Evaluating the impacts of fixing or estimating growth parameters, across life histories and data availability

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# Main questions

1. What types of data are informative for estimating growth inside an integrated model?
2. What quantity of data is needed to estimate growth inside an integrated model?
3. What are the tradeoffs, with respect to management reference points, between using external estimates of growth versus estimating growth inside an integrated model?
4. How does life history affect the estimation of growth across estimation methods, data type and quantity?

# Abstract

In statistical integrated age structured population models, there are two common practices used to incorporate somatic growth into the population dynamics. First, a parametric somatic growth model is fit externally to length-at-age data and the estimates are input to the model as fixed parameters. Second, the model simultaneously estimates growth parameters with other population dynamics and fishery processes. When growth is estimated externally to the stock assessment model, the effects of population dynamics and the cumulative effects of fishing on size-at-age on growth estimates are typically not accounted for. In addition, ignoring gear selectivity when estimating growth (internally or externally) is problematic because fisheries tend to select faster-growing fish. Therefore, growth estimated from unrepresentative data may not reflect the true population growth curve, which can lead to biased stock assessment results, biological reference points and management quantities. Furthermore, the quality and quantity of length- and age-composition data can affect the accuracy of parameter estimates and thus management reference points. Growth may be estimated internally when there is length composition data, or tag-recapture data. However, incorporating age-composition data in addition to length-composition data may or may not improve stock assessment estimates. For instance, even if length- and age-composition data are both available, the quality and quantity of this information can affect the accuracy of stock assessment outputs, with larger repercussions on some life-history types than others. Thus, estimation of growth parameters within a stock assessment model is not possible for all life-history types. Therefore, it is important to quantify the importance of different data types and quantity to stock assessment estimates across life-history types. Here we used ss3sim, a simulation framework utilizing Stock Synthesis, to evaluate the types and quantity of data that are needed to estimate somatic growth within an assessment model and the tradeoffs between estimating growth internally versus externally. The focus of this research is not only on the ability to estimate growth but also on the impact of potential model misspecification related to growth estimation on assessment-derived quantities of interest to management across contrasting life-history types. Measurements of bias and precision with respect to spawning stock biomass, fishing mortality level, and management reference points were used to quantify the performance of stock assessment models that internally estimated somatic growth parameters compared with stock assessment models that had somatic growth fixed at externally estimated values.

**Introduction**

The field of stock assessment has made substantial progress during the past 50 years (Quinn, 2003; Maunder and Piner, 2014), including but not limited to the inclusion of non-linear models, advancement of integrated analysis (Fournier and Archibald, 1982; Fournier *et al*., 2012), and development of length-based models (Beddington and Cooke, 1981; Quinn and Deriso, 1999). Nevertheless, stock assessment models rely on accurate estimation of demographic processes to adequately estimate reference points used to manage fisheries (Maunder, 2012). Somatic growth is a key process that drives productivity (Lorenzen & Enberg, 2002), and studies suggest that the manner in which growth is estimated within stock assessments may bias estimates of management reference points (McGarvey *et al*., 2007; Whitten *et al*., 2013). Bias in growth parameter estimates primarily arise as a result of i) failure to explicitly account for sampling and process error when estimating growth parameters and ii) low quality or limited availability of age- and length-composition data. However, the relative impacts of these issues on the performance of stock assessments are not well quantified across life history types.

In statistical integrated age structured population models, there are two alternative ways to translate between biomass quantities of data and quantities of interest (e.g., reported catches and estimated mature biomass, respectively) and the age-based quantities of the model (e.g., numbers at age of catches and numbers at age of mature fish): i) model parametric somatic growth (either estimated or fixed) or ii) use an empirical approach based on observed weights at age. There are two common practices used to incorporate somatic growth into the population dynamics. First and most common, a parametric somatic growth model is fit externally to length-at-age data and the estimates are input to the model as fixed parameters. Second, the model simultaneously estimates growth parameters with other population dynamics model components (e.g., recruitment, fishing, selectivity, etc.). In both approaches to model somatic growth, it is typically necessary to include a parameter that describes the coefficient of variation of length-at-age, which is usually difficult to estimate or is not available from previous age and growth studies.

