

1 How does growth misspecification affect
2 management advice derived from an
3 integrated fisheries stock assessment
4 model?

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16 **Abstract**

17 Analysts must make many decisions regarding model specification when fitting integrated fishery stock
18 assessment models. While variation in vital rates (i.e., recruitment, somatic growth, and natural
19 mortality) is common, capturing this variation in models fit to available data is often infeasible or
20 impractical. Failing to account for this variation can result in underestimates of uncertainty and even
21 biased estimates of stock status used for management advice. Here, we seek to determine how growth
22 misspecification affects management advice derived from integrated stock assessment models that use
23 the Stock Synthesis platform. We conduct a simulation-based case study on California Current petrale
24 sole (*Eopsetta jordani*) to test whether and how the inclusion or omission of somatic-growth variation
25 introduces bias into management reference points when estimation models misspecify growth.
26 Scenarios we explored included inter-annual and regime-like changes in two key parameters (k , the
27 initial slope of the growth curve, and L_2 , the asymptotic maximum length) used to model somatic growth
28 in Stock Synthesis. We find misspecification of growth can overestimate management quantities,
29 particularly the estimate of current biomass relative to the unfished biomass (stock depletion). This
30 results in an overly optimistic view of stock status. This bias may be mitigated or eliminated if the
31 assessment model includes growth variation. Including growth variation in the estimation model can
32 also reduce the uncertainty in estimated management quantities by correctly attributing process error
33 to somatic growth. However, the magnitude of detected biases is exceeded by the uncertainty when
34 data are limited, suggesting that estimating growth variation is helpful only in relatively data-rich stock
35 assessment models. We suggest authors of data-rich assessments consider incorporating time-varying
36 growth parameters into assessment models or decision tables more frequently to account for potential
37 biases and reduce uncertainty caused by temporal growth variation.

38 **Keywords:** fisheries stock assessment, time-varying growth, Stock Synthesis, *Eopsetta jordani*

39 **Highlights**

- 40 • We test how growth misspecification can affect estimated management quantities.
- 41 • A simplified stock assessment model is used as the operating and estimation model.
- 42 • Estimates are biased if regime-like changes in growth parameters are unmodeled.
- 43 • Estimating time-varying growth reduces bias but increases runtime.
- 44 • We recommend growth variation be considered for data-rich assessments.

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47 Introduction

48 Integrated fishery stock assessment models are a state-of-the-art tool used to generate
49 management advice for marine fisheries (Maunder and Punt 2013). These complex models jointly
50 estimate uncertainty and temporal variation in biological processes and account for measurement error
51 in data gathered from fishery-dependent and -independent sources (Methot and Wetzel 2013).
52 Although the ability to estimate large numbers of parameters simultaneously within such models is
53 advantageous for capturing complexity, stock assessment analysts still must make many simplifying
54 choices regarding model specification. Such choices include how to specify process variation in key
55 biological rates i.e., recruitment, somatic growth, and mortality. Despite evidence that all three of these
56 components vary across space, time (Clark et al. 1999; Gaichas et al. 2010), and/or age class (Whitten et
57 al. 2013), in practice, data and/or runtime is too limited to accurately estimate synchronous variation in
58 all three rates (Ono et al. 2015). As such, quantifying whether and how misspecification of variation in
59 vital rates can introduce bias and reduce precision of estimated management reference points is
60 necessary to help stock assessment analysts identify tradeoffs associated with model specification.
61 Historically, mechanistic temporal variation in somatic growth rates has rarely been included in
62 assessment models, and the consequences of this omission are not fully understood.

63 Size-at-age of marine fish across time or cohort may vary because of environmental drivers that
64 introduce variation into feeding and/or metabolic rates. Feeding and metabolic rates may increase or
65 decrease in sync due to changes in temperature (Cheung et al. 2012), or feeding rates alone may vary
66 because of changing food supply driven by density-independent (e.g., bottom-up changes in prey
67 biomass) (Black 2009) and/or density-dependent causes (i.e., intraspecies competition) (Rijnsdorp and
68 van Leeuwen 1992). Second, fishing patterns may affect size-at-age of individuals in the population.
69 Fishing selectively removes larger, faster-growing individuals from the population, therefore, population
70 size-at-age may decrease over time periods when fishing effort increases (Hilborn and Minte-Vera

71 2008). This effect may be significant in the short term, even when such size-selective pressure does not
72 drive fisheries-induced evolution towards smaller sizes on longer, evolutionary timescales. Either type of
73 variation may affect growth of all of the species' age classes or be manifest in specific cohorts (Stawitz et
74 al. 2015a). In this study, we focus on changes in growth occurring temporally across age classes but do
75 not limit our analysis to one cause of variation in population size-at-age.

76 Either driver of variation (environmental or fishing) could induce inter-annual deviates or
77 regime-like deviates from average size-at-age. For example, bottom-up effects on size-at-age could stem
78 from well-documented decadal oscillations in ocean conditions of the California Current ecosystem that
79 affect primary productivity (El-Nino Southern Oscillation: (McGowan et al. 1998), Pacific Decadal
80 Oscillation: (Mantua and Hare 2002)). Alternatively, growth variation driven by changing metabolic rates
81 could occur in response to inter-annual changes in temperature (Cheung et al. 2012). However, inter-
82 annual or periodic management changes that change fishing rates or fisheries selectivity could also
83 induce inter-annual or regime-like deviates to average size-at-age. Fishing rate changes annually in
84 response to Total Allowable Catch limits set by fisheries stock assessments (Rosenberg and Restrepo
85 1994). However, more sweeping policy reforms can result in long-term changes in harvest (Abbott et al.
86 2015). California Current groundfish were declared a disaster in 1999, and in subsequent years several
87 groundfish species were placed on rebuilding plans that reduced quotas (Warlick et al. 2018). These
88 management actions had repercussions on harvest rates spanning a decade, which in turn could affect
89 size-at-age in a regime-like pattern.

90 The way size-at-age data are used in integrated assessment models implies temporal variation in
91 the length-age key will affect estimates of biomass and fishing mortality, and applications have
92 confirmed this impact. Assessment model attempts to fit length-composition data can change estimates
93 of fishing mortality, while length-at-age variation affects biomass directly through the conversion from
94 abundance into biomass (Maunder et al. 2015). Previous work suggests incorporating time-varying

95 growth can improve the performance of population models (Helser and Brodziak 1998; Walters and
96 Wilderbuer 2000; Gårdmark et al. 2006); however, applications using realistic length-at-age data within
97 integrated fisheries stock assessment models are recent. A more applied study demonstrated that
98 spawning stock biomass estimated in an integrated assessment model may be significantly biased (up to
99 30%) if growth parameters decline over time and this trend is not accounted for (Kuriyama et al. 2016).
100 Recently, Miller et al. (2018) show incorporating process error in somatic growth within stock
101 assessment models impacts biological reference points. Practically, stock assessment authors require
102 further information on how feasible estimation of temporal growth trends is and whether it reduces bias
103 across types of growth variation and data availability. Temporal variation in the size-at-age data
104 available for assessment models may be difficult to detect due to measurement error or simultaneous
105 changes in sampling. Length-at-age data may be too noisy to estimate temporal variation in growth
106 parameters efficiently (Kuriyama et al. 2016), while sampled length-at-age statistics may vary due to
107 temporal changes in fishery selectivity (Thorson and Simpfendorfer 2009), even though population size-
108 at-age does not vary.

109 Including growth variation either empirically or mechanistically in population models can
110 improve model fits and estimation of process uncertainty; however, growth variation is infrequently
111 included in assessment models. The version of the von Bertalanffy growth curve (Bertalanffy 1957) used
112 in the Stock Synthesis software (Schnute 1981) is governed by three parameters: L_2 , the mean size at the
113 maximum age adult fish are well-represented in the data, L_1 , the mean size at the minimum age adult
114 fish are well-represented in the data, and k , the exponential rate of approach to L_2 (Ricker 1975).
115 Growth variation may be incorporated into stock assessments by estimating different fixed or random
116 effects on these parameters or by using an empirical weight-at-age table to convert age to mass. Stock
117 assessments for Pacific hake (*Merluccius productus*) have estimated regime-like variation in L_2 (Helser et
118 al. 2004) or used empirical weight-at-age fisheries-independent and -dependent data to capture size

119 variation (Taylor et al. 2015), resulting in improved fits to length composition data (Taylor et al. 2015).
120 When conducting the stock assessment model for walleye pollock (*Gadus chalcogrammus*), Ianelli et al.
121 (2016) found that including inter-annual random effects on growth increment improved model
122 prediction performance and provided a more realistic estimate of process uncertainty to use in
123 population projections. Empirical weight-at-age data may reduce bias compared to fixed or random
124 effects incorporated into the growth model (Kuriyama et al. 2016), but this approach is only feasible
125 when a very large amount of unbiased weight-at-age data can be collected. Additionally, use of sampled
126 weight-at-age does not offer insight into mechanistic causes for growth variation, a key component of
127 forecasting future implications for growth variation on management recommendations.

128 Here, we build upon previous theoretical work outlining the importance of including growth
129 variation in population models to provide practical advice for stock assessment analysts on when and
130 how to include growth variation. We explore how growth variation may affect a practical fisheries stock
131 assessment, that of California Current petrale sole (*Eopsetta jordani*) and explore whether realistic rates
132 of growth variation are detectable in an integrated stock assessment model and how they impact
133 management recommendations. This species represents an ideal test case, as petrale sole have been
134 shown to experience growth variation (Stawitz et al. 2015a) and have a large repository of both fishery-
135 dependent and -independent data. We determine whether several different types of empirically-derived
136 patterns of growth variation lead to biased or imprecise management advice under historical fishing
137 rates. We explore the effect of both regime-like (block) changes and inter-annual variation in the k and
138 L_2 growth parameters on estimates of management reference quantities. By comparing bias and
139 precision of management quantities across correctly and incorrectly specified growth model scenarios,
140 we can provide guidelines for stock assessment analysts regarding the feasibility and utility of
141 incorporating growth variation into an integrated stock assessment model.

