Implications of process error in selectivity for approaches to weighting compositional data in fisheries stock assessments

Ian J. Stewart[1] and Cole C. Monnahan[2]

[1] Corresponding author:
International Pacific Halibut Commission
2320 West Commodore Way, Suite 300
Seattle, WA 98199-1287
206-552-7667
Ian@iphc.int

[2] Quantitative Ecology and Resource Management
University of Washington
Seattle, WA 98195-5020
monnahc@uw.edu

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Abstract

Lack-of-fit in a stock assessment model can be related to both data weighting and the treatment of process error. Although these contributing factors have been studied separately, interactions between them are potentially problematic. In this study we set up a simple simulation intended to provide general guidance to analysts on the performance of an age-structured model under differing assignments of compositional data weight and process variance. We compared cases where the true sample size is under-, 'right-' or over-weighted, and the degree of process variance (in this case temporal variability in selectivity) is under, correctly, or overestimated. Each case was evaluated with regard to estimation of spawning biomass, and MSY-related quantities. We also explored the effects of the estimation of natural mortality, steepness, as well as incorrectly specifying process error in selectivity when there is none. Results showed that right-weighted estimation models assuming the correct degree of process error performed best in estimating all quantities. Underweighting produced larger relative errors in spawning biomass, particularly when too much process error was allowed. Conversely, overweighting produced larger errors mainly when the degree of process error was underestimated. MSY-related quantities were sensitive to both the estimation of natural mortality, and particularly steepness. We suggest that data weighting and the treatment of process error should not be considered independently: estimation is most likely to be robust when process error is allowed (even if overestimated) and when compositional data are not excessively down-weighted.

Highlights:

- Right-weighted estimation models assuming the correct degree of process error in fishery selectivity performed best in estimating spawning biomass, as well as the spawning biomass corresponding to MSY.
- Under-weighting tended to produce larger relative errors in spawning biomass when process error was correctly specified.
- Over-weighting produced larger errors mainly when the degree of process error was underestimated.
- MSY-related quantities were sensitive to both the estimation of natural mortality, and particularly steepness.
- Data-weighting and the treatment of process error in fishery selectivity should not be considered independently when constructing reliable stock assessments.

1 Introduction

Integrated statistical fisheries stock assessments are commonly used for the management of many important fish stock around the world (Fournier and Archibald 1982; Hilborn and Walters 1992; Maunder and Punt 2013; Megrey 1989; Quinn and Deriso 1999). Modern integrated models can be complex, considering multiple sources of data, with alternative error assumptions and relative weights (Maunder and Piner 2014; Maunder and Punt 2013). Two recent workshops have highlighted the importance of how selectivity, relative data weights and process error are treated in integrated assessment models (Maunder and others 2014 summary for data weighting workshop).

There are many sources of process error which may be important contributors to bias and imprecision in integrated stock assessments, including recruitment variability, mortality rates, growth, selectivity and catchability (e.g., Hurtado-Ferro and others 2014; Johnson and others 2015; Linton and Bence 2008; Ono and others 2015). Recent research has highlighted the inherent complexity in the treatment of selectivity, historically considered to be ‘nuisance’ parameters, but increasingly acknowledged to be important for unbiased estimates of stock size and trend (Maunder and others 2014). Misspecification of selectivity has long been known to produce bias in statistical catch-at-age models (Kimura 1990), and several recent studies have shown that time-varying selectivity may be expected in many cases (Sampson 2014; Sampson and Scott 2012). Misspecifying selectivity has also been implicated in retrospective patterns (Hurtado-Ferro and others 2014; Stewart and Martell 2014).

Data weighting is also a particularly problematic aspect of stock assessment (Francis 2011), and the focus of the recent CAPAM workshop (Ref. summary for this issue). Data weighting is an issue because, although they arise from separate processes, the true underlying error distribution and sampling variances for most (perhaps all) fisheries data are unknown (Maunder 2011). Further, the likelihoods that are used in most stock assessment models are often known to be convenient approximations (e.g., the multinomial), despite far greater known complexity in the underlying processes. The primary inputs for data weighting are the variance estimates assigned to indices of abundance and the sample sizes (or variances, depending on the likelihood function used) assigned to length- or age-composition data (hereafter 'composition data'). For instance, a research survey may collect lengths for thousands of fish, sampled from hundreds of hauls, but an effective sample size of 20 may ultimately be used in the assessment (Francis 2011; Stewart and Hamel 2014). The results of stock assessments are sensitive to data weighting, and the choice of method used is most consequential when there is model misspecification (Punt 2016). Several recent papers, and some in this issue, explore alternative methods for deriving weights after the model is assumed to be correctly specified (Citations pending other manuscripts in this issue).

However, existing research has largely focused on either the treatment of process error (e.g., estimation of time-varying fishery selectivity) or data weighting, but not both (although, see Thompson, this issue). Assuming one is known allows for several relatively simple methods (Maunder and Harley 2011; Thompson and Lauth 2012; Thorson and Taylor 2014), but when both are uncertain the problem becomes much more difficult. Lack-of-fit cannot necessarily be objectively assigned to either observation variance or process variance in a stock assessment (and there are other sources of both process and observation error, Linton and Bence 2008) based on model fit alone.

In this study, we structured a simulation approach to evaluate the performance of a simple age-structured model under combinations of different compositional data weighting and process error assumptions, and whether natural mortality, steepness of the stock-recruit curve, or both were estimated. This simple simulation is intended to provide general guidance to analysts, not in terms of which data weighting rules or approaches should be applied, but whether it is preferable to over- or under-estimate the weight placed on compositional data and whether the treatment of process error in fishery selectivity affects this choice.

