The Woods Hole Assessment Model and summary of the Research Track on Applying State-space Models

MAFMC SSC Meeting
14 May 2024

Tim Miller
Northeast Fisheries Science Center

NOAA FISHERIES

Outline

- WHAM model features
  - Random effects options
  - Environmental covariate effect options
  - Observation likelihood options
  - Biological Reference Point options
  - Projection options
  - Useful features: OSA residuals, auto-generated output, Simulations
- Peer-reviewed applications in NEUS to date
- Summary of peer-review of research track on applying state-space models
- Details of multi-stock WHAM and configuration for black sea bass research track peer-review model

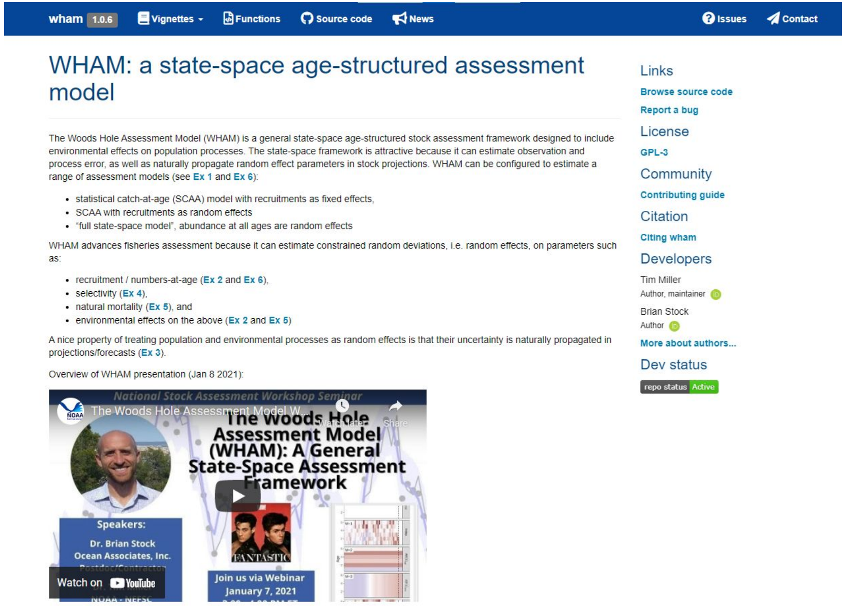
An open-source state-space assessment framework

- An R package available from Github
- Models can be completely configured using R package functionality
- Several tutorial vignettes
- Automatically produce a variety of output useful for both evaluating models and providing management advice.
- Tests to check package development.
- Several collaborators: **Brian Stock** (IMR) and others

R + TMB

The oods ole ssessment odel

WHAM:


wham 1.0.6 Vignettes Functions Source code News Issues Contact

WHAM: a state-space age-structured assessment model

The Woods Hole Assessment Model (WHAM) is a general state-space age-structured stock assessment framework designed to include environmental effects on population processes. The state-space framework is attractive because it can estimate observation and process error, as well as naturally propagate random effect parameters in stock projections. WHAM can be configured to estimate a range of assessment models (see Ex 1 and Ex 6):

- statistical catch-at-age (SCAA) model with recruitments as fixed effects,
- SCAA with recruitments as random effects
- "full state-space model", abundance at all ages are random effects

WHAM advances fisheries assessment because it can estimate constrained random deviations, i.e. random effects, on parameters such as:

- recruitment / numbers-at-age (Ex 2 and Ex 6),
- selectivity (Ex 4),
- natural mortality (Ex 5), and
- environmental effects on the above (Ex 2 and Ex 5)

A nice property of treating population and environmental processes as random effects is that their uncertainty is naturally propagated in projections/forecasts (Ex 3).

Overview of WHAM presentation (Jan 8 2021):

Links
Browse source code
Report a bug

License
GPL-3

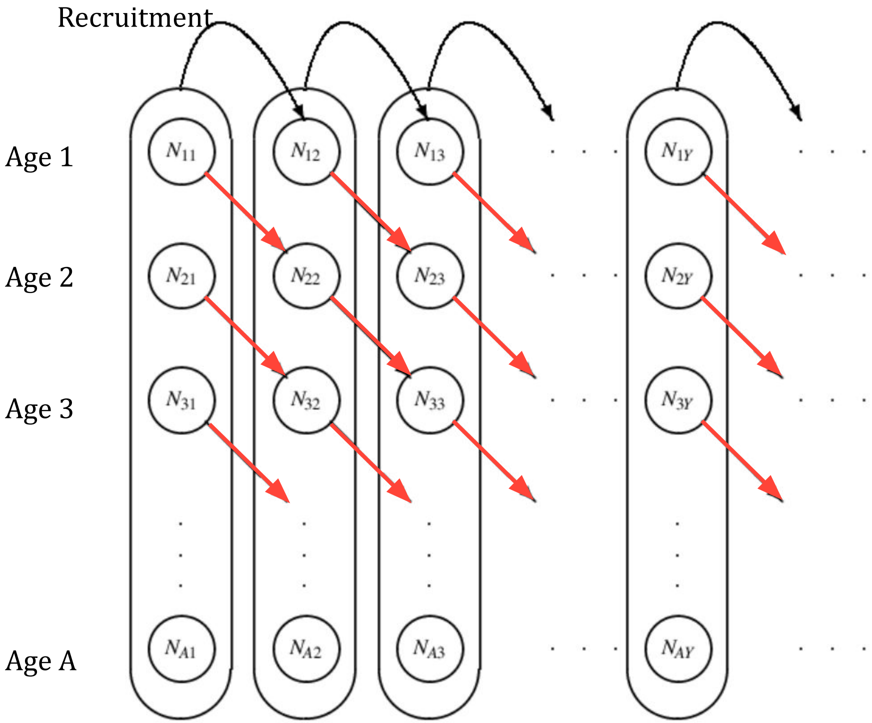
Community
Contributing guide

Citation
Citing wham

Developers
Tim Miller
Author, maintainer
Brian Stock
Author
More about authors...

