The Woods Hole Assessment Model (WHAM): a general state-space assessment framework that incorporates time- and age-varying processes via random effects and environmental covariates

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Abstract

WHAM is great.

Keywords

state-space; stock assessment; random effects; time-varying; environmental effects; recruitment; natural mortality; Template Model Builder (TMB)

1 Introduction

The last two decades have increasingly seen a push for more holistic, ecosystem-based fisheries management (Larkin, 1996; Link, 2002). In part, this is a recognition that considering single species in isolation produces riskier and less robust outcomes long-term (Patrick and Link, 2015). In several high-profile cases, fisheries management has failed to prevent collapses because they did not reduce fishing pressure in responses to changes in natural mortality (M), recruitment, or migration patterns caused by dynamics external to the stock in question (Northern cod: Shelton et al., 2006; Rose and Rowe, 2015; Gulf of Maine cod: Pershing et al., 2015; Pacific sardine: Zwolinski and Demer, 2012). This is particularly concerning in the context of climate change and the wide range of biological processes—often assumed to be constant—in stock assessments that are likely to be affected (Stock et al., 2011).

One approach to account for changing productivity is to explicitly link population processes to environmental covariates in single-species stock assessments, i.e. the mechanistic approach *sensu* Punt et al. (2014). Traditional single-species assessments are based on internal population dynamics and the effect of fishing mortality (F), and effects of the environment or interactions with other species are considered contextually rather than explicitly, even though fisheries scientists have long known that these are important drivers of time-varying population processes, e.g. recruitment, mortality, growth, and movement (Garstang, 1900; Hjort, 1914). (*TJM: However, temporal variation in weight at age, maturity at age can affect reference points in an empirical fasion in the NEUS*) Despite how counterintuitive this may seem to ecologists and oceanographers who study such relationships, the evidence for direct linkages to specific environmental covariates is often weak and can break down over time (McClatchie et al., 2010; Myers, 1998). Additionally, the primary goal of most assessments is to provide management advice on near-term sustainable harvest levels—not to explain ecological relationships. Even if an environmental covariate directly affects fish productivity, including the effect in an assessment may not improve management advice if the effect is weak (De Oliveira and Butterworth, 2005). Worse, including environmental effects in an assessment or management system has been shown to actually provide worse management in some cases (De Oliveira and Butterworth, 2005; Punt et al., 2014; Walters and Collie, 1988). This can be true even in cases of relatively well-understood mechanistic links between oceanic conditions and fish populations, as in the case of sea surface temperature and Pacific sardine (Hill et al., 2018; Zwolinski and Demer, 2012). Still, incorporating mechanistic environment-productivity links does have the potential to reduce uncertainty in reference points and improve projections of stock status (Miller et al., 2016) (*TJM: I think we showed large uncertainty when using projected temperature, right?*).

An alternative approach is to allow biological parameters to vary stochastically over time, i.e. the empirical approach *sensu* Punt et al. (2014). In this case, the variation is caused by a range of sources that are not explicitly modeled. Statistical catch-at-age (SCAA) models typically only estimate year-specific recruitment (R_t) and F_t, often as deviations from a mean that may be a function of spawning biomass, e.g. $\log R_t = \log R_0 + \epsilon_t$. The main reason that other parameters are assumed constant is simply that there are not enough degrees of freedom to estimate many time-varying parameters. One common solution is to penalize the deviations, e.g. $\epsilon_t \sim \mathcal{N}(0, \sigma_\epsilon^2)$, although the penalty terms, σ_ϵ^2, must be fixed or iteratively tuned and are therefore somewhat subjective (Aeberhard et al., 2018; Methot and Taylor, 2011; Methot and Wetzel, 2013; Xu et al., 2020). State-space models that treat parameters as unobserved states can, in principle, avoid such subjectivity by estimating the penalty terms as variance parameters constraining random effects and maximizing the marginal likelihood. In this way, state-space models can allow processes to vary in time while simultaneously estimating fewer parameters.

Although state-space stock assessments have existed for some time (Gudmundsson, 1994; Mendelssohn, 1988; Sullivan, 1992), the recent development of Template Model Builder (TMB, Kristensen et al., 2016) software to perform efficient Laplace approximation has greatly expanded their use (Cadigan, 2016; Miller et al., 2016; Nielsen and Berg, 2014). In addition to the key advantage of objectively estimating variance, or "data weighting", parameters, state-space models naturally predict unobserved states, and therefore handle missing data and short-term projections in a straightforward way (ICES, 2020). In comparisons with SCAA models, state-space models have been shown to have larger, more realistic, uncertainty (Miller and Hyun, 2018).

Retrospective bias can occur when changing environmental conditions lead to changes in productivity that are unaccounted for in stock assessments, and this is a concern commen to several groundfish stocks on the Northeast U.S. Shelf (Brooks and Legault, 2016). The Northeast U.S. Shelf ecosystem is rapidly changing, and this has motivated managers to make the "continue[d] development of stock assessment models that include environmental terms" a top priority (Hare et al., 2016). In addition to providing short-term (1-3 years) catch advice with reduced retrospective bias, it is hoped that environment-linked assessments will help create realistic rebuilding plans in the medium-term (3-10 years) for stocks that have not rebounded in response to dramatic decreases in F. For example, Miller et al. (2016) developed a state-space model for yellowtail flounder with an environmental effect on recruitment, which reduced retrospective patterns and residual variance. Additional applications using a similar state-space framework that include environmental effects on growth, M, and maturity have also proven promising (Miller and Hyun, 2018; Miller et al., 2018; O'Leary et al., 2019; Xu et al., 2018).

To address the needs of fisheries management in a changing climate, we seek an assessment framework that combines both the empirical and mechanistic approaches. Namely, it should be able to 1) estimate time-varying parameters as random effects (i.e. a state-space model), and 2) include environmental effects directly on biological parameters. The framework should also allow for easy testing against status quo SCAA models to ease gradual adoption through the "research track" or "benchmark" assessment process (Lynch et al., 2018). The objectives of this manuscript are to introduce the Woods Hole Assessment Model (WHAM) framework and demonstrate its ability to:

1. estimate time- and age-varying random effects on annual changes in abundance at age, M, and selectivity;
2. fit environmental time-series with process and observation error, missing data, and a link to a population process; and
3. simulate new data and random effects to conduct self- and cross-tests (*sensu* Deroba et al., 2015) to estimate bias in parameters and derived quantities.

Finally, we describe how the above are implemented using the open-source WHAM software package (Miller and Stock, 2020).

2 Methods

2.1 Model description

WHAM is a generalization and extension of Miller et al. (2016), which is in part a re-coding of the Age-Structured Assessment Program (ASAP, Legault and Restrepo, 1998; Miller and Legault, 2015) in TMB. WHAM retains characteristics of ASAP, such as its input file structure and reliance on empirical weight-at-age data, so that existing assessments in the U.S. Northeast can be easily replicated and tested against models with state-space and environmental effects in a single framework.

Either put core model equations here or in supplement

2.1.1 Processes with random effects

WHAM primarily diverges from ASAP through the implementation of random effects on three processes: inter-annual transitions in numbers at age (NAA), natural mortality (M), and selectivity (s), as well as allowing effects of environmental covariates ($Ecov$) on recruitment and natural mortality (but see ASAP4; Miller and Legault, 2015). The environmental covariates and their observations are treated using state-space models with true, unobserved values treated as random effects and observation on them having error. Other than environmental covariates, the processes are assumed to have a two dimensional (2D) first-order autoregressive (AR1) covariance structure over age and year, although correlation in either or both dimensions can be turned off. The 2D AR1 structure has been widely used to model deviations by age and year in the parameters $F_{a,y}$ (Nielsen and Berg, 2014), $M_{a,y}$ (Cadigan, 2016; Stock et al., n.d.), $s_{a,y}$ (Xu et al., 2019), and $N_{a,y}$ (Stock et al., n.d.), as well as in the catch ($C_{a,y}$) and survey index ($I_{a,y}$) observations (Berg and Nielsen, 2016).

2.1.1.1 Numbers at age (NAA)

The stock equations in WHAM that describe the transitions between numbers at age are identical to Miller et al. (2016) and Nielsen and Berg (2014):

$$\log N_{a,y} = \begin{cases} \log\left(f(SSB_{y-1})\right) + \varepsilon_{1,y}, & \text{if } a = 1 \\ \log\left(N_{a-1,y-1}\right) - Z_{a-1,y-1} + \varepsilon_{a,y}, & \text{if } 1 < a < A \\ \log\left(N_{A-1,y-1}e^{-Z_{A-1,y-1}} + N_{A,y-1}e^{-Z_{A,y-1}}\right) + \varepsilon_{A,y}, & \text{if } a = A \end{cases} \tag{1}$$

where $N_{a,y}$ are the numbers at age a in year y, Z is the total mortality rate $(F + M)$, f is the stock-recruit function, Y is the total number of observation and prediction years, and A represents the plus-group. In this analysis we demonstrate four possible models for the NAA deviations, $\varepsilon_{a,y}$.

m1 is most similar to a SCAA model, where only recruitment deviations, $\varepsilon_{1,y}$, are estimated (i.e. $\varepsilon_{a,y} = 0$ for $a > 1$ in Eqn 1). In m1, the recruitment deviations are assumed to be independent and identically distributed (IID):

$$\varepsilon_{1,y} \sim \mathcal{N}(0, \sigma_R^2)$$

The only difference between m1 and a SCAA is that annual recruitments are random effects and σ_R^2 is an estimated parameter within the model.

m2 is the same as m1, except that the recruitment deviations are stationary AR1 with autocorrelation parameter $-1 < \rho_R < 1$:

$$\varepsilon_{1,y+1} \sim \mathcal{N}(\rho_R \varepsilon_{1,y}, \sigma_R^2)$$

m3 is the "full state-space" model from Nielsen and Berg (2014) and Miller et al. (2016), where all numbers at age are independent random effects and:

$$\varepsilon_{a,y} \sim \begin{cases} \mathcal{N}\left(0, \sigma_R^2\right), & \text{if } a = 1 \\ \mathcal{N}\left(0, \sigma_a^2\right), & \text{if } a > 1 \end{cases} \tag{2}$$

where σ_a^2 for all ages $a > 1$ are assumed to be the same but different from age $a = 1$, i.e. recruitment. This assumption is sensible because variability of deviations between expected and realized recruitment are typically larger than deviations from expected abundance at older ages.

m4 treats the numbers at all ages as random effects, as in m3, but the NAA deviations have a 2D stationary AR1 structure as in Stock et al. (n.d.):

$$\mathbf{E} \sim \mathcal{MVN}\left(0, \Sigma\right)$$

where $\mathbf{E} = (\varepsilon_{1,1}, \ldots, \varepsilon_{1,Y-1}, \varepsilon_{2,1}, \ldots, \varepsilon_{2,Y-1}, \ldots, \varepsilon_{A,1}, \ldots, \varepsilon_{A,Y-1})'$ is a vector of all NAA deviations, $\mathbf{\Sigma}$ is the covariance matrix of $\mathbf{E}$ defined by:

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

and $-1 < \rho_a < 1$ and $-1 < \rho_y < 1$ are the AR1 coefficients in age and year, respectively. As in m3, σ_a^2 for all ages $a > 1$ are assumed to be the same but different from age $a = 1$, σ_R^2.

