**DTU Aqua**
National Institute of Aquatic Resources

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Mollie Brooks, Tobias K. Mildenberger and Anders Nielsen

DTU Aqua Report no. 384-2021

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## Colophon


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# Preface

This report is based on the project ”MSE Tools – Models and statistical tools for management strategy evaluation” (journal no. 33113-B-17-096) and funded by the European Maritime and Fisheries Fund and the Danish Fisheries Agency.

European Union
European Maritime and Fisheries Fund

HAV & FISK

We thank all the scientists who participated during the course of the project, contributed to discussing the results and helped identify future challenges.

DTU Aqua, Kgs. Lyngby
November 2021

# Content

# 1. MSEs for sprat and Norway pout stocks in the North Sea

To respond to ICES requests, we conducted management strategy evaluations (MSEs) of sprat in 2018 (ICES 2018 WKSPRAT) and of Norway pout in 2018 (ICES WKNPOUT 2018) and 2020 (Brooks and Nielsen 2020). As is the procedure in ICES, the simulations of each relevant fish stock (i.e. the operating models) were based on similar assumptions as the stock assessments. Both of these stocks have assessments that account for seasonality of the fisheries and the stocks due to the short-lived, fast-maturing features of these species. Because they recruit at age 0 and because of the seasonality, standard existing software such as FLR was not applicable. Both of these stocks are managed with an escapement strategy which requires an Fcap in order to be precautionary. The purpose of the MSEs was to estimate what values of Fcap would be precautionary. For Norway pout in 2018, we also evaluated numerous scenarios using combinations of Fcap, maximum TAC, and minimum TAC.

For sprat, we were able to implement both full and short-cut versions of the MSE. The full version includes the assessment model (SMS) in the feedback loop, whereas the short-cut simply adds observation error onto the quantities that would otherwise be estimated by the assessment. We showed that the short-cut version does a good job of mimicking the full version in many scenarios. For Norway pout, we were only able to implement a short-cut version of the MSE because it was not possible to run the assessment model (seasonal SAM) in an automated way.

# 2. Developing general methods for MSEs

We wrote software that is able to simulate stocks in a more general way than was previously possible. It is a package named "iamse" for the R statistical computing environment (Appendix A). As needed for short-lived stocks as described above, the software can simulate seasonality in the fishery dynamics and stock productivity. We were able to link it to SAM and SPiCT assessment models, but we were unable to connect it with SMS and seasonal SAM. SMS is not as easy to connect with the R environment because it is older and has input and output spread out over numerous files. With more time and expertise it might be possible to link with SMS, or it might be possible to make a new version of SMS in R. We determined that it would not be possible to run seasonal SAM in an automatic way as needed in an MSE because the assessment model is overparameterised and thus often has unidentifiable or highly correlated parameters, requiring manual tuning from experts.

# 3. Improved forecasting in SAM stock assessments

We implemented an extension to the state-space assessment model SAM to include a process model for weights (stock-weights and catch-weights) and proportion mature (Appendix B). This was also added to the forecast methods in SAM. We verified that it improves the models for 14 stocks. We expect that it will become the standard way to do forecasts from a SAM model, because it removes the subjectivity from selecting the number of years to average over, which was needed in the previous approach. By default the new options are turned off in SAM to ensure backwards compatibility (any previously defined assessment should keep giving the same results even with a new version of the program).

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# Appendix A. General MSE software

We developed a software package called "IAMSE" that allows to perform MSEs for any stock in a straight-forward and user-friendly way. The code is publicly available on GitHub at https://github.com/tokami/iamse. While the package is written in R and C++ guaranteeing fast computation, the full functionality can be accessed through R. The underlying simulation model is implemented with an intra-annual time step and able to reflect any desired temporal resolution (e.g. yearly or weekly time step). The high temporal resolution does not only facilitate parametrisation by aligning the time steps of simulation and assessment model, but also allows to explore various assumptions about the timing of recruitment, assessments, surveys, and management periods. The equations governing the population dynamics of the simulation model are described in detail in the supporting information of Mildenberger et al. (2021). The simulation model can be parametrised either based on life-history information of the stock understudy, such as growth parameters or length at 50% maturity, or by providing the required information explicitly from the output of an assessment model (e.g. natural mortality by age and season from the stochastic multi-species model;SMS; Lewy and Vinther, 2004) or in line with the input data of the assessment model (e.g. weight at age and season required by single-species SMS).

After the parametrisation of the simulation model, the software package allows to compare the performance of various assessment methods and management strategies. The software includes a variety of pre-defined harvest control rules (HCRs), functions to customise and create HCRs, as well as specific connectors to the stochastic assessment model (SAM; Nielsen and Berg 2014; Berg and Nielsen, 2016) and the stochastic surplus production model in continuous time (SPiCT; Pedersen and Berg, 2016); two assessment models that are commonly used within ICES for the assessment of data-rich and data-moderate stocks. Figure A1 shows the results of a quarterly MSE application of IAMSE parametrised to North Sea sprat four HCRs: fishing at true $F_{MSY}$, constant catch, fishing at $F_{MSY}$ estimated by SpiCT, and fishing at constant F estimated by SAM.

