Working Document for WGWIDE 2016

Forecasting stock parameters of Norwegian spring spawning herring using XSAM

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Abstract

The XSAM framework for assessing fish stocks includes a statistical catch at age model that allow for time series modeling of fishing mortality. The model framework was put forward during the benchmark meeting for Norwegian Spring Spawning herring in 2016 and it was decided to use this as the main assessment tool for NSS herring. The model runs forward in time and makes projections rather straight forward. It is shown how the modelling framework can be used to make predictions in time at the same time as accounting for all sources of variability captured by the model, i.e. variability in initial stock size estimates as well as variability due to the stochastic processes describing recruitment and mortality. For projection of stock parameters it is shown that the uncertainty in projected stock parameters is within reasonable limits for time horizons in which the stock parameters are not is affected by recruitment variability. Once the recruitment variability affects the projections, the uncertainty becomes so large that the estimates are of no practical use. For practical purposes this means that short term forecasts of NSS herring can be made within a time window of a few years which should be sufficient for the adopted management plan in use for this stock.

Introduction

At the benchmark meeting for Norwegian Spring Spawning herring in 2016 (ICES 2016) a model framework which is based on a statistical assessment model was presented as a candidate for assessing this fish stock. The group decided to use this model as the main candidate model for NSS herring. The key differences of the model compared to the former model for NSS herring is the shift from a deterministic model to a statistical model and the utilization of prior knowledge about sampling errors in input data for obtaining adequate weights of the various input data. The model runs forward in time and offers the possibility to model the fishing mortality as a time series model. For details about the model see Aanes 2016a and 2016b.

For a population dynamical model there are conceptually two sources of variability that will affect the uncertainty in predictions by the model: The first is the variability in the stochastic processes itself, in which the parameters are estimated (e.g. the variance in fishing mortality). The second source of variability is the uncertainty in the parameters which includes uncertainty in initial population states and any other parameter affecting the dynamical model. See Lande et al. (2003) for more details on this theme.

The model runs forward in time and thus in principle there are no difficulties in forward projections provided values of recruits. As pointed out in Aanes 2016a XSAM offers the flexibility to model the recruits as a process or to treat the recruits as fixed parameters to be estimated. If recruitment is modeled as a process, future recruitment is directly formulated in the model and XSAM will in principle provide prediction of recruits according to the chosen process model with variability determined by the variability in the process. Choosing a simple process model for recruits modeling recruitment such as a mean with a variance, it was found that the estimated numbers of recruits became practically identical compared to the alternative considering the recruitment as fixed parameters. The option of having fixed parameters requires that recruitment must be fed into the model for prediction purposes, whereas they will be directly available choosing the process variant. In the simple model chosen for recruitment in Aanes 2016a, the variability will reflect the variability of recruitment around the mean, which is very high for herring. This also means that the predicted recruitment basically will reflect the mean with the recruitment variability which is a model with poor predictive power and bound thus bound to be highly variable. However, the lack of a stock recruitment relationship for herring hampers the possibility of being able to make precise predictions of recruitment until the mechanisms at early life stages is better understood. Therefore, in this document, the option of model recruitment as a simple process as outlined will be used for illustrative purposes.

Stock parameters used for TAC advice are SSB and fishing mortalities ages 5 and older. Since NSS herring starts to mature at age 4 (Figure 1) the time before the projection is effected by variability in predictions of recruitment depend on the recruiting age in the model. If the recruiting age in the model is a_{min} the number of years that can be predicted by the model before predictions of recruitment will enter the prediction of SSB is $4 - a_{min}$. This means that using $a_{min} = 3$ gives the possibility of projecting 1 year ahead before prediction variability of recruitment effects prediction of SSB while using $a_{min} = 1$ enables 3 years of prediction of SSB.

A simulation based approach is taken to project the uncertainty forward in time and it is explained how appropriate measures of variability is obtained to explore effects of different TACs options on the stock parameters. To explore the effect of recruiting age in the model, two different model configurations are chosen as basis for the projections; one with recruiting age at age 3 and one at age 1.

Methods

The basis for forward projection is XSAM fitted to data available at ICES (2016) for the years 1988-2015. The model for fishing mortality is a separable model with noise where selectivity is modeled as a time series AR process as outlined in Aanes 2016a and 2016b. To explore the effect of the recruiting age in the model for predictions two different types of model setups are used. The first model is the model that were in focus at ICES (2016) using age span 3-12+ over the years 1988-2015 including Fleet 1 and 5. For the second model Fleet 4 and 6 including observations of 1 and 2 year olds were included enabling using the age span 1-12+. For illustrative purposes the reference F is chosen to be the unweighted average over ages 5-10 in this document. A summary of the estimates comparing the model fits is given in Figure 2 and shows that estimates of SSB and average F are very similar.

As most assessment models predicted values of stock and catch weight at age, natural mortality, and proportion mature at age are given as input over the years included in the prediction. Here, these values are chosen equal to the values available in the assessment year (see ICES 2016).

In the assessment year, y, XSAM provides estimates of recruits, fishing mortalities, and population sizes at age yielding estimates of SSB provided proportion mature at age, stock weights at age and natural mortalities are available. Note that XSAM also provides an estimate of fishing mortality in y utilizing catch predictions for y. Consequently, an estimate of SSB at the beginning of the quota year $y+1$ is directly available since

$$\widehat{SSB}_{y+1} = \sum_{a=1}^{A} \widehat{N}_{a+1,y+1} P_{a+1,y+1} w_{a+1,y+1} = \sum_{a=1}^{A} \widehat{N}_{a,y} exp\left(-\widehat{F}_{a,y} - \widehat{M}_{a,y}\right) P_{a+1,y+1} w_{a+1,y+1}$$

which forms the basis for applying the implemented management plan for this stock. Forward projection beyond this point becomes a natural extension due to the time dependencies inherent in the cohort dynamics and the time series model in XSAM. The issue is how to bring forward the variability in an appropriate way. A simulation based approach is used to obtain the variability in the forecast since it is easy to understand and implement.