2.1.1.2 Natural mortality (*M*)

For natural mortality, there are mean parameters for each age, μ_{M_a}, each of which may be estimated freely or fixed at the initial values. The μ_{M_a} may also be estimated in sets of ages, e.g. estimate one mean M shared across ages 3-5, $\mu_{M_3} = \mu_{M_4} = \mu_{M_5}$. There is also an option for M to be specified as a function of weight-at-age, $M_{a,y} = \mu_M \mathrm{W}_{a,y}^b$, as in Lorenzen (1996) and Miller and Hyun (2018). Regardless of whether μ_{M_a} are fixed or estimated, WHAM can also be configured to estimate deviations in M, $\delta_{a,y}$, as random effects analogous to the NAA deviations (Cadigan, 2016; Stock et al., n.d.):

$$\begin{aligned} \log\left(M_{a,y}\right) &= \mu_{M_a} + \delta_{a,y} \\ \mathrm{Cov}\left(\delta_{a,y}, \delta_{\tilde{a},\tilde{y}}\right) &= \tfrac{\sigma_M^2 \varphi_a^{|a-\tilde{a}|} \varphi_y^{|y-\tilde{y}|}}{\left(1-\varphi_a^2\right)\left(1-\varphi_y^2\right)} \end{aligned} \tag{3}$$

where σ_M^2, φ_a, and φ_y are the AR1 variance and correlation coefficients in age and year, respectively.

In this analysis, we demonstrate three alternative M random effects models. For simplicity, all models treat

μ_{M_a} as known, as in each of the original assessments. m1 is identical to the base NAA model, with no random effects on M ($\sigma_M^2 = \varphi_a = \varphi_y = 0$ and not estimated). m2 allows IID M deviations, estimating σ_M^2 but fixing $\varphi_a = \varphi_y = 0$. m3 estimates the full 2D AR1 structure for M deviations.

2.1.1.3 Selectivity (s)

As in ASAP and most other SCAA assessment frameworks, WHAM assumes separability in the fishing mortality rate by age and year, e.g. $F_{a,y} = F_y s_a$, where F_y is the "fully selected" fishing mortality rate in year y and s_a is the selectivity at age. We note that this differs from the approach in SAM (Nielsen and Berg, 2014), where the $F_{a,y}$ are estimated directly as multivariate random effects without the separability assumption. Three parametric forms are available (logistic, double-logistic, and decreasing-logistic), as well as a non-parametric option to estimate each s_a individually ("age-specific"). To allow for temporal changes in selectivity as in ASAP, WHAM can estimate selectivity in user-specified time blocks. WHAM estimates selectivity parameters on the logit scale to avoid boundary problems during estimation.

WHAM estimates annual full F_y and mean selectivity parameters as fixed effects. Deviations in selectivity parameters can be estimated as random effects, $\zeta_{p,y}$, with autocorrelation by parameter (p), year (y), both, or neither. This is done similarly to Xu et al. (2019), except that the deviations are placed on the parameters instead of the mean $s_{a,y}$ in order to guarantee that $0 < s_{a,y} < 1$. For example, logistic selectivity with two parameters a_{50} and k is estimated as:

$$\begin{aligned} s_{a,y} &= \frac{1}{1+e^{-(a-a_{50_y})/k_y}} \\ a_{50_y} &= l_{a_{50}} + \frac{u_{a_{50}} - l_{a_{50}}}{1+e^{-(\nu_1+\zeta_{1,y})}} \\ k_y &= l_k + \frac{u_k - l_k}{1+e^{-(\nu_2+\zeta_{2,y})}} \\ \operatorname{Cov}(\zeta_{1,y}, \zeta_{2,\tilde{y}}) &= \frac{\sigma_s^2 \phi_p \phi_y^{|y-\tilde{y}|}}{(1-\phi_p^2)(1-\phi_y^2)} \end{aligned} \tag{4}$$

where ν_1 is the logit-scale mean a_{50} parameter with lower and upper bounds $l_{a_{50}}$ and $u_{a_{50}}$, ν_2 is the logit-scale mean k parameter with lower and upper bounds l_k and u_k, σ_s^2 is the AR1 variance, and ϕ_p, and ϕ_y are the AR1 correlation coefficients by parameter and year.

Below, we demonstrate three models with random effect deviations on logistic selectivity, akin to those for M. m1 treats all numbers at age as independent random effects (i.e. NAA m3) but with no random effects on s ($\sigma_s^2 = \phi_p = \phi_y = 0$ and not estimated). m2 allows IID s deviations, estimating σ_s^2 but fixing $\phi_p = \phi_y = 0$. m3 estimates the full 2D AR1 structure for s deviations.

2.1.1.4 Environmental covariates (*Ecov*)

Environmental covariate data are modeled using state-space models with process and observation components. The true, unobserved values (or "latent states", X_y) are then linked to the population dynamics equations with user-specified lag. For example, recruitment in year y may be influenced by X_{y-1} (lag 1), while natural mortality in year y may be influenced by X_y (lag 0). Multiple environmental covariates may be included, but only as independent processes. The *Ecov* and population model years do not need to match, and missing years are allowed. In particular, including *Ecov* data in the projection period can be useful.

2.1.1.4.1 Process model

There are currently two options for the *Ecov* process model: a normal random walk and AR1. We model the random walk as in Miller et al. (2016):

$$X_{y+1}|X_y \sim \mathcal{N}\left(X_y, \sigma_X^2\right)$$

where σ_X^2 is the process variance and X_1 is estimated as a fixed effect parameter. One disadvantage of the random walk is that its variance is nonstationary. In short-term projections, $\hat{X}_y$ will be equal to the last estimate with an observation and the uncertainty of $\hat{X}_y$ will increase over time. If $\hat{X}_y$ influences reference points, this leads to increasing uncertainty in stock status over time as well (Miller et al., 2016).

For this reason, we generally prefer to model X_y as a stationary AR1 process as in Miller et al. (2018):

$$\begin{gathered}X_1 \sim \mathcal{N}\left(\mu_X, \frac{\sigma_X^2}{1-\phi_X^2}\right)\\ X_y \sim \mathcal{N}\left(\mu_X(1-\phi_X)+\phi_X X_{y-1}, \sigma_X^2\right)\end{gathered} \tag{5}$$

where μ_X, σ_X^2, and $|\phi_X| < 1$ are the marginal mean, variance, and autocorrelation parameters. In addition to having stationary variance, another important difference between the random walk and AR1 in short-term projections is that the AR1 will gradually revert to the mean over time, unless environmental covariate observations are included in the projection period.

2.1.1.4.2 Observation model

The environmental covariate observations, x_y, are assumed to be normally distributed with mean X_y and variance $\sigma_{x_y}^2$:

$$x_y | X_y \sim \mathcal{N}\left(X_y, \sigma^2_{x_y}\right)$$

The observation variance in each year, $\sigma^2_{x_y}$, can be treated as known with year-specific values (as in Miller et al., 2016) or one overall value shared among years. They can also be estimated as parameters, likewise either as yearly values or one overall value. If included, WHAM estimates yearly $\sigma^2_{x_y}$ as random effects with parameters μ_{σ_x} and σ_{σ_x}:

$$\sigma^2_{x_y} \sim \mathcal{N}\left(\mu_{\sigma_x}, \sigma^2_{\sigma_x}\right)$$

2.1.1.4.3 Link to population

WHAM currently provides options to link the modeled environmental covariate, X_y, to the population dynamics via recruitment or natural mortality. It is also sometimes useful to fit the *Ecov* model without a link to the population dynamics so that models with and without environmental effects have the same data in the likelihood and can be compared via AIC.

In the case of recruitment, the options follow Fry (1971) and Iles and Beverton (1998): "controlling" (density-independent mortality), "limiting" (carrying capacity effect, e.g. X_y determines the amount of suitable habitat), "lethal" (threshold effect, i.e. R_t goes to 0 at some X_y value), "masking" (X_y decreases $\mathrm{d}R/\mathrm{d}SSB$, as expected if X_y affects metabolism or growth), and "directive" (e.g. behavioral). Of these, WHAM currently allows controlling, limiting, or masking effects in the Beverton-Holt stock-recruit function, and controlling or masking effects in the Ricker function. For natural mortality, environmental effects are placed on μ_M, shared across ages.

Regardless of where the environment-population link is, the effect can be either linear or polynomial. WHAM includes a function to calculate orthogonal polynomials in TMB, akin to the `poly()` function in `R`.

2.1.2 Population observation model

The population observation likelihood components are the same as in ASAP: aggregate catch and abundance index for each fleet and survey, and age composition for each fleet and survey.

2.1.2.1 Catch

The predicted catch at age for fleet i, $\hat{C}_{a,y,i}$, is a function of $N_{a,y}$, $M_{a,y}$, $F_{y,i}$, $s_{a,y,i}$, and empirical weight at age, $W_{a,y,i}$. Then,

$$
\begin{aligned}
\hat{C}_{y,i} &= \textstyle\sum_a \hat{C}_{a,y,i} \\
\sigma^2_{C_{y,i}} &= e^{\eta_i}\sqrt{\log(\mathrm{CV}^2_{y,i}+1)} \\
\log(C_{y,i}) &\sim \mathcal{N}\left(\log(\hat{C}_{y,i}) - \frac{\sigma^2_{C_{y,i}}}{2}, \sigma^2_{C_{y,i}}\right)
\end{aligned}
\tag{6}
$$

where η_i are fleet-specific estimated parameters and $\mathrm{CV}^2_{y,i}$ are user-specified. The bias correction term, $-\frac{\sigma^2_{C_{y,i}}}{2}$, is included by default based on Aldrin et al. (2020) but can be turned off.

