



## Original Article

# Reducing retrospective patterns in stock assessment and impacts on management performance

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Retrospective patterns are consistent directional changes in assessment estimates of biomass in a given year when additional years of data are added to an assessment, and have been identified for a number of exploited marine stocks. Retrospective patterns are sometimes reduced by allowing population processes to vary over time in an assessment, but it is unclear how this practice influences management performance. We simulated stocks in which retrospective patterns were induced by forcing natural mortality, selectivity, or growth to vary over time. We then evaluated the impacts of reducing retrospective patterns by allowing population processes to vary in the assessment. In general, allowing selectivity, natural mortality, and growth to vary in the assessment decreased the magnitude of retrospective patterns in estimated spawning biomass, regardless of whether the true time-varying process was allowed to vary. However, the resulting reference points and management advice were sometimes drastically in error when a process other than the true time-varying process was allowed to vary, and these errors resulted in under-utilizing or over-exploiting the stock. Given the potential for error, identifying the important population processes that vary over time when addressing retrospective patterns should be a priority when providing management advice and may require increased longitudinal life history studies.

**Keywords:** climate change, management strategy evaluation, retrospective bias, retrospective pattern, stock assessment.

## Introduction

Stock assessments are often used to estimate the status of stocks relative to targets or limits for fishing mortality and spawning biomass. Estimates of status help managers understand likely consequences of alternative management measures (Legault *et al.*, 2009). Advice derived from stock assessments depends on the assumptions made in the modelling process; some of these assumptions may be violated. For example, climate change will influence variables (e.g. sea surface temperature and pH; Doney *et al.*, 2012) known to influence the productivity of a stock (Hollowed *et al.*, 2013). Changing environmental variables can also influence natural mortality (e.g. Walther *et al.*, 2002; Genner *et al.*, 2004) and growth (e.g. Hare, 2012). In addition, fishing practices can change over time and are known to affect the relative age or size

at which fish are selected in the fishery (Sampson, 2014, Stockhausen, 2015).

Changes in population processes over time unaccounted for in stock assessments can influence the ability of the models to estimate biomass (ICES, 2008; Hurtado-Ferro *et al.*, 2015). Retrospective patterns are considered “systematic inconsistencies among a series of estimates of population size based on increasing periods of data” (Mohn, 1999). These patterns can be caused by data inconsistencies and/or unaccounted for changes in population processes over time and can present problems in management (e.g. Butterworth, 1981; Sinclair *et al.*, 1991; Parma, 1993; Hamazaki and Zheng, 2012; Valero, 2012; Stewart and Martell, 2014). In practice, the appearance of a retrospective pattern suggests that an assessment will consistently over- or under-estimate spawning

biomass in the terminal year of the assessment (i.e. the year for which the estimate of stock size is used for catch advice and status determination), thus impacting the management advice provided. One way of avoiding retrospective patterns arising from changes in population process over time is to allow a process to vary within the assessment method—examples include: selectivity (Martell and Stewart, 2013), unaccounted for mortality (Cadigan and Farrell, 2005), and growth (e.g. Brooks and Legault, 2016; Thorson *et al.*, 2015). However, data to inform which process is time-varying can be difficult to obtain, and many of the processes modelled within assessments are confounded to some degree (Butterworth and Punt, 1990; Thompson, 1994). Furthermore, reference points for fishing mortality and stock status are key management quantities, and allowing processes to vary over time complicates the estimation of these reference points because selecting the frame of reference for the stock becomes more subjective.

Here, we explored the impacts of allowing a population process (i.e. growth, natural mortality, or fishery selectivity) to vary over time on management advice using management strategy evaluation (MSE). MSE has been used extensively to evaluate the performance of management strategies, which are combinations of monitoring schemes, assessment methods and harvest control rules (e.g. Smith *et al.*, 1999; Punt *et al.*, 2002; Ianelli *et al.*, 2011; Szuwalski and Punt, 2013). First, we simulated data in which population processes changed over time such that retrospective patterns arose when standard stock assessment methods (i.e. assessment models with constant natural mortality, growth, or selectivity) were applied to the simulated data. These data sets were then analysed with assessment models in which some population processes could vary over time. The time-varying assessment methods were then evaluated based on their ability to: (i) reduce retrospective patterns when the correct process was allowed to vary, (ii) reduce retrospective patterns when the incorrect process was assumed to vary, (iii) estimate the pattern in variation for the time-varying process, and (iv) estimate reference points and quantities used in management. Comparisons among model specifications for management over scenarios were then used to gauge the relative impact on removals and the population (i.e. management performance) caused by biases in estimates of management quantities resulting from mis-specified models.

## Methods

### Model framework

The simulation framework was comprised of three components: an operating model (including a model of how data are collected for use in assessments), an assessment method, and a harvest control rule. The operating model was an age- and length-structured population dynamics model that allowed for time-varying population and management processes (e.g. natural mortality or the uncertainty around survey estimates could vary over time). The assessment method was also an age- and length-structured (coded in AD Model Builder, Fournier *et al.*, 2012; see Appendix for model description and estimated parameters) and could be configured to allow growth, fishery selectivity, or natural mortality to vary over time. Quantities used in management (e.g. biomass, reference points, and allowable catches) were calculated after fitting the population dynamics model to the data sampled from the operating model. Data sources include the catch biomass from a single fishery, a survey index of abundance, and proportion-at-length data from both the fishery and the survey. The harvest

control rule (HCR) employed commonly used proxies for  $B_{MSY}$  and  $F_{MSY}$  (i.e.  $B_{35\%}$  and  $F_{35\%}$ ; Clark, 1991; see Appendix for details). The HCR specifies an upper limit for the total allowable catch (TAC) as a function of fishing mortality, which is then denoted as the overfishing limit (OFL) and set as a given year's removals. Similar to those used in many areas, the HCR is sloping, meaning that the fishing mortality rate ( $F_{35\%}$ ) is reduced when the stock drops below some target (here  $B_{35\%}$ ) and is held constant at higher stock size. The goal of the management strategies presented here is to maintain spawning biomass around  $B_{MSY}$  by recommending the appropriate OFL.

Hurtado-Ferro *et al.* (2015) examined how retrospective patterns arose in a simulation framework for a sardine-like, a cod-like, and a flatfish-like species. Retrospective patterns for each species were generated by applying assessment methods to data drawn from operating models in which a process varied over time that was not allowed to vary in the assessment. In this study, we used parameter values based on the cod-like life history scenario from Hurtado-Ferro *et al.* (2015) (Table 1). We look only at cod-like life history because flatfish-like species performed similarly to cod-like and parameter estimation of sardine-like dynamics were found to be too unstable for automated assessment and estimation of parameters given their highly variable productivity. Recruitment variability was set to a low value ( $\sigma_r = 0.001$ ) in projections so that the impact of different assessment methods on retrospective patterns could be more clearly evaluated.

### Simulation structure

Four assessment method configurations were applied to four operating model specifications. Each of these 16 cases included a 50-year period of historical data available for assessment and projections 10 years into the future (with an application of the assessment and HCR occurring in each of those years). Twenty simulations for each case should be sufficient for differences among the assessment methods be detected because  $\sigma_r$  was small. In each replicate, the simulated stock was assessed in each projected year and a total allowable catch calculated using the HCR based on estimated biomass and reference points was removed, after which the operating model dynamics were updated and the data for the next year's assessment and management cycle were generated. Sampling from the operating model was performed with uncertainties often seen in catch monitoring and scientific surveys (Table 1). The assessment methods differed in terms of whether a given population process (e.g. fishery selectivity, growth, or natural mortality) could vary over time (referred to as “Sel vary”, “Grow vary”, and “M vary”, respectively). Only a one of these processes was allowed to vary over time for a given assessment method variant, otherwise confounding between parameters would impair the ability of the assessment method to accurately and precisely estimate parameters used in the calculation of quantities used in management. A “base” assessment method in which fishery selectivity, growth, and natural mortality were not allowed to vary over time was included for comparison.

