The Woods Hole Assessment Model (WHAM): Incorporating environmental covariates into a state-space assessment framework

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Abstract

WHAM is great.

Keywords

state-space; stock assessment; mixed effects; random effects; time-varying; Template Model Builder (TMB)

1 Introduction

Grab stuff from NRC and Fish/Climate proposals.

1.1 Context: assessments in the U.S. Northeast

- Long history, high F (pre-data)
- Empirical weight-at-age
- Retrospective patterns
- ASAP3/4
- Operational vs. research-track
- The Northeast U.S. Shelf LME is rapidly changing. Top priority is to "continue development of stock assessment models that include environmental terms" (Hare et al., 2016).

1.2 Motivation #1: advantages of state-space stock assessments

- objective estimation of process errors and data weighting, e.g. σ_R, instead of ad-hoc
- inherently predict unobserved states, so predicting missing data/years and into the future is natural
- allow for time/age variation in demographic processes while estimating fewer parameters
- natural framework to include environmental time-series
- lower retros and AIC, larger (more realistic) uncertainty compared to SCAAs. Cite ICES state-space if in review.

(Aeberhard et al., 2018; Miller et al., 2016; Nielsen and Berg, 2014)

1.3 Motivation #2: allow for environmental effects

- Reduced retrospective patterns
- Lower residual variance

(Miller et al., 2016; Miller and Hyun, 2018; O'Leary et al., 2019)

1.4 How is WHAM different from SAM?

Not sure where to put this... may be more natural after introducing equations in Methods, some in Discussion. Definitely will be a question in readers' minds so may be good to introduce early?

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.

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.

1.5 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?

1.6 Overview

In summary, the NEFSC wants an assessment framework that i) estimates random effects (i.e. a state-space model), ii) includes environmental effects, and iii) is easy to test against status quo SCAA models (ASAP). The objectives of this manuscript are to introduce the WHAM framework and demonstrate unbiasedness in self- and cross-tests.

2 Methods

2.1 Model description

2.1.1 Unobserved states (random effects)

2.1.1.1 Numbers-at-age (survival)

2.1.1.2 Natural mortality (M)

2.1.1.3 Selectivity

2.1.1.4 Environmental covariate(s)

2.1.1.4.1 Time-series model

2.1.1.4.2 Observation model

2.1.1.4.3 Link to population

2.1.2 Data/observation model

2.1.2.1 Catch (agg, age comp)

2.1.2.2 Index (agg, age comp)

2.2 Simulation tests

We used the stocks in Table 1.

We used R (R Core Team, 2020). WHAM is available as an R package (Miller and Stock, 2020). OSA residuals.

3 Results

Sweet figures.

4 Discussion

4.1 Overview

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

4.2 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 survival 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?

4.3 Extensions

4.3.1 Multivariate spatiotemporal environmental data

4.3.2 Length/growth estimation

4.3.3 Ecov models

- AR(k)
- splines

- Gaussian process/EDM/Munch/Sugihara

4.4 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: Stocks used in simulation tests.

	Modules tested			Model dim		Biol. par.		Stock status	
Stock	NAA	M	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	2.52	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			9	86	0.2	1.65	4.30	0.12