WHAM includes seven options for the catch and index age compositions: multinomial, Dirichlet, Dirichlet-multinomial, logistic normal treating zero observations as missing, logistic normal pooling zero observations with adjacent age classes, and two types of zero-one inflated logistic normal.

2.1.2.2 Indices

The survey indices of abundance are handled identically to the aggregate catch as in Eqn. 6 and catch age compositions, except that the predicted index biomass at age i, $\hat{I}_{a,y,i}$ is a function of $N_{a,y}$, $Z_{a,y}$, $s_{a,y,i}$, $W_{a,y,i}$, and catchability, q_i.

2.1.3 Projections

default settings are to project 3 years (n.yrs = 3), use average maturity-, weight-, and natural mortality-at-age from last 5 model years to calculate reference points (avg.yrs), use fishing mortality in the last model year (use.last.F = TRUE), and continue the ecov process model (cont.ecov = TRUE

WHAM implements four options for handling the environmental covariate(s) in the projections. Exactly one of these must be specified in proj.opts if ecov is in the model:

```
(Default) Continue the ecov process model (e.g. random walk, AR1). Set cont.ecov = TRUE. WHAM will esti

Use last year ecov. Set use.last.ecov = TRUE. WHAM will use ecov value from the terminal year of the pop

Use average ecov. Provide avg.yrs.ecov, a vector specifying which years to average over the environmenta

Specify ecov. Provide proj.ecov, a matrix of user-specified environmental covariate(s) to use for proje
```

Note that for all options, if the original model fit the ecov in years beyond the population model, WHAM will use these already-fit ecov values for the projections

WHAM implements five options for handling fishing mortality in the projections. Exactly one of these must be specified in proj.opts:

```
(Default) Use last year F. Set use.last.F = TRUE. WHAM will use F in the terminal model year for projec

Use average F. Set use.avg.F = TRUE. WHAM will use F averaged over proj.opts$avg.yrs for projections (a

Use F at X% SPR. Set use.FXSPR = TRUE. WHAM will calculate and apply F at X% SPR, where X was set by in

Specify F. Provide proj.F, an F vector with length = proj.opts$n.yrs.

Specify catch. Provide proj.catch, a vector of aggregate catch with length = proj.opts$n.yrs. WHAM will
```

2.1.4 Bias correction

- Analytical obs error. (Aldrin et al., 2020).
- Analytical process error.
- TMB epsilon. (Thorson, 2019; Thorson and Kristensen, 2016)

Should these all be used?

2.2 Fits to original datasets

We used the stocks in Table 2. For each of the NAA and M models, we used the same selectivity parameterization and blocks as in the original assessments. For Georges Bank haddock, …

2.3 Simulation tests

Fit each model to original dataset. Use each model to simulate new data and random effects, keeping fixed effect parameters constant at values estimated in original fits. Re-fit each model to datasets simulated under each operating model.

We used R (R Core Team, 2020). WHAM is available as an R package (Miller and Stock, 2020). Table 1 summarizes the models fit for each process. Tutorials for how to specify additional random effect structures in WHAM are available at https://timjmiller.github.io/wham/.

3 Results

3.1 Original datasets

2D AR1 structure performed well across processes and stocks (Fig. 1).

3.1.1 Numbers-at-age

Fig. 2.

3.1.2 Natural mortality

Fig. 3.

3.1.3 Selectivity

Fig. 4.

3.1.4 Ecov-Recruitment

Fig. 5.

3.2 Simulation tests

Not all models converged. Fig. 6.

Bias is usually so tiny and not significant based on confidence intervals when the estimation and operating model are consistent. Bias is also often small when more complex models are fitted to less complicated operating model simulations. Bias of variance parameters is as expected (negative). REML should be used if more accurate estimation of these is a priority.

(Miller et al., 2018) The biased maximum likelihood estimation of the autoregres- sive process parameters we found in the simulation study was expected (Wilson 1989). The reduction in bias for most of these parameters using REML estimation was also expected (Cheang and Reinsel 2000), but substantial bias still remained,

3.2.1 Numbers-at-age

Fig. 7.

Fig. 8.

3.2.2 Natural mortality

Fig. 9.

Fig. 10.

3.2.3 Selectivity

Fig. 11.

Fig. 12.

3.2.4 Ecov-Recruitment

Fig. 13.

4 Discussion

4.1 Overview

Our results suggest that the WHAM package can be a useful tool for stock assessment when environmental effects on recruitment or natural mortality, variation in selectivity or natural mortality, or stochastic changes in the numbers at age are of interest. The simulation tests showed negligible or no bias in estimation of important assessment outputs (SSB, F, stock and harvest status).

We described WHAM. Sim tests showed no bias in self-tests (when estimation model matched operating model). Some bias in cross-tests.

Contrast mechanistic vs. empirical approaches. Empirical approaches allows time-varying productivity and with AR1 can propagate effect of changing productivity in short-term projections (Stock et al., n.d.). However, the empirical approach cannot predict values beyond extremes in observed time-series (*TJM: This is always true? I suspect certain types of time series models might predict outside of time series. E.g., if there is an increase with the last observation being the greatest, some higher order AR models might predict the next few observations higher than the last*). This is an issue because many ecosystems are changing to such extent that conditions in the near future have never been observed. E.g. last time it was close to this warm on the U.S. Northeast Shelf was the 1940s, and few fisheries or oceanographic time-series stretch back that far. Thus, longer term projections likely require mechanistic approach. Think about other sources of data? Fish catch, not just surveys + age data? Continuous Plankton Recorder (other side of Atlantic, but correlated?). 1951 was almost as warm (annual mean), but warm in winter instead of summer (diff seasonal change).

Mechanistic approach: more likely to find environmental effects in cases with:

- history of overfishing (Free et al., 2019)
- more rapid environmental change (Free et al., 2019)
- stocks at edge of species' range (Free et al., 2019)
- opportunistic species (short-lived) vs. longer-lived (Free et al., 2019)
- longer time series
- stronger signals (wider ranges of observed stock status and environmental conditions)
- periodic signal where we've recorded more than one cycle (e.g. PDO/sst sardine)
- lower trophic level (e.g. generally tighter relationship between PO and zooplankton, then small pelagics TL2, then TL3+). PO forecasting group look at zooplankton indices? See Perretti 2017 (recruitment regime shifts)

Reducing uncertainty may be just as valuable as improving accuracy / reducing bias.

4.2 Differences from other assessment model frameworks

How is WHAM different from SAM?

Not sure where to put this... some could be in Intro or Discussion. Definitely will be a question in readers' minds so may be good to introduce early?

WHAM estimates annual full F as fixed effects and selectivity of surveys or fisheries as constant or time-varying random effects with various autoregressive assumptions possible. SAM estimates FAA as a multivariate log-normal random walk. WHAM can estimate interannual transitions as random walk processes like SAM or as a function of autoregressive deviations. Alternatively (or simultaneously) WHAM can estimate deviations in natural mortality as autoregressive processes like NCAM (Cadigan, 2016). Uniquely, WHAM can model multiple covariate time series as state-space processes and include their effects (nonlinearly) in various ways on recruitment or natural mortality.

Like SS, ASAP, BAM, WHAM treats aggregate and composition observations separately for fisheries and indices. This differs from SAM where observations of numbers at age are treated as multivariate log-normal.

Most assessments in the U.S. assume separability in $F_{a,t}$, estimate F_t and Sel_a. WHAM does this. SAM estimates $F_{a,t}$ directly. WHAM and SAM also make different separability assumptions for the catch/index data (aggregate total + age comps vs. $C_{a,t}$ directly). Should be similar (?) but could test.

To move from traditional SCAA models to state-space models with random effects in the Northeast US, WHAM can be configured to fit models very similar to ASAP and therefore bridge between these frameworks. Goal is to replicate ASAP assessments in the U.S. Northeast. Can easily turn on/off random effects.

Observation model is natural for landings data that are measured as total weight plus age composition sampling. Age composition sampling often done separately with survey data.

Treating F and Sel separately can be useful for projections. Oftentimes we want to specify F in projections to calculate a reference point, as opposed to continuing a F time-series process.

4.3 Future work

WHAM will be used in upcoming research track assessments. Could transition to operational. Potential to improve several NEFSC assessments.

- 2D AR(1) selectivity. Most assessments in the U.S. assume separability in $F_{a,t}$, i.e. estimate F_t and Sel_a. WHAM does this. SAM estimates $F_{a,t}$ directly. WHAM and SAM make different separability assumptions for the catch/index data as well (aggregate total + age comps vs. $C_{a,t}$ directly). Should be similar (?) but could test.
- How many time/age-varying random effects can be estimated simultaneously? Stock et al. (n.d.) estimated random effect deviations in abundance at age and M, as well as an environmental covariate effect on recruitment.
- Ecov-Recruitment simulation study. How much information does Ecov need to have to be useful?

4.4 Extensions

4.4.1 Multivariate spatiotemporal environmental data

Most examples that include environment-recruitment effects are univariate, but in many cases it is likely that multiple factors have to align for successful recruitment (e.g. temperature and currents for Nassau Grouper).

4.4.2 Length/growth estimation

4.4.3 Ecov models

- AR(k)
- splines
- Gaussian process/EDM/Munch/Sugihara

4.5 Conclusion

Development of TMB has facilitated significant advancement in fisheries assessment, allowing us to treat population processes as random effects. A grand challenge in fisheries is to assess and manage stocks in a changing environment. Increasingly have the environmental data. Population time-series are lengthening. WHAM is a step in this direction.

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Supplementary material

More figures.

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Table 1: Model descriptions and estimated parameters. Parameter descriptions and equations are given in text. Note that the base model in the M module is NAA m1, and the base model in the Selectivity and Ecov-Recruitment modules is NAA m3. Ecov m1 fits the Cold Pool Index data and estimates σ_x in order to allow comparison to m2-m5 using AIC (same data needed in likelihood).