If growth is estimated externally to the stock assessment model, the effects of population dynamics and the cumulative effects of fishing on size-at-age on growth estimates are typically not accounted for. For example, recent studies have shown that mean length-at-age can vary year-by-year (Arnekleiv *et al*., 2006; Whitten *et al*., 2013), spatially (Gaertner *et al*., 2008), and between cohorts (Feltrim and Ernst, 2010). In addition, ignoring fishery selectivity when estimating growth (internally or externally), is known to be problematic because fisheries tend to select faster-growing fish. Therefore, accurate growth estimates are needed to represent individual growth in population dynamics models. Biased estimates of growth parameters can severally distort length-age keys, which are used to convert length to age in stock assessment models, and can also introduce bias in biological reference points for management quantities such as yield per recruit (Ricker, 1969; Parma and Deriso, 1990).

Furthermore, the quality and quantity of length- and age-composition data used in estimation can affect the accuracy of parameter estimates and thus management reference points. Growth may be estimated internally when there is length composition data, or tag-recapture data. However, incorporating age-composition data in addition to length-composition data may or may not improve estimates derived from stock assessment models (Fournier *et al*., 1998). For instance, even if length- and age-composition data are both available, the quality and quantity of this information can affect the accuracy of stock assessment outputs, with larger repercussions on some life-history types than others (Ono *et al*., 2014). Thus, estimation of growth parameters within a stock assessment model is not possible for all life-history types (Harley, 2002). Furthermore, length-independent aging of fish can be expensive and time-consuming. Therefore, it is important to quantify the importance of length-at-age data to stock assessment estimates across life-history types.

Simulation modelling was used here to quantify the types and quantity of data that are needed to estimate somatic growth within an assessment model and the tradeoffs between estimating growth internally versus externally. The focus of this research is not only on the ability to estimate growth, but also on the impact of potential model misspecification related to growth estimation on assessment-derived quantities of interest to management. Furthermore, we assessed how model performance and tradeoffs differ across three contrasting life-history types. Measurements of bias and precision with respect to spawning stock biomass, fishing mortality level, and management reference points were used to compare the performance of stock assessment models that internally estimated somatic growth parameters to those which fixed somatic growth parameters at externally estimated values. Many of these tradeoffs have not been well studied before. This research focuses on: i) What types of data are informative for estimating growth inside an integrated model; ii) What data quantity is needed to estimate growth inside an integrated model; iii) What are the tradeoffs between using external estimates of growth versus estimating growth inside an integrated model; and iv) How life history affects the estimation of growth across estimation methods, data type and quantity.

# Methods

**Overview**

Monte Carlo simulations were used to evaluate the performance of an integrated stock assessment framework, Stock Synthesis 3 (SS3, version V3.24O; Methot and Wetzel 2013), when somatic growth was either estimated internally or externally to the model across a range of life-history types and data quantity and quality. Each simulated truth (operating model; OM) was fit using five estimation methods (EM), hereinafter referred to as a scenario, where SS3 was used for both the OM and the EM. EM performance was determined by comparing estimates of relevant quantities (i.e., parameter estimates and reference points) with their “true” values as defined by the OM. Each scenario was repeated 100 times with different recruitment deviations and observation error for the 100 year time series. In cases of non-convergence or instability, additional scenario replicates were run to achieve the desired number of converged/accepted replicates (100). Convergence was evaluated as the ability of a model run to produce a covariance matrix. Simulations were conducted using the *ss3sim* simulation framework (Anderson *et al*. 2014a, b) in R (R Core Team, 2014).