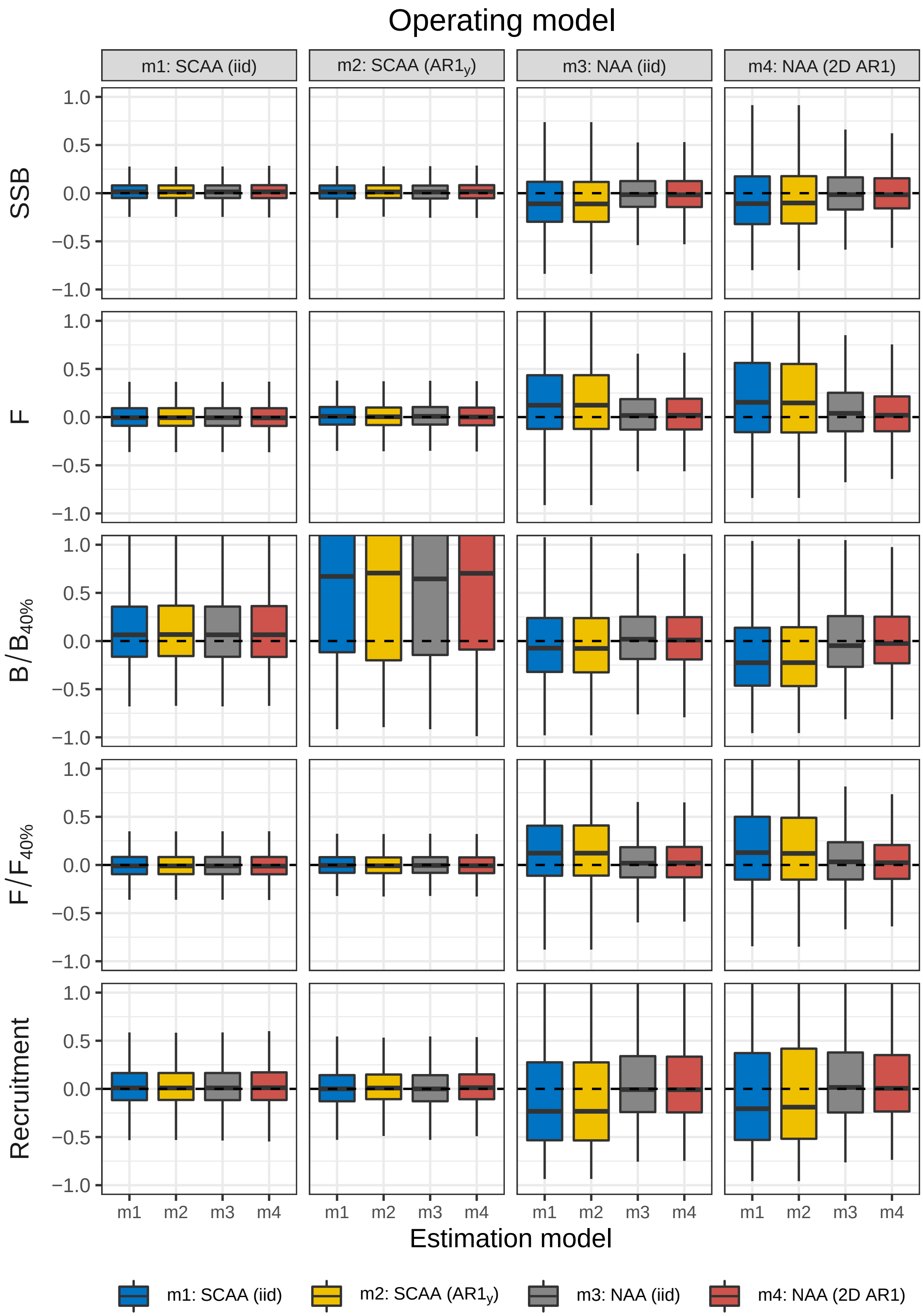


Figure 1: Relative error of key quantities estimated for Southern New England-Mid-Atlantic yellowtail flounder using four models of numbers-at-age (NAA) random effects. m1 = only recruitment deviations are random effects (most similar to traditional statistical catch-at-age, SCAA), and deviations are independent and identically distributed (IID). m2 = as m1, but with autocorrelated recruitment deviations (AR1). m3 = all NAA deviations are IID random effects. m4 = as m3, but deviations are correlated by age and year (2D AR1).