Model	Description	Estimated parameters
Numbers-at-age (NAA)		
m1: SCAA (IID)	Recruitment deviations are IID random effects	σ_R
m2: SCAA (AR1)	Recruitment deviations are autocorrelated (AR1) random effects	σ_R, ρ_y
m3: NAA (IID)	All NAA deviations are IID random effects	σ_R, σ_a
m4: NAA (2D AR1)	All NAA deviations are random effects with correlation by year and age (2D AR1)	σ_R, σ_a, ρ_y, ρ_a
Natural mortality (M)		
m1: none	No random effects on M	σ_R
m2: IID	M deviations are IID random effects	σ_R, σ_M
m3: 2D AR1	M deviations are random effects with correlation by year and age (2D AR1)	σ_R, σ_M, φ_y, φ_a
Selectivity (Sel)		
m1: none	No random effects on selectivity	σ_R, σ_a
m2: IID	Selectivity deviations are IID random effects	σ_R, σ_a, σ_{Sel}
m3: 2D AR1	Selectivity deviations are random effects with correlation by year and age (2D AR1)	σ_R, σ_a, σ_{Sel}, ϕ_y, ϕ_a
Ecov-Recruitment (Ecov)		
m1: RW-none	Ecov: random walk (RW), effect on β: none	σ_R, σ_a, σ_x
m2: RW-linear	Ecov: random walk (RW), effect on β: linear	σ_R, σ_a, σ_x, β_1
m3: RW-poly	Ecov: random walk (RW), effect on β: 2nd order polynomial (poly)	σ_R, σ_a, σ_x, β_1, β_2
m4: AR1-linear	Ecov: autocorrelated (AR1), effect on β: linear	σ_R, σ_a, σ_x, ϕ_x, β_1
m5: AR1-poly	Ecov: autocorrelated (AR1), effect on β: 2nd order polynomial (poly)	σ_R, σ_a, σ_x, ϕ_x, β_1, β_2

Table 2: Stocks used in simulation tests.

	Modules tested				Model dim		Biol. par.		Stock status	
Stock	NAA	M	Sel	Ecov	# Ages	# Years	M	σ_R	$\frac{B}{B_{40}}$	$\frac{F}{F_{40}}$
SNEMA yellowtail flounder	x	x		x	6	49	0.2-0.4	1.67	0.01	0.44
Butterfish	x	x			5	31	1.3	0.23	2.57	0.03
North Sea cod	x	x			6	54	0.2-1.2	0.87	0.14	2.00
Icelandic herring	x				11	30	0.1	0.55	0.40	1.81
Georges Bank haddock	x		x		9	86	0.2	1.65	5.16	0.12

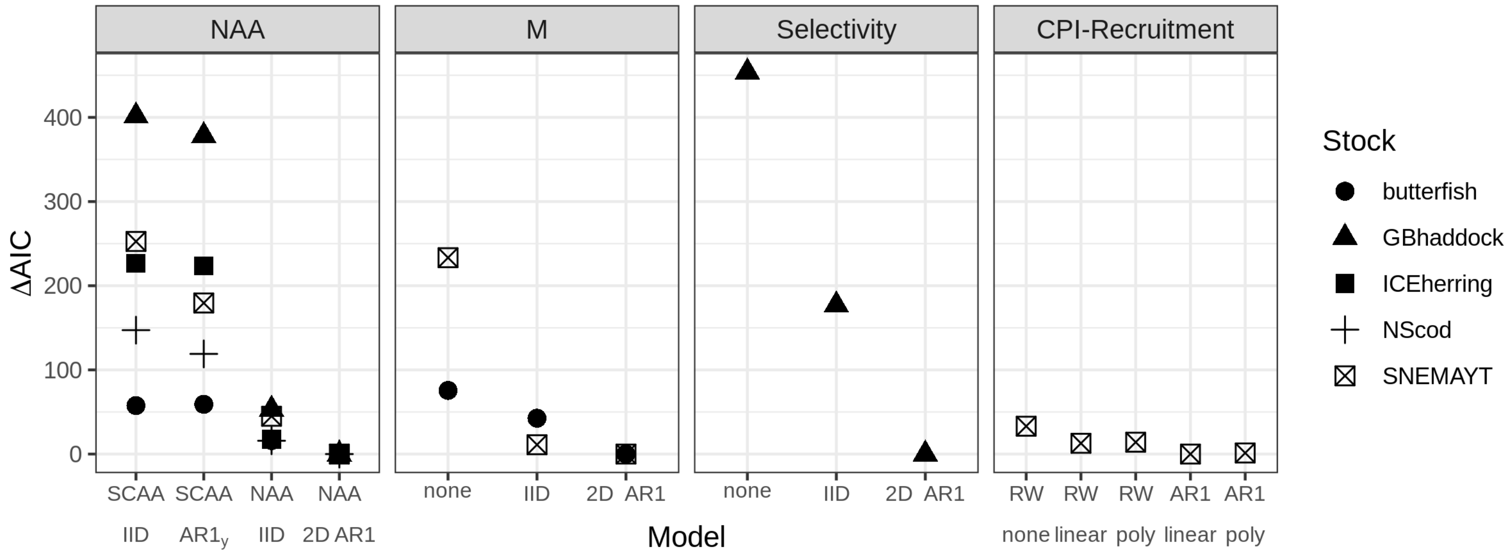

Figure 1: AIC differences by model and stock when fit to original datasets. Stock abbreviations: SNEMA yellowtail flounder (SNEMAYT), North Sea cod (NScod), Icelandic herring (ICEherring), and Georges Bank haddock (GBhaddock).

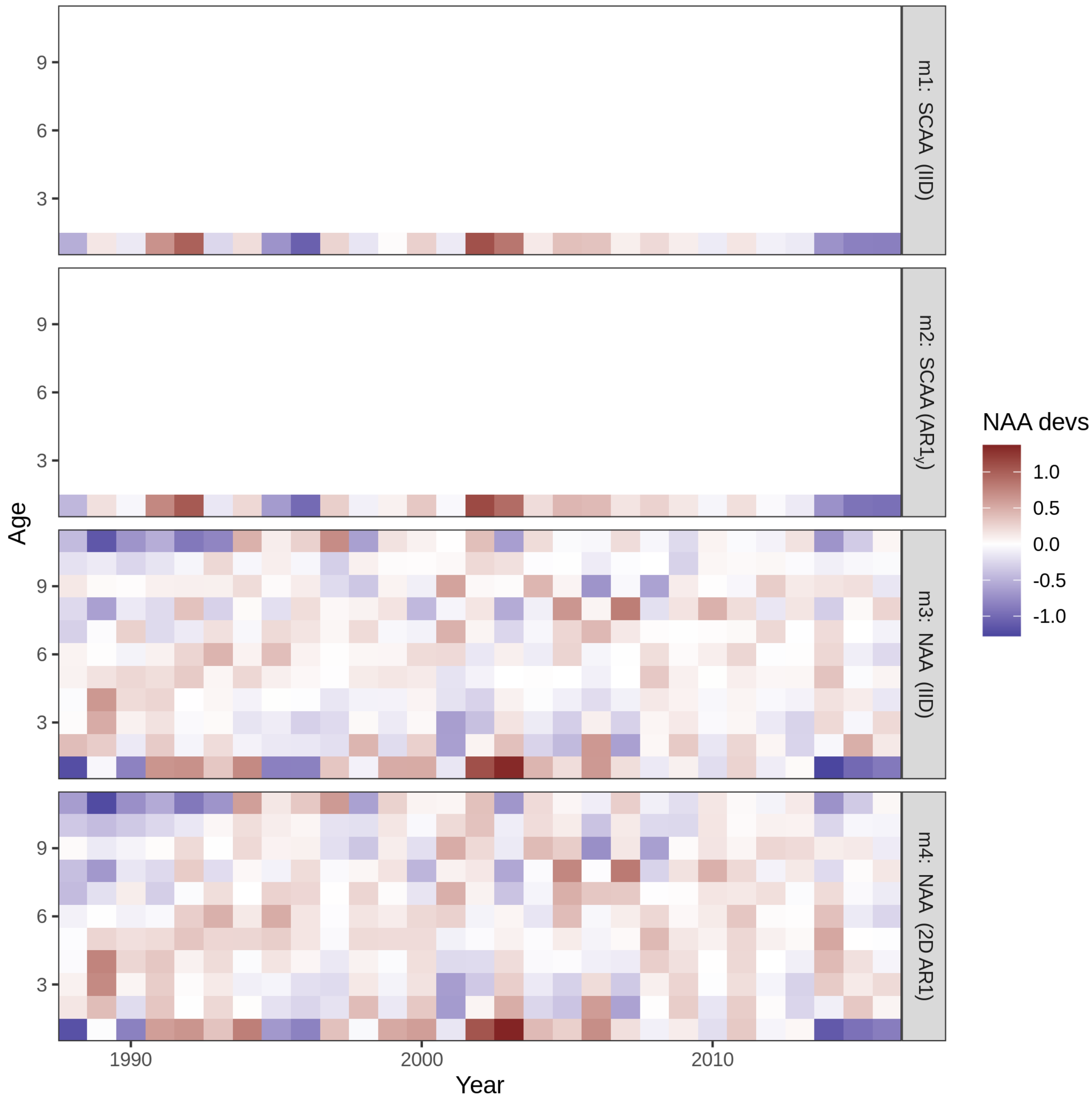

Figure 2: Abundanc-at-age deviations estimated for Icelandic herring using four models of numbers-at-age (NAA) random effects. m1 = only recruitment deviations are random effects (most similar to traditional statistical catch-at-age, SCAA), and deviations are independent and identically distributed (IID). m2 = as m1, but with autocorrelated recruitment deviations (AR1$_y$). m3 = all NAA deviations are IID random effects. m4 = as m3, but deviations are correlated by age and year (2D AR1).