The software package is validated and well tested. Nevertheless, future work should be allocated to the further development of the package. For example, the connector to the single-species SMS assessment model should be implemented. Furthermore, the conditioning on assessments based on various assessment models should be improved and more documentation, vignettes and help resources are needed.

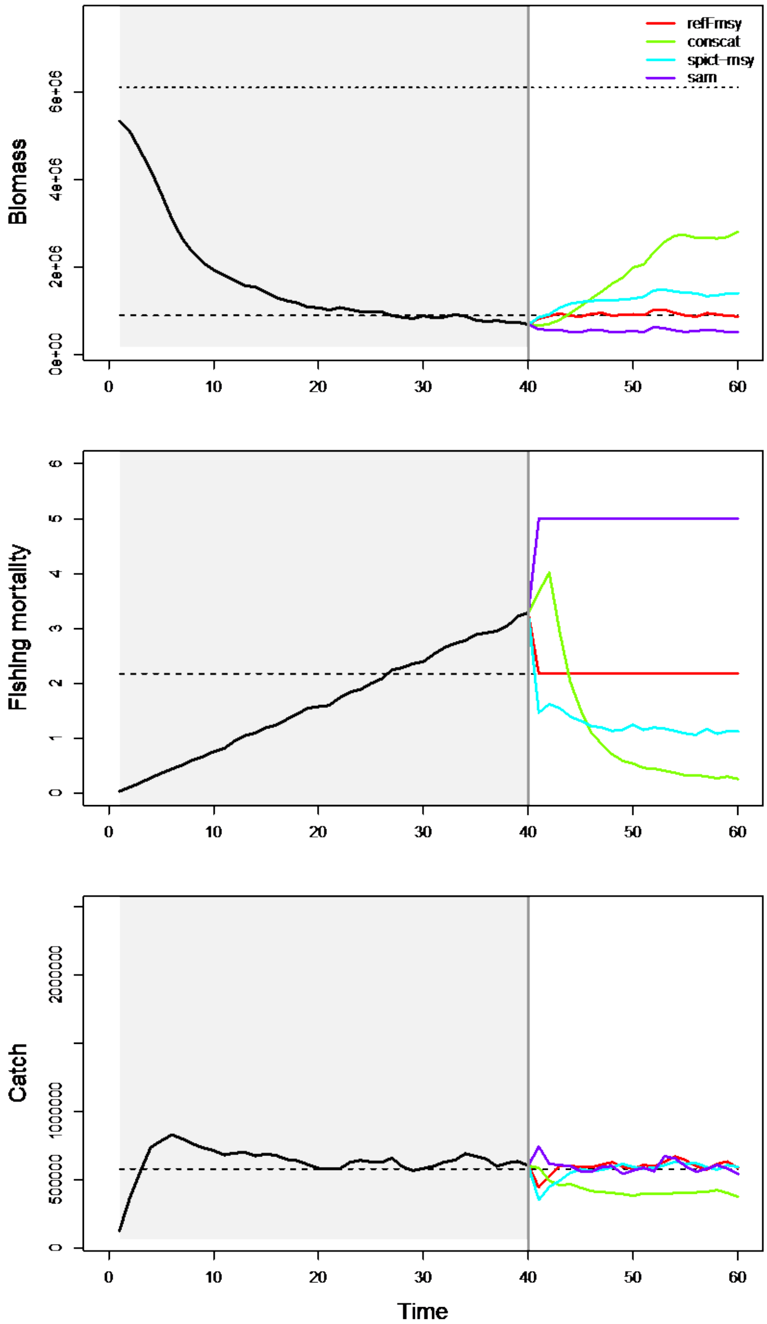


**Figure A1. Biomass, fishing mortality, and catch in weight resulting from the MSE of the North Sea sprat stock with various HCRs: fishing at true FMSY (refFmsy), constant catch (conscat), fishing with a constant F based on SAM (sam), and fishing at FMSY based on SPiCT (spict-msy). The dashed horizontal lines show the reference points (Bmsy, Fmsy, and MSY, for the three plots respectively), the dotted horizontal line in the biomass plot represents the virgin biomass (B0). The solid lines represent the median trajectories and the polygons cover 95% of the distribution.**

# Appendix B. Assessment models

## B.1. Purpose

In assessment and forecast of fish stocks there is a lot of focus on the correctly modelling the catches from commercial and scientific fleets, which is important, but for management the stock-weights, catch-weights, and proportion mature in each age group are equally important. Common assessment models estimate stock-sizes in numbers at age, but management is based on spawning stock biomass (SSB) and on total catch in weight, so information on weights and maturities are needed to produce those interesting quantities. Within the data period direct observations are used, and even if these should strictly be considered as observations subject to observation noise, they are treated as known constants. In the forecast period, which is directly used in management, simple ad-hoc rules are applied (e.g. average of last 5 years), and the resulting weights and maturities are treated as if known without error. This is not optimal. The focus in this work package is on providing a better, model based, alternative.