First it is explained how to account for the variability due to the stochastic processes in the model and the how to incorporate the uncertainty in the parameter estimates to obtain the total uncertainty captured by the model.

To obtain the variability due to the variability in the stochastic processes, a realized value of the stochastic process is obtained by sampling from the specified distribution. For example:

$$R_{y+1} = \theta_R e^{\delta_{y+1}}$$

where $\delta_{y+1} \sim N(0, \sigma_R^2)$, then a realized value of recruitment in $y+1$ is obtained by sampling a value of δ_{y+1} from $N(0, \sigma_R^2)$, say δ_{y+1}^* which gives R_{y+1}^*. Repeating this a large number of times n_r, gives $\left\{R_{y+1}^*\right\}_{i=1,\ldots,n_r}$, a sample distribution of the recruitment reflecting the variability due to the stochasticity in the recruitment process. The same approach is used for the fishing mortality which is the other stochastic process in XSAM.

To also account for the uncertainty in the parameter estimates, it is necessary to know the underlying distribution of the parameter itself to be able to sample values from this distribution. This means that another level in the sampling procedure is added: First a realization of the parameter is sampled using the sampling distribution of the parameter. Then a realization of the prediction is obtained by sampling from the stochastic process using the realized parameter as described above. In reality, some of the parameters are correlated such that the simultaneous distribution of the parameters, including the correlations is needed to correctly display the variability. TMB offers the possibility to obtain an approximation of the joint precision of the parameters including the correlation structure through the hessian (Kristensen 2014). This enables easy sampling from the simultaneous distribution of parameters. In this way the variability and correlation structures in the projected stock parameters is accounted for by first sampling parameters and then simulate the stochastic processes ahead for the respective parameters.

It should be noted that for parameters that are log normal distributed such as recruitment, it will be necessary to bias correct the realized values due to the fact that the values at the original scale is positively biased with $e^{0.5\sigma^2}$ where σ^2 is the variance in the distribution, otherwise the stochastic projections will be increasingly biased forward in time.

One of the major objectives of doing forecasts is to examine the effect on a prescribed TAC. The XSAM model includes a model for the fishing mortality and does not include the mechanism for setting TAC which usually is derived applying a harvest control rule or management plan on estimated stock parameters.

One of the issues in traditional forecasting concerns which selection pattern for F to use in the forecast. Having a time series model for the fishing mortality this choice can be made objectively by the predicted values directly provided by the model for F due to its time series structure.

First, it is important to realize that fixing appropriate combinations of the variance components in the model for fishing mortality to 0, this model includes a traditional separable model, separable model with noise, separable model with noise and time varying selection etc. (see Aanes 2016a for details). In any case a projection of fishing mortality is available directly from the model. This projection implicitly contains the projected values of the selection pattern $F_{a,y+1}/max(F_{a,y+1})$ regardless the actual value of the projected fishing mortalities. The actual value of fishing mortality may be far from the fishing mortality which correspond to the TAC of interest of several reasons: The time series models for F makes poor predictions due to large uncertainties in both parameters and large variances in the processes, and the TAC of interest may be derived differently from the process generating the actual catches in the past. Consequently, predictions of fishing mortalities applying the time series models without any restrictions will produce highly variable predictions. Anyway, the prediction will contain the models prediction of the selection pattern, and adjusting the predicted fishing mortality to match the TACs of interest will produce a prediction in correspondence with TACs, but keep the model prediction of the fishing pattern. In this way the time series features of the model is allowed to predict the selection pattern, whereas the predicted fishing mortality levels are according to the TACs. With this adjustment, XSAM can be used to provide projections of stock parameters including measures of uncertainties for any sets of TACs of interest.

As an example, the agreed management plan for NSS herring is implemented. The management plan is described in ICES (2014) and can be mathematically formulated as

$$F(B) = \begin{cases} F_{mp}, & B \geq B_{mp} \\ \alpha + \beta B, & B_{lim} < B < B_{mp} \\ F_{min}, & B < B_{lim} \end{cases}$$

Where F is the average fishing mortality in the quota year over a specified age range, B is the SSB in the quota year, F_{mp}, B_{mp}, F_{min} and B_{lim} reference points decided by ICES and the slope $\beta = (F_{mp} - F_{lim})/(B_{mp} - B_{lim})$, and intercept $\alpha = F_{mp} - \beta B_{mp}$.

Here, this rule is adapted to point estimates of biomasses as it would not be meaningful to use a distribution of biomasses since that would generate a distribution of Fs and consequently a distribution of TACs. To adapt the implementation of this harvest control rule to a statistical model, the actual values entering the rule is the point estimates. This means that first a deterministic projection is performed where the point estimates are used. This allows application of the harvest rule to produce an F which can be translated into a TAC. Having established the TAC based on the deterministic projection, a stochastic projection can be performed as outlined above. An alternative approach for adapting HCRs to predictions explicitly utilizing the uncertainties is found in Dankel et al (2016).

Results, discussion and conclusions

Two cases are explored in this document

1) The fishing mortality evolve according to the model for fishing mortality without any constraints
2) TAC is set according to the agreed management plan for NSS herring applied on point estimates of input parameters

For illustrative purposes the forecast is run 10 years ahead of the assessment year although this would normally not be done in practice.