2 Simulation approach

We used the ss3sim package (Anderson and others 2014; Anderson and others 2015) implemented in R (R Core Team 2016), to create an operating model with a very simple, but groundfish-like life history. This package uses the flexible software stock synthesis (Methot Jr and Wetzel 2013), coded in AD Model Builder (Fournier and others 2012) for both the operating and estimation models in simulations (i.e., self-testing instead of cross-testing; Deroba and others 2014). As in other published studies using ss3sim, this framework is well suited to relatively simple simulation experiments intended to target the effects of one to several factors with representative, but not necessarily realistic levels of model complexity (e.g., Hurtado-Ferro and others 2014; Monnahan and others 2015; Ono and others 2015). All code used to produce this study is based on open source tools and available online (Appendix A).

The operating model was used to generate replicate data sets including variability in annual recruitment, which were then fit with a range of estimation models; a summary of both models is provided below. Results were summarized via the distribution of relative error in the estimated spawning biomass across the time series, and a few key metrics related to Maximum Sustainable Yield (merely to illustrate the potentially differing effects on reference point estimation). We compared cases where the true sample size is under-, 'right-' or over-weighted, and the degree of process error (in this case temporal variability in fishery selectivity) is under, correctly, or overestimated. We also explored the effects of the estimation of natural mortality, steepness, as well as incorrectly specifying process error in fishery selectivity when there is none. A test was run with extremely large sample sizes to verify that model dynamics were performing as expected, and that the estimation models produced unbiased results when correctly specified.

2.1 Operating model specifications

The operating model was structured to be similar to many simple stock assessments with a moderately long time-series of observations, a single fishery responsible for the catch and a single fishery-independent survey (Table 1). Population dynamics are governed by fishing and natural mortality (M=0.2), with annually variable recruitment centered on a Beverton-Holt stock-recruitment function with an intermediate value for steepness (h=0.65). Selectivity for both the fishery and survey was asymptotic, using a simple parametric logistic form (implemented using the ascending side of the double-normal parameterization in stock synthesis; assuming asymptotic selectivity likely reducing the potential for confounding with natural mortality in all estimation models). Growth was specified as a von Bertalannfy curve with moderately rapid growth and a clear asymptote at older ages. Fishing effort, growth parameters, and all other parameters were fixed among simulations, with the only variability arising from recruitment deviations unique to each replicate, and stochastic generation of data.

The fishery and fishery-independent survey each produced compositional data (lengths and ages) for a subset of the time-series years (Table 1, Appendix A) based on a multinomial distribution matching the true population (i.e., unbiased) with samples sizes roughly consistent with those observed in ‘data-rich’ stock assessments. Two operating model scenarios were evaluated: 1) time–invariant fishery selectivity (no process error) and 2) a temporal trend in fishery selectivity (process error). The fishery selectivity trend corresponded to a linear decrease in the parameter defining the first size with 100% selectivity (as parameterized in stock synthesis), followed by a linear increase in that parameter over most of the informed time-series (Fig. 1). This pattern in fishery selectivity was selected over a simple ‘white-noise’ (independent random deviations from a mean) to mimic trends suspected in some stock assessments with directional changes in fishing behavior, biology or both (Stewart and Martell 2014). This type of change is more likely to produce systematic bias in the estimated demographics of the removals, and therefore potentially more import for analysts to consider.

The operating model time series resulted in a stock fished down from unexploited equilibrium relatively rapidly then recovering to slightly higher levels at the very end of the time-series, characteristic of some histories observed in actual stock assessments (Fig. 2). For each combination of operating model scenario and estimation model case (described below), 300 replicate time series were randomly generated.

2.2 Estimation models

Estimation models were correctly specified (matching the operating model) for all model parameters except: fishery selectivity, virgin recruitment, survey catchability and the set of specific factors explored: the degree of process error, the degree of observation error, the value for natural mortality, and the value for steepness of the stock-recruitment function (Table 2; we did not evaluate the more complicated case of natural mortality and steepness estimated simultaneously). The sample sizes were not tuned in the estimation model, but were specified as either too small (0.1x), right (1x), or too large (10x), relative to the true simulated sample size (x). Fishery selectivity was either assumed to be constant, or allowed to vary as an additive random walk over time (Methot 2015) in the estimation model (as if a trend might be expected by the analyst). The deviations for the random walk were constrained by a fixed sigma corresponding to either too little (sigma = 0), correctly specified (sigma = 0.5), or too large (sigma = 1.0). Preliminary analysis showed that allowing a random walk provided a parameterization that was capable of generally mimicking the true pattern (Fig. 3).

Each combination of factors (parameters estimated, compositional data weighting, and treatment of process error) represented a single case for the estimation model. Each case was fit to all 300 replicates for each of the two scenarios of the operating model. Fitting was performed via penalized maximum likelihood, with the sigmas for fishery selectivity and recruitment deviations specified as described above. In order to maintain the central tendency of the stock-recruitment function given lognormal variability in annual deviations, the bias correction for recruitment deviations (Methot and Taylor 2011) was adjusted to match the conditions of each case and then held constant across all replicates. This was performed by estimating the correction over the first 10 time-series, then using the average of these for all replicates within each case (this procedure has become relatively standard for simulation experiments; see Anderson et al. 2014 for more information). Convergence of the estimation model for all replicates was evaluated based on inversion of the Hessian matrix.

3 Results

Estimation model behavior across both operating model scenarios and all combinations of factors was robust, with all replicates converging for all scenarios.

In the simple operating model scenario without any process error in fishery selectivity, fitting estimation models assuming the correct value for steepness and natural mortality in all cases resulted in essentially unbiased and reasonably precise estimates of spawning biomass over the entire time-series (Median absolute relative error (MARE) = 0.05; Table 3, Fig. 4). The cases allowing for process error in fishery selectivity were similarly precise (MARE = 0.05) when compared to those correctly specified, as the penalty (sigma) constrained the deviations toward zero in the absence of signal in the data. When the composition data were over-weighted (by a factor of 10) from the true sample sizes, the time-series also showed more variability (presumably the estimated fishery selectivity was following random variability due to sampling error) but remained unbiased.