142 Methods

143 In this study, we used simulation to explore how growth variation and misspecification of
144 growth parameter values affects estimates of management quantities and growth parameters. Our goal
145 was to use the most realistic estimates of growth variation possible; therefore, we began by configuring
146 the integrated stock assessment model used in the management of petrale sole to provide input
147 parameter estimates for our operating model. To do this, we fit simplified versions of the stock
148 assessment model to empirical data using the Stock Synthesis (SS) software (Methot Jr and Wetzel
149 2013). We developed five alternative scenarios of growth variation that were used to simulate data from
150 operating models and fit estimation models across 30 scenarios (Table 1). The SS framework was used to
151 simulate and estimate data within *ss3sim*, an R package created to facilitate conducting simulations with
152 SS (Anderson et al. 2014), ensuring results are highly applicable to models used in fisheries
153 management. Finally, we compared estimated median relative errors (median standardized difference
154 between operating model (θ) and estimation model ($\hat{\theta}$) values, $RE = [\hat{\theta} - \theta]/\theta$) and 95% quantiles of
155 scalar management quantities and time-series estimates of spawning stock biomass between simulation
156 scenarios to test how misspecification of the somatic growth model affects management quantities
157 estimated from an integrated stock assessment model.

158 Model configuration

159 We started by simplifying the most recent petrale sole stock assessment model (Stawitz et al.
160 2015b) to ensure results could be clearly interpreted and to speed runtime to allow for many iterations.
161 Specifically, we removed time blocks of fishery selectivity and used a single logistic selectivity curve for
162 all fisheries and a logistic selectivity curve for the scientific survey, as it can be difficult to estimate
163 temporal variation in both somatic growth and selectivity in an integrated stock assessment model.
164 Next, we removed data on discarded fish and fish mean weight because these are relatively limited data
165 sets that minimally impact the model (Figure 1). We simplified the fleet dynamics of the fishery to a

166 single winter fleet and a single summer fleet (instead of spatially-distinct North and South fleets for each
167 season), aggregating catches across the two winter and two summer fisheries and removing length- and
168 age-composition data for the South fleets. South fleet composition data were removed because this
169 comprises a smaller portion of the catch. We then fixed two key biological parameters, natural mortality
170 (M) and the steepness of the stock-recruit relationship (h), at model estimated values to reduce the
171 number of parameters estimated in the estimation model. This enables the estimation model to better
172 estimate growth parameters that can be confounded with h and M and reduces model run time. We
173 also removed catch-per-unit-effort indices for the winter fishery from model fitting, fitting the model
174 instead only to indices of abundance estimated from scientific survey data. The catch-per-unit-effort
175 indices do not substantially impact model estimates since there are ample survey and catch data. We
176 altered the timing of removals to occur at the midpoint of each year to account for the combination of
177 winter and summer fleets. We also removed ageing error, effectively assuming age readings were
178 unbiased. Though Haltuch et al. 2013 documented bias in age estimates of petrale sole, ageing error and
179 time variation in growth are difficult to simultaneously estimate. Finally, we estimated each year's
180 instantaneous fishing mortality (F) as direct parameters, instead of iteratively adjusting this parameter
181 to more closely resemble observed catch. This was necessary to fix the annual F values at their "true"
182 (OM) values in the simulation analysis. At each step of simplification, we compared time series plots and
183 confidence intervals of biomass estimates between simplified models and full assessment models to
184 ensure species dynamics were still captured in our simplified model (Figure 1). Time series of biomass
185 estimates from these alterations with no visible difference to the base model are omitted from Figure 1.

186 Growth parameter variation

187 We hypothesized that parameters of the somatic growth equation used in the integrated
188 assessment model might vary temporally either 1) with shifts in a climate regime or 2) inter-annually as

189 deviations around the mean parameter value. The petrale sole assessment model estimates distinct
190 male and female growth parameters of the Schnute (1981) growth curve,

191
$$L_a = L_2 - (L_1 + L_2) + L_2(1 - \exp(-k(a_4 - a_3))) \quad \text{Eq. 1}$$

192 to account for substantial sexual dimorphism in growth. L_a represents the length of a fish of age a , a_3 is
193 the youngest age of adult fish well-sampled in the data, and a_4 is the oldest age of adult fish well-
194 sampled in the data. Eq. 1 is referred to as the base or constant growth model, as L_2 and k do not vary
195 temporally.

196 We used four types of growth variation in the operating and estimation models: two types of
197 variation each for L_2 , the growth parameter representing average length at the oldest age well-sampled
198 in the data, and k , the growth parameter representing the slope of the adult growth curve. The
199 differential equation from which the von Bertalanffy growth function is derived suggests the k
200 parameter captures catabolic processes (e.g. caused by temperature), while the L_2 parameter integrates
201 both anabolic and catabolic processes (e.g. changes in consumption and metabolic rates) (Charnov et al.
202 2013). These two types of variation were modelled using a discrete regime-like effect added to the
203 mean parameter value and an environmental index effect of inter-annual random-walk deviates from
204 the mean parameter value. We include a regime-like effect because we hypothesize annual deviates on
205 growth alone might underestimate how much growth variation can bias model outputs. Inter-annual
206 deviates were constrained to be centered on a mean value, while regime-like deviates can capture the
207 potentially more influential effect of a consistent step-wise increase or decrease in parameter values.

208 [Obtaining operating model growth variation parameters](#)

209 We chose to use the simplified stock assessment model fit in SS to obtain growth parameter
210 estimates for use in the operating model because this integrated model simultaneously models two
211 components that may affect estimates of growth: 1) a logistic size-selectivity curve and 2) fishing

212 mortality. We fit four alternative growth variation models, one each for regime-like and annual
213 deviations for both the k and L_2 parameters. We additionally fit one model with constant growth
214 parameters, as described above. The model was fit to empirical data from male and female fish
215 collected during two seasonal fisheries (summer and winter) and three surveys (Alaska Fisheries Science
216 Center early triennial survey, 1980-1992 and late triennial survey, 1995-2004; Northwest Fisheries
217 Science Center annual groundfish trawl survey: 2003-2014). We fit the alternative assessment models to
218 length- and age-composition data from the North fishery (summer and winter) and all survey data.
219 Survey data included conditional age-at-length compositions from the annual groundfish trawl survey
220 (Figure 2) that better inform growth variation parameter estimates for the operating model.

221 To obtain estimates for regime-like changes in growth parameters, we needed to specify the
222 regime intervals (time-blocks) for which growth parameters varied *a priori*. We hypothesized that three
223 different processes might induce regime-like changes in growth, so we evaluated the likelihood of length
224 composition data within SS to determine which of these were best to use as an operating model. It is
225 important to consider that model selection is biased towards inclusion of environmental covariates in
226 integrated assessment models if process error is not accounted for (Maunder and Watters, 2003); we
227 present these values as justification for the chosen operating model, but do not suggest the data
228 support a mechanistic cause for growth variation in California Current petrale sole based on this
229 analysis.

230 The first two investigated processes were the positive and negative phases of two well-known
231 oceanographic phenomena influencing Northeastern Pacific ecosystems, the El-Niño Southern
232 Oscillation (ENSO) (Wolter and Timlin 1993; Wolter and Timlin 1998) and the Pacific Decadal Oscillation
233 (PDO) (Mantua and Hare 2002). The final investigated process was based on changes in harvest pressure
234 (as measured by fishing mortality, F) that may also affect observed size-at-age by removing larger
235 individuals disproportionately (Hilborn and Minto-Vera 2008). To estimate years for growth parameter

236 time-blocks for ENSO and fishing mortality, we constructed regression trees using recursive partitioning
237 on their respective time series (ENSO index and F) from 1965 - 2014 as implemented in the rpart R
238 package (Breiman et al. 1984). A key benefit of this approach is that the lengths of the time-blocks are
239 estimated from empirical data, rather than chosen by the analyst. We tuned the minimum number of
240 observations required to attempt a split until the number of splits was less than or equal to 6. Time-
241 blocks for shifts in the PDO are taken from those estimated in Field (2007), which estimated k for
242 chilipepper rockfish (*Sebastes goodei*) with regime-like deviates along the U.S. Pacific coast. Mean L_2 and
243 k parameter values were unique to each sex, but time periods for regime-like deviates were shared
244 because there was no evidence for sex-specific time periods of growth variation. Methods for fitting
245 both types of variation within SS are detailed in Methot Jr and Wetzel 2013. We compared the
246 likelihoods estimated within SS for each of the three chosen time-blocks for both the k and L_2 growth
247 parameters. The time-blocks based on ENSO and the time-blocks based on F had nearly equivalent
248 likelihoods for both L_2 and k (Table 2), therefore we selected the time-blocks based on F for L_2 and k
249 because these models included fewer parameters. Therefore, time-blocks based on F (time-block: 1965-
250 1977, 1978-1986, 1987-2002, 2003-2014) are used in our operating models (Figure 3).

251 Simulation framework

252 We simulated data using the ss3sim R package (Anderson et al. 2014). This software uses SS to
253 generate expected values for age and length composition data, catch, and abundance from user-
254 supplied parameter inputs. These expected values, along with user-supplied process and observation
255 errors, are used by ss3sim to generate replicate data. Fishing mortality rates for the two fisheries
256 estimated in the base model are fixed in the operating model to ensure simulations reflect reality. When
257 simulations were run, estimated parameters were given initial values corresponding to the operating
258 model values, except where otherwise specified. Parameter values used in the simulation are given in
259 Supplementary Table 2. Though the petrale sole fishery spans 1876 to 2014, only the final 49 years of

260 data were used to simulate and estimate results, as age composition data were not available prior to
261 1965.

