

Progress on length based SAM

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Outline

- Background: SAM and time-varying selectivity
- Challenges in time-varying length based selectivity.
- Template Model Builder
- State-space Length structured ASsessment MOdel (SLASMO)

Focus here on fishing mortality $F_{a,y}$ (and later $F_{l,y}$)

- $F_{a,y}$ is the instantaneous fishing mortality rate for age group a in year y
- Define the selectivity as:

$$S_{a,y} = \frac{F_{a,y}}{\sum_{a} F_{a,y}},$$

Often the selectivity is scaled to have a maximum of one in each year.

- There are many other interesting aspects in stock assessment models.
 - Natural mortality
 - Effort
 - Survey design
 - Stock recruitment model
 - Prediction ability
 - Growth

...

Approaches used to model F



- Deterministic (Catch-at-age assumed known without error)
 - Extremely flexible $F_{a,y}$ model.
 - Ad-hoc smoothing often added
 - No quantification of uncertainties
- Full parametric. E.g:
 - $F_{a,y} = S_a f_y$ (S may be a parametrized function)
 - $-F_{a,y} = S_a f_y$ with separate S_a in time blocks
 - Splines with fixed degree of smoothness
 - Penalized deviances with fixed penalty

These choices are important



- These differences are not small and theoretical
- There are no objective way to choose between these two deterministic approaches
- There should really be an objective criteria. A statistical framework.

Further we need to predict

- Too much smoothing will bias the signal
- Too little smoothing will drown the signal in noise
- Correct amount will help you look ahead

• Correct amount should not be subjective.

State-space assessment models

• Allow us to include things like:

 $F_{3,y}$ is a random walk with step variance σ^2

- Importantly σ^2 is a model parameter estimated in the model.
- This model class^a is used in most other quantitative fields
- It is a very useful extension to full parametric statistical models.
- Introduced for stock assessment by Gudmundsson (1987,1994) and Fryer (2001).
- The reason state-space models have not been more frequently used in stock assessment is that software to easily handle these models has not been available. It is now!
- Has recently received increased attention (e.g. Brinch et al., 2011; Gudmundsson and Gunnlaugsson, 2012; Berg et al., 2013; Nielsen and Berg 2014)
- Can give very flexible models with low number of model parameters

^aa.k.a. random effects models, mixed models, latent variable models, hierarchical models, ...

Avoiding ad-hoc choices — Eastern Baltic Cod



• Using the State-space Assessment Model (SAM) gives us an objective criteria

Evolving selectivity — North Sea Cod



Year



Model selection ex: Correlated Random Walks

• Instead of independent random walks for F at different ages, we can allow those random walks to be correlated. Define $\Delta \log F_y = \log F_y - \log F_{y-1}$, then:

 $\Delta \log F_y \sim \mathcal{N}(0, \Sigma)$

- For all combination of ages $(a \neq \tilde{a})$:
 - **A)** Parallel: $\Sigma_{a,\tilde{a}} = \sqrt{\Sigma_{a,a}\Sigma_{\tilde{a},\tilde{a}}}$
 - **B)** Independent: $\Sigma_{a,\tilde{a}} = 0$
 - **C)** Compound symmetry: $\Sigma_{a,\tilde{a}} = \rho \sqrt{\Sigma_{a,a} \Sigma_{\tilde{a},\tilde{a}}}$
 - **D)** AR(1): $\Sigma_{a,\tilde{a}} = \rho^{|a-\tilde{a}|} \sqrt{\Sigma_{a,a} \Sigma_{\tilde{a},\tilde{a}}}$

Selectivities: North Sea cod





North Sea cod: Profile likelihood for the ρ -parameter for models C and D, $\rho = 1$ corresponds to model A, and $\rho = 0$ corresponds to model B.