The operating models from which data for assessment purposes were drawn differed in terms of the presence or absence of time-varying population processes (again, fishery selectivity, growth, and natural mortality). A “base” operating model in which fishery selectivity, growth, and natural mortality did not vary over time was used to establish a baseline for evaluating the performance of the assessment method components of the

**Table 1.** Parameters, estimation status, and values specified in the operating model (and assessment method when not estimated).

Parameter (units)	Symbol	Estimated	Value when specified
<b>Biology</b>			
Natural mortality (year <sup>-1</sup> )	$M$	S	0.2
Maximum length (cm)	$L_{\infty}$	N	132
Growth rate (year <sup>-1</sup> )	$k$	S	0.2
Age at which length is predicted to be 0	$t_0$	N	0.18
Length-weight scaling (kg cm <sup>-3</sup> )	$\alpha$	N	06.8e <sup>-6</sup>
Allometric factor	$\beta$	N	3.1
Length at age standard deviation	$\sigma_{len}$	N	15
Age at 50% maturity (year)	$p_{50}$	N	1.89
Age at 95% maturity (year)	$p_{95}$	N	2.50
Virgin recruitment (numbers)	$R_0$	N	100000
Steepness	$h$	N	0.65
Recruitment variability	$\sigma_r$	N	0.001
Average recruitment	$\bar{R}$	Y	NA
Recruitment deviations	$R_{dev}$	Y	NA
<b>Fishery</b>			
Length at 50% selection (fishery; cm)	$S^{50}$	Y	40
Length at 95% selection (fishery; cm)	$S^{90}$	Y	70
Length at 50% selection (survey; cm)	$S^{50}_{surv}$	Y	30
Length at 95% selection (survey; cm)	$S^{95}_{surv}$	Y	50
Catchability	$q$	N	1
Average fishing mortality	$\bar{F}$	Y	NA
Fishing mortality deviations	$F_{dev}$	Y	NA
<b>Time-varying parameters</b>			
Natural mortality	$M_y$	S	0.255
Growth rate	$k_y$	S	0.274
Length at 50% selection (fishery)	$S_{y,50\%}$	S	50
<b>Data collection</b>			
Coefficient of variation (catch biomass)	$CV_c$	N	0.05
Coefficient of variation (survey biomass)	$CV_s$	N	0.2
Length samples (catch)	$Nsamp_c$	N	200
Length samples (survey)	$Nsamp_s$	N	200
Length bins	$Bin$	N	25

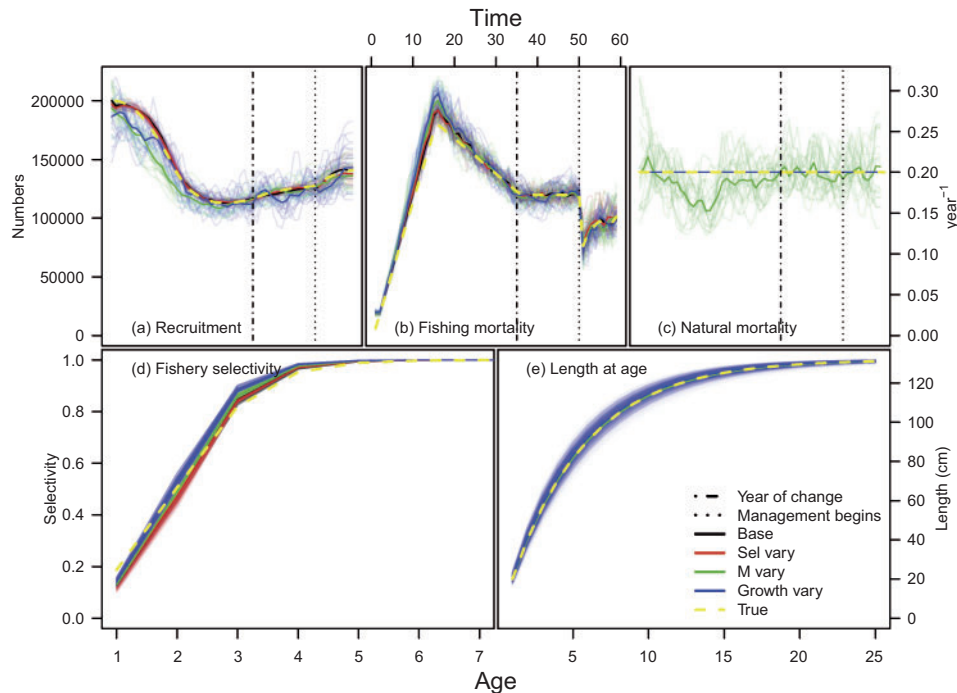
An “S” under the “estimated” column indicates that the parameter is “sometimes” estimated. For example, natural mortality is only estimated in assessments in which natural mortality is allowed to vary over time. “Time varying parameters” indicate the value that the parameter indicated in “Biology” or “Fishery” shifts to in year 35 of the simulation.  $R_0$ ,  $h$ , and  $\sigma_r$  are parameters in the operating model;  $\bar{R}$  and  $R_{dev}$  are parameters in the assessment method.

management strategy and to ensure assessment methods in which additional population processes were allowed to vary over time could return unbiased management quantities. Time-varying processes within the other operating models were modelled as sudden changes in parameters up or down in year 35 of the historical fishery (see Table 1 for the range of the changes). Sudden changes were modelled because they manifest retrospective patterns more strongly than gradual changes (Hurtado-Ferro *et al.*, 2015). Hurtado-Ferro *et al.* (2015) also showed that the timing of the change in a population process (e.g. the change happened 20 years vs. 5 years ago) did not greatly influence the magnitude of retrospective patterns observed in simulated assessments, so we only used operating models in which the change happened in year 35. Two operating models (base and “M vary”) with recruitment variability set higher ( $\sigma_r = 0.4$ ) formed the basis for projections using each of the four assessment methods to explore the impact of additional stochasticity.

Historical fishing mortality ( $F$ ) was specified to ramp up to ~175% of  $F_{35\%}$  ( $0.3^{-y_T}$ ) over 15 years, followed by a decline over 20 years to ~115% of  $F_{35\%}$  ( $0.2^{-y_T}$ ), which was then maintained until the projection began in year 50 (Figure 1b). A single fishing mortality pattern was considered because changing patterns in

$F$  were shown to have little influence the magnitude or direction of retrospective patterns (Hurtado-Ferro *et al.*, 2015). A “ramp up, back off, stabilize” pattern in fishing mortality may reflect a number of fishery settings and generally improves the ability of assessment models to estimate parameters determining population dynamics (Magnusson and Hilborn, 2007).