## B.2. Prediction based model selection study

To test and select a the best model based approach for predicting the biological model parameters (weights and maturities) we selected a fairly large number of stocks to use as validation data sets. The stocks were selected based on their availability of fairly long data series of the biological parameters. The stocks selected are: Northeast Atlantic Blue Whiting and Mackerel; Faroe Haddock and Saithe; North East Arctic Haddock, Saithe, and Cod; North Sea Cod, Haddock, Herring, Plaice, Saithe, Sole, and Whiting. These 14 stocks were agreed upon by the group before the different models were suggested or developed.

The model structures developed were all designed for the purpose of predicting e.g. 1-3 years forward. A large number of different suggestions were implemented and subjected to the same validation procedure on all 14 data sets. The suggested model types can broadly partitioned into : 0) Current practice (e.g. 5-year average), 1) Gaussian Markov Random Field with optional correlation in age, year, and/or cohort direction. 2) Separable age and year AR(1) structure with or without added cohort effect. These models were further be branched out by transformation of observations (none, logarithmic, or Box-Cox), by observation error, (none, independent, or correlated), and by their use of covariates (none or N). Further some models were restricted to be increasing within each cohort. A total of 34 model structures were implemented, validated, and compared.

The data on stock weights from the 14 different stocks were used evaluate and compare the 34 different model structures. Stock weights were chosen, because they are the best data consistently available from the the 14 stocks. During the model evaluation and test runs the last 10 years of the data from each stock were not used. The last 10 years were trimmed off and saved for the final evaluation. In the remaining data the models were set to predict the last 10 years successively 1, 2, and 3 years ahead. In the final evaluation and comparative runs the same procedure was repeated for the last 10 years of data. This approach was taken to ensure that the models were not unintentionally tuned/developed to predict anything specific to the last 10 years.

Each of the models predict stock-weights  in each age group, but it would be difficult to reach a coherent conclusion if different models predicted different age classes better, so to reach a joint conclusion, and to keep the evaluation focused on the real application of this modelling effort, it was decided to use the ability to predict SSB as the summarizing criteria. For each predicted year the age-specific predicted stock-weights are used to compute SSB (using maturities and N's from the assessment). This prediction is compared to the SSB calculated by using same maturities, N's, and the observed stock-weights. The comparison is done on logarithmic scale. Based on e.g. the 10 predictions calculated per stocks the root-mean-square-error (RMSE) is calculated and summarized by simple averages across stocks. 1, 2, and 3, year ahead predictions were compared.

Furthermore, it is important that the model structure is robust, so across all runs it was summarized how often the model converged (should be very close to 100%). Many of the suggested models would far too often not converge.

**Table B1. Example output for the model comparison. 6 of the best model approaches compared.**

| Model | nlog-Lik | AICc | AIC | RMSE.CV | Conv_rate_CV | RMSE.CV2 | RMSE.CV3 | Jit |
|---|---|---|---|---|---|---|---|---|
| 5-year Average | -244.9 | -487.7 | -487.7 | 0.086 | 1.00 | 0.101 | 0.118 | 0.00 |
| GMRF age, cohort | -375.1 | -723.3 | -724.3 | 0.068 | 1.00 | 0.088 | 0.102 | 0.01 |
| GMRF age, cohort, no obs noise | -371.1 | -717.5 | -718.4 | 0.068 | 1.00 | 0.087 | 0.102 | 0.00 |
| ARxAR increasing | -325.3 | -616.7 | -618.8 | 0.087 | 1.00 | 0.115 | 0.140 | 0.81 |
| GMRF increasing | -316.4 | -601.1 | -602.9 | 0.089 | 0.98 | 0.115 | 0.139 | 0.58 |
| ARxAR, no cohort, increasing | -397.2 | -767.6 | -768.6 | 0.069 | 1.00 | 0.093 | 0.111 | 0.20 |

The model structure selected was was the GMRF with correlations across ages within year and cohorts. This model is described in details below. In table B1 are shown the model performance output for some of the best performing models. Notice that the log-scale RMSE of the proposed model structure is 0.068 compared to 0.086 for the standard approach of using average over the last 5 years. This is a reduction of more than 20% averaged over 14 stocks.