262 Process error was introduced via simulated deviations from mean recruitment, in addition to
263 growth variation described above. Observation error was included in two ways: 1) around fishery-
264 independent indices of abundance and 2) through reducing age- and length-composition data sample
265 size. We simulated variation corresponding to a CV of 0.2 for the index of abundance from triennial
266 survey data for both data scenarios. For the annual trawl survey that spanned the final 14 years of the
267 time series, a CV of 0.1 was used for the data-rich scenario and a CV of 0.2 was used for the data-poor
268 scenario. All abundance indices were fit with lognormal error distributions. Both data-rich and data-poor
269 scenarios included 49 years of commercial composition data, which were fit using a multinomial
270 distribution. Simulations included 100 samples of fishery-dependent age- and length-composition data
271 and 500 samples of fishery-independent length- and conditional-age-at-length-composition data per
272 year in the data-rich scenario. In the data-poor scenario, 20 samples of age- and length-composition
273 data were included for each year, from all sources. The estimation routine used SS to fit models.
274 Scenarios are described in Table 2.

275 [Response metrics and convergence criteria](#)

276 To evaluate performance of models under different scenarios, we examined the relative error
277 and uncertainty of estimated biological reference points. Biological reference points evaluated included
278 the spawning stock biomass at maximum sustainable yield (SSB_{MSY}), final year stock depletion (current
279 spawning biomass relative to unfished spawning biomass), and unfished spawning stock biomass. Bias
280 was calculated as the relative error (standardized difference between operating model (θ) and
281 estimation model ($\hat{\theta}$) values, $RE = [\hat{\theta} - \theta]/\theta$) in each parameter or derived quantity θ . We also
282 calculated the uncertainty of estimated reference points in the estimation model as the width of the
283 95% quantile across all converged iterations. Finally, we examined the 95% quantile of bias across the

284 time series of estimated spawning stock biomass, because estimated bias in certain years of the
285 spawning stock biomass time series might be non-zero, even if the 95% quantile of bias of scalar
286 management quantity estimates (e.g. final year depletion) spans zero.

287 As in Monnahan et al. (2016), we recognize that fisheries stock assessments typically undergo
288 multiple convergence checks that are impractical at the scale of this simulation. Therefore, we include
289 results derived from simulations with a maximum gradient less than 0.1 with no parameters estimated
290 on specified bounds for which a Hessian could be estimated. Each scenario combination was run 100
291 times. To ensure 100 iterations were sufficient to stabilize estimates of bias, we ran the data-rich
292 scenarios for which there was the most and least bias for 500 iterations and compared the output bias
293 estimates (see supplementary materials). We report the percent of simulations converged out of the
294 100 iterations and only report summary metrics for iterations that meet the convergence criteria.

295 Results

296 Across all scenarios, there was a slight bias in estimated management reference points (e.g.
297 Final year's depletion [B/B_0], SSB_{msy}). In the base case, i.e. when both the operating and estimation
298 model did not include temporal variation in growth and data were rich, estimated final year depletion
299 and SSB_{msy} both showed a negative 4.00% bias (Table 4). Bias in estimated final year depletion was
300 highest (11%) in data-rich scenarios when L2 had regime-like deviates in the operating model and was fit
301 using a constant growth model. Including annual deviates in the estimation model resulted in the least
302 bias in final year's depletion (Table 4). In data-poor scenarios, the calculated error in estimates across
303 iterations spanned zero, suggesting the uncertainty was too high to detect bias. A more detailed
304 breakdown of results is presented below and illustrated in Table 4 and Figures 4 and 5.

305 *Effect of including growth variation in assessment model fit to empirical data*

306 When the simplified assessment model was fit to empirical data, including random walk
307 deviations in L_2 or k reduced the negative log-likelihood (NLL) of the model (NLL L_2 : 1300.56; k : 1306.02)
308 and improved fits to length-composition data (Length composition NLL: L_2 : 478.62; k : 467.37) over the
309 model with constant (and fewer) growth parameters (NLL = 1401.66; length composition NLL = 544.42).
310 Estimating regime-like deviations in L_2 (NLL: 1444.62; Length composition NLL: 602.75) or k (total NLL:
311 1461.08; Length composition NLL: 605.55) resulted in an increase in NLL with more parameters
312 compared to the constant growth model. When fit to empirical data, the time-blocks based on the
313 magnitude of fishing effort (F) for both k and L_2 had the lowest NLL with a higher number of parameters
314 [Table 2].

315 Estimated regime-like deviations were larger in magnitude than random walk deviations (Figure
316 3); attempts to constrain regime-like deviations to the magnitude of random walk deviations resulted in
317 regime-like deviation estimates hitting parameter bounds for both L_2 and k . Growth parameter
318 estimates (including temporal deviations) declined throughout the time series, excluding the first two
319 time-blocks for female L_2 , which were nearly equivalent. The estimated inter-annual deviations in
320 growth parameters oscillated between negative and positive values but had an extended period of
321 negative deviations (k : 1985-1995, L_2 : 1986-1995) and were positive in the last few years of the time
322 series (k : 2010-2014, L_2 : 2009-2014).

323 *Bias in management quantities in data-rich scenario*

324 Estimated management quantities such as SSB_{MSY} were most affected by misspecification in
325 growth when L_2 varied with regime-like deviates (Figure 4) and the operating model and estimation
326 model did not match. Bias in stock depletion was highest when L_2 varied with regime-like deviates
327 (10.80%) and was estimated as constant. Estimated depletion was slightly biased when k varied inter-
328 annually in the operating model but was estimated as constant (5.38%) and when L_2 experienced

329 regime-like variation in both the operating and estimation model (-5.78%). Estimated SSB_{MSY} was the
330 most biased when k varied with regime-like variation but was estimated as constant (-9.46%).

331 Conversely, management quantities were relatively unbiased in other scenarios where the
332 operating model included growth variation but the estimation model assumed constant growth.
333 Although biases across these scenarios are non-zero, they are comparable to the “best-case” scenario
334 (i.e., when an estimation model with constant growth is fit to data simulated from an operating model
335 with constant growth) that showed a -3.94% bias in estimated depletion and -3.60% bias in estimated
336 SSB_{MSY} . When L_2 varied inter-annually, stock depletion estimates showed even smaller bias (-2.51%).
337 When k had regime-like variation in the OM, but a constant EM was used, estimated depletion was only
338 slightly biased (3.80%). Estimated SSB_{MSY} was unbiased ($<\pm 5\%$) for all other scenarios including growth
339 variation.

340 Including temporal variation in the estimation model reduced bias in estimated management
341 quantities for operating models including growth variation, with lower bias in estimated depletion when
342 the estimation model included inter-annual deviates and lower bias in SSB_{MSY} when the estimation
343 model included regime-like variation (Figure 4). When L_2 had regime-like variation in the operating
344 model, bias in depletion estimates decreased in the estimation scenario where L_2 had regime-like
345 variation (-5.71%) and surprisingly, including inter-annual variation in L_2 in the estimation model
346 reduced bias even further (-2.31%). Similarly, when k varied with regimes in the operating model,
347 estimating regime-like variation in k decreased bias in estimated depletion (-4.34%), and estimating
348 inter-annual k variation decreased bias in estimated depletion even further (-2.24%). Relative error in
349 SSB_{MSY} was similarly low when L_2 varied in a regime-like pattern and was estimated as such (-1.48%) but
350 was slightly higher when L_2 varied in a regime-like pattern and was estimated with inter-annual deviates
351 (-4.23%). Estimated SSB_{MSY} was also unbiased when k varied in a regime-like pattern and was estimated
352 as such (-4.03%) or was estimated with inter-annual deviates (-4.44%).

353 Spawning stock biomass in a single year was overestimated by up to 15.99% if “true” regime-like
354 shifts in growth are not estimated (Figure 5), but there were no discernible trends in bias over time.
355 When L_2 varied in a regime-like pattern, spawning stock biomass was overestimated for most of the time
356 series (1.54%-15.99%, 1974-2014), unless the estimation model incorporated the same variation
357 pattern. Modeling L_2 with regime-like variation removed this bias (maximum bias in a single year:
358 $\pm 1.11\%$), and estimating L_2 with inter-annual variation reduced bias substantially (bias $< 5\%$ for all but
359 one year). Notably, spawning stock biomass in the first year of age composition data was still biased (-
360 7.29% in 1965, year of largest bias) when inter-annual variation in L_2 was estimated. Similarly, spawning
361 stock biomass was consistently underestimated (-4.71%--12.92%, 1965-2014) if k varied using a regime-
362 like shift and time-invariant growth was estimated. Estimates of spawning stock biomass were biased in
363 some years (relative error quantile did not overlap zero) when inter-annual variation in k was simulated
364 and a constant model was fit (11 years), or when k varied in a regime-like pattern but was estimated
365 with inter-annual variation (2 years). However, the relative error over the length of the time series was
366 centered around zero (mean median relative error: 0.0040 and 0.0080, respectively), suggesting overall
367 spawning stock biomass estimates were relatively unbiased.

368 *Decreased precision in data-rich scenario*

369 When a constant OM was fit with an EM including time-varying growth, estimates of depletion
370 across iterations was more variable (116.65%-210.75%) as compared to estimates from an EM with
371 constant growth (Figure 4). The estimation model including regime-like L_2 deviates fit to a constant OM
372 resulted in the most variable depletion estimates. When L_2 varied inter-annually, estimated depletion
373 was much more variable (229.60%-262.53%) when compared to the estimates from an OM and EM with
374 constant growth. When L_2 varied in a regime-like pattern, including growth variation in the estimation
375 model made depletion estimates more variable (152.47%- 193.16%). However, when regime-like
376 deviates in the k parameter were included in the OM and estimated using a model with constant or

377 inter-annual deviates in k , variability in estimated depletion decreased (92.86%-93.43%) as compared to
378 a constant model. Estimated uncertainty of SSB_{MSY} did not change in response to changes to growth
379 variation specifications.