**Operating models**

Three life-history types were simulated based on Pacific hake (*Merluccius productus*; Taylor *et al*., 2014), Pacific mackerel (*Trachurus symmetricus*, Crone *et al*., 2011), and yelloweye rockfish (*Sebastes ruberrimus*; Taylor and Wetzel, 2011). The contrasting life histories include a medium-lived, moderate-growing type (hake); a short-lived, fast-growing small pelagic type (mackerel); and a long-lived, slow-growing type (rockfish). Actual assessment models were simplified for the purposes of this paper. Simplified models are generally, but not strictly consistent with the actual assessment models and therefore results should not be compared to specific estimates from particular assessments. Models were simplified to have one sex, a Beverton-Holt stock-recruitment function, zero growth morphs, one survey, and one fishery to facilitate comparisons across life-history types.

Fishing followed a “two-way trip” scenario, where the fishery started in year 25 and linearly increased for 60 years to the value that produced 0.95*MSY* on the right limb of the production curve, followed by a 14 year linear decrease to the F corresponding to 0.95*MSY* on the left limb of the production curve (Figure 1). Thus, the first 25 years of the simulation acted as a burn in period. For all scenarios, catch data were assumed to be known without error. Fishery selectivity was length-based and mimicked the length-based maturity ogive (i.e., asymptotic), but with white noise added to the length at 50% selected to mimic the time-varying selectivity often seen in actual fishery data.

The base case survey started in year 75 and operated every other year, providing an index of abundance. Survey selectivity also mimicked the maturity ogive, though the length at which 50% of individuals were selected was specified as 80% of the length at which 50% of individuals are mature. Thus, the survey sampled younger fish and was time-invariant.

A description...

Figure 1. Fishing pattern, specifying a two-way trip based on *MSY*.

**Data types**

All survey composition data were generated using a multinomial distribution, which assumes homogeneous capture probabilities across bins and perfect mixing, whereas, fishery composition data were generated using a Dirichlet distribution to more accurately reflect the decreased information available from fishery data. Overdispersion in the fishery data was simulated using a standard deviation two times the size of standard deviation of a complementary multinomial distribution. Furthermore, all age composition data was subject to aging error based on the actual aging error assumed in the relevant assessment model. Length bins were 1 cm and age bins were 1 year, thus the number of length and age bins was specific to each life history.

Availability of composition data was the same for the fishery and survey, except that conditional age at length was available for the survey only. Conditional age at length is an alternative approach to modeling individual length- and age-observations. The approach consists of tabulating the sums of the age-length key matrix (with age across columns and length down rows) within rows as the standard length-frequency distribution and, instead of also tabulating the sums to the age margin, the distribution of ages in each row of the age-length key is treated as a separate observation, conditioned on the row (length) from which it came.

**Data quantity – note: this section is still in progress**

Data quantity for each available type will be determined after exploratory runs using 75 years of fishery length compositions; 25 years of age compositions, length compositions, and conditional age at length for the survey; and 25 years of age compositions for the fishery (base case). Sample size for each data type will be 50. We will explore OMs with one of the 6 following data types:

1. Only length composition

2. Only conditional age at length

3. Length composition and age compositions

4. Conditional age at length and age compositions

5. Length composition and conditional age at length

6. Length composition, age composition and conditional age at length

**Estimation model**

The following parameters were fixed at their true value for all scenarios: natural mortality (*M*), steepness (*h*), maturity, sigmaR, and aging error. The following parameters were estimated internally for all scenarios: survey catchability coefficient (set to 1 in OM), R0, rec devs, survey and fishery selectivity.

Growth was determined using a 4 parameter von Bertalanffy growth function (VBGF) where K, Linf, and CV for young and old and was estimated or fixed based on the following 5 cases:

1. Linf, K, and CVs fixed at the truth;

2. Linf, K, and CVs estimated internally;

3. Linf and K fixed at external estimates, CVs estimated internally;

4. Linf, K, and CVs fixed at external estimates;

5. Linf and K estimated internally and CVs fixed at external estimates.

Data used in the routine to externally estimate Linf, K, and CVs was generated by sampling lengths and ages for 100 fish derived from the expected mean length at age from the first year of the fishery. Sampling was distributed equally across age bins.

# Performance Metrics

Relative error (RE) and median absolute relative error (MARE) for: management targets (MSY, depletion, etc.), and growth parameters.

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