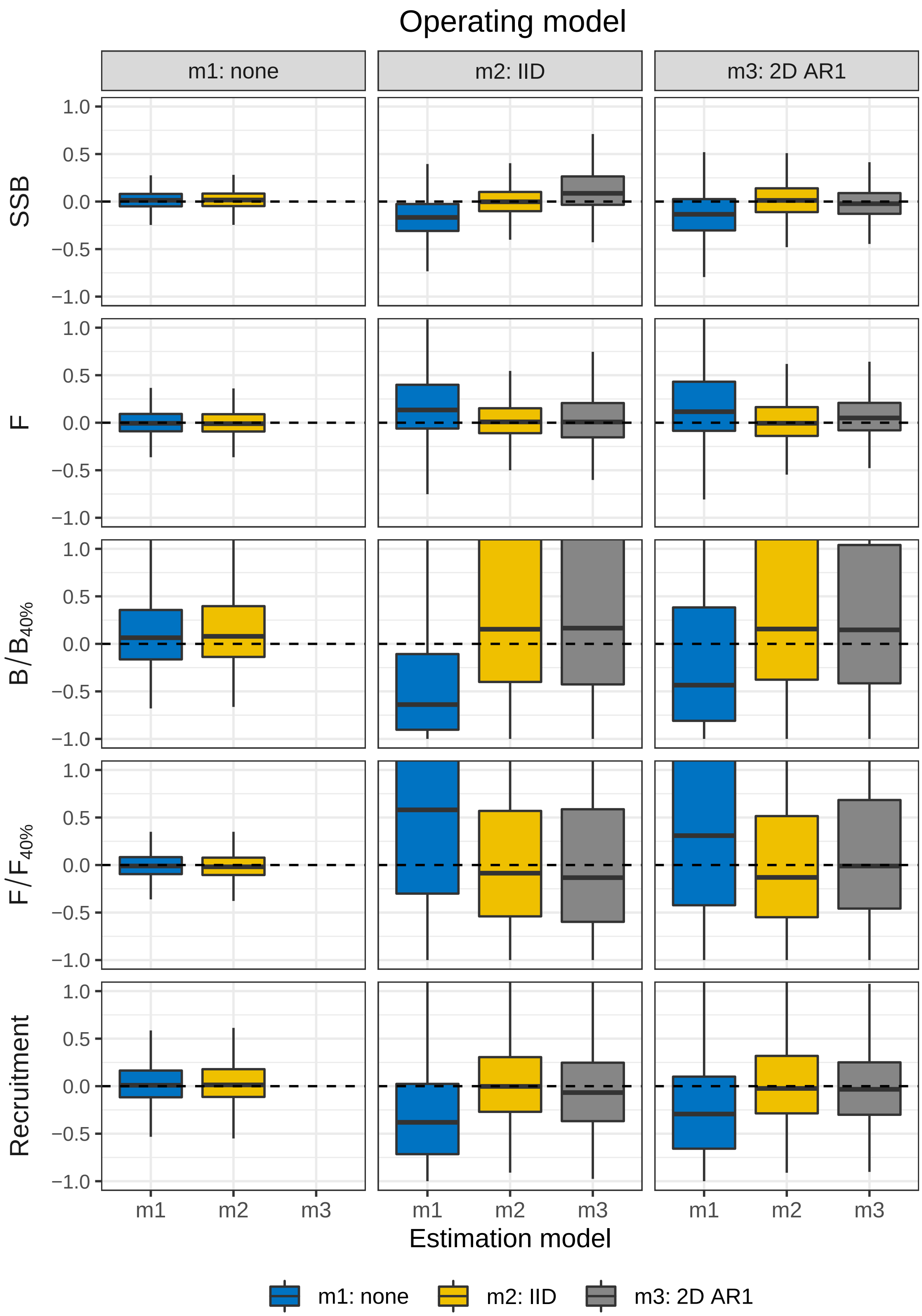