In the second operating model scenario, with process error in fishery selectivity, more interesting patterns were observed. Specifically, when natural mortality and steepness were correctly specified as well as the degree of process error, the time-series of spawning biomass estimates remained unbiased and relatively precise (MARE = 0.04-0.06 depending on compositional data weighting; Table 3, Fig. 5). However, when the estimation models were misspecified to have no process error, the time series became systematically biased (MARE = 0.05-0.26), as the fishery removals from the dynamics were also misspecified. Right-weighting only partially ameliorated this bias, and underweighting the composition data largely removed it (MARE = 0.05) likely allowing the unbiased survey index to drive the estimated trend).

For cases where natural mortality was not assumed to be known without error, the degree of bias and imprecision was substantial (MARE = 0.06-0.26; Table 3, Fig. 6). The worst performing case was represented by misspecified fishery selectivity and over-weighted compositional data (Fig. 6c). For this case, many replicates resulted in estimates of steepness equal to 1.0. Reducing the weight on the composition data improved the precision, but not the bias, as the misspecification remained. For the correctly specified selectivity sigma cases, the worst precision occurred when the data were underweighted, and there was little cost in imprecision to overweighting the data. A similar pattern was also observed even when too much process error in fishery selectivity was allowed.

For estimation models where fishery selectivity was misspecified and steepness was not assumed to be known, performance of all data weighting was poor (MARE = 0.40-0.51; Table 3, Figs. 7, 8). Correctly specifying fishery selectivity, or allowing too much process error performed appreciably better across all data weightings, with right-weighted data performing best (MARE = 0.11).

Overall, the simulation results showed that right-weighted estimation models assuming the correct degree of process error performed best in estimating the time-series of spawning biomass (Table 4), as well as the spawning biomass corresponding to MSY

(Table 5). Under-weighting produced larger relative errors in spawning biomass, particularly when too much process error was allowed. Conversely, overweighting produced larger errors mainly when the degree of process error was underestimated. MSY-related quantities were sensitive to both the estimation of natural mortality, and particularly steepness (Fig. 7).

4 Discussion

The results of this study are consistent with other recent work suggesting there is little cost besides increased run times to estimating process error even if not present, but potentially substantial bias resulting from misspecification due to the overly simplistic assumption that fishery selectivity is constant (Martell and Stewart 2014; Punt and others 2014; Thorson and Taylor 2014). However, more complex approaches to smoothing of fishery selectivity may perform somewhat differently (Maunder and Harley 2011), and if used, may warrant additional investigation. The bias due to misspecification in fishery selectivity, except in the case where all other model parameters are known perfectly and there is an unbiased trend index, cannot be ameliorated by adjustments to compositional data weighting. Put simply, analysts should be aware that they cannot weight their way out of a misspecified model!

Although purely objective methods for determining compositional data weighting and process error specification would be highly desirable for stock assessment analysts, we pragmatically assert that the specifics of any particular assessment may suggest tempering default approaches with a more subjective approach. There is a cost to down-weighting compositional data, except if the rest of the model is perfectly specified.

Where uncertainty is likely to exist in other scaling parameters (such as natural mortality and steepness) excessive down-weighting should be avoided.

Our results suggest that data weighting and the treatment of process error should be considered together: estimation is most likely to be robust when process error is allowed (even if overestimated) and when data are not excessively down-weighted. We recognize that the population dynamics simulated in this study are simple, and not likely to be specifically representative of individual species or life-history groups for which assessments may be conducted. As such, a general simulation is no substitute for careful examination of model performance given a particular configuration of observed data and life-history characteristics. Further, the approach taken here considers only several simple estimation models; more complex models may exhibit differing behavior and should also be explored in future studies. However, we suspect the trends across treatment of data and process error may be similar. Our results should serve as a starting point for analysts conducting assessments: they provide general conceptual guidance for an approach when neither the true degree of process error, nor the correct data weighting is known.

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Table 1. Operating model summary.

Specification	Value	Comment
Structure		
Time series length	100 years	
Catches	Years 27-100	Based on fixed vector of *Fs* (Fig. 2)
Fleets	2	Fishery and survey
Survey and fishery selectivity shape	Asymptotic	Two-parameter logistic
Stock-recruit function	Beverton-Holt	Parameterized with R_0 and h
Recruitment deviations	Annual	Randomly generated from lognormal
Biology	Single-sex	
Model parameters		
Log(R_0)	18.7	
Steepness (h)	0.65	
Recruitment variability (σ_r)	0.4	
Natural Mortality (M)	0.2	Of course
Survey catchability (Q)	1	
Length at age-1	20 cm	
Asymptotic length	132 cm	
Brody growth coefficient (k)	0.2	
CV of length-at-age	0.1	Constant across all ages
Survey selectivity slope	5.2	Log (width); constant over time
Survey selectivity peak length	41.8	Constant over time
Fishery selectivity slope	5.1	Log (width); constant over time
Fishery selectivity peak length	variable	Constant or with process error (Figure 1)
Selectivity process error (scenario 2)	Trend up and down in peak parameter	When treated as deviations, this trend results in the implied sigma below.
Implied selectivity sigma	0.5	
Data Generation		
Survey index data	Year 76-100	Biennial
Survey index sigma	0.2	In log space; constant across years
Survey length and age data	Year 76-100	Biennial
Survey length and age sample size	500 (each)	Generated from a multinomial
Fishery length and age data	Triennially from year 36-72, annually thereafter	
Fishery length and age sample size	100	Generated from a multinomial

Table 2. Estimation model factors; each combination across all levels of each was analyzed (except M and h were not simultaneously estimated).