Calculation of reference points may be influenced by differences introduced into estimated parameters resulting from allowing a process to vary over time in the assessment method. The proxies for  $B_{MSY}$  and  $F_{MSY}$  (i.e.  $B_{35\%}$  and  $F_{35\%}$ ) used here were calculated by first projecting the stock forward under zero fishing mortality and constant recruitment to identify virgin spawning biomass per recruit. Then,  $F_{35\%}$  was specified as the fishing mortality that reduced spawning biomass to 35% of virgin levels under constant recruitment (which has been shown to produce yields near maximum sustainable yield for a large range of shapes for the stock-recruitment relationship; Clark, 1991). A decision must be made about how to specify the parameters used when calculating reference points when a process is allowed to vary over time in the assessment, and best practices are not immediately clear. First, an increase in  $M$  results in an increase in per recruit targets for fishing mortality, yet this results in increased



**Figure 1.** Estimated and true processes for assessments applied to data collected from an operating model in which growth, selectivity, and natural mortality did not vary over time. Thick solid lines of a given colour represent the medians of the estimates for a given process, thin solid lines of a given colour (where visible—these often lay on top of one another) are simulation replicates, dashed yellow lines represent the “true” underlying process in the operating model, vertical dot and dash lines represent the point at which a process begins to vary over time, dotted lines indicate the first year the management strategy is applied. Estimated processes are shown from the final year of assessment. Colours for scenarios are consistent through Figures 2–7. The axis for fishing mortality (b) corresponds to the axis for natural mortality (c). See online copy for colors.

total mortality (Legault and Palmer, 2015). We chose to use the value in the last year of the historical period (which was also the true value over the projection period) to calculate reference points in the operating model. For example, if natural mortality shifted from  $0.2 \text{ yr}^{-1}$  to  $0.25 \text{ yr}^{-1}$  in year 35; natural mortality was specified as  $0.25 \text{ yr}^{-1}$  in the projection period used to calculate the reference points in the operating model. Given the step change modelled in the time-varying processes, the method adopted is most consistent with the provision in the Magnuson Stevens Act to manage to the current environmental conditions, but other perspectives exist on how to treat reference points under time-variation, particularly when there is not a clear change in regime (Legault and Palmer, 2015). Second, when estimating a yearly  $M$  (for example) deviation, using just the values for the final year can be problematic because estimates can be variable from year to year (depending on the weight placed on smoothness for the estimated process). We addressed this problem by taking an average over the last 10 years of the estimated population process to project the stocks when calculating reference points in the estimation model.

Finally, there are several other methods that can be undertaken to attempt to reduce retrospective patterns. For example, assuming some degree of missing catch in recent years (e.g. Legault et al., 2009) or assuming dome-shaped selectivity (e.g. Linton and Bence, 2011) can reduce retrospective patterns. However, including all possible methods is beyond the scope of this manuscript.

### Performance metrics

Retrospective patterns were quantified using a variant of Mohn’s rho (Mohn, 1999):

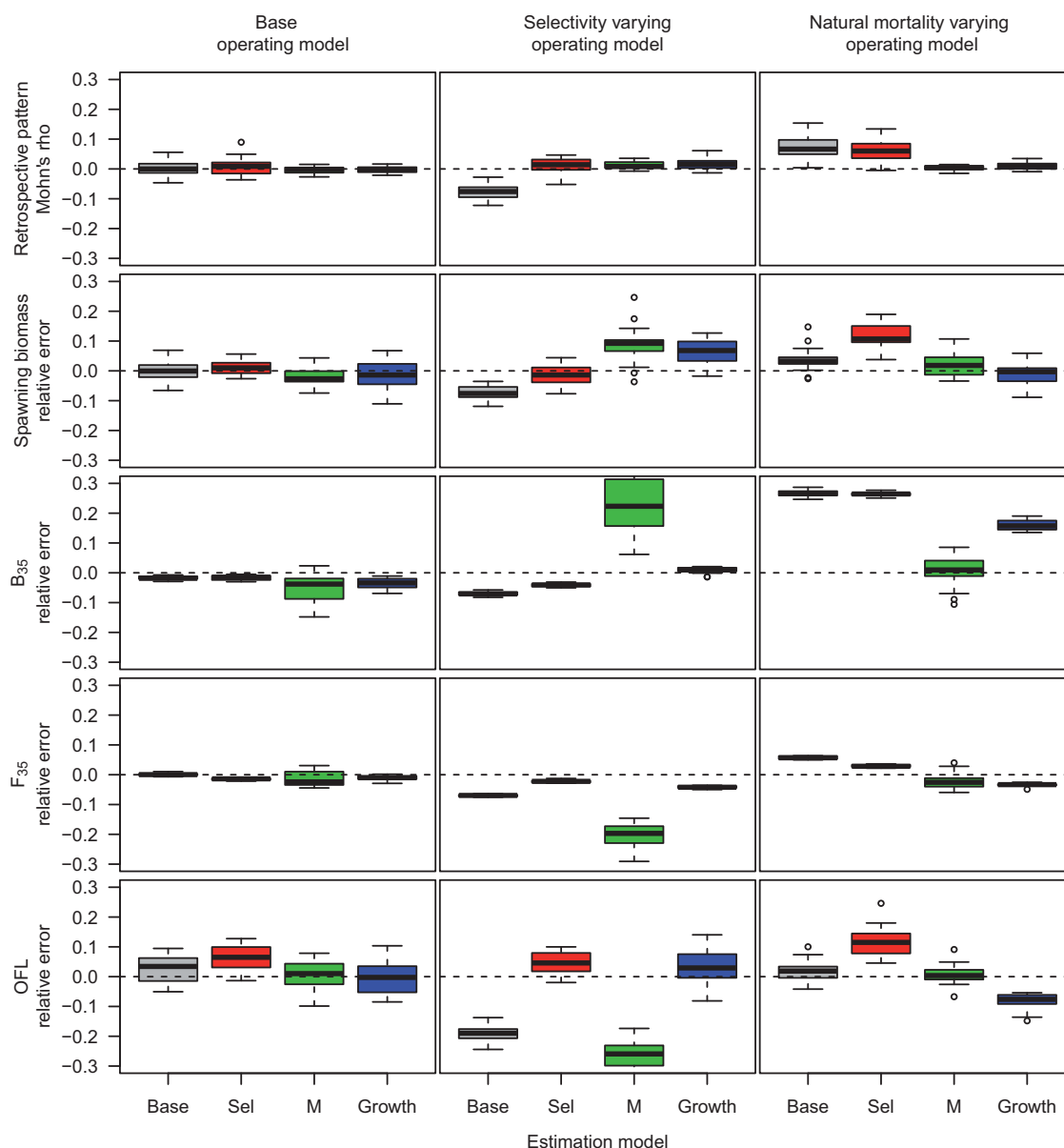
$$\rho = \frac{\overline{X_{Y-y,p}} - \overline{X_{Y-y,ref}}}{\overline{X_{Y-y,ref}}}$$

where  $X$  is the quantity for which Mohn’s rho was calculated,  $Y$  is the final year of a given projection,  $y$  is the last year of an assessment with fewer years of data available for assessment, and  $ref$  is the most recent assessment. This form of Mohn’s rho is slightly different than the original version in that it averages the deviations over replicates rather than summing. Mohn’s rho is presented with the last year of the projection (year 60) as the  $ref$  year and calculates Mohn’s rho for six years backwards from year 60.