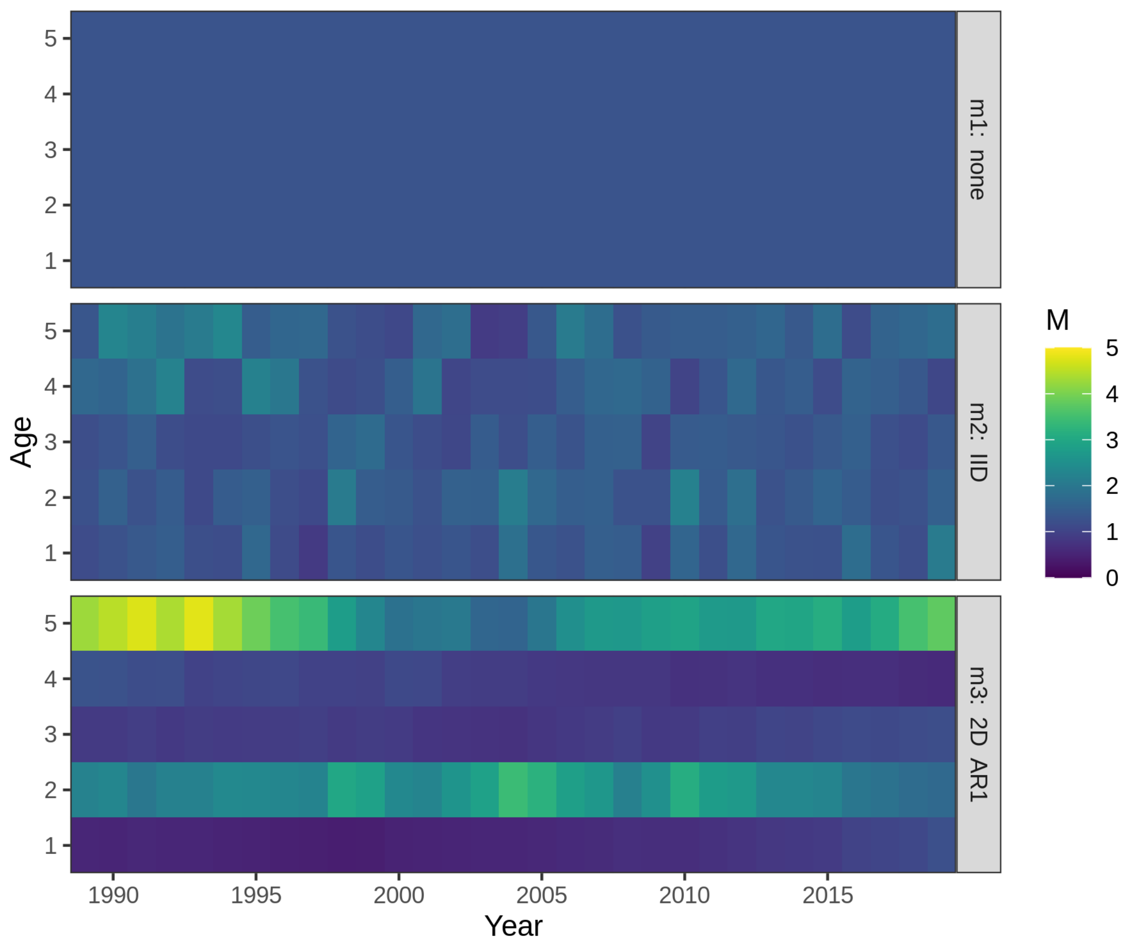

Figure 3: Natural mortality (M) estimated for butterfish using three random effects models. m1 = no random effects on M. m2 = M deviations are independent and identically distributed (IID). m3 = M deviations are correlated by age and year (2D AR1).

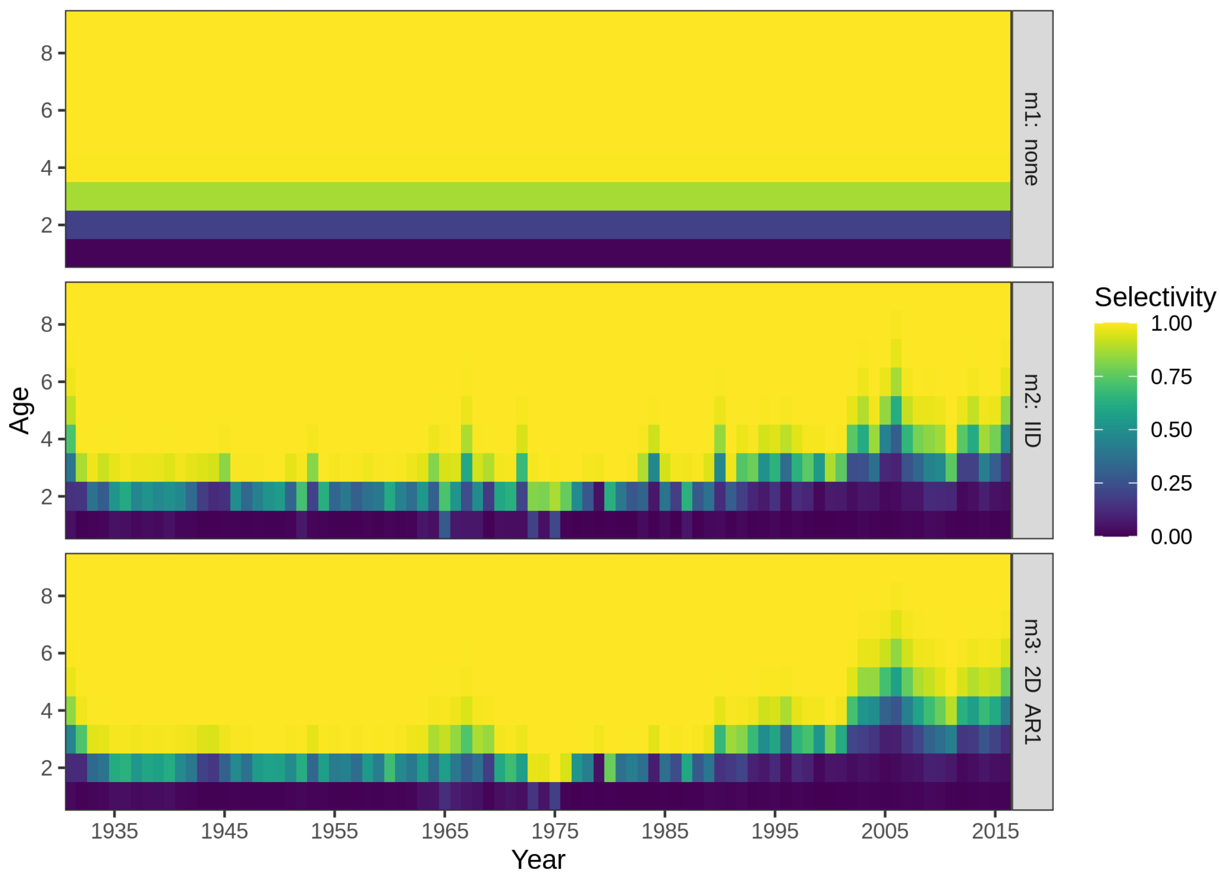

Figure 4: Selectivity estimated for Georges Bank haddock using three random effects models. m1 = no random effects (constant logistic selectivity). m2 = selectivity deviations are independent and identically distributed (IID). m3 = selectivity deviations are correlated by parameter and year (2D AR1).

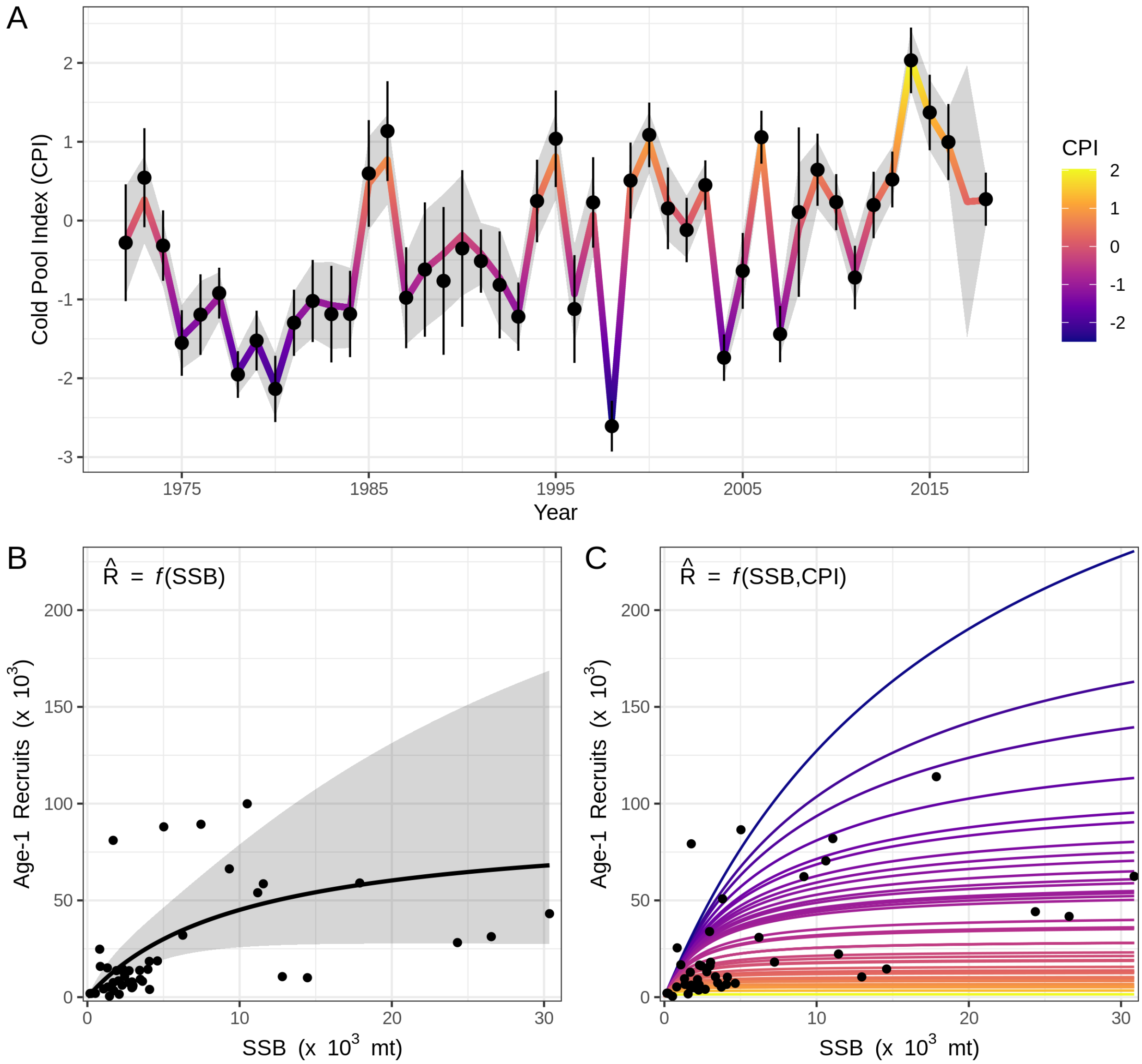

Figure 5: Beverton-Holt stock-recruit relationships fit for Southern New England-Mid Atlantic yellowtail flounder, with and without effects of the Cold Pool Index (CPI). A) CPI estimated from the model with lowest AIC (m4, AR1-linear). Points are observations with 95% CI, and the line with shading is the model-estimated CPI with 95% CI. Note the increased uncertainty surrounding the CPI estimate in 2017 (no observation). B) Estimates of spawning stock biomass (SSB), recruitment, and the stock-recruit function from the model without a CPI effect, m1. C) Estimates of SSB and recruitment from m4, with an effect of the CPI on β. Lines depict the expected stock-recruit relationship in each year t, given the CPI in year $t-1$ (color).

