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On the use of conditional age at length data as a likelihood component in integrated population dynamics models

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ABSTRACT

Integrated population dynamics models use a variety of data types, and all the data used impact modeled processes and estimated dynamics. Paired age-length data treated as conditional age-at-length (CAAL) data are increasingly being used as a data component in stock assessment models. The original intent of the use of CAAL data was to directly estimate the length-at-age process, including the associated variability in length-at-age. However, we show that introduction of CAAL data that are not representative of the age-structure of the population can cause bias and imprecision in estimates of not only growth, but also dynamics and management quantities. Estimation of an appropriate age-based observations-modeled process may improve model performance. We also show that even the use of representative CAAL data in a model with misspecified age-based systems-modeled processes (natural mortality and time-varying growth) can lead to bias and imprecision in growth, dynamics, and management quantities. In these cases, estimation of an age-based observations-modeled process magnified the bias and imprecision. Greater consideration of this type of data is needed.

1. Introduction

Quantitative assessment of the current status and future prospects of exploited marine fish stocks forms the basis of fisheries management. Assessment of status and prospects is typically conducted using population dynamics modeling, which attempts to recreate temporal changes in population abundance in response to fishing (Hilborn and Walters, 1992; Quinn and Deriso, 1999). With the rapid increase in computing power, both the richness of data and the complexity of corresponding assessment models have also increased (Maunder and Punt, 2013). To make use of the increasing amounts of data, assessment modeling has turned to fully-integrated statistical assessments (Fournier et al., 1998; Bull et al., 2012; Methot and Wetzel, 2013; Doonan et al., 2016). However, research into the implications of including new data types into assessment models has not kept pace with the rate of adoption of these new data.

Integrated assessment models rely on mathematical relationships (processes), some of which govern the population dynamics (systems-modeled processes) and others that link the estimated dynamics to data (observations-modeled processes) (Maunder and Piner, 2017). The scope of the process is determined by parameters, which can be estimated as part of the integrated model or fixed at pre-determined values. Parameters estimated as part of an integrated model are based on statistical comparisons of model expectations to observations (data). Systems-modeled processes can be thought of as the biological component of the assessment model, such as movement, recruitment, natural mortality, and growth. Observations-modeled processes can be thought of as estimates of the difference among the data, the estimated dynamics, and the true population. Common observations-modeled processes include survey selectivity and index catchability. Properly accounting for the difference between the estimated dynamics and the true population allows the information from the observations to be used

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to estimate the systems-modeled parameters. Unbiased estimates of the systems-modeled processes lead to unbiased recreation of the population dynamics (Maunder and Piner, 2017), which can then be used to develop sustainable harvest practices.

Integrated models can use data to inform modeled processes as long as an appropriate model expectation to the data can be calculated. Typical data for most age-structured assessments include catch by fleet (removals), indices of abundance (relative or absolute) from surveys, and age/size composition data (a measure of the age/size structure of the catch or surveys). In integrated models, all data impact estimates of almost all parameters as well as the population dynamics. However, the choice to include a specific data type is often made because those data are thought to directly inform a specific modeled process (e.g., composition data to inform fleet selectivity) and (or) indirectly inform other processes through estimated dynamics (e.g., composition data to inform recruitment estimates). It has been argued that the choice to include any data type should be made prior to modeling with a full understanding of what role that data plays in the recreation of the dynamics (Maunder and Piner, 2017). Similarly, it has been argued that a reduction of the influence of some specific data types may be necessary (Francis, 2011).

Conditional age-at-length (CAAL) data are paired age and length observations that are treated as a measure of the age distribution for a specific length (Hoyle and Maunder, 2005). The original intent of CAAL data was to inform the length-at-age process, including the associated variability in length-at-age (Taylor and Methot, 2013). Recent simulation studies showed that CAAL data provide more robust information on the variability in growth than the same data treated as observations of a length distribution for a specific age (Piner et al., 2016; Lee et al., 2017a). The use of CAAL data relies on comparing the observed age distribution for a given length to a model's expectation of that distribution. The model's expectations require an estimate of the age structure of the population, which is why these data are almost exclusively used inside the population dynamics model (Piner et al., 2016; Lee et al., 2017a). The typical use of CAAL data assumes each observation of age is a random sample from the population for the given length. Improperly modeled biological processes (e.g., age-based movement, natural mortality, growth, and recruitment) or sampling processes (e.g., age-based selection) which affect the probability of sampling a given age can lead to biased estimates of growth. In contrast, processes affecting the probability of sampling a specific length (e.g., length selective gear or size-based sampling) would not lead to biased estimates of growth (Piner et al., 2016; Lee et al., 2017a). If the length bins used to model the dynamics are too coarse, there may be some bias caused by the discrete approximation of the continuous processes of length and selectivity, but this is unlikely to be of any consequence for most commercially valuable fish species if the length bins are finer than 10 cm (Monnahan et al., 2016).

Despite the increasing use of CAAL data, little research has focused on its impact on model performance beyond the estimation of growth. In this paper, we explore factors that can lead to the CAAL data being unrepresentative of the population, as well as misspecifications of age-based systems-modeled processes that lead to biased expectations to representative CAAL observations. We demonstrate the effects of these factors on the estimated population dynamics and management quantities, including the growth process itself. Methods for potentially dealing with the factors influencing the observations of, and expectations to, CAAL data are evaluated. Based on those results some limited guidance is given on the use of CAAL data in assessment models.