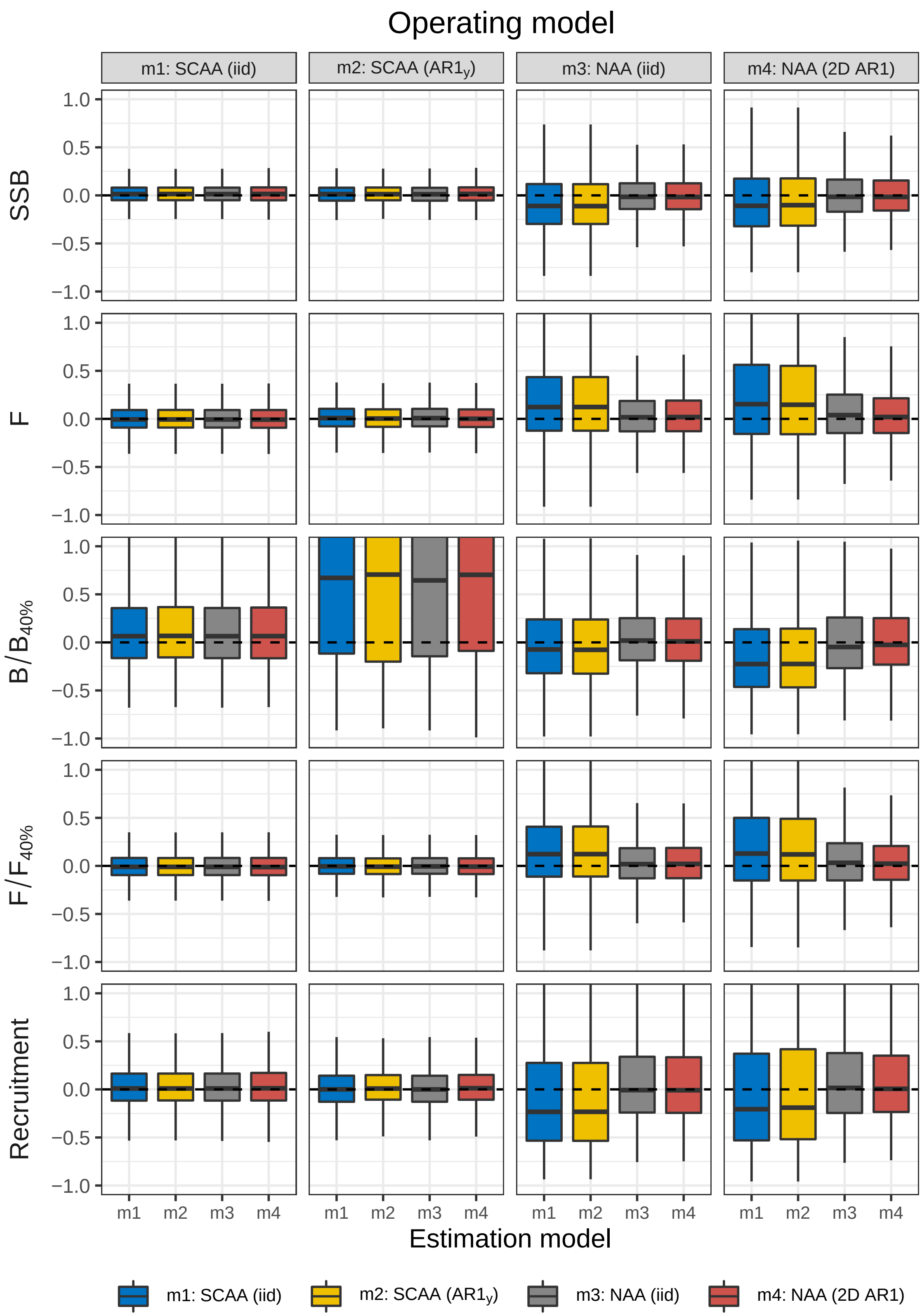


