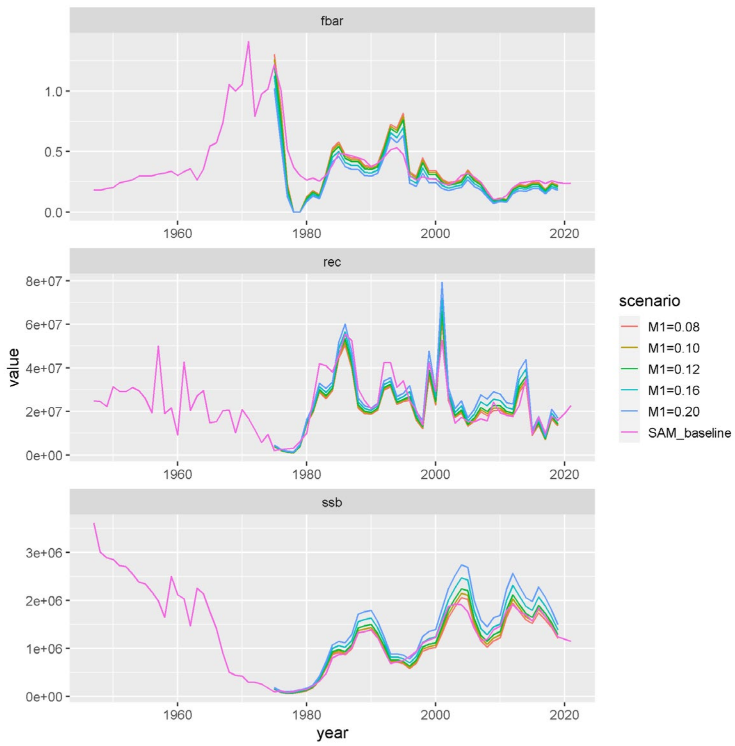


Figure 2.4. Comparison of stock trajectories estimated by the 2019 SMS and the SAM model (WKPELA 2018 final model configuration).

3 How to include the new natural mortality estimates?

The estimates provided by the SMS multispecies model provide the best available estimates of natural mortality for NSAS herring. However, as explained in the previous section, there is uncertainties related to the appropriate level of unaccounted background natural mortality M1 which remains an unknown. For the current SMS keyruns (2019) provided by WGSAM, M1=0.1. In order to deal with this uncertainty, the absolute level of the total natural mortality is considered variable as: M=M+addM with addM the additive scalor. The addM term is determined as the optimal fit of the assessment. In order to find the optimal assessment fit, the assessment model is run for a range of addM values and the negative log likelihood is computed. The lowest point in negative log likelihood corresponds to the absolute level of M that best fit data statistically.

The assessment profiling method was first proposed during WKPELA 2018 (ICES 2018). At this meeting, the additive scaling was of addM=0.11. However, this level of addM was derived from an interim model specification (Annex A3.1) which differed from the WKPELA 2018 final model configuration (Annex A3.2) that was agreed upon. In practice, the assessment profiling should have been performed using the WKPELA 2018 final model configuration to ensure consistency in the derivation of addM. The basis for the assessment models during HAWG 2018, 2019 and 2020 was addM=0.11 with the WKPELA 2018 final model configuration. The discrepancy in model configuration was only noticed at HAWG 2021. In this report, the base model is taken as the WKPELA 2018 final model configuration (Annex A3.2).

It is important to consider the merits of the assessment profiling methodology proposed here. The primary advantage of the method is to handle the varying absolute level in natural mortality vectors provided by WGSAM. In that context, a worthwhile test is to profile the assessment with the range of SMS key run available (2010, 2013, 2016, 2019) to ensure that the method stabilizes the assessment. Because each SMS key run has a different terminal year, the assessment of 2010 is taken to ensure that no extrapolating of M vectors is done for comparison. The results of each profiling is shown in Figure 3.1 and summarized in Table 3.1. Because the absolute level of each M vector differs (Figure 1.1), the dimension on which the negative log likelihood profile is plotted against is Mbar, the average of M through year and ages. The resulting stock trajectories are presented in Figure 3.2, to be contrasted to those from Figure 1.2. From these results, the profiled assessments with the last three SMS key runs (2013, 2016 and 2019) are very consistent. Only the oldest SMS key run (2010) exemplifies a small deviation in stock trajectory which is due to differences in trends in M at age (Figure 2.1). A summary of results for each SMS key run is presented in Figure 3.3. in Overall, the influence of the various keyruns is limited, suggesting the profiling method is robust against changes in SMS.

The test with varying SMS key runs only included data up to 2010. The results of the profiling of the base assessment model with the full range of data and the most up to date SMS key run (2019) are shown in **Error! Reference source not found.**. The optimum is found at addM=0. It is important to note that the level of additive M scaling introduced is closely linked to the absolute scaling of the HERAS survey across ages 3–8 and in turn the SSB level. In the base assessment model configuration, q=1.38.

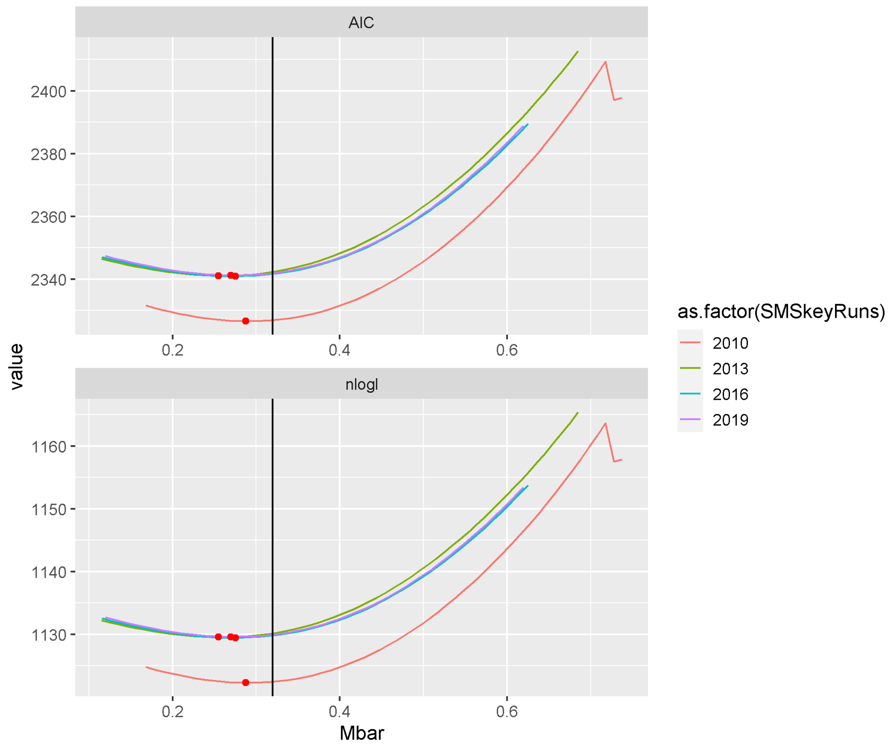


Figure 3.1. Assessment profiling for the assessment model using the four different SMS keyruns (2010, 2013, 2016 and 2019). The red circle markers correspond to the minimum negative log likelihood, considered the optimum assessment fit. The vertical black line is the absolute level of M (averaged across years and ages) for the SMS2019 keyrun.

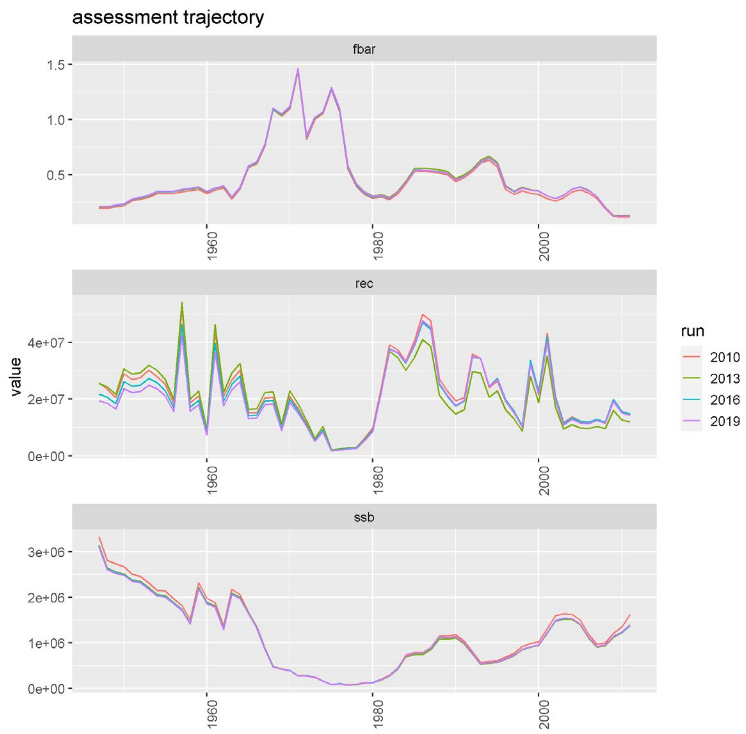


Figure 3.2. Assessment trajectory of assessment models ran with the four different SMS keyruns (2010, 2013, 2016 and 2019) at optimal point on the negative log likelihood. The assessment used for comparison runs to 2010.

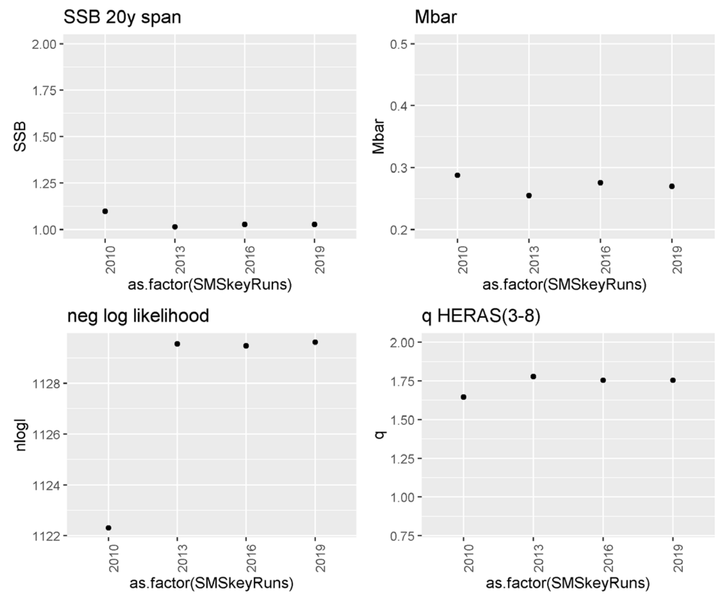


Figure 3.3: SSB, Mbar, negative log likelihood and HERAS catchability (q) for the different SMS keyruns (2010, 2013, 2016, 2019).

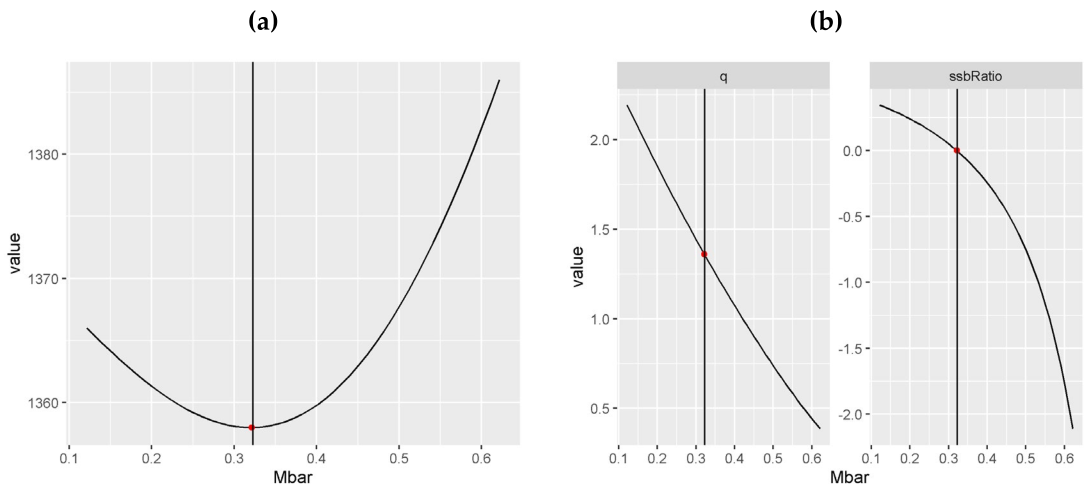


Figure 3.4. Base run assessment profiling. (a) negative log likelihood for different levels of additive scaling for M. (b) catchability of the HERAS (age 3–8) and ratio of SSB relative to baseline assessment (using SMS2019 without additive scaling for M). The red circle markers correspond to the minimum negative log likelihood, considered the optimum assessment fit. The vertical black line is the absolute level of M (averaged across years and ages) for the SMS2019 keyrun and corresponds to an additive scaling for M of 0.

Table 3.1. Estimated optimal additive M, the resulting Mbar, nlogl, AIC and HERAS q for the four different SMS keyruns (2010, 2013, 2016 and 2019)

addM	Mbar	SMSkeyRuns	nlogl	AIC	q
-0.15	0.287729	2010	1122.307	2326.613	1.646206
-0.13	0.254954	2013	1129.557	2341.115	1.779152
-0.05	0.275401	2016	1129.474	2340.948	1.754471
-0.05	0.269491	2019	1129.617	2341.235	1.754076

4 Sensitivity analysis

4.1 Background mortality sensitivity

As described in Section 2.1, the 2019 SMS model was ran with varying assumptions on M1 (0.08 to 0.2). In the hereby section, the NSAS assessment is profiled with these alternative runs of SMS2019. Results are presented in Figure 4.1 and summarized in Figure 4.2. Stock trajectories of profiled assessment with varying level of background mortality M1.

Table 4.1. Overall, the estimated additive scaling in M is consistent between the sensitivity runs. Some small differences in stock trajectories can be observed (**Error! Reference source not found.**), especially at high M1. This could be induced by the scaling of total M from M1 levels which is disproportional between ages, especially age 0–1 compared to 2+ (Figure 2.3).

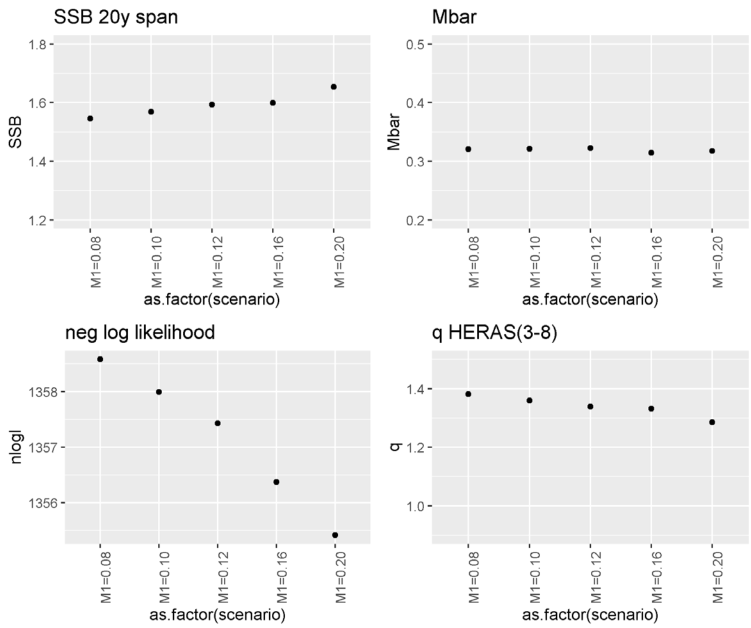


Figure 4.1. SSB, Mbar, negative log likelihood and HERAS catchability (q) for the different SMS 2019 keyruns M1 sensitivity scenarios.

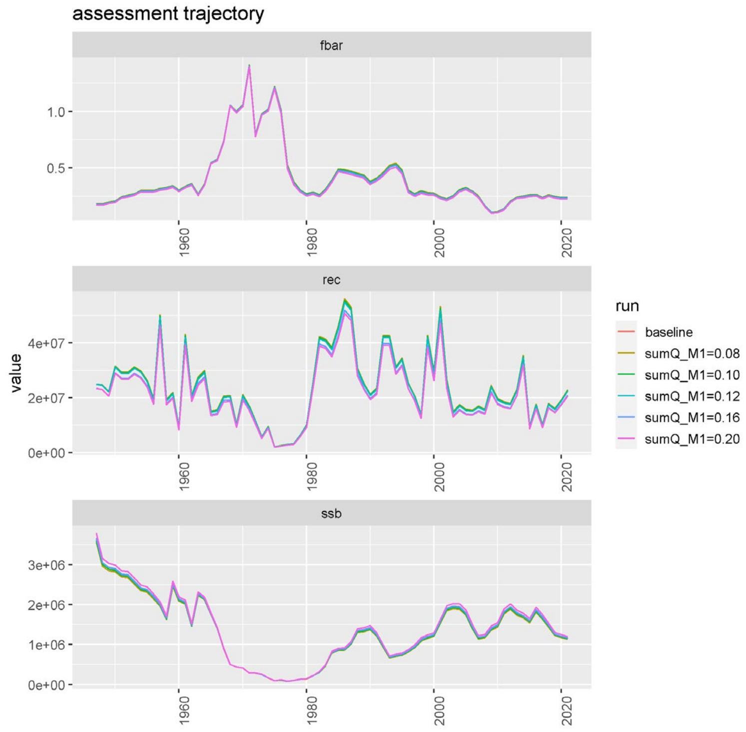


Figure 4.2. Stock trajectories of profiled assessment with varying level of background mortality M1.

Table 4.1. Estimated optimal additive M, the resulting Mbar, nlogl, AIC and HERAS q for the different SMS 2019 keyrun sensitivity scenarios.

addM	Mbar	scenario	nlogl	AIC	q
0.01	0.320368	M1=0.08	1358.579	2799.157	1.380784
0	0.321292	M1=0.10	1357.988	2797.976	1.359744
-0.01	0.322337	M1=0.12	1357.425	2796.849	1.338306
-0.04	0.314805	M1=0.16	1356.369	2794.738	1.331802
-0.06	0.317753	M1=0.20	1355.413	2792.827	1.285759

4.1.1 Retrospective

An important test for the profiling method is investigate whether it is sensitive to new data points. To that aim, a 10 year peel is performed and the profiling method is applied on each peel. Stock trajectories for these peels are put in perspective to those from the assessment in Figure 4.2. Expletively, larger deviations (relative to the retro run) through the entire time-series is obtained when the profiling on each peel is applied. This is because the natural mortality is scaled for the entire time-series as opposed to the retro run that only uses 1 year less of data for each peel. This results in an additional retrospective in SSB induced by the profiling method in the order of 5–10% (Figure 4.3(a)). In term of additive M scaling, there is a change from addM=-0.05 for the 2010 peel to addM=0.01 for the 2019 peel, i.e. an increase in Mbar of 0.06 over 10 years (Figure 4.3(b) and Table 4.2). This is associated with a significant drop in HERAS catchability (age 3–8), from 1.75 to 1.3 (Figure 4.3(b)).

(a) **(b)**

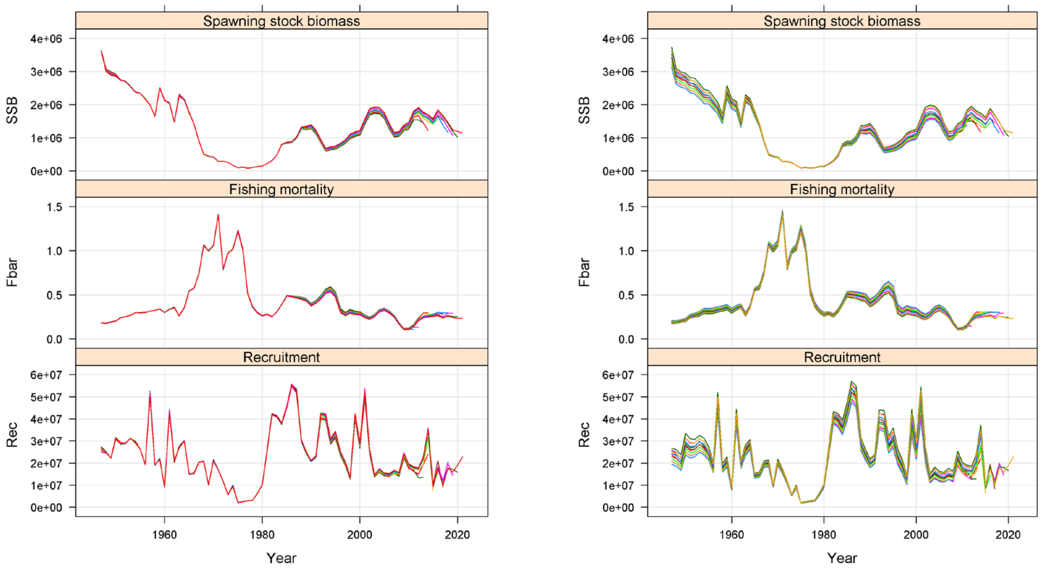


Figure 4.2. Comparison of retrospective patterns for the peels of the baseline assessment (a) and the peels of the baseline assessment with profiling for each year (b).

(a) **(b)**

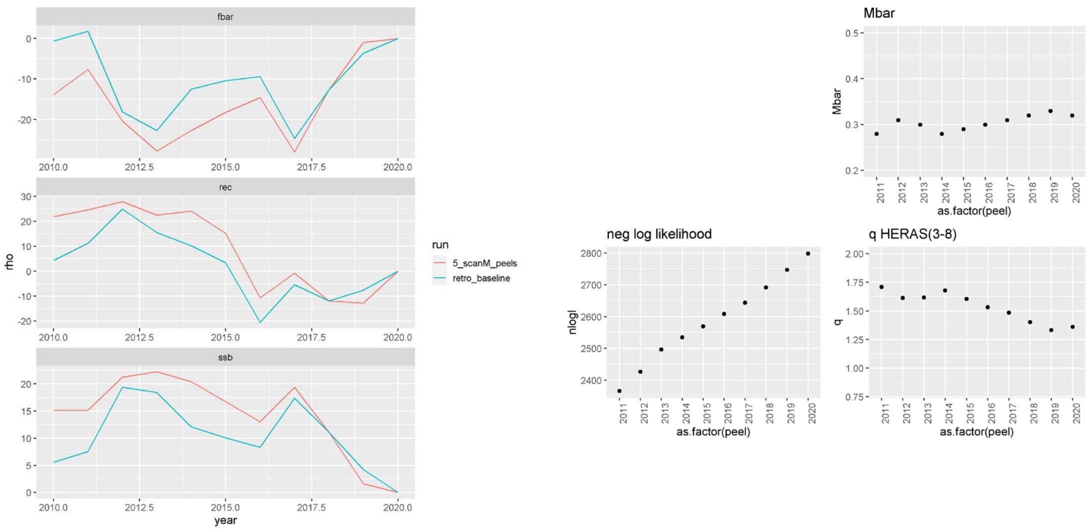


Figure 4.3. Mohn rho for the baseline assessment (a) and the baseline assessment with profiling for each year (b). Mohn rho is calculated with a 10 year span.

Table 4.2. Estimated optimal additive M, the resulting Mbar, nlogl, AIC and HERAS q for different assessment peels with profiling for each year.

addM	Mbar	peel	nlogl	AIC	q
0.01	0.331566	2019	1332.74	2747.479	1.331316
0	0.321859	2018	1304.564	2691.128	1.400535
-0.01	0.312038	2017	1280.778	2643.556	1.485261

addM	Mbar	peel	nlogl	AIC	q
-0.02	0.30211	2016	1263.23	2608.459	1.532431
-0.03	0.292077	2015	1243.706	2569.412	1.603478
-0.04	0.281952	2014	1226.277	2534.554	1.677538
-0.02	0.301738	2013	1207.2	2496.399	1.616747
-0.01	0.31144	2012	1172.187	2426.374	1.613822
-0.04	0.281063	2011	1141.936	2365.872	1.70839
-0.05	0.270627	2010	1129.617	2341.235	1.754076

4.2 Inclusion of correlation in selectivity patterns

In SAM there is the option to force a correlation structure on the selection patterns. The forced correlation (deviating from the correlation is being penalized in the nlogl) follows a power-law decline over the ages, such that age 1–2 is equally correlated to 2–3 and 5–6 but that the correlation is ^2 as low for age classes two ages apart etc. The inclusion of a correlation structure (as opposed to freely derived selection patterns) leads to small differences in correlation in fishing mortality-at-age (Figure 4.4). Only the age 0–1 relationship is impacted significantly, with a higher correlation when including a correlation structure in the SAM model (increased correlation coefficient from 0.36 to 0.6, Figure 4.4). In term of fishing selectivity, there is a good match with and without the correlation structure. Though, in the period around the closure of the fishery (1978–1979) one can observe substantial deviations in fishing selectivity patterns, due to the low catch number in this period (Figure 4.5). The differences in fit to the data are minor and hardly visible by the eye.

At WKPELA2018, the contributing factors for the discrepancy in the estimated values of additive M between the interim model and the final model configurations are as follows:

- Alternative input dataset used in the final model:
  - HERAS data age 2–8 used in interim, as opposed to age 1–8 in final WKPELA2018 model
  - IBTS-Q3 age 0-4 used in interim, as opposed to age 0–5 in final WKPELA2018 model
- corF parameter (which represents the correlation in fishing mortality) model turned on in interim model, and turned off in final WKPELA2018 model
- Alternative binding parameters

A close investigation between the interim and final WKPELA2018 model configurations (Annex A3.1 and A3.2 respectively) revealed that the most influential model parameter is the correlation selectivity patterns. Whilst for the final model configuration no correlation in selectivity patterns is estimated, the interim model configuration, the estimation of this parameter was turned on. This effect is shown in Figure 4.6 and Figure 4.9. HERAS catchability (age 3–8) from the baseline with fixed addM=0 (red circle markers) and baseline with profiling (blue circle markers).

Table 4.3. The inclusion of a correlation structure changes addM from 0 to 0.06 and the effect on the scaling of the assessment is substantial. The additional factors that induced an addM=0.11 at WKPELA2018 are different binding settings (observation variance and catchability) and retrospective (WKPELA2018 used the assessment with 2017 as the terminal year).

Perhaps the biggest impact of the inclusion of a correlation structure in fishing selectivity is around the closure period (1978–1979). This is reflected with a higher uncertainty in this period with the added correlation structure. To explore the impact this has on the profiling method of

M, the profiling is tested for a range of assessment starting years, from 1960 to 1988. Results are shown in Figure 4.7. Whilst the base run profiling exemplifies change in addM between -0.02 and 0.05, the use of the correlation structure in fishing selectivity reduces this dynamic range significantly with addM contained between 0.05 and 0.07. Interestingly, there is a convergence between the base and corF runs in addM for start year larger than 1982. An additional test fixing addM=0 in the base run throughout the historical peeling shows that the profiling per se is influenced by the historical period. This is exemplified by emergence of a pronounced trend in the catchability (q) of the HERAS (**Error! Reference source not found.**). However, introduction of a correlation in F among ages (corF) is able to remove such influence of the historical period on the profiling and gain even more stability to the estimation of the HERAS' q (Figure 4.7). These results warrant the use of a correlation structure in F especially in the context of assessment profiling as it is expected to bring additional stability and consistency.

(a) **(b)**

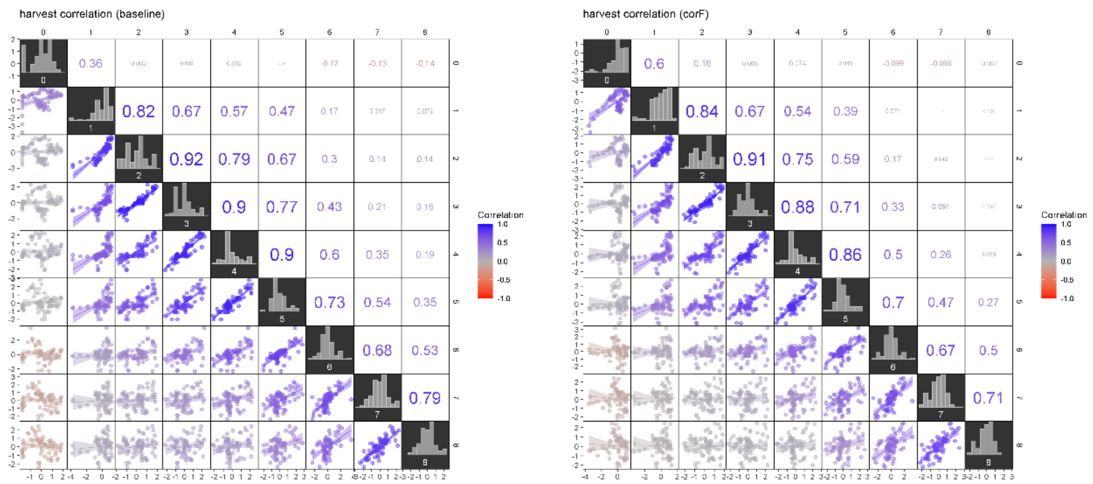


Figure 4.4. Internal consistency of fishing mortality-at-age. (a) correlation matrix for the baseline run. (b) correlation matrix for the run with the correlation in F toggled on.

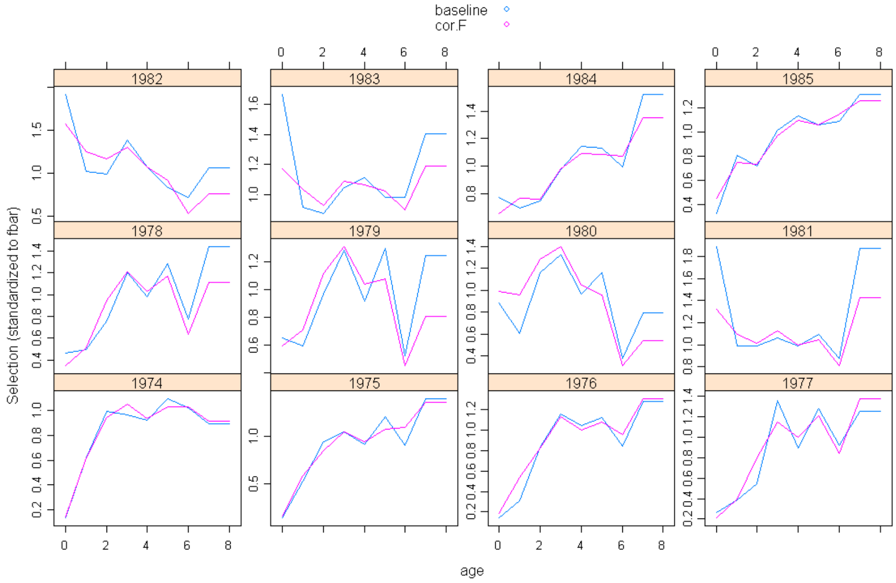


Figure 4.5. Estimated selection patterns under the baseline and corF scenarios for years around the closure of the fishing (1978–1979).

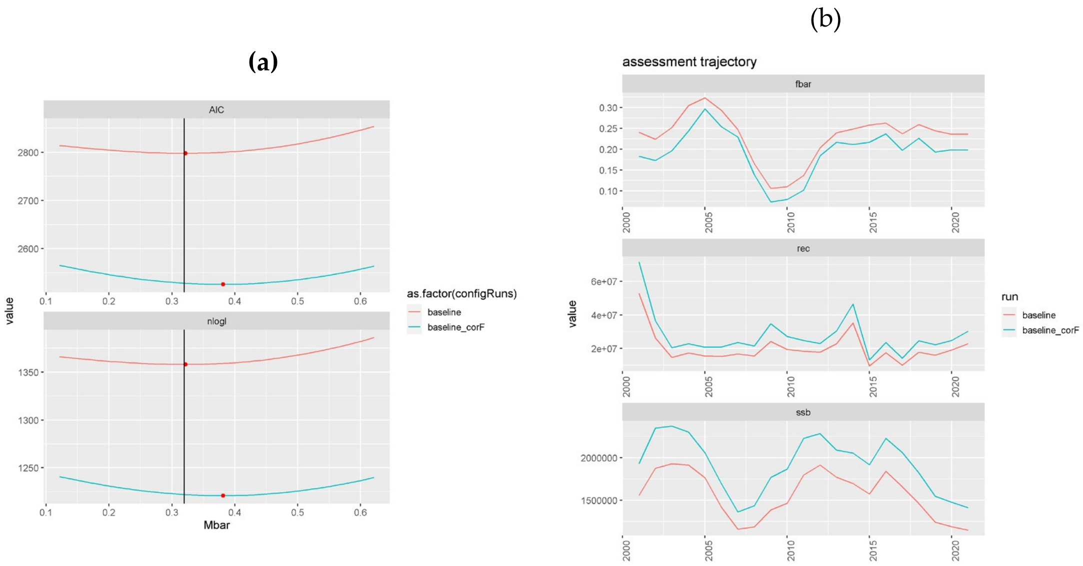


Figure 4.6. (a) AIC and negative log-likelihood of identical models except for the setting on fleet selectivity correlation. The corF scenario indicates a forced correlation structure. (b) Estimates stock trends under the two scenarios.

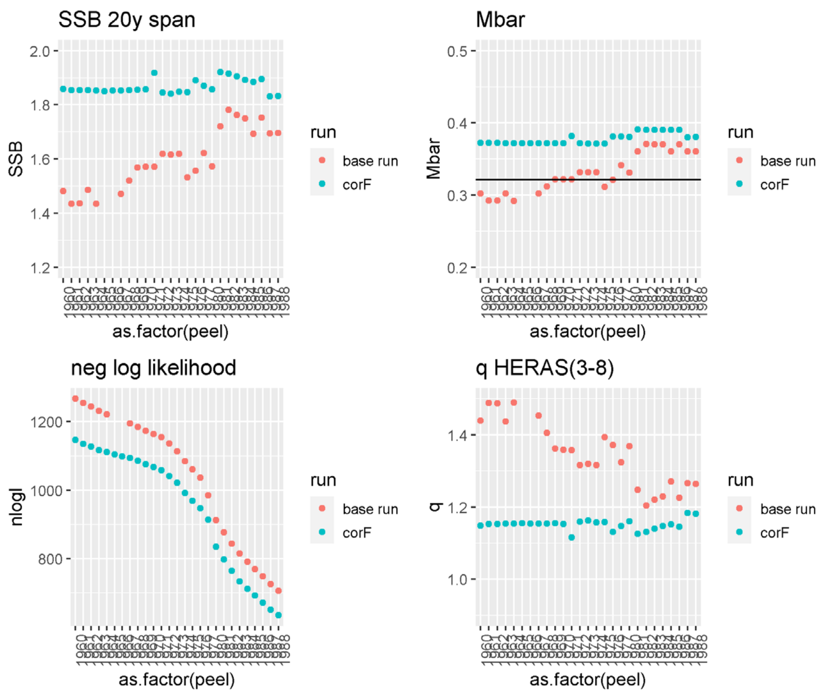


Figure 4.7. SSB, Mbar, negative log likelihood and HERAS catchability (q) for different assessment start year as a result of the profiling with two models: baseline (red circle markers) and baseline inclusive of correlation structure in fishing selectivity (blue circle markers).

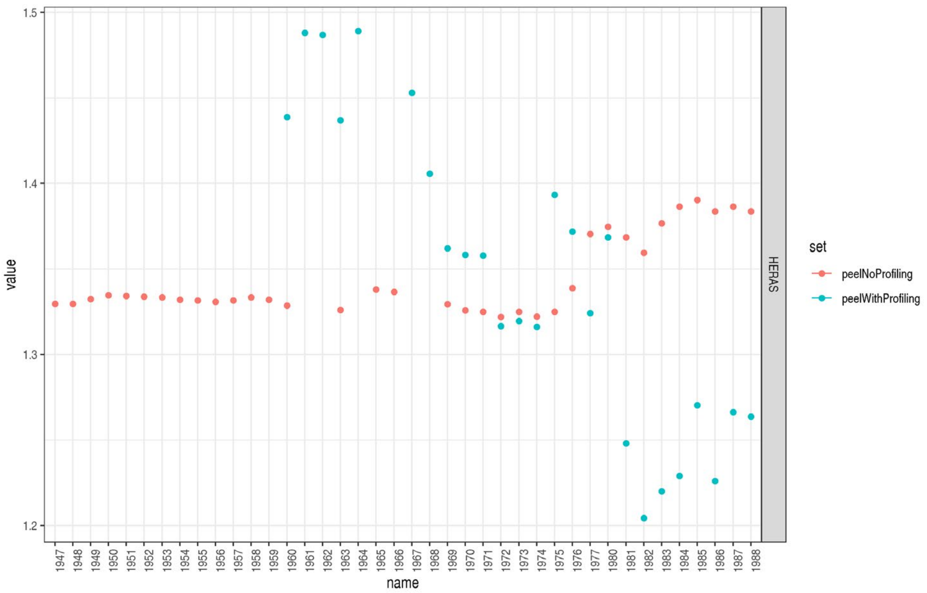


Figure 4.9. HERAS catchability (age 3–8) from the baseline with fixed addM=0 (red circle markers) and baseline with profiling (blue circle markers).

Table 4.3. Estimated optimal additive M, the resulting Mbar, nlogl, AIC and HERAS q for the two scenarios tested.

addM	Mbar	configRuns	nlogl	AIC	q
0	0.321484	baseline	1357.97	2797.94	1.360186
0.06	0.381484	baseline_corF	1220.937	2525.873	1.115359

5 Final model configuration

Results presented in Section 4.2 showed that the use of a correlation structure in fishing selectivity (corF parameter) is beneficial for the profiling of the assessment. A direct comparison of assessment models also revealed a clear improvement in AIC. These aspects motivate the inclusion of the corF parameter in the SAM model However, with this new model setup, it becomes necessary to re-evaluate parameter bindings to optimize model configuration. More specifically, it is needed to:

- Run a new additive M profiling of the assessment
- Optimize parameter bindings in line with: 1) the inclusion of corF, 2) the newly derived additive M rescaling parameter.

To optimize the parameter bindings, the following stepwise approach is employed:

Step 1: The profiling method used to estimate the additive M rescaling parameter for the assessment is performed on the WKPELA2018 final settings but with corF turned on;

Step 2: Using the configuration from 1, incremental changes in model parameter bindings are tested. The purpose of this is to determine the optimal model configuration and identify its sensitivity to any changes in parameter bindings.

Step 3: In an iterative manner, the profiling for the additive M rescaling parameter is run a second time on the optimal configuration derived from step 2. Attention is made to examine to what extent the result of the second profiling is different from the result of the first profiling in step 1.

First, the result of profiling for step 1 is shown in Figure 5.1 and yield an optimal M rescaling of addM=0.06. In step 2, a range of incremental changes (Table 5.1) are introduced and their effect is evaluated against the AIC. Four changes are found to improve the assessment fit (Figure 5.2):

- Binding of age 1–3 in catchability of IBTSQ3 (alt4). Drop of 0.286 in AIC, very minor.
- Change in observation variance for the HERAS survey, freeing ages 1 to 3 (alt5). Drop of 3.1 in AIC
- Binding of age 1–2 in catchability of HERAS (alt8). Drop of 1.9 in AIC
- Binding the observation variance for the catches as 0–1, 2–6 and 7–8. Drop of 1.98 in AIC.

Combining the different changes, the drop in AIC is of 8. Important to note is that the change in IBTSQ3 catchability (1) only leads a to minor reduction in AIC. However, it has an impact on the further profiling in step 3. This is shown in Figure 5.3. For this reason, the final model settings include changes 2–4 relative to WKPELA 2018. The second profiling of the assessment with the optimal parameter bindings leads to addM=0.06, same as in Step 1 (Figure 5.3). A summary of differences in model parameter bindings is presented in Table 5.2.

Using the data available in 2021, a comparison of assessment models under IBPNSherring2021 and WKPELA2018 configurations is given in Figure 5.4 to Figure 5.6. The new model combined with the new assessment profiling (leading to addM=0.06) yield smaller SSB and higher fishing mortality (Figure 5.4). The catchability for the HERAS survey on core ages (3–8+) is of 1.1 (as opposed to 0.93) (Figure 5.5) previously, in line with the expectation in catchability for this survey. As for the observation variance, the new model yields higher estimates for catches age 0–1 but lower levels for older ages (Figure 5.6).

Model configuration might be revisited in forthcoming benchmarks and an update of the profile of the assessment will have to be conducted. The use of the assessment profiling and the correlation in fishing selectivity are Until new changes in model configuration are introduced, addM=0.06 will be kept constant though assessment profiling will be explored during HAWG working groups.

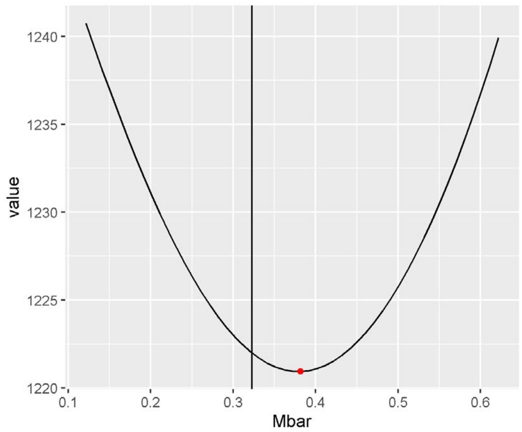


Figure 5.1. Profiling for step 1 of optimization of parameter bindings.