2. Materials and methods

2.1. Overview of simulation

Synthetic populations were created using stochastic operating models (OMs) and used to generate corresponding fisheries/survey data that match the synthetic population dynamics with assumed process and observation errors. Three OMs were developed based on different systems-modeled processes (hypotheses about the biology of the stock), as described below. We used the Stock Synthesis (SS 3.24Z; Methot and Wetzel, 2013) population dynamics software to create 500 synthetic populations (Fig. App.A.1) and associated simulated data sets for each OM based on stochastically generated recruitment and fishing mortality controlling the systems- and observations- modeled processes. Synthetic fisheries/surveys data that represent one realization of a synthetic population for a given OM were generated using the bootstrapping module in SS. This data set was then analyzed by a set of estimation models (EM) to estimate model processes and dynamics. The OM parameters and dynamics serve as the control and were compared to the EM parameters and dynamics to determine bias and precision of the EM estimates.

2.2. Operating models

Population dynamics were simulated from 1980 to 2016 with specific differences in the systems-modeled processes. OM1 is spatially explicit with one-directional time invariant age-based movement between two areas. Instead of a spatial pattern, OM2 has time-varying length-at-age relationship (growth), and OM3 has growth as in OM1 but age-specific natural mortality (Table 1). OM1-EM combinations evaluate the effect of the use of CAAL data that are unrepresentative of the population due to an un-modeled age-based movement. OM2-EM combinations evaluate the effect of an un-modeled variation in growth with representative CAAL data, and OM3-EM combinations evaluate the effect of misspecifying an age-specific M with representative CAAL data.

2.2.1. Data component and associated processes

The data component of OM1 included a fishery in area 2, which impacts the majority of age classes and primarily lands adults, and two fishery-independent surveys (one survey for each area, Fig. App.A.2). The data component of OM2 and OM3 included a fishery and a fishery-independent survey. Data generated included annual catch (in numbers) for the fishery, annual absolute abundance (in numbers) for each survey, annual length composition of the catch for the fishery and each survey, and annual conditional-age-at-length (CAAL) for each survey (Fig. App.A.2). The use of CAAL data only from survey in the simulation follows the pattern of many stock assessments to reduce the influence of any additional process error in the fishery dynamics, such as time-varying selectivity.

The catch observations were assumed to be known without error. Each abundance observation was assumed to be proportional to the available absolute abundance with a scaling factor at one for each survey (known as catchability coefficient) and was generated with a bias-corrected lognormal error distribution with standard deviation at 0.1 for simplicity (i.e., a survey sample error for available absolute abundance expressed as coefficients of variation was assumed at 0.1). This 10% coefficients of variation of each observation error in the OMs was to assign primacy to the abundance data (Francis, 2011) and to provide deterministic effect of observation errors. Each length composition observation was generated with the assumption of a multinomial error with variance described by sample size = 50 for simplicity. The distribution of ages for a given length bin for each CAAL observation was also generated with the assumption of a multinomial error structure with variance described by sample size = 10, where the length bin was structured as a 2-cm interval from 8 cm to 52 cm and age bin was from age 0 to age 15. The maximum age bin defined as an accumulator for all older ages was 15 years. The CAAL observations represent a total of 230 samples across the 23 length bins, which is greater than the sample size used for the length compositions. This difference is consistent with the common pattern of the effective sample size of marginal composition data being lower than the number of fish sampled due to

Table 1
Data types and parameter values that were used to develop each operating model (OM). Simulated data included catch, survey index, length composition, and conditional age-at-length data. Annual recruitment deviations and fishing mortality values were drawn from the appropriate distribution for each year of the simulation. Gaussian random variables are represented by Normal (mean, standard deviation). "NA" denotes that the parameter was not applicable to the OM.