Dev status
repo status Active

WHAM is an age-structured model



Configuration options for abundance at age:

1) Statistical catch-at-age (no random effects)

$$\log N_{a,y} = f(\log N_{a-1,y-1})$$

2) Statistical catch-at-age, random recruitment

$$\log N_{1,y} = \log\left(f\left(\mathrm{SSB}_{y-1}\right)\right) + \varepsilon_{1,y}$$

3) “Full state-space” (survival random effects)

$$\log N_{a,y} = \log\left(N_{a-1,y-1}\right) - Z_{a-1,y-1} + \varepsilon_{a,y}$$

Random effects

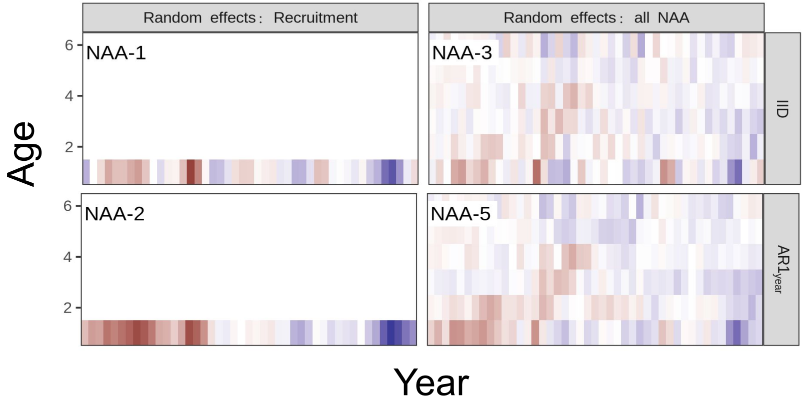
Options for alternative covariance structures (AR1, iid, etc)

- Recruitment (year)
- Interannual transitions in abundance at age (“survival”) (year, age)
- Natural mortality (year, age)
- Selectivity (fishery or index) (year, age)
- Catchability (year)
- Hidden (imperfectly observed) environmental/climate variables (year)
- Movement (year,age)(development branch)
- *Growth (development branch)*

Time- and age-varying processes

Biological processes are often **correlated by year and age**

- Recruitment
- Inter-annual transitions ("Survival")
- Natural mortality
- Selectivity
- Catchability
- Movement (development branch)




```
NAA_re = list(sigma="rec+1", cor="iid"))
```

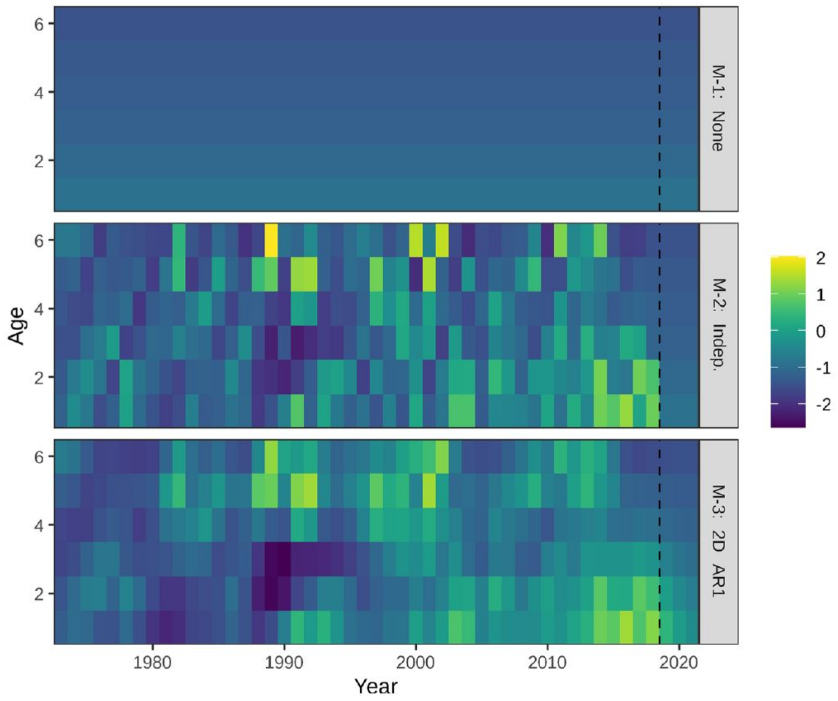
Code	Description	Parameters
"none"	time-constant (no deviation)	
"iid"	independent, identically-distributed	σ^2
"ar1"	autoregressive-1 (correlated across ages/parameters)	σ^2, ρ_a
"ar1_y"	autoregressive-1 (correlated across years)	σ^2, ρ_y
"2dar1"	2D AR1 (correlated across both years and ages/parameters)	σ^2, ρ_a, ρ_y

$$\mathrm{Cov}\left(\varepsilon_{a,y}, \varepsilon_{\tilde{a},\tilde{y}}\right) = \frac{\sigma_a \sigma_{\tilde{a}} \rho_a^{|a-\tilde{a}|} \rho_y^{|y-\tilde{y}|}}{\left(1-\rho_a^2\right)\left(1-\rho_y^2\right)}$$

Time- and age-varying processes

Biological processes are often **correlated by year and age**

- Recruitment
- Inter-annual transitions ("Survival")
- Natural mortality
- Selectivity
- Catchability
- Movement (development branch)



log(M) Gaussian random effects (iid, 2DAR1)

Estimate or fix mean M parameters:

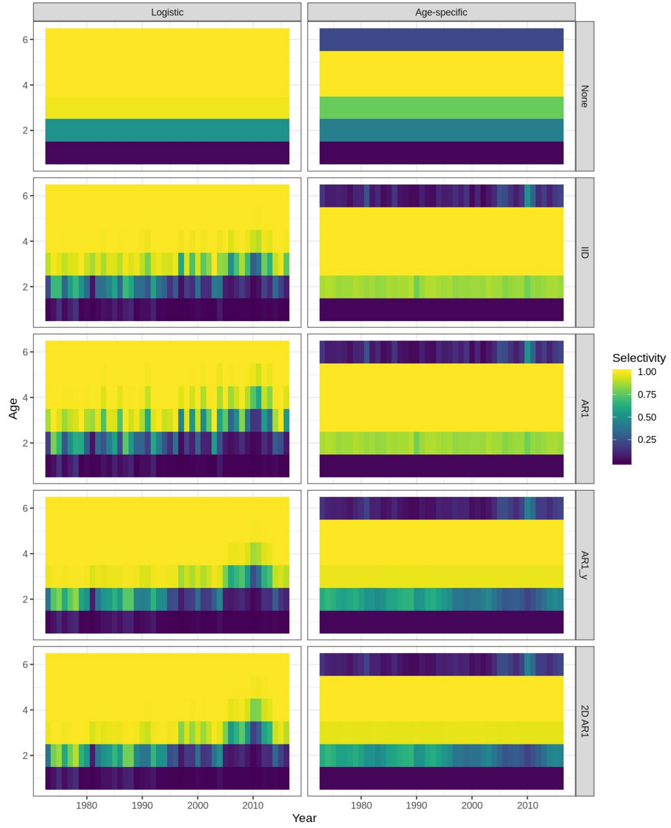
- constant across ages
- age-specific
- function of weight-at-age