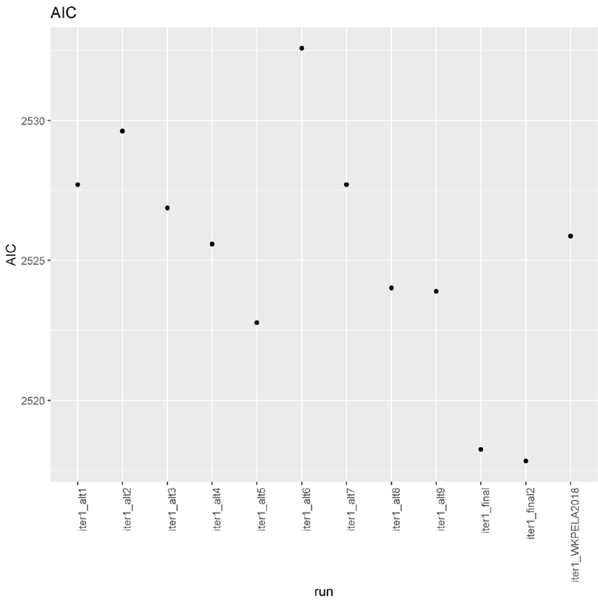


Figure 5.2. Change in AIC for each step changes listed in Table 5.1.

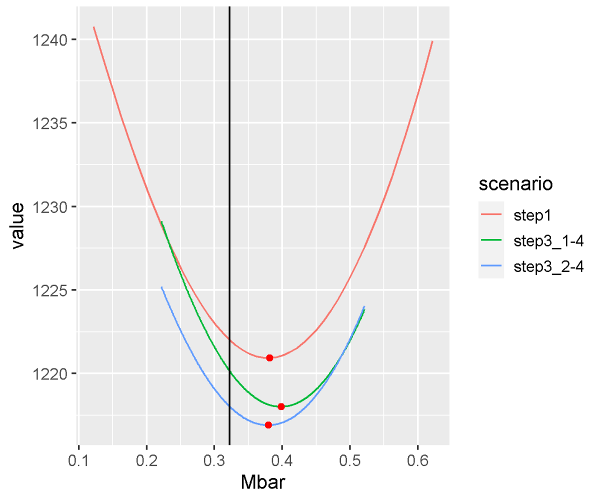


Figure 5.3. Negative log likelihood profiling for step 1 (red line) and at step 3 with the two final models listed in Table 2 (green and blue lines). The selected final model is the one yielding comparable addM, final2, depicted by the blue curve.

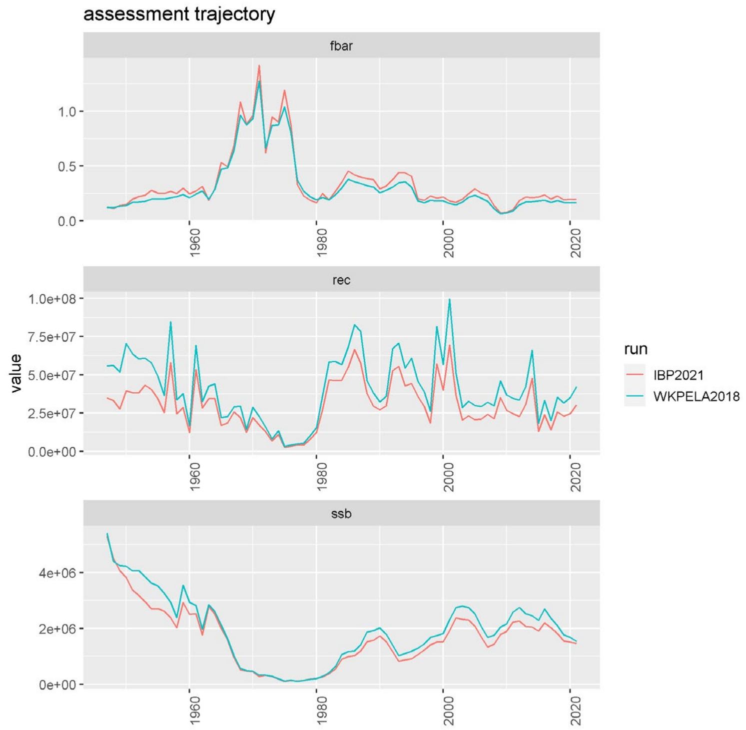


Figure 5.4. Comparison of NSAS stock trajectories with 2021 between WKPELA2018 (addM=0.11) and IBPNSherring2021 (addM=0.06) model configurations.

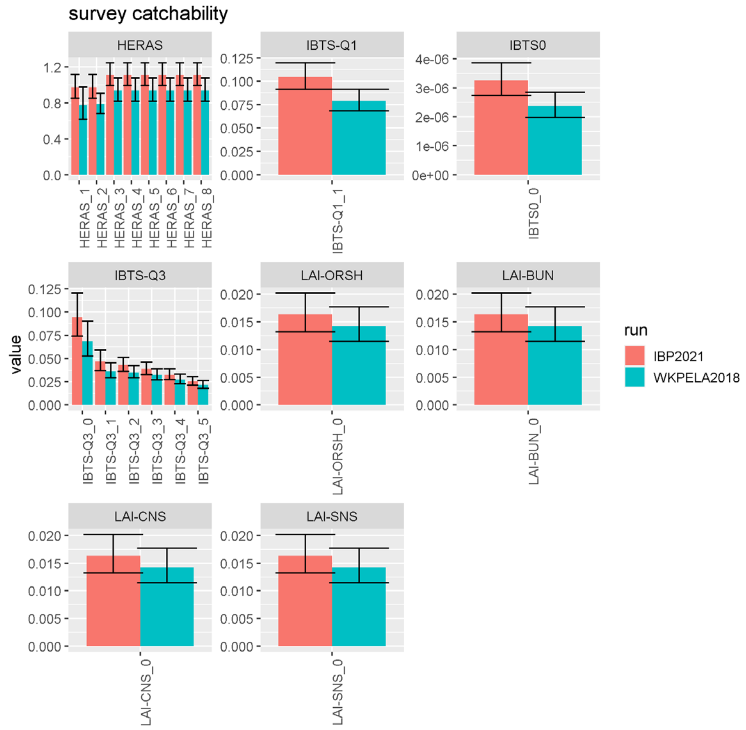


Figure 5.5. Comparison of survey catchabilities estimated by the SAM model with the 2021 data between WKPELA2018 (addM=0.11) and IBPNSherring2021 (addM=0.06) model configurations.

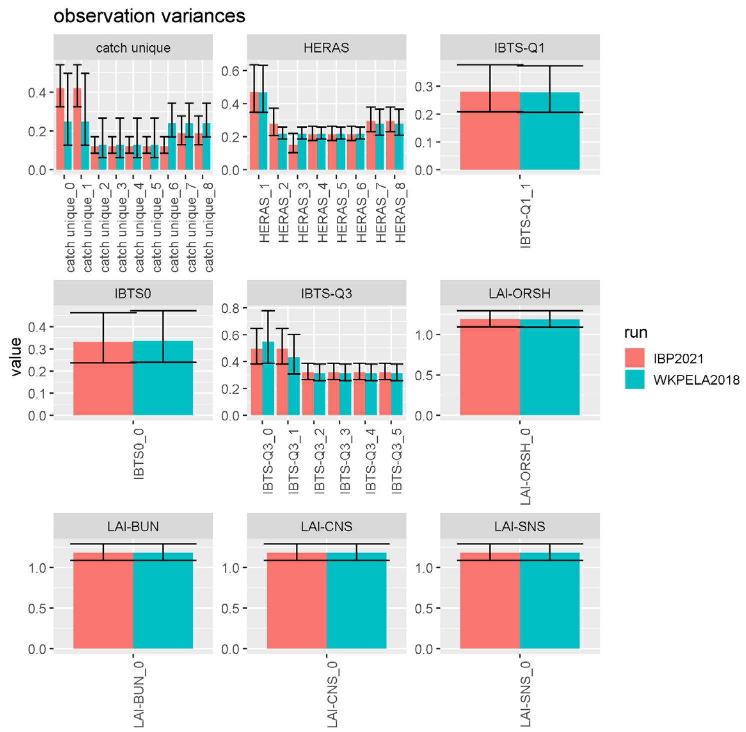


Figure 5.6. Comparison of observation variances estimated by the SAM model with the 2021 data between WKPELA2018 (addM=0.11) and IBPNSherring2021 (addM=0.06) model configurations.

Table 5.1. Incremental changes for the optimization of the parameter bindings.

<table>
<tr><th>Run name</th><th>Description</th><th>WKPELA2018</th><th>Incremental change</th></tr>
<tr><td>alt1</td><td>catch obs.var age 0 and 1 free</td><td><pre>
Slot "obs.vars":
              age
fleet   0 1 2 3 4 5 6 7 8
  catch unique 0 0 1 1 1 1 2 2 2
  HERAS   -1 3 4 4 4 4 4 5 5
  IBTS-Q1   -1 6 -1 -1 -1 -1 -1 -1 -1
  IBTS0   7 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3   8 9 10 10 10 10 -1 -1 -1
  LAI-ORSH   11 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN   11 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS   11 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS   11 -1 -1 -1 -1 -1 -1 -1 -1
</pre></td><td><pre>
Slot "obs.vars":
              age
fleet   0 1 2 3 4 5 6 7 8
  catch unique 0 1 2 2 2 2 3 3 3
  HERAS   -1 4 5 5 5 5 5 6 6
  IBTS-Q1   -1 7 -1 -1 -1 -1 -1 -1 -1
  IBTS0   8 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3   9 10 11 11 11 11 -1 -1 -1
  LAI-ORSH   12 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN   12 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS   12 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS   12 -1 -1 -1 -1 -1 -1 -1 -1
</pre></td></tr>
<tr><td>alt2</td><td>f.var age 0 and 1 free</td><td><pre>
Slot "f.vars":
              age
fleet   0 1 2 3 4 5 6 7 8
  catch unique 0 0 1 1 1 1 2 2 2
  HERAS   -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q1   -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS0   -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3   -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-ORSH   -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN   -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS   -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS   -1 -1 -1 -1 -1 -1 -1 -1 -1
</pre></td><td><pre>
Slot "f.vars":
              age
fleet   0 1 2 3 4 5 6 7 8
  catch unique 0 1 2 2 2 2 3 3 3
  HERAS   -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q1   -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS0   -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3   -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-ORSH   -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN   -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS   -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS   -1 -1 -1 -1 -1 -1 -1 -1 -1
</pre></td></tr>
<tr><td>alt3</td><td>IBTSQ3 obs.var freed age 5</td><td><pre>
Slot "obs.vars":
              age
fleet   0 1 2 3 4 5 6 7 8
  catch unique 0 0 1 1 1 1 2 2 2
  HERAS   -1 3 4 4 4 4 4 5 5
  IBTS-Q1   -1 6 -1 -1 -1 -1 -1 -1 -1
  IBTS0   7 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3   8 9 10 10 10 10 -1 -1 -1
  LAI-ORSH   11 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN   11 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS   11 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS   11 -1 -1 -1 -1 -1 -1 -1 -1
</pre></td><td><pre>
Slot "obs.vars":
              age
fleet   0 1 2 3 4 5 6 7 8
  catch unique 0 0 1 1 1 1 2 2 2
  HERAS   -1 3 4 4 4 4 4 5 5
  IBTS-Q1   -1 6 -1 -1 -1 -1 -1 -1 -1
  IBTS0   7 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3   8 9 10 10 10 11 -1 -1 -1
  LAI-ORSH   12 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN   12 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS   12 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS   12 -1 -1 -1 -1 -1 -1 -1 -1
</pre></td></tr>
</table>

Run name	Description	WKPELA2018	Incremental change
alt4	IBTSQ3 q bind age 1-3	Slot "catchabilities": age fleet 0 1 2 3 4 5 6 7 8 catch unique -1 -1 -1 -1 -1 -1 -1 -1 -1 HERAS -1 1 2 3 3 3 3 3 3 IBTS-Q1 -1 4 -1 -1 -1 -1 -1 -1 -1 IBTS0 0 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q3 5 6 7 8 9 10 -1 -1 -1 LAI-ORSH 11 -1 -1 -1 -1 -1 -1 -1 -1 LAI-BUN 11 -1 -1 -1 -1 -1 -1 -1 -1 LAI-CNS 11 -1 -1 -1 -1 -1 -1 -1 -1 LAI-SNS 11 -1 -1 -1 -1 -1 -1 -1 -1	Slot "catchabilities": age fleet 0 1 2 3 4 5 6 7 8 catch unique -1 -1 -1 -1 -1 -1 -1 -1 -1 HERAS -1 1 2 3 3 3 3 3 3 IBTS-Q1 -1 4 -1 -1 -1 -1 -1 -1 -1 IBTS0 0 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q3 5 6 6 6 7 8 -1 -1 -1 LAI-ORSH 9 -1 -1 -1 -1 -1 -1 -1 -1 LAI-BUN 9 -1 -1 -1 -1 -1 -1 -1 -1 LAI-CNS 9 -1 -1 -1 -1 -1 -1 -1 -1 LAI-SNS 9 -1 -1 -1 -1 -1 -1 -1 -1
alt5	obs.var HERAS	Slot "obs.vars": age fleet 0 1 2 3 4 5 6 7 8 catch unique 0 0 1 1 1 1 2 2 2 HERAS -1 3 4 4 4 4 4 5 5 IBTS-Q1 -1 6 -1 -1 -1 -1 -1 -1 -1 IBTS0 7 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q3 8 9 10 10 10 10 -1 -1 -1 LAI-ORSH 11 -1 -1 -1 -1 -1 -1 -1 -1 LAI-BUN 11 -1 -1 -1 -1 -1 -1 -1 -1 LAI-CNS 11 -1 -1 -1 -1 -1 -1 -1 -1 LAI-SNS 11 -1 -1 -1 -1 -1 -1 -1 -1	Slot "obs.vars": age fleet 0 1 2 3 4 5 6 7 8 catch unique 0 0 1 1 1 1 2 2 2 HERAS -1 3 4 5 6 6 6 7 7 IBTS-Q1 -1 8 -1 -1 -1 -1 -1 -1 -1 IBTS0 9 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q3 10 11 12 12 12 12 -1 -1 -1 LAI-ORSH 13 -1 -1 -1 -1 -1 -1 -1 -1 LAI-BUN 13 -1 -1 -1 -1 -1 -1 -1 -1 LAI-CNS 13 -1 -1 -1 -1 -1 -1 -1 -1 LAI-SNS 13 -1 -1 -1 -1 -1 -1 -1 -1
alt6	f.var all free except plus group	Slot "f.vars": age fleet 0 1 2 3 4 5 6 7 8 catch unique 0 0 1 1 1 1 2 2 2 HERAS -1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q1 -1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS0 -1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q3 -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-ORSH -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-BUN -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-CNS -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-SNS -1 -1 -1 -1 -1 -1 -1 -1 -1	Slot "f.vars": age fleet 0 1 2 3 4 5 6 7 8 catch unique 0 1 2 3 4 5 6 7 7 HERAS -1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q1 -1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS0 -1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q3 -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-ORSH -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-BUN -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-CNS -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-SNS -1 -1 -1 -1 -1 -1 -1 -1 -1
alt7	f.var binding 0-1, 4-5, 6-8	Slot "f.vars": age fleet 0 1 2 3 4 5 6 7 8 catch unique 0 0 1 1 1 1 2 2 2 HERAS -1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q1 -1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS0 -1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q3 -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-ORSH -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-BUN -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-CNS -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-SNS -1 -1 -1 -1 -1 -1 -1 -1 -1	Slot "f.vars": age fleet 0 1 2 3 4 5 6 7 8 catch unique 0 0 1 2 3 3 4 4 4 HERAS -1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q1 -1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS0 -1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q3 -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-ORSH -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-BUN -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-CNS -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-SNS -1 -1 -1 -1 -1 -1 -1 -1 -1

Run name	Description	WKPELA2018	Incremental change
alt8	q HERAS binding age 1-2	Slot "catchabilities": age fleet 0 1 2 3 4 5 6 7 8 catch unique -1 -1 -1 -1 -1 -1 -1 -1 -1 HERAS -1 1 2 3 3 3 3 3 3 IBTS-Q1 -1 4 -1 -1 -1 -1 -1 -1 -1 IBTS0 0 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q3 5 6 7 8 9 10 -1 -1 -1 LAI-ORSH 11 -1 -1 -1 -1 -1 -1 -1 -1 LAI-BUN 11 -1 -1 -1 -1 -1 -1 -1 -1 LAI-CNS 11 -1 -1 -1 -1 -1 -1 -1 -1 LAI-SNS 11 -1 -1 -1 -1 -1 -1 -1 -1	Slot "catchabilities": age fleet 0 1 2 3 4 5 6 7 8 catch unique -1 -1 -1 -1 -1 -1 -1 -1 -1 HERAS -1 1 1 2 2 2 2 2 2 IBTS-Q1 -1 3 -1 -1 -1 -1 -1 -1 -1 IBTS0 0 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q3 4 5 6 7 8 9 -1 -1 -1 LAI-ORSH 10 -1 -1 -1 -1 -1 -1 -1 -1 LAI-BUN 10 -1 -1 -1 -1 -1 -1 -1 -1 LAI-CNS 10 -1 -1 -1 -1 -1 -1 -1 -1 LAI-SNS 10 -1 -1 -1 -1 -1 -1 -1 -1
alt9	obs.var catches binding 0-1, 2-6,7-8	Slot "obs.vars": age fleet 0 1 2 3 4 5 6 7 8 catch unique 0 0 1 1 1 1 2 2 2 HERAS -1 3 4 4 4 4 4 5 5 IBTS-Q1 -1 6 -1 -1 -1 -1 -1 -1 -1 IBTS0 7 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q3 8 9 10 10 10 10 -1 -1 -1 LAI-ORSH 11 -1 -1 -1 -1 -1 -1 -1 -1 LAI-BUN 11 -1 -1 -1 -1 -1 -1 -1 -1 LAI-CNS 11 -1 -1 -1 -1 -1 -1 -1 -1 LAI-SNS 11 -1 -1 -1 -1 -1 -1 -1 -1	Slot "obs.vars": age fleet 0 1 2 3 4 5 6 7 8 catch unique 0 0 1 1 1 1 1 2 2 HERAS -1 3 4 4 4 4 4 5 5 IBTS-Q1 -1 6 -1 -1 -1 -1 -1 -1 -1 IBTS0 7 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q3 8 9 10 10 10 10 -1 -1 -1 LAI-ORSH 11 -1 -1 -1 -1 -1 -1 -1 -1 LAI-BUN 11 -1 -1 -1 -1 -1 -1 -1 -1 LAI-CNS 11 -1 -1 -1 -1 -1 -1 -1 -1 LAI-SNS 11 -1 -1 -1 -1 -1 -1 -1 -1
final	alt9+alt8+alt5 + alt4		
final2	alt9+alt8+alt5		

Table 5.2. Differences in model parameter bindings (catchabilities, variance in F random walk process, observation variance) between the final model issued by WKPELA2018 and the interim model used to derive the M profiling of the assessment.

	Catchabilities	f.var	Obs.var
WKPELA2018 final model	age fleet 0 1 2 3 4 5 6 7 8 catch unique -1 -1 -1 -1 -1 -1 -1 -1 -1 HERAS -1 1 1 2 2 2 2 2 2 IBTS-Q1 -1 3 -1 -1 -1 -1 -1 -1 -1 IBTS0 0 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q3 4 5 5 5 6 7 -1 -1 -1 LAI-ORSH 8 -1 -1 -1 -1 -1 -1 -1 -1 LAI-BUN 8 -1 -1 -1 -1 -1 -1 -1 -1 LAI-CNS 8 -1 -1 -1 -1 -1 -1 -1 -1 LAI-SNS 8 -1 -1 -1 -1 -1 -1 -1 -1	age fleet 0 1 2 3 4 5 6 7 8 catch unique 0 0 1 1 1 1 2 2 2 HERAS -1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q1 -1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS0 -1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q3 -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-ORSH -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-BUN -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-CNS -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-SNS -1 -1 -1 -1 -1 -1 -1 -1 -1	age fleet 0 1 2 3 4 5 6 7 8 catch unique 0 0 1 1 1 1 1 2 2 HERAS -1 3 4 5 6 6 6 7 7 IBTS-Q1 -1 8 -1 -1 -1 -1 -1 -1 -1 IBTS0 9 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q3 10 11 12 12 12 12 -1 -1 -1 LAI-ORSH 13 -1 -1 -1 -1 -1 -1 -1 -1 LAI-BUN 13 -1 -1 -1 -1 -1 -1 -1 -1 LAI-CNS 13 -1 -1 -1 -1 -1 -1 -1 -1 LAI-SNS 13 -1 -1 -1 -1 -1 -1 -1 -1

<table>
<tr><th></th><th>Catchabilities</th><th>f.var</th><th>Obs.var</th></tr>
<tr><td>WKPELA2018 ‘interim’ profiling model</td><td><pre>
                age
fleet   0 1 2 3 4 5 6 7 8
  catch unique -1 -1 -1 -1 -1 -1 -1 -1 -1
  HERAS   -1 -1 2 3 3 4 4 4 4
  IBTS-Q1   -1 0 -1 -1 -1 -1 -1 -1 -1
  IBTS0   1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3   5 6 6 7 7 -1 -1 -1 -1
  LAI-ORSH   8 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS   8 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN   8 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS   8 -1 -1 -1 -1 -1 -1 -1 -1
</pre></td><td><pre>
                age
fleet   0 1 2 3 4 5 6 7 8
  catch unique 0 0 1 1 1 1 2 2 2
  HERAS   -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q1   -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS0   -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3   -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-ORSH   -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS   -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN   -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS   -1 -1 -1 -1 -1 -1 -1 -1 -1
</pre></td><td><pre>
                age
fleet   0 1 2 3 4 5 6 7 8
  catch unique 0 0 0 0 1 1 1 1 1
  HERAS   -1 -1 2 2 3 3 3 4 4
  IBTS-Q1   -1 8 -1 -1 -1 -1 -1 -1 -1
  IBTS0   10 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3   5 6 6 7 7 -1 -1 -1 -1
  LAI-ORSH   9 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS   9 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN   9 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS   9 -1 -1 -1 -1 -1 -1 -1 -1
</pre></td></tr>
<tr><td>IBPNSherring2021 final model</td><td><pre>
                age
fleet   0 1 2 3 4 5 6 7 8
  catch unique -1 -1 -1 -1 -1 -1 -1 -1 -1
  HERAS   -1 1 1 2 2 2 2 2 2
  IBTS-Q1   -1 3 -1 -1 -1 -1 -1 -1 -1
  IBTS0   0 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3   4 5 6 7 8 9 -1 -1 -1
  LAI-ORSH   10 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN   10 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS   10 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS   10 -1 -1 -1 -1 -1 -1 -1 -1
</pre></td><td><pre>
                age
fleet   0 1 2 3 4 5 6 7 8
  catch unique 0 0 1 1 1 1 2 2 2
  HERAS   -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q1   -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS0   -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3   -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-ORSH   -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN   -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS   -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS   -1 -1 -1 -1 -1 -1 -1 -1 -1
</pre></td><td><pre>
                age
fleet   0 1 2 3 4 5 6 7 8
  catch unique 0 0 1 1 1 1 1 2 2
  HERAS   -1 3 4 5 6 6 6 7 7
  IBTS-Q1   -1 8 -1 -1 -1 -1 -1 -1 -1
  IBTS0   9 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3   10 10 11 11 11 11 -1 -1 -1
  LAI-ORSH   12 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN   12 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS   12 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS   12 -1 -1 -1 -1 -1 -1 -1 -1
</pre></td></tr>
</table>

6 Estimation of reference points

6.1 Background to previous reference points

North Sea herring benefits from a long time-series, including information at low recruitment/SSB (Figure 6.2). However, a shift in productivity has been observed in the last 20 years. The most likely year at which this regime shift occurred in 2002 (HAWG, 2020). This change in regime shift is extremely influential and was accounted for at WKPELA 2018 which followed approach was used:

- Use of the full time-series (1947-onward) for the derivation of limit reference points
- Use of a short time-series (2002-onward) for the derivation of MSY reference points. This period tentatively corresponds to a low productivity regime of the stock experienced in recent years.

6.2 Sensitivity analysis

Using the final model (Section 5), a sensitivity analysis on the reference point calculations was performed. This analysis included: 1) the testing a mix of model types, 2) a range of values for FCV (assessment error) and FPhi (autocorrelation) and 3) a range of start years for the derivation of MSY reference points. In detail results are given in a series of working documents (WD04–08). However, several conclusions emerged:

- The influence of FPhi and FCV is somewhat limited. These values are derived from the historical assessment retrospective. The default values are used: FCV=0.16 and FPhi=0.47.
- The start year is expectedly very influential for the estimation of MSY reference points. However, this aspect should be based on information from the literature rather than mechanistic testing. Since WKPELA 2018 , there is no new information from the literature available and the 2002-onward period was retained as most likely period exemplifying a regime shift in productivity. It is often recommended to account for productivity regime shifts mechanistically instead of discarding data points. However, in the case of NSAS, there is no mechanisms that has clearly been identified and implementable.
- During WKPELA 2018 , a model mix was used for the derivation of MSY reference points: 85% Ricker and 15% segmented regression. However, with the use of the 2002-onward period, all the recruitment/SSB pairs are located at SSB levels larger than the peak of the Ricker curve. This aspect was overlooked at WKPELA 2018 . The application of the mixed model approach now yields a mix of 95% Ricker/5% segmented regression (Figure 6.1). This mix is largely biased toward the Ricker model because of the lack of data points at low SSB/recruitment (for the 2002-onward time-series). Consequently, only a segmented regression model is used for the derivation of MSY refence points.

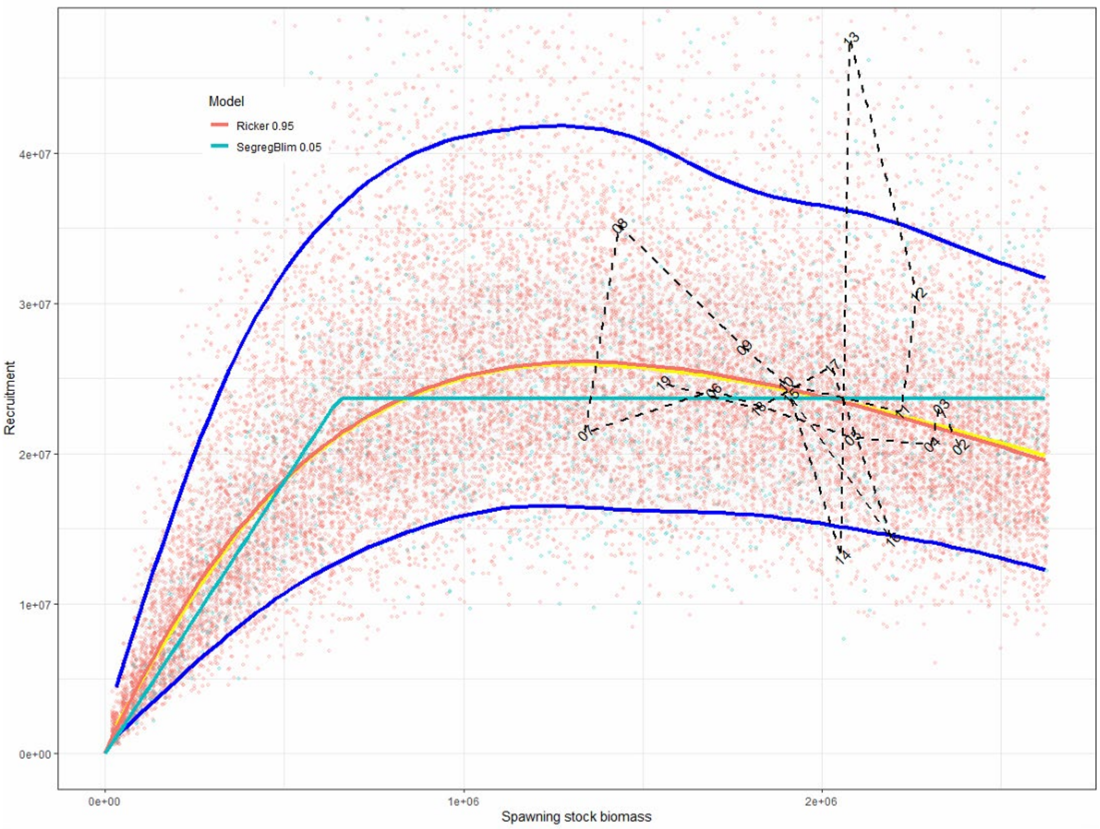


Figure 6.1. Simulated stock and recruitment curves using both Ricker and SegregBlim models, applied to the data of WKNSHERRING 2021.

6.3 B_{lim} and PA reference points

For the derivation of the limit reference points, the use of the full extent of the time-series leads to very low B_{lim} estimates. This is induced by the post-collapse recovery period which has recruitment/SSB pairs in this period are at a high steepness (Figure 6.2(b)). For NSAS, it has been shown that the productivity regime differs depending on whether the stock is increasing or decreasing (Nash *et al.*, 2009). Moreover, the stock dynamics during the post-collapse is clearly different from for the rest of the time-series. The rationale for this choice was that the presence of very severe density-dependence at the current stock size could not be justified on the current knowledge of the ecology and population dynamics of the NSAS herring population. This motivates the exclusion of this period for the derivation of limit reference points. The approach is as follows:

- B_{lim} is estimated with the exclusion of the post-collapse recovery period.
- B_{pa} is estimated from B_{lim} (min s.d. is 0.2)

An important aspect is the extent of the exclusion period that is used and testing over the 1979–2001 period was performed. For all the sensitivity test, 1979 is used as the start year of the exclusion period and the end year is: 1986, 1990, 1994, 1998 or 2002. Resulting B_{lim} and B_{pa} values are as follows:

Firstyear	lastyear	Blim	Bpa
1979	1986	877120	959680
1979	1990	874198	956483
1979	1994	877190	959756
1979	1998	866158	947686
1979	2002	839284	918282

The exclusion of years between 1998 and 2002 lead to the largest changes in B_{lim}, though somewhat limited. However, the choice of excluding the full extent of the 1979–2001 period is not well substantiated. following stock dynamics the end of the post-collapse recovery period can tentatively be set at 1990 (Figure 6.2). The resulting stock recruitment relationship is shown in Figure 6.3(a).

6.4 MSY reference points

When estimating MSY reference points, it is paramount to take into account the recent regime shift in productivity. In that context, the 2002-onward time-series is used solely with the segmented regression model. However, drawing from information from the limit reference points, the inflexion point of the segmented regression is defined as B_{lim}. MSY reference points are then estimated using the 2002-onward period (corresponding to the new low productivity regime) but using stock recovery information from full time-series but without the exclusion period. The stock recruitment relationship is shown in Figure 6.3(b) and diagnostic plots are given in Figure 6.4. The code used to calculate reference points is on the TAF Github:

https://github.com/ices-taf/2021_her.27.3a47d_IBP_assessment/blob/main/refpoints.r

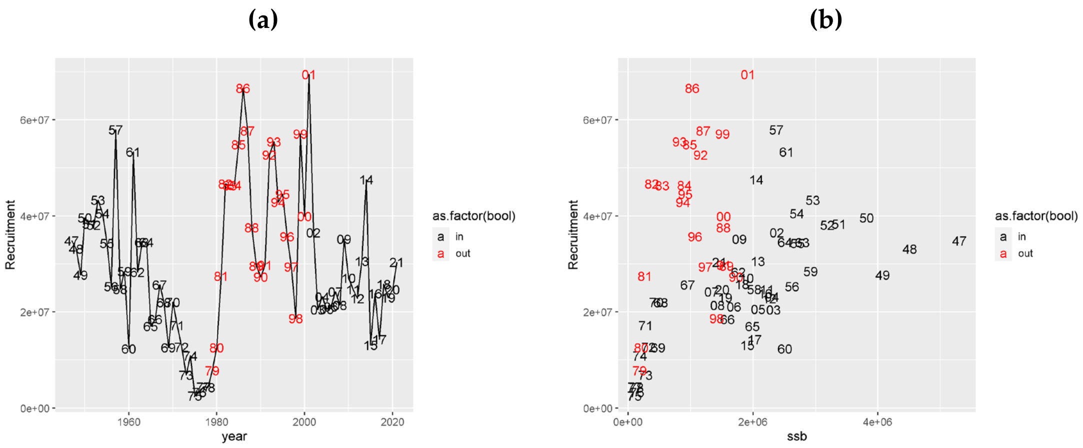


Figure 6.2. SRR for NSAS herring. (a) recruitment time-series as estimated by the SAM model. (b) NSAS recruitment vs. SSB for the full time-series (SAM model estimations). The makers in red are those that are considered being kept out for the computation of reference points.

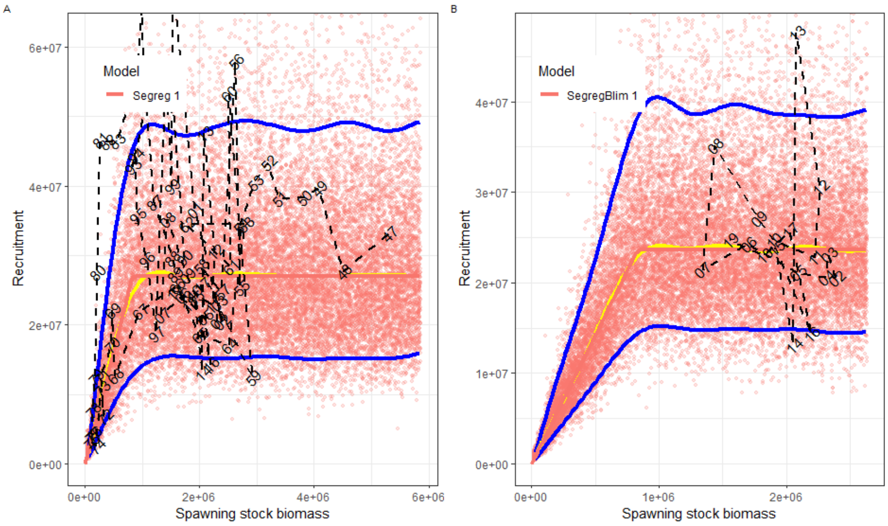


Figure 6.3. SRR relationships: A) Breakpoint analysis for B_{lim}, B) segmented regression through B_{lim} on short time-series

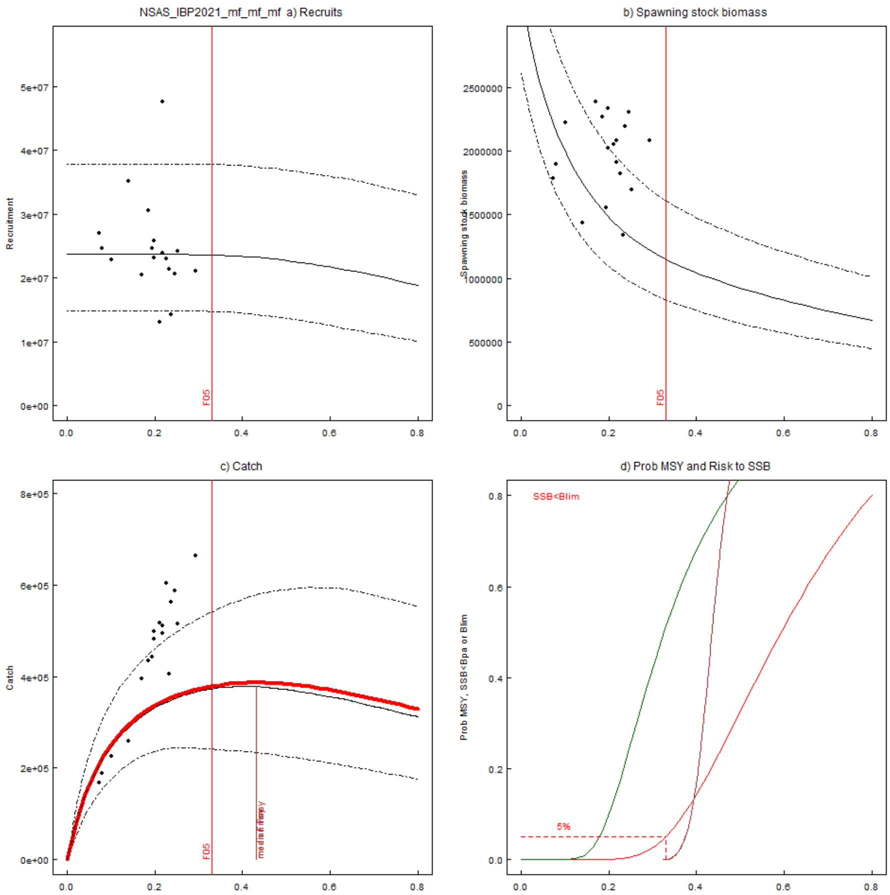


Figure 6.4. MSY reference points diagnostics.

6.5 Final reference points

Framework ^	Reference point	Old Value	Old Technical basis	Old Source	New value	New basis
MSY approach	MSY $B_{trigger}$	1 400 000	5th percentile of B_{FMSY}	ICES (2018b)	1 232 828	unchanged
	F_{MSY}	0.26	Stochastic simulations with a segmented regression and Ricker stock–recruitment curve from the short time-series (2002–2016).	ICES (2018b)	0.31	Same rationale with extended time series (2002–2020)
Precautionary approach	B_{lim}	800 000	Breakpoint in the segmented regression of the stock–recruitment time-series (1947–2016).	ICES (2018b)	874 198	Breakpoint in the segmented regression of the stock–recruitment time-series (1947–2020, excluding the recovery period 1979-1990).
	B_{pa}	900 000	$B_{pa} = B_{lim} \times \exp(1.645 \times \sigma)$ with $\sigma \approx 0.10$, based on the average *CV* from the terminal assessment year.	ICES (2018b)	956 483	$B_{pa} = B_{lim} \times \exp(1.645 \times \sigma)$ with $\sigma \approx 0.06$, based on the σ from the terminal assessment year.
	F_{lim}	0.34	$F_{P50\%}$ leading to 50% probability of SSB > B_{lim} with a segmented regression and Ricker stock–recruitment curve (2002–2016).	ICES (2018b)	0.39	The F that on average leads to Blim
	F_{pa}	0.30	$F_{pa} = F_{lim} \times \exp(-1.645 \times \sigma)$ with $\sigma \approx 0.08$, based on the average *CV* from the terminal assessment year.	ICES (2018b)	0.31	The F that provides a 95% probability for SSB to be above Blim (FP05 with AR)

6.6 Summary and reflection on changes in reference points

B_{lim}

- Due to the collapses of the NSAS herring stock there is reasonable understanding of when recruitment impairment may become visible.
- It's been shown that the recovery of the stock is different from a decline of the stock in terms of SSB – R relationship
- As such, estimating B_{lim} from the full time-series but excluding the period in which the stock recovered quickly from the collapse is considered appropriate.
- The new estimate indicates B_{lim} to be higher compared to previous calculations, in line with the assumption of a lower steepness of the SR curve by dropping the years of rapid recovery

B_{pa}

- The assessment is blessed with many high-quality data sources, including appropriate and full coverage sampling of the catch and 4 additional surveys that cover all life-stages of NSAS.
- As such, it is to be expected that the assessment has high precision on estimating stock trends.
- Estimated value of B_{pa} has approximately the same buffer to B_{lim} as in the previous estimation of reference points and is hence scaled upwards from the previous estimation

F_{msy}

- Sustainable exploitation in the short to medium term should be informed by information from recent productivity and selectivity expectations. As such, trimming down the time-series to only the past 2 decades is justified.
- The only realistic option to fit an SR curve through these points was either a segmented regression through B_{lim}, assuming same recruitment independent of stock size above B_{lim} or a Ricker curve (Beverton and Holt didn't fit).
- The Ricker curve showed very strong density-dependence for which no scientific evidence has ever been presented for this herring stock. As such, it was considered inappropriate.
- Using a segmented regression fit to estimate Fmsy does result in a rather flat theoretical catch-curve.
- In eqSim, the selection patterns is sampled from the last 10 years. For NSAS, the selection patterns have changed. In the 2010s, the selectivity of ages 2–4 was high. Since this period, the selection pattern on these ages have reduced. This is exemplified by the change of selectivity curve from dome shaped to continuous increase (see figure below). The effect of this change over time can be quantified: under the IBP settings but up to 2017 (WPKELA, 2018), FMSY would come out as 0.28. The effect of added data points since 2017 is then an increase of 0.03 in FMSY.
- As such, the numerical value of Fbar is being less influenced by younger ages as selectivity pattern for these ages have decreased.