Description	OM1 (directional age-based movement)	OM2 (time-varying growth)	OM3 (age-specific natural mortality)
Data			
Dynamics calculated	1980–2016, annually		
Number of areas	2	1	1
Number of fleets	1 in the adult area	1	1
Number of survey indices	2 (1 survey per area)	1	1
Number of fleets with length composition data	3 (1 fishery, 2 surveys)	2 (1 fishery, 1 survey)	2 (1 fishery, 1 survey)
Number of fleets with conditional age-at-length data	2 (2 surveys)	1 (1 survey)	1 (1 survey)
Parameter/variable			
Growth			
Maximum age	15 years		
Length at age 1 (L_1, cm)	12		
CV at age 1	0.1		
Length at *Linf* (L_{inf}, cm)	53.4	For 1980–2000: randomly selected fast (45.6 cm) or slow (53.4 cm) growth. For 2001–2016: 53.4 cm if fast growth or 45.6 cm if slow growth was in 1980–2000	53.4
CV at age *Linf*	0.1		
Growth coefficient (K)	0.25	0.25 if *Linf* = 53.4 or 0.3 if *Linf* = 45.6	0.25
Movement			
Fraction of fish moving from area 1 to area 2 at age 0	0.2	NA	NA
Fraction of fish moving from area 1 to area 2 at age 7 and older	0.999	NA	NA
Beverton-Holt stock-recruitment relationship			
Log unfished recruitment ln(R_0) ('000's fish)	15		
Standard deviation for recruitment in log space (σ_R)	1.4		
Spawner-recruit steepness	0.86		
Annual recruitment deviations in log space (1970–2016)	Temporal process follows Normal (0, σ_R)		
Mortality			
Natural morality (age-specific M, yr^{-1})	0.2 for all ages	0.2 for all ages	0.4 at age 0, 0.35 at age 1, 0.3 at age 2, 0.25 at age 3, and 0.2 at age 4 and older
Annual apical fishing mortality (F, yr^{-1}) for each fleet (1980–2016)	Generated with mean of F equal to M (Fig. App.A.1)		
Initial fishing mortality	0		
Reproduction			
Proportion maturity at age	0.2 at age 2, 0.25 at age 3, 0.4 at age 4, 0.5 at age 5, and 1 at age 6 and older		
Survey catchability	1		
Selectivity patterns			
Fishery	Time-invariant length-based asymptotic pattern. Length at inflection and width for 95% selection were fixed at 30 cm and 8, respectively. (Fig. App.A.3) All ages available in the area are selected by the fishery.		
Survey(s)	All ages and lengths available in the area are selected by the survey(s).		

lack of independence among fish sampled at the same time (Stewart and Hamel, 2014), while CAAL data are typically assumed to be independent samples of all ages found within a given length bin (e.g., Wetzel et al., 2017). The sample sizes of 50 for each length composition and 10 for each CAAL observation were to provide deterministic effect of observation errors for all OMs.

Selectivity for the fishery was assumed to be time-invariant and length-based using a time-invariant logistic functional form (Fig. App.A.3). This function is composed of two parameters (see Appendix A, Section 1.10 in Methot and Wetzel, 2013): with operating model values for the length at inflection at 30 cm and width for 95% selection at 8 for simplicity. The survey was assumed to select all ages and lengths available for all OMs.

2.2.2. Biological assumptions

Some of biological assumptions (e.g., steepness, natural mortality, and growth) were based on the Pacific Hake (Taylor et al., 2015). Recruitment was defined as the number of age-0 individuals at the start of each year and modeled using a Beverton-Holt spawner-recruitment curve defined by two parameters (Mace and Doonan, 1988): natural log of unfished recruitment (ln(R_0)), which was set at 15, and steepness, which was set at 0.86 for all OMs. In the OM1, age-0 fish were assumed to be found in both areas with 80% of age-0 fish in area 1. Thirty-seven recruitment deviations (1980–2016) representing year-specific recruitment levels (Methot and Taylor, 2011) were drawn from a normal distribution with mean at 0 and standard deviation in log space fixed at 1.4, which vary over time within each simulated population for all OMs.

In the OM1, age-based one-directional movement rates from area 1 to area 2 were a logistic function of age increasing from 20% at age 0 to 99.9% at age 7 and older (Fig. 1a). These rates produce a pattern of younger fish present in area 1 with few (1% of fish) remaining in that area after maturation at age 5.

Biological processes (natural mortality, growth, and maturity) were assumed to be the same for both areas in OM1. Growth of fish was assumed to follow a von Bertalanffy growth function (von Bertalanffy, 1938) and was reparametrized with length at age 1 (L_1) set for all OMs at 12 cm, asymptotic length (*Linf*) set at 53.4 cm, growth coefficient (K)

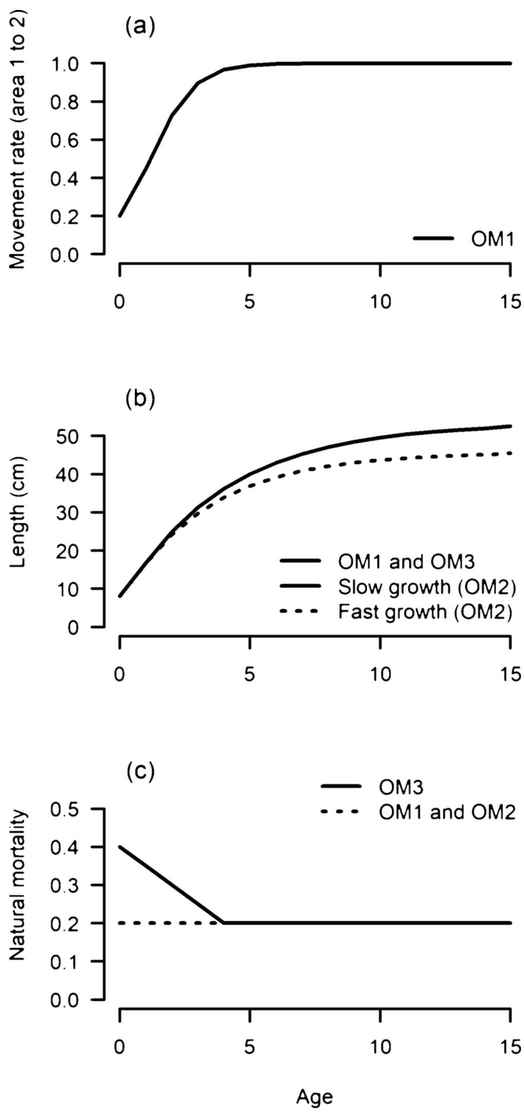

Fig. 1. Age-based systems-modeled process assumed in each operating model: (a) one-directional age-specific movement rate (in proportion) for fish move from area 1 to area 2 (OM1), (b) length-at-age relationship with random changes from slow growth (solid line) to fast growth (dotted line) or vice versa in 2001 (OM2), and (c) age-specific natural mortality is highest at age 0, decline at age 2–3, and remains constant after age 4 (OM3).