Process error	**Data weight**	**Natural mortality (M)**	**Steepness (h)**
S0: None (Sigma = 0)	D_1: Under-weighted (x0.1)	M0: Fixed	h0: Fixed
S1: Sigma = 0.5	D_2: Right-weighted (x1)	M1: Estimated	h1: Estimated
S2: Sigma = 1.0	D_3: Over-weighted (x10)		

Table 3. Median absolute relative error over the entire estimated time series of spawning biomass for each combination of operating model scenario and estimation model case.

Process error	Natural mortality	Steepness	Under-weighted (D1)	Right-weighted (D2)	Over-weighted (D3)
Operating model without process error in selectivity					
S0	M0	h0	0.05	0.05	0.05
S0	M0	h1	0.11	0.09	0.13
S0	M1	h0	0.05	0.05	0.05
S1	M0	h0	0.05	0.05	0.05
S1	M0	h1	0.11	0.09	0.13
S1	M1	h0	0.05	0.05	0.05
S2	M0	h0	0.05	0.05	0.05
S2	M0	h1	0.11	0.09	0.13
S2	M1	h0	0.05	0.05	0.05
Operating model with process error in selectivity					
S0	M0	h0	0.05	0.12	0.26
S0	M0	h1	0.40	0.45	0.51
S0	M1	h0	0.06	0.11	0.26
S1	M0	h0	0.05	0.04	0.06
S1	M0	h1	0.18	0.11	0.15
S1	M1	h0	0.05	0.04	0.06
S2	M0	h0	0.05	0.04	0.06
S2	M0	h1	0.12	0.11	0.15
S2	M1	h0	0.05	0.04	0.05

Table 4. Median absolute relative error in estimated SSB_{MSY} for each combination of operating model scenario and estimation model case.

Process error	Natural mortality	Steepness	Under-weighted (D1)	Right-weighted (D2)	Over-weighted (D3)
Operating model without process error in selectivity					
S0	M0	h0	0.05	0.05	0.05
S0	M0	h1	0.11	0.09	0.13
S0	M1	h0	0.05	0.05	0.05
S1	M0	h0	0.05	0.05	0.05
S1	M0	h1	0.11	0.09	0.13
S1	M1	h0	0.05	0.05	0.05
S2	M0	h0	0.05	0.05	0.05
S2	M0	h1	0.11	0.09	0.13
S2	M1	h0	0.05	0.05	0.05
Operating model with process error in selectivity					
S0	M0	h0	0.05	0.12	0.26
S0	M0	h1	0.40	0.45	0.51
S0	M1	h0	0.06	0.11	0.26
S1	M0	h0	0.05	0.04	0.06
S1	M0	h1	0.18	0.11	0.15
S1	M1	h0	0.05	0.04	0.06
S2	M0	h0	0.05	0.04	0.06
S2	M0	h1	0.12	0.11	0.15
S2	M1	h0	0.05	0.04	0.05

Figure captions

Figure 1. Trend in the fishery selectivity parameter defining the first size at 100% selectivity (upper panel), and the resulting fishery selectivity curve (lower panel) used in the operating model at years 26 (and the full time-series when sigma = 0), 40, and 100.

Figure 2. Time series plot of median spawning biomass across replicates (a), from the operating models with and without process error in selectivity. The *y*-axis units are arbitrary and left off for clarity. Instantaneous fishing mortality (F), constant across all replicates (b).

Figure 3. Median fishery selectivity parameter deviations estimated across all replicates, with (bottom row) and without (top row) process error in the operating model (natural mortality and steepness are fixed at the true values; M0 and h0). Columns represent the level of process error specified in the EM.

Figure 4. Time series estimates of relative error in spawning biomass (shading indicates the 25, 50, 75, and 95th percentiles) for the operating model with no process error, and estimation models do not estimate natural mortality (M0) or steepness (h0).

Figure 5. Time series estimates of relative error in spawning biomass (shading indicates the 25, 50, 75, and 95th percentiles) for the operating model with process error (scenario 2), and estimation models that do not estimate natural mortality (M0) or steepness (h0).

Figure 6. Time series estimates of relative error in spawning biomass (shading indicates the 25, 50, 75, and 95th percentiles) for the operating model including process error, and estimation models estimating natural mortality (M1).

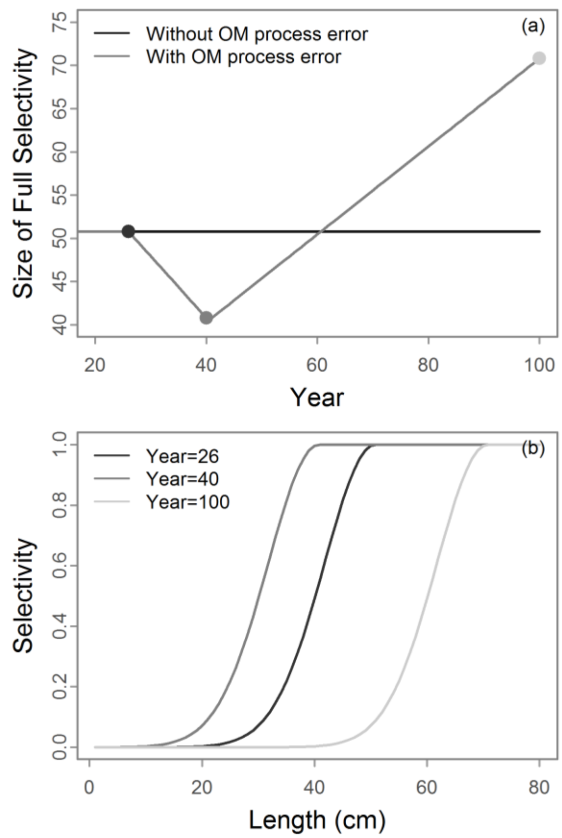
Figure 7. Distribution of relative error in spawning biomass producing MSY across all cases of the estimation model, and both operating model scenarios.