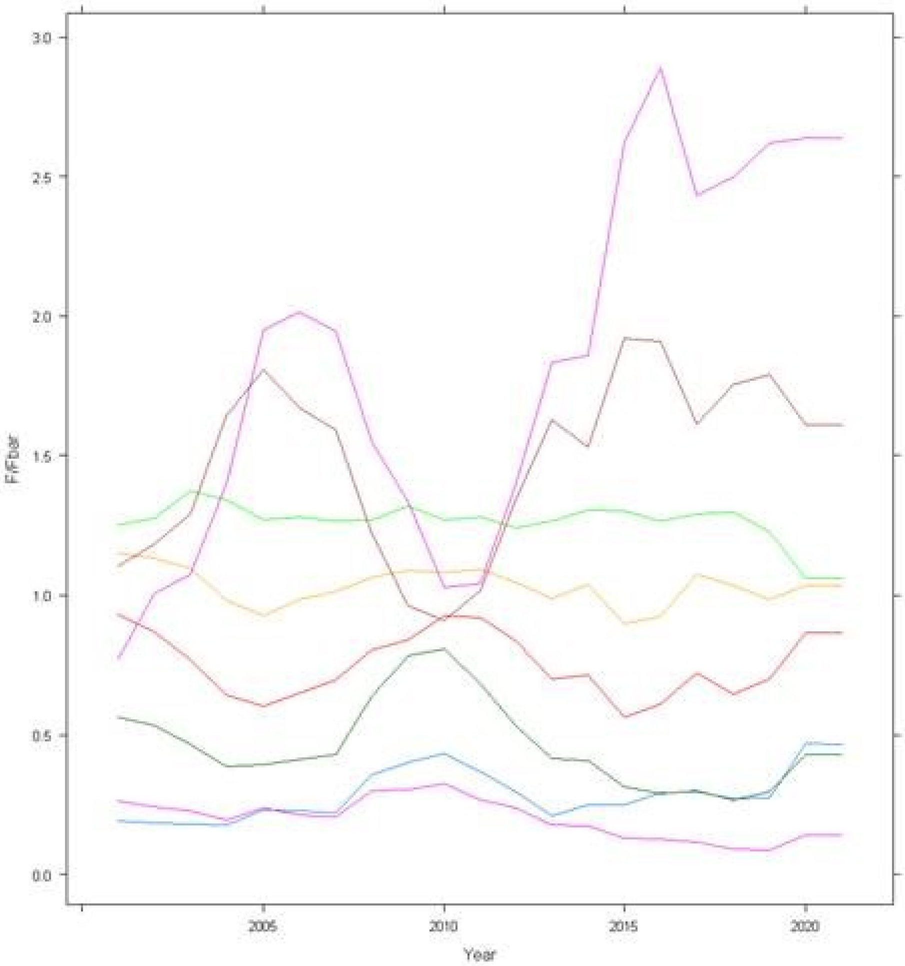


Figure 6.5. Selection pattern of the NSAS fishery at age. Top lines represent oldest ages, bottom lines represent youngest ages.

- This practically means that although it looks like F_{msy} has increased by a lot, it is to a large degree a matter of change in selection pattern than an increase in F being proposed.
- In summary, the drivers for the change in F_{MSY} compared to values derived at WKPELA2018 are two folds:
  - Change in model settings
  - Historic changes, especially due to changing selection patterns relative to the 2010’s

MSY $B_{trigger}$

- The 5th percentile B_{MSY} is less than B_{pa} and according to ICES guidelines B_{pa} should be used as the biomass trigger (ICES, 2021). However, for this stock Bpa and Blim are close due to the low assessment uncertainty which is not idea for a biomass trigger point. In line with the approach at WKPELA2018 the 50th percentile of B_{MSY} is taken as the estimate for MSY $B_{trigger}$. In the past the basis was mis-specified in the WKPELA report and subsequent advice sheet. This basis for this value may need to be updated after ICES workshops on reference points WKREF later in 2021.

7 External reviewers report

The external reviewers participated in the workshop covering detailed issues related to the North Sea Herring Inter-Benchmark process (IBP). They agreed with the technical approach taken to resolve the issues and found that the conclusions and decisions made result in a suitable approach for providing management advice to ICES on this stock. The determination of reference points was done after the IBP meetings partly by correspondence and was less conclusive in terms of results and process. Observations from the external reviewers on this particular issue can be found below.

7.1 Profiling method to inform on the absolute level of M

The reason an IBP was required was due to an error made during the last benchmark. The accepted approach of likelihood profiling over alternative M additive scalars was done but with an assessment model configuration that differed from that agreed for the final benchmark assessment. Specifically, the correlation structure for F was turned off and this differed from the agreed approach. During the IBP, these differences in configuration were illustrated along with their impact on model results.

During the IBP we reviewed the application of variable natural mortalities as estimated by the multi species assessment model SMS. In general, this manner of accounting for time variant processes due to foodwebs resulted in improved fits. These improvements apparently arise from adding information on the abundance and consumption of key predators. This alleviates some concern that the SMS model uses almost the same input information (for NS Herring) as used in the assessment. On balance, the relative impact on assessment uncertainty is difficult to know (both parameter and structural). We also noted that there were changes in the absolute level of M between SMS keyruns over the years. Although the changes in the level of M can be explained by updates in the model configuration (e.g. changes in consumption rates, changes from single species benchmarks that are carried over into SMS, addition of predators), it shows that the absolute level of M is uncertain and influenced by several parameters and processes simulated in SMS. In addition, an assumption has to be made on the residual mortality (M1, mortality caused by other processes than predation). The assumption on M1 is a qualified guess only. In contrast to the absolute level of M, the relative changes over time were stable between SMS keyruns.

There are plausible arguments for using the time variant natural mortalities from SMS which we support. Additionally, a profiling method from the last herring benchmark adding an extra *M* component ("addM") as an extra parameter (M=M(SMS)+addM) seems reasonable. This provides a way to get further information on the level of M and compare that with the single species input data and the herring assessment in general.

The profiling method itself was scrutinized with the help of several sensitivity runs. It turned out that the method is able to buffer against jumps in the outcomes of SMS keyruns. The results are reasonable and led to final M values that appear to be within the uncertainty margins that need to be assumed for SMS output especially if also structural uncertainties are taken into account (and the qualified guess on M1). However, we note that the profiling approach and results depend on other model settings (e.g. correlation in F or binding of certain parameters). We also note a retrospective pattern in the outcomes of the profiling. This pattern was low in absolute terms, but can be quite high when expressed relative to the original value of addM. Overall, we consider the externally derived M values to be appropriate to use in the North Sea herring single species stock assessment.

The profiles were sensitive to time-series length. In particular, results were affected if the period of the fishery closure was included or not. When excluded, e.g, if 1984 was set as the model's first year, the retrospective pattern from profiles were more stable. Including a correlation structure in F among ages also tended to reduce the sensitivity of profiling over alternative addM values. Importantly, including the correlation in F among ages (corF) configuration improved the stability in the estimation of the HERAS' catchability coefficient. Therefore, the analysts are justified in including the correlation structure in F among ages.

7.2 IBP assessment configuration

Including the correlation structure in F among ages had a minor impact on the overall assessment results, especially for recent years. The main impact was in the CV around the catch estimates for ages 0 and 1. The CV increased especially around the years when the fishery was closed. This can be expected given the rapid changes and bad quality of catch information during this period. Also, the CV around recruitment estimates increases in the run with correlation in F turned on. Overall, the AIC is better if the correlation in F option was selected compared to when it was not. We therefore accept it as a plausible alternative for use.

The IBP assessment model tested this configuration, to re-evaluate the profiles of the addM parameter. The profiling result (addM= 0.06) was found to be consistent and the diagnostics from the final IBP assessment show no major issues based on residual patterns and Mohn's Rho. Given the limited ability the review Team had in using only a virtual format for meeting and discussing results, the Team concluded that the model as configured at the end of the IBP was acceptable for use as a basis for advice.

7.3 Observations from the external reviewers regarding the determination of reference points

During the IBP several options were tested to derive reference points based on the ICES guidelines. Also, sensitivity runs were carried out with Eqsim to understand the influence of different settings (e.g. F_{cv} and F_{phi}). Subsequently there were meetings and a lengthy e-mail thread about the calculations and recommended approach. Based on these activities, the IBP external reviewers made the following observations.

7.3.1 Assumption on productivity and the stock-recruit relationship

The experts concluded that the NSAS stock is currently in a low productivity regime and therefore F_{MSY} is calculated based on the SSB – recruitment estimates from 2002 onwards. Given that all the recruitment/SSB estimates after 2002 are located at SSB levels on the right a Ricker curve and there is not much evidence of strong density-dependence at the current SSB levels, it was decided to use a segmented regression only for the estimation of F_{MSY} and other *F* based reference points. The external reviewers agree with this decision.

7.3.2 Issues related to B_{lim}, B_{pa} and MSY $B_{trigger}$ estimation

The NSAS stock assessment covers a long period and includes a time of stock collapse near the end of the 1970s. Experts argued that including the full period (and the collapse) is beneficial and can inform the point where recruitment gets impaired (i.e. B_{lim}). The experts also argued that the stock dynamics before the collapse and during the recovery period were different. Consequently, an argument to use the full period and exclude the recovery period (1979 – 1990) to estimate a

B_{lim} was made. While the argument has some logic, the reviewers considered that expecting future behaviour to be similar to conditions that occurred in the 1970s may be a strong assumption. The ecosystem of the North Sea changed considerably during these last decades. There was a pronounced regime shift at the end of the 1980s and a smaller one apparent around 1998. Furthermore, effects of climate change likely impact the stock negatively given that herring are a boreal species and those in the North Sea are at their southern distribution edge. Unsurprisingly, the reviewers found that data on stock responses over a range of SSB and environmental conditions would be needed to accurately judge the SSB level where recruitment would likely be impaired. This hampers the ability to provide a robust estimate of B_{lim}, in our view.

As presented during the meetings, the estimation of B_{pa} from B_{lim} involved using the terminal SSB error term (sigma$_{SSB}$) estimated by the assessment model. This value is very low (0.06) and this affects the B_{pa} estimate as it would be close to B_{lim} and thus unlikely to respond in a timely way to management actions before declining B_{lim}. While the text and e-mail thread makes special note of the high-quality data available for this stock, from a management perspective an alternative might be considered. For example, the WGNSSK has specified a minimum sigma SSB of 0.2 to add a larger buffer between B_{pa} and B_{lim}.

We note that the SSB at MSY $B_{trigger}$ is the reference point where fishing mortality starts to get reduced below F_{MSY} in the current ICES reference point system. This is a separate consideration from the buffer between B_{pa} and B_{lim}). Examining the practice of estimating MSY $B_{trigger}$ from WKPELA 2018 (as repeated during this IBP) we noted that the estimate was slightly above 1.23 million tonnes. As this is considerably higher than B_{lim}, downward adjustments to F_{MSY} are invoked and should allow time for management actions to reduce the chance of further declines and hence, avoid encountering SSB near B_{pa} (and B_{lim}).

Unfortunately, in comparing the script and output for estimating MSY $B_{trigger}$ we noted an inconsistency with the specifications in the guidelines for reference point calculations. The guidelines state that MSY $B_{trigger}$ = max(Bpa, $SSB_{5\%ile}$) where $SSB_{5\%ile}$ is the 5th percentile of simulated SSB when fishing at F_{MSY}, with F_{cv} and F_{phi} set to zero). The report noted 1.23 million tonnes but our findings indicate that this corresponds to the median equilibrium SSB when fishing at Fp05= F_{MSY}. As noted, this was a carryover from the work done in WKPELA 2018 . The 5th percentile of the simulated distribution appears to be considerably lower than the median and close B_{lim}. As such, the MSY $B_{trigger}$ would become B_{pa} according to the guidelines. [However, if sigma$_{SSB}$ is increased to a minimum of 0.2the difference to the IBP MSY $B_{trigger}$ may be less extreme]

As reviewers, we could not weigh in on the impact of deviating from the guidelines and suggest that this would be up to ACOM to decide. The same approach has already been used in WKPELA 2018 and we understand that there may be revisions to the guidelines soon. At the IBP estimated MSY $B_{trigger}$ value, we note that it is more precautionary than the value arising from the 5th percentile of the simulations. As noted above, should MSY $B_{trigger}$ be re-estimated following the guidelines, then the discussion around B_{pa} and a minimum sigma (0.2, see above) becomes important. Regardless of the final decision, the external reviewers note that a clear description of the technical basis for MSY $B_{trigger}$ is needed along with a rationale.

7.3.3 Estimation of F_{MSY}

A range of three options to estimate F_{MSY} in the IBP working document based on a segmented regression for the stock-recruit relationship was presented. Two of them resulted in an F_{MSY} greater than 0.3 as determined by Fp05 as precautionary lower limit. The third option, in which the only data used were from the recent period, estimated a breakpoint that effectively gave a low slope at the origin and hence reflected low productivity (F_{MSY}=0.18).

The F_{MSY} values in excess 0.3 are higher than what has been estimated during WKPELA 2018 three years ago. The exact reason is unclear (but in e-mail exchanges and meetings, it was suggested that the more recent selection pattern resulted in a shift towards older fish which can change the value of F_{MSY} on its own. In terms of process, we are unclear whether these assertions can be considered as contributions to the IBP. Scientifically, it seems like a sensible explanation and could also be more closely linked to where the breakpoint is specified/estimated for the different stock-recruit relationships that were examined (i.e. between the WKPELA 2018 and the IBP). Another concern (but consistent with the recent low recruitment estimates) was the fact that the recent fishing mortalities were much lower than 0.3 but the stock continued to decline.

The higher estimate of F_{MSY} leads to a relatively high probability that the stock will fall below the IBP estimated MSY $B_{trigger}$ and therefore it is likely that the stock needs to be managed on the slope of the ICES harvest control rule under the agreed combination of F_{MSY} and MSY $B_{trigger}$.

If a stock has a high probability to fall below MSY $B_{trigger}$, effects from time-lags until a management decision can be reached and uncertainties in assessments and forecasts become more critical. This also affects the estimated probability of the stock declining to below B_{lim}. Eqsim results were shown in a full MSE (in 2019) to exceed precautionary levels (ICES WKNSMSE 2019) and that as time permits, updating an MSE (including further tests of Eqsim settings) with the alternative productivity scenarios (like the three options presented in the working paper on reference points) would be worthwhile. This may help guide the next benchmark process for this stock and obviate the need to consider alternative applications of Eqsim settings.

In the absence of more data (see also observations on B_{lim}), a more precautionary alternative given the current low productivity period would be to assume that recruitment below the lowest SSB observed during this period (B_{loss}) would be impaired (like option 3 in the working document on reference points). Alternatively, following the guidance of the existing notions (e.g. that B_{MSY} is in the range of 1.2–1.3 million t) could be applied recognizing that future data and guidance would be forthcoming in the next few years.

8 References

ICES. 2014. Interim Report of the Working Group on Multispecies Assessment Methods (WGSAM), 20–24 October 2014, London, UK. ICES CM 2014/SSGSUE:11. 104 pp.

ICES. 2016. Report of the Working Group on Multispecies Assessment Methods (WGSAM), 9–13 November 2016, Woods Hole, USA. ICES CM 2016/SSGEPI:20. 206 pp.

ICES. 2018. Report of the Benchmark Workshop on Pelagic Stocks (WKPELA 2018), 12–16 February 2018, ICES HQ, Copenhagen, Denmark. ICES CM 2018/ACOM:32. 313 pp.

ICES. 2019. EU and Norway request concerning the long-term management strategy of cod, saithe, and whiting, and of North Sea autumn-spawning herring. In Report of the ICES Advisory Committee, 2019. ICES Advice 2019, sr.2019.06, https://doi.org/10.17895/ices.advice.4895.

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

ICES. 2021. Working Group on Multispecies Assessment Methods (WGSAM; outputs from 2020 meeting). ICES Scientific Reports. 3:10. 231 pp. https://doi.org/10.17895/ices.pub.7695.

ICES. 2021. ICES fisheries management reference points for category 1 and 2 stocks.

Technical Guidelines. In Report of the ICES Advisory Committee, 2021. ICES Advice 2021, Section 16.4.3.1. https://doi.org/10.17895/ices.advice.7891.

Nash, R.D.M, Dickey-Collas, M., Kell, L.T. 2009. Stock and recruitment in North Sea herring (*Clupea harengus*); compensation and depensation in the population dynamics. Fisheries Research 95(1). 88–97.

Nielsen A. and C. Berg. Estimation of time-varying selectivity in stock assessments using state-space models Fish. Res., 158 (2014), pp. 96–101, 10.1016/j.fishres.2014.01.014.

Nielsen A., Niels T Hintzen, Henrik Mosegaard, Vanessa Trijoulet, Casper W Berg, Multi-fleet state-space assessment model strengthens confidence in single-fleet SAM and provides fleet-specific forecast options, ICES Journal of Marine Science, 2021;, fsab078, https://doi.org/10.1093/icesjms/fsab078.

Annex 1: List of participants

Name	Institute	Country (of institute)	E-mail
Jonathan Ball	Cefas	UK	Jonathan.ball@cefas.co.uk
Valerio Bartolino	SLU	Sweden	valerio.bartolino@slu.se
Florian Berg	University of Bergen	Norway	florian.berg@hi.no
Benoit Berges	Wageningen Marine Research	Netherlands	benoit.berges@wur.nl
Neil Campbell	Marine Scotland Science	UK	neil.campbell@gov.scot
Cindy van Damme	Wageningen University and Research	Netherlands	cindy.vandamme@wur.nl
Afra Egan	Marine Institute	Ireland	afra.egan@marine.ie
Niels Hintzen	Wageningen University and Research	Netherlands	niels.hintzen@wur.nl
Kirsten Birch Håkansson	DTU-Aqua	Denmark	kih@aqua.dtu.dk
Jim Ianelli (invited expert)	NOAA	USA	Jim.ianelli@noaa.gov
Ciaran Kelly (chair)	Marine Institute	Ireland	ciaran.kelly@marine.ie
Alexander Kempf (invited expert)	Thünen Institute	Germany	Alexander.kempf@thuenen.de
Cecilie Kvamme	University of Bergen	Norway	cecilie.kvamme@hi.no
Steve Mackinson	Scottish Pelagic Fishermen's Association	UK	steve.mackinson@scottish-pelagic.co.uk
Henrik Mosegaard	DTU-Aqua	Denmark	hm@aqua.dtu.dk
Richard Nash	Cefas	UK	richard.nash@cefas.co.uk
Campbell Pert	Marine Laboratory	UK	campbell.pert@gov.scot
Norbert Rohlf	Thünen Institute	Germany	norbert.rohlf@thuenen.de
Martin Pastoors	Pelagic Freezer-Trawler Association	Netherlands	mpastoors@pelagicfish.eu
Claus Reedtz Sparrevohn	Danish Pelagic Producers' Organisation	Denmark	crs@pelagisk.dk
Vanessa Trijoulet	DTU-Aqua	Denmark	vtri@aqua.dtu.dk

Annex 2: Resolutions

The Inter-Benchmark Protocol on North Sea Herring, chaired by Ciaran Kelly (Ireland), and reviewed by Alexander Kempf (Germany) and Jim Ianelli (USA) will be established and will meet by correspondence from June 8–10 2021 to:

a) Investigate methods to bring consistency in the scaling of the assessment arising from updates in SMS:
    a. Evaluate optimal model configuration;
    b. Investigate the sensitivity of methods and assumptions about M on the assessment of NSAS herring. This includes investigating the assessment profiling method developed at WKPELA 2018.
b) Carry out the 2021 NSAS assessment based on the updated NSAS assessment model.
c) Update reference points based on the updated NSAS assessment model.

The IBP will report by 10 July for the attention of the ACOM.

Annex 3: Model configurations

A3.1 WKPELA 2018 assessment model configuration used for M profiling

```
An object of class "FLSAM.control"
Slot "name":
[1] "Final Assessment"

Slot "desc":
[1] "Imported from a VPA file. ( ./data/index.txt ).  Tue Feb 13 23:48:25 2018"

Slot "range":
   min     max plusgroup   minyear   maxyear   minfbar   maxfbar
     0       8         8      1947      2017         2         6

Slot "fleets":
catch unique    HERAS    IBTS-Q1    IBTS0    IBTS-Q3    LAI-ORSH    LAI-CNS    LAI-
BUN    LAI-SNS
           0        2          2        2          2           6          6          6          6

Slot "plus.group":
plusgroup
   TRUE

Slot "states":
          age
fleet          0  1  2  3  4  5  6  7  8
  catch unique  0  1  2  3  4  5  6  7  7
  HERAS        -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q1      -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS0        -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-ORSH     -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS      -1 -1 -1 -1 -1 -1 -1 -1 -1

Slot "logN.vars":
0 1 2 3 4 5 6 7 8
0 1 1 1 1 1 1 1 1

Slot "logP.vars":
[1] 0 1 2

Slot "catchabilities":
          age
fleet          0  1  2  3  4  5  6  7  8
  catch unique -1 -1 -1 -1 -1 -1 -1 -1 -1
  HERAS        -1 -1  2  3  3  4  4  4  4
  IBTS-Q1      -1  0 -1 -1 -1 -1 -1 -1 -1
```

```
  IBTS0        1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3      5  6  6  7  7 -1 -1 -1 -1
  LAI-ORSH     8 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS      8 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN      8 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS      8 -1 -1 -1 -1 -1 -1 -1 -1

Slot "power.law.exps":
              age
fleet          0  1  2  3  4  5  6  7  8
  catch unique -1 -1 -1 -1 -1 -1 -1 -1 -1
  HERAS       -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q1     -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS0       -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3     -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-ORSH    -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS     -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN     -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS     -1 -1 -1 -1 -1 -1 -1 -1 -1

Slot "f.vars":
              age
fleet          0  1  2  3  4  5  6  7  8
  catch unique  0  0  1  1  1  1  2  2  2
  HERAS       -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q1     -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS0       -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3     -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-ORSH    -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS     -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN     -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS     -1 -1 -1 -1 -1 -1 -1 -1 -1

Slot "obs.vars":
              age
fleet          0  1  2  3  4  5  6  7  8
  catch unique  0  0  0  0  1  1  1  1  1
  HERAS       -1 -1  2  2  3  3  3  4  4
  IBTS-Q1     -1  8 -1 -1 -1 -1 -1 -1 -1
  IBTS0       10 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3      5  6  6  7  7 -1 -1 -1 -1
  LAI-ORSH     9 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS      9 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN      9 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS      9 -1 -1 -1 -1 -1 -1 -1 -1

Slot "srr":
[1] 0

Slot "scaleNoYears":
[1] 0
```

```
Slot "scaleYears":
[1] NA

Slot "scalePars":
     age
years  0 1 2 3 4 5 6 7 8

Slot "cor.F":
[1] 2

Slot "cor.obs":
              age
fleet          0-1 1-2 2-3 3-4 4-5 5-6 6-7 7-8
  catch unique  NA  NA  NA  NA  NA  NA  NA  NA
  HERAS         -1  -1  NA  NA  NA  NA  NA  NA
  IBTS-Q1       -1  -1  -1  -1  -1  -1  -1  -1
  IBTS0         -1  -1  -1  -1  -1  -1  -1  -1
  IBTS-Q3        0   0   0   0  -1  -1  -1  -1
  LAI-ORSH      -1  -1  -1  -1  -1  -1  -1  -1
  LAI-CNS       -1  -1  -1  -1  -1  -1  -1  -1
  LAI-BUN       -1  -1  -1  -1  -1  -1  -1  -1
  LAI-SNS       -1  -1  -1  -1  -1  -1  -1  -1

Slot "cor.obs.Flag":
[1] ID ID ID ID AR ID ID ID ID
Levels: ID AR US

Slot "biomassTreat":
[1] -1 -1 -1 -1 -1 -1 -1 -1 -1

Slot "timeout":
[1] 3600

Slot "likFlag":
[1] LN LN LN LN LN LN LN LN LN
Levels: LN ALN

Slot "fixVarToWeight":
[1] FALSE

Slot "simulate":
[1] FALSE

Slot "residuals":
[1] FALSE

Slot "sumFleets":
logical(0)
```

A3.2 WKPELA 2018 final assessment model configuration

```
An object of class "FLSAM.control"
Slot "name":
[1] "North Sea Herring"

Slot "desc":
[1] "Imported from a VPA file. ( ./bootstrap/data/index.txt ).  Wed May 26 11:49:48 2021"

Slot "range":
     min       max plusgroup   minyear   maxyear   minfbar   maxfbar
       0         8         8      1947      2021         2         6

Slot "fleets":
catch unique       HERAS     IBTS-Q1       IBTS0     IBTS-Q3    LAI-ORSH     LAI-BUN     LAI-
CNS     LAI-SNS
           0           2           2           2           2           6           6           6           6

Slot "plus.group":
plusgroup
     TRUE

Slot "states":
              age
fleet          0  1  2  3  4  5  6  7  8
  catch unique  0  1  2  3  4  5  6  7  7
  HERAS        -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q1      -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS0        -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-ORSH     -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS      -1 -1 -1 -1 -1 -1 -1 -1 -1

Slot "logN.vars":
0 1 2 3 4 5 6 7 8
0 1 1 1 1 1 1 1 1

Slot "logP.vars":
[1] 0 1 2

Slot "catchabilities":
              age
fleet          0  1  2  3  4  5  6  7  8
  catch unique -1 -1 -1 -1 -1 -1 -1 -1 -1
  HERAS        -1  1  2  3  3  3  3  3  3
  IBTS-Q1      -1  4 -1 -1 -1 -1 -1 -1 -1
  IBTS0         0 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3       5  6  7  8  9 10 -1 -1 -1
  LAI-ORSH     11 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN      11 -1 -1 -1 -1 -1 -1 -1 -1
```

```
  LAI-CNS      11 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS      11 -1 -1 -1 -1 -1 -1 -1 -1

Slot "power.law.exps":
             age
fleet         0  1  2  3  4  5  6  7  8
  catch unique -1 -1 -1 -1 -1 -1 -1 -1 -1
  HERAS        -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q1      -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS0        -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-ORSH     -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS      -1 -1 -1 -1 -1 -1 -1 -1 -1

Slot "f.vars":
             age
fleet         0  1  2  3  4  5  6  7  8
  catch unique  0  0  1  1  1  1  2  2  2
  HERAS        -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q1      -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS0        -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-ORSH     -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS      -1 -1 -1 -1 -1 -1 -1 -1 -1

Slot "obs.vars":
             age
fleet         0  1  2  3  4  5  6  7  8
  catch unique  0  0  1  1  1  1  2  2  2
  HERAS        -1  3  4  4  4  4  4  5  5
  IBTS-Q1      -1  6 -1 -1 -1 -1 -1 -1 -1
  IBTS0         7 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3       8  9 10 10 10 10 -1 -1 -1
  LAI-ORSH     11 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN      11 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS      11 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS      11 -1 -1 -1 -1 -1 -1 -1 -1

Slot "srr":
[1] 0

Slot "scaleNoYears":
[1] 0

Slot "scaleYears":
[1] NA
```

```
Slot "scalePars":
     age
years  0 1 2 3 4 5 6 7 8

Slot "cor.F":
[1] 2

Slot "cor.obs":
             age
fleet         0-1 1-2 2-3 3-4 4-5 5-6 6-7 7-8
  catch unique  NA  NA  NA  NA  NA  NA  NA  NA
  HERAS         -1  NA  NA  NA  NA  NA  NA  NA
  IBTS-Q1       -1  -1  -1  -1  -1  -1  -1  -1
  IBTS0         -1  -1  -1  -1  -1  -1  -1  -1
  IBTS-Q3        0   0   0   0   0  -1  -1  -1
  LAI-ORSH      -1  -1  -1  -1  -1  -1  -1  -1
  LAI-BUN       -1  -1  -1  -1  -1  -1  -1  -1
  LAI-CNS       -1  -1  -1  -1  -1  -1  -1  -1
  LAI-SNS       -1  -1  -1  -1  -1  -1  -1  -1

Slot "cor.obs.Flag":
[1] ID ID ID ID AR ID ID ID ID
Levels: ID AR US

Slot "biomassTreat":
[1] -1 -1 -1 -1 -1 -1 -1 -1 -1

Slot "timeout":
[1] 3600

Slot "likFlag":
[1] LN LN LN LN LN LN LN LN LN
Levels: LN ALN

Slot "fixVarToWeight":
[1] FALSE

Slot "simulate":
[1] FALSE

Slot "residuals":
[1] FALSE

Slot "sumFleets":
logical(0)
```

A3.3 IBPNSHerring2021 final model configuration (single fleet)

```
An object of class "FLSAM.control"
Slot "name":
[1] "North Sea Herring"

Slot "desc":
[1] "Imported from a VPA file. ( ./bootstrap/data/index.txt ).  Wed May 26 11:49:48 2021"

Slot "range":
   min    max plusgroup   minyear   maxyear   minfbar   maxfbar
     0      8         8      1947      2021         2         6

Slot "fleets":
catch unique      HERAS     IBTS-Q1       IBTS0     IBTS-Q3    LAI-ORSH     LAI-BUN     LAI-
CNS     LAI-SNS
     0          2          2          2          2          6          6          6          6

Slot "plus.group":
plusgroup
   TRUE

Slot "states":
            age
fleet          0  1  2  3  4  5  6  7  8
  catch unique  0  1  2  3  4  5  6  7  7
  HERAS        -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q1      -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS0        -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-ORSH     -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS      -1 -1 -1 -1 -1 -1 -1 -1 -1

Slot "logN.vars":
0 1 2 3 4 5 6 7 8
0 1 1 1 1 1 1 1 1

Slot "logP.vars":
[1] 0 1 2

Slot "catchabilities":
            age
fleet          0  1  2  3  4  5  6  7  8
  catch unique -1 -1 -1 -1 -1 -1 -1 -1 -1
  HERAS        -1  1  1  2  2  2  2  2  2
  IBTS-Q1      -1  3 -1 -1 -1 -1 -1 -1 -1
  IBTS0         0 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3       4  5  6  7  8  9 -1 -1 -1
  LAI-ORSH     10 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN      10 -1 -1 -1 -1 -1 -1 -1 -1
```

```
  LAI-CNS      10 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS      10 -1 -1 -1 -1 -1 -1 -1 -1

Slot "power.law.exps":
             age
fleet          0  1  2  3  4  5  6  7  8
  catch unique -1 -1 -1 -1 -1 -1 -1 -1 -1
  HERAS        -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q1      -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS0        -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-ORSH     -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS      -1 -1 -1 -1 -1 -1 -1 -1 -1

Slot "f.vars":
             age
fleet          0  1  2  3  4  5  6  7  8
  catch unique  0  0  1  1  1  1  2  2  2
  HERAS        -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q1      -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS0        -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-ORSH     -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS      -1 -1 -1 -1 -1 -1 -1 -1 -1

Slot "obs.vars":
             age
fleet          0  1  2  3  4  5  6  7  8
  catch unique  0  0  1  1  1  1  1  2  2
  HERAS        -1  3  4  5  6  6  6  7  7
  IBTS-Q1      -1  8 -1 -1 -1 -1 -1 -1 -1
  IBTS0         9 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3      10 10 11 11 11 11 -1 -1 -1
  LAI-ORSH     12 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN      12 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS      12 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS      12 -1 -1 -1 -1 -1 -1 -1 -1

Slot "srr":
[1] 0

Slot "scaleNoYears":
[1] 0

Slot "scaleYears":
[1] NA
```

```
Slot "scalePars":
     age
years  0 1 2 3 4 5 6 7 8

Slot "cor.F":
[1] 2

Slot "cor.obs":
             age
fleet          0-1 1-2 2-3 3-4 4-5 5-6 6-7 7-8
  catch unique  NA  NA  NA  NA  NA  NA  NA  NA
  HERAS         -1  NA  NA  NA  NA  NA  NA  NA
  IBTS-Q1       -1  -1  -1  -1  -1  -1  -1  -1
  IBTS0         -1  -1  -1  -1  -1  -1  -1  -1
  IBTS-Q3        0   0   0   0   0  -1  -1  -1
  LAI-ORSH      -1  -1  -1  -1  -1  -1  -1  -1
  LAI-BUN       -1  -1  -1  -1  -1  -1  -1  -1
  LAI-CNS       -1  -1  -1  -1  -1  -1  -1  -1
  LAI-SNS       -1  -1  -1  -1  -1  -1  -1  -1

Slot "cor.obs.Flag":
[1] ID ID ID ID AR ID ID ID ID
Levels: ID AR US

Slot "biomassTreat":
[1] -1 -1 -1 -1 -1 -1 -1 -1 -1

Slot "timeout":
[1] 3600

Slot "likFlag":
[1] LN LN LN LN LN LN LN LN LN
Levels: LN ALN

Slot "fixVarToWeight":
[1] FALSE

Slot "simulate":
[1] FALSE

Slot "residuals":
[1] FALSE

Slot "sumFleets":
logical(0)
```

A3.4 IBPNSHerring2021 final model configuration (single fleet)

```
An object of class "FLSAM.control"
Slot "name":
[1] "North Sea herring multifleet"

Slot "desc":
[1] "Imported from a VPA file. ( ./bootstrap/data/index.txt ).  Wed Aug 25 12:28:03 2021"

Slot "range":
      min       max plusgroup    minyear    maxyear    minfbar    maxfbar
        0         8         8       1947       2021          2          6

Slot "fleets":
 catch A catch BD  catch C    HERAS  IBTS-Q1    IBTS0  IBTS-Q3 LAI-ORSH  LAI-BUN  LAI-CNS
LAI-SNS sumFleet
       0        0        0        2        2        2        2        6        6        6        6        7

Slot "plus.group":
plusgroup
     TRUE

Slot "states":
          age
fleet       0  1  2  3  4  5  6  7  8
  catch A  -1  0  1  2  3  4  5  6  6
  catch BD  7  8  9 10 10 10 -1 -1 -1
  catch C  -1 11 12 13 14 14 14 -1 -1
  HERAS    -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q1  -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS0    -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3  -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-ORSH -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN  -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS  -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS  -1 -1 -1 -1 -1 -1 -1 -1 -1
  sumFleet -1 -1 -1 -1 -1 -1 -1 -1 -1

Slot "logN.vars":
0 1 2 3 4 5 6 7 8
0 1 1 1 1 1 1 1 1

Slot "logP.vars":
[1] 0 1 2

Slot "catchabilities":
          age
fleet       0  1  2  3  4  5  6  7  8
  catch A  -1 -1 -1 -1 -1 -1 -1 -1 -1
  catch BD -1 -1 -1 -1 -1 -1 -1 -1 -1
  catch C  -1 -1 -1 -1 -1 -1 -1 -1 -1
  HERAS    -1  1  1  2  2  2  2  2  2
```

```
  IBTS-Q1  -1  3 -1 -1 -1 -1 -1 -1 -1
  IBTS0     0 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3   4  5  6  7  8  9 -1 -1 -1
  LAI-ORSH 10 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN  10 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS  10 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS  10 -1 -1 -1 -1 -1 -1 -1 -1
  sumFleet -1 -1 -1 -1 -1 -1 -1 -1 -1

Slot "power.law.exps":
          age
fleet       0  1  2  3  4  5  6  7  8
  catch A  -1 -1 -1 -1 -1 -1 -1 -1 -1
  catch BD -1 -1 -1 -1 -1 -1 -1 -1 -1
  catch C  -1 -1 -1 -1 -1 -1 -1 -1 -1
  HERAS    -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q1  -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS0    -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3  -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-ORSH -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN  -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS  -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS  -1 -1 -1 -1 -1 -1 -1 -1 -1
  sumFleet -1 -1 -1 -1 -1 -1 -1 -1 -1

Slot "f.vars":
          age
fleet       0  1  2  3  4  5  6  7  8
  catch A  -1  0  1  1  1  1  2  2  2
  catch BD  3  4  4  4  4  4 -1 -1 -1
  catch C  -1  5  6  7  7  7  7 -1 -1
  HERAS    -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q1  -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS0    -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3  -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-ORSH -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN  -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS  -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS  -1 -1 -1 -1 -1 -1 -1 -1 -1
  sumFleet -1 -1 -1 -1 -1 -1 -1 -1 -1

Slot "obs.vars":
          age
fleet       0  1  2  3  4  5  6  7  8
  catch A  -1  0  1  1  1  1  1  2  2
  catch BD  3  4  5  5  5  5 -1 -1 -1
  catch C  -1  6  7  8  8  8  8 -1 -1
  HERAS    -1  9 10 11 12 12 12 13 13
  IBTS-Q1  -1 14 -1 -1 -1 -1 -1 -1 -1
  IBTS0    15 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3  16 16 17 17 17 17 -1 -1 -1
```

```
  LAI-ORSH 18 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN  18 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS  18 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS  18 -1 -1 -1 -1 -1 -1 -1 -1
  sumFleet -1 -1 -1 -1 -1 -1 -1 -1 -1

Slot "srr":
[1] 0

Slot "scaleNoYears":
[1] 0

Slot "scaleYears":
[1] NA

Slot "scalePars":
     age
years  0 1 2 3 4 5 6 7 8

Slot "cor.F":
[1] 2 2 2

Slot "cor.obs":
         age
fleet      0-1 1-2 2-3 3-4 4-5 5-6 6-7 7-8
  catch A   NA  NA  NA  NA  NA  NA  NA  NA
  catch BD  NA  NA  NA  NA  NA  NA  NA  NA
  catch C   NA  NA  NA  NA  NA  NA  NA  NA
  HERAS     -1  NA  NA  NA  NA  NA  NA  NA
  IBTS-Q1   -1  -1  -1  -1  -1  -1  -1  -1
  IBTS0     -1  -1  -1  -1  -1  -1  -1  -1
  IBTS-Q3    0   0   0   0   0  -1  -1  -1
  LAI-ORSH  -1  -1  -1  -1  -1  -1  -1  -1
  LAI-BUN   -1  -1  -1  -1  -1  -1  -1  -1
  LAI-CNS   -1  -1  -1  -1  -1  -1  -1  -1
  LAI-SNS   -1  -1  -1  -1  -1  -1  -1  -1
  sumFleet  -1  -1  -1  -1  -1  -1  -1  -1

Slot "cor.obs.Flag":
 [1] ID   ID   ID   ID   ID   ID   AR   ID   ID   ID   ID   <NA>
Levels: ID AR US

Slot "biomassTreat":
 [1] -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1

Slot "timeout":
[1] 3600

Slot "likFlag":
 [1] LN LN LN LN LN LN LN LN LN LN LN LN
Levels: LN ALN
```

```
Slot "fixVarToWeight":
[1] FALSE

Slot "simulate":
[1] FALSE

Slot "residuals":
[1] TRUE

Slot "sumFleets":
[1] "A"  "BD" "C"
```

Annex 4: Working documents

Natural mortality of North Sea autumn spawning herring as generated by SMS key-runs

Martin Pastoors[1]

07/06/2021 17:42

Introduction

In this document, an exploration is presented of the natural mortality estimates of NSAS herring as generated by the different WGSAM North Sea keyruns in 2011, 2014, 2017 and 2020.

The patterns in M on herring are further explored by reviewing the stock trends of the major predators and the total consumption of herring by these predators.

M by WR (facet) and Key run (colour)

Read from: SMS_NSAS_M_raw.csv

The 2010 key run gave the highest M on all ages. Key runs 2017 and 2020 are relatively similar.

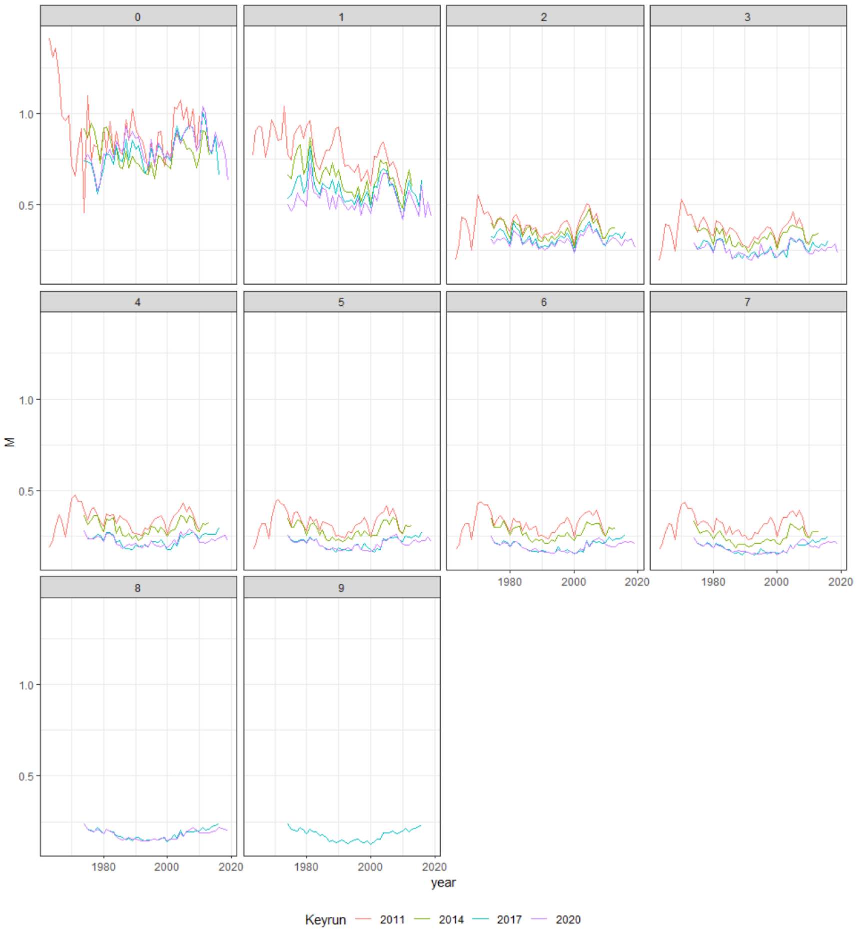


Figure 1 M by WR (facet) and Key run (colour)

M by Key run (facet) and WR (colour)

Total natural mortality by key run (facets) and by age (colours).

Key run 2011 gave high and variable estimates of M at age 0 (WR).