The ability of a given assessment method to accurately estimate quantities used to compute management reference points was quantified by calculating the relative error between true reference points ( $B_{35\%}$  and  $F_{35\%}$ ), current biomass, and the catch limit (see Appendix), and their estimated counterparts:

$$RE_y = \frac{\hat{X}_y - X_y^{true}}{X_y^{true}}$$

where,  $\hat{X}_y$  is the estimated quantity and  $X_y^{true}$  is the true quantity in year  $y$ . Relative errors in estimated spawning biomass,



**Figure 2.** Performance metrics for assessment methods (x axis) applied to data from: (i) an operating model in which growth, selectivity, and natural mortality were **constant** over time (column 1), (ii) an operating model in which **selectivity varied over time** (column 2), and (iii) an operating model in which **natural mortality varied over time** (column 3). Mohn's rho was computed at the end of the 10-year projection period with a 6 year peel (each box represents 20 values of Mohn's rho). Relative errors were calculated for each quantity for each of the projection years (i.e. 200 estimates: 20 simulations × 10 years). See online copy for colors.

estimated  $B_{35\%}$ , and estimated  $F_{35\%}$  were calculated for all scenarios for each year of the projection period. Relative error in the TAC was also reported for each year and scenario. The median absolute relative error (MARE) is reported as a measure of bias in the text. Non-convergence of models was checked for by ensuring the maximum gradient was  $<0.01$  (which provided positive definite Hessian matrices indicating reasonably tuned estimates).

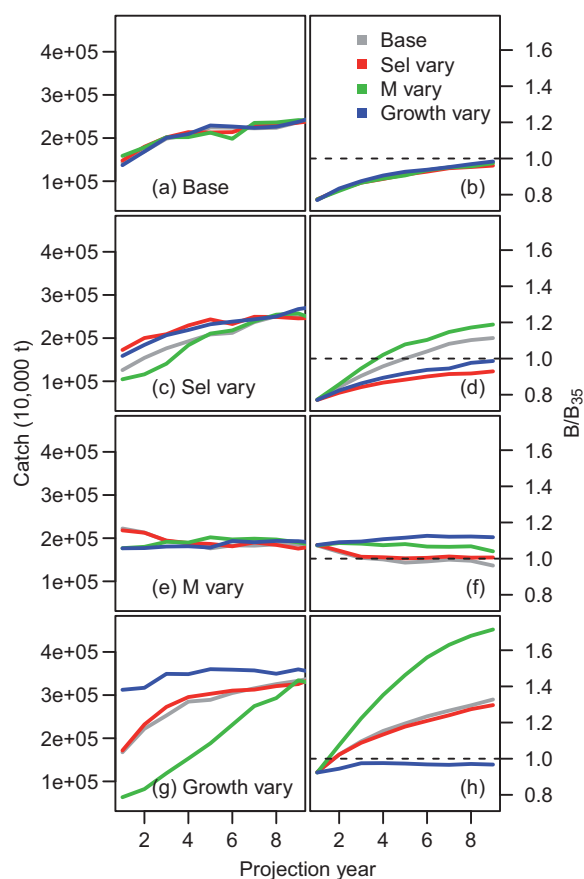
## Results

### No time-varying processes in the operating model

Estimates of spawning biomass were relatively unbiased for all assessment methods when selectivity, natural mortality, and growth

were constant over time (Figure 2; MARE near 0 for all scenarios). Retrospective patterns were also small with median Mohn's rho  $<0.01$  (Figure 2). The MAREs for target fishing mortalities and target biomasses were near 0 with some small differences among scenarios. For example, the assessment method allowing natural mortality to vary over time led the largest variability in the estimates of the reference points. Despite these differences, the MARE of the calculated OFLs varied little among scenarios and were relatively small (Figure 2). Population processes were all estimated relatively accurately (Figure 1). The unbiased estimation of all management quantities by the assessment methods resulted in nearly identical yield trajectories, which, in turn, resulted in nearly identical "status" trajectories (i.e. the ratio of





**Figure 3.** Median catch for each assessment method (line) by scenario (panel) and median true “status” as calculated by the true current biomass divided by the true target biomass. The dashed line in right column indicates the target spawning biomass. Units for catch are 10000t. See online copy for colors.

the current spawning biomass to the target biomass) that converge on 1 (Figure 3a and b).

These results demonstrate that all assessment methods considered here could provide unbiased estimates of management quantities when natural mortality, selectivity, and growth were held constant in the operating model. Furthermore, basing management on any of these models resulted in essentially the same yield and biomass trajectory that converged on the target biomass, which fulfilled the stated management goals. However, the variability in quantities used in management increased when population processes could vary within the assessment compared to the assessment in which growth, natural mortality and selectivity were held constant. Variability in management quantities also increased when additional recruitment variability was added, but remained unbiased (results not shown).

### Time-varying selectivity in the operating model

A retrospective pattern appeared in the “base” assessment method (median Mohn’s rho  $\sim -0.07$ ; Figure 2) when selectivity varied over time in the operating model. Allowing natural mortality, growth, or selectivity to vary over time in the assessment method reduced the observed retrospective pattern (median Mohn’s rho  $\sim 0.0$ ; Figure 2). The assessment methods in which growth or selectivity could vary over time returned nearly unbiased estimates of

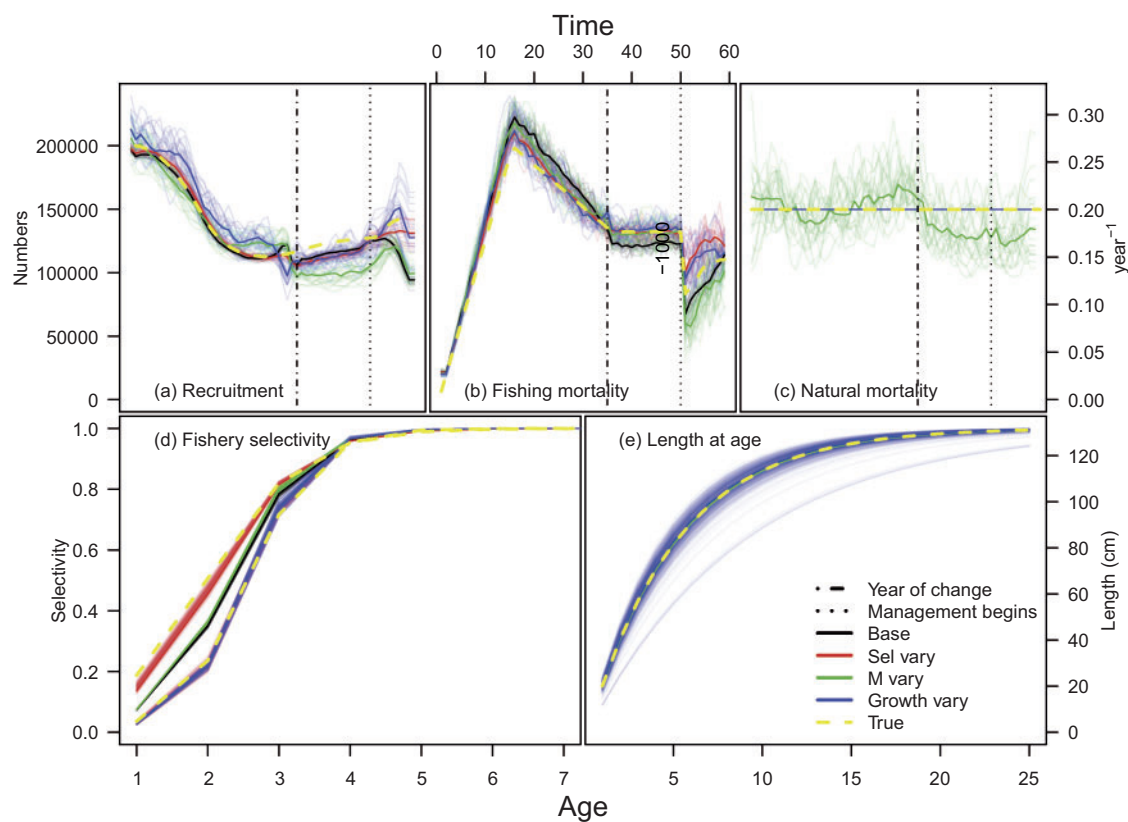
reference points, which led to OFLs that were also close to unbiased. Biases in reference points and estimated biomass from the assessment methods in which either no process or natural mortality could vary resulted in negatively biased estimates of the OFL for all scenarios. The scenario in which selectivity could vary over time in the assessment led to estimated OFLs with the smallest bias (MARE  $\sim -0.03$ ; Figure 2). Population processes were less well estimated compared to operating model configurations with no variation (e.g. recruitment and fishing mortality were biased, particularly in recent years); however, the assessment method that allowed selectivity to vary over time matched the patterns in changing selectivity well (Figure 4). The base assessment and the assessment in which natural mortality varied over time converged on spawning biomasses above the target biomass through the removal of relatively small catches early in the projection period (Figure 3c and d).