The results of case 1 using the model starting at age 3 are shown in Figure 3. First note that the recruitment prediction represents the estimated mean recruitment along with its variability as expected and is of little value for prediction of recruitment as such. The prediction of SSB shows a dramatic increase in uncertainty beyond 2 years of prediction and is thus of little practical value after 3 years. The reason for the dramatic increase is that the prediction of recruits enter the prediction of SSB in the year after the quota year since a significant part of the 4 year olds are mature (Figure 1). Also note how the uncertainty in the parameters (e.g. starting values of the predictions) increases the uncertainty compared to only accounting for the uncertainty in the stochastic processes. When F evolves according to the model, the variability in F increases dramatically from the assessment year and onwards. The reason is that the process for F as such is highly stochastic and follows typical pictures of standard AR forecasting. Consequently, the future catches are also highly uncertain, although the mean approaches average catches over the observation range. If the model starts at age 1 instead of age 3 (Figure 4), there is one notable difference: the SSB can be forecasted with higher precision for some more years. More specifically the decrease in precision is delayed with 2 years since the model uses the signals from the younger ages without interference of the recruitment process. A more useful forecast is forecasting based on TACs. Figure 5 shows the forecast when a TAC is set according to the management plan using point estimates of SSB as input to derive the TAC based on the models prediction of fishing pattern. The consequence is that the levels of F become more precise since the catches are constrained. And again, the result of decreasing the models age for recruitment to age 1 is to have the additional increase in precision for SSB for some more years (Figure 6).

All results in Figures 4-6 illustrates how the precision in key parameters (SSB and F) decreases with time as the assessment year becomes closer and further decreases more rapidly with time after the assessment year in the forecasts.

For the actual quota setting it is the short time forecast that is important. Based on these scenarios it is evident that SSB can be predicted with reasonable error 1 year ahead of the quota year if the recruiting age is 3, but it can be improved somewhat if the recruiting age is lowered to 1 (Figure 7). The same applies for the fishing mortality provided that the catches are constrained which they usually are applying a applying a harvest control rule. The “bump” in the F estimates occurring in the assessment year applying the management plan is caused by an assumption that the actual future catch will equal the TAC without any error, whereas the actual catch in the assessment year is permitted to have an error according to the specified prediction error of the predicted catch in the assessment year (see Aanes 2016a for details).

Having quantified the precision levels in the forecasts also means that any risks related to the parameters may be quantified. For example the probability of SSB being above Blim in the year after the quota year or probability of F being above or below Fpa.

It is important to notice that the estimated levels of precision are based on the assumption that the projected input data for weights at age, proportion mature at age and natural mortality is correct. If precision levels of the predictions of these parameters are known, they can easily be accounted for in the forecast since simulations are used for quantification.

Increasing the precision in estimates depend on having data of good quality and high precision available. Since the estimates makes the basis for forecasting this will also increase the precision in the forecasts, but precision in the forecasts after recruitment enters the forecast of SSB depend on the precision in the predicted recruitment. Prediction of recruitment will be important for medium and long term forecasting and puts the emphasis on the recruitment process. For short term forecasting this need is not so crucial whenever recruitment prediction does not affect the estimates of SSB which is the basis in the implemented management plan. For NSS herring, the recruitment age cannot be lower than age 3 to maintain reasonable levels of precision in the short term forecast, and it might be considered to lower the models recruitment age to increase levels of precision in the forecast.

References

Aanes, S. 2016a. A statistical model for estimating fish stock parameters accounting for errors in data: Applications to data for Norwegian Spring-spawning herring. WD4 in ICES. 2016. Report of the Benchmark Workshop on Pelagic stocks (WKPELA), 29 February–4 March 2016, ICES Headquarters, Copenhagen, Denmark. ICES CM 2016/ACOM:34. 106pp.

Aanes, S. 2016b. Diagnostics of models fits by XSAM to herring data. WD12 in ICES. 2016. Report of the Benchmark Workshop on Pelagic stocks (WKPELA), 29 February–4 March 2016, ICES Headquarters, Copenhagen, Denmark. ICES CM 2016/ACOM:34. 106pp.

Dankel, D.J., Vølstad, J.H., and Aanes S. 2016. Communicating uncertainty in quota advice: the case for Confidence Interval Harvest Control Rules (CI-HCRs) for fisheries. Canadian Journal of fisheries and Marine Science 73 (2): 309-317.

ICES. 2016. Report of the Benchmark Workshop on Pelagic stocks (WKPELA), 29 February–4 March 2016, ICES Headquarters, Copenhagen, Denmark. ICES CM 2016/ACOM:34. 106pp.

ICES. 2014. Advice basis. In Report of the ICES Advisory Committee, 2014. ICES Advice 2014, Book 9.

Kristensen, K. 2014. TMB: General random effect model builder tool inspired by ADMB. R pack-age version 1.1.

Lande, R., S. Engen, and B.-E. Sæther. 2003. Stochastic population dynamics in ecology and conservation. Oxford University Press, Oxford.