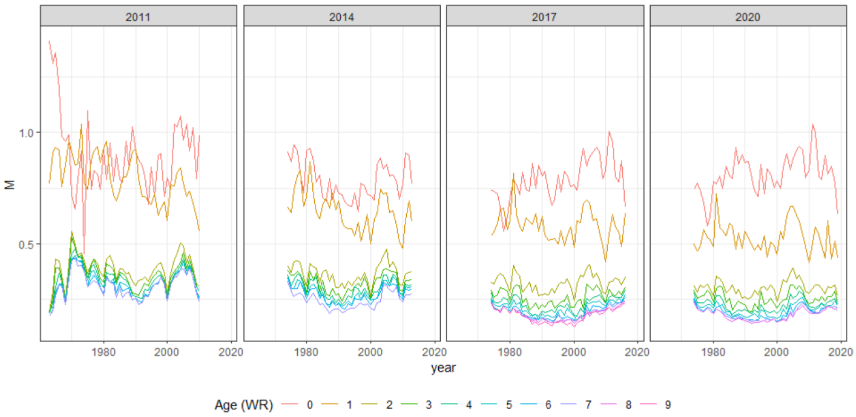


Figure 2 M by Key run (facet) and WR (colour)

standardized M (z-scores) by WR (facet) and Key run (colour)

Z scores were calculated by subtracting the mean and dividing by the standard deviation. Patterns in M by age are generally comparable with low M's in the 1990s and higher Ms in the 2000s

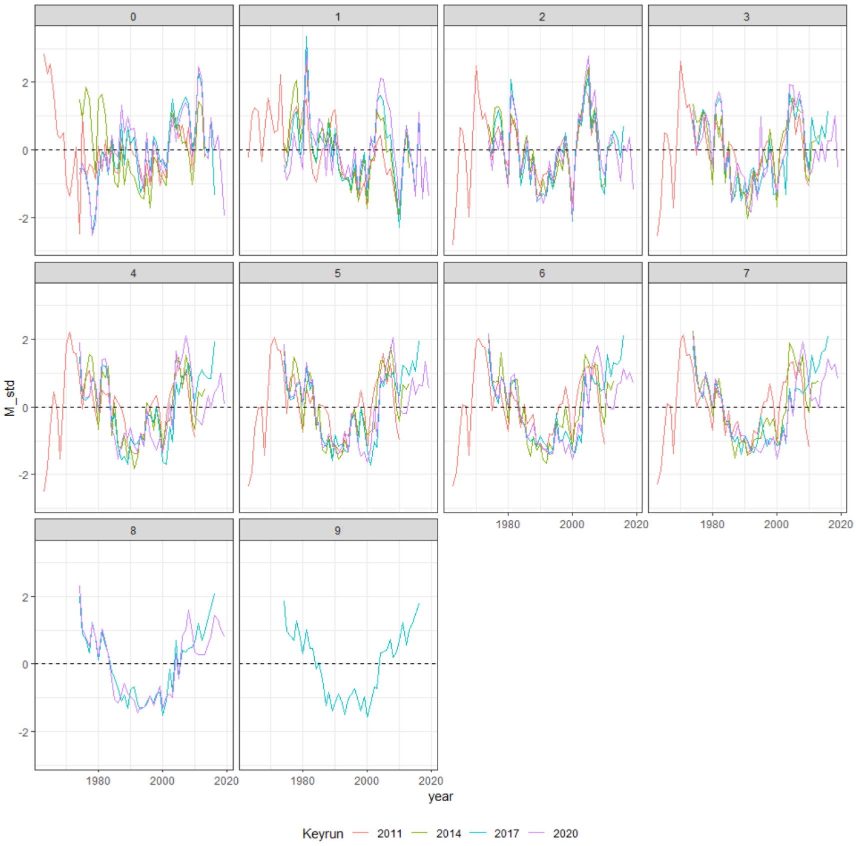


Figure 3 standardized M (z-scores) by WR (facet) and Key run (colour)

Figure 4 standardized M (z-scores) by Key run (facet) and WR (colour)

M summarized by decade by age (WR, facets) and Key run (colour)

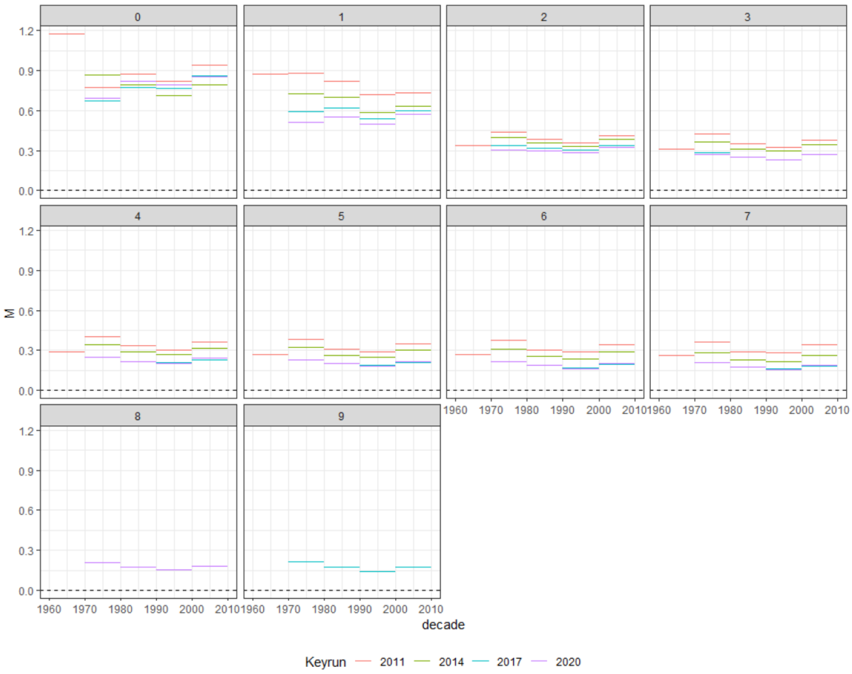


Figure 5 M summarized by decade by age (WR, facets) and Key run (colour)

M for ages 0-1 and 2-6, summarized by decade (x-axis) and Key run (colour)

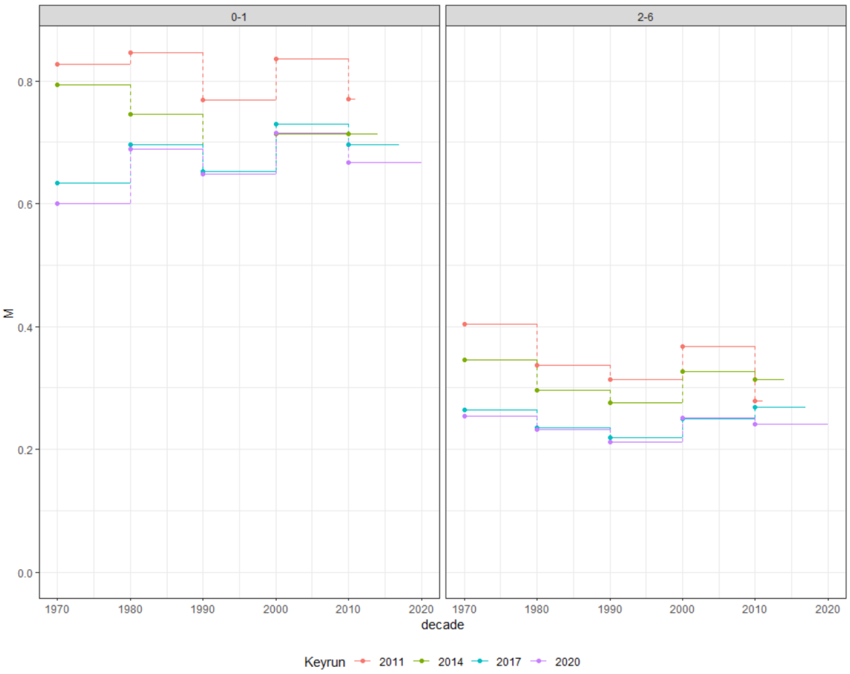


Figure 6 M for ages 0-1 and 2-6, summarized by decade (x-axis) and Key run (colour)

Stock trends in SMS

Total mean biomass by species and year (averaged over quarters) derived from keyruns 2011, 2014, 2017, 2020 (summary.out files).

Biomass of North Sea horse mackerel is a constant external and fixed quantity (horse mackerel is important for the M on age 0 herring). Saithe is the most important predator on herring. The assessment of saithe seems reasonably consistent.

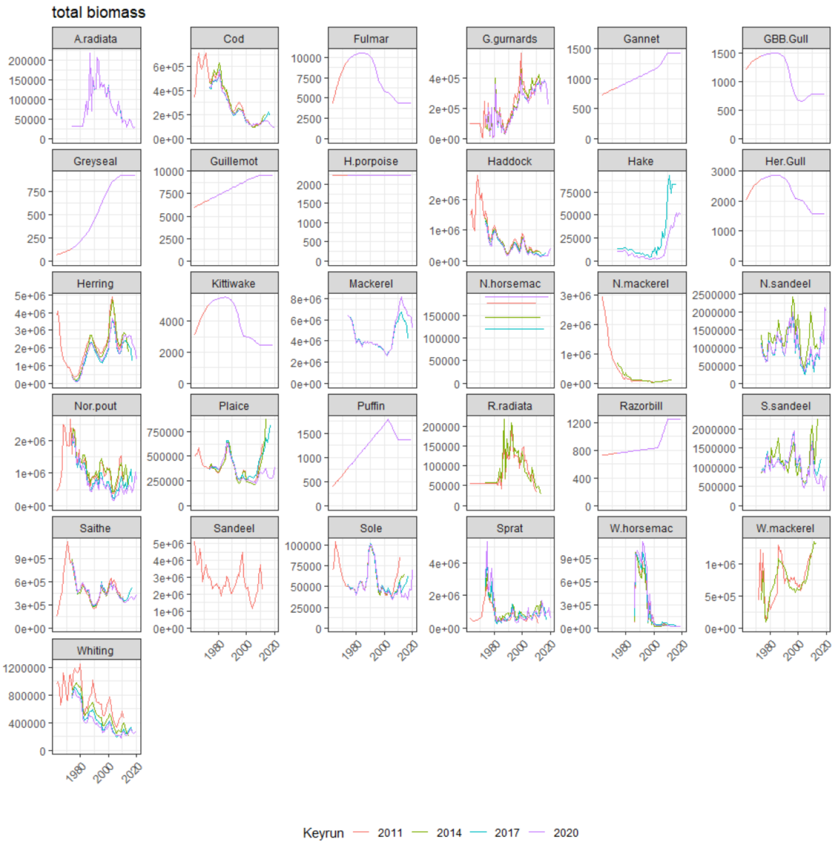


Figure 7 Stock trends in SMS

M2 on herring in SMS

Total M2 (summed over quarters) by keyrun and age (WR) (partial_m2.out files). Predator species indicated by colours. Mackerel and North Sea horse mackerel are the two most important species in terms of M on age 0, whiting and saithe on age 1 and cod and saithe on the older ages. Gurnards were estimated to have a substantial impact on age 0 in the 2014 and 2017 key runs but is estimated to be less influential in the 2020 key run

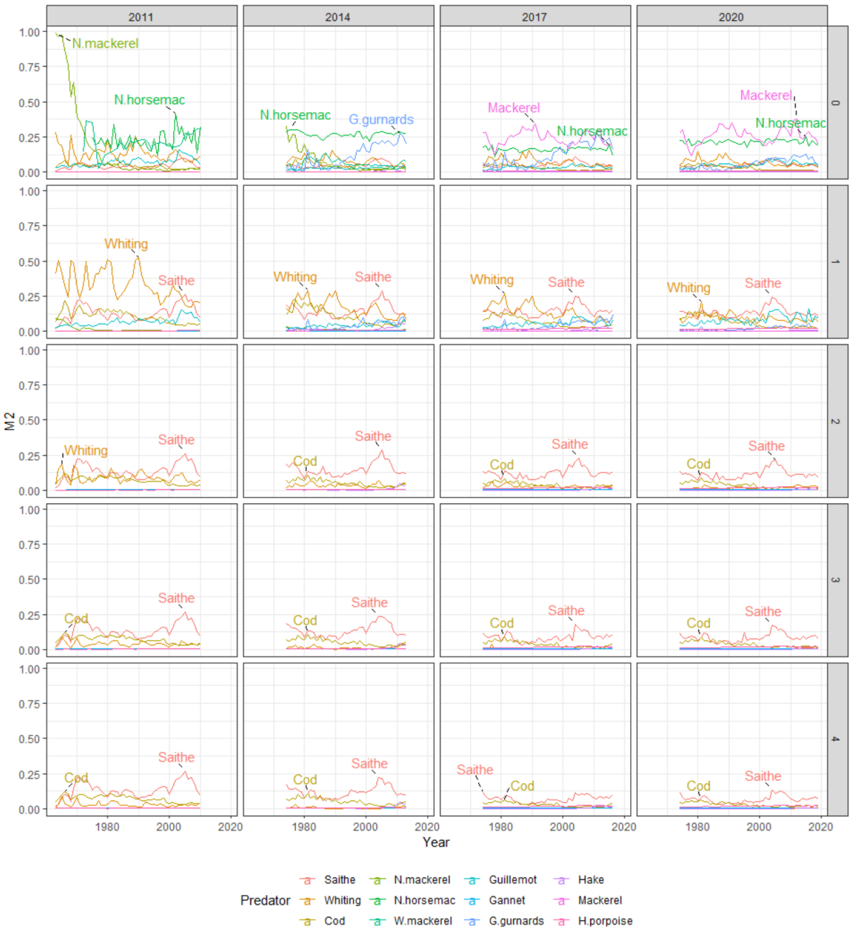


Figure 8 M2 on herring in SMS

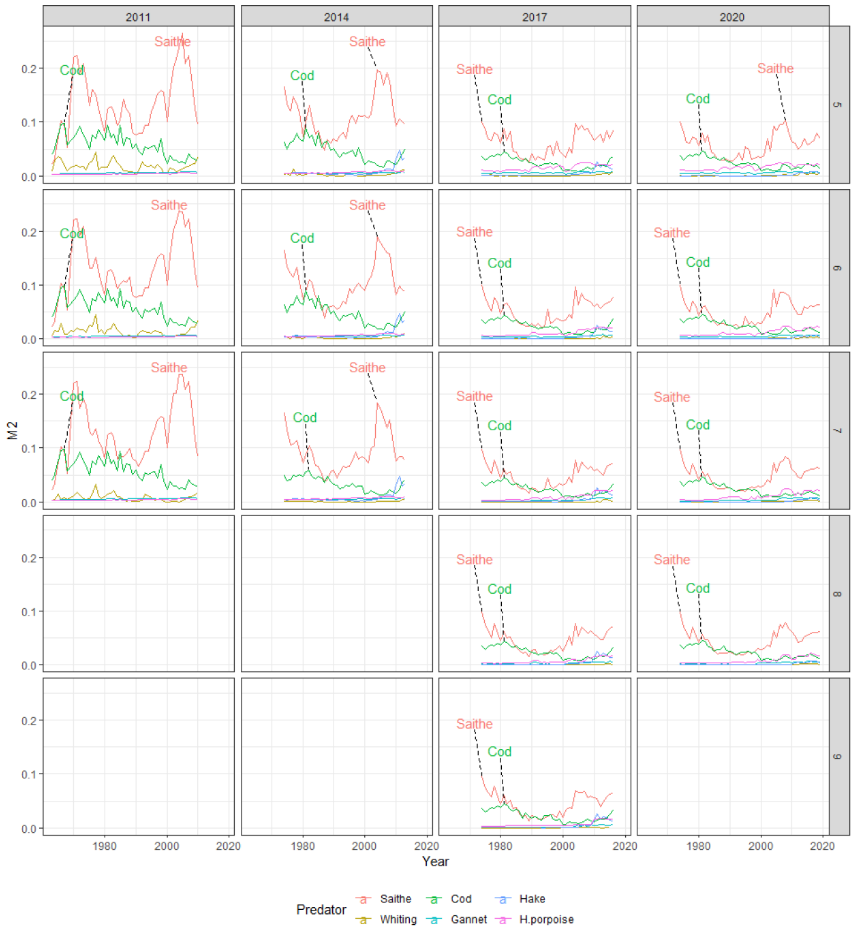


Figure 9 M2 on herring in SMS

M2 on herring in SMS

Retrospective estimates of Total M2 generated by predator species and year (summed over quarters) derived from keyruns 2011, 2014, 2017, 2020 (partial_m2.out files).

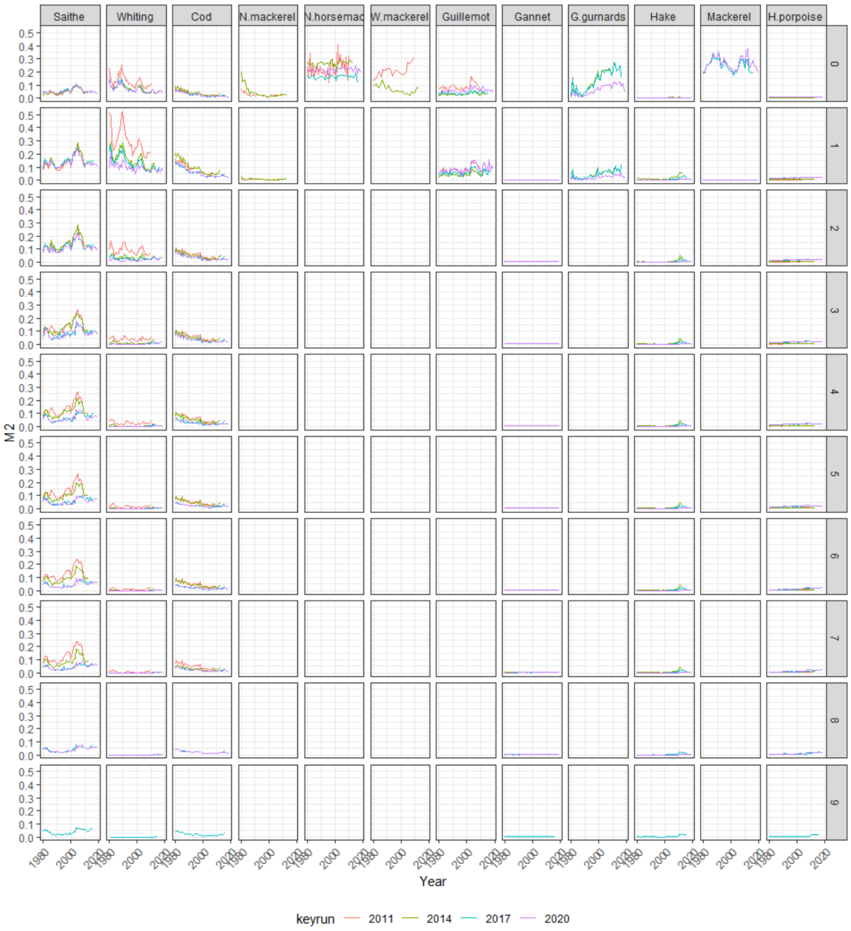


Figure 10 M2 on herring in SMS

Who eats herring

Total biomass of herring consumed by different predators (taken from who_eats_whom.csv). Around 50% of the adult herring that is predated by other species is taken by saithe.

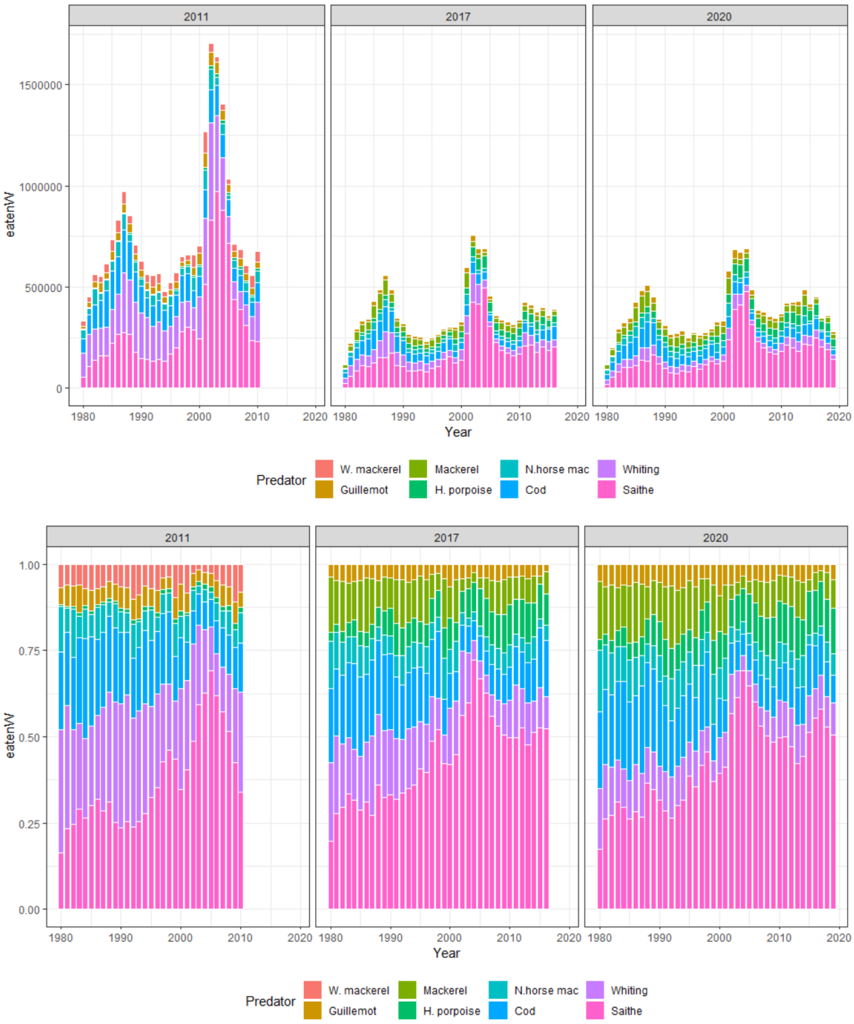


Figure 11 Who eats herring

Who eats herring, by age

Total biomass of herring consumed by age by different predators (taken from who_eats_whom_level1.csv)..

Figure 12 Who eats herring, by age

Conclusions

- Four North Sea key runs evaluated (2011, 2014, 2017 and 2020) on the impact of predators on herring.
- Patterns in M are relatively different for age 0, age 1 and ages 2 and above.
- M on herring is generally estimated to have decreased between 1975-2000 and increased after 2000.
- Mackerel and North Sea horse mackerel are most influential predators on age 0 herring. North Sea horse mackerel is treated as an external predator in the SMS model, with a constant biomass. Mackerel is derived from a fitting mechanism. It is not completely clear how the proportion of mackerel in the North Sea is derived.
- Whiting and saithe are the main predators on age 1 herring age.
- Cod and saithe are the main predators on herring from ages 2 and up.
- Consumption of herring by saithe is substantailly lower in the 2017 and 2020 keyruns compared to the 2011 and 2014 key runs (why?)
- Consumption of herring has been high in the period 2001-2005 (why?)
- Overall consumption of herring by predators has been in the order of 250-500 thousand tonnes over the last decade.

NSAS herring assessment model parameter bindings

Benoit Berges[1*], Niels Hintzen[1]

[1] Wageningen Marine Research, The Netherlands

[*] benoit.berges@wur.nl

1 WKPELA2018 AND HAWG 2021

The North Sea Autumn Spawning (NSAS) herring assessment model used by HAWG is the State-Space Assessment Model (SAM).

During WKPELA2018, the profiling method used to parameterise additive natural mortality for the NSAS herring assessment was performed using an interim model configuration; not the configuration applied in the final model used in the assessment. This interim model yielded an absolute level of rescaling of 0.11 to apply to M for all ages and years. Due to an oversight, this value, derived from the interim model configuration was incorrectly applied to the final model configuration agreed at the benchmark. This oversight was discovered during the 2021 HAWG meeting, where the profiling procedure was carried out again with the final model configuration. The result was that the level of rescaling to apply to M should have been 0.

The contributing factors for the discrepancy in the estimated values of additive M between the interim model and the final model configurations are as follows:

- Alternative input data set used in the final model:
    - HERAS data age 2-8 used in interim, as opposed to age 1-8 in final WKPELA2018 model
    - IBTS-Q3 age 0-4 used in interim, as opposed to age 0-5 in final WKPELA2018 model
- corF parameter (which represents the correlation in fishing mortality) model turned on in interim model, and turned off in final WKPELA2018 model
- Alternative binding parameters (see Table 1)

The biggest contributing factor to this change in the result of the additive M profiling method used in the assessment is whether 'corF' is turned on or off. The corF parameter forces a correlation structure on the selectivity patterns across ages. The forced correlation (deviating from the correlation is being penalized in the nlogl) follows a power-law decline over the ages, such that age 1-2 is equally correlated to 2-3 and 5-6 but that the correlation is ^2 as low for age-classes two ages apart etc.

Following discussions at IBPNSherring2021, it was decided to reverse the decision made at WKPELA 2018 to have corF turned off in the final assessment model configuration and to have it turned on. With this new model setup, it becomes necessary to re-evaluate parameter bindings, the details of which are documented below.

Table 1: differences in model parameter bindings (catchabilities, variance in F random walk process, observation variance) between the final model issued by WKPELA2018 and the interim model used to derive the M profiling of the assessment.

	Catchabilities	f.var	Obs.var
WKPELA2018 final model	age fleet 0 1 2 3 4 5 6 7 8 catch unique -1 -1 -1 -1 -1 -1 -1 -1 -1 HERAS -1 1 1 2 2 2 2 2 2 IBTS-Q1 -1 3 -1 -1 -1 -1 -1 -1 -1 IBTS0 0 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q3 4 5 5 5 6 7 -1 -1 -1 LAI-ORSH 8 -1 -1 -1 -1 -1 -1 -1 -1 LAI-BUN 8 -1 -1 -1 -1 -1 -1 -1 -1 LAI-CNS 8 -1 -1 -1 -1 -1 -1 -1 -1 LAI-SNS 8 -1 -1 -1 -1 -1 -1 -1 -1	age fleet 0 1 2 3 4 5 6 7 8 catch unique 0 0 1 1 1 1 2 2 2 HERAS -1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q1 -1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS0 -1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q3 -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-ORSH -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-BUN -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-CNS -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-SNS -1 -1 -1 -1 -1 -1 -1 -1 -1	age fleet 0 1 2 3 4 5 6 7 8 catch unique 0 0 1 1 1 1 1 2 2 HERAS -1 3 4 5 6 6 6 7 7 IBTS-Q1 -1 8 -1 -1 -1 -1 -1 -1 -1 IBTS0 9 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q3 10 11 12 12 12 12 -1 -1 -1 LAI-ORSH 13 -1 -1 -1 -1 -1 -1 -1 -1 LAI-BUN 13 -1 -1 -1 -1 -1 -1 -1 -1 LAI-CNS 13 -1 -1 -1 -1 -1 -1 -1 -1 LAI-SNS 13 -1 -1 -1 -1 -1 -1 -1 -1
WKPELA2018 'interim' profiling model	age fleet 0 1 2 3 4 5 6 7 8 catch unique -1 -1 -1 -1 -1 -1 -1 -1 -1 HERAS -1 -1 2 3 3 4 4 4 4 IBTS-Q1 -1 0 -1 -1 -1 -1 -1 -1 -1 IBTS0 1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q3 5 6 6 7 7 -1 -1 -1 -1 LAI-ORSH 8 -1 -1 -1 -1 -1 -1 -1 -1 LAI-CNS 8 -1 -1 -1 -1 -1 -1 -1 -1 LAI-BUN 8 -1 -1 -1 -1 -1 -1 -1 -1 LAI-SNS 8 -1 -1 -1 -1 -1 -1 -1 -1	age fleet 0 1 2 3 4 5 6 7 8 catch unique 0 0 1 1 1 1 2 2 2 HERAS -1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q1 -1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS0 -1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q3 -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-ORSH -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-CNS -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-BUN -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-SNS -1 -1 -1 -1 -1 -1 -1 -1 -1	age fleet 0 1 2 3 4 5 6 7 8 catch unique 0 0 0 0 1 1 1 1 1 HERAS -1 -1 2 2 3 3 3 4 4 IBTS-Q1 -1 8 -1 -1 -1 -1 -1 -1 -1 IBTS0 10 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q3 5 6 6 7 7 -1 -1 -1 -1 LAI-ORSH 9 -1 -1 -1 -1 -1 -1 -1 -1 LAI-CNS 9 -1 -1 -1 -1 -1 -1 -1 -1 LAI-BUN 9 -1 -1 -1 -1 -1 -1 -1 -1 LAI-SNS 9 -1 -1 -1 -1 -1 -1 -1 -1

2 IBPNSHERRING2021 INCREMENTAL CHANGES

Method

The decision during IBPNSherring2021to turn corF on represents a change in configuration, which requires the need to:

- Run a new additive M profiling of the assessment
- Optimize parameter bindings in line with: 1) the inclusion of corF, 2) the newly derived additive M rescaling parameter.

To optimize the parameter bindings, the following stepwise approach is employed:

- <u>**Step 1:**</u> The profiling method used to estimate the additive M rescaling parameter for the assessment is performed on the WKPELA2018 final settings but with corF turned on;
- <u>**Step 2:**</u> Using the configuration from 1, incremental changes in model parameter bindings are tested. The purpose of this is to determine the optimal model configuration and identify its sensitivity to any changes in parameter bindings.
- <u>**Step3:**</u> In an iterative manner, the profiling for the additive M rescaling parameter is run a second time on the optimal configuration derived from step 2. Attention is made to examine to what extent the result of the second profiling is different from the result of the first profiling in step 1.

Result

- <u>**Step 1:**</u> The profiling result is shown in Figure 1 and yields an optimal M rescaling of addM=0.06.

- <u>**Step 2:**</u> The model with WKPELA2018 final settings and addM=0.06 is tested against the incremental changes listed in Table 2. The effect of each change is evaluated against the AIC. Four changes are found to improve the assessment fit:
  1. Binding of age 1-3 in catchability of IBTSQ3 (alt4). Drop of 0.286 in AIC, very minor.
  2. Change in observation variance for the HERAS survey, freeing ages 1 to 3 (alt5). Drop of 3.1 in AIC
  3. Binding of age 1-2 in catchability of HERAS (alt8). Drop of 1.9 in AIC
  4. Binding the observation variance for the catches as 0-1, 2-6 and 7-8. Drop of 1.98 in AIC.

  Combining the different changes, the drop in AIC is of 8. Important to note is that the change in IBTSQ3 catchability (1) only leads a to minor reduction in AIC. However, it has an impact on the further profiling in step 3. This is shown in Figure 3. For this reason, the final model settings include changes 2-4 relative to WKPELA2018.
- <u>**Step 3:**</u> The second profiling leads to addM=0.06, same as in Step 1. The profile is shown in Figure 3 (blue line).

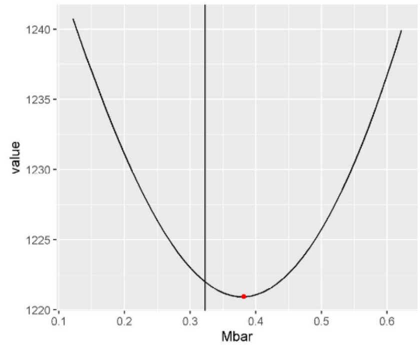


Figure 1: profling for step 1 of optimization of parameter bindings.

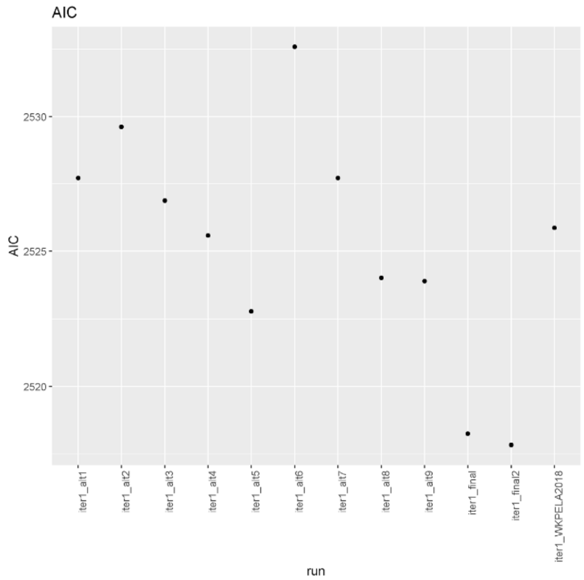


Figure 2: change in AIC for each step changes listed in Table 2.

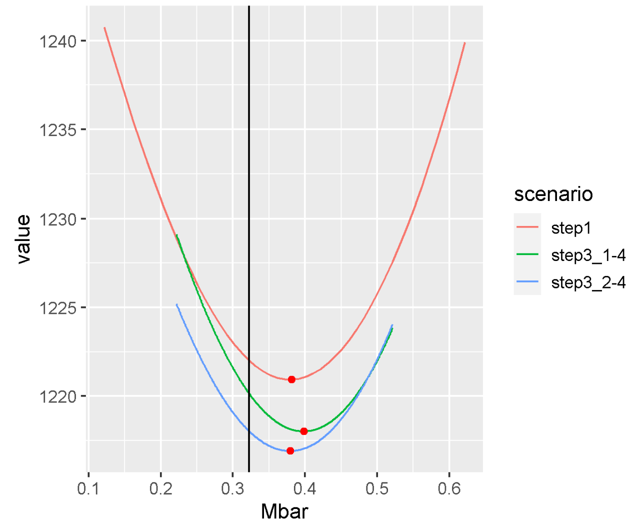


Figure 3: negative log likelihood profiling for step 1 (red line) and at step 3 with the two final models listed in Table 2 (green and blue lines). The selected final model is the one yielding comparable addM, final2, depicted by the blue curve.

Table 2: incremental changes for the optimization of the parameter bindings.

Run name	Description	WKPELA2018	Incremental change
alt1	catch obs.var age 0 and 1 free	Slot "obs.vars": age fleet 0 1 2 3 4 5 6 7 8 catch unique 0 0 1 1 1 1 2 2 2 HERAS -1 3 4 4 4 4 4 5 5 IBTS-Q1 -1 6 -1 -1 -1 -1 -1 -1 -1 IBTS0 7 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q3 8 9 10 10 10 10 -1 -1 -1 LAI-ORSH 11 -1 -1 -1 -1 -1 -1 -1 -1 LAI-BUN 11 -1 -1 -1 -1 -1 -1 -1 -1 LAI-CNS 11 -1 -1 -1 -1 -1 -1 -1 -1 LAI-SNS 11 -1 -1 -1 -1 -1 -1 -1 -1	Slot "obs.vars": age fleet 0 1 2 3 4 5 6 7 8 catch unique 0 1 2 2 2 2 3 3 3 HERAS -1 4 5 5 5 5 5 6 6 IBTS-Q1 -1 7 -1 -1 -1 -1 -1 -1 -1 IBTS0 8 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q3 9 10 11 11 11 11 -1 -1 -1 LAI-ORSH 12 -1 -1 -1 -1 -1 -1 -1 -1 LAI-BUN 12 -1 -1 -1 -1 -1 -1 -1 -1 LAI-CNS 12 -1 -1 -1 -1 -1 -1 -1 -1 LAI-SNS 12 -1 -1 -1 -1 -1 -1 -1 -1
alt2	f.var age 0 and 1 free	Slot "f.vars": age fleet 0 1 2 3 4 5 6 7 8 catch unique 0 0 1 1 1 1 2 2 2 HERAS -1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q1 -1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS0 -1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q3 -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-ORSH -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-BUN -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-CNS -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-SNS -1 -1 -1 -1 -1 -1 -1 -1 -1	Slot "f.vars": age fleet 0 1 2 3 4 5 6 7 8 catch unique 0 1 2 2 2 2 3 3 3 HERAS -1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q1 -1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS0 -1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q3 -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-ORSH -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-BUN -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-CNS -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-SNS -1 -1 -1 -1 -1 -1 -1 -1 -1
alt3	IBTSQ3 obs.var freed age 5	Slot "obs.vars": age fleet 0 1 2 3 4 5 6 7 8 catch unique 0 0 1 1 1 1 2 2 2 HERAS -1 3 4 4 4 4 4 5 5 IBTS-Q1 -1 6 -1 -1 -1 -1 -1 -1 -1 IBTS0 7 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q3 8 9 10 10 10 10 -1 -1 -1 LAI-ORSH 11 -1 -1 -1 -1 -1 -1 -1 -1 LAI-BUN 11 -1 -1 -1 -1 -1 -1 -1 -1 LAI-CNS 11 -1 -1 -1 -1 -1 -1 -1 -1 LAI-SNS 11 -1 -1 -1 -1 -1 -1 -1 -1	Slot "obs.vars": age fleet 0 1 2 3 4 5 6 7 8 catch unique 0 0 1 1 1 1 2 2 2 HERAS -1 3 4 4 4 4 4 5 5 IBTS-Q1 -1 6 -1 -1 -1 -1 -1 -1 -1 IBTS0 7 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q3 8 9 10 10 10 11 -1 -1 -1 LAI-ORSH 12 -1 -1 -1 -1 -1 -1 -1 -1 LAI-BUN 12 -1 -1 -1 -1 -1 -1 -1 -1 LAI-CNS 12 -1 -1 -1 -1 -1 -1 -1 -1 LAI-SNS 12 -1 -1 -1 -1 -1 -1 -1 -1
alt4	IBTSQ3 q bind age 1-3	Slot "catchabilities": age fleet 0 1 2 3 4 5 6 7 8 catch unique -1 -1 -1 -1 -1 -1 -1 -1 -1 HERAS -1 1 2 3 3 3 3 3 3 IBTS-Q1 -1 4 -1 -1 -1 -1 -1 -1 -1 IBTS0 0 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q3 5 6 7 8 9 10 -1 -1 -1 LAI-ORSH 11 -1 -1 -1 -1 -1 -1 -1 -1 LAI-BUN 11 -1 -1 -1 -1 -1 -1 -1 -1 LAI-CNS 11 -1 -1 -1 -1 -1 -1 -1 -1 LAI-SNS 11 -1 -1 -1 -1 -1 -1 -1 -1	Slot "catchabilities": age fleet 0 1 2 3 4 5 6 7 8 catch unique -1 -1 -1 -1 -1 -1 -1 -1 -1 HERAS -1 1 2 3 3 3 3 3 3 IBTS-Q1 -1 4 -1 -1 -1 -1 -1 -1 -1 IBTS0 0 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q3 5 6 6 6 7 8 -1 -1 -1 LAI-ORSH 9 -1 -1 -1 -1 -1 -1 -1 -1 LAI-BUN 9 -1 -1 -1 -1 -1 -1 -1 -1 LAI-CNS 9 -1 -1 -1 -1 -1 -1 -1 -1 LAI-SNS 9 -1 -1 -1 -1 -1 -1 -1 -1
alt5	obs.var HERAS	Slot "obs.vars": age fleet 0 1 2 3 4 5 6 7 8 catch unique 0 0 1 1 1 1 2 2 2 HERAS -1 3 4 4 4 4 4 5 5 IBTS-Q1 -1 6 -1 -1 -1 -1 -1 -1 -1 IBTS0 7 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q3 8 9 10 10 10 10 -1 -1 -1 LAI-ORSH 11 -1 -1 -1 -1 -1 -1 -1 -1 LAI-BUN 11 -1 -1 -1 -1 -1 -1 -1 -1 LAI-CNS 11 -1 -1 -1 -1 -1 -1 -1 -1 LAI-SNS 11 -1 -1 -1 -1 -1 -1 -1 -1	Slot "obs.vars": age fleet 0 1 2 3 4 5 6 7 8 catch unique 0 0 1 1 1 1 2 2 2 HERAS -1 3 4 5 6 6 6 7 7 IBTS-Q1 -1 8 -1 -1 -1 -1 -1 -1 -1 IBTS0 9 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q3 10 11 12 12 12 12 -1 -1 -1 LAI-ORSH 13 -1 -1 -1 -1 -1 -1 -1 -1 LAI-BUN 13 -1 -1 -1 -1 -1 -1 -1 -1 LAI-CNS 13 -1 -1 -1 -1 -1 -1 -1 -1 LAI-SNS 13 -1 -1 -1 -1 -1 -1 -1 -1
alt6	f.var all free except plus group	Slot "f.vars": age fleet 0 1 2 3 4 5 6 7 8 catch unique 0 0 1 1 1 1 2 2 2 HERAS -1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q1 -1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS0 -1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q3 -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-ORSH -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-BUN -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-CNS -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-SNS -1 -1 -1 -1 -1 -1 -1 -1 -1	Slot "f.vars": age fleet 0 1 2 3 4 5 6 7 8 catch unique 0 1 2 3 4 5 6 7 7 HERAS -1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q1 -1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS0 -1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q3 -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-ORSH -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-BUN -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-CNS -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-SNS -1 -1 -1 -1 -1 -1 -1 -1 -1

alt7	f.var binding 0-1, 4-5, 6-8	Slot "f.vars": age fleet 0 1 2 3 4 5 6 7 8 catch unique 0 0 1 1 1 1 2 2 2 HERAS -1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q1 -1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS0 -1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q3 -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-ORSH -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-BUN -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-CNS -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-SNS -1 -1 -1 -1 -1 -1 -1 -1 -1	Slot "f.vars": age fleet 0 1 2 3 4 5 6 7 8 catch unique 0 0 1 2 3 3 4 4 4 HERAS -1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q1 -1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS0 -1 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q3 -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-ORSH -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-BUN -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-CNS -1 -1 -1 -1 -1 -1 -1 -1 -1 LAI-SNS -1 -1 -1 -1 -1 -1 -1 -1 -1
alt8	q HERAS binding age 1-2	Slot "catchabilities": age fleet 0 1 2 3 4 5 6 7 8 catch unique -1 -1 -1 -1 -1 -1 -1 -1 -1 HERAS -1 1 2 3 3 3 3 3 3 IBTS-Q1 -1 4 -1 -1 -1 -1 -1 -1 -1 IBTS0 0 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q3 5 6 7 8 9 10 -1 -1 -1 LAI-ORSH 11 -1 -1 -1 -1 -1 -1 -1 -1 LAI-BUN 11 -1 -1 -1 -1 -1 -1 -1 -1 LAI-CNS 11 -1 -1 -1 -1 -1 -1 -1 -1 LAI-SNS 11 -1 -1 -1 -1 -1 -1 -1 -1	Slot "catchabilities": age fleet 0 1 2 3 4 5 6 7 8 catch unique -1 -1 -1 -1 -1 -1 -1 -1 -1 HERAS -1 1 1 2 2 2 2 2 2 IBTS-Q1 -1 3 -1 -1 -1 -1 -1 -1 -1 IBTS0 0 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q3 4 5 6 7 8 9 -1 -1 -1 LAI-ORSH 10 -1 -1 -1 -1 -1 -1 -1 -1 LAI-BUN 10 -1 -1 -1 -1 -1 -1 -1 -1 LAI-CNS 10 -1 -1 -1 -1 -1 -1 -1 -1 LAI-SNS 10 -1 -1 -1 -1 -1 -1 -1 -1
alt9	obs.var catches binding 0-1, 2-6,7-8	Slot "obs.vars": age fleet 0 1 2 3 4 5 6 7 8 catch unique 0 0 1 1 1 1 2 2 2 HERAS -1 3 4 4 4 4 4 5 5 IBTS-Q1 -1 6 -1 -1 -1 -1 -1 -1 -1 IBTS0 7 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q3 8 9 10 10 10 10 -1 -1 -1 LAI-ORSH 11 -1 -1 -1 -1 -1 -1 -1 -1 LAI-BUN 11 -1 -1 -1 -1 -1 -1 -1 -1 LAI-CNS 11 -1 -1 -1 -1 -1 -1 -1 -1 LAI-SNS 11 -1 -1 -1 -1 -1 -1 -1 -1	Slot "obs.vars": age fleet 0 1 2 3 4 5 6 7 8 catch unique 0 0 1 1 1 1 1 2 2 HERAS -1 3 4 4 4 4 4 5 5 IBTS-Q1 -1 6 -1 -1 -1 -1 -1 -1 -1 IBTS0 7 -1 -1 -1 -1 -1 -1 -1 -1 IBTS-Q3 8 9 10 10 10 10 -1 -1 -1 LAI-ORSH 11 -1 -1 -1 -1 -1 -1 -1 -1 LAI-BUN 11 -1 -1 -1 -1 -1 -1 -1 -1 LAI-CNS 11 -1 -1 -1 -1 -1 -1 -1 -1 LAI-SNS 11 -1 -1 -1 -1 -1 -1 -1 -1
final	alt9+alt8+alt5 + alt4		
final2	alt9+alt8+alt5		