Time- and age-varying processes

- Recruitment
- Inter-annual transitions (“Survival”)
- Natural mortality
- Selectivity
- Catchability
- Movement (development branch)

“blocks” indexed to particular years of indices and fleets

- logistic (increasing or decreasing), double logistic, or age-specific
- constant, iid, or 1D or 2D AR1 processes for annual parameter values
- Gaussian on logit scale

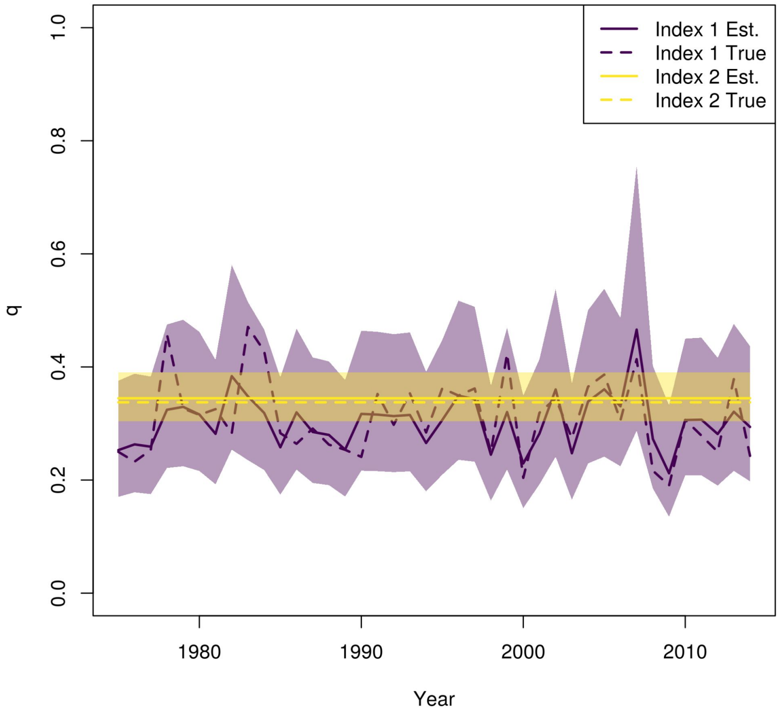


Time- and age-varying processes

- Recruitment
- Inter-annual transitions (“Survival”)
- Natural mortality
- Selectivity
- Catchability
- Movement (development branch)

Gaussian iid, or AR1 processes on logit scale

$$\log\left(\frac{q_y - b_l}{b_u - q_y}\right) = \mu_q + \epsilon_{q,y}$$



Time- and age-varying processes

- Recruitment
- Inter-annual transitions ("Survival")
- Natural mortality
- Selectivity
- Catchability
- Movement (development branch)
  - Fixed effects (mean, variance, correlation parameters) are stock, region->region, season specific
  - random effects by year and/or age
  - movement can be modeled as
    - probabilities sequential to mortality
    - instantaneous rate simultaneous to mortality rates

$$f(\mu_{s,r,r',t,y,a}) = \theta_{s,r,r',t} + \epsilon_{s,r,r',t,y,a} \quad r \neq r'$$

$$Cov\left(\epsilon_{s,r,r',t,y,a}, \epsilon_{s,r,r',t,y',a'}\right) = \frac{\rho_{s,r,r',t,A}^{|a-a'|}\rho_{s,r,r',t,Y}^{|y-y'|}\sigma_{s,r,r',t}^2}{\left(1-\rho_{s,r,r',t,A}^2\right)\left(1-\rho_{s,r,r',t,Y}^2\right)}$$

additive logit transformation for probabilities sequential to survival:

$$f(\mu_{s,r,r',t,y,a}) = \log\left(\frac{\mu_{s,r,r',t,y,a}}{1-\sum_{r'}\mu_{s,r,r',t,y,a}}\right)$$

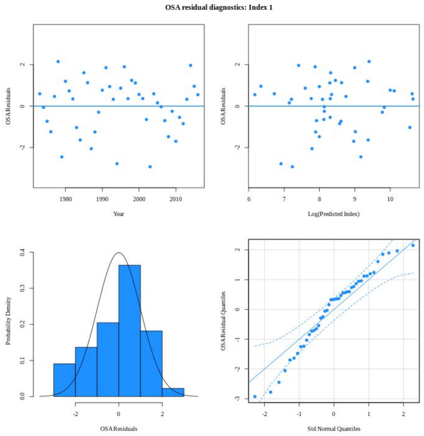
log transformation for instantaneous rates:

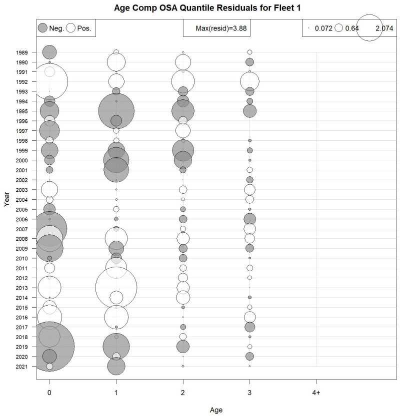
$$f(\mu_{s,r,r',t,y,a}) = \log(\mu_{s,r,r',t,y,a})$$

Data components

All observations have error

- Aggregate catch (fleet-specific)
  - log-normal
- Catch age composition (fleet-specific)
  - Several likelihood options
- Aggregate indices (biomass or numbers)
  - log-normal
- Index age composition (biomass or numbers)
  - Several likelihood options
- **Optional**: Environmental/Climate observations
  - normal
- *Tagging data not yet included*





State-space models for the covariate

- Imperfectly observed environmental variables can affect
  - Recruitment
  - Natural mortality (by age)
  - Index catchability
  - Movement (development)
- User-defined lag between covariate and population effect
- Effects options are “linear” or orthogonal polynomial
- Each covariate can have multiple effects
- Multiple covariates can be included

Covariate state-space models:

1. Random walk

$$\boldsymbol{\theta} = (x_1, \sigma_x^2, \sigma_y^2)$$
$$x_t = x_{t-1} + \mathcal{N}(0, \sigma_x^2)$$
$$y_t = x_t + \mathcal{N}(0, \sigma_y^2)$$

2. AR1

$-1 < \phi < 1$

$$\boldsymbol{\theta} = (\mu, \sigma_x^2, \sigma_y^2, \phi)$$
$$x_t = \mu + \phi x_{t-1} + \mathcal{N}(0, \sigma_x^2)$$
$$y_t = x_t + \mathcal{N}(0, \sigma_y^2)$$

Environmental effects on...