### Time-varying natural mortality in the operating model

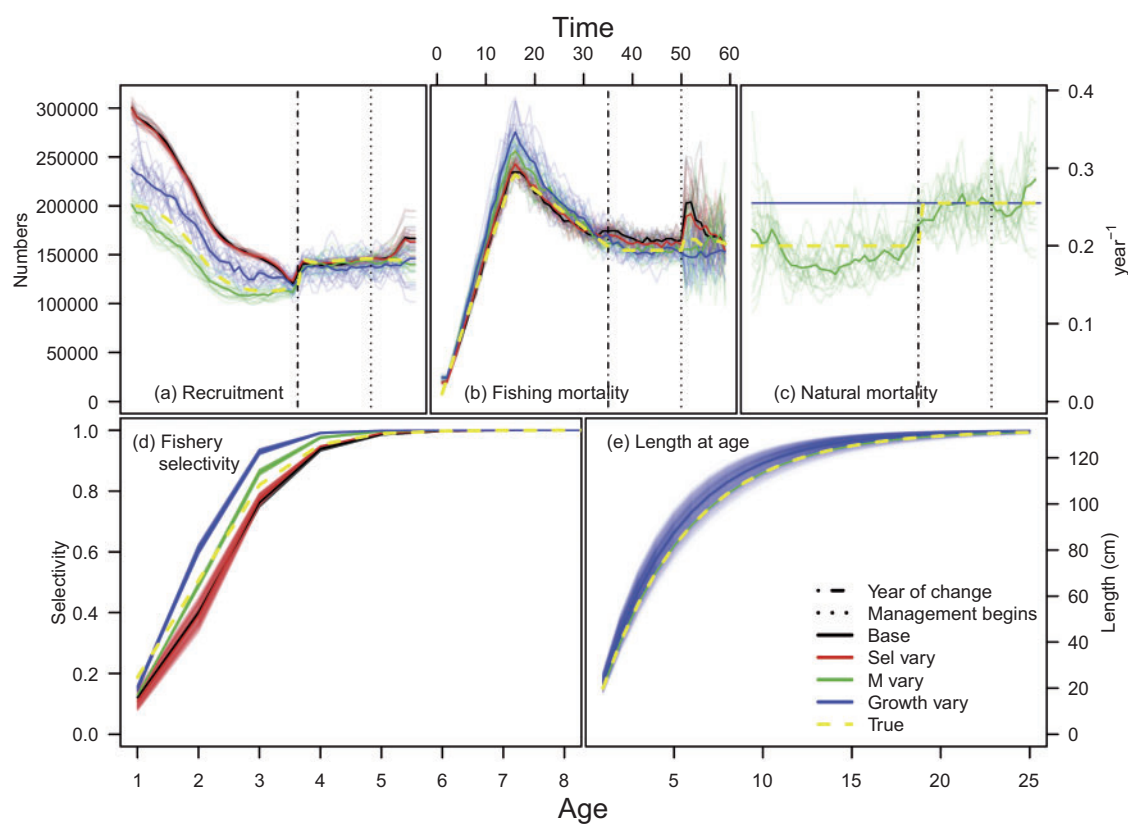
A retrospective pattern again appeared for the “base” assessment method when natural mortality varied over time (Mohn’s rho  $\sim 0.08$ , which increased to  $\sim 0.1$  when  $\sigma_r$  was increased to 0.4), and allowing natural mortality or growth to vary over time in the assessment method reduced this pattern whereas allowing selectivity to vary did not (Figure 2). Estimated target biomasses were positively biased (Figures 2) for all assessment methods except for that in which natural mortality could vary in the assessment. Although both the assessments allowing natural mortality and growth to vary reduced the retrospective patterns in spawning biomass substantially (Figure 2), only the assessment in which natural mortality could vary led to unbiased estimates of the target biomass. Of the time-varying assessment methods, only the assessment allowing natural mortality to vary returned unbiased estimates of the OFL (Figure 2). Interestingly, catch advice from the base model was close to unbiased, despite large biases in the constituent reference points and biomass estimates. The assessment method allowing natural mortality to vary over time nearly approximated the true natural mortality (Figure 5c), but population processes in other assessments (e.g. recruitment and selectivity) were poorly estimated as the models attempted to compensate for changing natural mortality (Figure 5a and d). Spawning biomass for all projections began slightly above the target biomass and the base assessment and the assessment in which selectivity varied quickly reached the true target biomass. The stocks for which management was based on assessments in which growth and selectivity varied equilibrated above the target biomass (Figure 3e and f).

### Time-varying growth in the operating model

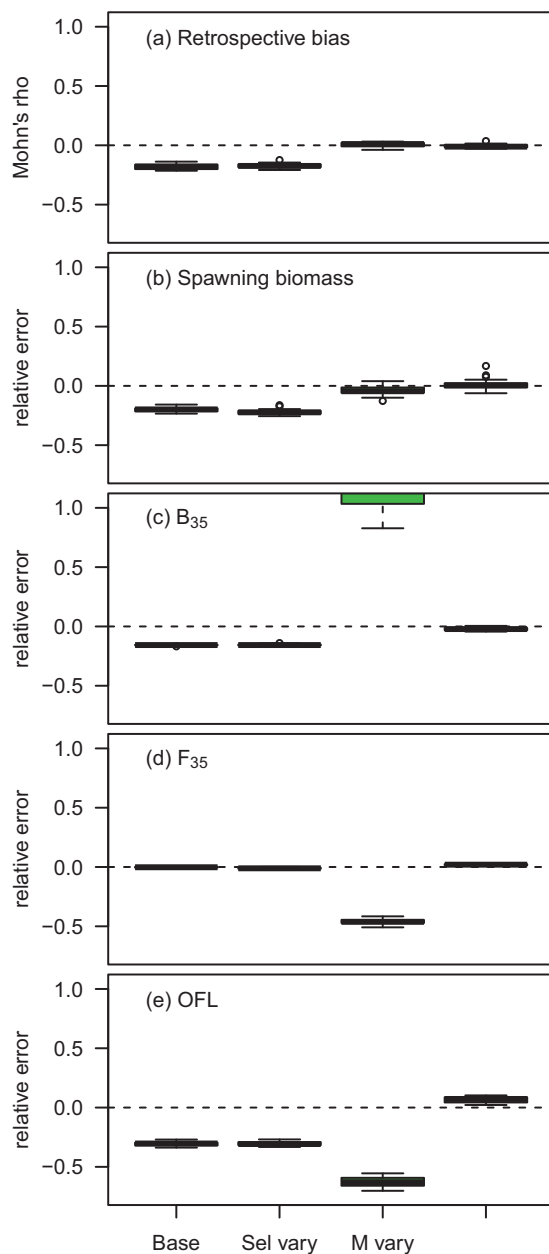
Allowing growth to vary over time in the operating model also led to retrospective patterns in estimated spawning biomass from the base assessment (Mohn’s rho  $-0.17$ ; Figure 6). Only the assessment methods allowing natural mortality or growth to vary over time substantially reduced this pattern. The assessment method that allowed natural mortality to vary reduced the retrospective pattern at the cost of large biases in calculated reference points (Figure 6). These biases in reference points translated to much lower recommended OFLs compared to other scenarios (Figure 6). Only the assessment in which growth was allowed to vary was able to estimate the OFL with minimal bias. Estimates of underlying population processes were all poor compared to results from other operating models, but the assessment method in



**Figure 4.** Estimated and true processes for assessments applied to data collected from an operating model in which selectivity varied over time. See online copy for colors.