380 *Effect of data limitation*

381 In data poor scenarios, the effect of growth misspecification on estimated management
382 quantities was generally masked by the increase in uncertainty resulting from less data. However, in
383 some data-poor scenarios, median relative error did not overlap zero for the entirety of the time series.
384 This occurred when L_2 or k varied in a regime-like pattern but was estimated as constant. In these
385 scenarios, median relative error was positive (11.11% L_2 , 3.80%, k) in the data-rich scenario, but negative
386 (-1.24% L_2 , -9.24% k) in the data-poor scenario. Also, in these scenarios, 95% quantiles of relative error
387 for spawning stock biomass did not overlap zero for some years. Finally, as expected, reducing the
388 amount of available data increased the uncertainty; the width of the 95% quantiles of relative error in
389 depletion in the data-poor scenario ranged from 207.32% - 469.72% the quantile width in the data-rich
390 scenario. Uncertainty in SSB_{MSY} increased less with data removal (quantile widths ranged from 120.73% -
391 210.28%).

392 *Convergence*

393 Estimation models specifying regime-like variation in k only converged when all other growth
394 parameters were fixed at their true values. Some iterations did not converge when L_2 was simulated and
395 estimated with inter-annual variation (96% of iterations converged) and when a constant model was fit
396 to simulated regime-like (98%) or inter-annual (98%) variation in k . Some iterations did not converge in
397 the data-poor case when a constant model was fit to data simulated with interannual growth deviations
398 (98%) and in the data-rich case when a constant model was fit to simulated data with regime-like
399 variation (97%). In both the data-rich and data-poor case, convergence was poor (90%) when a model

400 including inter-annual deviates was fit to simulated data with regime-like deviates. All other scenarios
401 converged 100% of the time.

402 Discussion

403 Our results suggest misspecification of temporal variation in growth in practical stock
404 assessment models can introduce bias into estimated management reference quantities, but that this
405 bias is mitigated or eliminated by estimating time-varying growth inside the assessment model in some
406 cases. For petrale sole, time-varying growth has been documented previously (Stawitz et al. 2014);
407 estimating time-varying growth parameters within the integrated assessment model yields a better fit to
408 length composition data. However, in data-poor scenarios (i.e., sample sizes <50), biases in management
409 reference points caused by growth misspecification were masked by uncertainty in these estimates. Bias
410 was worst in cases where growth parameters varied in a regime-like pattern, but bias was reduced
411 whether regime-like or inter-annual deviations in growth parameters were estimated. These findings
412 suggest stock assessment authors should consider incorporating time-variation in growth parameters to
413 reduce bias if there is evidence variation occurs and there are at least fifty samples per year of
414 composition data spanning several decades.

415 This suggests stock assessment authors should consider incorporating inter-annual growth
416 variation in assessment models on a case-by-case basis. Particularly, stock status (i.e. depletion)
417 estimated for stocks that experience decreasing regime-like shifts in growth are likely to be the most
418 biased because of growth misspecification. Therefore, these stocks are good candidates for estimation
419 of time-varying growth. Detecting regime shifts is difficult on ecological time scales, and therefore,
420 regime-like patterns in growth may only be detectable if several decades of age- and length-composition
421 data are available (Andersen et al. 2009). In our simulation, regime-like shifts followed a “step-down”
422 pattern, so it may be that the direction of growth variation (i.e., constant decrease) is more important in
423 determining whether this variation introduced bias than the pattern (i.e., regime-like vs. inter-annual).

424 Time-blocks that roughly corresponded to periods of increased fishing effort were used to simulate
425 growth variation in this analysis. Many species are known to have experienced a period of significant
426 increase in harvest (i.e., 1985-1995 for petrale sole; Stawitz et al. 2015) and could be good targets for
427 incorporating time-varying growth, as increased fishing rates can depress size-at-age in the wild
428 population (Brander 2007; Hilborn and Minto-Vera 2008; Robinson et al. 2016). Incorporating time-
429 varying growth in estimation models when growth is constant reduced precision in final year depletion;
430 however, an estimation model incorporating time-varying growth increased depletion precision when
431 growth had regime-like variation. This suggests it may be prudent to explore if including time variation
432 in growth within a stock assessment model improves precision of management quantity estimates if it is
433 uncertain if growth varies. If growth is hypothesized to vary, stock assessment authors should explore
434 providing estimates of management quantities from models with alternative growth specifications to
435 managers in the form of model sensitivities and decision tables. Alternatively, models with alternative
436 growth specifications could be included as part of a model ensemble used to inform stock assessments
437 (Stewart and Martell 2015).

438 Practical considerations, namely convergence issues, run time, and data availability, limit the
439 benefits of including time-varying growth parameters to data-rich to data-moderate assessment models.
440 The original petrale sole stock assessment model converges well, and yet, estimating regime-like
441 variation in k led to difficulties obtaining convergence. It is likely that estimates of time-varying growth
442 would be more difficult to obtain had the key parameters of h and M not been fixed in our simulations.
443 However, fixing h and M at incorrect values may also introduce bias into estimated management
444 quantities (Clark 1999, Mangel et al. 2013), leaving analysts with the difficult choice of estimating time-
445 varying growth but introducing bias by fixing h and M values, or vice-versa. In another stock assessment
446 model application with time-varying k values (Field 2007), other growth parameters were also fixed.
447 Estimating time-varying growth is therefore infeasible for stock assessment models that already

448 experience poor convergence. Extremely data-rich stock assessments may also not benefit from time-
449 varying growth estimation, for both performance and accuracy reasons. For instance, in this example,
450 modeling temporal variation increased runtime by a factor of two (for estimation of time regime-like
451 variation) or three (for estimation of inter-annual deviations), and therefore, estimating growth might
452 restrict an analyst's ability to explore other model sensitivities for models fit to vast quantities of
453 composition data. However, if there is evidence supporting time-varying growth, then sensitivity model
454 runs to such data-rich assessments should be explored. Kuriyama et al. (2016) suggest that in very data
455 rich cases, the incorporation of empirical weight-at-age data reduces bias caused by time-varying
456 growth in estimates of spawning stock biomass more than estimation of time-varying parameters.
457 Conversely, when data are limited, we show estimates of management quantities are not precise
458 enough to be affected by time-varying growth, similar to He et al. (2016). Therefore, modeling growth
459 variation may only be practical in data-moderate (>50 age- and length-composition samples per year) to
460 data-rich (>1000 composition samples per year) cases.

461 Selecting growth parameters in which to model variation, as well as what type of variation to
462 include, also depended more on practical rather than theoretical considerations. Though the Schnute
463 (1981) reparameterization of the von Bertalanffy (1957) growth curve is more numerically stable, k and
464 L_{∞} are inherently negatively correlated (Pilling et al. 2002) and it is difficult to isolate which parameter of
465 the growth curve varies from biological data. Thorson and Minte-Vera (2014) found changes in weight-
466 at-age are difficult to isolate from those in growth (as measured by k), but that 45% of the variation in
467 their data set is explained by k variation. Like Zhu et al (2016), we found temporal variation in k was
468 more difficult to estimate than that in L_2 within an integrated assessment model. Furthermore, although
469 growth scenarios with simulated regime-like variation introduced greater bias into management
470 estimates from constant estimation models, estimating inter-annual variation in growth parameters
471 reduced bias in estimated quantities substantially in these scenarios. Furthermore, inter-annual

472 deviations in growth were easier to estimate (for k) than regime-like variation, likely because models
473 including regime-like variation include more parameters. Finally, estimation of regime-like variation
474 necessitates that analysts pre-specify the number and length of each time-block of variation, and this
475 requires breakpoint analysis to be conducted external to the assessment model.

476 The somatic growth patterns that we estimated and then used to specify the simulation may
477 capture or correlate with temporal variation in other demographic processes; however, we argue these
478 patterns are still the most realistic available. Alternative forms of temporal demographic variation were
479 not explored for the empirical data. It is therefore plausible that temporal changes in age- and length-
480 composition data used in this simulation are actually the product of temporal variation in natural
481 mortality, fishing mortality, or recruitment. Covariation in demographic rates is certainly non-zero
482 (Parma and Deriso 1990; Thorson et al. 2015); however, incorporating this covariation into assessment
483 models used to manage fisheries is likely infeasible until these patterns of covariation are better
484 estimated and documented in the literature.

485 Fisheries selectivity is well-known to vary with time, and since selectivity is often length-based,
486 patterns of time-varying selectivity may be confounded with time-varying growth (Thorson and
487 Simpendorfer 2009). For this reason, estimating time-varying growth and time-varying selectivity
488 concurrently in an integrated assessment is generally not feasible. We recommend analysts examine
489 management changes occurring concurrently with periods of observed changes in sampled size-at-age.
490 If fisheries regulations, gear use, or fishing locations changed, this could indicate time-varying selectivity
491 causes variation in sampled size-at-age, but variation in data that is not explained by management
492 changes could instead be attributed to time-varying growth. Our results suggest if time-varying growth
493 patterns are attributed to changes in selectivity and fit using constant growth parameters, this may
494 introduce bias into estimated life history parameters and biological reference points.