3 IBPNSHERRING2021 FINAL MODEL CONFIGURATION

List here the changes made, then a tabulate or appendix, the full details of the configruation

APPENDIX 1: FULL MODEL CONFIGURATION WKPELA2018 ASSESSMENT PROFILING

```
An object of class "FLSAM.control"
Slot "name":
[1] "Final Assessment"

Slot "desc":
[1] "Imported from a VPA file. ( ./data/index.txt ).  Tue Feb 13 23:48:25 2018"

Slot "range":
     min      max plusgroup   minyear   maxyear   minfbar   maxfbar
       0        8         8      1947      2017         2         6

Slot "fleets":
catch unique       HERAS     IBTS-Q1       IBTS0     IBTS-Q3   LAI-ORSH     LAI-CNS
LAI-BUN     LAI-SNS
         0           2           2           2           2          6           6           6           6

Slot "plus.group":
plusgroup
    TRUE

Slot "states":
              age
fleet           0  1  2  3  4  5  6  7  8
  catch unique  0  1  2  3  4  5  6  7  7
  HERAS        -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q1      -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS0        -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-ORSH     -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS      -1 -1 -1 -1 -1 -1 -1 -1 -1

Slot "logN.vars":
0 1 2 3 4 5 6 7 8
0 1 1 1 1 1 1 1 1

Slot "logP.vars":
[1] 0 1 2
```

```
Slot "catchabilities":
             age
fleet          0  1  2  3  4  5  6  7  8
  catch unique -1 -1 -1 -1 -1 -1 -1 -1 -1
  HERAS        -1 -1  2  3  3  4  4  4  4
  IBTS-Q1      -1  0 -1 -1 -1 -1 -1 -1 -1
  IBTS0         1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3       5  6  6  7  7 -1 -1 -1 -1
  LAI-ORSH      8 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS       8 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN       8 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS       8 -1 -1 -1 -1 -1 -1 -1 -1

Slot "power.law.exps":
             age
fleet          0  1  2  3  4  5  6  7  8
  catch unique -1 -1 -1 -1 -1 -1 -1 -1 -1
  HERAS        -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q1      -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS0        -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-ORSH     -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS      -1 -1 -1 -1 -1 -1 -1 -1 -1

Slot "f.vars":
             age
fleet          0  1  2  3  4  5  6  7  8
  catch unique  0  0  1  1  1  1  2  2  2
  HERAS        -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q1      -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS0        -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-ORSH     -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS      -1 -1 -1 -1 -1 -1 -1 -1 -1

Slot "obs.vars":
```

```
              age
fleet          0  1  2  3  4  5  6  7  8
  catch unique  0  0  0  0  1  1  1  1  1
  HERAS        -1 -1  2  2  3  3  3  4  4
  IBTS-Q1      -1  8 -1 -1 -1 -1 -1 -1 -1
  IBTS0        10 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3       5  6  6  7  7 -1 -1 -1 -1
  LAI-ORSH      9 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS       9 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN       9 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS       9 -1 -1 -1 -1 -1 -1 -1 -1

Slot "srr":
[1] 0

Slot "scaleNoYears":
[1] 0

Slot "scaleYears":
[1] NA

Slot "scalePars":
     age
years  0 1 2 3 4 5 6 7 8

Slot "cor.F":
[1] 2

Slot "cor.obs":
              age
fleet          0-1 1-2 2-3 3-4 4-5 5-6 6-7 7-8
  catch unique  NA  NA  NA  NA  NA  NA  NA  NA
  HERAS         -1  -1  NA  NA  NA  NA  NA  NA
  IBTS-Q1       -1  -1  -1  -1  -1  -1  -1  -1
  IBTS0         -1  -1  -1  -1  -1  -1  -1  -1
  IBTS-Q3        0   0   0   0  -1  -1  -1  -1
  LAI-ORSH      -1  -1  -1  -1  -1  -1  -1  -1
  LAI-CNS       -1  -1  -1  -1  -1  -1  -1  -1
  LAI-BUN       -1  -1  -1  -1  -1  -1  -1  -1
  LAI-SNS       -1  -1  -1  -1  -1  -1  -1  -1
```

```
Slot "cor.obs.Flag":
[1] ID ID ID ID AR ID ID ID ID
Levels: ID AR US

Slot "biomassTreat":
[1] -1 -1 -1 -1 -1 -1 -1 -1 -1

Slot "timeout":
[1] 3600

Slot "likFlag":
[1] LN LN LN LN LN LN LN LN LN
Levels: LN ALN

Slot "fixVarToWeight":
[1] FALSE

Slot "simulate":
[1] FALSE

Slot "residuals":
[1] FALSE

Slot "sumFleets":
logical(0)
```

APPENDIX 2: FULL MODEL CONFIGURATION WKPELA2018 FINAL ASSESSMENT MODEL

```
An object of class "FLSAM.control"
Slot "name":
[1] "North Sea Herring"

Slot "desc":
[1] "Imported from a VPA file. ( ./bootstrap/data/index.txt ).  Wed May 26 11:49:48 2021"

Slot "range":
   min     max plusgroup  minyear  maxyear  minfbar  maxfbar
     0       8        8     1947     2021        2        6

Slot "fleets":
catch unique       HERAS     IBTS-Q1      IBTS0     IBTS-Q3    LAI-ORSH     LAI-BUN
LAI-CNS     LAI-SNS
         0           2           2           2           2           6           6           6           6

Slot "plus.group":
plusgroup
    TRUE

Slot "states":
              age
fleet          0  1  2  3  4  5  6  7  8
  catch unique  0  1  2  3  4  5  6  7  7
  HERAS        -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q1      -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS0        -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-ORSH     -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS      -1 -1 -1 -1 -1 -1 -1 -1 -1

Slot "logN.vars":
0 1 2 3 4 5 6 7 8
0 1 1 1 1 1 1 1 1

Slot "logP.vars":
[1] 0 1 2
```

```
Slot "catchabilities":
            age
fleet          0  1  2  3  4  5  6  7  8
  catch unique -1 -1 -1 -1 -1 -1 -1 -1 -1
  HERAS        -1  1  2  3  3  3  3  3  3
  IBTS-Q1      -1  4 -1 -1 -1 -1 -1 -1 -1
  IBTS0         0 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3       5  6  7  8  9 10 -1 -1 -1
  LAI-ORSH     11 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN      11 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS      11 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS      11 -1 -1 -1 -1 -1 -1 -1 -1

Slot "power.law.exps":
            age
fleet          0  1  2  3  4  5  6  7  8
  catch unique -1 -1 -1 -1 -1 -1 -1 -1 -1
  HERAS        -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q1      -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS0        -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-ORSH     -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS      -1 -1 -1 -1 -1 -1 -1 -1 -1

Slot "f.vars":
            age
fleet          0  1  2  3  4  5  6  7  8
  catch unique  0  0  1  1  1  1  2  2  2
  HERAS        -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q1      -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS0        -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-ORSH     -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS      -1 -1 -1 -1 -1 -1 -1 -1 -1

Slot "obs.vars":
```

```
             age
fleet          0  1  2  3  4  5  6  7  8
  catch unique  0  0  1  1  1  1  2  2  2
  HERAS        -1  3  4  4  4  4  4  5  5
  IBTS-Q1      -1  6 -1 -1 -1 -1 -1 -1 -1
  IBTS0         7 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3       8  9 10 10 10 10 -1 -1 -1
  LAI-ORSH     11 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN      11 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS      11 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS      11 -1 -1 -1 -1 -1 -1 -1 -1

Slot "srr":
[1] 0

Slot "scaleNoYears":
[1] 0

Slot "scaleYears":
[1] NA

Slot "scalePars":
     age
years  0 1 2 3 4 5 6 7 8

Slot "cor.F":
[1] 2

Slot "cor.obs":
             age
fleet          0-1 1-2 2-3 3-4 4-5 5-6 6-7 7-8
  catch unique  NA  NA  NA  NA  NA  NA  NA  NA
  HERAS         -1  NA  NA  NA  NA  NA  NA  NA
  IBTS-Q1       -1  -1  -1  -1  -1  -1  -1  -1
  IBTS0         -1  -1  -1  -1  -1  -1  -1  -1
  IBTS-Q3        0   0   0   0   0  -1  -1  -1
  LAI-ORSH      -1  -1  -1  -1  -1  -1  -1  -1
  LAI-BUN       -1  -1  -1  -1  -1  -1  -1  -1
  LAI-CNS       -1  -1  -1  -1  -1  -1  -1  -1
  LAI-SNS       -1  -1  -1  -1  -1  -1  -1  -1
```

```
Slot "cor.obs.Flag":
[1] ID ID ID ID AR ID ID ID ID
Levels: ID AR US

Slot "biomassTreat":
[1] -1 -1 -1 -1 -1 -1 -1 -1 -1

Slot "timeout":
[1] 3600

Slot "likFlag":
[1] LN LN LN LN LN LN LN LN LN
Levels: LN ALN

Slot "fixVarToWeight":
[1] FALSE

Slot "simulate":
[1] FALSE

Slot "residuals":
[1] FALSE

Slot "sumFleets":
logical(0)
```

APPENDIX 3: IBPNSHERRING FULL MODEL CONFIGURATION

```
An object of class "FLSAM.control"
Slot "name":
[1] "North Sea Herring"

Slot "desc":
[1] "Imported from a VPA file. ( ./bootstrap/data/index.txt ).  Wed May 26 11:49:48 2021"

Slot "range":
     min       max plusgroup   minyear   maxyear   minfbar   maxfbar
       0         8         8      1947      2021         2         6

Slot "fleets":
catch unique       HERAS     IBTS-Q1       IBTS0     IBTS-Q3    LAI-ORSH     LAI-BUN
LAI-CNS      LAI-SNS
           0           2           2           2           2           6           6           6           6

Slot "plus.group":
plusgroup
    TRUE

Slot "states":
              age
fleet          0  1  2  3  4  5  6  7  8
  catch unique  0  1  2  3  4  5  6  7  7
  HERAS        -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q1      -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS0        -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-ORSH     -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS      -1 -1 -1 -1 -1 -1 -1 -1 -1

Slot "logN.vars":
0 1 2 3 4 5 6 7 8
0 1 1 1 1 1 1 1 1

Slot "logP.vars":
[1] 0 1 2
```

```
Slot "catchabilities":
         age
fleet         0  1  2  3  4  5  6  7  8
  catch unique -1 -1 -1 -1 -1 -1 -1 -1 -1
  HERAS        -1  1  1  2  2  2  2  2  2
  IBTS-Q1      -1  3 -1 -1 -1 -1 -1 -1 -1
  IBTS0         0 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3       4  5  6  7  8  9 -1 -1 -1
  LAI-ORSH     10 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN      10 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS      10 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS      10 -1 -1 -1 -1 -1 -1 -1 -1

Slot "power.law.exps":
         age
fleet         0  1  2  3  4  5  6  7  8
  catch unique -1 -1 -1 -1 -1 -1 -1 -1 -1
  HERAS        -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q1      -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS0        -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-ORSH     -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS      -1 -1 -1 -1 -1 -1 -1 -1 -1

Slot "f.vars":
         age
fleet         0  1  2  3  4  5  6  7  8
  catch unique  0  0  1  1  1  1  2  2  2
  HERAS        -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q1      -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS0        -1 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-ORSH     -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS      -1 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS      -1 -1 -1 -1 -1 -1 -1 -1 -1

Slot "obs.vars":
         age
```

```
fleet          0  1  2  3  4  5  6  7  8
  catch unique  0  0  1  1  1  1  1  2  2
  HERAS        -1  3  4  5  6  6  6  7  7
  IBTS-Q1      -1  8 -1 -1 -1 -1 -1 -1 -1
  IBTS0         9 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3      10 10 11 11 11 11 -1 -1 -1
  LAI-ORSH     12 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN      12 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS      12 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS      12 -1 -1 -1 -1 -1 -1 -1 -1

Slot "srr":
[1] 0

Slot "scaleNoYears":
[1] 0

Slot "scaleYears":
[1] NA

Slot "scalePars":
     age
years  0 1 2 3 4 5 6 7 8

Slot "cor.F":
[1] 2

Slot "cor.obs":
              age
fleet          0-1 1-2 2-3 3-4 4-5 5-6 6-7 7-8
  catch unique  NA  NA  NA  NA  NA  NA  NA  NA
  HERAS         -1  NA  NA  NA  NA  NA  NA  NA
  IBTS-Q1       -1  -1  -1  -1  -1  -1  -1  -1
  IBTS0         -1  -1  -1  -1  -1  -1  -1  -1
  IBTS-Q3        0   0   0   0   0  -1  -1  -1
  LAI-ORSH      -1  -1  -1  -1  -1  -1  -1  -1
  LAI-BUN       -1  -1  -1  -1  -1  -1  -1  -1
  LAI-CNS       -1  -1  -1  -1  -1  -1  -1  -1
  LAI-SNS       -1  -1  -1  -1  -1  -1  -1  -1

Slot "cor.obs.Flag":
```

```
[1] ID ID ID ID AR ID ID ID ID
Levels: ID AR US

Slot "biomassTreat":
[1] -1 -1 -1 -1 -1 -1 -1 -1 -1

Slot "timeout":
[1] 3600

Slot "likFlag":
[1] LN LN LN LN LN LN LN LN LN
Levels: LN ALN

Slot "fixVarToWeight":
[1] FALSE

Slot "simulate":
[1] FALSE

Slot "residuals":
[1] FALSE

Slot "sumFleets":
logical(0)
```

NSAS assessment scaling

Benoit Berges[1*], Niels Hintzen[1]

[1] Wageningen Marine Research, The Netherlands

[*] benoit.berges@wur.nl

SUMMARY

Contents

1 BACKGROUND

1.1 NSAS assessment

The assessment for North Sea Herring (NSAS) is using commercial and survey data and span the 1947-2020 period. It is using the SAM stock assessment model (Nielsen and Berg 2014). The stock assessment was benchmarked in 2018 (ICES 2018) and underwent a management strategy evaluation in 2019 (ICES 2019). Despite the latter, there is no agreed management strategy to date for this stock and under the ICES framework, the F_{msy} advice rule takes precedence for the advice. The latest stock assessment model run is shown in Figure 1-1.

The North Sea herring stock is harvested by 4 fleets:

- A fleet: human consumption in the North Sea and Eastern Channel
- B fleet: bycatch of herring (in the sprat fishery) in the North Sea
- C fleet: human consumption in 3.a
- D fleet: bycatch of herring (in the sprat fishery) in the 3.a

The corresponding data for catches at age are available from 1947 but are only disaggregated by fleet from 1997. While most of the catches are from the A-fleet, other fleets are of importance because of the mixing with the Western Baltic spring (WBSS) spawning stock. Also of importance is the selectivity between the different fleets. Whilst the A fleet harvests ages 2+, the fishing pressure from other fleets (B, C and D) is significant for ages 0-1.

The assessment model is informed by 5 surveys:

- IHLS (larvae abundance index, LAI): survey focuses on the early larvae life stage of NSAS and covers the four different stock components: Orkney/Shetland, Buchan, Central North Sea (CNS), Southern North Sea (SNS). The influence of this survey is limited but remain important as it provides information on stock components.
- IBTS-Q1 (age 0): late larvae survey (MIK net) taking place Q1 of each year on all stock components except Downs. This is usually a good indicator of recruitment.
- IBTS-Q1 (age 1): bottom trawl survey taking place Q1 of each year which provides clear information on the survivors to the fishery.
- IBTS-Q3 (age 0-5): bottom trawl survey taking place Q3 of each year
- HERAS (age 2-9+): acoustic survey covering the full extent of the NSAS and WBSS stocks and is conducted yearly in June/July. The derived indices cover age 2+ and are very influential to the stock assessment model.

The observation variance by data source as estimated by the model is shown in Figure 1-2.

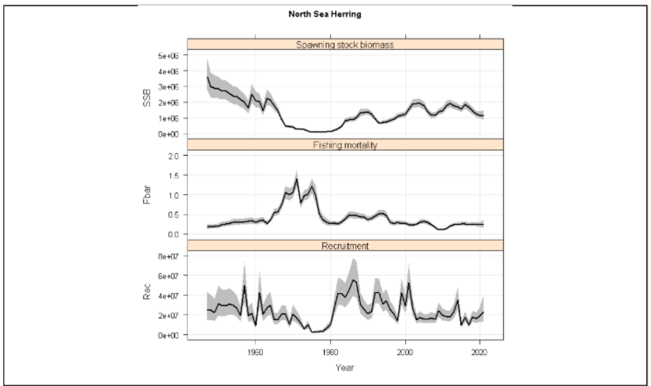


Figure 1-1: NSAS stock trajectories as estimated by the assessment model.

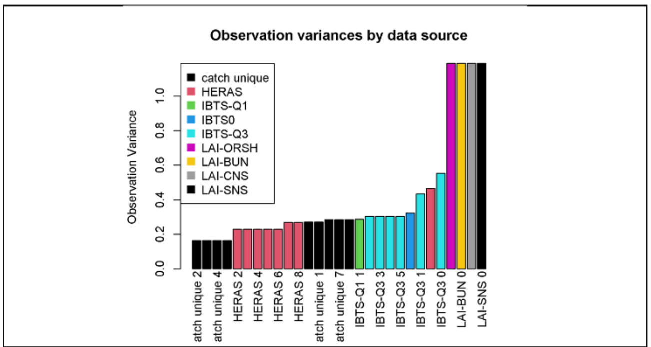


Figure 1-2: NSAS observation variance by data source as estimated by the assessment model.

1.2 Natural mortality for the NSAS assessment

The assessment of NSAS uses mortality input from the North Sea SMS-model provided every 3-4 years by the Working Group on Multispecies Assessment Methods (WGSAM) (ICES 2021). In 2020 WGSAM carried out new SMS key runs and provided a new natural mortality estimate for NSAS. This new natural mortality spans the 1974-2019 period across ages 0-8.

The SMS model provides raw values for the natural mortality at age (Figure 1-3). The input to the assessment is the natural mortality at age smoothed using a loess smoother (0.5 in span, order 2). The natural mortality outside the time period covered by the key run (1947-1973 and 2019-2021) are extrapolated using a 5 year running average (Figure 1-4).

The SMS multispecies model computes the interactions between species and estimate the predation mortality M2 from the species included in the model. The total natural mortality is the combination of the predation mortality M2 estimated by the model and the residual background mortality M1 which is a fixed value input to the model. For NSAS, the level of M1 inputted to SMS is of M1=0.1 and likely originates from estimates made during the closure of the fishery in 1978-1979 when the stock was at an ultimate low.

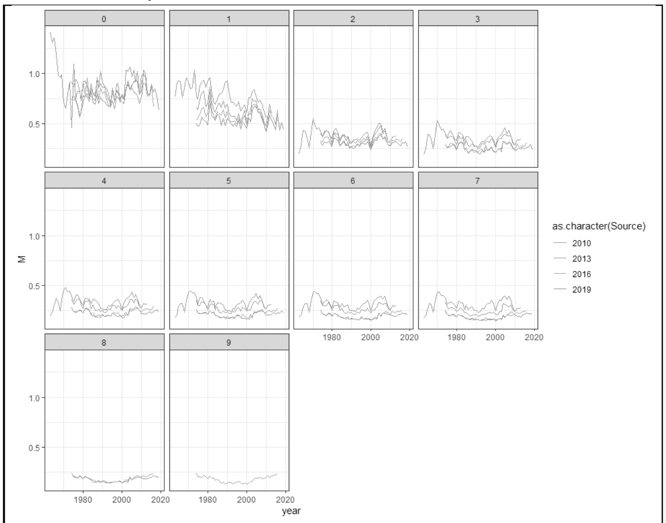


Figure 1-3: raw natural mortality vectors for all SMS keyruns (SMS2010, SMS2013, SMS2016, SMS2019).

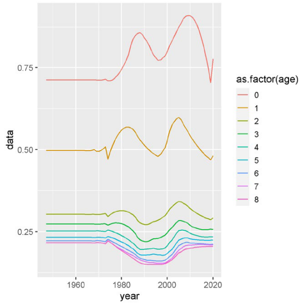


Figure 1-4: smoothed natural mortality vector for the 2019 key run.

1.3 Issues leading to the IBP

It has been shown that updating the stock assessment to use the most recent SMS key run natural mortality estimates is associated with large changes in the perception of the NSAS stock. This is mainly due to the varying absolute levels of the M vectors at age between the different SMS key runs. This is exemplified in Figure 1-5 where the absolute level of the four different natural mortality vectors (2010, 2013, 2016, 2019) are compared per decade. Whilst the 2016 and 2019 SMS key runs yield similar levels, there was a significant change from 2013 to 2016. Figure 1-6 shows the SSB estimated by the NSAS assessment model as of 2010 with the different natural mortality SMS vectors. One can observed a scaling induced by the use of different SMS key runs.

The external information available on appropriate absolute levels of M are lacking (see WD WKPELA 2018, Mackinson & Hintzen) and are limited to estimates of biomass by the HERAS acoustic survey and life-history based empirical estimates of M. Given the limited ability to use this information to prevent rescaling in between SMS key run updates, a profiling method was developed. The method consists of the testing of the fit of the assessment model for a range of additive rescaling (fixed across years and ages, i.e. adding a single value, identical by age and year, to all Ms at age/year) for M. The optimal fit (AIC and negative log-likelihood) of the assessment model is then taken as the additive level of rescaling to be applied to M.

However, for the profiling performed during WKPELA2018 (associated with the 2017 SMS key run), a benchmark interim model specification was used yielding an absolute level of rescaling of 0.11 in M. In other words, the interim model on which the profiling was based and the final selected model from the benchmark different in model configuration. This resulting additive M of 0.11 was deemed plausible by the benchmark group and reviewers, especially in light of the resulting catchability of the HERAS survey which was estimated to be close to 1. The profiling method was not rerun with the final assessment setup that was agreed during the benchmark.

This difference in setup was discovered at HAWG2021 when rerunning the profiling of the assessment as this was the first time a new SMS key run had become available. Recalculation of the profiling method applied to the final WKPELA2018 assessment model suggested an additive M of 0. Moreover, the investigation also revealed that changing the absolute level of the M vectors based on the profiling of the assessment model is sensitive to specific model configuration parameters. It was unclear why these changes in data and model settings during the benchmark had such a large effect on the profiling results. This aspect was not explored at WKPELA2018 but is paramount in light of what was discovered at HAWG2021. Moreover, changing the correction factor on M would lead to a significant change in the perception of the stock and the need to re-evaluate reference points.

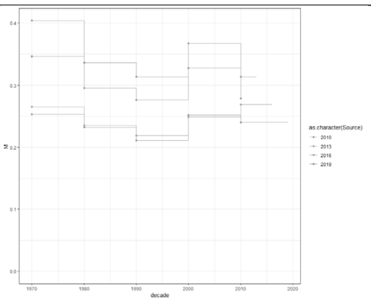


Figure 1-5: M for ages 2-6 WR only, summarized by decade (x-axis) and Key run (colour).

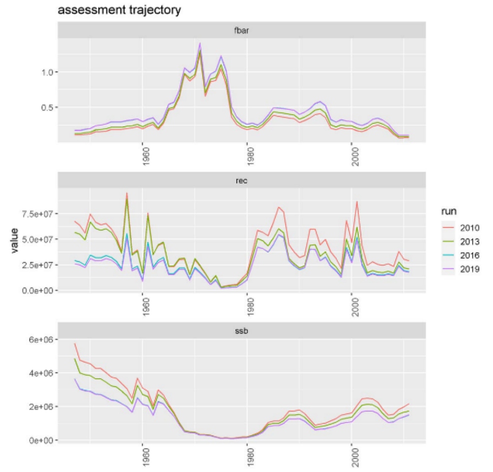


Figure 1-6: NSAS assessment model with 2010 as terminal year with natural mortality taken from the four available SMS keyruns: 2010, 2013, 2016 and 2019.

1.4 IBPNSHerring terms of reference

In light of the issues introduced in Section 1.3, The Terms of Reference (ToR) for IBPNSHerring are as follows:

i. Investigate methods to bring consistency in the scaling of the assessment arising from updates in SMS.
   a. Evaluate optimal model configuration.
   b. Investigate the sensitivity of methods and assumptions about M on the assessment of NSAS herring. This includes investigating the assessment profiling method developed at WKPELA2018.

ii. Carry out the 2021 NSAS assessment based on the updated NSAS assessment model.

iii. Update reference points based on the updated NSAS assessment model.

1.5 Work scope

The work undertaken in preparation to the IBP revolves around the handling of the natural mortality for the NSAS assessment model. The tasks for this IBP are divided in four components:

1) Exploration of scaling methodologies. Essential to the IBP, this task will investigate methodologies to estimate the scaling of the assessment outputs. The outcome will be the adoption of the most appropriate method to handle natural mortality (e.g. based on stability and robustness).

2) Independent estimation of residual natural mortality. This task is aimed at providing independent information to 1).
3) Derivation of reference points based on final model. Based on final natural mortality and model configuration derived in 1), this task consists in deriving reference points.

The hereby working document reports on the results from task 1). The scaling of the NSAS assessment is closely linked to the absolute level of natural mortality. Whilst the natural mortality vector is provided by WGSAM, its absolute level is in part defined by the level of fixed background mortality M1=0.1. There is therefore uncertainties to what absolute level of natural mortality is applicable to the assessment and in turn the absolute scaling of the assessment. Whilst reference points are relative to the scaling of the assessment, a change in absolute level is detrimental to the process of deriving a management plan, e.g. by the mean of management strategy evaluations (MSEs). It is therefore important to bring consistency in the scaling of the assessment. To that aim, an additive scaling of the natural mortality is sought, informed by the level of fit of the assessment (using the negative log likelihood). In order to test stability and robustness of the profiling method, simulation testing is undertaken for:

- all SMS keyruns available (2019, 2016, 2013, 2011)
- SMS sensitivity runs on M1
- 10 year peels
- Alternative models:
  - Correlation in selectivity patterns
  - Fixed HERAS catchability in core ages
- Alternative binding settings
- Alternative time periods

The code developed for this IBP is freely available on github:
https://github.com/ices-taf/2021_her.27.3a47d_IBP_assessment.git

2 METHODS AND RESULTS

2.1 Background mortality sensitivity

An important input in the SMS model is the unaccounted background mortality M1. In the model, it is fixed and the total natural mortality is estimated per quarter as M=M1+M2 with M2 the predation mortality from predators accounted for in the model. The value used for herring is M1=0.1, a value provided by HAWG and fixed across ages and years. This is the value used for the baseline assessment. There is uncertainties associated with M1: magnitude, trends over time, trends over ages. In order to test the NSAS assessment model against various levels of M1, sensitivity runs of the SMS was performed with values ranging from 0.08 to 0.2. The resulting natural mortality vectors at age are shown in Figure 2-1. One can observe an increase in total M with increasing M1 for ages 2+. The derived stock trajectories for NSAS herring are shown in Figure 2-2. Increase in M1 leads to a decrease in Fbar and an increase in SSB. It is interesting to note that the trends from the SMS model are very similar to those estimated by the baseline SAM assessment model. The summary statistics for all species and the herring component of the model are shown in Table 2-1 and Table 2-2 respectively. There is no abrupt change in likelihood, suggesting none of the values tested leads to a drastic change in the SMS model. The best fit for the SMS model is for M1=0.08.

Commented [BB1]: I cannot recall why age 0 scales inversely and age 1 scaling is limited.

The results from the 2019 SMS run can be explored with the app available at:
http://ono.dtuaqua.dk:8282/SMSapp/

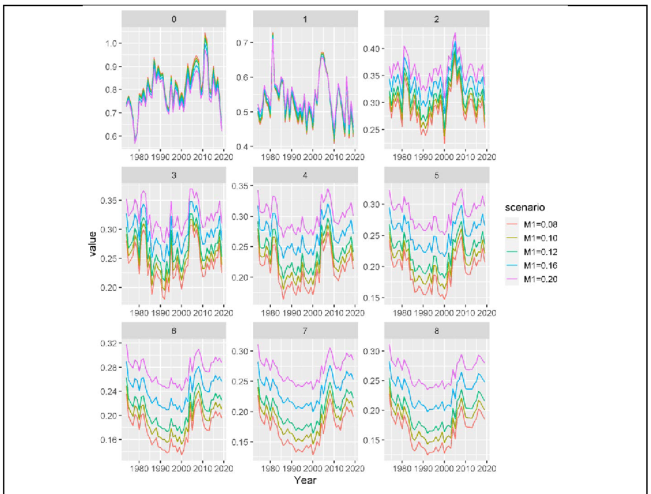


Figure 2-1: natural mortality at age M resulting from the SMS model with a range of values used for

background mortality.

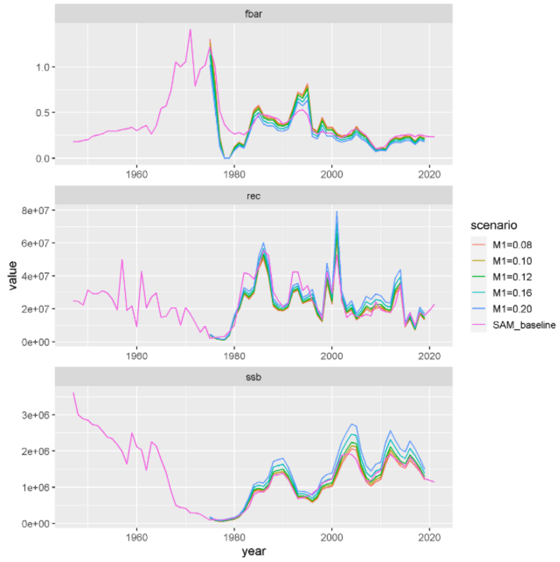


Figure 2-2: comparison of stock trajectories estimated by SMS and SAM.

Table 2-1: Summary statistics from the 2019 SMS keyrun for all species. The best fit is found for M1=0.08.

label	catch	CPUE	SSB.Rec	stomachs	all	n.par	neg.log.lil
M1=0.08	-1707.2	-828.645	-72.2621	-4736.54	-7344.65	1867	-5453.71
M1=0.10	-1705.07	-828.77	-72.4312	-4736.57	-7342.85	1867	-5451.78
M1=0.12	-1702.85	-828.754	-72.5895	-4736.6	-7340.79	1867	-5449.61
M1=0.16	-1698.11	-828.224	-72.8386	-4736.7	-7335.87	1867	-5444.57
M1=0.20	-1693.06	-826.943	-72.9781	-4736.92	-7329.91	1867	-5438.59

Table 2-2: summary statistics from the 2019 SMS keyrun for herring. The best fit is found for M1=0.08.

		Unweighted likelihood contributions			
label	Species	catch	CPUE	SSB.Rec	sum
M1=0.08	Herring	231.50	-181.96	-8.05	41.49
M1=0.10	Herring	233.60	-181.95	-8.24	43.41
M1=0.12	Herring	235.82	-181.80	-8.42	45.60
M1=0.16	Herring	240.56	-180.96	-8.76	50.83
M1=0.20	Herring	245.65	-179.35	-9.04	57.26

2.2 Log likelihood profiling

2.2.1 Base run

The estimates provided by the SMS multispecies model provide the best available estimates of natural mortality for NSAS herring. However, there is uncertainties related to the appropriate level of unaccounted background natural mortality M1 which remains an unknown. For the current SMS keyruns (2019) provided by WGSAM, M1=0.1. The level of M1 is particularly influential for the scaling of the NSAS assessment (Figure 1-6).

The method employed here consists in scanning the fit of the assessment across a range of additive M rescaling: M=M+addM. The optimal assessment fit (found as the lowest negative log likelihood) provides the model with the absolute level of M that best fit data statistically.

First, the assessment with the 2019 SMS keyrun is tested. The corresponding negative log likelihood profile is shown in Figure 2-3(a). Figure 2-3(a) shows the catchability of the HERAS survey across ages 3-8 and the SSB level relative to the baseline assessment. Because different SMS keyruns exemplify varying absolute levels (Figure 1-5), values are plotted against Mbar, the average of M over years and ages. The optimum is found at addM=0.

The effect of addM values to the assessment parameters is shown in Figure 2-4, Figure 2-5 and Figure 2-6.

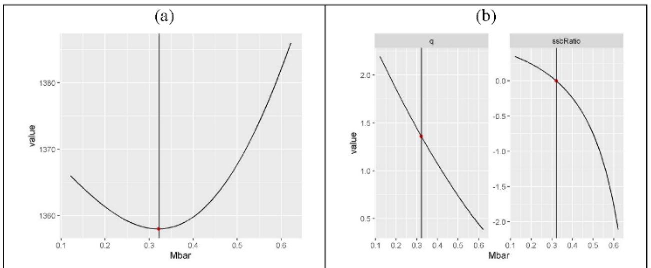


Figure 2-3: base run assessment profiling. (a) negative log likelihood for different levels of additive scaling for M. (b) catchability of the HERAS (age 3-8) and ratio of SSB relative to baseline assessment

(using SMS2019 without additive scaling for M). The red circle markers correspond to the minimum negative log likelihood, considered the optimum assessment fit. The vertical black line is the absolute level of M (averaged across years and ages) for the SMS2019 keyrun and corresponds to an additive scaling for M of 0.

(a)	(b)

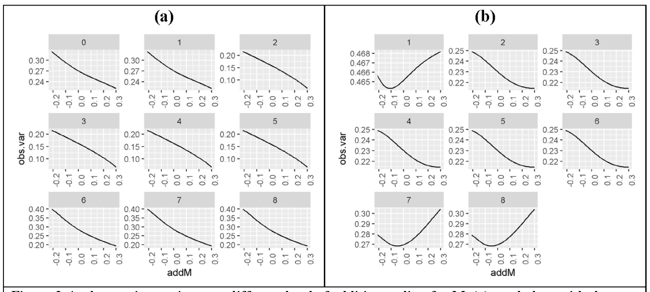


Figure 2-4: observation variance at different level of additive scaling for M. (a) catch data with the following age binding: 0-1, 2-5, 6-8. (b) HERAS survey data with the following age binding: 1, 2-6, 7-8.

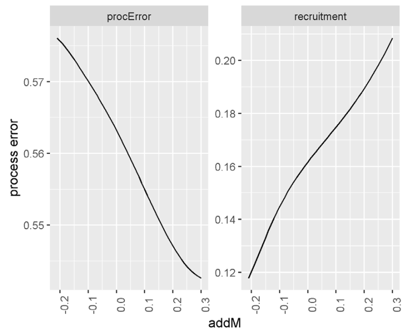


Figure 2-5: process error variance at different level of additive scaling for M. (a) process error variance in numbers at age. (b) process error variance in recruitment.

(a)	(b)

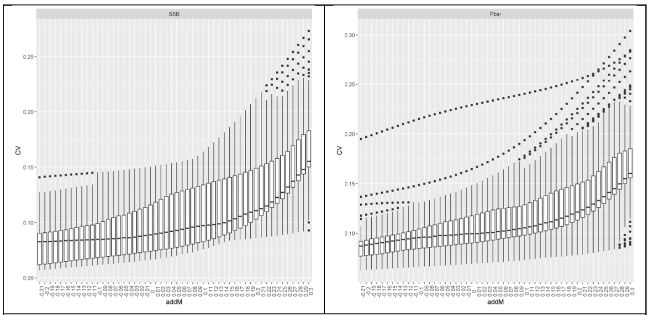


Figure 2-6: uncertainty in SSB and fbar as boxplot for all years in assessment (1947-2020) at different level of additive scaling for M. (a) SSB. (b) fbar

2.2.2 Natural mortality keyruns

Here, the negative log likelihood profiling method is tested against the four vectors of naturality available from the SMS model: 2010 keyrun, 2013 keyrun, 2016 keyrun, 2019 keyrun. Because each SMS keyrun has a different terminal year, the assessment of 2010 is taken to ensure that no extrapolating of M vectors is done for comparison.

The negative likelihood profiles are shown in Figure 2-7 and summarized in Table 2-3. The resulting stock trajectories are presented in Figure 2-8 and a summary of optimum runs is presented in Figure 2-9. Only the 2010 SMS keyrun exemplifies a small deviation in stock trajectory, due to changes implemented in the subsequent SMS runs. Overall, the influence of the various keyruns is limited, suggesting the profiling method is robust against changes in SMS. For example, the 2016 and 2019 exemplify very similar results.

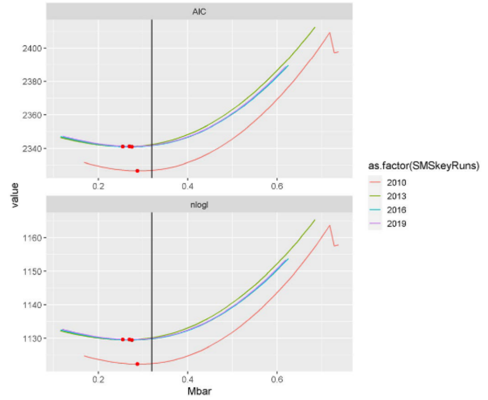


Figure 2-7: assessment profiling for the assessment model using the four different SMS keyruns (2010, 2013, 2016 and 2019). The red circle markers correspond to the minimum negative log likelihood, considered the optimum assessment fit. The vertical black line is the absolute level of M (averaged across years and ages) for the SMS2019 keyrun.

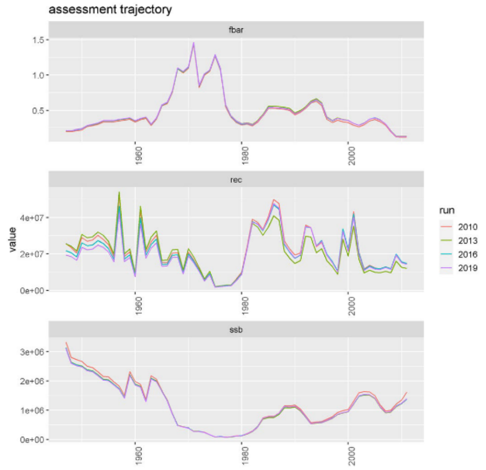


Figure 2-8: assessment trajectory of assessment models ran with the four different SMS keyruns (2010, 2013, 2016 and 2019) at optimal point on the negative log likelihood. The assessment used for comparison runs to 2010.

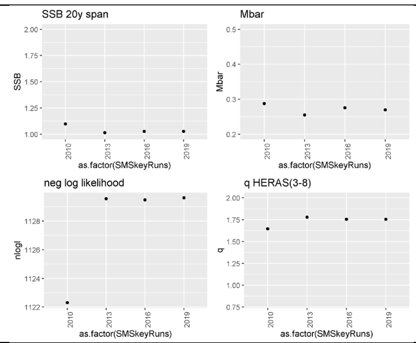


Figure 2-9: SSB, Mbar, negative log likelihood and HERAS catchability (q) for the different SMS keyruns (2010, 2013, 2016, 2019).

Table 2-3: Estimated optimal additive M, the resulting Mbar, nlogl, AIC and HERAS q for the four different SMS keyruns (2010, 2013, 2016 and 2019)

addM	Mbar	SMSkeyRuns	nlogl	AIC	q
-0.15	0.287729	2010	1122.307	2326.613	1.646206
-0.13	0.254954	2013	1129.557	2341.115	1.779152
-0.05	0.275401	2016	1129.474	2340.948	1.754471
-0.05	0.269491	2019	1129.617	2341.235	1.754076

2.2.3 Background mortality sensitivity

As described in Section 2.1, the 2019 SMS model was ran with varying assumptions on M1 (0.08 to 0.2). In the hereby section, the NSAS assessment is profiled with these alternative runs of SMS2019. Results are presented in Figure 2-10-Figure 2-12 and summarized in Table 2-4. Overall, the estimated additive scaling in M is consistent between the sensitivity runs. Some small differences in stock trajectories can be observed (Figure 2-11), especially at high M1. This could be induced by the scaling of total M from M1 levels which is disproportional between ages, especially age 0-1 compared to 2+ (Figure 2-1).