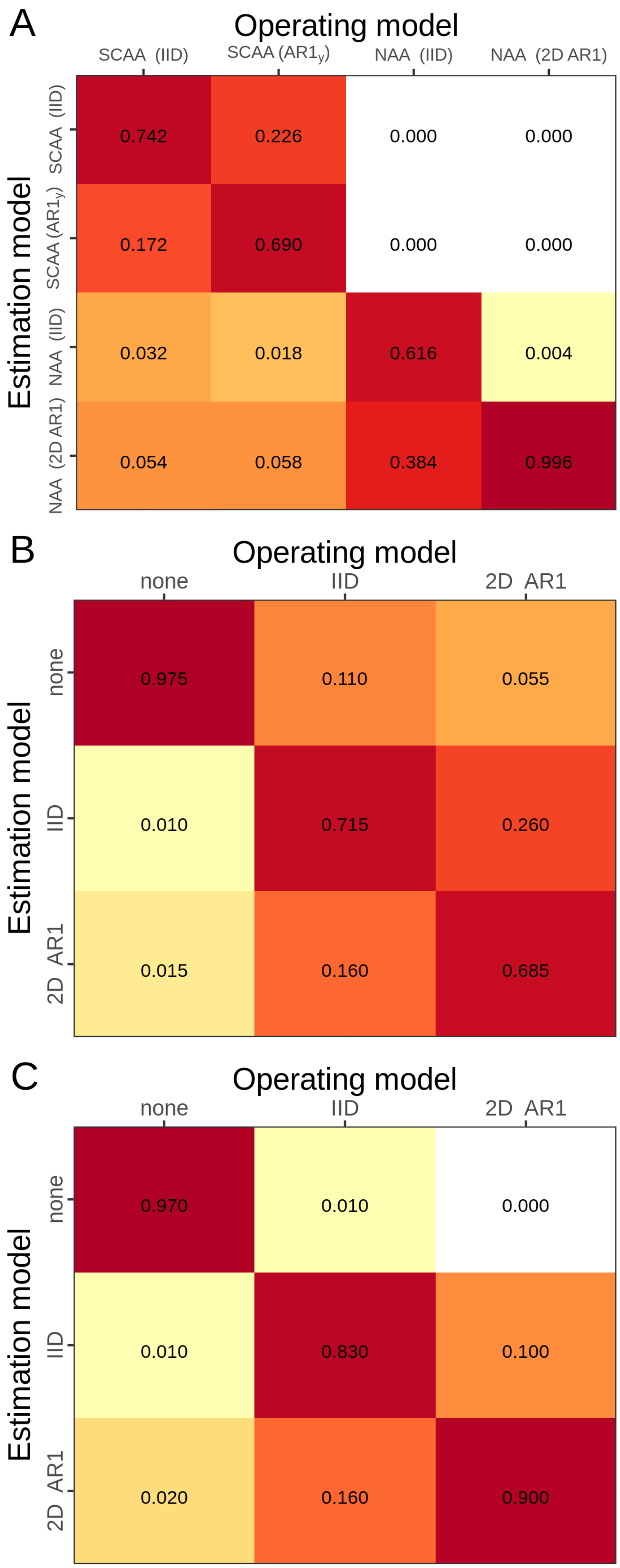

Figure 6: Proportion of simulations in which each model had the lowest AIC. A) Numbers-at-age (NAA), aggregated across all five stocks. B) Natural mortality (M), aggregated over two stocks (SNEMAYT and NScod). C) Selectivity (GBhaddock). Not all estimation models converged for each simulation, even when the operating model matched.

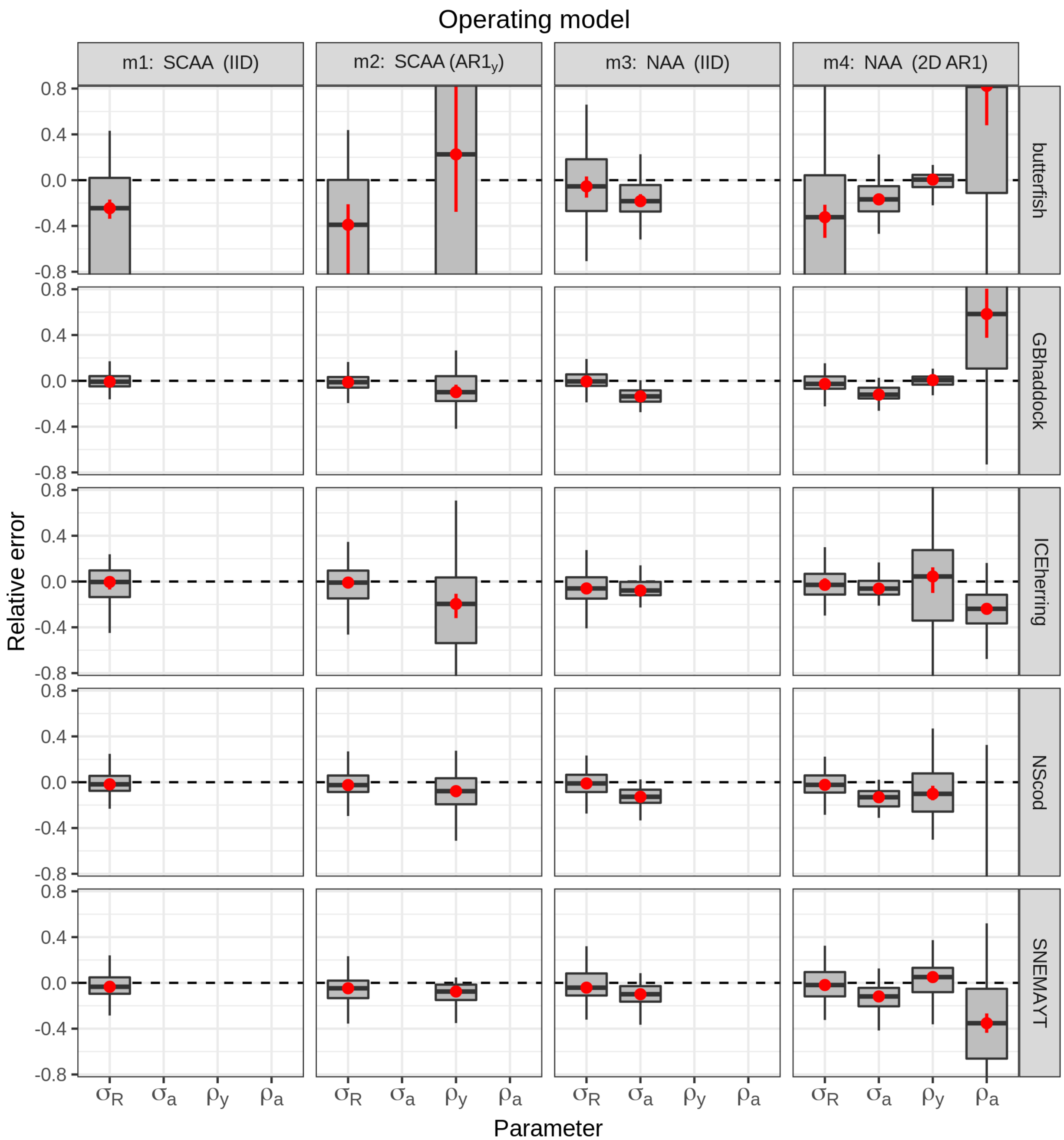

Figure 7: Relative error of parameters constraining numbers-at-age (NAA) random effects. Four models were used to simulate 100 datasets keeping fixed effect parameters constant, and then re-fit to each simulated dataset. m1 = only recruitment deviations are random effects (most similar to traditional statistical catch-at-age, SCAA), and deviations are independent and identically distributed (IID). m2 = as m1, but with autocorrelated recruitment deviations (AR1$_y$). m3 = all NAA deviations are IID random effects. m4 = as m3, but deviations are correlated by age and year (2D AR1). Relative error was calculated as $\frac{\hat{\theta}_i}{\theta} - 1$, where $\hat{\theta}_i$ was the estimate in simulation i for parameter θ, and θ was the true value (estimate from original dataset). Red points and lines show median relative error with 95% CI.