495 All demographic rates as well as sampling processes (i.e., selectivity) vary over time, both
496 independently and synergistically; here, we suggest process error due to somatic growth variation
497 should be considered more explicitly by stock assessment analysts. While observations of somatic
498 growth are imperfectly observed, growth variation is more directly measurable than changes in
499 recruitment or natural mortality, and therefore, realistic estimates of variation may be easier to attain
500 for species with many (>50) age- and length-composition samples spanning several decades.
501 Furthermore, although incorporating time-varying natural mortality may improve accuracy in
502 assessment models (Jiao et al. 2012), miss-specifying natural mortality as time-varying may introduce
503 bias into model estimates (Fu and Quinn 2000). Therefore, if it is unclear whether mortality or growth
504 varies, it may be safer to incorporate time-varying growth, as the same negative effects were not
505 observed in this study if “true” growth was constant but was estimated as time-varying. Future work
506 should evaluate the applicability of these results to other long-lived fishes with differing morphologies
507 and life histories (i.e., rockfish and gadoids) to determine how broadly these conclusions may extend.

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513 References

- 514 Abbott, J.K.; Haynie, A.C.; Reimer, M.N. Hidden flexibility: institutions, incentives, and the margins of
515 selectivity in fishing. *Land Economics*. 91:169-195; 2015
- 516 Andersen, T.; Carstensen, J.; Hernández-García, E.; Duarte, C.M. Ecological thresholds and regime shifts:
517 approaches to identification. *Trends in Ecology & Evolution*. 24:49-57; 2009
- 518 Anderson, S.C.; Monnahan, C.C.; Johnson, K.F.; Ono, K.; Valero, J.L. ss3sim: an R package for fisheries
519 stock assessment simulation with Stock Synthesis. *PLoS ONE*. 9:e92725; 2014
- 520 Bertalanffy, L.v. Quantitative Laws in Metabolism and Growth. *The Quarterly Review of Biology*. 32:217-
521 231; 1957

522 Black, B.A. Climate-driven synchrony across tree, bivalve, and rockfish growth-increment chronologies of
523 the northeast Pacific. *Marine Ecology Progress Series*. 378:37-46x`; 2009

524 Brander, K.M. The role of growth changes in the decline and recovery of North Atlantic cod stocks since
525 1970. *ICES Journal of Marine Science*. 64:211-217; 2007

526 Breiman, L.; Friedman, J.; Stone, C.J.; Olshen, R.A. *Classification and regression trees*: Chapman and
527 Hall/CRC; 1984

528 Charnov, E. L., Gislason, H., & Pope, J. G. (2013). Evolutionary assembly rules for fish life histories. *Fish
529 and Fisheries*, 14(2), 213-224.

530 Cheung, W.L.; Jorge, L.S.; John, D.; Thomas, L.F.; Vicky, W.Y.L.; Palomares, M.L.D.; Reg, W.; Pauly, D.
531 Shrinking of fishes exacerbates impacts of global ocean changes on marine ecosystems. *Nature
532 Climate Change*. 3:254-258; 2012

533 Clark, W.G. 1999. Effects of an erroneous natural mortality rate on a simple age-structured stock
534 assessment. *Canadian Journal of Fisheries and Aquatic Sciences*. 56(10): 1721 - 1731.

535 Clark, W.G.; Hare, S.R.; Parma, A.M.; Sullivan, P.J.; Trumble, R.J. Decadal changes in growth and
536 recruitment of Pacific halibut (*Hippoglossus stenolepis*). *Canadian Journal of Fisheries and
537 Aquatic Sciences*. 56:242-252; 1999

538 Field, J.C. Status of the Chilipepper rockfish, *Sebastes goodei*, in 2007. Portland, OR: Pacific Fishery
539 Management Council; 2007

540 Fu, C.; Quinn, T.J. Estimability of natural mortality and other population parameters in a length-based
541 model: *Pandalus borealis* in Kachemak Bay, Alaska. *Canadian Journal of Fisheries and Aquatic
542 Sciences*. 57:2420-2432; 2000

543 Gaichas, S.K.; Aydin, K.Y.; Francis, R.C. Using food web model results to inform stock assessment
544 estimates of mortality and production for ecosystem-based fisheries management. *Canadian
545 Journal of Fisheries and Aquatic Sciences*. 67:1490-1506; 2010

546 Gårdmark, A.; Jonzén, N.; Mangel, M. Density-dependent body growth reduces the potential of marine
547 reserves to enhance yields. *Journal of Applied Ecology*. 43:61-69; 2006

548 He, X., Field, J.C., Pearson, D.E., Lefebvre, L.S. Age sample sizes and their effects on growth estimation
549 and stock assessment outputs: Three case studies from U.S. West Coast fisheries. 180: p. 92 -
550 102; 2016

551 Helser, T.E.; Brodziak, J.K.T. Impacts of density-dependent growth and maturation on assessment advice
552 to rebuild depleted U.S. silver hake (*Merluccius bilinearis*) stocks. *Canadian Journal of Fisheries
553 and Aquatic Sciences*. 55:882-892; 1998

554 Helser, T.E.; Methot Jr, R.D.; Fleischer, G.W. Stock assessment of Pacific hake (Whiting) in U.S. and
555 Canadian waters in 2003. Portland, OR: Pacific Fishery Management Council; 2004

556 Hilborn, R.; Minto-Vera, C.V. Fisheries-Induced changes in growth rates in marine fisheries: are they
557 significant? *Bulletin of Marine Science*. 83:95-105; 2008

558 Ianelli, J.N.; Honkalehto, T.; Barbeaux, S.; Fissel, B.; Kotwicki, S. Assessment of the walleye pollock stock
559 in the Eastern Bering Sea. Anchorage, AK: North Pacific Fishery Management Council; 2016

560 Jiao, Y.; Smith, E.P.; O'Reilly, R.; Orth, D.J. Modelling non-stationary natural mortality in catch-at-age
561 models. *ICES Journal of Marine Science*. 69:105-118; 2012

562 Kuriyama, P.T.; Ono, K.; Hurtado-Ferro, F.; Hicks, A.C.; Taylor, I.G.; Licandeo, R.L.; Johnson, K.F.;
563 Anderson, S.C.; Monnahan, C.C.; Rudd, M.B.; Stawitz, C.C.; Valero, J.L. An empirical weight-at-
564 age approach reduces estimation bias compared to modeling parametric growth in integrated,
565 statistical stock assessment models when growth is time varying. *Fisheries Research*. 180:119-
566 127; 2016

567 Mangel, M. MacCall, A.D., Brodziak, J., Dick, E.J., Forrest, R.E., Pourzand, R. Ralston, S. A perspective on
568 steepness, reference points, and stock assessment. *Canadian Journal of Fisheries and Aquatic
569 Sciences*, 70(6): 930-940; 2013

570 Maunder, M.N. and Piner, K.R. Contemporary fisheries stock assessment: many issues still remain. ICES
571 Journal of Marine Science. 72(1):7-18; 2015

572 Mantua, N.J.; Hare, S.R. The Pacific Decadal Oscillation. Journal of Oceanography. 58:35-44; 2002

573 Maunder, M.N.; Punt, A.E. A review of integrated analysis in fisheries stock assessment. Fisheries
574 Research. 142:61-74; 2013

575 Maunder, M. N., & Watters, G. M. (2003). A general framework for integrating environmental time series
576 into stock assessment models: model description, simulation testing, and example. *Fishery*
577 *Bulletin*, 101(1), 89-99.

578 McGowan, J.A.; Cayan, D.R.; Dorman, L.M. Climate-ocean variability and ecosystem response in the
579 Northeast Pacific. Science. 281:210-217; 1998

580 Methot Jr, R.D.; Wetzel, C.R. Stock synthesis: a biological and statistical framework for fish stock
581 assessment and fishery management. Fisheries Research. 142:86-99; 2013

582 Miller, T.J., O'Brien, L., Fratantoni, P.S. Temporal and environmental variation in growth and maturity
583 and effects on management reference points in Georges Bank Atlantic cod. Canadian Journal of
584 Fisheries and Aquatic Science. 75(12):2159-2171; 2018

585 Monnahan, C.C.; Ono, K.; Anderson, S.C.; Rudd, M.B.; Hicks, A.C.; Hurtado-Ferro, F.; Johnson, K.F.;
586 Kuriyama, P.T.; Licandeo, R.R.; Stawitz, C.C.; Taylor, I.G.; Valero, J.L. The effect of length bin
587 width on growth estimation in integrated age-structured stock assessments. Fisheries Research.
588 180:103-112; 2016

589 Ono, K.; Licandeo, R.; Muradian, M.L.; Cunningham, C.J.; Anderson, S.C.; Hurtado-Ferro, F.; Johnson, K.F.;
590 McGilliard, C.R.; Monnahan, C.C.; Szuwalski, C.S.; Valero, J.L.; Vert-Pre, K.A.; Whitten, A.R.; Punt,
591 A.E. The importance of length and age composition data in statistical age-structured models for
592 marine species. ICES Journal of Marine Science: Journal du Conseil. 72:31-43; 2015

593 Parma, A.M.; Deriso, R.B. Dynamics of age and size composition in a population subject to size-selective
594 mortality: effects of phenotypic variability in growth. Canadian Journal of Fishery and Aquatic
595 Sciences. 47:274-289; 1990

596 Pilling, G.M.; Kirkwood, G.P.; Walker, S.G. An improved method for estimating individual growth
597 variability in fish, and the correlation between von Bertalanffy growth parameters. Canadian
598 Journal of Fisheries and Aquatic Sciences. 59:424-432; 2002

599 Ricker, W.E. Computation and interpretation of biological statistics of fish populations. Fisheries
600 Research Board of Canada Bulletin. 191:382; 1975

601 Rijnsdorp, A.D.; van Leeuwen, P.I. Changes in growth of North Sea plaice since 1950 in relation to
602 density, eutrophication, beam-trawl effort, and temperature. ICES Journal of Marine Science.
603 3:1199-1213; 1992