Recruitment models:

$$\hat{R}_t =$$

1. Random walk (No effects) $e^{\log R_{y-1}+\epsilon_y}$
2. Mean (no SRR) $e^{\mu_R+\boxed{\beta E_y}+\epsilon_y}$
3. Beverton-Holt

Controlling $\dfrac{aS_{y-1}e^{\boxed{\beta E_y}+\epsilon_y}}{1+bS_{y-1}}$ / Limiting $\dfrac{aS_{y-1}e^{\epsilon_y}}{1+bS_{y-1}e^{\boxed{\beta E_y}}}$ / Masking $\dfrac{aS_{y-1}e^{\epsilon_y}}{e^{\boxed{\beta E_y}}+bS_{y-1}}$

4. Ricker

$aS_{y-1}e^{-bS_{y-1}+\boxed{\beta E_y}+\epsilon_y}$ / $aS_{y-1}e^{-bS_{y-1}(1+\boxed{\beta E_y})+\epsilon_y}$

Controlling / Masking

Iles & Beverton (1998)

Catchability models:

linear in logit space

$$\log\left(\frac{q_y-b_l}{b_u-q_y}\right)=\mu_q+\boxed{\beta E_y}+\epsilon_{q,y}$$

M models:

1. log-linear $\log M_{y,a}=\mu_{M,a}+\boxed{\beta_a E_y}+\epsilon_{y,a}$
2. allometric $\log M_{y,a}=\log(a)+b\log(W_{y,a})+\boxed{\beta_a E_y}+\epsilon_{y,a}$

Movement models:

linear in (additive) logit space or log-space

$$f(\mu_{s,r,r',t,y,a})=\theta_{s,r,r',t}+\boxed{\beta E_y}+\epsilon_{s,r,r',t,y,a}$$

Environmental and random effects on…

Recruitment models:

$$\hat{R}_t =$$

1. Random walk (No effects) $e^{\log R_{y-1} + \boxed{\epsilon_y}}$
2. Mean (no SRR) $e^{\mu_R + \beta E_y + \boxed{\epsilon_y}}$
3. Beverton-Holt

   Controlling $\dfrac{aS_{y-1}e^{\beta E_y + \boxed{\epsilon_y}}}{1 + bS_{y-1}}$ / Limiting $\dfrac{aS_{y-1}e^{\boxed{\epsilon_y}}}{1 + bS_{y-1}e^{\beta E_y}}$ / Masking $\dfrac{aS_{y-1}e^{\boxed{\epsilon_y}}}{e^{\beta E_y + bS_{y-1}}}$
4. Ricker

   $aS_{y-1}e^{-bS_{y-1} + \beta E_y + \boxed{\epsilon_y}}$ / $aS_{y-1}e^{-bS_{y-1}(1+\beta E_y) + \boxed{\epsilon_y}}$

   Controlling / Masking

Iles & Beverton (1998)

Catchability models:

linear in logit space

$$\log\left(\frac{q_y - b_l}{b_u - q_y}\right) = \mu_q + \beta E_y + \boxed{\epsilon_{q,y}}$$

M models:

1. log-linear $\log M_{y,a} = \mu_{M,a} + \beta_a E_y + \boxed{\epsilon_{y,a}}$
2. allometric $\log M_{y,a} = \log(a) + b\log(W_{y,a}) + \beta_a E_y + \boxed{\epsilon_{y,a}}$

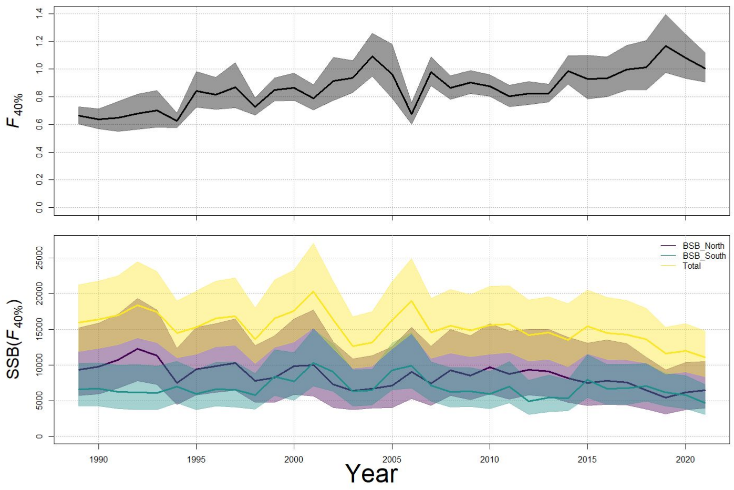
Movement models:

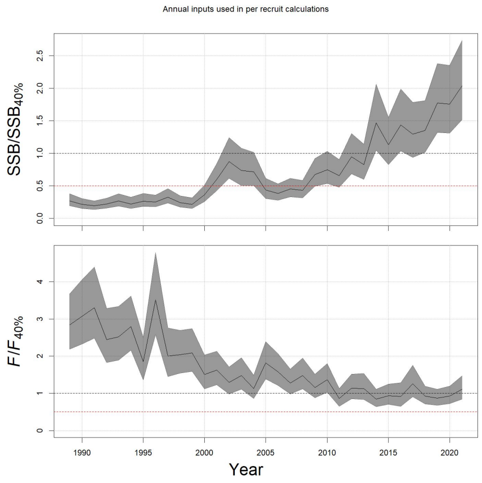
linear in (additive) logit space or log-space

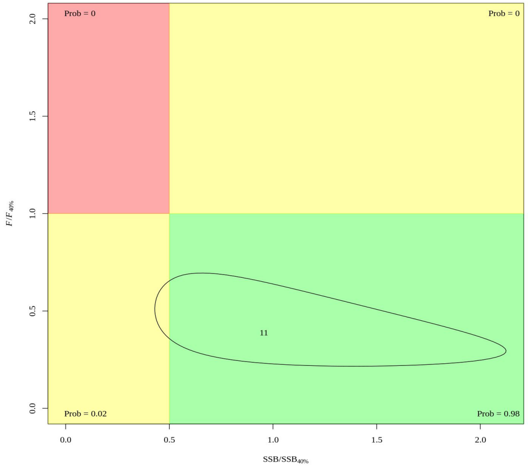
$$f(\mu_{s,r,r',t,y,a}) = \theta_{s,r,r',t} + \beta E_y + \boxed{\epsilon_{s,r,r',t,y,a}}$$

Annual and prevailing BRPs and status

- Internally calculated reference points and status
- Allows uncertainty in parameters to be propagated