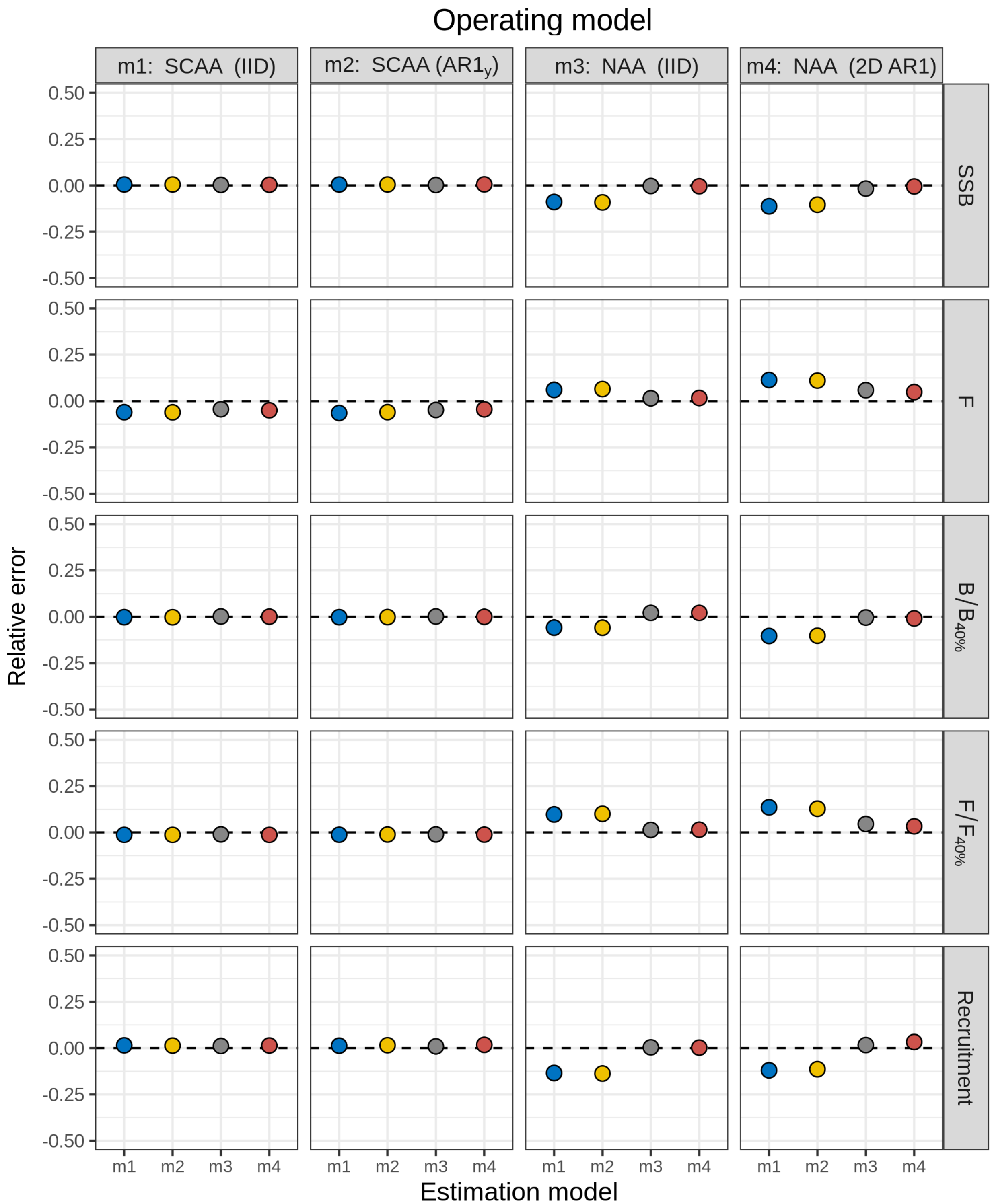

Figure 8: Relative error of key quantities estimated for Icelandic herring using four models of numbers-at-age (NAA) random effects. m1 = only recruitment deviations are random effects (most similar to traditional statistical catch-at-age, SCAA), and deviations are independent and identically distributed (IID). m2 = as m1, but with autocorrelated recruitment deviations ($AR1_y$). m3 = all NAA deviations are IID random effects. m4 = as m3, but deviations are correlated by age and year (2D AR1).

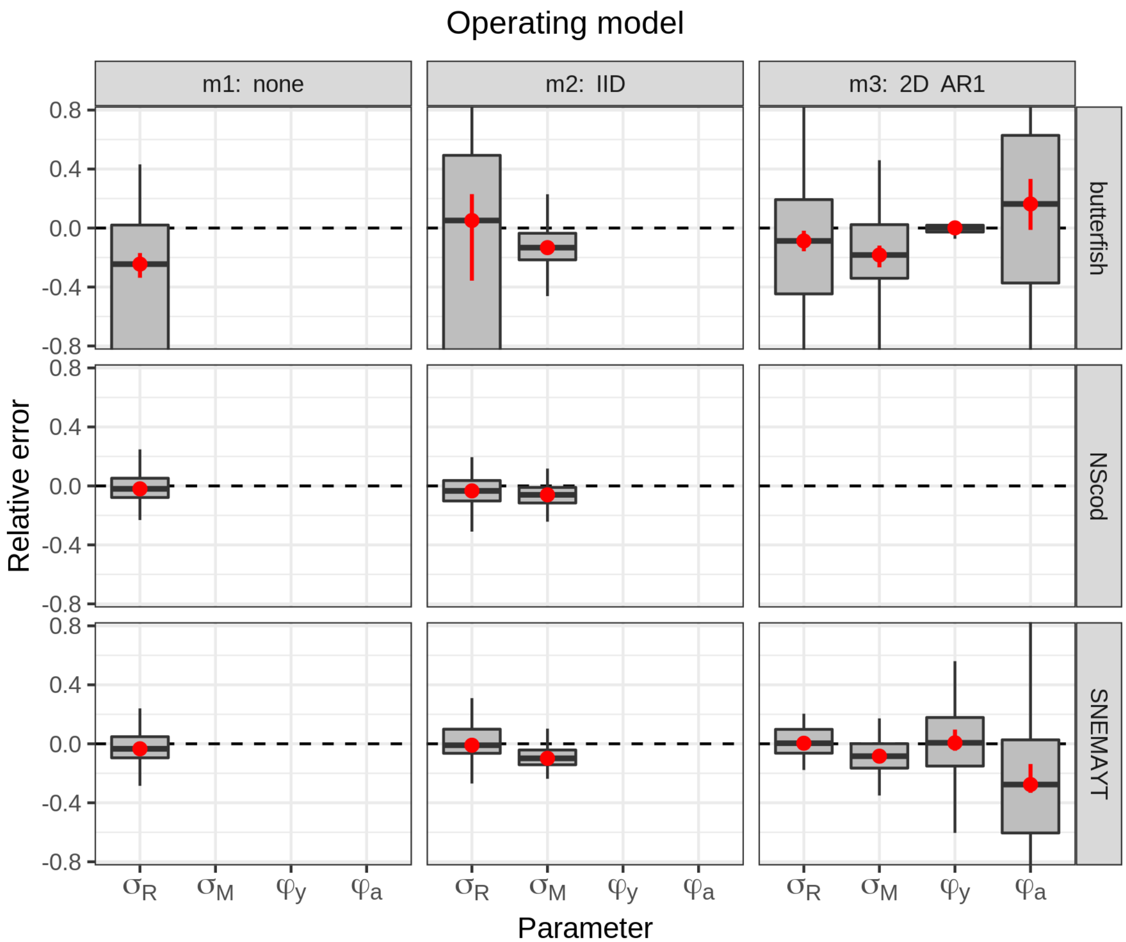

Figure 9: Relative error of parameters constraining natural mortality (M) random effects. Three models were used to simulate 100 datasets keeping fixed effect parameters constant, and then re-fit to each simulated dataset. m1 = no random effects on M. m2 = M deviations were independent and identically distributed (IID). m3 = M deviations were correlated by age and year (2D AR1). Relative error was calculated as $\frac{\hat{\theta}_i}{\theta} - 1$, where $\hat{\theta}_i$ was the estimate in simulation i for parameter θ, and θ was the true value (estimate from original dataset). Red points and lines show median relative error with 95% CI. Stock abbreviations: SNEMA yellowtail flounder (SNEMAYT) and North Sea cod (NScod, m3 did not converge).

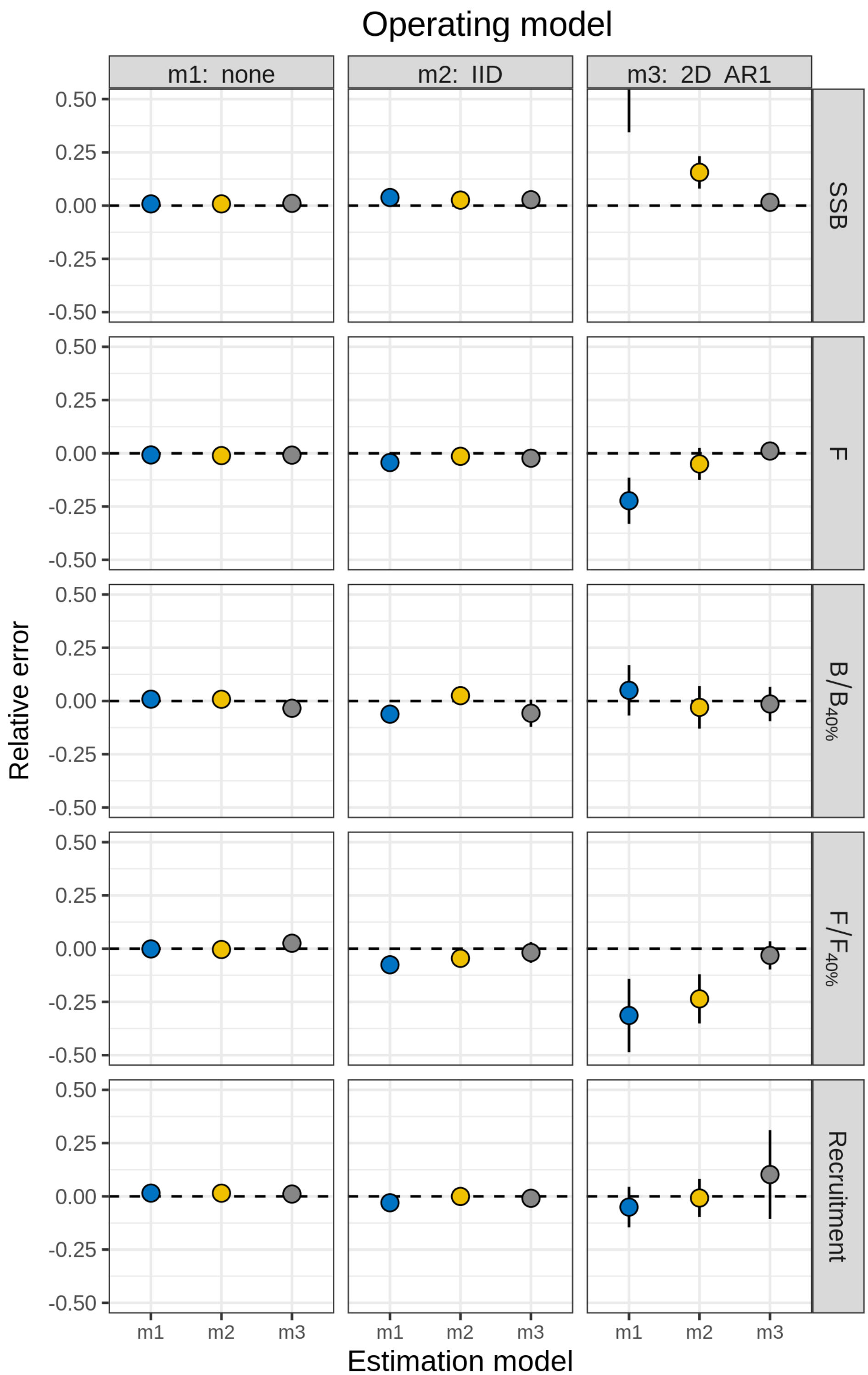

Figure 10: Relative error of key quantities estimated for butterfish using three models of natural mortality (M) random effects. m1 = no random effects on M. m2 = M deviations are independent and identically distributed (IID). m3 = M deviations are correlated by age and year (2D AR1).