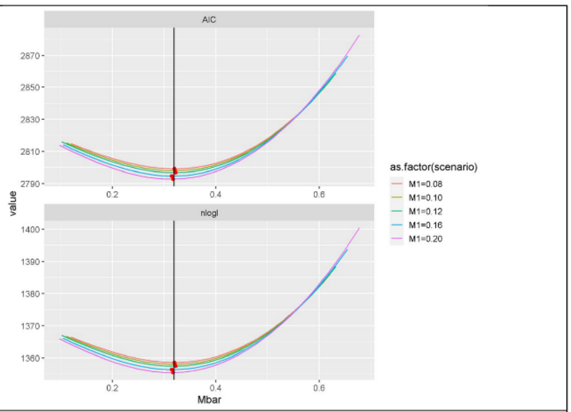
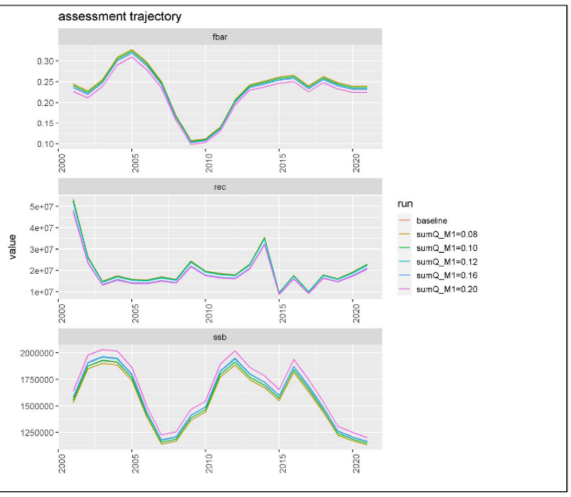


Figure 2-10: assessment profiling for the assessment model using different level of background mortality M1 (0.08 to 0.2). The red circle markers correspond to the minimum negative log likelihood, considered the optimum assessment fit. The vertical black line is the absolute level of M (averaged across years and ages) for the SMS2019 keyrun.



18

Figure 2-11: assessment trajectory of assessment models using different level of background mortality M1 (0.08 to 0.2) at optimal point on the negative log likelihood profile. The baseline assessment is using the SMS2019 keyrun with M1=0.1.

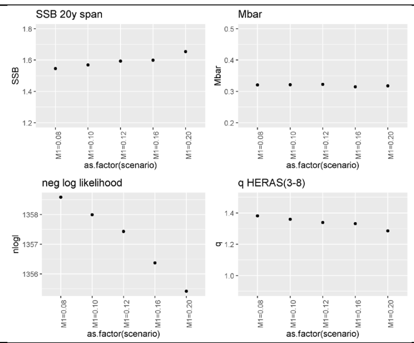


Figure 2-12: SSB, Mbar, negative log likelihood and HERAS catchability (q) for the different SMS 2019 keyruns M1 sensitivity scenarios.

Table 2-4: Estimated optimal additive M, the resulting Mbar, nlogl, AIC and HERAS q for the different SMS 2019 keyrun sensitivity scenarios.

addM	Mbar	scenario	nlogl	AIC	q
0.01	0.320368	M1=0.08	1358.579	2799.157	1.380784
0	0.321292	M1=0.10	1357.988	2797.976	1.359744
-0.01	0.322337	M1=0.12	1357.425	2796.849	1.338306
-0.04	0.314805	M1=0.16	1356.369	2794.738	1.331802
-0.06	0.317753	M1=0.20	1355.413	2792.827	1.285759

2.2.4 Retrospective

An important test for the profiling method is investigate whether it is sensitive to new data points. To that aim, a 10 year peel is performed and the profiling method is applied on each peel. Stock trajectories for these peels are put in perspective to those from the assessment in Figure 2-13. Expletively, larger deviations (relative to the retro run) through the entire time series is obtained when the profiling on each peel is applied. This is because the natural mortality is scaled for the entire time series as opposed to the retro run that only uses 1 year less of data for each peel. This results in an additional retrospective in SSB induced by the profiling method in the order of 5-10% (Figure 2-14). In term of additive M scaling, there is a change from addM=-0.05 for the 2010 peel to addM=0.06, i.e. an increase in Mbar of 0.06 over 10 years (Figure 2-15 and Table 2-5). This is associated with a significant drop in HERAS catchability (age 3-8), from 1.75 to 1.3.

(a)	(b)

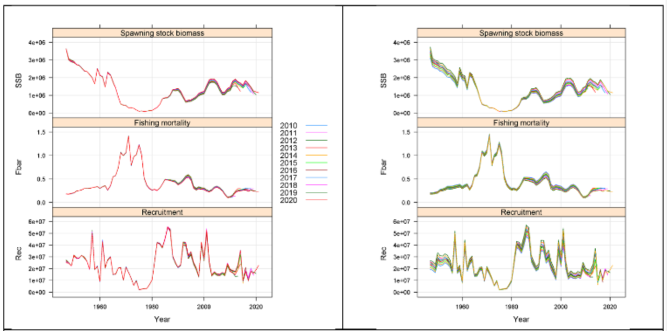


Figure 2-13: comparison of retrospective patterns for the peels of the baseline assessment (a) and the peels of the baseline assessment with profiling for each year (b).

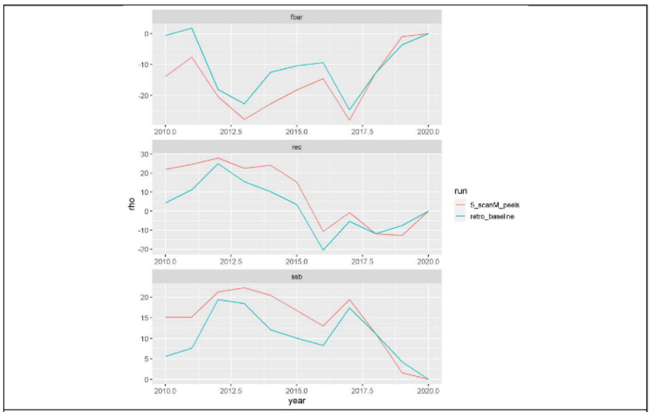


Figure 2-14: mohn rho for the baseline assessment (a) and the baseline assessment with profiling for each year (b). Mohn rho is calculated with a 10 year span.

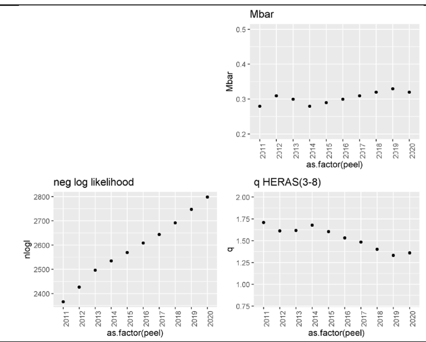


Figure 2-15: Mbar, negative log likelihood and HERAS catchability (q) for the different SMS 2019 keyruns M1 sensitivity scenarios.

Table 2-5: Estimated optimal additive M, the resulting Mbar, nlogl, AIC and HERAS q for different assessment peels with profiling for each year.

.

addM	Mbar	peel	nlogl	AIC	q
0.01	0.331566	2019	1332.74	2747.479	1.331316
0	0.321859	2018	1304.564	2691.128	1.400535
-0.01	0.312038	2017	1280.778	2643.556	1.485261
-0.02	0.30211	2016	1263.23	2608.459	1.532431
-0.03	0.292077	2015	1243.706	2569.412	1.603478
-0.04	0.281952	2014	1226.277	2534.554	1.677538
-0.02	0.301738	2013	1207.2	2496.399	1.616747
-0.01	0.31144	2012	1172.187	2426.374	1.613822
-0.04	0.281063	2011	1141.936	2365.872	1.70839
-0.05	0.270627	2010	1129.617	2341.235	1.754076

2.3 Log likelihood profiling with correlation in selectivity patterns

2.3.1 Base case

In SAM there is the option to force a correlation structure on the selection patterns. This setting was used in the interim benchmark model during WKPELA2018 (ICES 2018). The forced correlation (deviating from the correlation is being penalized in the nlogl) follows a power-law decline over the ages, such that age 1-2 is equally correlated to 2-3 and 5-6 but that the correlation is ^2 as low for age-classes two ages apart etc. The inclusion of a correlation structure (as opposed to freely derived selection patterns) leads to small differences in correlation in fishing mortality at age (Figure 2-16). Only the age 0-1 relationship is impacted significantly, with a higher correlation when including a correlation structure in the SAM model (increased correlation coefficient from 0.36 to 0.6, Figure 2-16). In term of fishing selectivity, there is a good match with and without the correlation structure.

Though, in the period around the closure of the fishery (1978-1979) one can observe substantial deviations in fishing selectivity patterns, due to the low catch number in this period (Figure 2-17). The differences in fit to the data are minor and hardly visible by the eye.

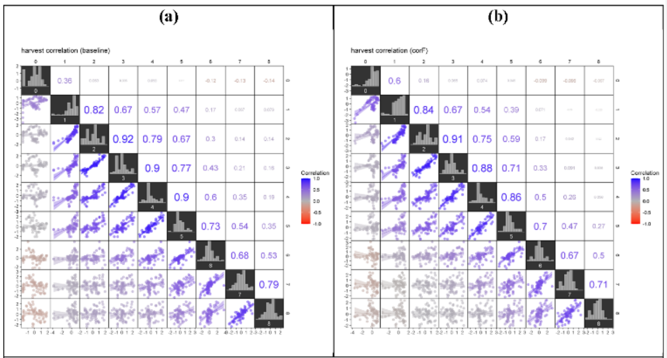


Figure 2-16: internal consistency of fishing mortality at age. (a) correlation matrix for the baseline run. (b) correlation matrix for the run with the correlation in F toggled on.

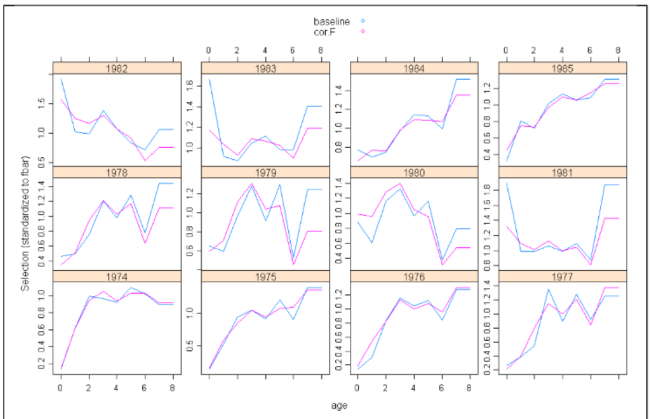


Figure 2-17: Estimated selection patterns under the baseline and corF scenarios for years around the closure of the fishing (1978-1979).

The parameter for the correlation structure on the selection patterns is particularly important in relation with the assessment profiling. At WKPELA2018, the profiling of the assessment was ran with the correlation structure toggled on (alongside divergent binding settings) whilst the final model did not include it. This led to addM=0.11. However, the final model is the one currently used at the assessment group. At HAWG2021, it was found that running the profiling of the assessment without the correlation structure toggled on leads to a drastic change in additive M rescaling. This effect is shown in Figure 2-18 and Table 2-6. The inclusion of a correlation structure changes addM from 0 to 0.06 and the effect on the scaling of the assessment is substantial (Figure 2-19). The additional factors that induced an addM=0.11 at WKPELA2018 are different binding settings (observation variance and catchability) and retrospective (WKPELA2018 used the assessment with 2017 as the terminal year). One of the estimates that is affected most by the difference in correlation setting is the CV of the estimate parameters of the F-random walk (Figure 2-20).

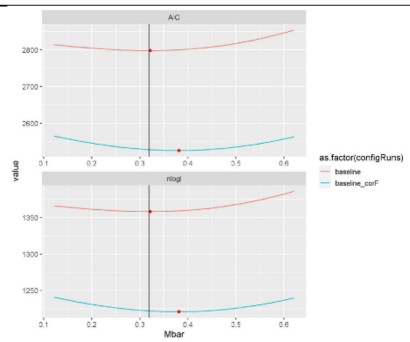


Figure 2-18: AIC and negative log-likelihood of identical models except for the setting on fleet selectivity correlation. The corF scenario indicates a forced correlation structure.

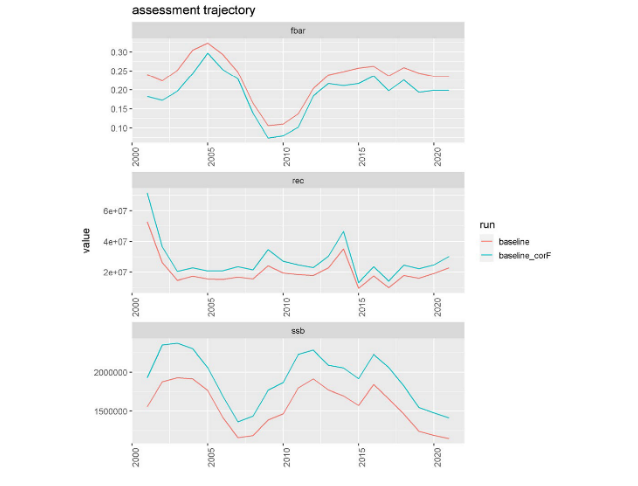


Figure 2-19: Estimates stock trends under the two scenarios.

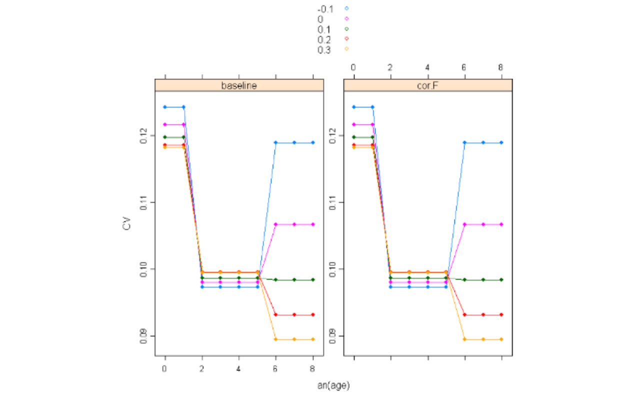


Figure 2-20: Estimated CVs of the F-random walks for the baseline and corF scenarios. Different coloured lines indicate different addM runs ranging from subtracting 0.1 from the M vectors to adding

24

0.3 to the M vectors. Age combinations 0-1, 2-5 and 6-8 are estimated by single parameters. Under changes in additive M values, the CV of especially the older ages changes substantially.

Table 2-6: Estimated optimal additive M, the resulting Mbar, nlogl, AIC and HERAS q for the two scenarios tested.

addM	Mbar	configRuns	nlogl	AIC	q
0	0.321484	baseline	1357.97	2797.94	1.360186
0.06	0.381484	baseline_corF	1220.937	2525.873	1.115359

2.3.2 Effect of the catch closure time period

As exemplified in Section 2.3.1, there is differences in selectivity patterns around the closure period (1978-1979) when using a correlation structure in fishing mortality. Moreover, assessment uncertainty is much higher in the period with the added correlation structure. To explore the impact this has on the profiling method of M, it is tested for a range of assessment starting years, from 1960 to 1988. Results are shown in Figure 2-21 and summarized in Table 2-7. Whilst the base run profiling exemplifies change in addM between -0.02 and 0.05, the use of the correlation structure in fishing selectivity reduces this dynamic range significantly with addM contained between 0.05 and 0.07. Interestingly, there is a convergence between the base and corF runs in addM for start year larger than 1982. An additional test fixing addM=0 in the base run throughout the historical peeling shows that the profiling per se is influenced by the historical period. This is exemplified by emergence of a pronounced trend in the catchability (q) of the HERAS (Figure 2-22). However, introduction of a correlation in F among ages (corF) is able to ~~This suggests the closure period has a strong effect when profiling the assessment~~remove such influence of the historical period on the profiling and gain even more stability to the estimation of the HERAS' q (Figure 2-21).

Commented [VB2]: As mentioned yesterday, during these test (addM=0) it appeared clear that there are other parameters in the model (ie, process errors on both F and N) that are influenced by the historical period regardless of the profiling (at least this is the result on the baserun without corF). I think it would be confounding to have this here, but if we have a section about aspects that will deserve more attention in the next benchmark it would be worth to add few lines there (I'm happy to do that).

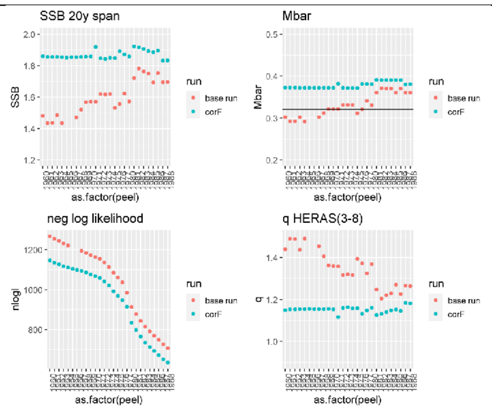


Figure 2-21: SSB, Mbar, negative log likelihood and HERAS catchability (q) for different assessment start year as a result of the profiling with two models: baseline (red circle markers) and baseline

inclusive of correlation structure in fishing selectivity (blue circle markers).

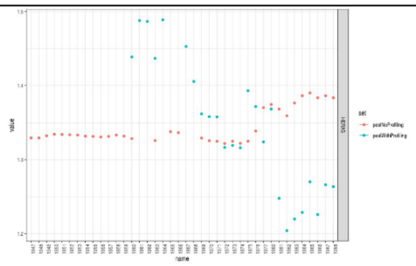


Figure 2-22: HERAS catchability (age 3-8) from the baseline with fixed addM=0 (red circle markers) and baseline with profiling (blue circle markers).

Commented [VB3]: I haven't updated figures numbers after this new one for fear to mess up internal referencing

Formatted: Normal

Table 2-7: estimated optimal additive M, the resulting Mbar, nlogl, AIC and HERAS q for different assessment starting years and different model settings: baseline and baseline inclusive of correlation structure in fishing selectivity.

peel	addM	Mbar	nlogl	AIC	q	ssbAbs	addM	Mbar	nlogl	AIC	q	ssbAbs
	Correlation in F						Baseline					
1960	0.05	0.372259	1146.968	2377.935	1.148629	1.859049	-0.02	0.302259	1266.666	2615.332	1.438759	1.48112
1961	0.05	0.372217	1134.714	2353.428	1.152523	1.853939	-0.03	0.292217	1254.05	2590.099	1.48794	1.434884
1962	0.05	0.372173	1126.648	2337.297	1.15326	1.853724	-0.03	0.292173	1244.325	2570.651	1.486702	1.436715
1963	0.05	0.372128	1116.676	2317.353	1.15374	1.854155	-0.02	0.302128	1231.229	2544.459	1.437016	1.485561
1964	0.05	0.372081	1111.108	2306.217	1.154457	1.852698	-0.03	0.292081	1221.374	2524.749	1.48893	1.435458
1965	0.05	0.372032	1103.837	2291.675	1.155544	1.850607						
1966	0.05	0.371983	1098.864	2281.727	1.154158	1.852311						
1967	0.05	0.371931	1093.507	2271.015	1.153748	1.853056	-0.02	0.301931	1195.053	2472.106	1.452921	1.470971
1968	0.05	0.371876	1085.549	2255.098	1.153984	1.854966	-0.01	0.311876	1183.897	2449.794	1.405669	1.520443
1969	0.05	0.371817	1075.542	2235.084	1.154658	1.855203	0	0.321817	1173.426	2428.851	1.362082	1.568608
1970	0.05	0.371761	1067.467	2218.935	1.152944	1.85711	0	0.321761	1163.32	2408.64	1.358245	1.571837
1971	0.06	0.381703	1058.183	2200.366	1.115638	1.91847	0	0.321703	1154.662	2391.324	1.357713	1.5719
1972	0.05	0.371639	1041.113	2166.226	1.15966	1.846301	0.01	0.331639	1135.686	2353.372	1.316537	1.619838
1973	0.05	0.371566	1021.744	2127.488	1.162306	1.841534	0.01	0.331566	1112.737	2307.474	1.31954	1.616165
1974	0.05	0.371484	991.9974	2067.995	1.157044	1.848767	0.01	0.331484	1085.023	2252.046	1.316126	1.61985
1975	0.05	0.371444	968.9793	2021.959	1.158454	1.84682	-0.01	0.311444	1060.732	2203.465	1.393304	1.531436
1976	0.06	0.381373	947.4224	1978.845	1.131555	1.89115	0	0.321373	1035.909	2153.818	1.371907	1.556332
1977	0.06	0.381273	913.775	1911.55	1.147176	1.869635	0.02	0.341273	984.8889	2051.778	1.324133	1.622303
1980	0.06	0.380865	834.4916	1752.983	1.16044	1.857274	0.01	0.330865	912.0564	1906.113	1.36832	1.572033
1981	0.07	0.390715	797.3816	1678.763	1.125646	1.921211	0.04	0.360715	877.3392	1836.678	1.248075	1.720906
1982	0.07	0.39057	764.1947	1612.389	1.131346	1.915559	0.05	0.37057	844.2026	1770.405	1.204413	1.782299
1983	0.07	0.39044	733.326	1550.652	1.139607	1.904615	0.05	0.37044	814.5663	1711.133	1.219952	1.763233
1984	0.07	0.390326	711.4704	1506.941	1.147096	1.891613	0.05	0.370326	791.1689	1664.338	1.229054	1.75029
1985	0.07	0.390229	692.5532	1469.106	1.15207	1.884714	0.04	0.360229	769.317	1620.634	1.270167	1.693597
1986	0.07	0.390179	672.0487	1428.097	1.145336	1.895538	0.05	0.370179	747.9566	1577.913	1.226048	1.75312
1987	0.06	0.380263	651.2872	1386.574	1.182868	1.83165	0.04	0.360263	725.4372	1532.874	1.266289	1.693969
1988	0.06	0.380551	634.8088	1353.618	1.181159	1.833147	0.04	0.360551	706.355	1494.71	1.263651	1.696752

2.4 Log likelihood profiling with fixed HERAS catchability

The HERAS survey is an important component of the NSAS assessment, being the most influential source of information after catch data (Figure 1-2). As a result, the catchability parameter of the HERAS survey is strongly linked with the absolute scaling of the assessment. An alternative assessment model consists in fixing the catchability for the HERAS survey across core ages (3-8). The result of the profiling for the alternative model is shown in Figure 2-22(b), in contrast to the profiling of the baseline model (Figure 2-22(a)). It is clear that the use of a fixed catchability reduces the deviation in stock trajectories. This is also associated with in general lower observation variances (Figure 2-23). Though, the process error in recruitment is significantly inflated with the use of this alternative model (Figure 2-23).

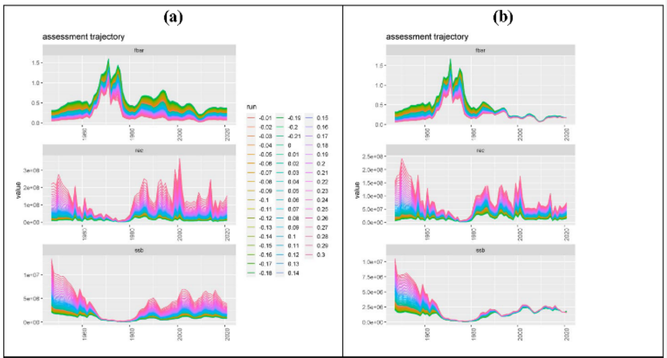


Figure 2-23: stock trajectories for different levels of additive scaling for M. (a) Baseline. (b) Case with fixed HERAS catchability (age 3-8)

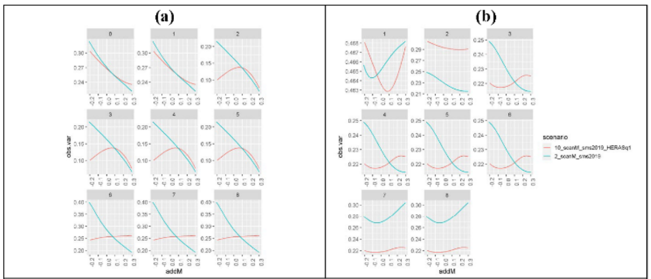


Figure 2-24: comparison of observation variance at different level of additive scaling for M for the baseline model and the model using a fixed HERAS catchability (3-8). (a) catch data. (b) HERAS

survey data.

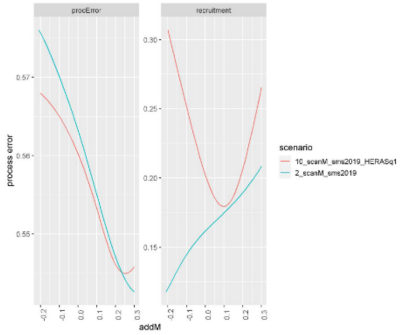


Figure 2-25: comparison of process error variance at different level of additive scaling for M for the baseline model and the model using a fixed HERAS catchability (3-8). (a) process error variance in numbers at age. (b) process error variance in recruitment.

2.5 Model comparison

2.5.1 Model testing

In previous sections, 3 models have been tested:

- Baseline model
- Inclusion of correlation structure in selectivity patterns
- Fixing of the HERAS catchability across ages 3-8

The difference in profiling between these three models is first presented in Figure 2-25. The use of a fixed catchability for the HERAS survey yields addM=0.08 and results in the highest SSB and Mbar levels. The use of the correlation structure induces addM=0.06. In contrast, profiling the baseline model yield addM=0. The differences between models can be alleviated by using a start year greater than 1982, cropping the catch closure period. This is shown in Figure 2-26.

The results of further testing of each model are presented in Figure 2-27 (SMS keyruns from 2010 to 2019), Figure 2-28 (varying M1 levels in 2019 SMS model), Figure 2-29 and Figure 2-30 (retrospective from 10 year peel).

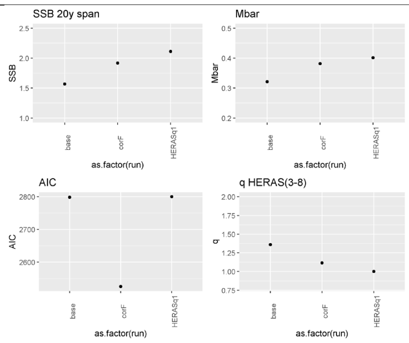


Figure 2-26: comparing the profiling of the assessment for three different models: baseline, baseline inclusive of correlation structure in fishing selectivity, baseline with fixed HERAS catchability across ages 3-8.

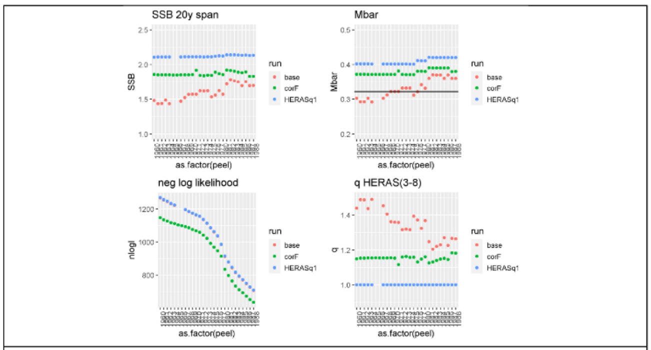


Figure 2-27: SSB, Mbar, negative log likelihood and HERAS catchability (q) for different assessment start year as a result of the profiling. Three models are compared: baseline (red circle markers), baseline inclusive of correlation structure in fishing selectivity (green circle markers), baseline with fixed HERAS catchability across ages 3-8 (blue circle markers).

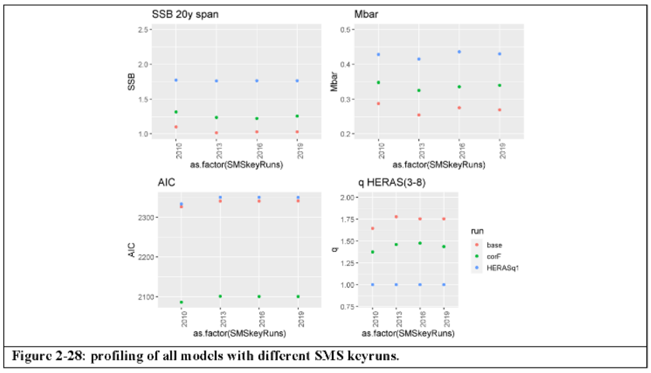


Figure 2-28: profiling of all models with different SMS keyruns.

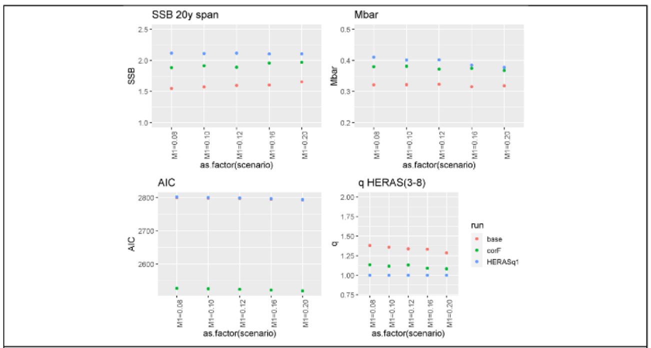


Figure 2-29: profiling of all models with different level of M1 in the SMS model.

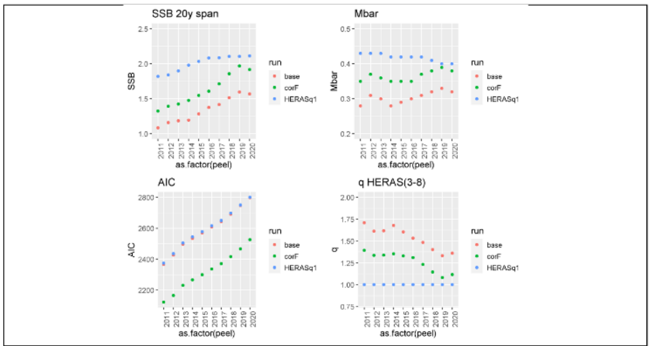


Figure 2-30: profiling of all models with 10 year peel.

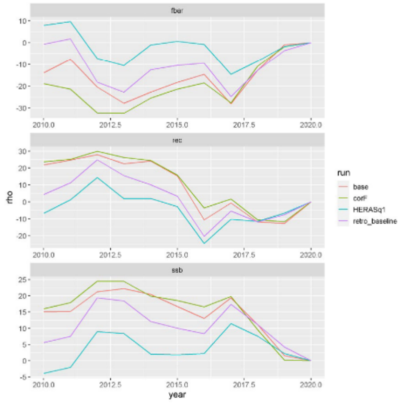


Figure 2-31: retrospective for the profiling of all models and compared to retro run (labelled as retro_baseline).

2.5.2 Sensitivity to parameter bindings

Table 2-8: observation variance bindings.

<table>
<tr><th>Baseline</th><th>Alt1</th><th>Alt2</th></tr>
<tr>
<td><pre>
Slot "obs.vars":
                age
fleet   0 1 2 3 4 5 6 7 8
  catch unique   0 0 1 1 1 1 2 2 2
  HERAS   -1 3 4 4 4 4 4 5 5
  IBTS-Q1   -1 6 -1 -1 -1 -1 -1 -1 -1
  IBTS0   7 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3   8 9 10 10 10 10 -1 -1 -1
  LAI-ORSH   11 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN   11 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS   11 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS   11 -1 -1 -1 -1 -1 -1 -1 -1
</pre></td>
<td><pre>
Slot "obs.vars":
                age
fleet   0 1 2 3 4 5 6 7 8
  catch unique   0 0 0 0 1 1 1 1 1
  HERAS   -1 2 3 3 3 3 3 4 4
  IBTS-Q1   -1 5 -1 -1 -1 -1 -1 -1 -1
  IBTS0   6 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3   7 8 9 9 9 9 -1 -1 -1
  LAI-ORSH   10 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN   10 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS   10 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS   10 -1 -1 -1 -1 -1 -1 -1 -1
</pre></td>
<td><pre>
Slot "obs.vars":
                age
fleet   0 1 2 3 4 5 6 7 8
  catch unique   0 1 2 2 2 2 3 3 3
  HERAS   -1 3 4 4 4 4 4 5 5
  IBTS-Q1   -1 6 -1 -1 -1 -1 -1 -1 -1
  IBTS0   7 -1 -1 -1 -1 -1 -1 -1 -1
  IBTS-Q3   8 9 10 10 10 10 -1 -1 -1
  LAI-ORSH   11 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-BUN   11 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-CNS   11 -1 -1 -1 -1 -1 -1 -1 -1
  LAI-SNS   11 -1 -1 -1 -1 -1 -1 -1 -1
</pre></td>
</tr>
</table>

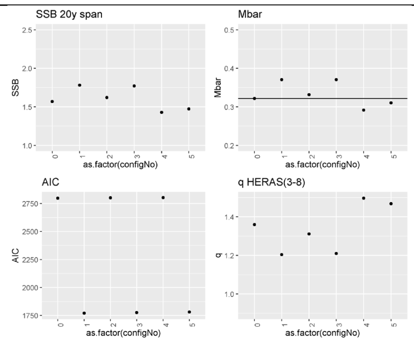


Figure 2-32: comparison of the profiling of the baseline assessment with a range of binding settings with and without the inclusion of the fishery closure period.

The model configurations are as follows:

0: Baseline bindings + full time series

1: Baseline bindings + start year 1982

2: alt1 bindings + full time series

3: alt1 bindings + start year 1982

4: alt2 bindings + full time series

5: alt2 bindings + start year 1982

Table 2-9: estimated optimal additive M, the resulting Mbar, nlogl, AIC and HERAS q for different configurations.

addM	Mbar	configNo	configRuns	nlogl	AIC	q	ssbAbs
0	0.321484	0	baseline	1357.97	2797.94	1.360186	1.568347
0.05	0.37057	1	baseline_noClosure	844.2026	1770.405	1.204413	1.782299
0.01	0.331484	2	alt1	1360.593	2801.187	1.311184	1.621686
0.05	0.37057	3	alt1_noClosure	848.3603	1776.721	1.209748	1.771422
-0.03	0.291484	4	alt2	1360.076	2802.151	1.497273	1.429271
-0.01	0.31057	5	alt2_noClosure	849.9072	1781.814	1.468997	1.47203

3 CONCLUSION

The results of the simulation testing presented above showed that:

- The assessment profiling method is robust against changes in SMS runs. Only the use of the 2010 SMS keyrun leads to discrepancies due to differences in SMS model settings. However, the profiling of the assessment using the 2016 and 2019 SMS keyruns show very similar results. It is envisioned that changes in future SMS keyruns will be limited relative to SMS 2019.
- Changing the background mortality M1 in SMS yields different scaling at ages 0-1. Applying the profiling using SMS ran with a range of values for M1 shows a slight scaling of the assessment for large M1 values.
- There is a strong retrospective effect with the assessment profiling method. New data points in the time series will likely introduce a change in the assessment scaling
- The period around the closure of the fishery (1978-1979) is influential in the profiling of the assessment.
- The model configuration is influential. Two alternative models were tested: inclusion of correlation structure in fishing selectivity and fixing of HERAS catchability. Overall, the use of these two models improved stability, particularly the use of a fixed HERAS catchability.
- Though not thoroughly explored, the binding of parameters can be influential.

REFERENCES

ICES. 2018. "Report of the Benchmark Workshop on Pelagic Stocks (WKPELA 2018)." In *ICES HQ, Copenhagen, Denmark. ICES CM 2018/ACOM:32*, 313.

———. 2019. "Workshop on North Sea Stocks Management Strategy Evaluation (WKNSMSE)." *ICES Scientific Reports* 1:12: 378. https://doi.org/doi.org/10.17895/ices.pub.5090.

———. 2021. "Report of the Working Group on Multispecies Assessment Methods (WGSAM)."

Nielsen, Anders, and Casper W. Berg. 2014. "Estimation of Time-Varying Selectivity in Stock Assessments Using State-Space Models." *Fisheries Research* 158 (October): 96–101. https://doi.org/10.1016/j.fishres.2014.01.014.

Working document 04 to IBPNSherring 2021

Sensitivity analysis on North Sea herring reference points estimation using Eqsim

Martin Pastoors

17/06/2021 15:19

1 Introduction

This document is summarizing the sensitivity analysis that was carried out on North Sea herring reference points as part of the Interbenchmark on North Sea herring (IBPNSherring 2021). The background to the work is that the assessment of North Sea herring was changed during the IBP because of the new natural mortality estimates generated by WGSAM 2020 and because an error had been identified in the assessment procedure during HAWG 2021.

When running the default reference point estimation for North Sea herring at the IBPNSherring 2021, it was discovered that the estimated Fmsy was out of range of what was expected for a pelagic stock like herring. The default approach to reference point estimation was basically identical to the methods used in HAWG 2016 and WKPELA 2018, using the same steps in the calculation process that follows the standard ICES guidelines on reference points. The steps involve, inter alia, the estimation of Blim based on a segmented regression over the whole time series of SSB and recruitment (1947 onwards). Bpa is then estimated on the basis of the uncertainty in the terminal year of the SAM assessment (resulting in an sd is 0.06) and the application of the standard Bpa formula (Bpa = Blim * exp(1.645*sd)). These values are independent of the actual estimation of Fmsy.

An additional analysis was carried out on the estimation of Fcv and Fphi, the two input parameters that measure the uncertainty and autocorrelation in the advice process. These were re-estimated using an updated time series of assessment outputs and reconstruction of F from historical short term forecasts (ref: WD by Martin Pastoors). The estimated values were Fcv = 0.16 and Fphi = 0.47 using a 12 year time-window.

However, closer inspection of the Fmsy estimates, showed that they were quite sensitive to different assumptions about the stock recruitment curves to be included and some other input assumptions.

2 Material and methods

It was decided to carry out a more comprehensive sensitivity analysis to explore the sensitivity of Fmsy estimates to the startyear of the data-series, the combination of stock recruitment curves and different values of Fcv and Fphi. The assessment that the sensitivity analysis was based on was run *NSAS_IBP_FINAL_20210610_1332.RData* that is available on the IBPNSher-ring sharepoint.

Here we explored the following variations in input:

- Startyear: 1980, 1990, 2002 (2002 was used in WKPELA 2018)
- Stock recruitment curves: all possible permutations of Beverton-Holt (BH), Ricker (R), Segmented regression (SR) and Segmented regression through Blim (SRB). This resulted in 15 possible permutations, ranging from 1 to 4 stock recruitment curves being used.
- Fcv from 0 to 0.4 in steps of 0.1 (estimated value: 0.16)
- Fphi from 0 to 0.8 in steps of 0.2 (estimated value: 0.47)

In total this resulted in 1125 different runs. Each run consisted of 250 replicates. Normally, one would use 2000 replicates for the estimation of reference points, but with the constraints on simulation time we reduced that 250 replicates which may affect the final precision but does allow the type of sensitivity analysis that was intended.

The simulation code used is shown in the annex (here commented out because of the long simulation time).

3 Results

All the fitted stock-recruitment curves for data starting in 2002

All the fitted stock-recruitment curves for the data starting in 2002 are shown in the plot below. In general the Beverton-Holt curves are very flat because no steepness parameter is included in the fitting mechanism. The Ricker curve tends to dominate the estimates when it is included, probably because of the downward sloping in the SRR data (high biomass with relatively low recruitment).

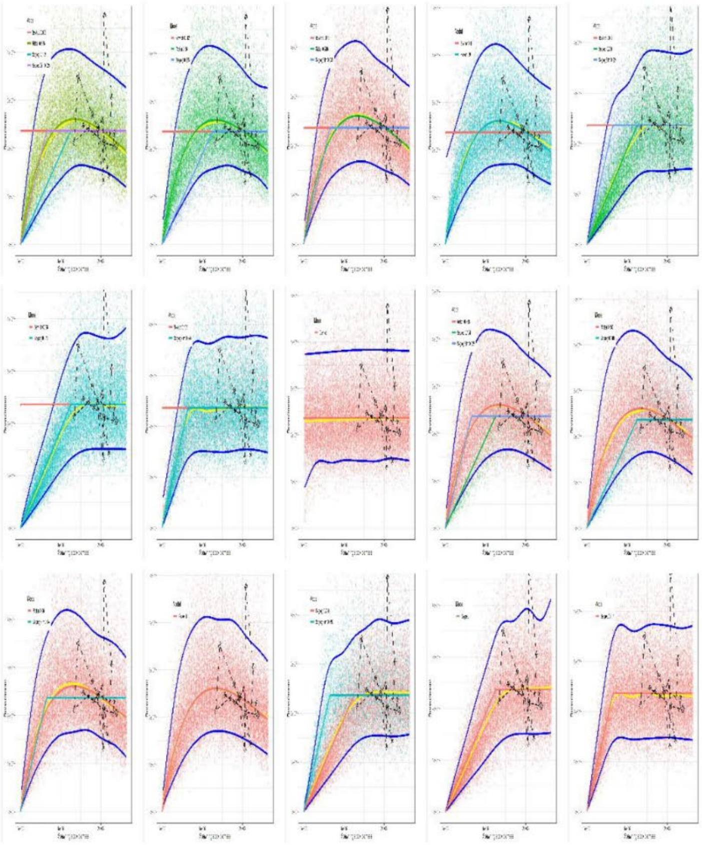


Figure 1: SRR plots for the 15 different combination of stock recruitment combinations for the data series starting in 2002.

Weights allocated to the different stock-recruitment curves

The weights allocated in EqSim to the different stock recruitment curves is shown below as the proportion of the 250 iterations.

Ricker seems to be the preferred SRR given the herring SRR data, independent on the starting year. This is probably driven by the low recruitment at high stock size. If Ricker is not included, the Segmented regression is the preferred SRR. Beverton & Holt and Segmented regression through Blim both have the properties of (very) high steepness and low weight in the estimates.