## B.3. The model for weights

The weights, which are mean weight at age in the stock (SW) and mean weight at age in the catch (CW) are collected each year from surveys and from the commercial landings. The values are based on weighing age- and length- specified samples, so some uncertainty can be expected on the yearly observed values. However it must be expected that the true weights do vary from year to year, so simply averaging all years would likely lead to biases. Furthermore, we need to predict these weights a number of years forward (e.g. 3), because they are needed to calculate the important outputs from the explored management options. From our prediction based model selection study (described above) we selected a model, which include observation uncertainty, but also allow the true weights to develop over time, and further is the optimal for prediction. The details of the selected model are explained here:

The model is a state-space model, where the unobserved true weights by age and year are described by a so-called Gaussian Markov Random Field (GMRF). A GMRF is a stochastic process, where the correlation structure is expresses via the inverse covariance structure and the neighborhood structure. The inverse specification allows for fast computations, because the most time consuming part of evaluating a multivariate Gaussian is the part where the covariance matrix is inverted. The structure selected for weights is the structure where weights from neighboring age groups are correlated within a year and where weights from neighboring age classes are correlated within cohorts. Furthermore, mean weights are estimated for each age group (or combination of age groups). The process model for the true weights can be written precisely as:

$(\log W_{ay})_{a=1,\ldots,A;y=1\ldots Y} \sim N(m,\sigma^2 R)$, where $m_{ay}=\mu_a$ and

$$(R^{-1})_{ay,a'y'}=\begin{Bmatrix} -\phi_1, if y = y' \wedge |a-a'| = 1 \\ -\phi_2, if\big((y-y') = 1 \wedge (a-a') = 1\big) \vee \big((y-y') = 1 \wedge (a-a') = 1\big) \\ 1 - n_{ay}^{(a)}\phi_1 - n_{ay}^{(d)}\phi_2, if y = y' \wedge a = a' \\ 0, otherwise \end{Bmatrix}$$

Here $n_{ay}^{(a)}$ is the number of neighbors in the age direction a given age (a), year (y) combination has (1 if youngest of oldest age group 2 otherwise), and $n_{ay}^{(d)}$is the same in the diagonal (cohort) direction.

The above is an exact formulation, but in more understandable terms the model has a mean level for each age group, a correlation parameter describing correlation between weight at age within a year (year effect) and a separate correlation parameter describing correlation between weight at age within a cohort (cohort effect).

Between all structures tested this process formulation gave the best forward prediction of unobserved log-weights. Furthermore the structure is sensible, because year-specific conditions (e.g. w.r.t. food availability) can affect the mean weight of many age groups within a year (year effect), and a given cohort can have experienced similar conditions in the past (e.g. in its first year), which will decrease or increase the weights of that cohort in many years following (cohort effect).

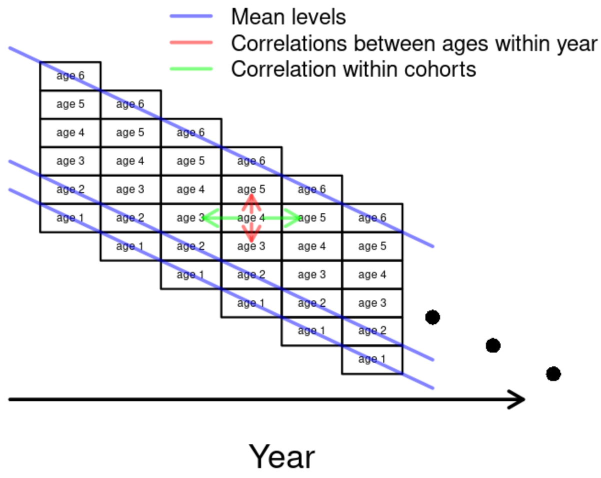


**Figure B1. The structure of the process model, where a mean level is assigned to each age group, and the correlation is across cohort and across ages within year.**

To allow and account for uncertainty in the observed weights, it is assumed that the observations of log-weights follow a normal distribution with mean given by the process described above. The observation variance can optionally be configured to be separate for some age groups.

## B.4. The model for maturity

Proportion mature (or “maturity ogive” (MO)) is a number between 0 and 1 indicating the fraction of spawning mature fish within a given group. It is sampled for each combination of year and age group. There are many challenges in setting up an appropriate model for the maturity data. The observations are bounded between zero and one and many observations exactly at the boundaries. As is often the case with fisheries data only a summary of the observations are available (here only the fraction is given and not the original samples, or even the number of samples used to estimate the fraction). Furthermore, for a given stock the working group may in the past have made decisions to substitute the yearly maturity proportion estimates with e.g. an average over many years, and the original yearly estimates are now unavailable. Hence it is important that the solution is pragmatic, as robust as possible, and able to supply plausible forecasts even in sub-optimal data situations.

Similarly to the model for the weights the model for the proportion mature is a state space model where the unobserved true proportions mature are described by a stochastic process. Since the observations themselves are known to be bounded between zero and one the process is setup at the logit scale. This allow the process to be unconstrained and constructed as a Gaussian Markov Random Field while at the same time predicting observations only within the interval from zero to one. The same correlation structure is used as was derived for weights (with correlations among ages within each year and within cohorts), but the correlation parameters are estimated separately for proportion mature.