**Figure 5.** Estimated and true processes for assessments applied to data collected from an operating model in which natural mortality varied over time. See online copy for colors.



**Figure 6.** Performance metrics for assessment methods (x axis) applied to data from an operating model in which **growth varied over time** (note that the range of the y axis differs from Figure 2). Mohn's rho was computed at the end of the 10-year projection period with a 6 year peel (each box represents 20 values of Mohn's rho). Relative errors were calculated for each quantity for each of the projection years (i.e. 200 estimates: 20 simulations  $\times$  10 years). (Note that the y axis has changed for this figure compared to the previous figures of the same structure.) See online copy for colors.

which growth varied led to estimates most similar to the true underlying dynamics (Figure 7). Managing with estimates of management quantities from the assessment that allowed growth to vary over time returned the stock close to the true target biomass, but all other assessments under-exploited the resource (Figure 3g and h).

## Discussion

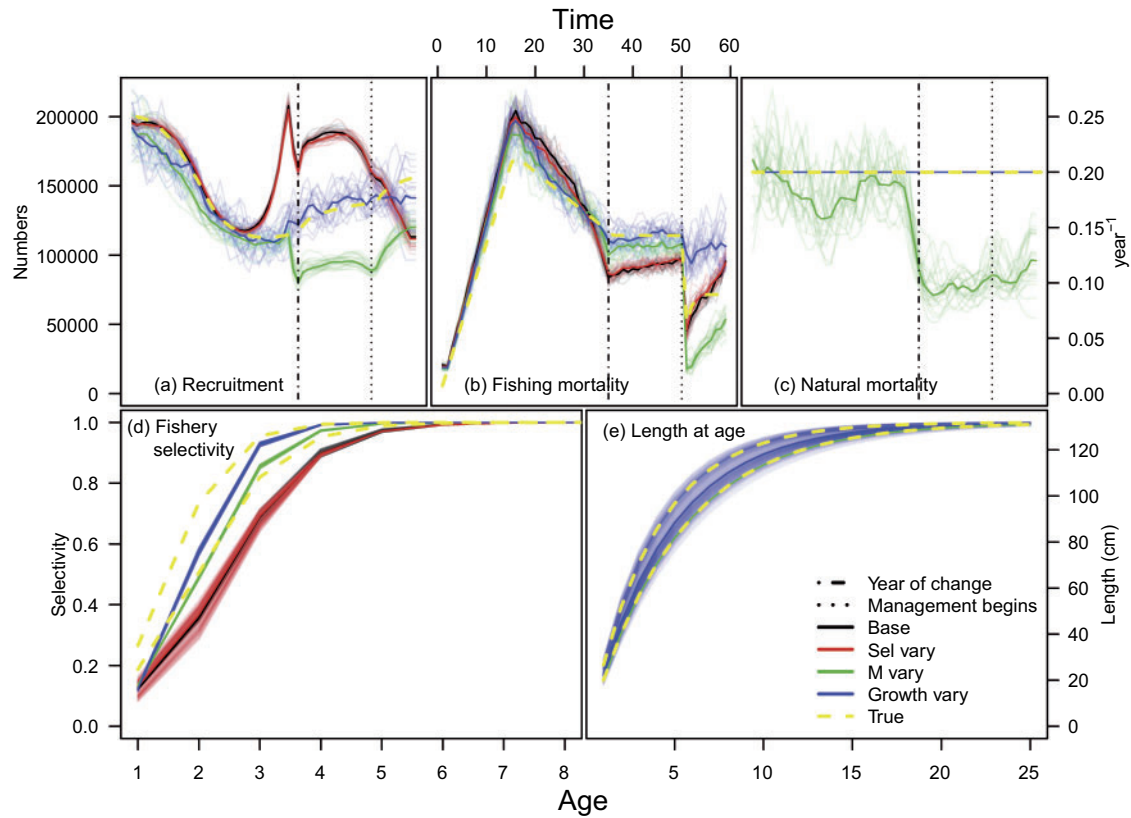
Allowing an assessment more freedom through allowing a process to vary over time can often reduce retrospective patterns in estimated spawning biomass regardless of their origin. Allowing the correct process to vary in the assessment produces estimates of management quantities with the least bias, but some processes can mimic changes in other processes and reduce retrospective patterns (though never better than allowing the correct process to vary can in this analysis; Table 2). For example, allowing natural mortality or growth to vary in the assessment method resulted in larger decreases in Mohn's rho than allowing selectivity to vary over time when natural mortality or growth varied in the operating model. Similarly, allowing natural mortality or selectivity to vary in the assessment method reduced the retrospective patterns more effectively than allowing growth to vary when selectivity was varying in the operating model.

Some of the difference in the ability of assessment methods to reduce a retrospective pattern depends on the process varying in the operating model. For example, time-varying fishery selectivity has little effect on other population processes affecting the dynamics of the system—it influences removals from the population and reference points. Consequently, assessment methods with time-varying selectivity reduced the retrospective patterns when the true time-varying process was selectivity (from the operating model) and estimated other population processes with relatively little bias. However, changes in natural mortality precipitate changes in recruitment because virgin spawning biomass changes when natural mortality changes. Changes in growth have even larger knock-on effects than natural mortality by causing changes in length-at-age (and consequently selectivity-at-age) and recruitment (e.g. Figure 7). The increasing complexity of the impacts of changing selectivity, natural mortality, and growth provide some insight to the inability of all assessment methods (except the assessment in which growth varied over time) to estimate the population processes and management quantities effectively when growth varied over time in the operating model.

Allowing natural mortality to vary was the most flexible way of removing retrospective patterns based on our results. However, a reduction in a retrospective pattern in estimated spawning biomass did not always translate to improvements in the bias of quantities used to calculate allowable catches such as estimated spawning biomass and reference points. Identifying the correct process to allow to vary was critical to estimating reference points without bias. For example, allowing natural mortality or selectivity to vary in the assessment both decreased the retrospective pattern from the resulting estimates of spawning biomass when the underlying operating model had time-varying selectivity, but only the assessment in which selectivity varied led to relatively unbiased reference points. This pattern was mirrored in the other scenarios.

Certainty around what process is varying should be a prerequisite for providing management advice with an assessment that addresses a retrospective pattern by allowing a process to vary in the assessment. However, data to determine which process is varying over time are often unavailable and the true reference points are obviously not available for comparison. Still, it may be possible to narrow down the process that is varying by applying assessment methods that allow each process to vary in turn. In our results, time-variation in only two of the three tested processes eliminated the retrospective patterns for a given operating





**Figure 7.** Estimated and true processes for assessments applied to data collected from an operating model in which growth varied over time. See online copy for colors.

**Table 2.** Pairwise comparison of median Mohn’s rho for estimated spawning biomass from estimation models and operating model scenarios.