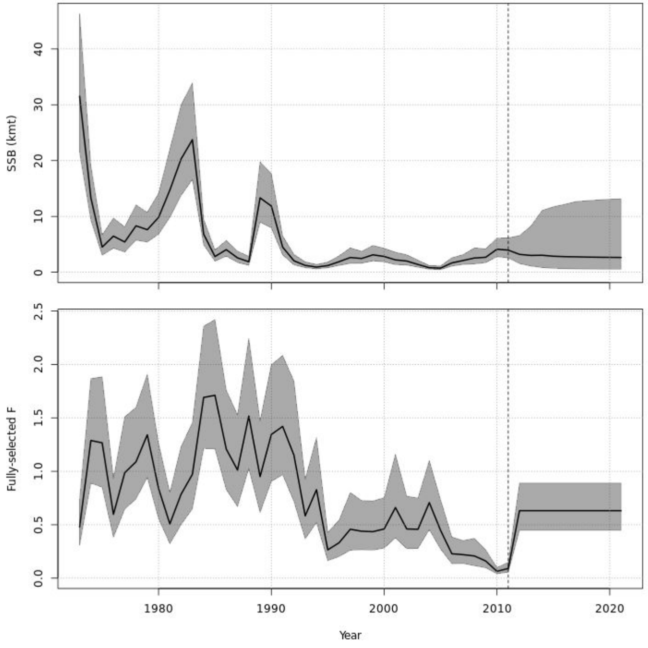


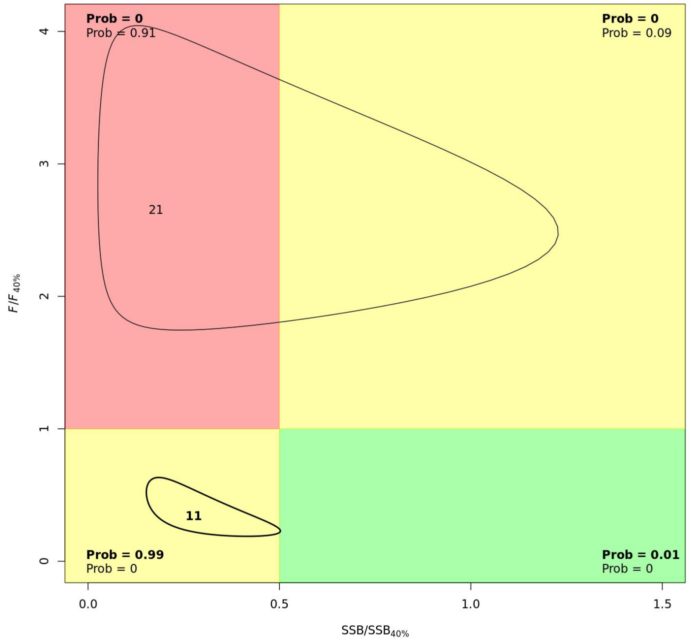


Projections

Random effects (and uncertainty) can be projected

Can specify catch, status quo F, average F, F(X%SPR), FMSY

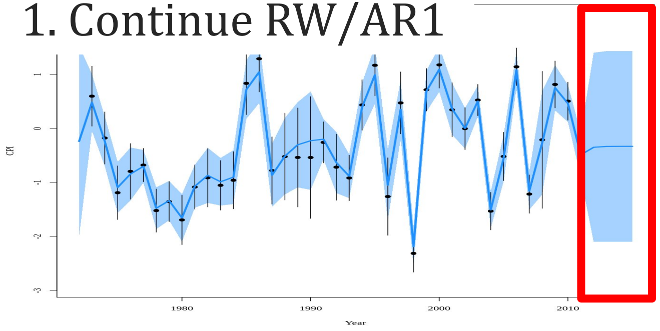




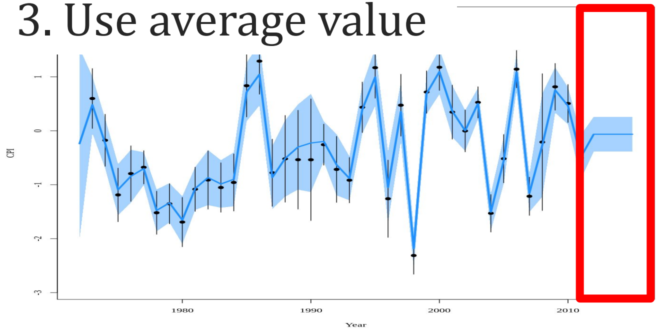
Projections

Several options for treating environmental covariates

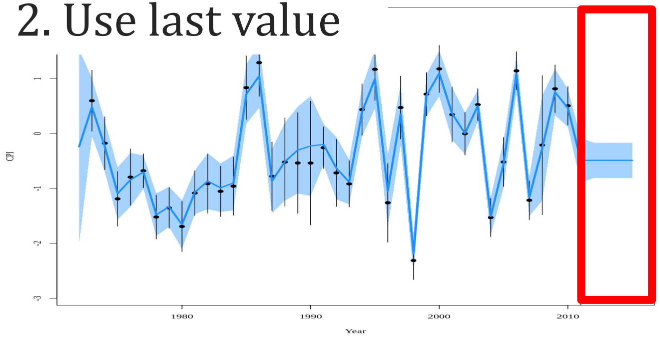
1. Continue RW/AR1



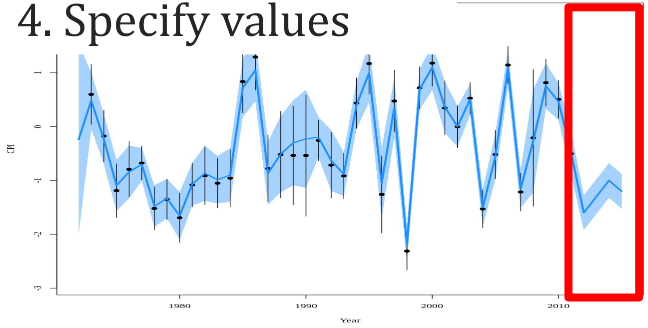
3. Use average value



2. Use last value



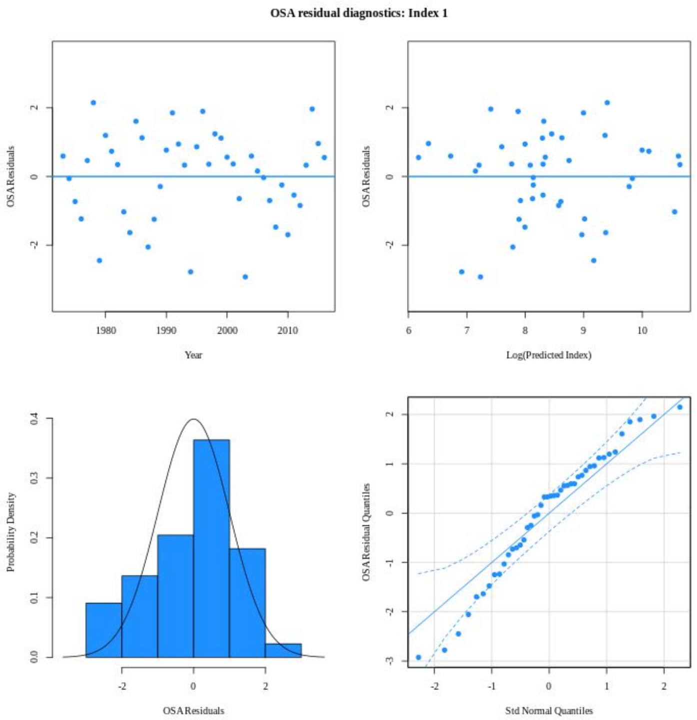
4. Specify values



OSA residual diagnostics

One step ahead (OSA) residuals

- provides independent residuals for correlated observations
- available for all observation types: aggregate catch and indices, age composition, environmental covariates