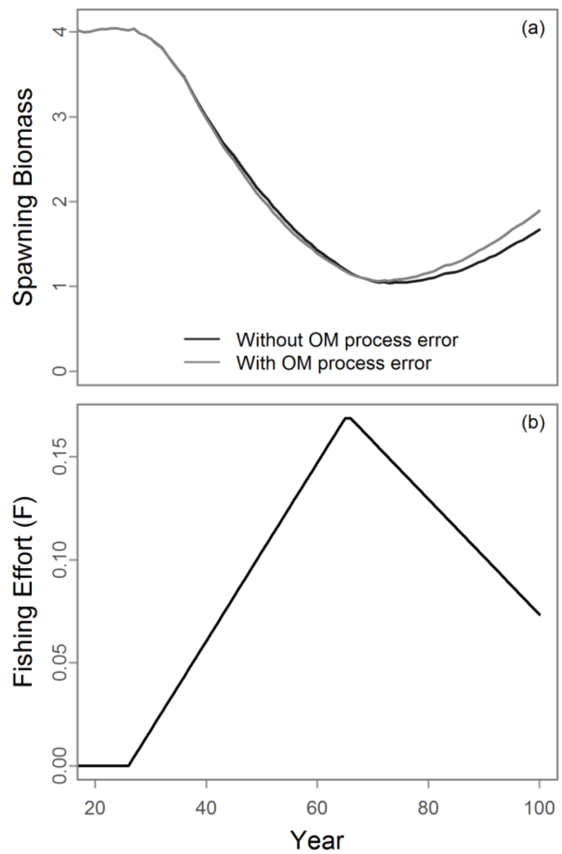
Figure 8. Distribution of relative error in spawning biomass over all years for all cases of the estimation model, and both operating model scenarios.

Supplementary material

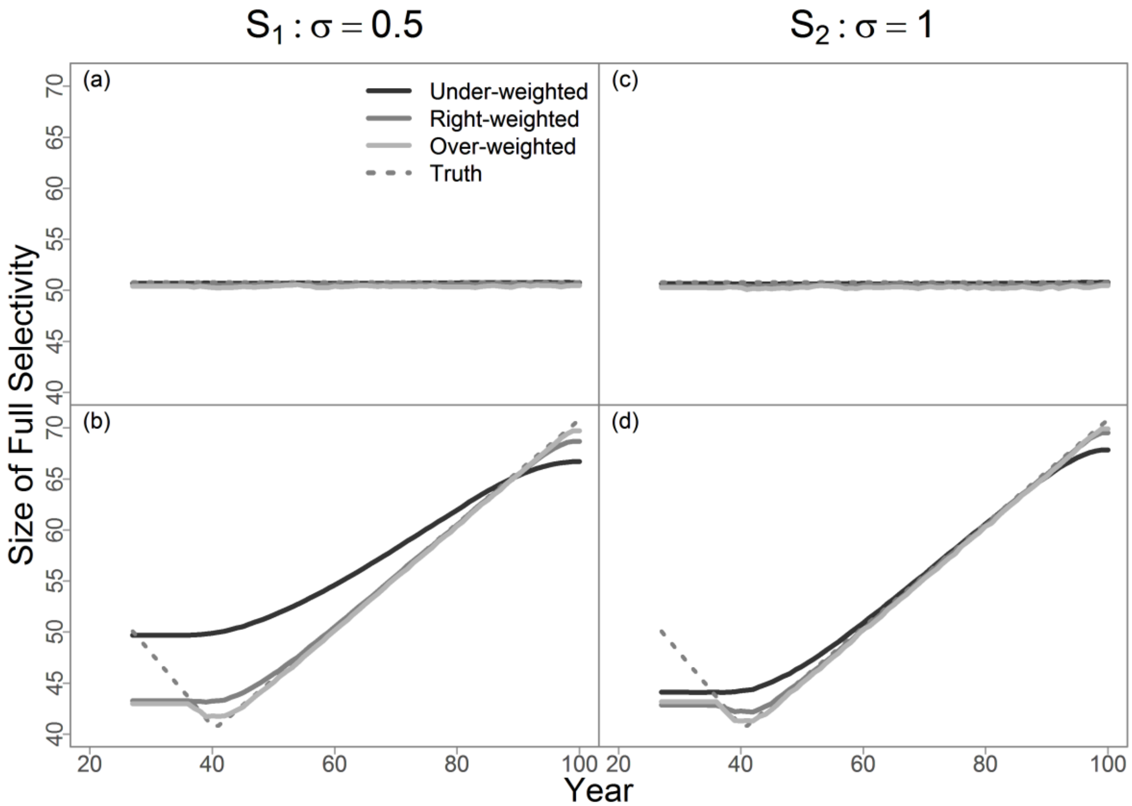
Appendix A

This simulation study can be fully reproduced with widely accessible open-source tools. The website https://github.com/ss3sim/procdata contains all model configuration files, results, additional figures, and code to rerun the simulation. We encourage interested readers to explore and extend the simulation if desired.