		Estimation model			
		Base	Selectivity	Nat. mortality	Growth
Operating model	Base	0.00	0.01	−0.00	−0.00
	Selectivity	−0.08	0.01	−0.01	−0.02
	Nat. mortality	0.07	0.06	−0.00	−0.01
	Growth	−0.18	−0.17	0.01	0.01

model (e.g. only growth and natural mortality eliminated retrospective patterns when growth was time-varying in the operating model). This observation allows one process to be eliminated from the potential origins of the retrospective pattern and is therefore useful in identifying research priorities for collecting data to determine the varying process (Szuwalski and Punt, 2012). In addition to this process of elimination, model diagnostics such as residuals from the fits to survey length composition data may indicate model misspecification. It should also be noted that other sources of retrospective patterns are possible (e.g. missing catch data) and these sources should be ruled out before pursuing time variation in life history as a potential fix for retrospective patterns. Additionally, various functional forms for the life history processes in question are also possible (beyond those considered here), so when performing similar analyses for actual stocks, it will be important to test those different forms (e.g. dome-shaped selectivity). Finally, recruitment variability

(which was very low in this analysis) and constraints placed upon the functional form of estimated time-varying process may also influence the fits of assessments in which time-varying processes are estimated, which in turn may modify the observed relationships between reductions in retrospective patterns by different assessment methods presented here. In any case, it will likely be increasingly important to conduct longitudinal studies of life history characteristics (e.g. continuous tagging studies) and fishery performance (e.g. side-by-side tows or camera studies for selectivity) as a regular part of scientific activities and develop and incorporate methods to fit to longitudinal data on population processes in assessments.

We showed that, even when the data for assessment are quite informative (as was the case in our simulations), retrospective patterns can arise (though the retrospective patterns produced were smaller in magnitude than are often seen in actual assessments) and result in biased management advice. The impact of

biases in management advice on calculated allowable catches and the resulting status of a population will vary based on the direction and magnitude of the changes in population processes. The presence of time-varying processes in exploited marine populations requires careful examination of the assumptions attached to reference points that are used in management. Here, we modelled discrete shifts from one vector of parameters determining population processes to another. Consequently, the true reference points over the projection period were relatively easy to calculate. However, the influence of environmental variables or changes in fleet dynamics (for example) on population processes is not always as straightforward. The concept of a reference point requires a prediction of what a population could be in the future under different fishing circumstances and population dynamics. Prediction of the character of fleet or population processes in the future can be difficult, but is still necessary to provide actionable management advice in many frameworks. Currently, most assessments assume the future will be much like the past. Management strategy evaluations exist that explore incorporating a changing climate into management advice, but have shown little improvements under predominantly stationary forcing (Punt *et al.*, 2013). As environmental variables exhibit more non-stationarity, mechanistic studies will be increasingly important in formulating appropriate reference points and avoid biases (retrospective and otherwise) in quantities used in management (Szuwalski and Hollowed, 2016). Non-stationarity in population processes can contribute to difficulties in prediction of fishery dynamics (Szuwalski and Thorson, 2017) and causes of time-varying population processes can include trophic restructuring under intense fishing (e.g. Szuwalski *et al.*, 2017), predator/prey effects (Burgess *et al.*, 2017), or shifting population centroids (e.g. Pinsky *et al.*, 2013). Management frameworks that can accommodate expected changes in population processes in the future will also need to be developed in fisheries where they do not already exist. In the absence of definitive data on the origin of retrospective patterns, analysts may find sensitivity analyses that allow several processes to vary one by one (similar to this analysis) in the assessment useful in identifying the risk associated with different assumptions about time-variation in population processes.

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## Appendix

### Operating model

#### Population dynamics model

The population dynamics model was a single-sex, age-structured model that tracked the number of individuals in an age class by year,  $N_{a,y}$ , and allowed natural mortality,  $M_y$  to vary over time.

$$N_{a,y} = N_{a-1,y-1} e^{-(S_{a-1,y-1} F_{y-1} + M_{y-1})} \quad (A1)$$

$$N_{0,y} = R_y \quad (A2)$$

$$M_y = e^{(M_{avg} + M_{dev,y})} \quad (A3)$$

Mean recruitment followed a Beverton-Holt stock-recruit relationship parameterized in terms of steepness ( $h$ ; the expected proportion of virgin recruitment entering the population when spawning biomass is 20% of virgin levels),  $R_0$  (virgin recruitment) and  $SB_0$  (virgin spawning biomass). Recruitment variation ( $\omega_y$ ) was log-normally distributed with mean 0 and standard deviation  $\sigma_r$ .

$$R_y = \frac{SB_y 4hR_0}{(SB_0)(1-h) + SB_y(5h-1)} e^{\omega_y - \frac{\sigma_r^2}{2}} \quad (A4)$$

$$SB_y = \sum_a N_{a,y} Mat_a W_{a,y} \quad (A5)$$

Annual fishing mortality,  $F_y$ , was comprised of a separable annual selectivity at length curve in the estimation model as a logistic curve:

$$S_{l,y} = \frac{1}{1 + e^{\frac{\log(19) \frac{l - S_{l,y}^{50}}{S_{l,y}^{95} - S_{l,y}^{50}}}{l_y}}}} \quad (A6)$$

where  $S_{l,y}^{50}$  and  $S_{l,y}^{95}$  determine the length  $l$  at which the probabilities of capture are, respectively, 50% and 95% in year  $l$ . Selectivity parameters were specified in the operating model in terms of length (Equation A6) and converted to age conditional upon the length-at-age curve by rearranging Equation (A8) (which is conditional upon growth). Time variation in selectivity parameters in the operating model was specified by a vector input by the user. Maturity,  $Mat_a$ , is also a logistic function of age and two estimated parameters ( $p_{50}$  and  $p_{95}$ , which were the age at which the probability of maturing is 50% and 95%, respectively) and assumed constant over time:

$$Mat_a = \left(1 + e^{\log(19) \frac{a - p_{50}}{p_{95} - p_{50}}}\right)^{-1} \quad (A7)$$

Length-at-age followed a growth increment von Bertalanffy form:

$$L_{a,y=1} = L_{\infty} (1 - e^{-k_y(1-t_0)}) \quad (A8)$$

$$L_{a=1,y} = L_{\infty} (1 - e^{-k_y(1-t_0)}) \quad (A8a)$$

$$L_{a,y} = L_{a-1,y-1} + (L_{\infty} - L_{a-1,y-1})(1 - e^{-k_y}) \quad (A8b)$$

where  $L_{\infty}$  is the maximum length during year  $y$ ,  $k_y$  was the growth rate in year  $y$  and  $t_0$  was the age corresponding to a predicted length of 0. Changes in  $k_y$  were specified as a vector in the operating model. Weight was a constant function of length:

$$W_{a,y} = \alpha L_{a,y}^{\beta} \quad (A9)$$

Conditional length-at-age for both the catch and survey were calculated from the numbers at age matrix by specifying a single standard deviation  $\sigma_{len}$  and the expected length-at-age determined using Equation (A9). The array,  $LA_{a,z,y}$  with  $a$  rows representing the number of age classes and  $z$  columns representing the number of length bins during year  $y$  contained the probability of an individual of age  $a$  being length  $z$  (i.e. the proportion of each age class in each length bin). Length bins were pre-specified.

$$LA_{a,z,y} = \frac{1}{\sqrt{2\pi\sigma_{len}^2}} e^{-\frac{(L_{a,y} - Bin_z)^2}{2\sigma_{len}^2}} \quad (A10)$$

$$LA_{a,z,y} = \frac{LA_{a,z,y}}{\sum_a LA_{a,z,y}} \quad (A11)$$

where  $Bin_z$  was a vector of the midpoints of the specified length bins. Numbers at length were calculated from this matrix of (normalized) probabilities of length-at-age by multiplying each row by the number of individuals at age and then summing over rows (i.e. age).