set at 0.25 $year^{-1}$, and coefficients of variation in length at age 1 (CV_A_1) and at the theoretical average maximum length (CV_A_{Linf}) set at 0.1 in OM1 and OM3 (Fig. 1b; Appendix A, Section 1.5 in Methot and Wetzel, 2013). CVs in length for all other ages were assumed to be set at 0.1. Growth was further assumed to change in 2001 for OM2, where either fast (K = 0.3 and $Linf$ = 45.6) or slow (K = 0.25 and $Linf$ = 53.4) growth was randomly selected after 2001 for each simulated population. The implementation of time-varying growth in Stock Synthesis causes the growth increment for each cohort to be a function of the current size relative to the new asymptotic size. Thus, the change in growth parameters leads to smooth changes in growth curves for each cohort and fish do not shrink even if the new $Linf$ is smaller than their current size (Methot and Wetzel, 2013).

Natural mortality (M) was assumed to be age-specific in OM3 with higher rates before fish reach 40% mature at age 4 (Fig. 1c) and constant over all ages in OM1 and OM2. For all OMs, annual fishing mortality rates were generated for each simulated population from the functional form described in the Appendix A of Carruthers et al. (2012), which allows the fishing mortality rate to increase for 20 years since 1980, then randomly vary from decreasing to increasing given an overall mean fishing mortality rate equal to the natural mortality rate (Fig. App.A.1). Non-equilibrium initial conditions were implemented by including recruitment deviations for 10 years prior to the first year of the modeling time period. The initial conditions were assumed that there was no impact of fishing prior to the first year.

2.3. Estimation models

The estimation models (EMs) applied to data generated by each iteration of all three OM's were identical in the following ways: each assumed a single area, parameters for growth, unfished recruitment, recruitment deviations, and selectivity were estimated and others were fixed at the same values as the operating models (Table 2), and the coefficients of variations for the survey and effective sample sizes for the length compositions and CAAL data were assumed to be the same as in the operating models. The values used in the operating models were used as initial values for the estimated parameters. Five estimation models were considered. In some, CAAL data that were unrepresentative of the population were used (e.g., EM2 and EM4 in OM1) or an age-based system-modeled process was misspecified (e.g., EM2 and EM4 in OM2 or OM3), and in others, an alternative approach to account for the unrepresentative CAAL data or misspecification was introduced (e.g., EM5 in all three OMs).

1 EM1, the self-testing model, used data generated from each OM except that CAAL data were not used. The purpose of EM1 is to evaluate the estimates of dynamics and the growth process assuming perfect or nearly perfect understanding of the system and data (i.e., catch, index, and length compositions). For the single area OMs 2 and 3, the data structure and parameterization in EM1 were identical to those of OM except that growth, unfished recruitment, recruitment deviations, and selectivity were estimated (Tables 1 and 2). However, EM1 fit to the data generated from spatial OM1 differed from OM (Tables 1 and 2) because the single area fleets-as-areas (FAA) approach was employed (Cope and Punt, 2011; Hurtado-Ferro et al., 2014; Waterhouse et al., 2014). The FAA approach estimates both age- and length- based selectivity to account for the age-class availability due to movement and contact selectivity, respectively, and was found to be a reasonable approximation of un-modeled age-based movement (Lee et al., 2017b). The EM1 in OM1 thus estimated both age-specific age- and double-normal length- based selectivity for the fishery (Table 2), where the double-normal function with smooth transitions is composed of three components: an ascending limb for small fish (asc), a flat top that makes selectivity coefficient as 1.0 (top), and a descending limb for large fish (dsc). These three components are connected at two intersections using steep logistic functions (Methot and Wetzel, 2013). Spatial survey abundance indices and survey length compositions generated from OM1 were aggregated across two areas (details in Appendix B). The aggregated survey abundance index and length compositions were used in the single-area EM1.
2 EM2, the misspecified model without the CAAL data (starting from EM1), is similar to EM1 except that the model is misspecified. The purpose of EM2 is to evaluate the effect of misspecifying age-based systems-modeled processes (un-modeled temporal variability in growth for OM2 and misspecified age-specific natural mortality for OM3) on the estimates of dynamics and the growth process. Data structures (i.e., catch, index, and length compositions) and parameterization were identical to those of EM1 except that time-invariant growth was estimated when fitting to data generated by OM2 (Table 2) and natural mortality was fixed at the constant rate across all ages for data generated by OM3 (Table 2). Because the CAAL data were not used, the test of the unrepresentative CAAL data for OM1 was not applicable in EM2.
3 EM3, the self-test model, used data generated from each OM, but

Table 2
Parameterization of the five estimation models (EMs) for OM1, OM2, and OM3; EM2 is only applied to data generated by OM2 and OM3. When the OM is not specified, the cell applies to all three OMs. Ditto mark (") denotes the same assumption as in the EM1, "Est." or "Fix." denote that the parameter was estimated or fixed with the value in parentheses, respectively, and "TV" denotes that the estimated parameter varied through time (between 1980–2000 and 2001–2016).