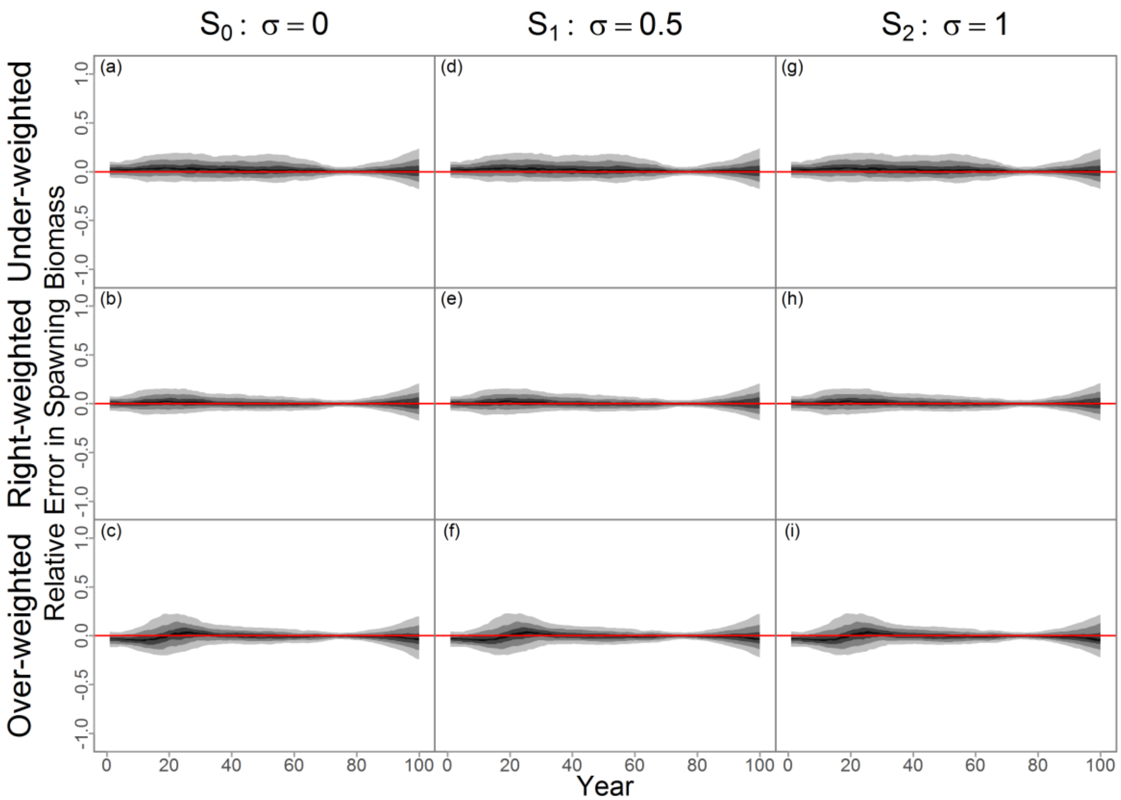

(a)
Without OM process error
With OM process error
Size of Full Selectivity
75
70
65
60
55
50
45
40
20
40
60
80
100
Year
(b)
Year=26
Year=40
Year=100
Selectivity
1.0
0.8
0.6
0.4
0.2
0.0
0
20
40
60
80
Length (cm)



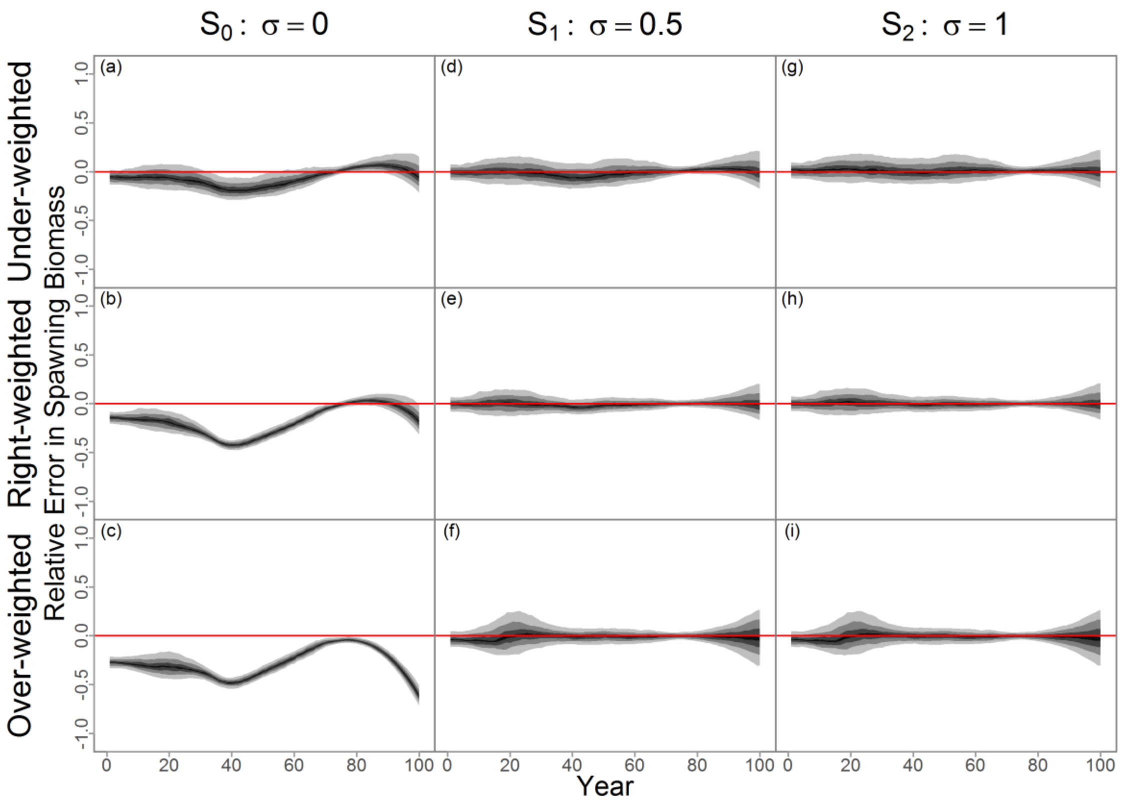
(a)
Spawning Biomass
0
1
2
3
4
Without OM process error
With OM process error
(b)
Fishing Effort (F)
0.00
0.05
0.10
0.15
20
40
60
80
100
Year