$$N_{z,y} = \sum_a N_{a,y} LA_{a,z,y} \quad (A12)$$

The catch weight during year  $y$  was calculated as:

$$C_y = \sum_a \frac{S_{a,y} F_y}{S_{a,y} F_y + M_y} \left(1 - e^{-(S_{a,y} F_y + M_y)}\right) N_{a,y} W_{a,y} \quad (A13)$$

The survey-selected biomass at the time of the survey was calculated as:

$$B_y = \sum_a N_{a,y} S_a^{surv} W_{a,y} \quad (A14)$$

where  $S_a^{surv}$  was the survey selectivity defined as:

$$S_a^{surv} = \frac{1}{1 + e^{\frac{\log(19) \frac{a - S_{surv}^{50}}{S_{surv}^{95} - S_{surv}^{50}}}{l_y}}}} \quad (A15)$$

As with fishery selectivity, the parameters associated with survey selectivity ( $S_{surv}^{50}$  and  $S_{surv}^{95}$ , the length at which the probability of being selected in the fishery is 50% and 95%, respectively) were specified according to length and then transformed to age within the operating model conditional upon growth. Survey selectivity at length was constant over time.



### Data simulation

Catch biomass, catch length frequencies, fishery-independent survey indices of abundance and survey length frequencies were generated using the operating model with error to be used in the estimation models for each year in the simulation. Observed catch biomass and survey biomass were modelled as:

$$\hat{C}_y^{obs} = C_y e^{\epsilon_y - \frac{\sigma_\epsilon^2}{2}} \quad (A16)$$

$$\hat{B}_y^{obs} = B_y e^{\epsilon_y - \frac{\sigma_\epsilon^2}{2}} \quad (A17)$$

where  $\epsilon_y$  is a normally distributed random variable with a mean of 0 and a pre-specified standard deviation  $\sigma_\epsilon$ . Values for the coefficients of variation for all data sources are in Table 1. Observed length frequencies for both the catch and the survey are generated by sampling the true numbers at length calculated above using the “sample” function in R a specified number of times (see Table 1 for sample sizes).

### Assessment method and harvest control rule

The equations governing the population dynamics within the assessment matched those of the operating model. Table 1 lists the estimable parameters of the assessment method. Annual deviations from the mean were additional fixed-effects parameters with specified penalties (see “likelihood components” below) when natural mortality, growth or selectivity were time-varying natural mortality. Within the estimation method, survey selectivity was estimated based on age and growth parameters were not estimated in the “base” model. Average recruitment ( $\mu_R$ ) within the assessment method was estimated with annual deviations ( $R_{dev,y}$ ); Equation A18).

$$R_y^{est} = e^{(\mu_R + R_{dev,y})} \quad (A18)$$

Fishery selectivity at age was estimated within the assessment as deviations around a mean.

$$S_{a,y} = \frac{1}{1 + e^{\frac{\log(19) * (a - (S_a^{50} + S_y^{50}))}{(S_a^{95} + S_{a,y}^{95}) - (S_a^{50} + S_{a,y}^{50})}}} \quad (A19)$$

### Likelihood components

The assessment method was fit to the data generated from the operating model based on four likelihood components. The log-likelihoods (ignoring constants) for catch and the survey index of abundance were log-normal:

$$\Pi_1 = \frac{(\log(C_y^{obs}) - \log(C_y^{est}))^2}{\log(CV_c^2 + 1)} \quad (A20)$$

$$\Pi_2 = \frac{(\log(B_y^{obs}) - \log(B_y^{est}))^2}{\log(CV_B^2 + 1)} \quad (A21)$$

Catch and survey length frequencies were fit under the assumption of multinomial sampling:

$$\Pi_3 = \begin{cases} N_{smp} P_{l,y}^{obsC} \log(P_{l,y}^{estC}) & \text{if } P_{l,y}^{obsC} > 0.01 \\ 0 & \text{if } P_{l,y}^{obsC} \leq 0.01 \end{cases} \quad (A22)$$

$$\Pi_4 = \begin{cases} N_{smp} P_{l,y}^{obsB} \log(P_{l,y}^{estB}) & \text{if } P_{l,y}^{obsB} > 0.01 \\ 0 & \text{if } P_{l,y}^{obsB} \leq 0.01 \end{cases} \quad (A23)$$

where  $P_{l,y}^{obsC}$  was the observed proportion at length of the catch in year  $y$ ,  $P_{l,y}^{estC}$  was the predicted proportion at length in year  $y$  of the catch,  $P_{l,y}^{obsB}$  was the observed proportion at length of the survey biomass in year  $y$ , and  $P_{l,y}^{estB}$  was the predicted proportion at length of the survey biomass in year  $y$ . The data were weighted with the same CVs and sample sizes with which they were generated (Table 1). Small penalties were added to the objective function to ensure the smoothness of estimated recruitment, fishing mortality, time-varying natural mortality, time-varying selectivity, and time-varying growth in the form of:

$$\Pi_x = \gamma_x (V_y - V_{y+1})^2 \quad (A24)$$

where  $V_y$  is the vector of the deviations associated with recruitment, fishing mortality, natural mortality, selectivity and/or growth and  $\gamma_x$  is the weight applied to each likelihood component (specified as a CV of  $\sim 0.41$  for all quantities because it produced estimates that were not overly variable, but still contributed little to the objective function).

### Harvest control rule

Management targets used in the harvest control rule were based on proxies for the biomass at which maximum sustainable yield occurs ( $B_{MSY}$ ) and the fishing mortality that produces that biomass at equilibrium ( $F_{MSY}$ ) using spawning-biomass-per-recruit methods (e.g. Clark, 1991; NPFMC, 2007).  $F_{35\%}$ , or the fishing mortality that reduces spawning biomass per recruit (SBPR) to 35% of virgin levels is used as a target fishing mortality for Alaskan crab fisheries (NPFMC, 2007).  $B_{35\%}$  was calculated as the SBPR corresponding to  $F_{35\%}$  multiplied by an average recruitment calculated from the entire time series of estimated recruitments. Calculated values of  $F_{35\%}$  and  $B_{35\%}$  were used in conjunction with a control rule to adjust the proportion of  $F_{35\%}$  that was applied to the population based on the status of the population relative to  $B_{35\%}$ . The fishing mortality derived from Equation (A23) was deemed the fishing mortality corresponding to the TAC (which coincides with the OFL), the  $F_{OFL}$ , and was applied to the population to find the TAC using Equation (A14).

$$F_{OFL} = \begin{cases} 0 & \text{if } \frac{SB_{cur}}{B_{35\%}} \leq \theta \\ \frac{F_{35\%} \left( \frac{SB_{cur}}{B_{35\%}} - \phi \right)}{1 - \phi} & \text{if } \theta < \frac{SB_{cur}}{B_{35\%}} \leq 1 \\ F_{35\%} & \text{if } SB_{cur} > B_{35\%} \end{cases} \quad (A25)$$

Where,

$SB_{cur}$  The currently estimated mature biomass in the projected year for TAC determination

$B_{35\%}$  Mature biomass resulting from fishing at  $F_{35\%}$

$F_{35\%}$  Fishing mortality that reduces the mature biomass per recruit to 35% of the unfished level

$\theta$  Determines the slope of the descending limb of the control rule (specified as 0.25 here)

$\phi$  Fraction of  $B_{35\%}$  below which fishing mortality is zero (specified as 0.05 here)