	EM1	EM2 (only for OM2&3)	EM3	EM4	EM5
Data					
Dynamics calculated	1980-2016	"	"	"	"
Number of areas	1	"	"	"	"
Number of fleets	1	"	"	"	"
Number of survey indices	1 (correctly weighted)	"	"	"	OM1: 2 OM2&3: "
Number of fleets with length composition data	2 (1 fishery, 1 correctly weighted survey)	"	"	"	OM1: 3 (1 fishery, 2 surveys) OM2&3: "
Number of fleets with conditional age-at-length data	0	"	OM1: 1 (1 correctly weighted survey) OM2&3: 1 (1 survey)	OM1: 1 (1 unweighted survey) OM2&3: 1 (1 survey)	OM1: 2 (2 surveys) OM2&3: 1 (1 survey)
Parameter/variable					
Natural mortality	OM1&2: Fix. (0.2 for all ages) OM3: Fix. (0.4 at age 0, 0.35 at age 1, 0.3 at age 2, 0.25 at age 3, and 0.2 at age 1 and older)	OM2: " OM3: Fix. (0.2 for all ages)	OM1&2: " OM3: "	OM1&2: " OM3: Fix. (0.2 for all ages)	OM1&2: " OM3: Fix. (0.2 for all ages)
Growth					
Length at age 1 (L_1, cm)	Est.	"	"	"	"
CV at age 1	Est.	"	"	"	"
Length at *Linf* (L_{inf}, cm)	OM2: Est. TV OM1&3: Est.	OM2: Est. OM3: "	OM2: " OM1&3: "	OM2: Est. OM1&3: "	OM2: Est. OM1&3: "
CV at age *Linf*	Est.	"	"	"	"
Growth coefficient (K)	OM2: Est. TV OM1&3: Est.	OM2: Est. OM3: "	OM2: " OM1&3: "	OM2: Est. OM1&3: "	OM2: Est. OM1&3: "
Recruitment					
Log unfished recruitment ln(R_0) ('000's fish)	Est.	"	"	"	"
Standard deviation for recruitment in log space (σ_R)	Fix. (1.4)	"	"	"	"
Steepness	Fix. (0.86)	"	"	"	"
Recruitment deviations in log space (1970–2016)	Est.	"	"	"	"
Survey catchability	Fix. (1)	"	"	"	"
Selectivity patterns					
Fishery (that catch adult)					
Length-based contact	OM1: Est., dome-shaped OM2&3: Est., asymptotic	"	"	"	"
Age-based availability	OM1: Est., age-specific (ages 1–3) OM2&3: All ages are selected	"	"	"	"
Survey					
Length-based contact	All lengths are selected	"	"	"	"
Age-based availability	All ages are selected	"	"	"	OM1: Est., age-specific (ages 1–6 for the survey 1 and 2) OM2: Est., TV age-specific (ages 1–15) OM3: Est., age-specific (ages 1–15)
No. of estimated parameters	OM1: 59 OM2: 57 OM3: 55	OM2: 55 OM3: 55	OM1: 59 OM2: 57 OM3: 55	OM1: 59 OM2: 55 OM3: 55	OM1: 71 OM2: 85 OM3: 70
Percentage of runs with positive-definite Hessian matrices	OM1: 100% OM2: 99.8% OM3: 100%	OM2: 100% OM3: 99.8%	OM1: 99.2% OM2: 100% OM3: 100%	OM1: 92.2% OM2: 100% OM3: 100%	OM1: 85.6% OM2: 87.8% OM3: 96.2%

unlike EM1 it used the CAAL data. The purpose of EM3 is to evaluate the estimates of dynamics and the growth process assuming perfect or nearly perfect understanding of the system and data (i.e., catch, index, length compositions, and CAAL). Data structures and parameterization were identical to those of EM1 except that spatial CAAL data generated from OM1 were correctly weighted across two areas assuming equal numbers of samples in each area to represent the true population age distribution at length (details in Appendix B).

4 EM4, the misspecified model with the CAAL data, is similar to EM3 except that the model is misspecified or the CAAL data are unrepresentative. The purpose of EM4 is to evaluate the effect of using unrepresentative CAAL data or misspecifying age-based systems-modeled processes (un-modeled temporal variability in growth for OM2 and misspecified age-specific natural mortality for OM3) on the estimates of dynamics and the growth process. Data structures (catch, index, length compositions, and CAAL) and parameterization were identical to those of EM3 except that spatial CAAL data generated from OM1 were unweighted assuming equal numbers of samples in each area (details in Appendix B), time-invariant growth was estimated for OM2 (Table 2), and natural mortality was fixed at the constant rate across all ages for OM3 (Table 2).