604 Robinson James, P.W.; Williams Ivor, D.; Edwards Andrew, M.; McPherson, J.; Yeager, L.; Vigliola, L.;
605 Brainard Russell, E.; Baum Julia, K. Fishing degrades size structure of coral reef fish communities.
606 Global Change Biology. 23:1009-1022; 2016

607 Rosenberg, A.A.; Restrepo, V.R. Uncertainty and risk evaluation in stock assessment advice for U.S.
608 marine fisheries. Canadian Journal of Fisheries and Aquatic Sciences. 51:2715-2720; 1994

609 Schnute, J. A versatile growth model with statistically stable parameters. Canadian Journal of Fisheries
610 and Aquatic Sciences. 38:1128-1140; 1981

611 Stawitz, C.C.; Essington, T.E.; Branch, T.A.; Haltuch, M.A.; Hollowed, A.B.; Spencer, P.D. A state-space
612 approach for detecting growth variation and application to North Pacific groundfish. Canadian
613 Journal of Aquatic and Fishery Sciences. 72:1316-1328; 2015a

614 Stawitz, C.C.; Hurtado-Ferro, F.; Kuriyama, P.T.; Trochta, J.T.; Johnson, K.F.; Haltuch, M.A.; Hamel, O.S.
615 Stock assessment update: status of the U.S. petrale sole resource in 2014. Portland, OR.: Pacific
616 Fishery Management Council; 2015b

617 Stewart, I.J.; Martell, S.J.D. Reconciling stock assessment paradigms to better inform fisheries
618 management. *ICES Journal of Marine Science*. 72:2187-2196; 2015

619 Taylor, I.G.; Grandin, C.; Hicks, A.C.; Taylor, N.G.; Cox, S. Status of the Pacific hake (whiting) stock in U.S.
620 and Canadian waters in 2015. Joint Technical Committee of the U.S. and Canada Pacific
621 Hake/Whiting Agreement; National Marine Fishery Service; Canada Department of Fisheries and
622 Oceans; 2015

623 Thorson, J.T.; Minte-Vera, C.V. Relative magnitude of cohort, age, and year effects on size at age of
624 exploited marine fishes. *Fisheries Research*; 2014

625 Thorson, J.T.; Monnahan, C.C.; Cope, J.M. The potential impact of time-variation in vital rates on
626 fisheries management targets for marine fishes. *Fisheries research*. 169:8-17; 2015

627 Thorson, J.T.; Simpfendorfer, C.A. Gear selectivity and sample size effects on growth curve selection in
628 shark age and growth studies. *Fisheries Research*. 98:75-84; 2009

629 Walters, G.E.; Wilderbuer, T.K. Decreasing length at age in a rapidly expanding population of northern
630 rock sole in the eastern Bering Sea and its effect on management advice. *Journal of Sea
631 Research*. 44:17-26; 2000

632 Warlick, A.; Steiner, E.; Guldin, M. History of the West Coast groundfish trawl fishery: tracking
633 socioeconomic characteristics across different management policies in a multispecies fishery.
634 *Marine Policy*. 93:9-21; 2018

635 Whitten, A.R.; Klaer, N.L.; Tuck, G.N.; Day, R.W. Accounting for cohort-specific variable growth in
636 fisheries stock assessments: a case study from south-eastern Australia. *Fisheries Research*.
637 142:27-36; 2013

638 Wolter, K.; Timlin, M.S. Monitoring ENSO in COADS with a seasonally adjusted principal component
639 index. *Proc of the 17th Climate Diagnostics Workshop*. Norman, OK: NOAA/NMC/CAC, NSSL,
640 Oklahoma Clim. Survey, CIMMS and the School of Meteor., Univ. of Oklahoma; 1993

641 Wolter, K.; Timlin, M.S. Measuring the strength of ENSO events - how does 1997/1998 rank? *Weather*.
642 53:315-324; 1998

643 Zhu, J., Maunder, M.N., Aires-da-Silva, A.M., Chen, Y. Estimation of growth within Stock Synthesis
644 models: Management implications when using length-composition data. *Fisheries Research*.
645 180: 87 - 91. 2016.

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648 **Tables**

649 *Table 1 – Scenarios tested span 15 permutations of operating and estimation model growth*
 650 *specifications, and each scenario is run for both the data-rich and data-poor scenario.*

Operating model specification	Estimation model specifications
Inter-annual deviates on L_2 simulated using assessment model fit to fishery & survey data	Inter-annual L_2 deviates, Constant
Regime-like deviates on L_2 simulated from assessment model fit to fishery & survey data	Inter-annual L_2 deviates, Regime-like L_2 deviates, Constant
Inter-annual deviates on k simulated using assessment model fit to fishery & survey data	Inter-annual k deviates, Constant
Regime-like deviates on k simulated from assessment model fit to fishery & survey data	Inter-annual k deviates, Regime-like k deviates, Constant
Constant	Inter-annual L_2 deviates, Regime-like L_2 deviates, Constant, Inter-annual k deviates, Regime-like k deviates

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653 *Table 2 – Time-blocks evaluated for periods of growth variation. Negative log likelihoods are*
 654 *derived from the simplified assessment model fit to available data. Asterisk (*) denotes selected*
 655 *time-block for k and L_2 and the number in parentheses represents the number of parameters*
 656 *used to fit each model.*

Regime Name	Fishing mortality (198)	ENSO	PDO (Field 2007)
Time-block years	1965-1977, 1978-1986, 1987-2002, 2003-2014	1965-1976, 1977-1998, 1999-2014	1965-1979, 1980- 1988, 1989-1991, 1992-1998, 1999- 2006, 2007-2014
Negative log likelihood (k)	1461.08* (201)	1467.44 (199)	1462.42 (205)
Negative log likelihood (L_2)	1444.62* (198)	1460.06 (196)	1448.21 (202)

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658

659 *Table 3 – Negative log likelihood (NLL) and estimated growth parameters (k: slope of somatic*
660 *growth curve; L₂: mean asymptotic size at maximum age, CV₁: CV of length-at-age at age a, CV₂:*
661 *CV of length-at-age at age A) for alternative models (rows) when a simplified assessment model*
662 *was fit to empirical data. * denotes values that were fixed to ensure convergence.*

Model	# pars	NLL	Females				Males			
			k	L ₂ (cm)	CV ₁	CV ₂	k	L ₂ (cm)	CV ₁	CV ₂
Base model	215	1401.66	0.14	54.44	0.20	0.02	0.19	43.54	0.15	0.04
k inter-annual		1306.02	0.13*	54.89	0.19	0.02	0.20*	44.14	0.15	0.04
L ₂ inter-annual		1300.56	0.15	54.44*	0.19	0.03	0.24	43.54*	0.14	0.05
k regime-like	201	1461.08	0.14*	54.83	0.20	0.02	0.19*	43.85	0.15	0.04
L ₂ regime-like	198	1448.02	0.13	54.44	0.19	0.02	0.23	43.54	0.14	0.05

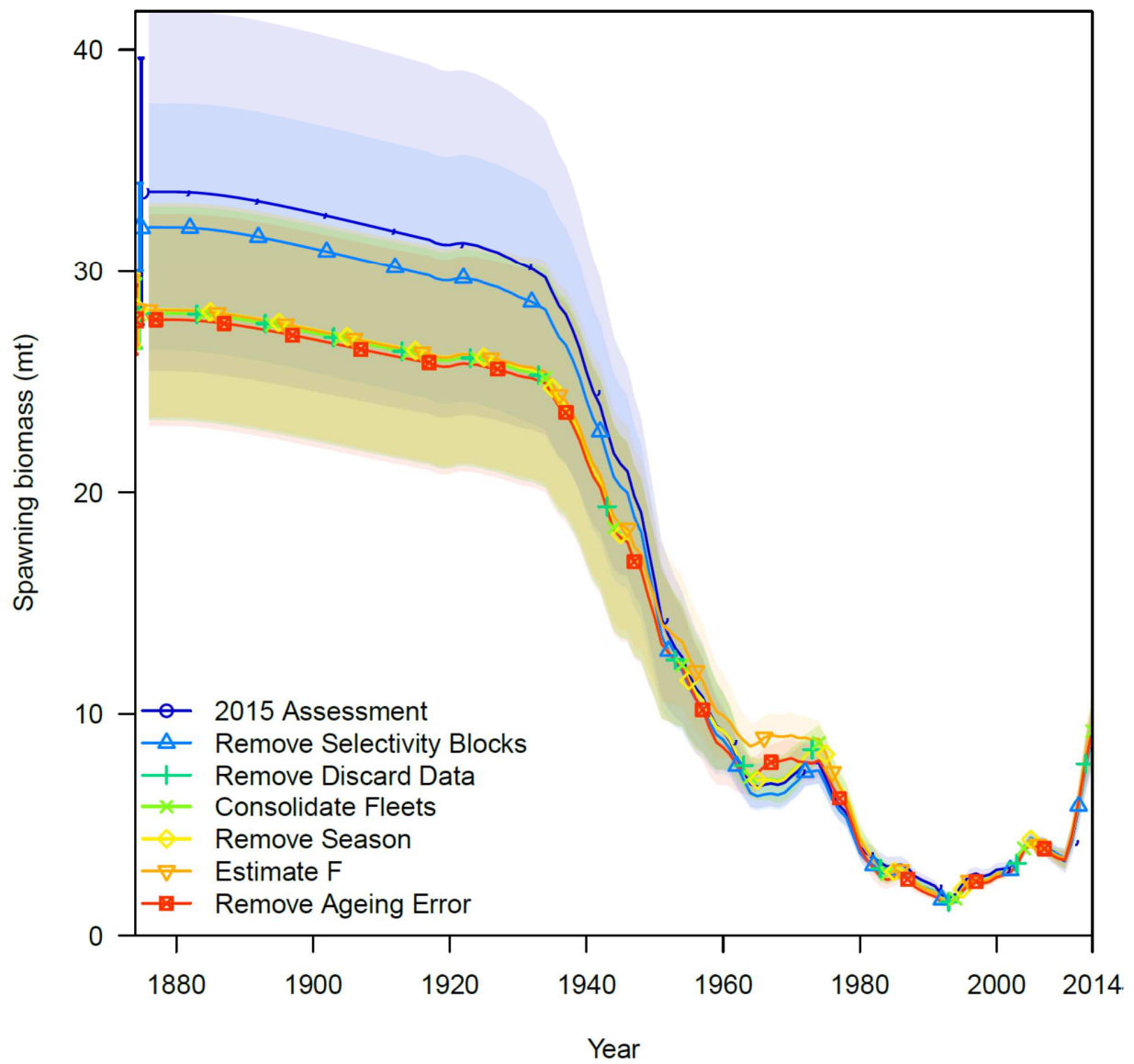
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665 *Table 4 - Summary of results across scenarios. Presented numbers are median values of scenario*
666 *runs across converged iterations. Rank is from most to least biased.*