The observations are assumed to be beta distributed. The beta distribution forms a very flexible distribution between zero and one. The beta distribution is parameterized such that for a given predicted mean proportion mature $\mu_{MO}$ the variance becomes $\mu_{MO}\,(1-\mu_{MO})/(1+\tau_{MO})$. Where $\tau_{MO}$is a positive precision parameter, which is further bounded to be below 1000 for increased numerical stability. This mean variance-relationship mimics the observed pattern that pro-portions near one or zero are very certain and proportions in the middle of the range are the most uncertain. Such proportion mature observations each originate from a number of samples of mature or immature individuals. Estimating the proportion from such observations would result in the same mean-variance relationship (assuming independent samples).

## B.5. Implementation in assessment model SAM

The selected models for weights (stock weight (SW), and catch weight (CW)) and proportion mature (MO) are implemented as configurable options in the state-space assessment model SAM, and hence are ready to use for any assessment using SAM. By default the new options are turned off. This is not to be taken as an indication that the new options are not generally preferable – they are – but merely to ensure backwards compatibility (any previously defined assessment should keep giving the same results even with a new version of the program).

Previously the raw observations of weights and maturity were used by the assessment model simply as covariates, which means that they were treated as constants without uncertainty. Because of this the actual observations were already read into the program, so no change to the program was required for the data part.

The new configuration part is kept to a minimum to make these options easy to try out and use. Consider e.g. the case of stock weights. The default configuration is the following for a stock with 6 age classes:

```
$stockWeightModel
# Integer code describing the treatment of stock weights in the model (0 use as known, 1 use as
# observations to inform stock weight process (GMRF with cohort and within year correlations))
 0

$keyStockWeightMean
# Coupling of stock-weight process mean parameters (not used if stockWeightModel==0)
 NA NA NA NA NA NA

$keyStockWeightObsVar
# Coupling of stock-weight observation variance parameters (not used if stockWeightModel==0)
 NA NA NA NA NA NA
```

The code ‘0’ indicate that the stock weight model is turned off (stock weights are used as given and treated as know without uncertainty). Because the model is turned off there is no need to supply mean value or variance configuration, so they are not assigned ‘NA’. The fields are shown even when not assigned to make it simpler for the user to turn it on.

If the new option is to be turned on, then the configuration can be changed into the following:

```
$stockWeightModel
# Integer code describing the treatment of stock weights in the model (0 use as known, 1 use as
# observations to inform stock weight process (GMRF with cohort and within year correlations))
 1

$keyStockWeightMean
# Coupling of stock-weight process mean parameters (not used if stockWeightModel==0)
 0 1 2 3 4 5

$keyStockWeightObsVar
# Coupling of stock-weight observation variance parameters (not used if stockWeightModel==0)
 0 0 0 0 0 0
```

Here the stock weight model is turned on by setting the code to ‘1’. The model is further configured to use a separate mean value for each age class, but a common variance parameter (on log-scale).

The configuration options are set in the same way for catch weights and for proportion mature with the exception that the observation variance cannot be configured to be age-specific for proportion maturity. The options can be turned on or off individually, and separate parameters are estimated for each of the three extensions.

Whenever the new options for modelling weights and maturities are turned on they can be used in the forecasts. There are certainly benefits to using these options for the historic assessment of the stock alone (less randomly fluctuating estimates and more correctly estimated uncertainties), but the main reason to model weights and maturities is to be able to forecast them better.

The forecast function in the SAM package aims to forecast the stock in a model-consistent way, which was obviously problematic when there was no model included for weights and maturities and hence ad-hoc options like averaging previous years were used. If the new options for modelling weights and maturities are turned on when running the assessment, then the forecast function will by default use the process model to predict future weights and maturities. So for instance the following line:

```
mySQForecast <- forecast(fit, fscale=c(1,1,1,1))
```

which is a standard line for making a ‘status quo’ forecast with SAM. If the new options were turned on during the model fitting (described above), then line will produce a forecast of all relevant quantities (e.g. SSB, catch, F,…), based on weights and proportions mature predicted according to the new process models. This forecast will utilize the estimated correlations and mean values estimated from all data up to the current year. If the new process models were not used during the model fitting, then the weights and proportions mature will be predicted simply by averages of the last 5 years. This setup will make it effortless for the working groups to use this new approach.

For comparative purposes it is possible to turn off the new forecast options even if the new options were used during the model fitting. In the above example this can be done by

mySQForecast <- forecast(fit, fscale=c(1,1,1,1), useSWmodel=FALSE, useCWmodel=FALSE, useMOmodel=FALSE)

It is naturally not possible to turn the new options on in the forecast part if the new options were not used during the model fitting, and trying to will result in an error message.

## B.6. Results (example)

In this section the results will be exemplified first for the individual parts, and then combined in the assessment model and in the forecasts.

The example used here is the North East Arctic Cod stock. This assessment is being bench-marked in early February 2021 and the model extension is being proposed for this stock (later in February it is being proposed for North Sea Cod). Turning the process modelling options on for North East Arctic Cod is done exactly as described above.