5 EM5, the age-based selectivity model, built on EM4. The purpose of EM5 is to evaluate whether estimation of additional age-specific

selectivity linked to the survey CAAL data instead of having age-specific selectivity equal to 1.0 can account for the unrepresentative CAAL data or the misspecified age-based systems-modeled processes on the estimates of dynamics and the growth process. For the single area OMs 2 and 3, data structures (catch, index, length composition, and CAAL) and parameterization were identical to those of EM4 except that time-varying age-specific selectivity for the survey was estimated from age 1 to 15 for OM2 (Table 2) and time-invariant age-specific selectivity for the survey was estimated from age 1 to 15 for OM3 (Table 2). The time-varying age-based selectivity for OM2 was parameterized as a random walk from ages 1 to 15, with the parameters for each age allowed to change in 2001 (see supplementary material in Lee et al., 2017b). However, the EM5 fit to the data generated from the spatial OM1 differed in data structure and parameterization (Tables 1 and 2). Unlike EM4, spatial survey abundance indices, length compositions, and CAAL data generated from OM1 were all used without aggregation by estimating age-based selectivity for both surveys from age 1 to 6.

2.4. Simulation statistics

We evaluated the performance of the estimation models based on convergence of the model (determined by percentage of runs with positive definite Hessian matrices) and the distribution of relative errors for some quantities of interest and absolute errors for others. Relative errors were calculated for spawning biomass in 2016 (SSB_{2016}), recruitment in 2016 ($Recruits_{2016}$), fishing mortality in 2016 (F_{2016}), spawning biomass at maximum sustainable yield (SSB_{MSY}), fishing mortality at maximum sustainable yield (F_{MSY}), unfished spawning biomass (SSB_0), depletion in 2016 (ratio of SSB_{2016} to SSB_0; $Depletion_{2016}$), and length at age 1 (L_{age1}), asymptotic length (L_{inf}), and growth coefficient (K), whereas absolute errors were calculated for coefficient of variation in the length at age 1 (CV_A_1) and coefficient of variation in the length at age at the theoretical average maximum length (CV_A_{Linf}). Equilibrium MSY was calculated by assuming that the distribution of fishing effort among fleets and areas remains constant at the average over the last 3 years. Percent relative error (RE_d^j) is defined as the percentage difference between estimated value (Est_d^j) from the EM and control value ($Control_d^j$) from the OM divided by control value for quantity (j) for a given simulation run (d).

$$RE_d^j = \frac{Est_d^j - Control_d^j}{Control_d^j} \times 100\% \tag{1}$$

Absolute error (AE_d^j) is defined as the difference between estimated value (Est_d^j) from the EM and the control value ($Control_d^j$) from the OM for quantity (j) for a given simulation run (d).

$$AE_d^j = Est_d^j - Control_d^j \tag{2}$$

For a given quantity, RE and AE values from the converged simulation runs were summarized as median (MRE or MAE) and standard deviation of the mean (StdRE or StdAE) as a measure of the bias and precision, respectively. We use "unbiased" to describe results with MRE within -10% to 10% and "moderately unbiased" when the MRE is within -15% to 15%.

3. Results

3.1. The effect of the use of unrepresentative CAAL data due to un-modeled age-based movement (OM1)

When CAAL data from the surveys were excluded in EM1, the estimates of the growth, terminal year quantities, and management quantities were moderately unbiased using the FAA approach (MREs between -10% and 13%) (Table 3; Fig. App.C.1). Thus any bias for the other EMs is due to inclusion and/or treatment of the CAAL data and not due to the approximation of the spatial patterns with age-based selectivity.

Table 3
Median and standard deviation of the mean (in parentheses) of relative error values by EMs using data generated by OM1. Values are given for important terminal year, management, and growth quantities. For the quantities coefficients of variation in length at age 1 (CV_A_1) and at the theoretical average maximum length (CV_A_{Linf}), median and the standard deviation of the mean of absolute error values are given instead of relative error values.

	Estimation models in the OM1			
	EM1	EM3	EM4	EM5
SSB_{2016}	2 (6)	2 (6)	39 (13)	9 (8)
$Recruits_{2016}$	−1 (33)	0 (31)	−23 (30)	2 (24)
F_{2016}	1 (5)	0 (5)	1 (6)	−4 (5)
SSB_{MSY}	13 (29)	2 (27)	78 (32)	6 (28)
F_{MSY}	2 (1)	4 (1)	21 (1)	4 (1)
SSB_0	12 (30)	3 (28)	100 (27)	6 (29)
$Depletion_{2016}$	−10 (27)	−2 (29)	−30 (23)	2 (28)
L_{age1}	0 (1)	0 (0)	−18 (1)	−1 (0)
L_{inf}	0 (1)	−1 (1)	13 (2)	−1 (1)
K	0 (3)	2 (1)	5 (3)	4 (2)
CV_A_1	−0.001 (0.003)	−0.002 (0.001)	0.075 (0.003)	0 (0.001)
CV_A_{Linf}	−0.001 (0.01)	0.021 (0.005)	0.044 (0.006)	0.025 (0.005)