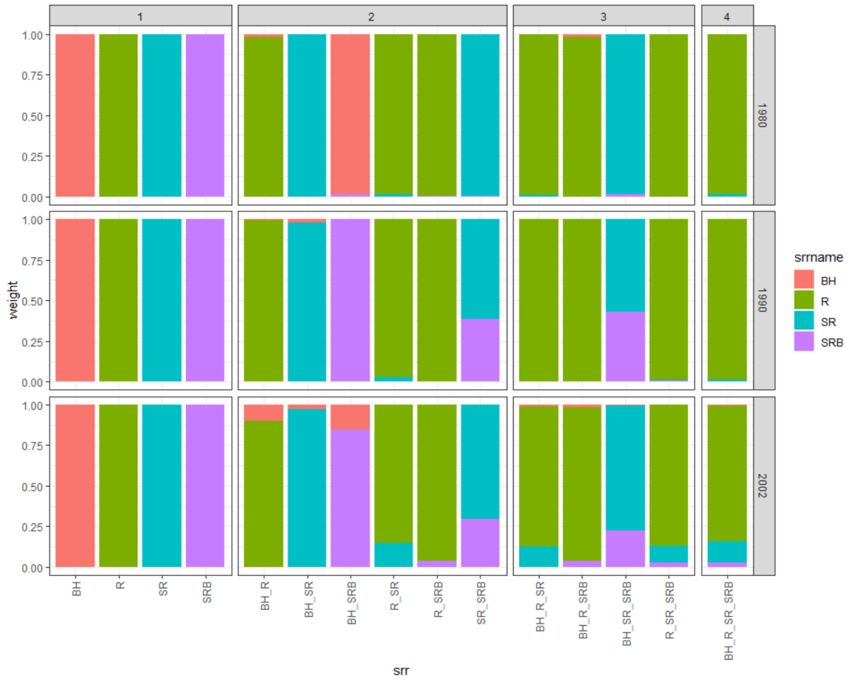


Figure 2: Weights allocated to the different SRR curves for the 15 different permutations of stock recruitment curves. Columns indicate the number of Stock recruitment curves fitted and rows indicate the starting year. Stock recruitment curves: BH (Beverton & Holt), R (Ricker), SR (Segmented regression), SRB (Segmented regression through Blim).

Comparison of Fmsy relative to SRR and Fcv

First we are exploring the sensivitity of Fmsy to the stock recruitment curves (columns) and Fcv (rows) relative to the startyear of the data (x-axis) and the values of Fphi (colours). General pattern is that later startyear for the analysis leads to lower estimates of Fmsy (lower productivity).

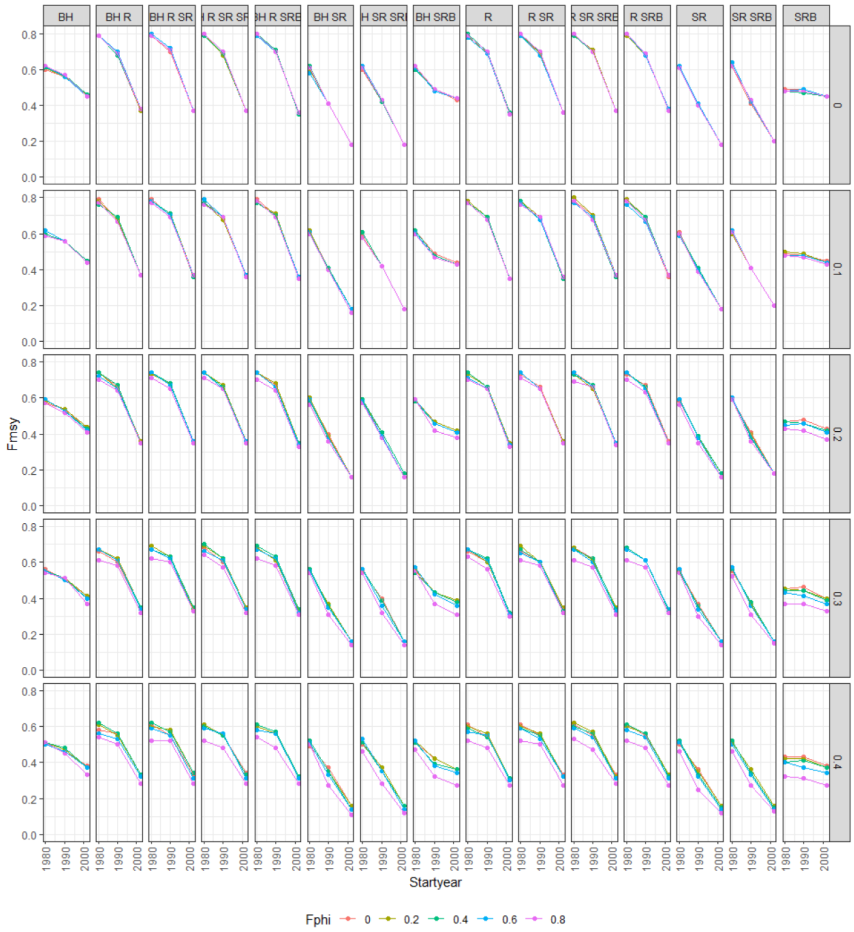


Figure 3: Fmsy in relation to SRR curveys and starting year. Columns indicate the stock recruitment curve(s) and rows indicate the different values of Startyear. Colours indicate the values of Fphi. Fcv on the x-axis and estimated Fmsy on the y-axis.

Comparison of Fmsy relative to SRR and Startyear

Secondly we are exploring the sensivitity of Fmsy to the stock recruitment curves (columns) and Startyear (rows) relative to the Fcv (x-axis) and the values of Fphi (colours). Substantial difference in level of Fmsy occur, depending on the SRR curve(s) used. Analyses with Ricker included in the set of SRR curves, tend to generate higher values of Fmsy than curves where only segmented regression or Beverton and Holt are included. Higher Fcv leads to lower estimates of Fmsy.

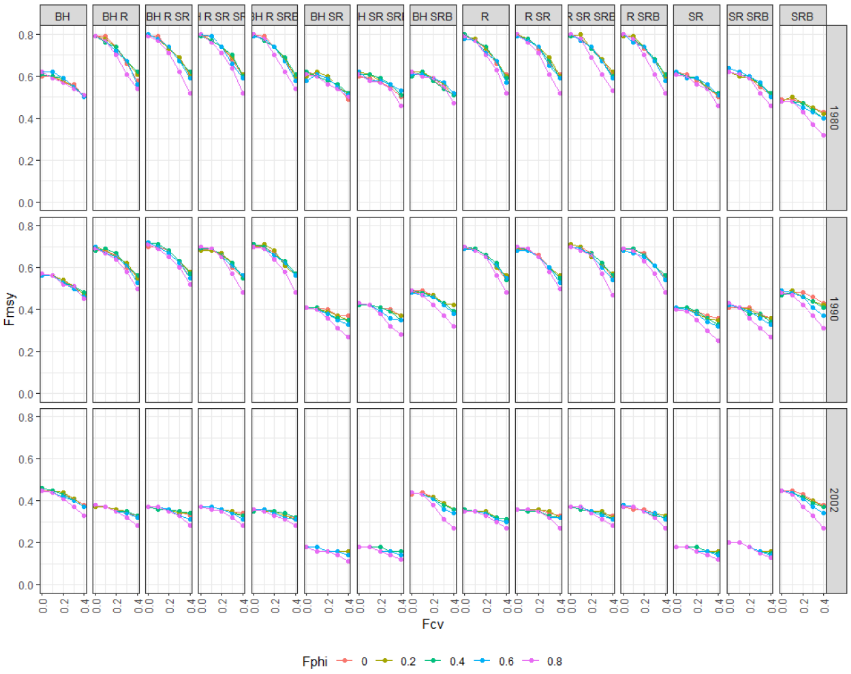


Figure 4: Fmsy in relation to SRR curveys and starting year. Columns indicate the stock recruitment curve(s) and rows indicate the different values of Startyear. Colours indicate the values of Fphi. Fcv on the x-axis and estimated Fmsy on the y-axis.

Comparison of Fmsy relative to Fcv and Startyear

Thirdly we are exploring the sensivitity of Fmsy to the Fcv (columns) and Startyear (rows) relative to the SRR curves (x-axis) and the values of Fphi (colours). Again, this clearly shows that Substantial difference in level of Fmsy occur, depending on the SRR curve(s) used. Fphi only has an impact on Fmsy for larger Fcv.

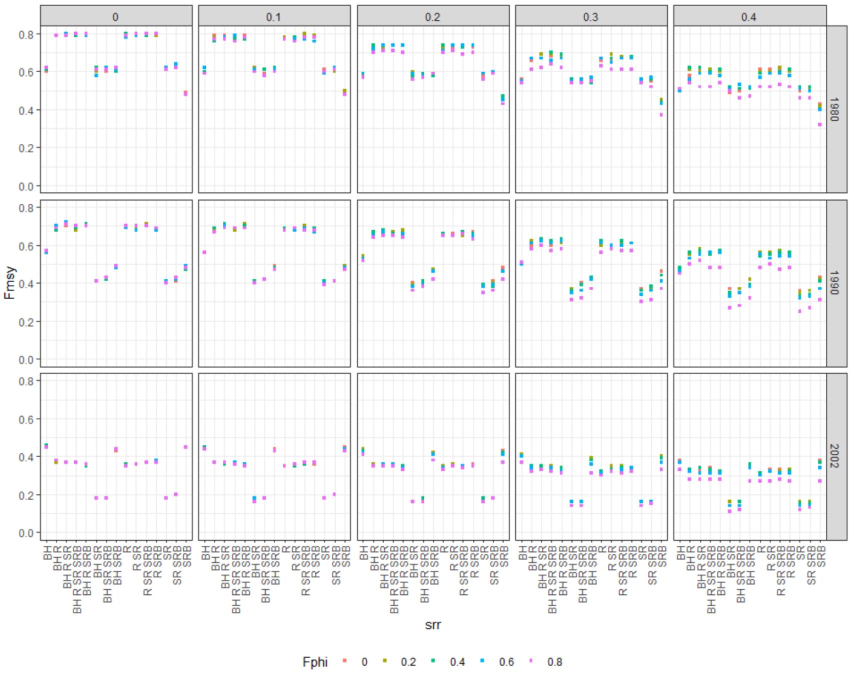


Figure 5: Fmsy in relation to Fcv and starting year. Columns indicate the values of Fcv and rows indicate the different starting years. Colours indicate the values of Fphi. SRR curve(s) on the x-axis and estimated Fmsy on the y-axis.

4 Discussion

The sensitivity analysis has shown that the major indeterminacies in estimating Fmsy for North Sea herring, using Eqsim, are not so much in the values of Fcv and Fphi, but rather in the selection of the starting year and in the selection of the stock recruitment curves being used. The estimate is very sensitive to the use of the Ricker curve because the data suggests a downward sloping recruitment (i.e. low recruitment at high biomass). When the Ricker curve is used, the peak of the dome is to the left of the data points, leading to a relatively high Fmsy. If, on the other hand, Ricker is not included but Segmented regression is included, the values of Fmsy tend to be substantially lower. In the default setting of reference point estimation according to the stock annex, both the Ricker and the segmented regression through Blim are supposed to be used. From this sensitivity analysis, we now understand that this combination leads to a high weight on Ricker, because of the downward sloping at the right hand side of the SRR plot, and the weak fit of the segmented regression through Blim.

In general, we found that segmented regression through Blim is not a sensible approach when the data is all to the right of Blim, as it tends to generate a too high steepness.

Although the analysis has shown that the major sensitivities are in the startyear for the data to be used and in the stock recruitment curves, this does not solve the challenge on how to come up with a sensible approach to estimating reference points for this stock. If we were to change the default method of estimating reference points, we would not only have changed the assessment during this benchmark but we would also have changed the procedure for estimating reference points. This would require very careful argumentation on why we would select one option over the other, while there may be very little scientific rationale of choosing one over the other.

Annex: simulation code

```
rm(list=ls())

library(icesTAF)

# follow the order of loading (1) FLCore and (2) msy as SR functions have same name but different formulation
taf.library(FLCore)
taf.library(stockassessment)
taf.library(FLSAM)
taf.library(msy)

library(methods)
library(tidyverse)
library(dplyr)

# mkdir("refpoints")
# mkdir(file.path("refpoints","input"))
# mkdir(file.path("refpoints","output"))
# mkdir(file.path("refpoints","plots"))
#
# source("Refpoints functions.R")
#
# # Combine all function
# combine_all <- function(srr = "Bevholt", simplify=TRUE) {
#   t <- character()
#   for (i in 1:length(srr)) {
#     t <- c(t, combn(srr, i, FUN = NULL, simplify = simplify))
#   }
#   print(t)
#   return(t)
# }
#
# # settings
# filename  = "NSAS_IBP_FINAL_20210610_1332.RData"
# nsim      = 250
# nsteps    = 40
# Fphisteps = 0.1
#
# # load assessment data
# load(file.path("model","assessment", filename))
# NSH.sam <- NSH.samBind1 # specific fix because the NSH.sam is called NSH.samBind1 in the RData file
#
# # get max year and set ranges
# maxyear <- as.integer(NSH@range["maxyear"])
# bio.years = c((maxyear-9),maxyear)
# sel.years = c((maxyear-9),maxyear)
#
# # -------------------------------------------------------------------------------------------------------
# # 1. Get estimate of Blim at breakpoint using the whole time series and calculate Bpa from it
# # -------------------------------------------------------------------------------------------------------
# FIT_segregBlim <- eqsr_fit(NSH,nsamp=nsim, models = "Segreg", rshift=1)
#
# Blim           <- round(FIT_segregBlim$sr.det$b)
#
# #Now calculate the uncertainty in SSB in terminal year. We need the sd that belongs to log(ssb) to calculate Bpa
# logssb    <- subset(ssb(NSH.sam),year==maxyear)
# sdmin     <- function(sdestim){
#   return(abs(0.025 - dnorm(log(logssb$lbnd),log(logssb$value),sdestim)))}
# sdSSB     <- optimize(sdmin,interval=c(1e-4,0.2))$minimum
#
# Bpa       <- Blim * exp(1.645*sdSSB)  # MP 878 kT
# Bpa       <- round(Bpa)  # rounding to neareast tonne
#
#
# # -------------------------------------------------------------------------------------------------------
# # 2. parameterize the segreg model with Blim breakpoint and (roughly) geomean rec above this
# # -------------------------------------------------------------------------------------------------------
# SegregBlim  <- function(ab, ssb) log(ifelse(ssb >= Blim,
#                                             ab$a * Blim,
#                                             ab$a * ssb))
#
# # Generate SRR permutations
# t <- combine_all(c("Bevholt","Ricker","Segreg", "SegregBlim"), simplify = FALSE)
#
# # Initiate empty data frame for reference points
# refpts <- data.frame(stringsAsFactors = FALSE)
#
```

```
# # loop over startyear
# for (Startyear in c(1980, 1990, 2002)) {
#
#   # ------------------------------------------------------------------------------------------------------------
#   # 3. truncate the NSH object
#   # ------------------------------------------------------------------------------------------------------------
#   NSHtrunc <- trim(NSH, year=Startyear:maxyear)
#
#   # loop over stock recruitment models
#
#   for (i in 1:length(t)) {
#
#     # ------------------------------------------------------------------------------------------------------------
#     # 4. fit the stock recruitment model(s)
#     # ------------------------------------------------------------------------------------------------------------
#
#     srr <- paste(as.character(t[[i]]), collapse=" ")
#
#     assign(paste("FIT",i, sep="_"),
#            eqsr_fit(NSHtrunc, nsamp = nsim, models = as.character(t[[i]]), rshift=1))
#
#     tmp <- get(paste("FIT",i,sep="_"))
#     srrweight <- paste(tmp$sr.det$n, collapse="/")
#
#     print(eqsr_plot(get(paste("FIT",i,sep="_")), n=2e4, ggPlot=TRUE))
#     ggsave(filename=file.path("refpoints","plots", paste0("eqsr_fit_", Startyear, srr,".jpg")), device="jpeg")
#
#     # ------------------------------------------------------------------------------------------------------------
#     # 5. Get Flim and thereby Fpa. Run EqSim with no MSY Btrigger (i.e. run EqSim with Btrigger=0), and Fcv=Fphi=0
#     # ------------------------------------------------------------------------------------------------------------
#     SIM1 <- eqsim_run(get(paste("FIT",i, sep="_")),
#                       bio.years        = c((maxyear-9),maxyear),
#                       bio.const        = FALSE,
#                       sel.years        = c((maxyear-9),maxyear),
#                       sel.const        = FALSE,
#                       recruitment.trim = c(3, -3),
#                       Fcv              = 0,
#                       Fphi             = 0,
#                       Blim             = Blim,
#                       Bpa              = Bpa,
#                       Btrigger         = 0,
#                       Fscan            = seq(0,0.80,len=nsteps),
#                       verbose          = FALSE,
#                       extreme.trim     = c(0.01,0.99))
#
#     Flim      <- SIM1$Refs2["catF","F50"]   # MP: 0.341
#
#     # Loop over Fcv and Fphi
#
#     for (Fcv in seq(0, 0.4, 0.1)) {
#       for (Fphi in seq(0, 0.8, 0.2)) {
#
#         # ------------------------------------------------------------------------------------------------------------
#         # 6. Run EqSim with assessment error but no MSY Btrigger (i.e. run EqSim with Btrigger=0),
#         #    to get initial FMSY ;
#         #   (#DM: not yet, check Fp05=Fpa later) if this initial FMSY value is > Fpa, reduce it to Fpa
#         # ------------------------------------------------------------------------------------------------------------
#
#         SIM2 <- eqsim_run(get(paste("FIT",i, sep="_")),
#                           bio.years = bio.years,
#                           bio.const = FALSE,
#                           sel.years = sel.years,
#                           sel.const = FALSE,
#                           recruitment.trim = c(3, -3),
#                           Fcv       = Fcv,
#                           Fphi      = Fphi,
#                           Blim      = Blim,
#                           Bpa       = Bpa,
#                           Btrigger  = 0,
#                           Fscan     = seq(0,0.80,len=nsteps),
#                           verbose   = FALSE,
#                           extreme.trim=c(0.01,0.99))
#
#         Fmsy      <- SIM2$Refs2["lanF","medianMSY"] #0.275
#
#         # Select MSY Btrigger   (from schematic guidelines: yes, yes, no -> 5th percentile of MSYBtrigger
#         MSYBtrigger <- SIM2$Refs2["catB","F05"]  # MP 1396 kT
#         MSYBtrigger <- round(MSYBtrigger) # rounding
#
#         # ------------------------------------------------------------------------------------------------------------
#         # 7. Check if FMSY is precautionary, so do a scan on Fp05. If Fmsy is larger than Fp05, reduce to Fp05
```

```
#         # ------------------------------------------------------------------------------------------------------------
#         SIM3 <- eqsim_run(get(paste("FIT",i, sep="_")),
#                           bio.years = bio.years,
#                           bio.const = FALSE,
#                           sel.years = sel.years,
#                           sel.const = FALSE,
#                           recruitment.trim = c(3, -3),
#                           Fcv       = Fcv,
#                           Fphi      = Fphi,
#                           Blim      = Blim,
#                           Bpa       = Bpa,
#                           Btrigger  = MSYBtrigger,
#                           Fscan     = seq(0,0.80,len=nsteps),
#                           verbose   = FALSE,
#                           extreme.trim=c(0.01,0.99))
#
#         # If the precautionary criterion (FMSY < Fp.05) evaluated is not met, then FMSY should be reduced to  Fp.05.
#         Fp05      <- SIM3$Refs2["catF","F05"] # MP: 0.256
#         #DM: define new Fpa here
#         Fpa <- Fp05
#         #DM: if Fpa > Flim, then Flim will be undefined
#         # if (Fpa>Flim) Flim <- NA
#
#         # propFmsy  <- subset(SIM3$pProfile, round(Ftarget, 2)==round(Fmsy,2) & variable=="Blim")$value
#         if (Fmsy > Fp05 & !is.na(Fp05)) {Fmsy <- Fp05}
#
#         # ------------------------------------------------------------------------------------------------------------
#         # 8. final set of reference points
#         # ------------------------------------------------------------------------------------------------------------
#         #DM - use ICES rounding
#         Flim    <- round(Flim,2)
#         Fpa    <- round(Fpa,2)
#         Fmsy    <- round(Fmsy,2)
#
#         print(paste("Startyear ", Startyear,
#                     "Srr", paste(i,srr, sep=" "),
#                     "Fcv", Fcv,
#                     "Fphi", Fphi,
#                     "Fmsy", Fmsy, sep=" "))
#
#         refpts <- bind_rows(
#           refpts,
#           data.frame(Startyear  = Startyear,
#                      srr        = srr,
#                      srrweight  = srrweight,
#                      Fcv        = Fcv,
#                      Fphi       = Fphi,
#                      Flim       = Flim,
#                      Fpa        = Fpa,
#                      Fp05       = Fp05,
#                      Fmsy       = Fmsy,
#                      Blim       = Blim,
#                      Bpa        = Bpa,
#                      MSYBtrigger= MSYBtrigger)
#         )
#       } # end of loop over Fphi
#     } # end of loop over Fcv
#   } # End of loop over SRRs
# } # end of loop over startyear
#
#
# save(refpts, file=file.path("refpoints","output", "refpoints sensitivity analysis.RData"))

load(file=file.path("refpoints","output", "refpoints sensitivity analysis.RData"))
refpts <-
  refpts %>%
  mutate(
    srr = gsub("Bevholt","BH", srr),
    srr = gsub("Ricker","R", srr),
    srr = gsub("SegregBlim","SRB", srr),
    srr = gsub("Segreg","SR", srr),
    srr = as.character(srr)
  )
```

Working document 05 to IBPNSherring 2021

Sensitivity analysis on North Sea herring reference points estimation using Eqsim: sensitivity to slope and breakpoint

Martin Pastoors

15/07/2021 14:29

1 Introduction

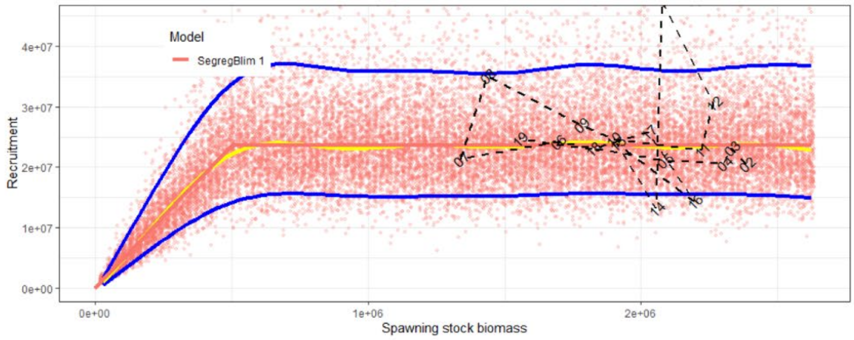
This document is summarizing the sensitivity analysis that was carried out on North Sea herring reference points as part of the Interbenchmark on North Sea herring (IBPNSherring 2021). The background to the work is that the assessment of North Sea herring was changed during the IBP because of the new natural mortality estimates generated by WGSAM 2020 and because an error had been identified in the assessment procedure during HAWG 2021.

2 Material and methods

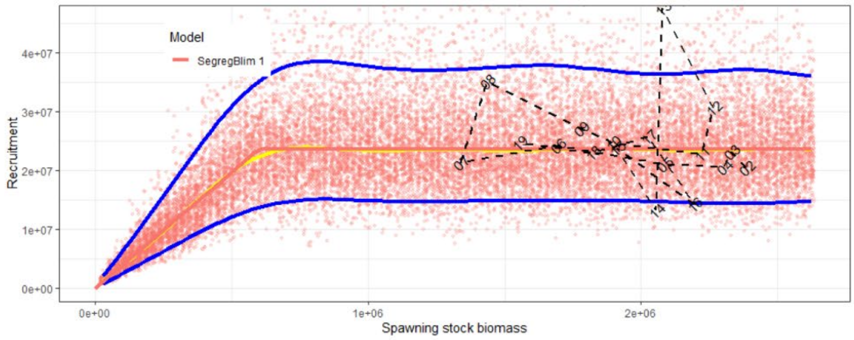
Explore sensitivity of Fmsy estimate to breakpoint in the SRR data (i.e. fixing the slope) and using segmented regression through Blim to estimate Fmsy. This is achieved by running the Eqsim code on fixed SRR breakpoint values from 0.5 tot 1.2 Mt and using segmented regression through the breakpoints to estimate Fmsy reference points.

3 Results

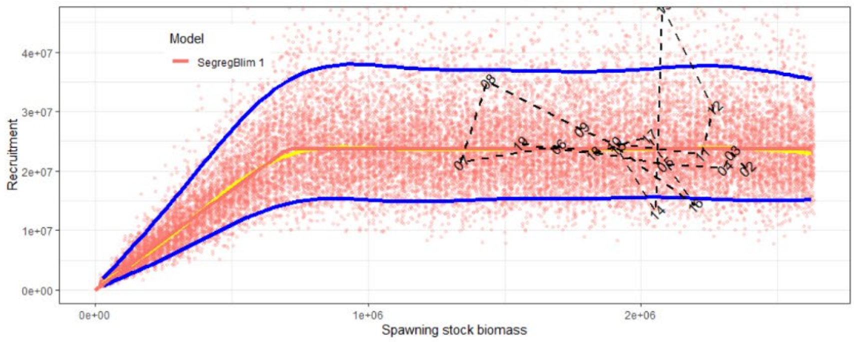
Below are the stock and recruitment plots for the data from 2002 onwards, with different values for SRR breakpoints.



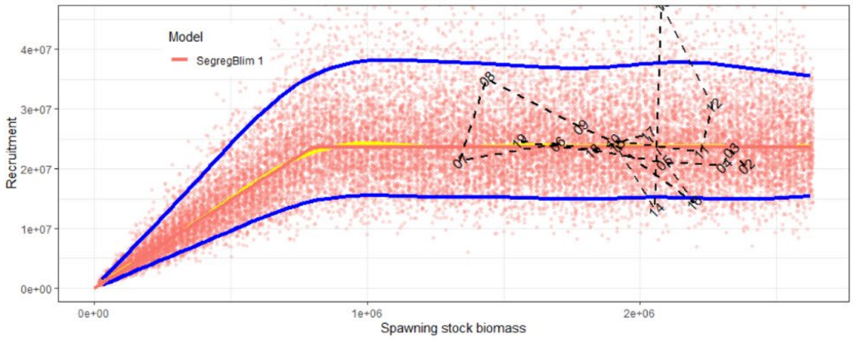
[1] "Blim 5e+05 Fmsy 0.52"



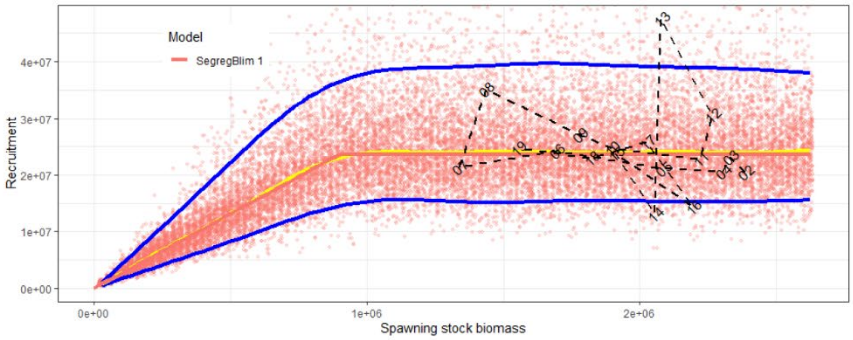
[1] "Blim 6e+05 Fmsy 0.46"



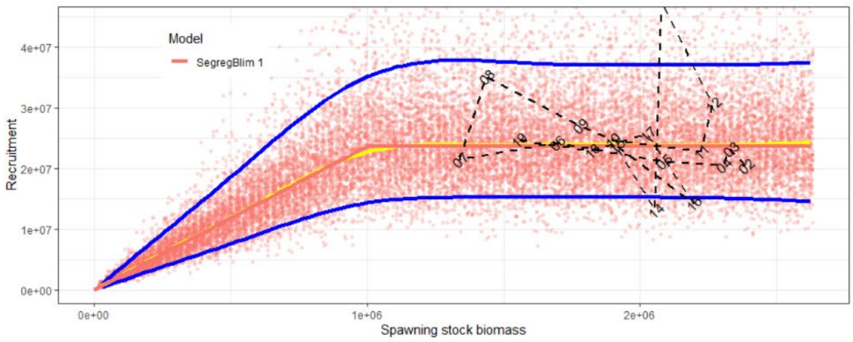
[1] "Blim 7e+05 Fmsy 0.41"



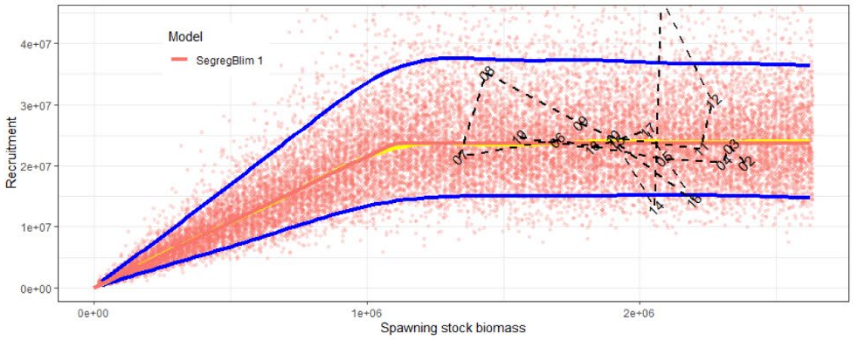

```
[1] "Blim  8e+05 Fmsy 0.34"
```



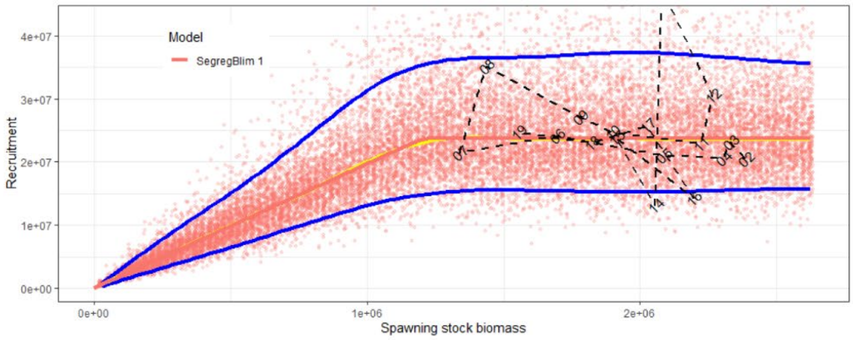

```
[1] "Blim  9e+05 Fmsy 0.3"
```




```
[1] "Blim  1e+06 Fmsy 0.25"
```



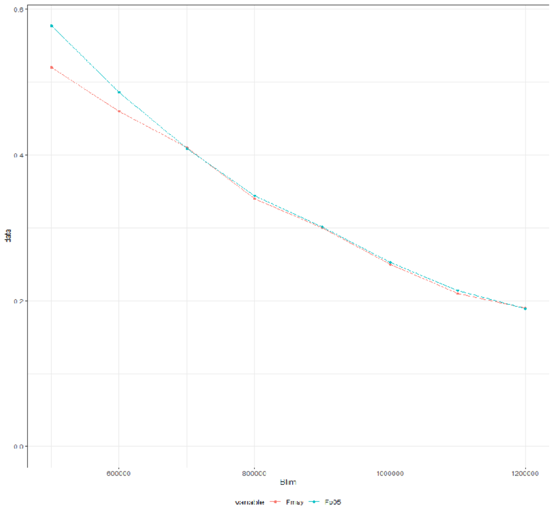
[1] "Blim 1100000 Fmsy 0.21"



[1] "Blim 1200000 Fmsy 0.19"

Relationship between (fixed) Blim and Fp05 and Fmsy

The relationship between the breakpoints used (note that the breakpoints are fixed in the simulation code; not estimated) and Fmsy and Fp05 is shown in the plot below. Each value of the breakpoint is associated with a steepness of the SRR curve: a low breakpoint is associated with a high steepness and a high breakpoint with a low steepness. And steepness is linked to Fmsy: high steepness is high Fmsy, low steepness is low Fmsy. Fp05 is constraining Fmsy from a breakpoint of 700 000 and above.



4 Discussion

Slope (steepness) in segemented regression is strongly related to the Fmsy estimate that is generated within EqSim. Fp05 is constraining estimates of Fmsy for SRR breakpoints of 700 000 and higher.

Working document 06 to IBPNSherring 2021

Sensitivity analysis on North Sea herring reference points estimation using Eqsim: sensitivity to years to be excluded

Martin Pastoors

10/08/2021 12:06

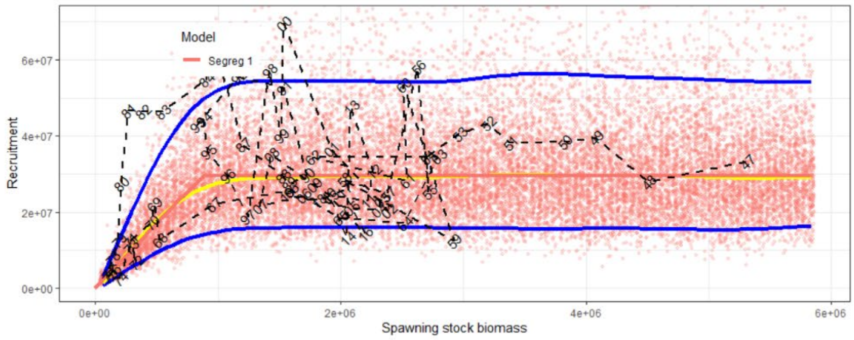
1 Introduction

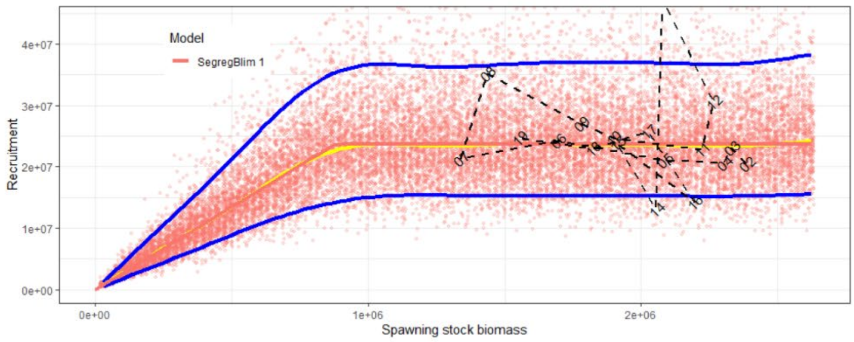
This document is summarizing the sensitivity analysis that was carried out on North Sea herring reference points as part of the Interbenchmark on North Sea herring (IBPNSherring 2021). The background to the work is that the assessment of North Sea herring was changed during the IBP because of the new natural mortality estimates generated by WGSAM 2020 and because an error had been identified in the assessment procedure during HAWG 2021.

2 Material and methods

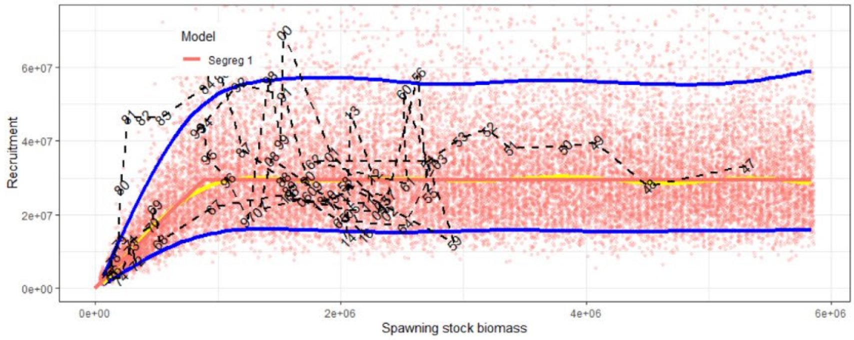
Explore sensitivity of reference points to the years to be excluded from the analysis.

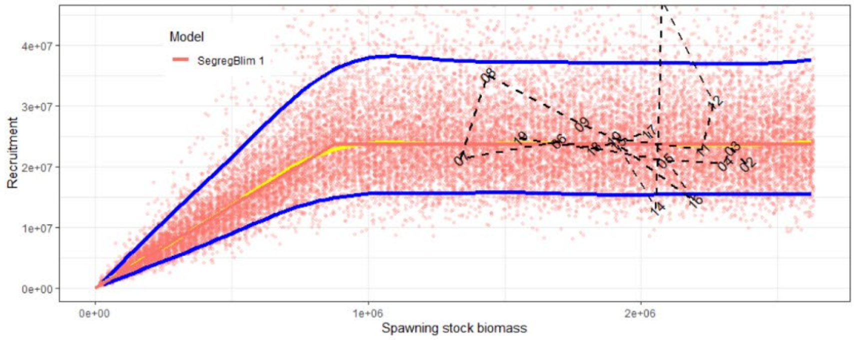
3 Results



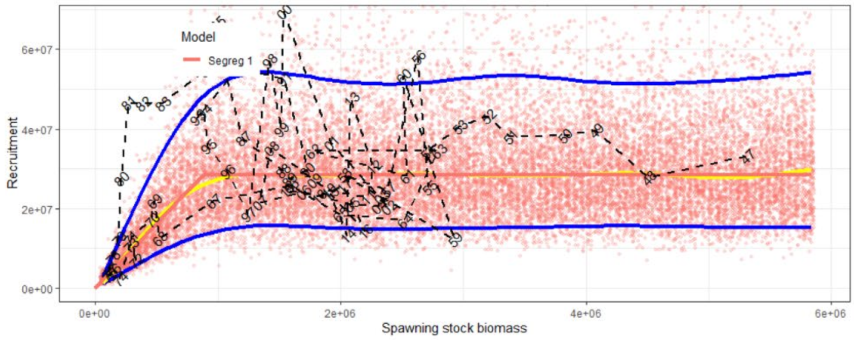


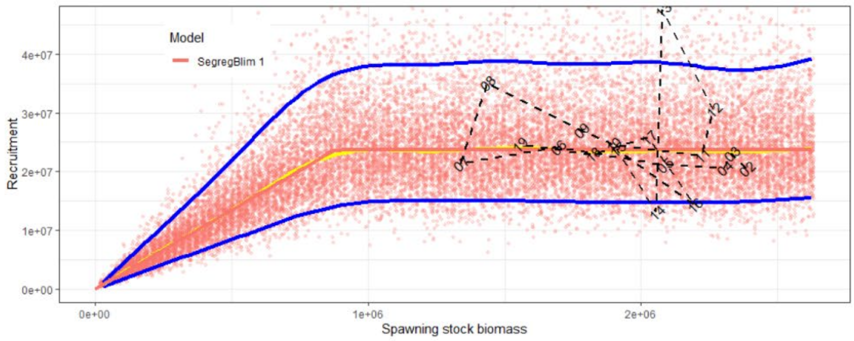

```
[1] "Blim  877120 Fmsy 0.31"
```



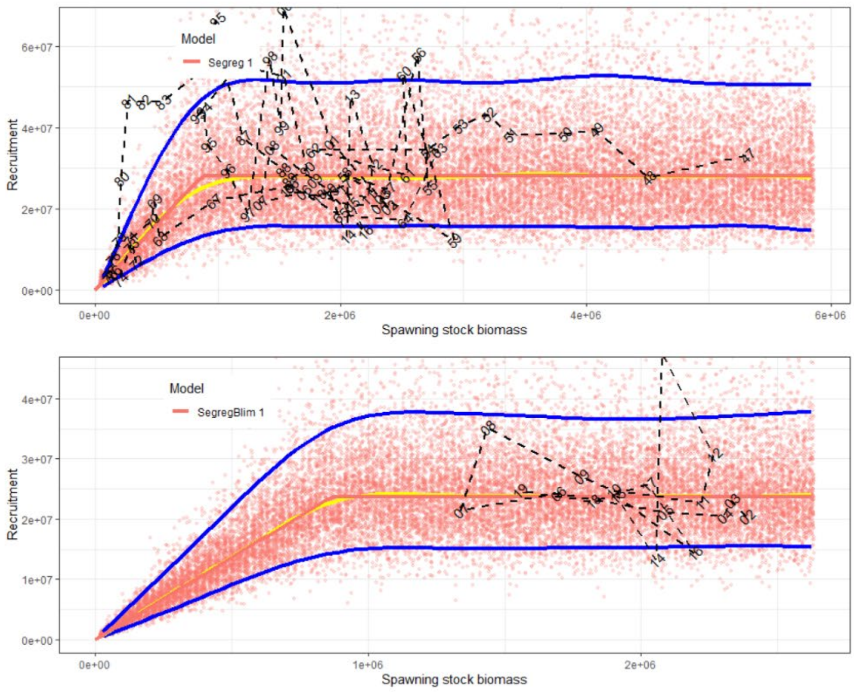



```
[1] "Blim  874198 Fmsy 0.3"
```

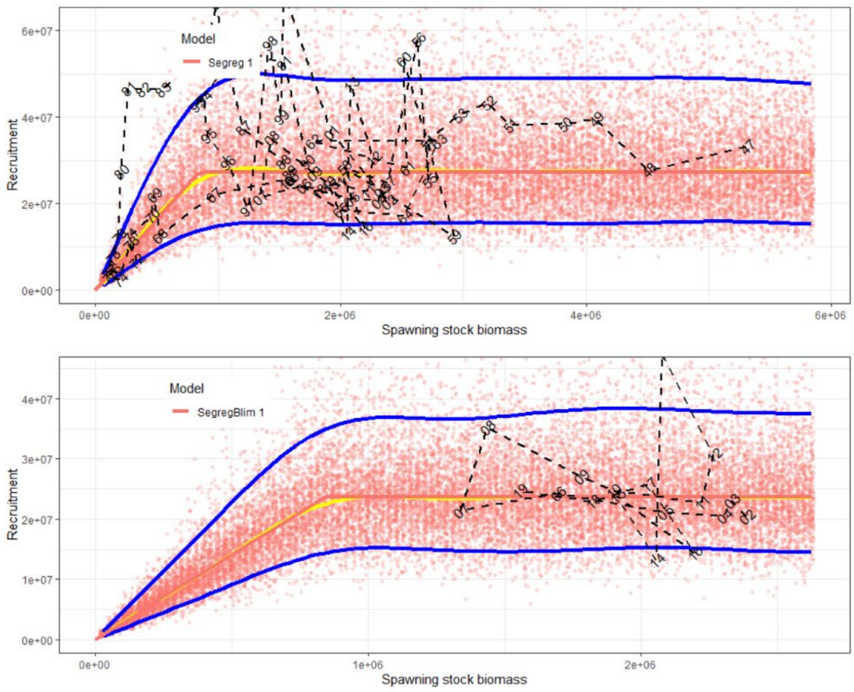





```
[1] "Blim  877190 Fmsy 0.31"
```




```
[1] "Blim  866158 Fmsy 0.31"
```




```
[1] "Blim  839284 Fmsy 0.33"
```

The years to exclude from the fitting of the SRR to determine the Blim has been varied starting from 1979 and ending in either 1986, 1990, 1994, 1998 or 2002.