Figure 2: Relative error of key quantities estimated for Southern New England-Mid-Atlantic yellowtail flounder using three models of natural mortality (M) random effects. m1 = no random effects on M. m2 = M deviations are independent and identically distributed (IID). m3 = M deviations are correlated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

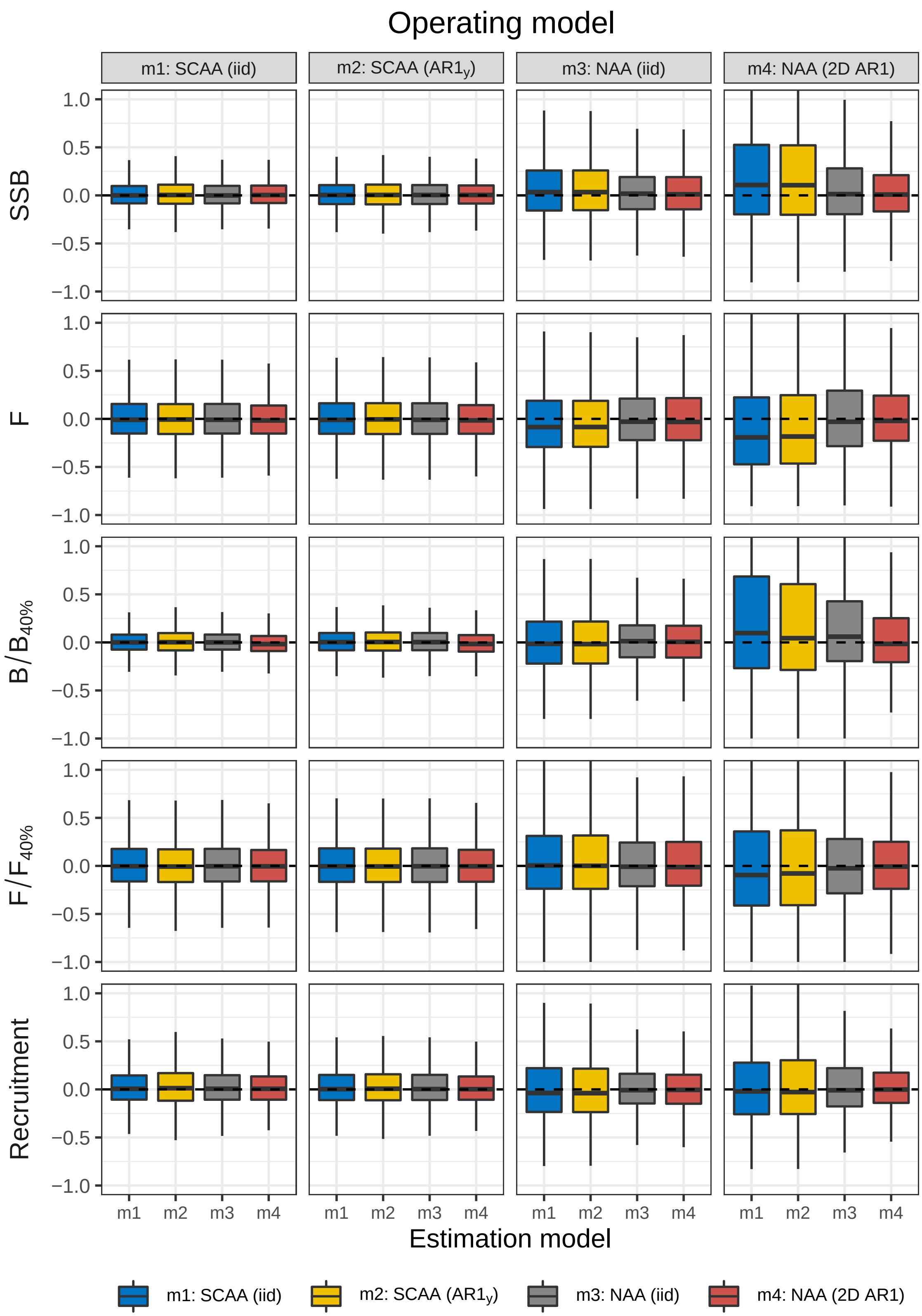
4.5 Stock: Southern New England-Mid Atlantic (SNEMA) Yellowtail Flounder