When CAAL data from the surveys were included in the estimation models (EM3, EM4, and EM5), the representativeness of the CAAL data influenced the estimates of the growth, terminal year quantities, and management quantities. If the CAAL data from both surveys (one survey per area) were weighted correctly with respect to the population age structure (EM3), the estimates of all quantities were unbiased (MREs between -2% and 4%; Table 3, Fig. App.C.1). In particular, the estimates of SSB_{MSY}, SSB_0, and $Depletion_{2016}$ from EM3 were improved compared to not including the representative CAAL data (EM1). The estimates of growth from EM3 were unbiased (MREs between -1% and 2%) with improved precision. If the CAAL data from both surveys were unweighted (EM4), the estimates of growth, terminal year quantities, and management quantities were biased and imprecise. However, estimating an age-based selectivity (EM5) by linking to the survey CAAL

Table 4
Median and standard deviation of the mean (in parentheses) of relative error values by EMs using data generated by OM2. Values are given for important terminal year, management, and growth quantities. For the quantities coefficients of variation in length at age 1 (CV_A_1) and the theoretical average maximum length (CV_A_{Linf}), median and the standard deviation of the mean of absolute error values are given instead of relative error values. "NA" denotes that the parameter was not applicable to the estimation model.

	Estimation models in the OM2				
	EM1	EM2	EM3	EM4	EM5
SSB_{2016}	0 (8)	−3 (18)	1 (7)	−5 (25)	67 (36)
$Recruits_{2016}$	9 (45)	7 (45)	14 (43)	14 (44)	36 (43)
F_{2016}	−1 (7)	−1 (7)	−2 (7)	−2 (8)	−28 (12)
SSB_{MSY}	11 (29)	4 (36)	4 (26)	3 (31)	16 (36)
F_{MSY}	0 (3)	2 (3)	2 (2)	3 (5)	4 (4)
SSB_0	8 (29)	10 (30)	4 (26)	6 (31)	28 (33)
$Depletion_{2016}$	−8 (25)	−9 (35)	−3 (25)	−5 (44)	37 (50)
L_{age1}	0 (2)	1 (3)	−1 (0)	−1 (1)	−1 (1)
L_{inf}	0 (1)	1 (3)	−1 (1)	0 (4)	0 (4)
L_{inf_2}	0 (2)	NA	−3 (1)	NA	NA
K	0 (3)	0 (6)	5 (2)	6 (3)	6 (3)
K_2	−1 (5)	NA	7 (2)	NA	NA
CV_A_1	−0.005 (0.004)	−0.005 (0.005)	0.001 (0.002)	0.003 (0.002)	0.001 (0.002)
CV_A_{Linf}	0.011 (0.009)	0.026 (0.015)	0.020 (0.004)	0.030 (0.006)	0.038 (0.007)

Table 5
Median and standard deviation of the mean (in parentheses) of relative error values by EMs using data generated by OM3. Values are given for important terminal year, management, and growth quantities. For the quantities coefficients of variation in length at age 1 (CV_A_1) and the theoretical average maximum length (CV_A_{Linf}), median and the standard deviation of the mean of absolute error values are given instead of relative error values.

	Estimation models in the OM3				
	EM1	EM2	EM3	EM4	EM5
SSB_{2016}	−1 (7)	29 (12)	1 (7)	33 (13)	82 (20)
$Recruits_{2016}$	4 (38)	−14 (35)	8 (35)	−12 (33)	−10 (32)
F_{2016}	1 (7)	−16 (6)	1 (7)	−16 (6)	−28 (9)
SSB_{MSY}	15 (26)	24 (28)	8 (25)	21 (28)	32 (33)
F_{MSY}	0 (1)	4 (2)	3 (1)	8 (1)	8 (1)
SSB_0	15 (26)	22 (28)	9 (25)	20 (27)	30 (33)
$Depletion_{2016}$	−13 (24)	7 (29)	−6 (25)	12 (30)	42 (31)
L_{age1}	0 (2)	0 (2)	0 (0)	0 (0)	0 (0)
L_{inf}	0 (1)	0 (1)	−2 (1)	−2 (1)	−2 (1)
K	0 (3)	−1 (3)	5 (1)	5 (1)	5 (2)
CV_A_1	−0.003 (0.004)	0 (0.005)	0.001 (0.002)	0.001 (0.002)	−0.001 (0.002)
CV_A_{Linf}	0.004 (0.013)	0.005 (0.013)	0.022 (0.005)	0.024 (0.005)	0.030 (0.008)

data, reduced the bias in growth, terminal year quantities, and management quantities from EM4.

3.2. The effect of the un-modeled temporal variability in growth (OM2)

When CAAL data from the survey were excluded, the estimates of the growth, terminal year, and management quantities were moderately unbiased (MREs between -9% and 11% for the EM1 and EM2) (Table 4, Fig. App.C.2). However, the un-modeled temporal variability in growth degraded the precision of SSB_{2016}, SSB_{MSY}, $Depletion_{2016}$, and all the growth parameters (EM2).