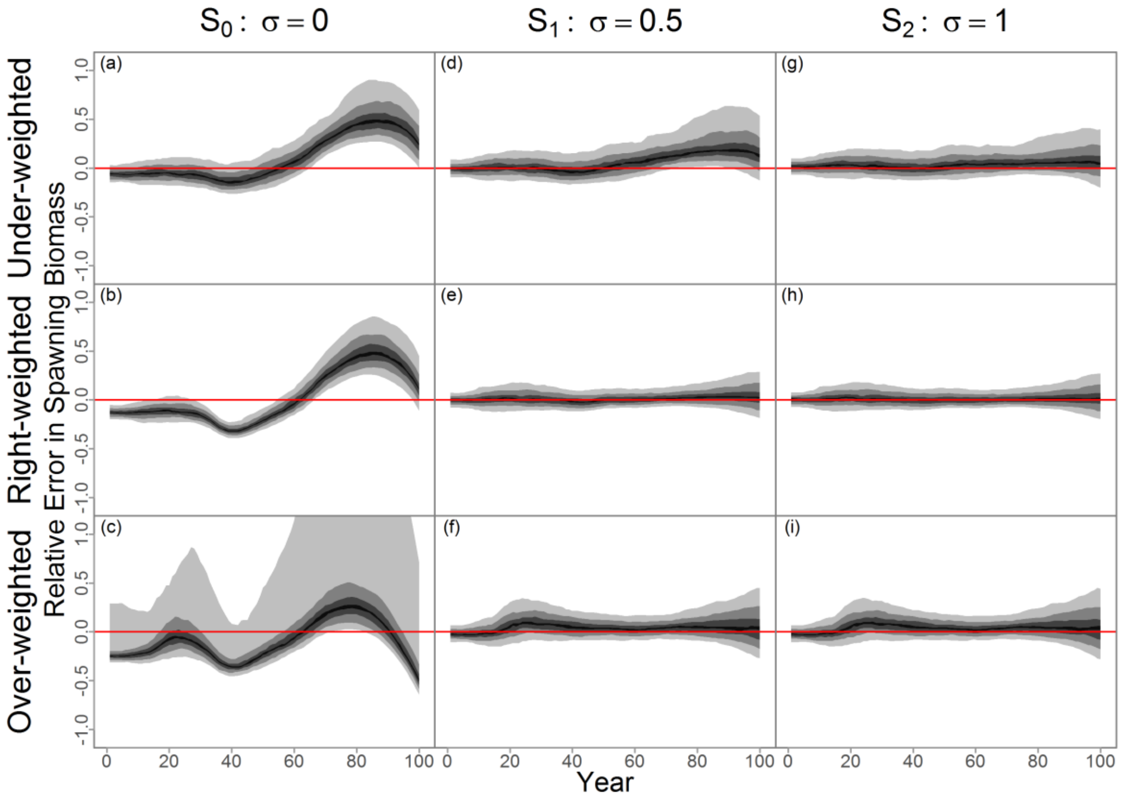
$S_1 : \sigma = 0.5$
$S_2 : \sigma = 1$
(a)
(b)
(c)
(d)
Under-weighted
Right-weighted
Over-weighted
Truth
Size of Full Selectivity
Year