4.5.1 Model: Numbers-at-age (NAA)



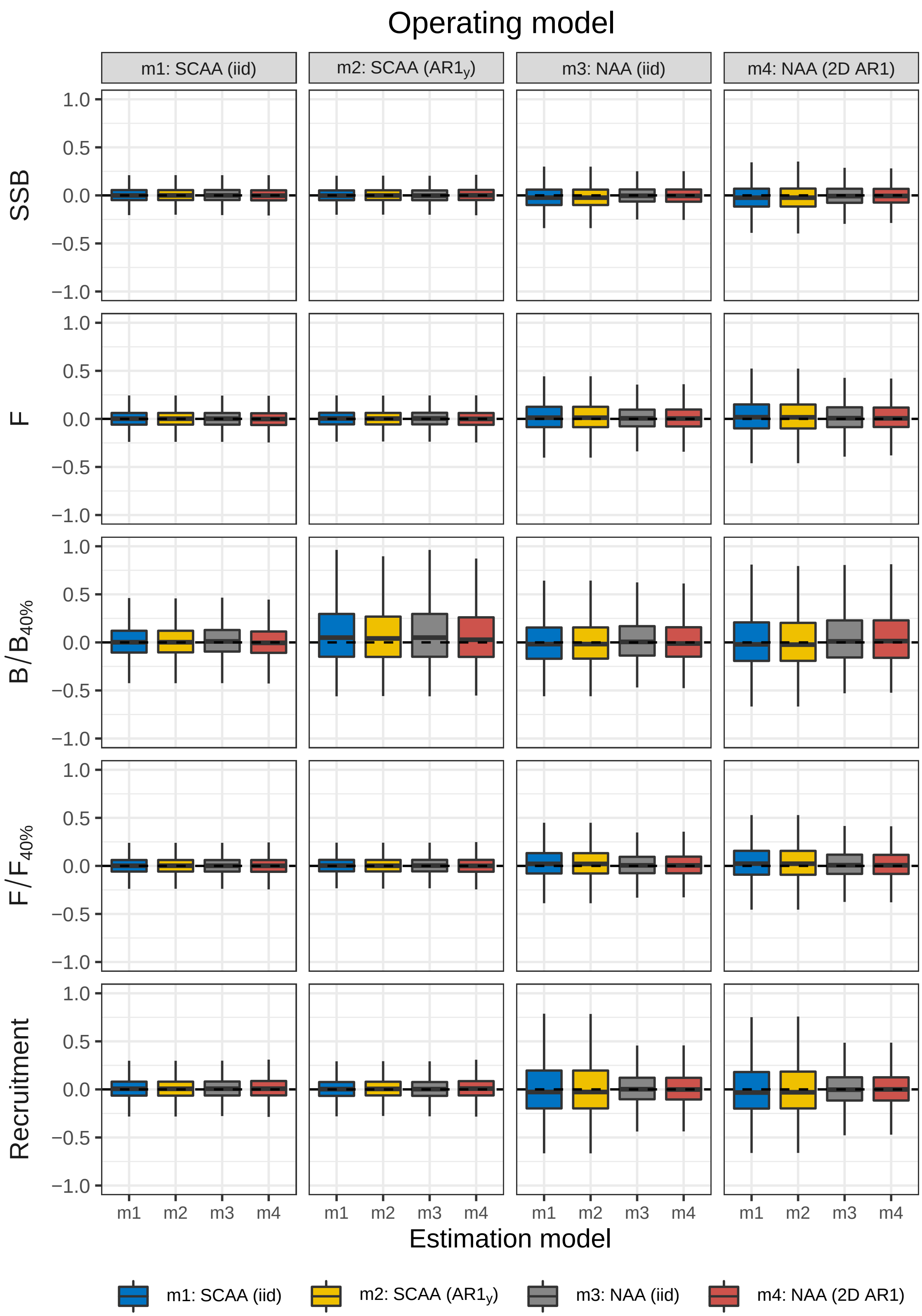
4.6 Stock: Butterfish

4.6.1 Model: Numbers-at-age (NAA)



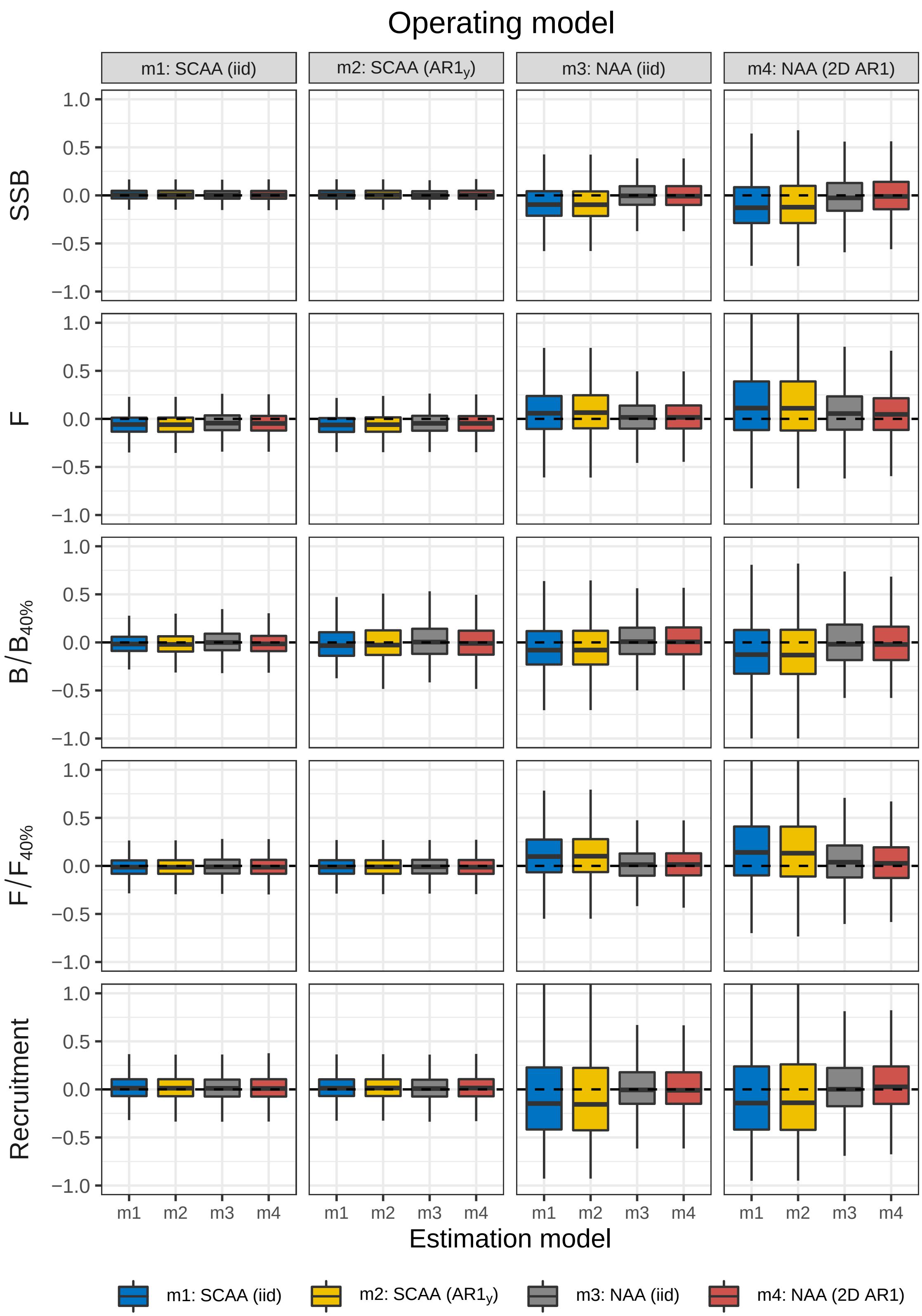
4.7 Stock: North Sea Cod

4.7.1 Model: Numbers-at-age (NAA)



4.8 Stock: Icelandic Herring

4.8.1 Model: Numbers-at-age (NAA)



4.9 Stock: Georges Bank Haddock

4.9.1 Model: Numbers-at-age (NAA)