Preliminary run: Namibian hake



Namibian Hake

North Sea Cod





Model					Model				
Name	А	В	\mathbf{C}	D	Name	А	В	\mathbf{C}	D
σ_F	0.30	0.41	0.38	0.50	σ_F	0.11	0.10	0.11	0.11
σ_R	1.16	0.69	0.81	0.77	σ_R	0.51	0.52	0.50	0.51
σ_S	0.67	0.44	0.53	0.53	σ_S	0.14	0.09	0.10	0.10
σ_C	0.40	0.33	0.32	0.15	$\sigma_{C_{a=1}}$	0.80	0.69	0.76	0.71
$\sigma_{I,1}$	0.95	0.99	0.98	0.98	$\sigma_{C_{a=2}}$	0.28	0.16	0.21	0.20
$\sigma_{I,2}$	0.51	0.62	0.56	0.54	$\sigma_{C_a>3}$	0.08	0.11	0.09	0.09
$\sigma_{I,3}$	0.27	0.38	0.32	0.31	$\sigma_{I_{a-1}}$	0.61	0.64	0.63	0.64
$\sigma_{I,4}$	0.55	0.61	0.56	0.59	$\sigma_{I_a > 2}$	0.27	0.28	0.28	0.28
ho			0.62	0.83	$\rho^{u \ge 2}$			0.91	0.95
AIC	1898.23	1901.69	1866.18	1816.04	AIC	333.44	372.04	309.40	293.63

Challenges in time-varying length based selectivity.

- The dimension is typically one order of magnitude higher
- More time steps are often needed
- Even more important to get correlation structure right





All of the above means longer run times — what can be done about that?

Template Model Builder (TMB):

- Developed by Kasper Kristensen, DTU
- ADMB inspired R-package
- Combines external libraries: CppAD, Eigen, CHOLMOD
- Continuously developed since 2009, < 10000 lines of code
- Implements Laplace approximation for random effects
- C++ Template based
- Automatic sparseness detection
- Parallel computing supported on three levels: BLAS, parallel templates, and R.



Timings!

Example	Time (TMB)	Speedup (TMB vs ADMB)			
longlinreg	11.3	0.9			
mvrw	0.3	97.9			
nmix	1.2	26.2			
$orange_big$	5.3	51.3			
sam	3.1	60.8			
sdv_multi	11.8	37.8			
socatt	1.6	6.9			
spatial	8.3	1.5			
thetalog	0.3	22.8			



TMB: summary

- TMB combines automatic differentiation and the Laplace approximation for estimation in complex non-linear latent variable models (state-space, hierarchical models, Gaussian Markov random fields)
- Can handle very high dimensional problems ($\sim 10^6$ random effects) through automatic detection and exploitation of sparseness structure wrt. random effects
- Orders of magnitude faster than other well-known methods (ADMB, BUGS)
- Good support for parallel computations
- R package and examples available at http://tmb-project.org

Reduce number of processes

- Too slow to have a process for each length class
- Proposed solution:
 - Select a number of lengths \tilde{l}_i (e.g. $\tilde{l}_1, \ldots, \tilde{l}_8$ equidistant)
 - Define a multivariate β_t process as:

$$\beta_{t+1} = \beta_t + \eta_t$$
, with $\eta_t \sim \mathcal{N}(0, \Sigma)$

- F at other lengths are calculated from a spline interpolation in the length direction



$$F_{l,t} = \psi \text{logit}^{-1}(\mathcal{S}_{(\tilde{l}_1,\beta_{1,t}),\dots}(l))$$

Time

Simulation study: Purely length-based approach

- Lengths in the dynamics
 - Follow the population length distribution directly
 - The dynamics is using Von Bertalanffy growth $dl_t = k(L_{\infty} l_t)dt$
 - Separate process for recruitment (four steps per year)
- Lengths in the observations
 - F_{lt} is simulated as $f_t S_l$ where S_l is a time-varying double normal selectivity
 - $-F_{lt}$ is estimated via the non-parametric F-at-length field (prev. slide)
 - Catch-at-length are predicted as:

$$C_{lt} = \frac{F_{lt}}{F_{lt} + M_l} (1 - e^{-(F_{lt} + M_l)}) N_{lt}$$

- Data range
 - 50 years of data simulated
 - total catch-at-length quarterly
 - three length-based surveys

Simulated vs. estimated F



Summary

- State-space formulation is a natural representation of fish stock assessment models
- Makes it possible to avoid many ad-hoc tweaks
- Allows both process and measurement noise
- Selectivity (and other parameters) can be time-varying
- The number of model parameters can be kept reasonable low
- Prediction is straight-forward
- We now have the tool to handle these models (TMB)
- High dimension of length based selectivity is a numerical challenge
- Non-parametric F-field (random effects interpolated) is a promising approach
- Simulation study demonstrated that approach is identifiable and fast.
- More info at: http://stockassessment.org and http://tmb-project.org