Figures

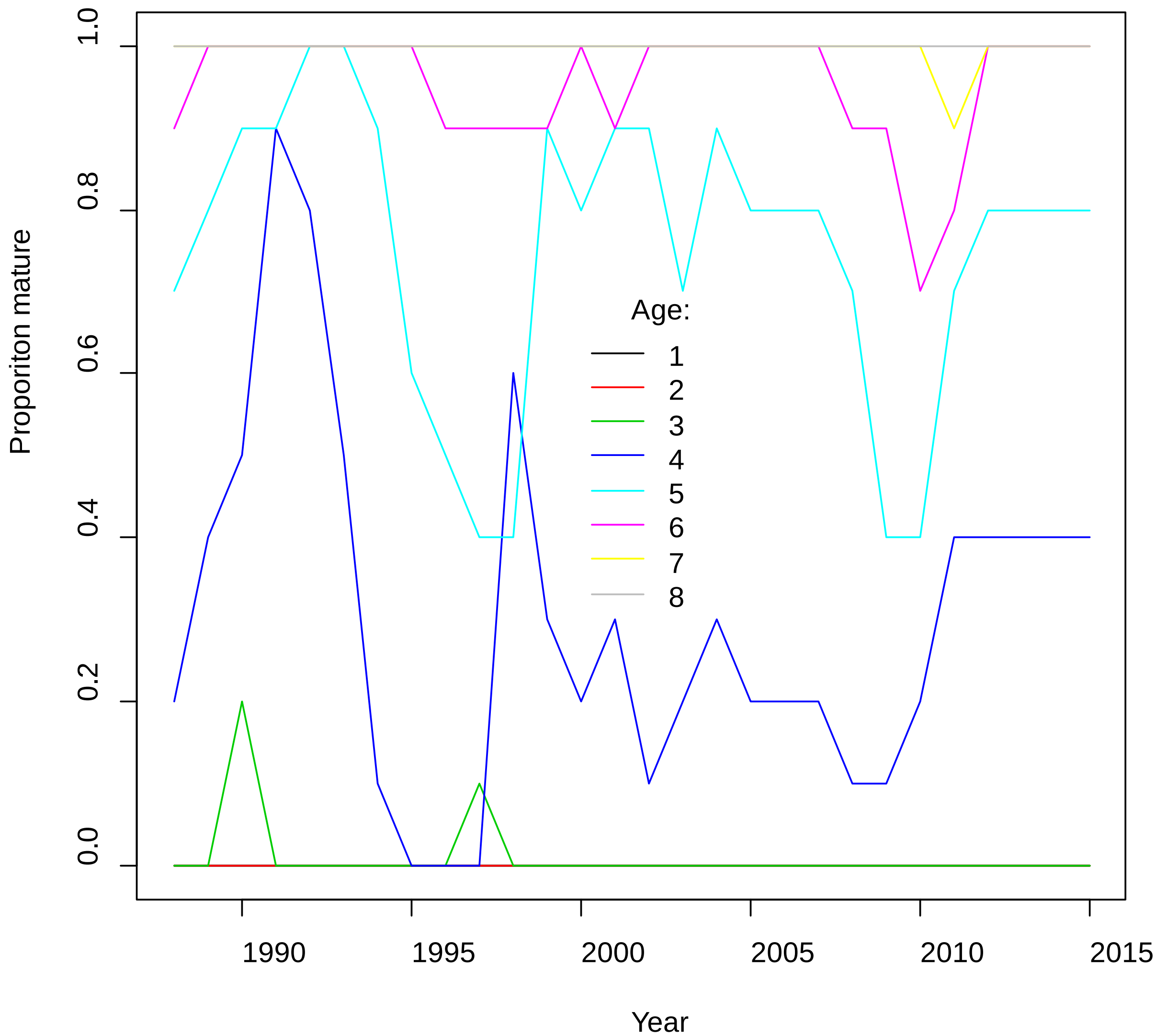

Figure 1. Proportion mature at ages 1-8 for NSS herring for the years 1988-2015. For ages older than 8, all individuals are mature, and thus not shown.