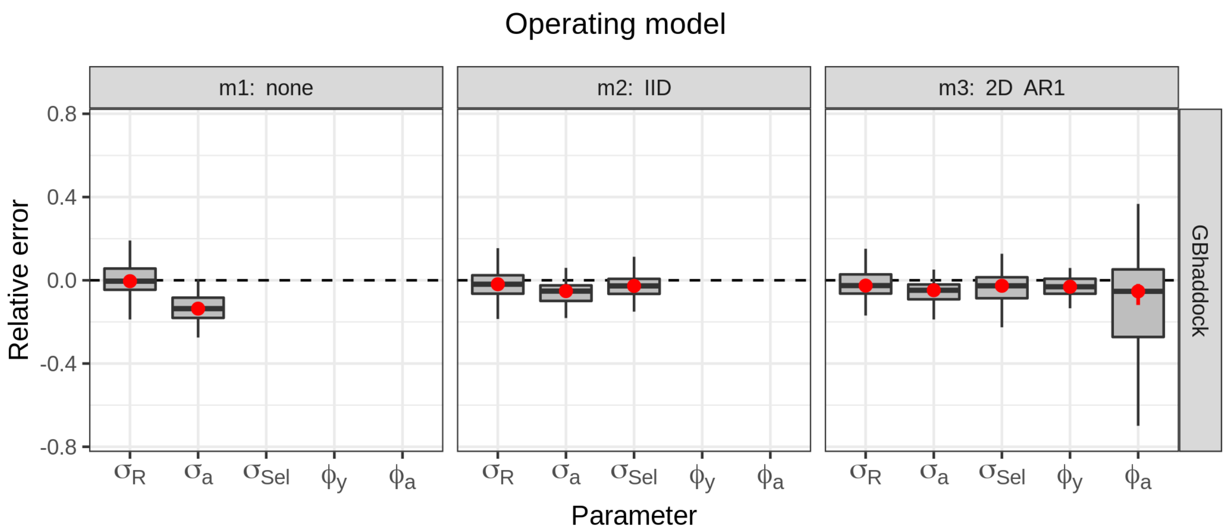

Figure 11: Relative error of parameters constraining selectivity random effects for Georges Bank haddock (GBhaddock). Three models were used to simulate 100 datasets keeping fixed effect parameters constant, and then re-fit to each simulated dataset. m1 = no random effects (constant selectivity). m2 = selectivity deviations were independent and identically distributed (IID). m3 = selectivity deviations were correlated by parameter and year (2D AR1). Relative error was calculated as $\frac{\hat{\theta}_i}{\theta} - 1$, where $\hat{\theta}_i$ was the estimate in simulation i for parameter θ, and θ was the true value (estimate from original dataset). Red points and lines show median relative error with 95% CI.

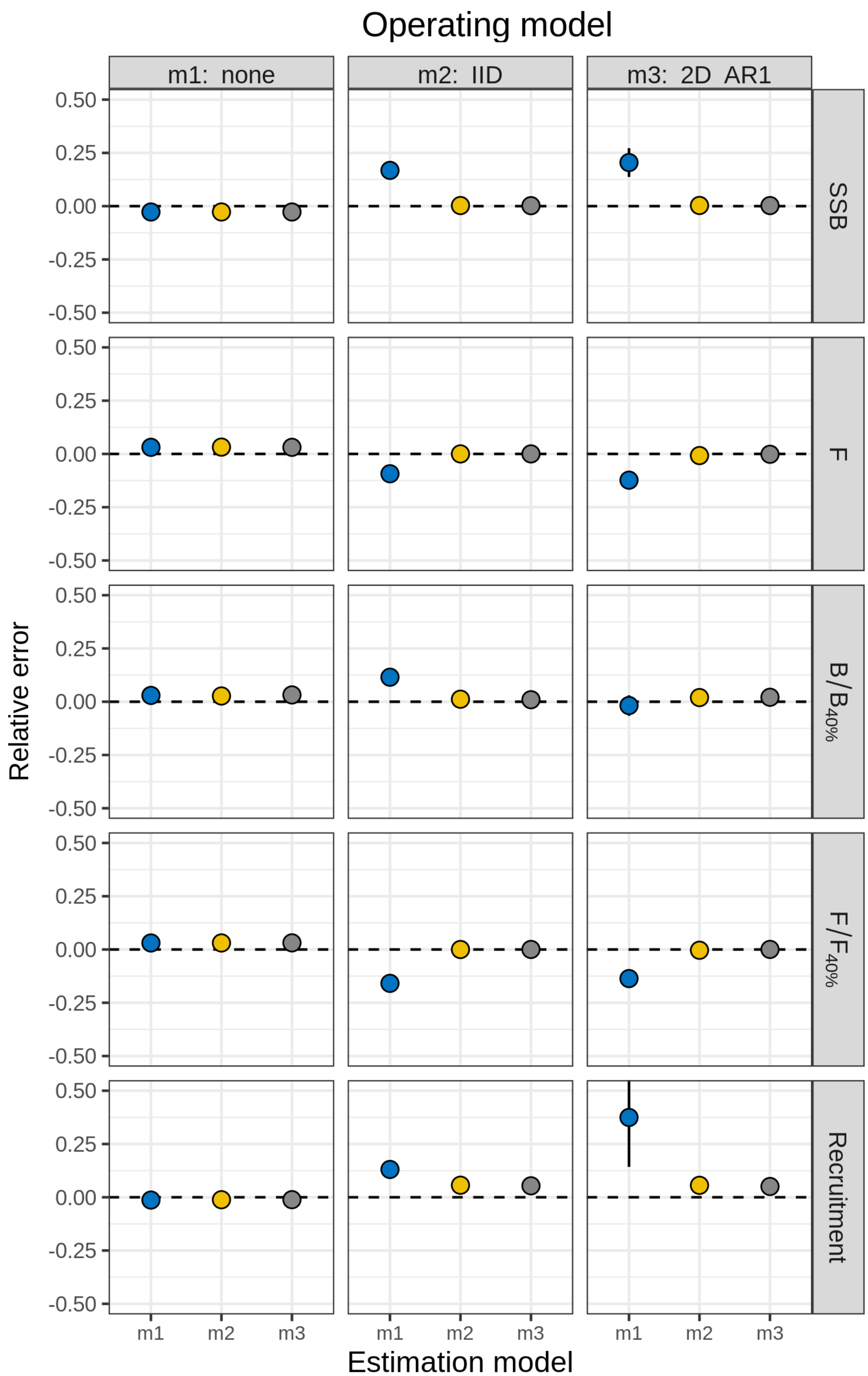

Figure 12: Relative error of key quantities estimated for Georges Bank haddock using three models of selectivity random effects. m1 = no random effects (constant logistic selectivity). m2 = selectivity deviations are independent and identically distributed (IID). m3 = selectivity deviations are correlated by parameter and year (2D AR1).

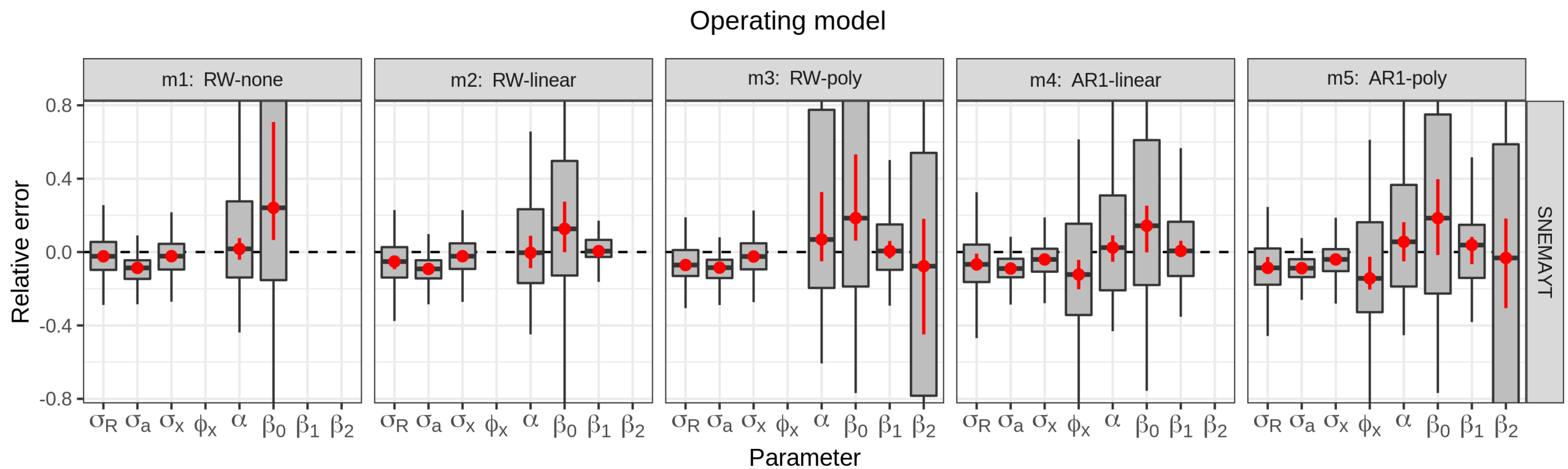

Figure 13: Relative error of parameters constraining variation in recruitment for Southern New England-Mid Atlantic yellowtail flounder (SNEMAYT). Five models were used to simulate 100 datasets keeping fixed effect parameters constant, and then re-fit to each simulated dataset. All models estimated recruitment using the Beverton-Holt function and included CPI effects on β: $\hat{R}_{t+1} = \frac{\alpha S_t}{1+e^{\beta_0+\beta_1 x_t+\beta_2 x_t^2} S_t}$. m1 = Cold Pool Index (CPI) modeled as a random walk (RW) with no effect on recruitment ($\beta_1 = \beta_2 = 0$). m2 = CPI as RW, linear effect on β. m3 = CPI as RW, 2nd order polynomial effect on β. m4 = CPI as AR1, linear effect. m5 = CPI as AR1, polynomial effect. Relative error was calculated as $\frac{\hat{\theta}_i}{\theta} - 1$, where $\hat{\theta}_i$ was the estimate in simulation i for parameter θ, and θ was the true value (estimate from original dataset). Red points and lines show median relative error with 95% CI.