Environ Ecol Stat (2017) 24:317–339
DOI 10.1007/s10651-017-0372-4

Validation of ecological state space models using the Laplace approximation

Uffe Høgsbro Thygesen[1] · Christoffer Moesgaard Albertsen[1] · Casper Willestofte Berg[1] · Kasper Kristensen[1] · Anders Nielsen[1]

Fisheries Research 257 (2023) 106487

Contents lists available at ScienceDirect

Fisheries Research

urnal homepage: www.elsevier.com/locate/fishres

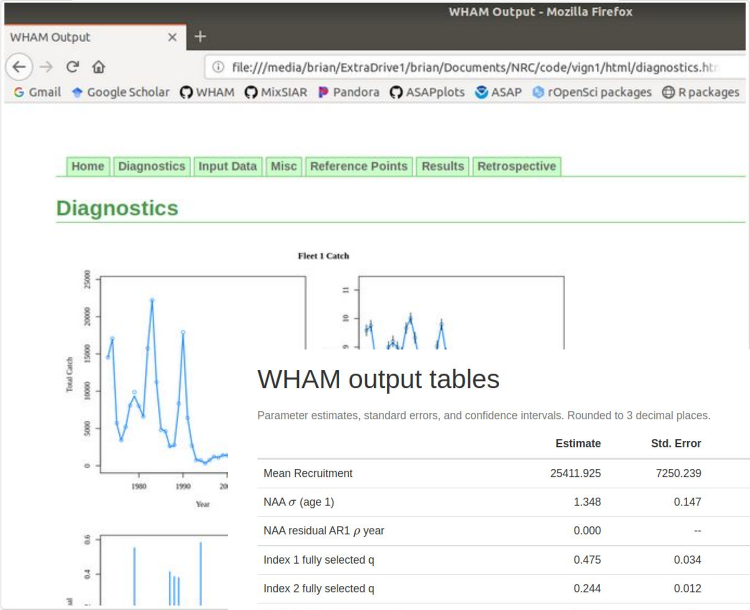
Model validation for compositional data in stock assessment models: Calculating residuals with correct properties

Vanessa Trijoulet[a,*], Christoffer Moesgaard Albertsen[a], Kasper Kristensen[a], Christopher M. Legault[b], Timothy J. Miller[b], Anders Nielsen[a]

[a] *National Institute of Aquatic Resources, Technical University of Denmark, Kemitorvet 201, DK-2800 Kgs. Lyngby, Denmark*
[b] *Northeast Fisheries Science Center, National Marine Fisheries Service, National Oceanic and Atmospheric Administration, 166 Water Street, Woods Hole, MA 02543, USA*

Automatically generated outputs

```r
plot_wham_output(mod=m4, out.type='html')
```



WHAM output tables

Parameter estimates, standard errors, and confidence intervals. Rounded to 3 decimal places.

	Estimate	Std. Error	95% CI lower	95% CI upper
Mean Recruitment	25411.925	7250.239	14527.220	44452.134
NAA σ (age 1)	1.348	0.147	1.088	1.669
NAA residual AR1 ρ year	0.000	--	--	--
Index 1 fully selected q	0.475	0.034	0.412	0.548
Index 2 fully selected q	0.244	0.012	0.222	0.268
Block 1: Selectivity for age 1	0.036	0.003	0.031	0.042
Block 1: Selectivity for age 2	0.352	0.018	0.317	0.387
Block 1: Selectivity for age 3	0.821	0.038	0.734	0.884
Block 1: Selectivity for age 4	1.000	--	--	--
Block 1: Selectivity for age 5	1.000	--	--	--
Block 1: Selectivity for age 6+	0.154	0.019	0.119	0.196
Block 2: Selectivity for age 1	0.027	0.003	0.022	0.035

```r
check_convergence(m1)
```

```
#> stats:nlminb thinks the model has converged: mod$opt$conve
#> Maximum gradient component: 1.01e-07
#> Max gradient parameter: log_F1
#> TMB:sdreport() was performed successfully for this model
```

```r
res <- compare_wham_models(mods, fname=
```

```
#>          AIC   rho_R rho_SSB rho_Fbar
#> m4 -1466.9 0.3610  0.0091  -0.0106
#> m2 -1172.7 3.1589 -0.0735  -0.0167
#> m3  4107.1 0.1287  0.0304  -0.0162
#> m1  4846.5 0.8207  0.1905  -0.2322
```

Thanks
to r4ss and
ASAPplots!

Online Tutorials

wham 1.0.6 | Vignettes | Functions | Source code | News | Contact

- Overview
- Ex 1: The basics
- Ex 2: Recruitment linked to an environmental covariate (Cold Pool Index)
- Ex 3: Projecting / forecasting random effects
- Ex 4: Selectivity with time- and age-varying random effects
- Ex 5: Time-varying natural mortality linked to the Gulf Stream Index
- Ex 6: Numbers-at-age / survival deviations as random effects
- Ex 7: Debugging WHAM models
- Ex 8: Compare ASAP and WHAM model results
- Ex 9: Retrospective predictions
- Ex 10: Operating models and MSE
- Ex 11: Catchability configurations

WHAM: ... assess...