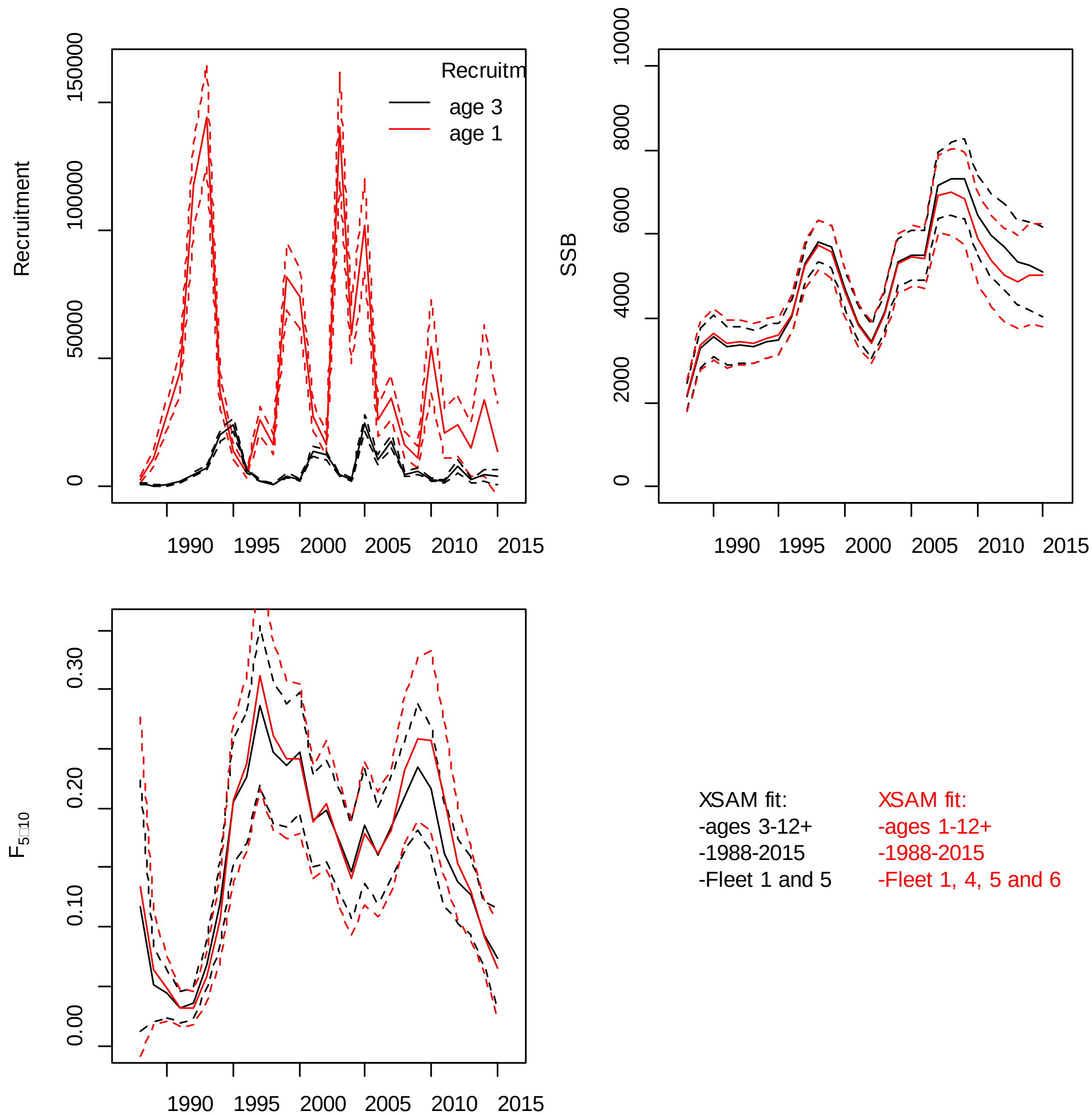

Figure 2. Summary of 2 different XSAM fits for 1988-2015. The black lines show the fit where the model is started at age 3 and includes Fleet 1 and 5. The red lines show the fit where the model is set to start at age 1 and adding data for ages 1 and 2 by Fleet 4 and 5. The broken lines are the respective approximate 95% confidence intervals.

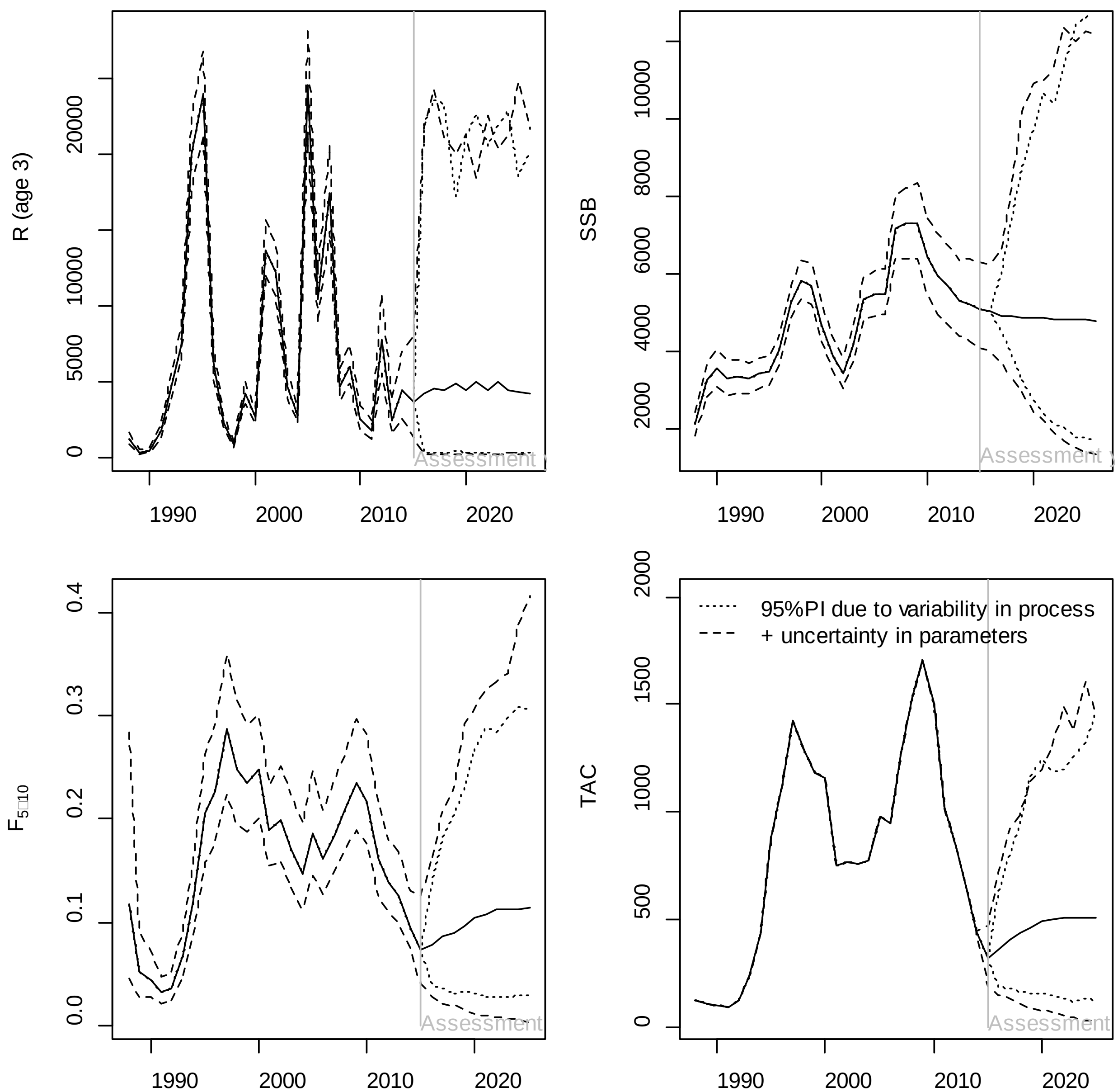

Figure 3. Estimates and prediction of recruitment (top left), SSB (top right), average fishing mortality ages 5-10 (bottom left), and total catches (bottom right), 10 years after assessment year without constraining F using XSAM when the model starts at age 3. The dotted lines shows the 95% prediction intervals accounting only process variability and broken lines the 95% prediction intervals accounting for total uncertainty (uncertainty in parameters in addition to process variability, broken lines). The assessment year is shown by the gray line. The prediction intervals are estimated by percentiles of the distributions obtained by 1000 simulated time series.