Estimates of Blim are mostly sensitive to the ending years of the exclusion period 1998 or 2002. Similarly, estimates of Fmsy are all similar - because of comparable steepness - between these scenarios.

firstyear	lastyear	Fcv	Fphi	Flim	Fpa	Fp05	Fmsy	Blim	Bpa	MSYBtrigger
1979	1986	0.16	0.47	0.39	0.31	0.305	0.31	877120	959680	1233553
1979	1990	0.16	0.47	0.39	0.3	0.303	0.3	874198	956483	1232822
1979	1994	0.16	0.47	0.39	0.31	0.305	0.31	877190	959756	1239180
1979	1998	0.16	0.47	0.41	0.31	0.314	0.31	866158	947686	1224601
1979	2002	0.16	0.47	0.42	0.33	0.325	0.33	839284	918282	1204401

4 Discussion

Recommended exclusion period: 1979-1990.

Working document 07 to IBPNSherring 2021

Three scenarios on North Sea herring reference point estimation using Eqsim

Martin Pastoors

1 Introduction

This document presents three scenarios for estimating reference points for North Sea herring as part of the Interbenchmark on North Sea herring (IBPNSherring 2021). The background to the work is that the assessment of North Sea herring was changed during the IBP because of the new natural mortality estimates generated by WGSAM 2020 and because an error had been identified in the assessment procedure during HAWG 2021.

2 Material and methods

After a number of sensitivity analysis on North Sea herring reference points had been presented, the IBPNSherring identified three final scenarios to be explored:

1. Blim estimated from full time series excluding 1979-2001 / Bpa estimated from Blim (min sd is 0.2) / Time series truncated 2002-2020 / Segmented regression through Blim (i.e. slope from the full time series – 1979-2001)
2. Bpa estimated from short time series 2002-2020 (small dynamic range, F below Fmsy) / Blim estimated from Bpa (min sd is 0.2) / Segmented regression through Blim (i.e. slope from the full time series – 1979-2001)
3. Blim estimated from full time series excluding 1979-2001 / Bpa estimated from Blim (min sd is 0.2) / Time series truncated 2002-2020 / Segmented regression through the data (i.e. slope based on breakpoint in data 2002-2020)

For reference points, both the 'raw Fmsy' is calculated (without applicaton of the MSY Btrigger) and the final Fmsy that does use the MSY Btrigger and may therefore be constrained by Fp05.

3 Results

3.1 Scenario 1:

- Blim estimated from full time series excluding 1979-2001
- Bpa estimated from Blim (min sd is 0.2)
- Time series truncated 2002-2020
- Segmented regression through Blim (i.e. slope from the full time series – 1979-2001)

Flim	Fpa	Fmsyraw	Fmsy	Fp05	Blim	Bpa	MSYBtrigger	Fcv	Fphi
0.42	0.33	0.345	0.33	0.329	833125	1157692	1189620	0.16	0.47

Table 1.1 Scenario 1. Reference points

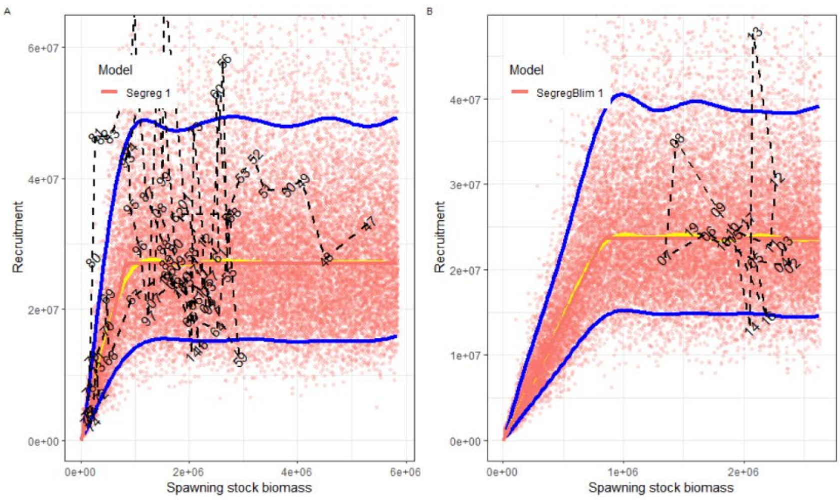


Figure 1.1 Scenario 1. SRR relationships: A) Breakpoint analysis for Blim, B) segmented regression through Blim on short time series

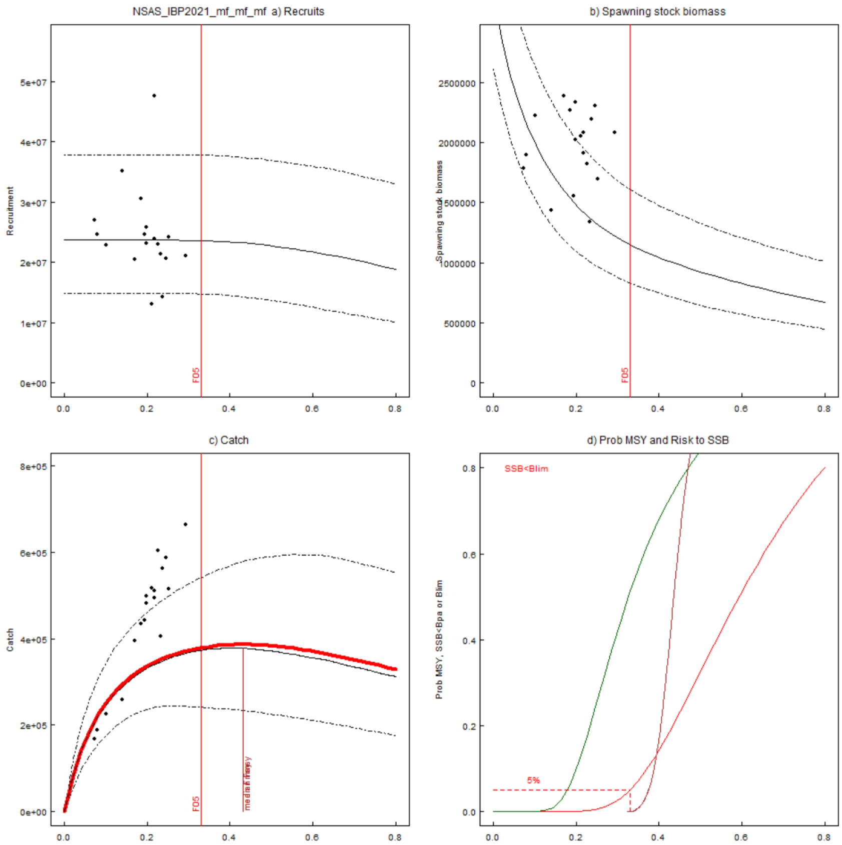


Figure 1.2 Scenario 1 MSY diagnostics

3.2 Scenario 2

- Bpa estimated from short time series 2002-2020 (small dynamic range, F below Fmsy)
- Blim estimated from Bpa (min sd is 0.2)
- Segmented regression through Blim (i.e. slope from the full time series – 1979-2001)

Flim	Fpa	Fmsyraw	Fmsy	Fp05	Blim	Bpa	MSYBtrigger	Fcv	Fphi
0.38	0.3	0.32	0.3	0.295	900686	1251574	1266883	0.16	0.47

Table 2.1 Scenario 2. Reference points

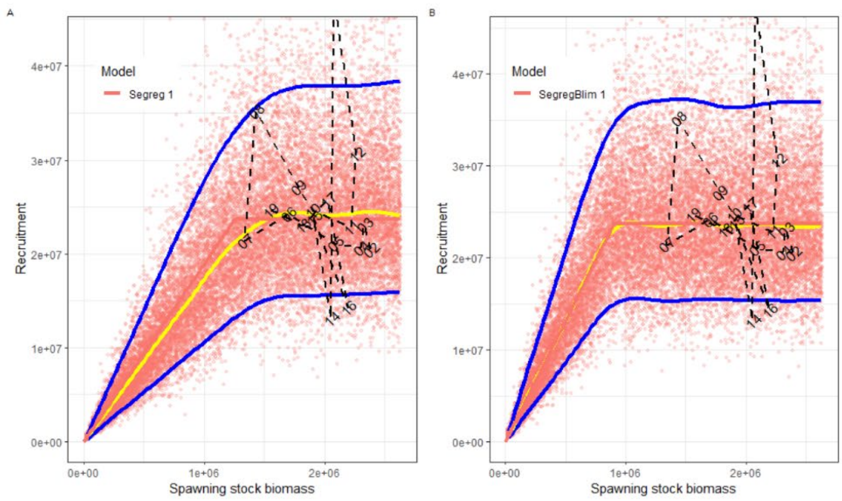


Figure 2.1 Scenario 2. SRR relationships: A) Breakpoint analysis for Blim, B) segmented regression through Blim on short time series

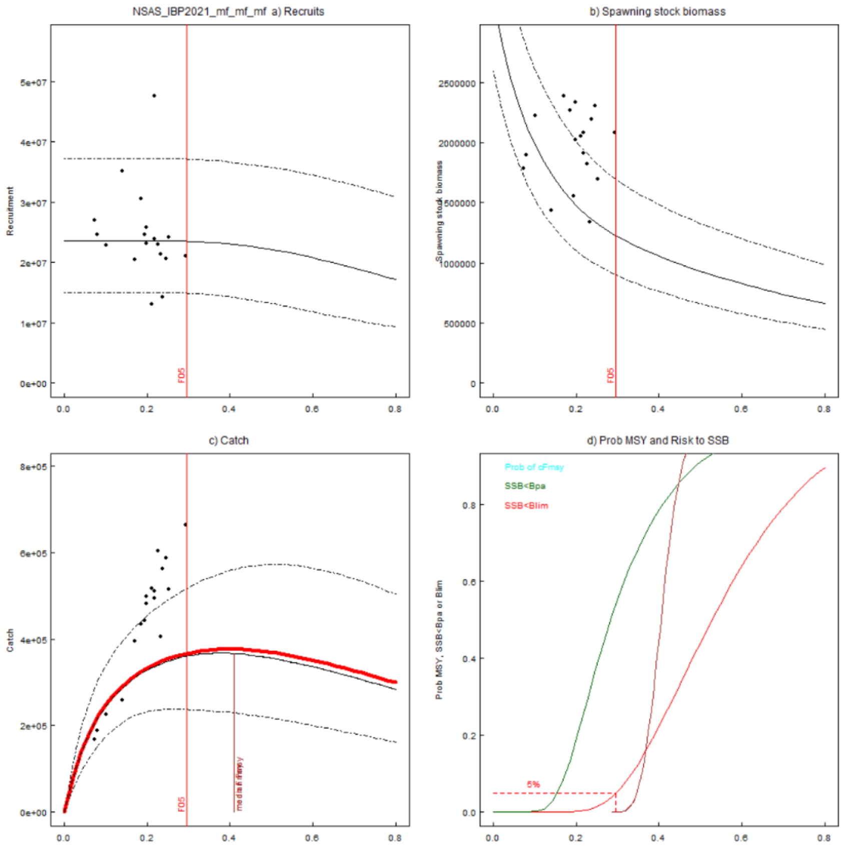


Figure 2.2 Scenario 2 MSY diagnostics

3.3 Scenario 3

- Blim estimated from full time series excluding 1979-2001
- Bpa estimated from Blim (min sd is 0.2)
- Time series truncated 2002-2020
- Segmented regression through the data (i.e. slope based on breakpoint in data 2002-2020)

Flim	Fpa	Fmsyraw	Fmsy	Fp05	Blim	Bpa	MSYBtrigger	Fcv	Fphi
	0.27	0.175	0.175	0.268	833125	1157692	1601920	0.16	0.47

Table 3.1 Scenario 3. Reference points

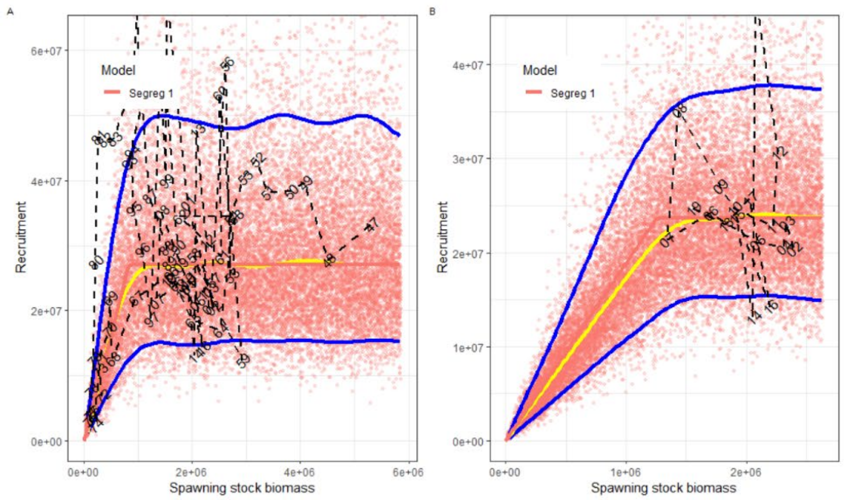


Figure 3.1 Scenario 3. SRR relationships: A) Breakpoint analysis for Blim, B) segmented regression through Blim on short time series

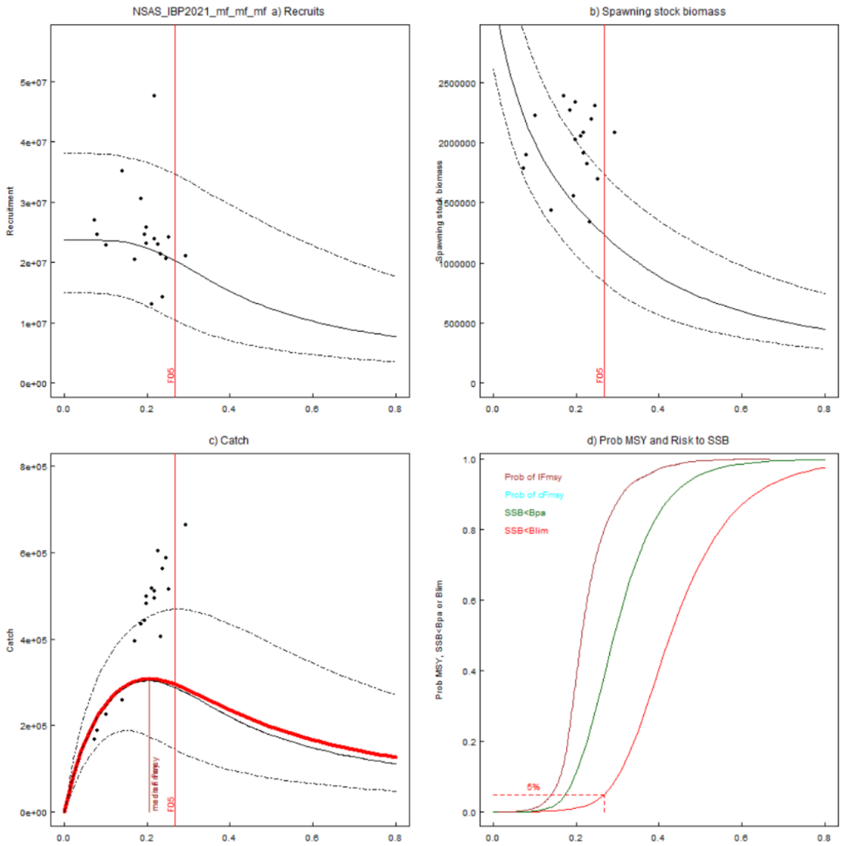


Figure 3.2 Scenario 3 MSY diagnostics

4 Discussion

The three scenarios presented in this WD make very different assumptions about the procedure for deriving reference points and the valid data to be used.

- Both scenario 1 and scenario 3 estimate Blim from full time series excluding the years 1979-2001 (years after the collapse). Blim () is therefore based on the historical period (1947-1978) and the recent low productivity period (2002 onwards).
- Scenario 1 uses the breakpoint of Blim in the segmented regression to estimate Fmsy. Because Blim is relatively low, there is a relatively high steepness, which generated a relatively high Fmsy (0.33).
- Scenario 2 is only using the recent, low productivity data from 2002 onwards. Because there is no clear trend in the SR pairs within this period, and because the F has been at or below Fmsy, the breakpoint is taken as Bpa, and Blim is derived from that using the standard formula. Then the Blim is used in the segmented regression to estimate Fmsy, which ends up at 0.29.
- Scenario 3 allows the segmented regression to estimate Fmsy to choose the breakpoint from the short, low productivity period. So although Blim is the same as in scenario 1, the breakpoint for the Fmsy analysis is far to the right. THis leads to a low slope and therefore also a low estimate for Fmsy (0.18).

Scenario 3 has a relatively weak underpinning as there is a large discrepancy between the procedure for estimating Blim and the procedure for estimating Fmsy. Scenarios 1 and 2 both have merits and drawbacks. The choice for removing the years 1979-2001 from the data series in scenario 1 (and 3) is not very well substantiated. It is argued that the rebuilding after the collapse had a very different dynamics and steepness compared to other years. However, that does not provide a full argumentation of why all the years until 2001 would need to be removed. On the other hand, scenario one does allow to follow the ‘classical’ route of estimating Blim from a long time series, thereby fixing the productivity (steepness).

Scenario 2 is fully based on an analyses on the most recent period that has been shown to be a period of low productivity. Therefore, Bpa and Blim are closely coupled to this low productivity. However, it is taking the inverse route from Bpa to Blim that does seem somewhat odd for the long data series of North Sea herring.

All in all, there are no easy choices when it comes to finalizing the reference points for North Sea herring.

Working document 08 to IBPNSherring 2021

IBPNSherring North Sea herring referent point scenarios using Eqsim

Martin Pastoors and Benoit Berges

Compilation of previous working documents (15/07/2021 17:04 v1, 10/08/2021 09:45 v2, 11/08/2021 v3)

Contents

1 Introduction

This document presents three scenarios for estimating reference points for North Sea herring as part of the Inter-benchmark on North Sea herring (IBPNSherring 2021). The background to the work is that the assessment of North Sea herring was changed during the IBP because of the new natural mortality estimates generated by WGSAM 2020 and because an error had been identified in the assessment procedure during HAWG 2021.

2 Material and methods

2.1 Baseline rationale

North Sea herring benefits from a long time series, including information at low recruitment/ssb (Figure 1). At WKPELA2018, the following approach was used:

- Use of the full time series (1947-onward) for the derivation of limit reference points
- Use of a short time series (2002-onward) for the derivation of MSY reference points. This period tentatively corresponds to a low productivity regime of the stock experienced in recent years.

Using the agreed final model at the IBPNSherring meeting, a sensitivity analysis on the reference point calculations was further performed. This analysis included testing a mix of model types, a range of values for FCV and FPhi and a range of start years for the derivation of MSY reference points. In detail results are given in a separate working document. However, several conclusions emerged:

- The influence of FPhi and FCV is somewhat limited. These values are derived from the historical assessment retrospective. The default values are used: FCV=0.16 and FPhi=0.47.
- The start year is expectedly very influential for the estimation of MSY reference points. However, this aspect should be based on information from the literature rather than mechanistic testing. Since WKPELA2018, there is no new information from the literature available and the group retained the 2002-onward period as most likely period exemplifying a regime shift in productivity. It is often recommended to account for productivity regime shifts mechanistically instead of discarding data points. However, in the case of NSAS, there is no mechanisms that has clearly been identified.
- A model mix was used for the derivation of MSY reference points during WKPELA: 85% Ricker and 15% segmented regression. However, with the use of the 2002-onward period, all the recruitment/ssb pairs are located at SSB levels larger than the peak of the Ricker curve. This aspect was overlooked at WKPELA2018. The mix model approach at IBPNSherring yielded a mix of 95% Ricker/5% segmented regression. This mix is largely biased toward the Ricker model because of the lack of data points at low SSB/recruitment for the 2002-onward time series. The IBPNSherring group then the solely use a segmented regression model for the derivation of MSY refence points.

The initial scenario presented during IBPNSherring was as follows:

Limit reference point using the full time series

MSY reference point estimated using a segmented regression through Blim and the 2002-onward period

This initial scenario was deemed not satisfactory by the group because of the high steepness induced by the use of the full time series. This was partly due to the recruitment/SSB pairs around the post-collapse recovery period.

2.2 Final scenarios

The IBPNSherring group identified three final scenarios to be explored:

1. Limit reference point estimated from full time series but without the exclusion period (post-collapse stock recovery).

   MSY reference points estimated using the 2002-onward period (corresponding to the new low productivity regime) but using stock recovery information from full time series but without the exclusion period.

   a) Limit reference points

      ➔ Full Time series without exclusion period

      i. Blim estimated

      ii. Bpa estimated from Blim (min sd is 0.2)

   b) MSY reference points

      ➔ Short time series 2002-2020

      i. Segmented regression through Blim (i.e. slope from the full time series without exclusion period)

2. Limit reference estimated using the 2002-onward period, corresponding to the new low productivity regime

   MSY reference points using the 2002-onward period, corresponding to the new low productivity regime.

   a) Limit reference points

      ➔ Short time series 2002-2020

      i. Bpa estimated from short time series 2002-2020 (small dynamic range, F below Fmsy)

      ii. Blim estimated from Bpa (min sd is 0.2)

   b) MSY reference points

      ➔ Short time series 2002-2020

      i. Segmented regression through Blim (i.e. slope from short time series)

3. Limit reference point estimated from full time series but but without the exclusion period (post-collapse stock recovery).

   MSY reference points estimated using the 2002-onward period (corresponding to the new low productivity regime), stock recovery from the same period.

   a) Limit reference points

      ➔ Full Time series without exclusion period

      i. Blim estimated from full time series without exclusion period

      ii. Bpa estimated from Blim (min sd is 0.2)

   b) MSY reference points

➔ Time series truncated 2002-2020

i. Segmented regression through the data (i.e. slope based on breakpoint in data 2002-2020)

For reference points, both the 'raw Fmsy' is calculated (without application of the MSY Btrigger) and the final Fmsy that does use the MSY Btrigger and may therefore be constrained by Fp05.

2.3 Exclusion period

An important aspect of scenarios 1 and 3 is the extend of the exclusion period that is used. The largest period used is 1979-2002, spanning the year with the lowest SSB to the year with the start of the low productivity regime experienced in recent years. However, the dynamics of the stock between 1979 and 2002 is varying (Figure 1) and excluding the whole 1979-2002 period might not be appropriate. In order to identify a more appropriate exclusion period, the different end years for this period were tested. This testing was done solely for scenario 1 which was deemed more appropriate than scenario 3.

3 Results

First, the results from the initial scenario derived during IBPNSherring is given in Figure 2 and Table 1. This scenario made use of the full time series for the derivation of the limit reference points and used a segmented regression through Blim for the derivation of FMSY reference points. The IBPNSherring group deemed that scenario unviable because of the low Blim estimated. However, for NSAS, it has been shown that the productivity regime varying based on whether the stock is increasing or decreasing. In addition, the group identified that the inclusion of the data points from the post-collapse recovery period has a strong effect on the Blim estimation, lowering the estimates significantly. This is because recruitment/SSB pairs in this period are at a high steepness. This aspect motivated the derivation of reference points using alternate scenarios that exclude the post-collapse recovery period.

The results for the different scenarios identified as viable are shown in Figure 3-5. For scenarios 1 and 3, the exclusion period used is 1979-2001. The corresponding results are presented in Table 2-4.

For scenario 1, further sensitivity tests on the end year of the exclusion period were performed. This exclusion period is influential for the estimation of the limit reference points and in turn the MSY reference points as a segmented regression through Blim is used. For all the sensitivity test, 1979 is used as the start year of the exclusion period and the end year is: 1986, 1990, 1994, 1998 or 2002. The SRR for each sensitivity test is shown in Figure 6. Resulting limit reference points are given in Table 5. It is interesting to note that results are very similar with end year 1986, 1990 and 1994: Fmsy=0.31, Blim=877000. The exclusion of years between 1998 and 2002 lead to larger changes with slightly smaller Blim and larger Fmsy.

4 Discussion

The three scenarios presented in this WD make very different assumptions about the procedure for deriving reference points and the valid data to be used.

- Both scenario 1 and scenario 3 estimate Blim from the full time series but excluding the post-collapse stock recovery period, chosen as 1979-2001 at most. Blim is therefore based on both the historical period prior to the post-collapse recovery period (1947-1978) and the period excluding the post-collapse recovery period.
- Scenario 1 uses the breakpoint of Blim in the segmented regression to estimate Fmsy.

- Scenario 2 is using the recent, low productivity data from 2002 onwards for both the limit and MSY reference points. Because there is no clear trend in the SR pairs within this period, and because the F has been at or below Fmsy, the breakpoint is taken as Bpa, and Blim is derived from that using the standard formula. Then Blim is used in the segmented regression to estimate Fmsy.
- Scenario 3 allows the segmented regression to estimate Fmsy to choose the breakpoint from the short, low productivity period. So although Blim is the same as in scenario 1, the breakpoint for the Fmsy analysis is larger than with the segmented regression through Blim.

As a baseline for scenarios 1 and 3, the full extend of the exclusion period is taken, i.e. 1979-2001. Under scenario 3 for the derivation of MSY referent points, the breakpoint is estimated as Bloss (lowest observed biomass in the 2002-onward period) and is in turn much larger than Blim. This has the effect of lowering FMSY significantly (Table 1 and 3), from 0.33 with the segmented regression through Blim to 0.175 with the breakpoint at Bloss. This aspect makes scenario 3 somewhat unrealistic.

Scenario 1 presents an alternative route to the 'classical' derivation of limit reference points. Usually, Blim is estimated from a long time series whilst a part of the time series is chosen to be excluded here (post-collapse recovery period). Such an approach is defendable as the rebuilding after the collapse had a very different dynamics and steepness compared to other years. The inclusion of the full time series leads to very high steepness induced by high SSB/recruitment pairs from the post-collapse recovery (Figure 1). Including the post-collapse period leads to very low Blim estimates (651370, Table 1) and in turn very high FMSY (0.43, Table 1). The IBPNSherring group decided that the initial scenario approach was not satisfactory.

Scenario 2 is solely based on the most recent period that has been shown to be a period of low productivity (2002-onward). This period is used for both the derivation of the limit reference points and the MSY reference points. As a result, Bpa and Blim are closely coupled to this low productivity. However, it is taking the inverse route, deriving Blim from Bpa (estimated as Bloss). The approach of scenario 2 makes the assumption that the regime shift has changed the dynamic of the stock completely, including the recovery dynamics. The main drawback of this approach is the discarding of most of the time series available which is debatable. In the case of North Sea herring, this is somewhat odd as valuable information exists with the collapse of the stock (data points at low recruitment/ssb pairs).

The choice for removing the years 1979-2001 from the data series in scenario 1 (and 3) is not very well substantiated. It is argued that the rebuilding after the collapse had a very different dynamics and steepness compared to other years. However, that does not provide a full argumentation of why all the years until 2001 would need to be removed. On the other hand, scenario 1 does allow to follow the 'classical' route of estimating Blim from a long time series, thereby fixing the productivity (steepness).

The strenghts and weaknesses of scenario 1-3 can be summarized as follows:

SCENARIO	STRENGTHS	WEAKNESSES
1	Follow classical route of estimating Blim from a long time series	Period 1979-2001 to leave out is not well substantiated High steepness in SRR mostly derived from historic period that may no longer be applicable in the current low productivity regime
2	Derives steepness from recent low productivity regime	Ignores all information from the long time series available for herring, including

		collapse and recovery Derivation of Blim is based on the standard formala from Bpa.
3	Derives steepness from recent low productivity regime	Large difference between procedure for dealing with Blim and with Fmsy.

Scenario 1 is the recommended option as it is the approach that makes use of the most data points whilst mitigating the effect of high steepness induced by the post-collapse recovery phase. However, the choice of moving the years 1979-2001 from the data series is not very well substantiated and sensitivity testing for a range of exclusion periods was performed. From the results presented in Table 5, the exclusion of years between 1998 and 2002 lead to the largest changes in Blim. Moreover, following stock dynamics (Figure 1) the end of the post-collapse recovery period can tentatively be set at 1990.

We recommend the use of scenario 1 with the 1979-1990 exclusion period:

Fcv	Fphi	Flim	Fpa	Fp05	Fmsy	Blim	Bpa	MSYBtrigger
0.16	0.47	0.39	0.3	0.303	0.3	874198	956483	1232822

Table 1: *initial scenario reference points (unsatisfactory).*

Flim	Fpa	Fmsyraw	Fmsy	Fp05	Blim	Bpa	MSYBtrigger	Fcv	Fphi
0.56	0.44		0.43	0.44	651370	712681	968331	0.16	0.47

Table 2: *Scenario 1. Reference points*

Flim	Fpa	Fmsyraw	Fmsy	Fp05	Blim	Bpa	MSYBtrigger	Fcv	Fphi
0.42	0.33	0.345	0.33	0.329	833125	1157692	1189620	0.16	0.47

Table 3: *Scenario 2. Reference points*

Flim	Fpa	Fmsyraw	Fmsy	Fp05	Blim	Bpa	MSYBtrigger	Fcv	Fphi
0.38	0.3	0.32	0.3	0.295	900686	1251574	1266883	0.16	0.47

Table 4: *Scenario 3. Reference points*

Flim	Fpa	Fmsyraw	Fmsy	Fp05	Blim	Bpa	MSYBtrigger	Fcv	Fphi
	0.27	0.175	0.175	0.268	833125	1157692	1601920	0.16	0.47

Table 5: *Scenario 1 reference points results under different exclusion periods for Blim estimation.*

Firstyear	lastyear	Fcv	Fphi	Flim	Fpa	Fp05	Fmsy	Blim	Bpa	MSYBtrigger
1979	1986	0.16	0.47	0.39	0.31	0.305	0.31	877120	959680	1233553
1979	1990	0.16	0.47	0.39	0.3	0.303	0.3	874198	956483	1232822
1979	1994	0.16	0.47	0.39	0.31	0.305	0.31	877190	959756	1239180
1979	1998	0.16	0.47	0.41	0.31	0.314	0.31	866158	947686	1224601
1979	2002	0.16	0.47	0.42	0.33	0.325	0.33	839284	918282	1204401

Figure 1: *SRR for North Sea herring*

Top: recruitment time series as estimated by the SAM model.

Bottom: NSAS recruitment vs SSB for the full time series (SAM model estimations). The makers in red are those that are considered being kept out for the computation of reference points.

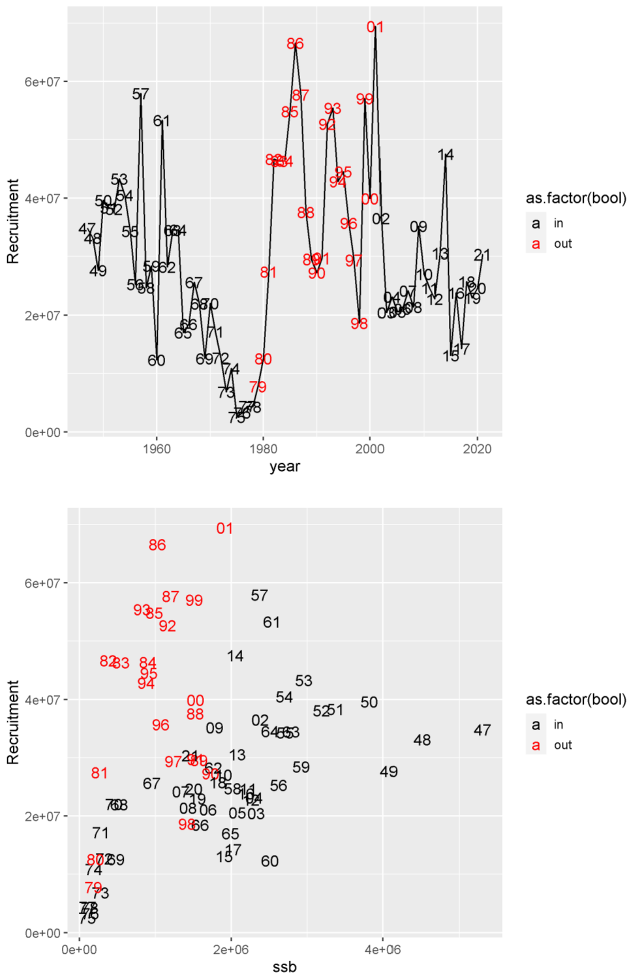


Figure 2: *Initial scenario (unsatisfactory) SRR relationships: left) Breakpoint analysis for Blim, right) segmented regression through Blim on short time series*

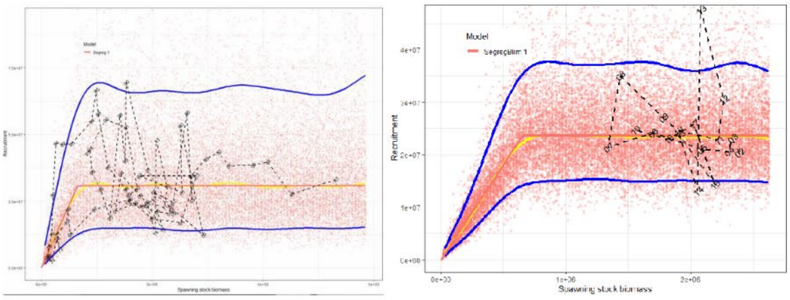


Figure 3: *reference points results from scenario 1*

Top: 1. SRR relationships: A) Breakpoint analysis for Blim, B) segmented regression through Blim on short time series

Bottom: MSY diagnostics

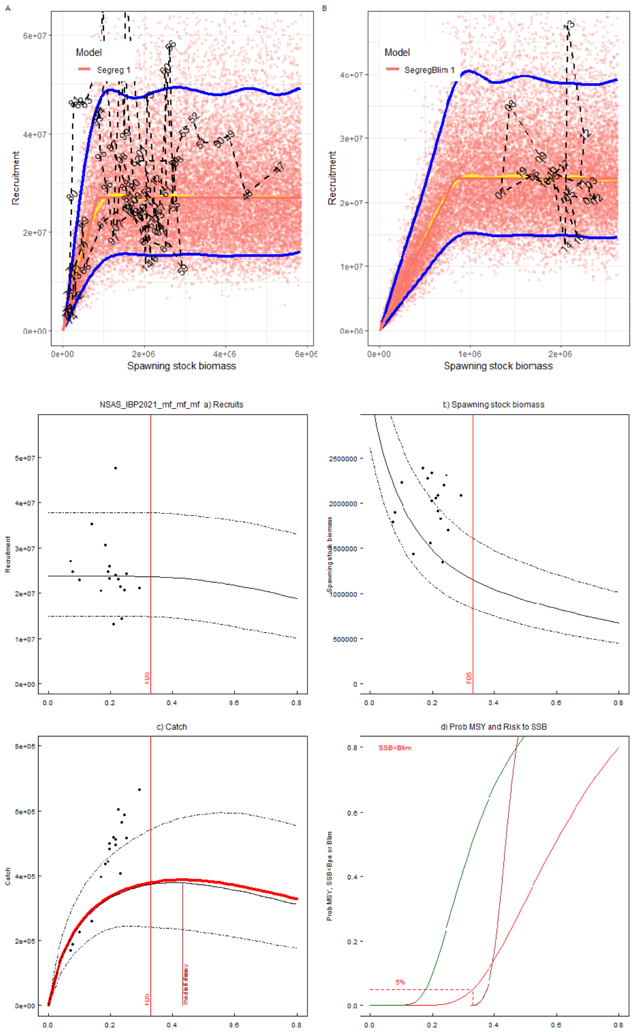


Figure 4: *reference points results for scenario 2*

Top: 1. SRR relationships: A) Breakpoint analysis for Blim, B) segmented regression through Blim on short time series

Bottom: MSY diagnostics

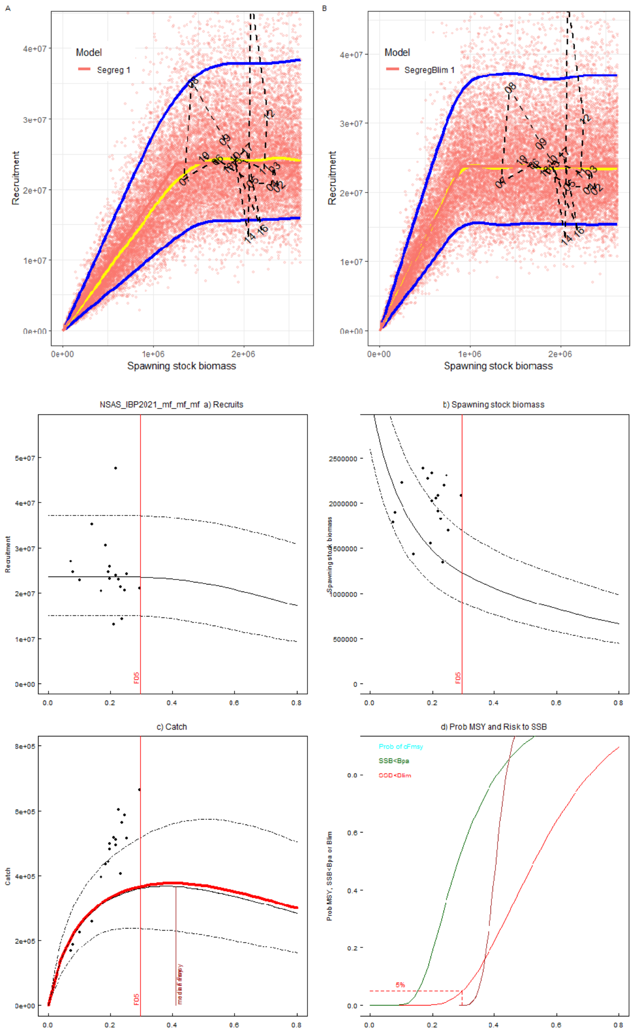


Figure 5: *reference points results from scenario 3*

Top: 1. SRR relationships: A) Breakpoint analysis for Blim, B) segmented regression through Blim on short time series

Bottom: MSY diagnostics

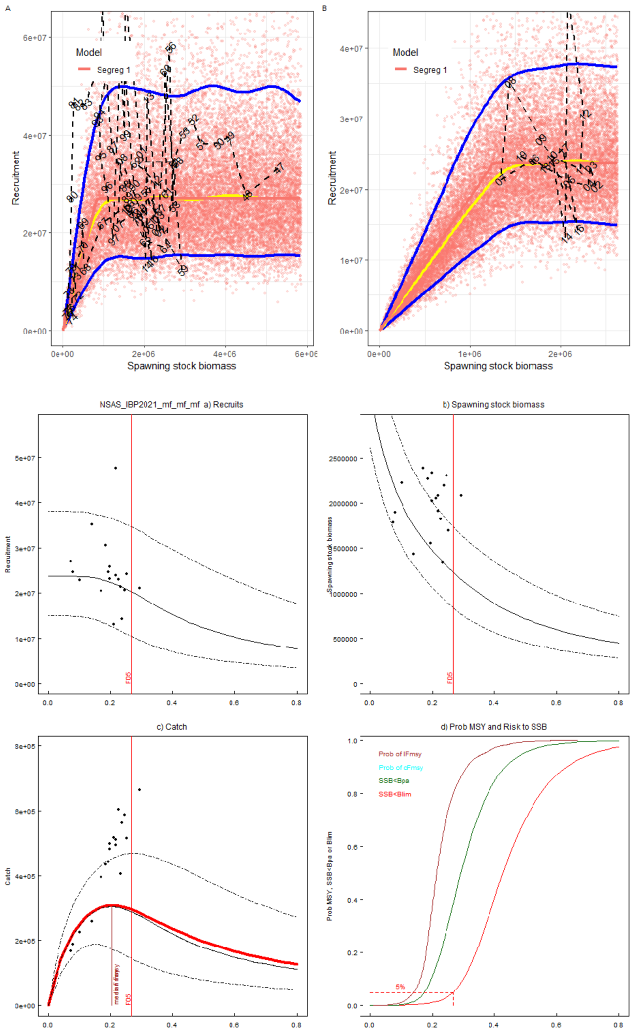


Figure 6: *scenario 1 limit reference points estimation under different post-collapse exclusion periods 1979-endYear. Respective graphs show different endYear values, respectively in display order: 1986, 1990, 1994, 1998 and 2002.*