The Woods Hole A... sment framework designed to include ... attractive because it can esti... ct parameters in stock projections. W... and Ex 6):

- statistical cat...
- SCAA with r...
- "full state-space model", abundance at all ages are random effects

WHAM advances fisheries assessment because it can estimate constrained random deviations, i.e. random effects, on parameters such as:

- recruitment / numbers-at-age (Ex 2 and Ex 6),
- selectivity (Ex 4),
- natural mortality (Ex 5), and
- environmental effects on the above (Ex 2 and Ex 5)

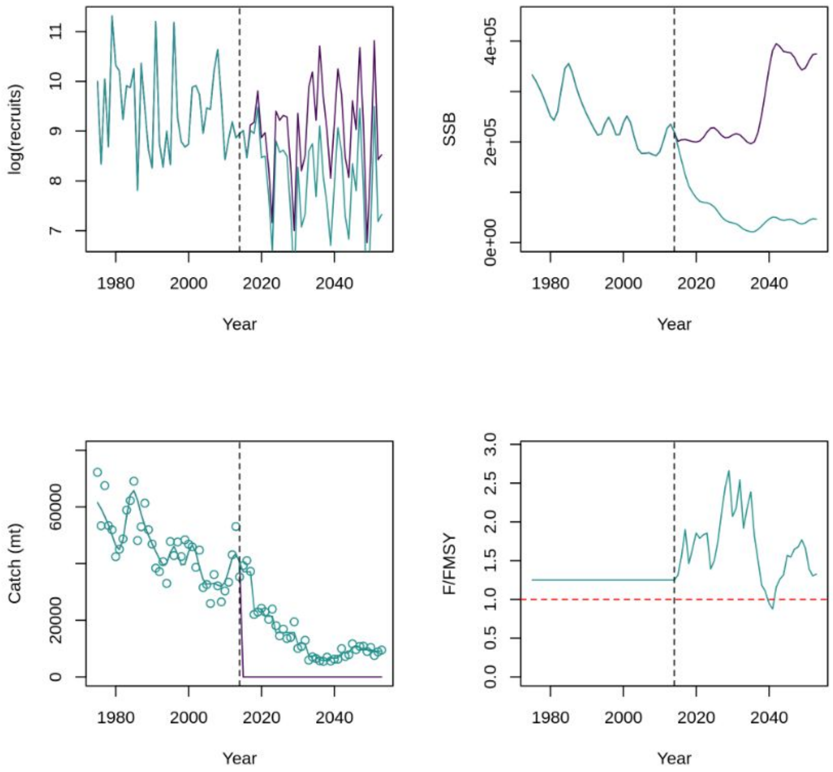
A nice property of treating population and environmental processes as random effects is that their uncertainty is naturally propagated in projections/forecasts (Ex 3).

https://timjmiller.github.io/wham/articles/index.html

Simulations, including MSE

Operating model/MSE usage

- can be used for simulating populations and data as well as estimation
- Used this way in Index-based Methods Research Track and state-space Research Track
- Used for testing reliability of models in stock-specific research tracks.



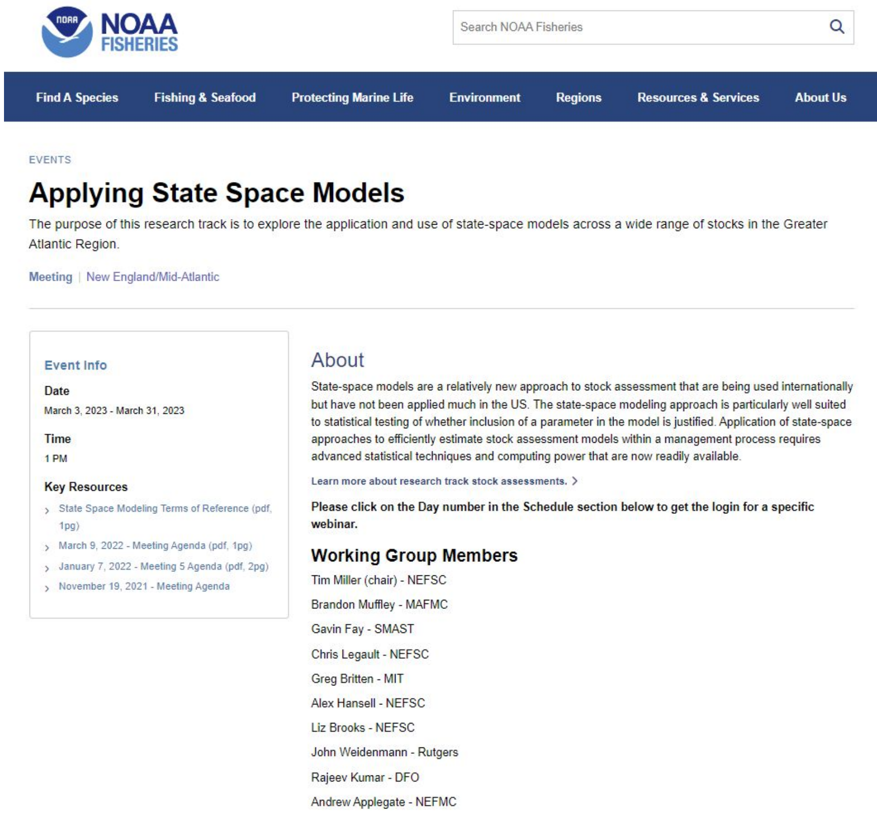
Peer-reviewed to date

- Atlantic butterfish
- Atlantic bluefish
- American plaice
- GB haddock
- Eastern GB haddock
- WGOM Atlantic cod
- EGOM Atlantic cod
- SNE Atlantic cod
- GB cod
- black sea bass
- golden tilefish
- Acadian redfish
- GB winter flounder
- GOM haddock
- Atlantic mackerel

Research track on applying state space models

https://www.fisheries.noaa.gov/event/applying-state-space-models

- Peer-reviewed in February 2024
- Ambitious terms of reference
- WG reviewed previous work relevant to each TOR
- Several large simulation studies conducted to inform TORs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EVENTS

Applying State Space Models

The purpose of this research track is to explore the application and use of state-space models across a wide range of stocks in the Greater Atlantic Region.

Meeting | New England/Mid-Atlantic

Event Info

Date

March 3, 2023 - March 31, 2023

Time

1 PM

Key Resources

- State Space Modeling Terms of Reference (pdf, 1pg)
- March 9, 2022 - Meeting Agenda (pdf, 1pg)
- January 7, 2022 - Meeting 5 Agenda (pdf, 2pg)
- November 19, 2021 - Meeting Agenda

About

State-space models are a relatively new approach to stock assessment that are being used internationally but have not been applied much in the US. The state-space modeling approach is particularly well suited to statistical testing of whether inclusion of a parameter in the model is justified. Application of state-space approaches to efficiently estimate stock assessment models within a management process requires advanced statistical techniques and computing power that are now readily available.

Learn more about research track stock assessments. >

Please click on the Day number in the Schedule section below to get the login for a specific webinar.

