Review of literature for state-space assessment project

**2014, Nielsen & Berg, “Estimation of time-varying selectivity in stock assessments using state-space models”, Fisheries Research.**

Explored time-varying selectivity.

Define selectivity at age a in year y as Sa,y = Fa,y / suma(Fa,y)

Explored four different structures on Fa,y:

(A) Equal and constant F’s

(B) Uncorrelated F’s (rho = 0)

(C) A single, identical correlation for all ages (rho = x, termed compound symmetry)

(D) Correlation between ages is an AR(1) function of difference between ages (rho = x|age diff|)

Process variance in F was held constant across ages and time. The correlation between F’s across ages was varied.

Simulation tested using north sea cod case (N = 100). And a north sea cod case study.

Simulation test suggests the model is able to capture the data-generating model (Fig 2).

Model D was best according to AIC (time-varying selectivity that is correlated according to an AR1 process over ages).

Large differences in terminal year SSB and F depending on correlation structure.

**2016, Berg & Nielsen, “Accounting for correlated observations in an age-based state-space stock assessment model”, ICES Journal of Marine Science.**

Explored correlated observations.

The general correlation structure to be considered is Rax,ay = 0.5|dax – day|  which means the correlation between any age-x and age-y is a function of the difference between the two ages. The distances between any two ages can be treated as a vector of parameters which allows for the correlation to vary depending on the age.

(1) Uncorrelated observations

(2) AR(1) correlation between ages

(3) Irregular AR(1) between ages (distance varies with age, termed IRAR(1))

(4) Unconstrained for commercial catches, irregular AR(1) for surveys

(5) Unconstrained for both

They performed a simulation study to verify that the model could recapture the correct parameter values and states (supplement). Their procedure seems to work well at differentiating between true model 1 and model 5.

In the case studies, model 4 always performed best, model 5 was sometimes close. Model 1 (independent observation error) was never close.

Large differences were found in Bmsy and Fmsy when comparing the model with independent error (model 1) to the model with correlated error (model 5).

**2016, Albertsen, Nielsen, Thygesen, “Choosing the observational likelihood in state-space stock assessment models”, CJFAS.**

They explored different observation likelihoods for (i) total & proportion-at-age, and (ii) numbers-at-age.

13 models total applied to four case studies.

In general, models that included correlated observations had better AIC than those with independent observations.

Catch advice varies quite a bit depending on whether the observations are assumed independent or correlated.

**2017, Thygesen et al., “Validation of ecological state space models using the Laplace approximation”, Environ. Eco. Stat.**

Used one-step-ahead residuals as a tool to validate that the correct model structure was chosen. Idea being that one-step-ahead residuals should be IID if the model is correctly specified. If problems are evident one can sometimes use the patterns in the residuals to diagnose the problem and improve the model. Simulations and a case study was presented.

**2018, Aeberhard et al., “Review of State-Space Models for Fisheries Science”, Annual Review of Statistics and Its Application.**

A review of stock assessment, state-space models, and particularly the use of state-space models in stock assessment.

North Sea cod case study of SAM.

**2018, Aldrin et al., “Comments on incongruous formulations in the SAM (state-space assessment model) model and consequences for fish stock assessment”, Fisheries Research.**

They say that the process error can (should?) be interpreted as variation in natural mortality, which means it should be included in the catch equation in addition to the population equation. If you don’t, then the population equation is “incongruous” with the catch equation.

They show that there is some bias when you simulate with process error in mortality and fit with the standard sam model.

They also highlight how the catch observation equation implies that observed catch is a factor of exp(sd/2) higher than the true catch. This implies that the estimated catch will be lower than the observed by this amount on average. They suggest a fix by changing the mean of the error to be a function of the sd.

Similarly, they show that the F equation implies that F will increase by exp(sd\_f/2) each year. Which is a strange model assumption. They suggest the same modification.

I think the same argument could be made for N.

They also list some process error sd’s from other stocks.

**2018, Nielsen & Berg, “Response to: Comments on incongruous formulations in the SAM (state-space assessment model) model and consequences for fish stock assessment,” Fisheries Research.**

Response to Aldrin’s paper.They state that the model is different not wrong. They point out that although the mean F and Catch will increase over time when not conditioned on data, the median is stable. The difference is a modeling choice. Catch projections in SAM are based on the median so the bias is not present. The alternative catch equation is interesting and should be investigated further, although in cursory analyses it had minimal effect.

**2018, Subbey, “Parameter estimation in stock assessment modelling: caveats with gradient-based algorithms,” ICES Journal of Marine Science.**

Subbey points out how it can be difficult for AD algorithms to find optimum parameter values when the model has a complicated likelihood surface.

**2018, Okamura, “Comparison of the performance of age-structured models with few survey indices,” ICES Journal.**

Compared cs-VPA, ridge-VPA and SAM when using only ssb and recruitment indices to fit the models. CS-VPA assumes constant selectivity in the final years, whereas ridge-VPA allows selectivity to vary while applying a penalty for excessive variation.

They also used age-specific indices to fit ridge-VPA and SAM.

**1992, Sullivan, “A Kalman filter approach to catch-at-length analysis,” Biometrics.**