Data amount	OM, EM scenario	Median end year depletion bias	Median bias in SSB_{MSY}	Rank of depletion bias
Poor	Constant, Constant	-0.06	-0.03	5
Rich	Constant, Constant	-0.04	-0.04	7
Poor	Constant, L2 devs	-0.06	-0.03	5
Rich	Constant, L2 devs	-0.04	-0.03	7
Poor	Constant, L2 regimes	-0.07	-0.03	4
Rich	Constant, L2 regimes	-0.05	-0.04	6
Poor	Constant, k devs	-0.03	-0.02	8
Rich	Constant, k devs	-0.04	-0.03	7
Poor	Constant, k regimes	-0.05	-0.04	6
Rich	Constant, k regimes	-0.04	-0.04	7
Poor	L2 Devs, Constant	-0.05	-0.04	6
Rich	L2 Devs, Constant	-0.03	-0.04	8
Poor	L2 Devs, L2 devs	-0.06	-0.06	5
Rich	L2 Devs, L2 devs	-0.05	-0.04	6
Poor	k Devs, Constant	0.06	0.00	5
Rich	k Devs, Constant	0.05	0.01	6
Poor	k Devs, k devs	0.03	0.01	8
Rich	k Devs, k devs	-0.03	-0.04	8
Poor	L2 regimes, constant	-0.02	0.00	9
Rich	L2 regimes, constant	0.11	-0.02	1
Poor	L2 regimes, L2 regimes	-0.06	-0.04	5
Rich	L2 regimes, L2 regimes	-0.06	-0.01	5
Poor	L2 regimes, L2 devs	-0.02	-0.09	9
Rich	L2 regimes, L2 devs	-0.02	-0.04	9
Poor	k regimes, constant	-0.09	-0.07	2
Rich	k regimes, constant	0.04	-0.09	7
Poor	k regimes, k regimes	-0.05	-0.05	6
Rich	k regimes, k regimes	-0.02	-0.04	9
Poor	k regimes, k regimes	-0.08	-0.04	3
Rich	k regimes, k regimes	-0.04	-0.04	7

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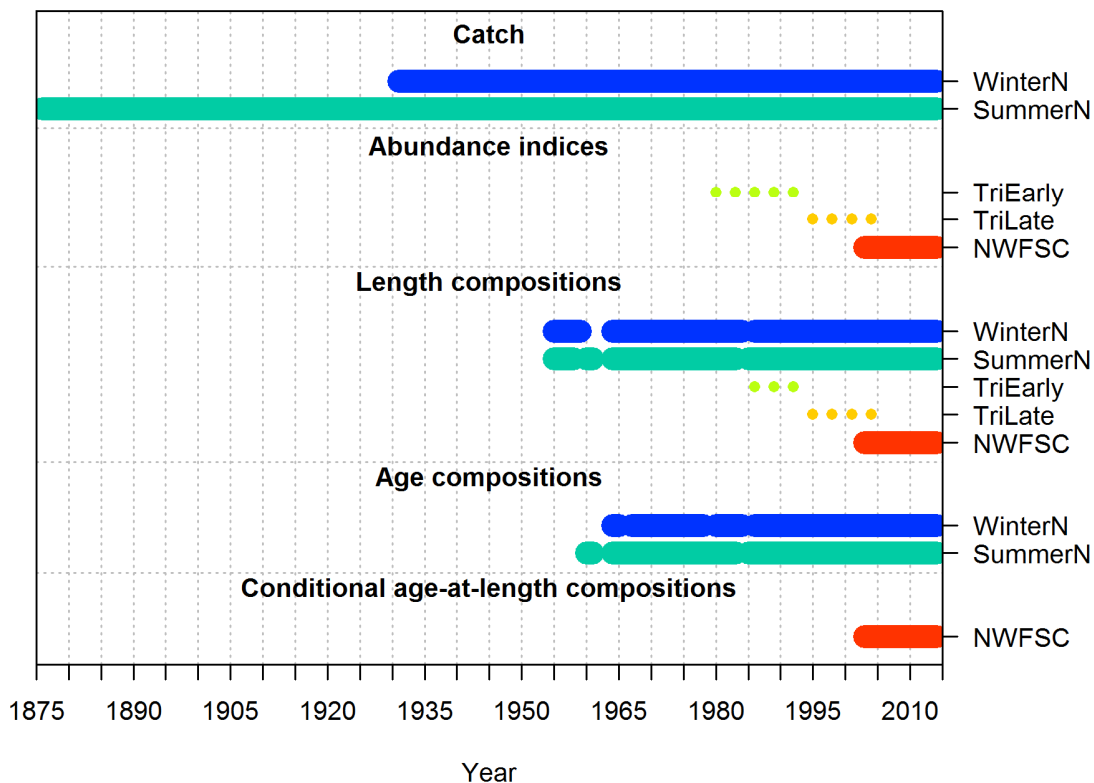


669

670 Figure 1 - Comparison of spawning stock biomass trajectories as model simplification occurred (from top
 671 to bottom). Dark blue represents the assessment model used for the 2015 update assessment; red
 672 represents the final simulation model. Shaded areas represent 95% confidence intervals.

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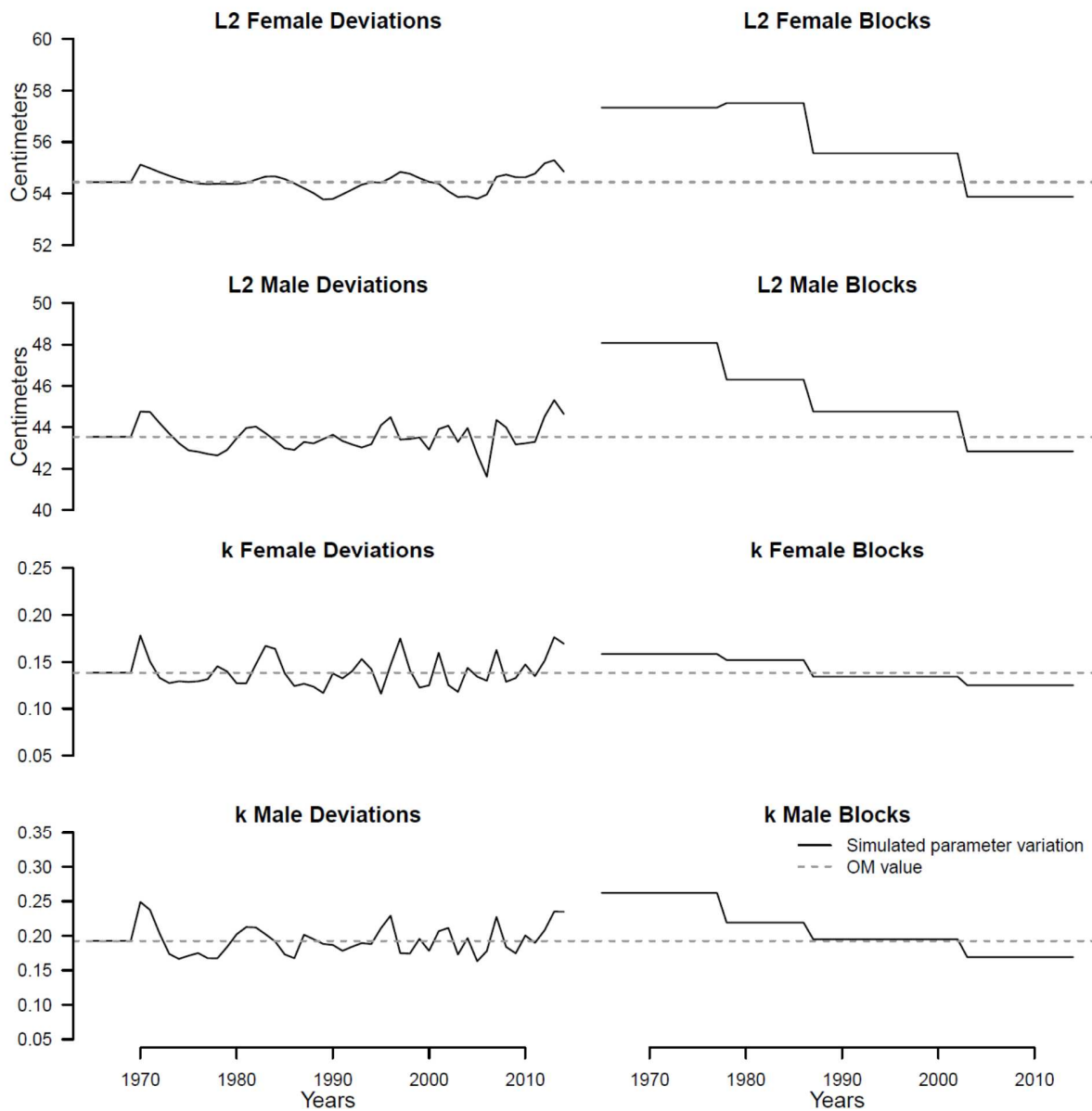
Data by type and year



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675 Figure 2 - Illustration of data used in the simplified stock assessment model used to obtain the operating
676 model values by year and type.