Working Group Members

Tim Miller (chair) - NEFSC
Brandon Muffley - MAFMC
Gavin Fay - SMAST
Chris Legault - NEFSC
Greg Britten - MIT
Alex Hansell - NEFSC
Liz Brooks - NEFSC
John Weidenmann - Rutgers
Rajeev Kumar - DFO
Andrew Applegate - NEFMC

Peer-review of the Research Track on Applying State-Space Models

Terms of references:

- TOR 1: Develop guidelines for diagnosing and selecting preferred state-space model structures. Comment on when alternative random effects assumptions and observation models are appropriate.
- TOR 2: Investigate the efficacy of estimating stock-recruit functions within state-space models and their utility in generating scientific advice.
- TOR 3: Develop guidelines for including ecosystem and environmental effects in assessment models and how to treat them for generating biological reference points and scientific advice.
- TOR 4:Through simulation studies, evaluate relative performance of traditional and state-space models with respect to management metrics such as average and variability in catch, and stock and fishing mortality status. Consider factors such as life history type, sources of model-misspecification (as causes of retrospective patterns), and environmental effects.
- TOR 5: Demonstrate any possible effects on stock status and scientific advice with incremental changes from statistical catch-at-age to full state-space model for applicable Northeast US stocks.

Bottom Line

- Terms of references 1, 2, 3, 5 were fully met
- Term of reference 4 was not met (as expected)
  - Panel recommends finding resources to complete this work
- Panel affirmed all recommendations/guidelines for TORs 1,2,3
- Panel recommended using WHAM for the four stocks in TOR5, but peer-review of model configurations required in management track
- Panel made a few further recommendations for best practices

TOR 1 Guidelines

Recommendations by the WG are:

1. Treat recruitment as random effects so that variance and correlation parameters can be estimated
   1.1. Use model selection methods to determine an appropriate time series model for the latent annual recruitments to ensure reliable projections.
2. Consider as many sources of process error as might be plausible and practical, but be aware of unintended implications for management reference points and catch advice.
   2.1. If these models estimate no variability in particular process errors, then those process errors can safely be removed for parsimony and better convergence properties.
   2.2. Caution is warranted with process error on natural mortality as it has been shown to result in biased estimation of model output for management in some scenarios and the resulting natural mortality estimates have direct consequences for management reference points.

TOR 1

3. When non-negligible mis-reporting of catch is plausible, estimation of catch process errors should be considered, and estimated errors inspected for bias (i.e. can help reveal under-reporting).
4. When reliable external estimates of observation error variance are available treat them as known in the assessment model, particularly when they are low relative to process errors.
    4.1. When measurement error variance is large, self-test simulations are important to ensure the model is reliable.
5. Perform posterior check of all random effects as described by Thygesen et al (2017) for evidence of model misspecification.

TOR 1

6. When using MASE with time-series cross-validation, we recommend using the denominator as described by Hyndman and Koehler (2006). A generalization of MASE using (randomized) quantile prediction errors is needed.
    6.1. When there are multiple indices and composition observations each year, rolling fits should not incrementally include each type of observation in a given year, because they are correlated due to the autoregressive process errors.
    6.2. A generalization of MASE is needed that uses (randomized) quantile prediction errors as described by Thygesen et al (2017) for one-step-ahead residuals.
    6.3. Note that catch in the prediction year can not generally be excluded and predicted.
7. Use a broad suite of metrics and diagnostic tools to evaluate relative performance of alternative models.
    7.1. Statistical reliability and AIC as a model selection tool are better when there is contrast in fishing pressure, stock size and process errors over time and more precise index and age composition observations are available.

Further comments by Panel on TOR 1

- Make recruitment decoupling the default option for WHAM
- Estimation of M (scale) will often be difficult unless there is large contrast in F and especially periods with low catches (and F) so that most of the total mortality rates implied by survey age compositions can be attributed to M.
- Estimating time-variation in M will often be more feasible, but convergence still may be problematic.
- Agreed some bias in estimation of assessment output should be expected, but trends in bias over several years is not expected
- Accurate estimation/partitioning of observation and process variance is improved with multiple indices. Essentially multiple observations each year improve this accuracy.
- AIC was demonstrated to be useful in some situations.

TOR 2

Recommendations by the WG are:

1. Consider the level of information in the stock assessment data for the stock-recruit relationship. Positive responses to these questions increase the likelihood for reliable inferences
   a. Is the time series sufficiently long?
   b. Is there evidence of good contrast in spawning stock biomass over time?
   c. Are index and age composition observations relatively precise?
   d. Is variation in recruitment residuals (sigma-R) relatively low?
2. Estimate the stock-recruit relationship simultaneously and internal to the state-space stock assessment model.
3. Self-tests as described in TOR 1 would be prudent to confirm reliability of stock-recruit parameter estimates and biological reference points derived from them.
4. Consider alternative autocorrelation models for recruitment residuals. This will be important primarily in defining how recruitment is predicted in short-term projections.

Further comments by Panel on TOR 2

- Recommend inspecting plot of stock and recruitment estimates from model without the assumption of a relationship.
- The assumed distribution for recruitment deviations may be influential in whether the relationship can be estimated. Heavy-tailed distributions may be more appropriate for some stocks
- Also include jitter analyses in the suite of model checking diagnostics.

TOR 3

Draft recommendations by the WG are:

Because the mechanistic effects of environmental covariates on demographic parameters can have direct and consequential effects on both biological reference point estimation and projections, the following guidance is recommended:

1. Limit investigations to covariates that biology suggests close links of the covariate to the particular demographic parameter.
2. Evaluate effects of covariates using models that also include temporal variation in the parameter which the covariate is hypothesized to affect.
3. Check whether error in environmental covariate observation is low relative to other data sources as this improves reliability of inference and estimability.
4. Fix parameters describing environmental process variability where information is known.
5. Avoid the ‘masking’ functional form when relating stock-recruitment relationships to an environmental covariate (until further work can diagnose issues).
6. Ensure good contrast in the environmental covariate(s).
7. Conduct retrospective comparisons of models with and without covariate effects to confirm inferences are consistent as the number of years with observations changes.
8. Conduct self-tests as described in TOR 1 to confirm reliability of the estimation of effect size the covariate has on assessment model parameter estimates.

Further comments by Panel on TOR 3

- Recommend further simulation scenarios with fixed trends in environmental covariates
- Recommend closed-loop simulations evaluating performance for management quantities (TOR4)
- Consider multiple effects of covariates in simulation studies
- Simulation studies show that data quality is important.

Next steps

- Implement any recommended changes in WHAM (by the WG and the Panel)
  - change recruitment decoupling default
  - add posterior check of random effects.
  - add jittering function
  - add option(s) to estimate catch mis-reporting
- Bring working papers into manuscript form for peer review publications.
- Finalize report for Center Reference Document