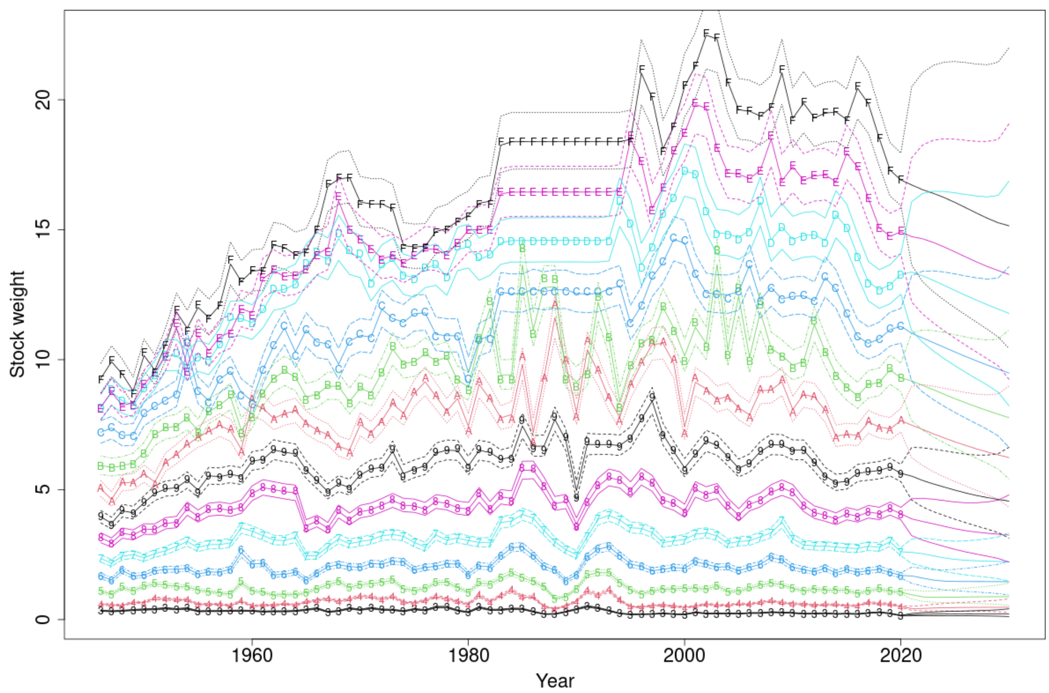


**Figure B2. Stock mean weights for North East Arctic Cod (ages 3-15) and the predictions from the process model.**

The process model for stock weights follow the observations fairlyclosely and predicts the stock weights some years forward (figure B2). To make the graph less clustered we will focus on a few age groups age 8, 11, and 14 (symbol “8”, “B”, and “E” in figure B2). Removing the last 5 stock weight observations from all ages from the model fitting allow us to study how the model predicts these last 5 weights.