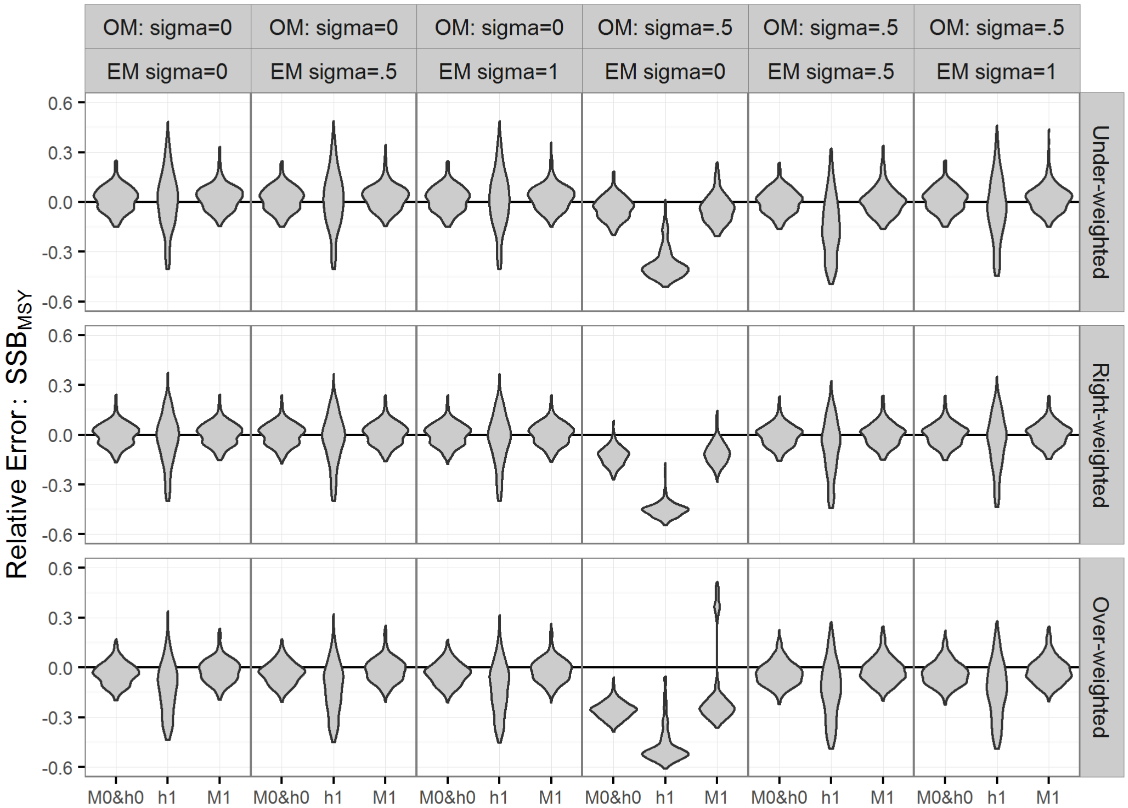


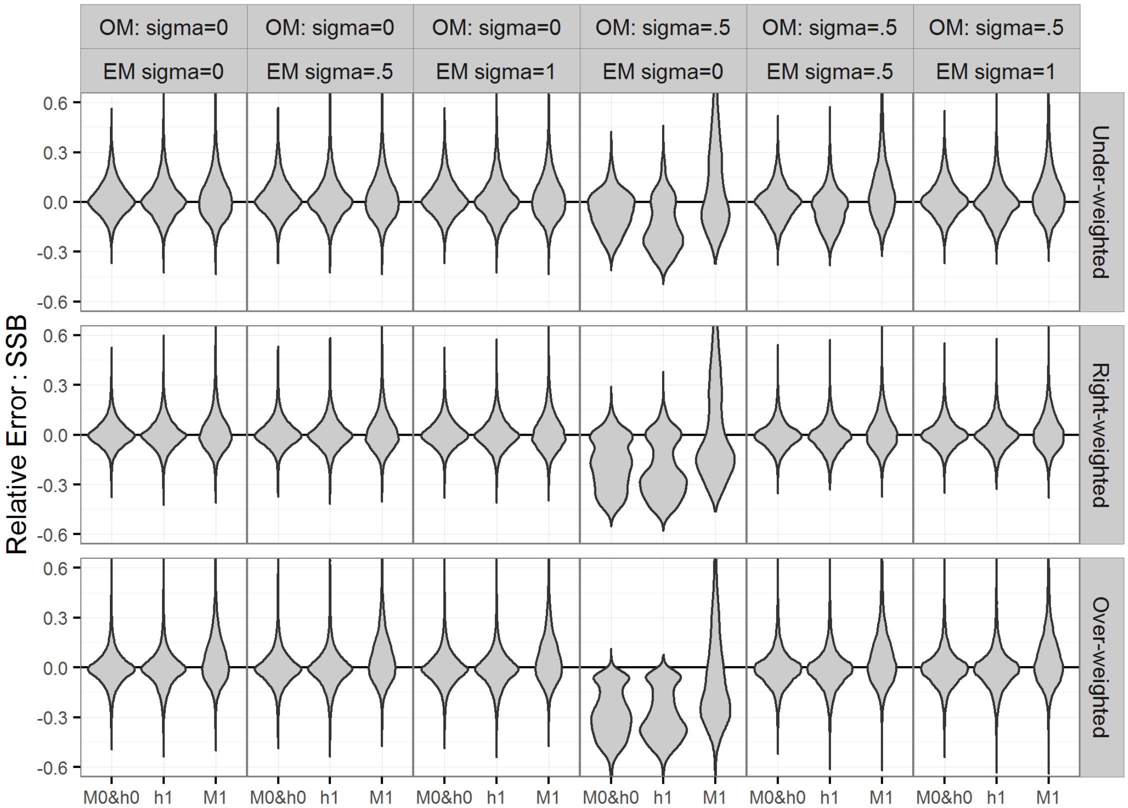
$S_0: \sigma = 0$
$S_1: \sigma = 0.5$
$S_2: \sigma = 1$
Under-weighted
Right-weighted
Over-weighted
Relative Error in Spawning Biomass
(a)
(b)
(c)
(d)
(e)
(f)
(g)
(h)
(i)
1.0
0.5
0.0
-0.5
-1.0
0
20
40
60
80
100
Year



$S_0: \sigma = 0$
$S_1: \sigma = 0.5$
$S_2: \sigma = 1$
Under-weighted
Right-weighted
Over-weighted
Relative Error in Spawning Biomass
(a)
(b)
(c)
(d)
(e)
(f)
(g)
(h)
(i)
1.0
0.5
0.0
-0.5
-1.0
0
20
40
60
80
100
Year


$S_0 :\ \sigma = 0$
$S_1 :\ \sigma = 0.5$
$S_2 :\ \sigma = 1$
Under-weighted
Right-weighted
Over-weighted
Relative Error in Spawning Biomass
Year
(a)
(b)
(c)
(d)
(e)
(f)
(g)
(h)
(i)
1.0
0.5
0.0
-0.5
-1.0
0
20
40
60
80
100


OM: sigma=0
OM: sigma=0
OM: sigma=0
OM: sigma=.5
OM: sigma=.5
OM: sigma=.5
EM sigma=0
EM sigma=.5
EM sigma=1
EM sigma=0
EM sigma=.5
EM sigma=1
Under-weighted
Right-weighted
Over-weighted
Relative Error : SSB$_{MSY}$
0.6
0.3
0.0
-0.3
-0.6
M0&h0
h1
M1


OM: sigma=0
OM: sigma=0
OM: sigma=0
OM: sigma=.5
OM: sigma=.5
OM: sigma=.5
EM sigma=0
EM sigma=.5
EM sigma=1
EM sigma=0
EM sigma=.5
EM sigma=1
Under-weighted
Right-weighted
Over-weighted
Relative Error : SSB
0.6
0.3
0.0
-0.3
-0.6
M0&h0
h1
M1