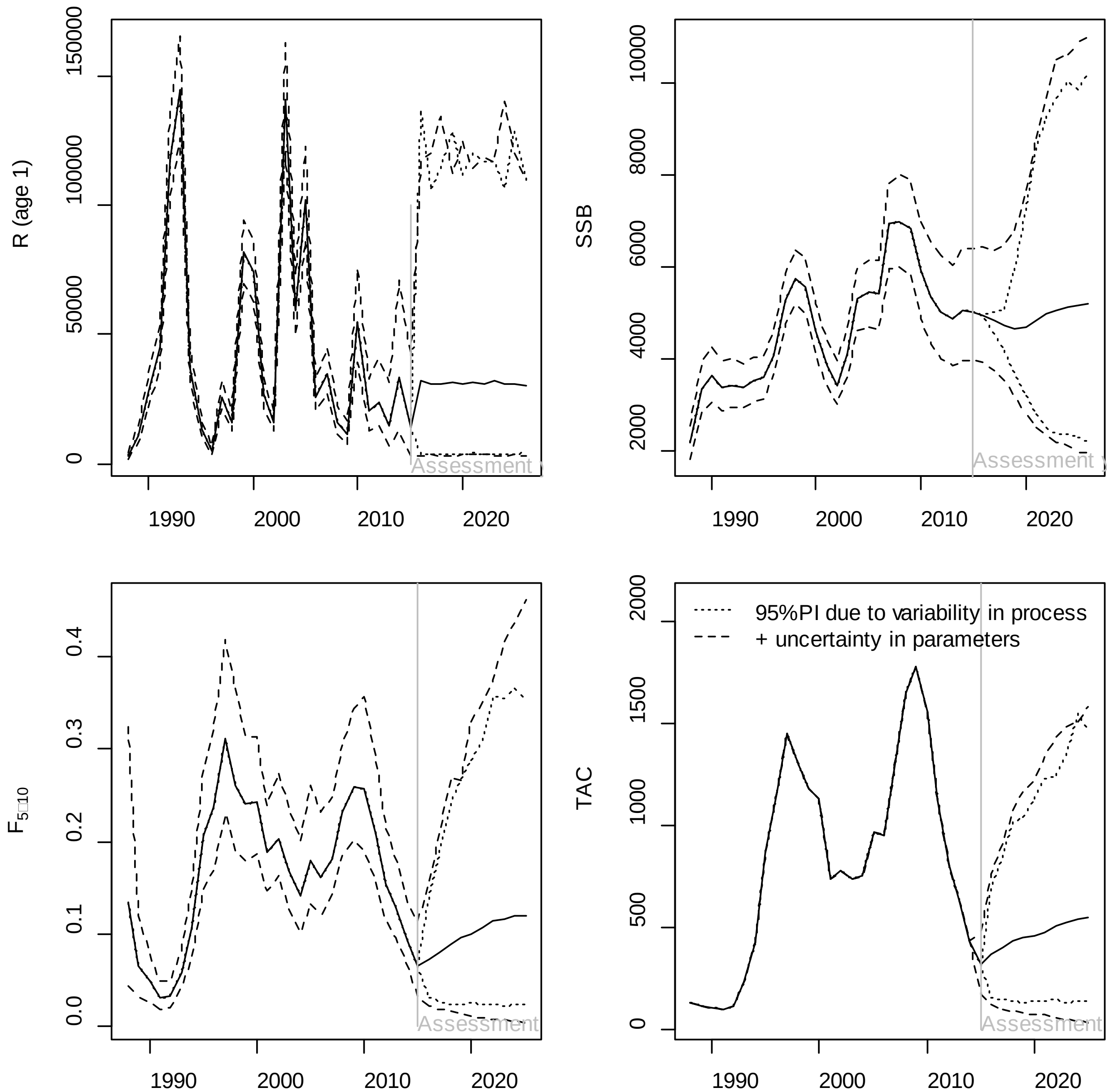

Figure 4. Estimates and prediction of recruitment (top left), SSB (top right), average fishing mortality ages 5-10 (bottom left), and total catches (bottom right), 10 years after assessment year without constraining F using XSAM when the model starts at age 1. The dotted lines shows the 95% prediction intervals accounting only process variability and broken lines the 95% prediction intervals accounting for total uncertainty (uncertainty in parameters in addition to process variability, broken lines). The assessment year is shown by the gray line. The prediction intervals are estimated by percentiles of the distributions obtained by 1000 simulated time series.