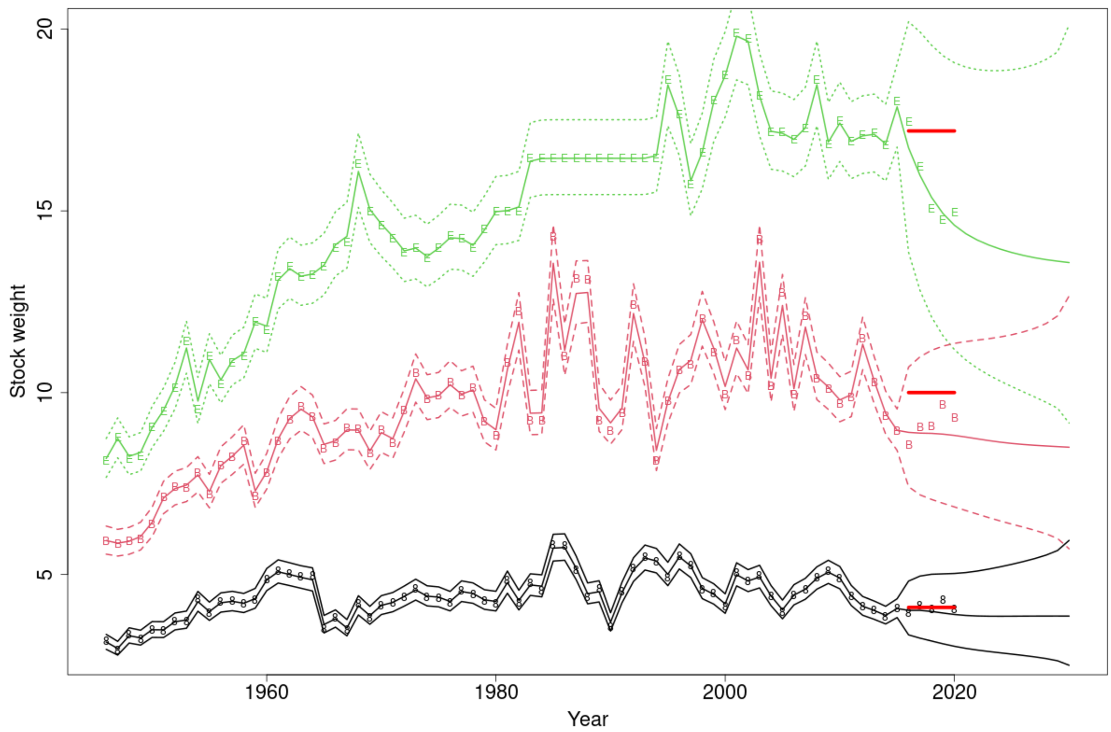


**Figure B3. Stock weights for ages 8, 11, and 14. The last 5 observations are not used in the fitting procedure, but are predicted by the model (solid and dashed lines). The thick red lines show the standard prediction procedure of using average over the last 5 years.**

The process model predicts the stock weights forward. Looking at the last 5 years the process based model gives a closer prediction compared to the standard procedure of using an average of the 5 most recent years (Fig. B3). Furthermore the prediction uncertainty is estimated. The process model is capable of producing these predictions, because the correlations within the cohort is used in combination with the overall means estimated in the historic period.

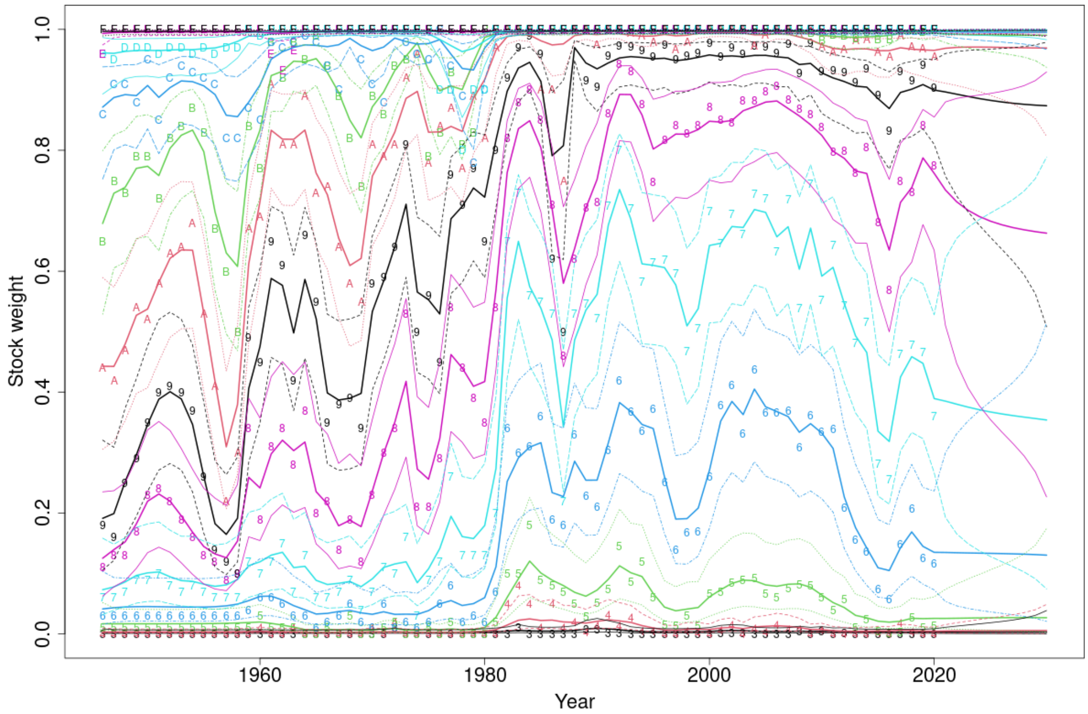


**Figure B4. Proportion mature observed for North East Arctic Cod and the predictions from the corresponding process model.**

The proportion mature can be studied in the same way. The process model is able to adapt to the historic observations and the confidence intervals are wide where the observations are very fluctuating, but very narrow where the proportion is either constant zero or one (Fig. B4). The model can provide predictions, but when inspected closely for certain ages they appear to be biased downwards. This is likely caused by the historic much lower proportion mature of these ages, which gives the process model a much lower mean values to revert to. A possible improvement would be to only use the observations from e.g. 1980 to fit the process.

As explained above all of these process models are included in the assessment model and can be used within. In the historic period we see little difference for North East Arctic Cod. The process model is closely fitting the observed weight and maturity data, so e.g. the spawning stock biomass is only slightly modified in the historic period (Fig. B5). The only difference seen (on close inspection) is that the SSB estimated with the process model options included is slightly smoother, because it assigns some of the fluctuations in weights and maturity to observation noise, but the difference is barely noticeable. The difference is however clear when the forecast period is also considered. The predicted SSB from the process model is below SSB predicted from the standard model (Fig B5).