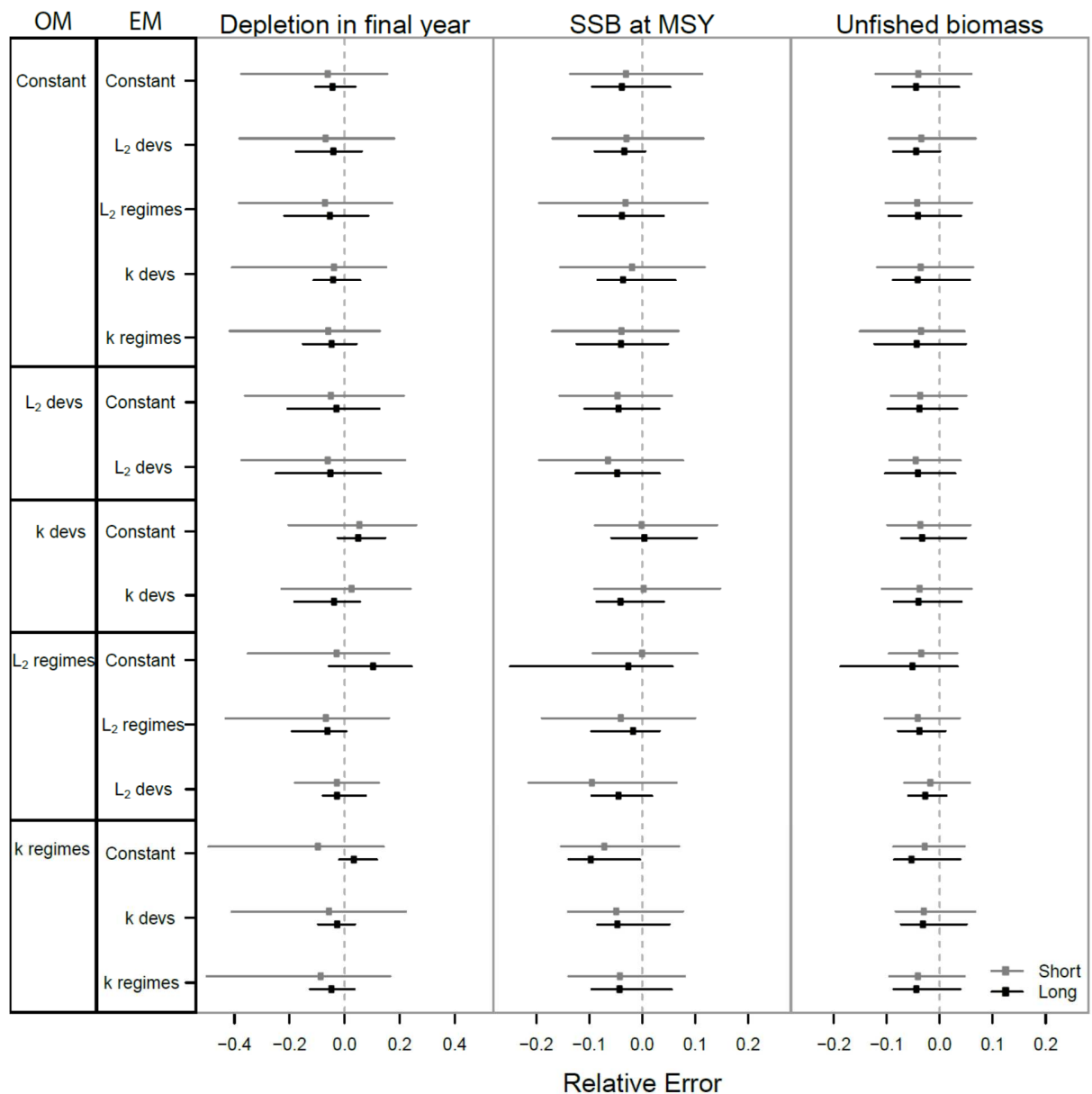
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679 Figure 3 - Input growth-parameter variation across four scenario configurations. Gray, dashed line
 680 represents starting parameter value, and black line represents simulated patterns under alternative
 681 growth scenarios for male (left) and female (right) fish. Simulated patterns are taken from fits to actual
 682 data using Stock Synthesis.

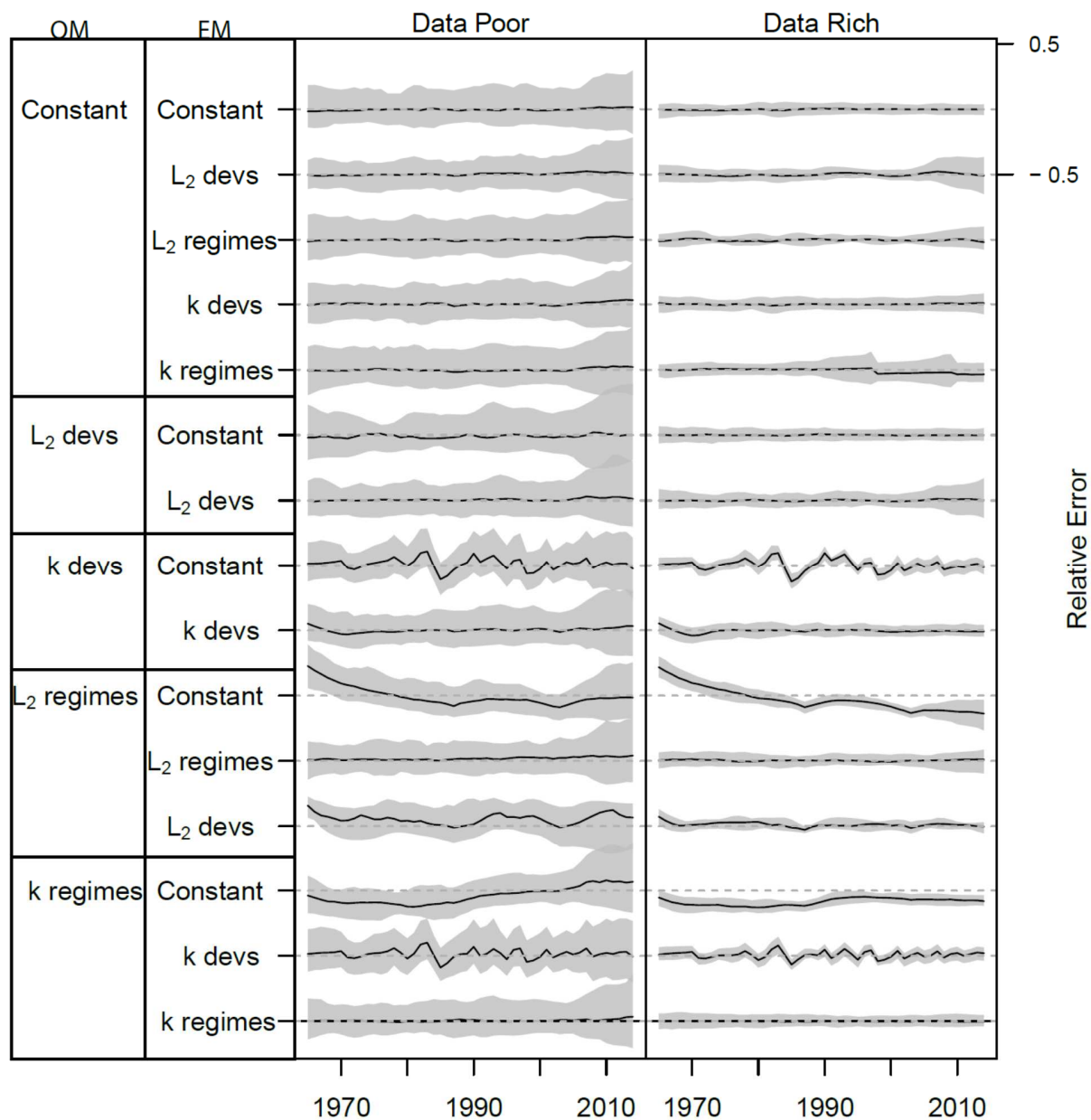
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684

685 Figure 4 - Median (point) and 95% quantiles (lines) of relative error in estimates of depletion in the final
 686 model year (left), spawning stock biomass (SSB) at maximum sustainable yield (MSY) (middle), and
 687 unfished biomass in the first model year, 1876 (right). Operating model configurations (OM) and
 688 estimation model configurations (EM) for each scenario are specified on the left. Results are for both the
 689 data-poor (gray) and -rich (black) scenarios and the vertical, dashed line indicates where zero bias
 690 occurs.

691



692

693 Figure 5 - Time series of relative error in estimated spawning stock biomass over time for which age
 694 composition data exists (1965 – 2014). Gray shaded area represents the 95% quantile, while the black
 695 line represents the median. The straight black line represents no error over the time series would occur.
 696 Each scenario is presented on the same scale, with a maximum pictured error of +0.5 and -0.5.
 697 Estimation model configurations (EM) and operating model configurations (OM) for each scenario are
 698 on the left. The numbers to the right of the lines for depletion bias rank the bias, from highest to lowest,
 699 with starred values denoting the data-rich scenarios.

700