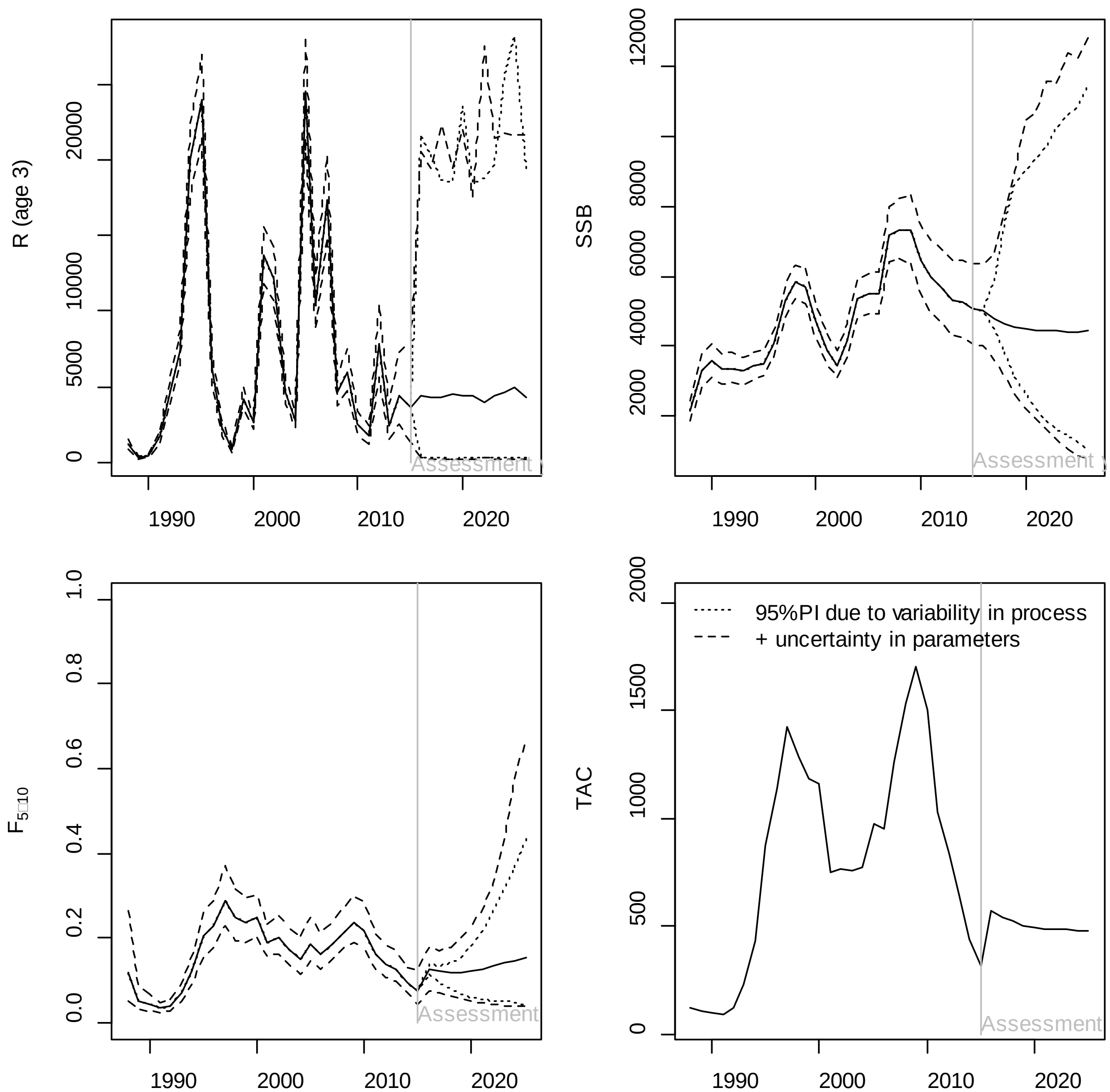

Figure 5. Estimates and prediction of recruitment (top left), SSB (top right), average fishing mortality ages 5-10 (bottom left), and total catches (bottom right), 10 years after assessment year where F is constrained according to TAC applying the management plan using XSAM when the model starts at age 3. The dotted lines shows the 95% prediction intervals accounting only process variability and broken lines the 95% prediction intervals accounting for total uncertainty (uncertainty in parameters in addition to process variability, broken lines). The assessment year is shown by the gray line. The prediction intervals are estimated by percentiles of the distributions obtained by 1000 simulated time series.