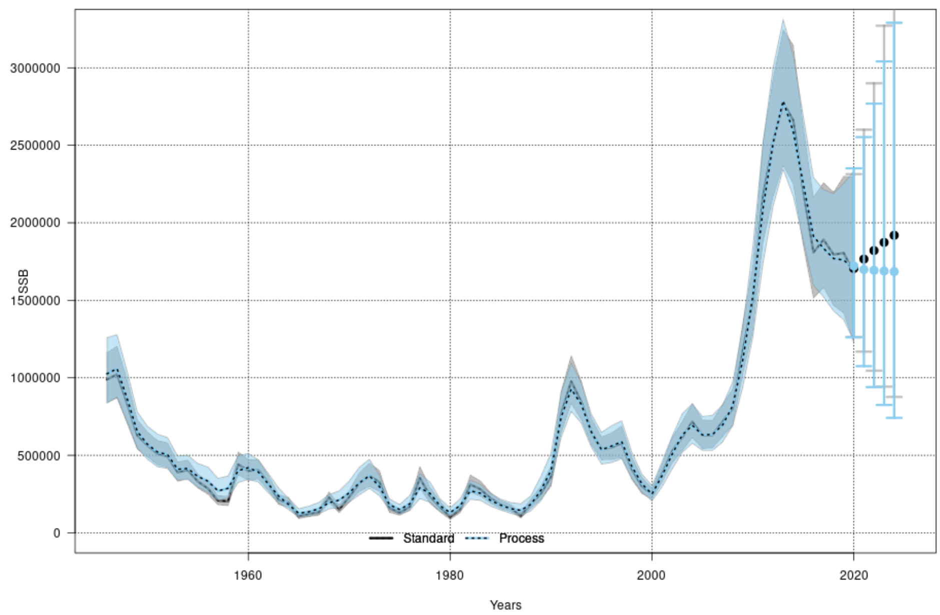


**Figure B5. Spawning stock biomass for North East Arctic Cod estimated and predicted with status quo fishing pressure with and without process model for weights and maturity.**

The estimated catch is again similar in the historic period, but the forecast shows a clear difference between using the recent five year average or the process model to predict the catch weights in the forecast period (Fig. B6).

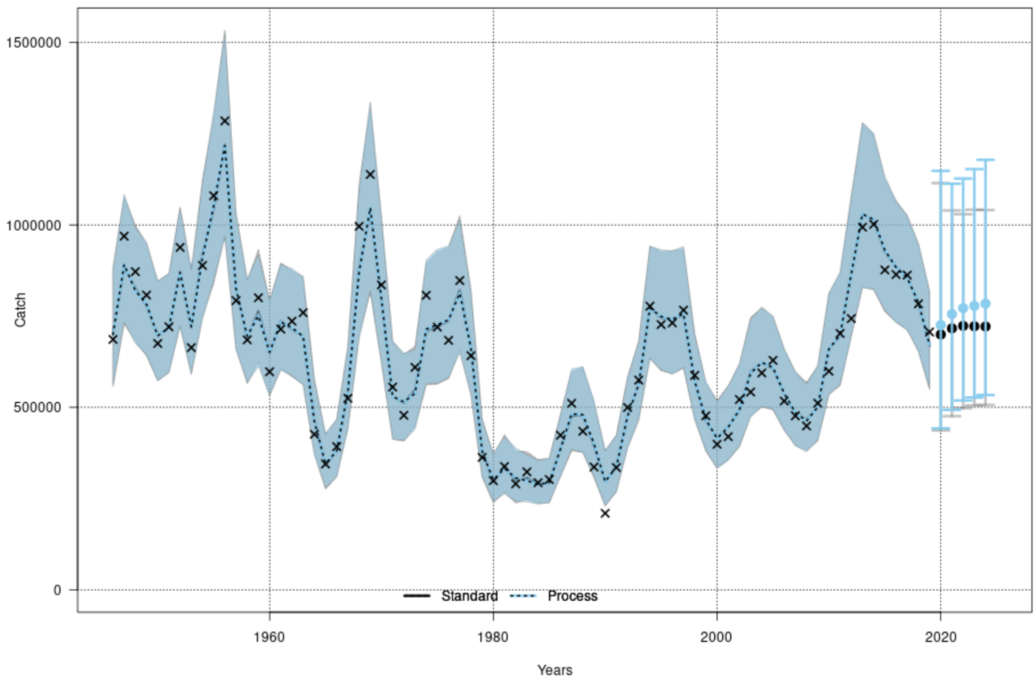


**Figure B6: Predicted and observed catch for North East Arctic Cod. Status quo fishing pressure is used to forecast with and without process model included.**

## B.7. Conclusion

The model extension to the state-space assessment model SAM to include a process model for weights (stock-weights and catch-weights) and proportion mature has been researched, developed, validated, and implemented. The process has further been added to the forecast, and it is expected that it will become the standard way to do forecasts from a SAM model, because it removes the subjectivity from selecting the number of years to average over, which was needed in the previous approach.

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