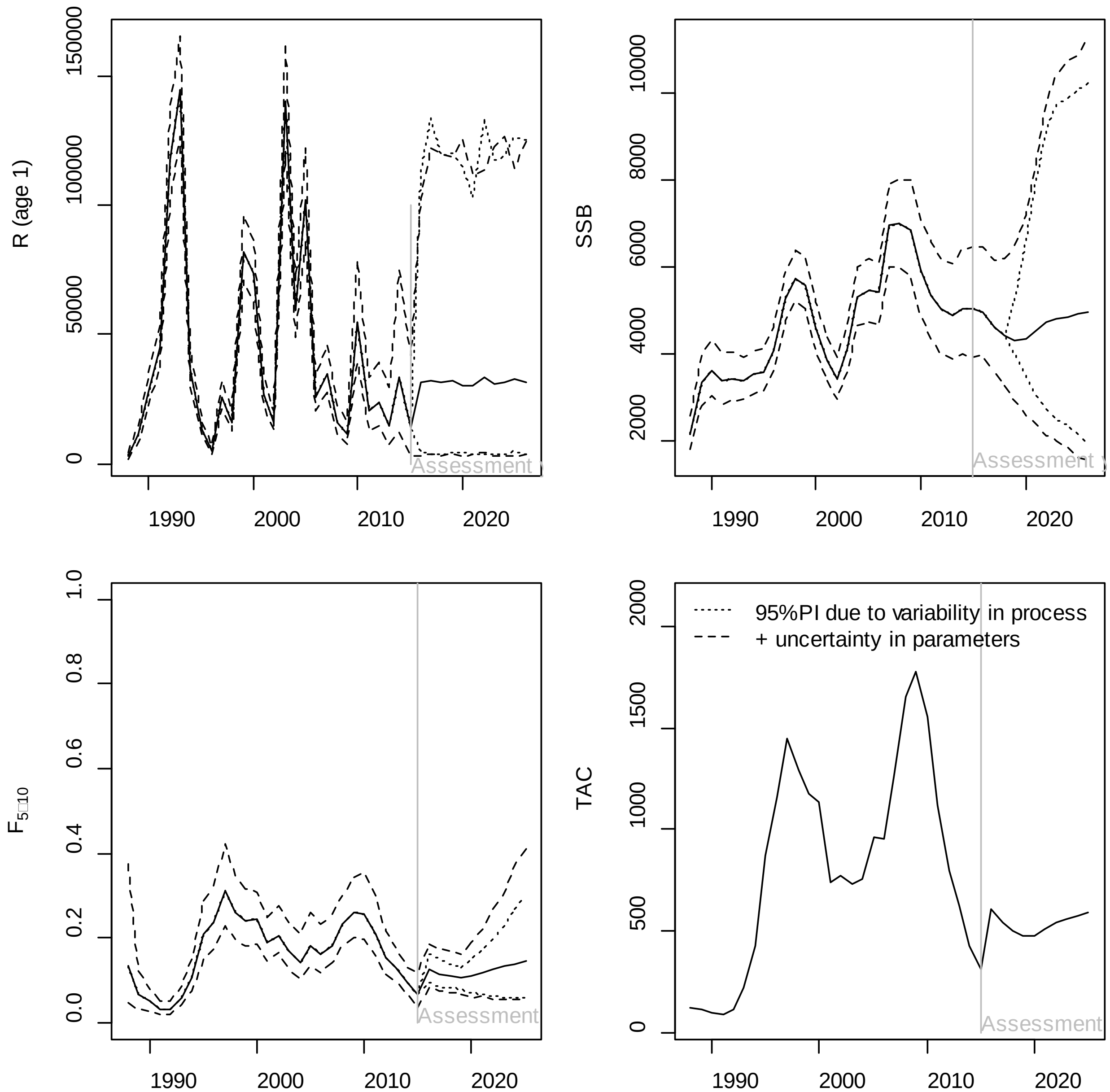

Fig 6. Estimates and prediction of recruitment (top left), SSB (top right), average fishing mortality ages 5-10 (bottom left), and total catches (bottom right), 10 years after assessment year where F is constrained according to TAC applying the management plan using XSAM when the model starts at age 1. The dotted lines shows the 95% prediction intervals accounting only process variability and broken lines the 95% prediction intervals accounting for total uncertainty (uncertainty in parameters in addition to process variability, broken lines). The assessment year is shown by the gray line. The prediction intervals are estimated by percentiles of the distributions obtained by 1000 simulated time series.

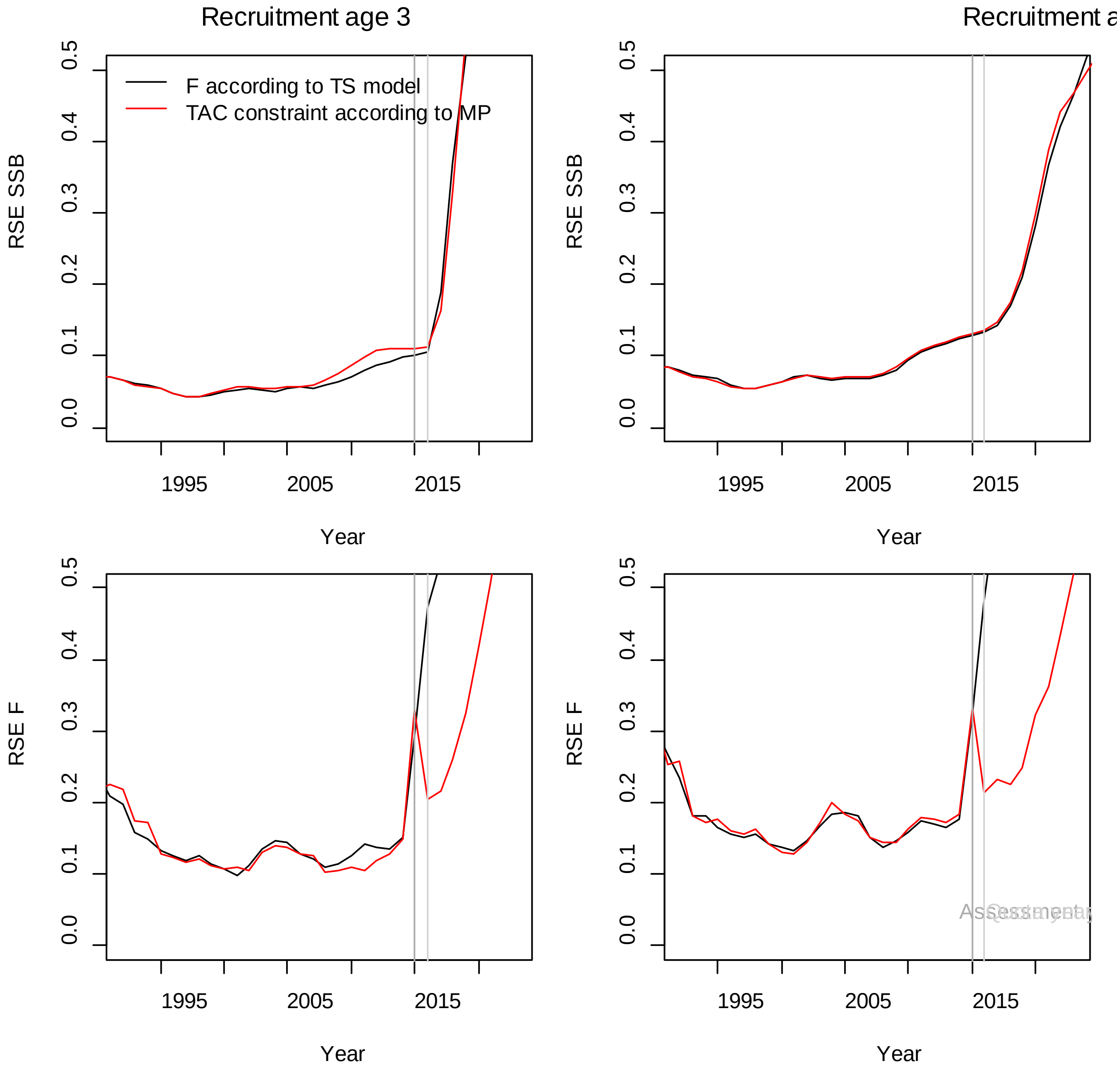

Figure 7. Estimated relative standard error (se/mean) of SSB (top row) and average F ages 5-10 (bottom row) using recruitment age 3 (left column) and age 1 (right column) without any constraint on F (F evolves according to the TS model) (black lines) and applying catch constraint according to management plan (red lines).