When CAAL data from the survey were included with correctly specified temporal variation in growth (EM3), the estimates of terminal year and management quantities were moderately unbiased (MREs between -3% and 14%) with similar precision to those in EM1. In particular, the estimates of SSB_{MSY}, SSB_0, and $Depletion_{2016}$ from EM3 were improved from not including the CAAL data (EM1). The estimates of growth from EM3 were unbiased (MREs between -3% and 7%) with improved precision. Although the median estimates of the terminal year and management quantities were generally unaffected by the un-modeled temporal variation in growth (MREs between -5% and 14% for the EM4), the precision for most quantities degraded. In addition to the decrease in precision, the quantities of SSB_{2016}, F_{MSY}, and L_{inf} had bimodal estimates (Fig. App.C.2). Unlike OM1, estimating time-varying age-based selectivity for the survey did not reduce the bias (EM5).

3.3. The effect of the misspecified age-specific natural mortality (OM3)

With correctly specified age-specific M, the estimates of the growth, terminal year, and management quantities were moderately unbiased when CAAL data from the survey were excluded (MREs between -13% and 15% for the EM1) (Table 5, Fig. App.C.3). The estimates of all terminal year and management quantities were degraded due to misspecified age-specific M (MREs between -16% and 29% for the EM2).

When CAAL data from the survey were included with correctly specified age-specific M (EM3), the estimates of terminal year and management quantities were unbiased (MREs between -6% and 9%) with similar precision to those in EM1. The estimates of growth from the EM3 were unbiased (MREs between -2% and 5%) with improved precision. Again, the estimates of all terminal year and management quantities were degraded due to misspecified the age-specific M (MREs between -16% and 33% for the EM4), but the estimates of growth were unaffected. Unlike OM1, estimating age-based selectivity for the survey did not reduce the bias (EM5).

4. Discussion

4.1. Cautions of including CAAL data

This work demonstrates that CAAL data provide direct information to an assessment model not only on the growth process but also the other systems-modeled processes controlling the age-structure of the population. This should not be surprising as the model expectation for CAAL data is derived from the expectation of the growth process as well as the population's age-structure (Piner et al., 2016; Lee et al., 2017a). Thus, when unrepresentative CAAL data are used, without accounting for this bias through estimation of an appropriate age-based process (OM1), the model must use either the length-at-age process and/or other systems-modeled processes controlling the population age structure to match CAAL observations. When systems-modeled processes estimates are compromised by unrepresentative CAAL data, substantial bias or imprecision is likely in the estimates of the dynamics and management quantities.

Including representative CAAL data as a likelihood component in the assessment model does not guarantee unbiased estimates of the length-at-age process; those data needed to be included in a correctly specified model. If the systems-modeled processes are misspecified, the estimates of growth from representative CAAL data will also be biased. However, including representative CAAL data in misspecified models did not increase bias in most important dynamics and management quantities beyond that due to the systems-modeled misspecification itself.

4.2. Preventing bias

Ideally, the CAAL data introduced into the assessment model should be representative of the population. Ensuring that CAAL data are representative may entail a statistical treatment of the observations that requires knowledge about spatial/habitat patterns in abundance by age which may be lacking. When the CAAL data cannot be made representative, estimating the correct age-based modeled processes accounting for the unrepresentativeness of the data is needed. In many cases a spatially-explicit model could be used (Berger et al., 2017), or alternatively age-based selectivity could approximate the age-based spatial process (Lee et al., 2017b). However, naïve use of age-based selectivity in cases with misspecified systems-modeled processes and representative CAAL data magnified the estimation bias in many important model quantities.

4.3. Benefits of use of CAAL data

With so many potential factors and processes influencing the appropriate use of CAAL data, it may be reasonable to ask why should this type of data be included in assessments? Appropriate use of CAAL data provides a direct measure of the age structure of the population, which imparts considerable information to the estimation process. In one of our examples (OM2) appropriate use of CAAL data was shown to stabilize SSB-related management quantities even when other parts of the model had been misspecified (OM2). There are advantages even in well-specified models. Appropriate use of CAAL data will likely reduce bias and improve precision of the estimates of the growth process and SSB-related management quantities. Researchers will need to weigh the risks with rewards from using this type of data.

4.4. Limitations of this study

Caveats associated with this study limits the scope of the interpretation of these results. Firstly, this work simplified the actual problems facing population dynamics modeling to isolate effects of CAAL data. Perhaps most limiting in our study was that the simulated length composition data were unbiased, informative, and derived from a time-invariant observation process. This 'ideal' composition data provided more reliable information on the population age structure than should be expected in real applications, which likely stabilized model results. This is why EM1 is able to estimate growth even when the CAAL data were not included. Intentionally generating better data than should be expected in real-world applications allowed for more interpretable comparisons of specific changes in model structure but at the cost of realism. If all potential real-world sources of error were included, the study might have captured more of the real variability in estimates that should be expected but also likely would obscure the relative differences in performance between models. Although we explored the impact of time-varying growth, we did not consider changes in average size-at-age (Rosa Lee's phenomenon) caused by length-based mortality (Taylor and Methot, 2013). We also did not explore all potential factors affecting the representativeness of, or expectations to, CAAL data (e.g., spatial patterns in recruitment), nor did we explore all possible ways of dealing with problems from including CAAL data in an assessment, such as data weighting (Francis, 2011). For these and many other reasons, more research needs to be conducted on how to use this kind of data.

4.5. Conclusions

This study should not be the final word on the use of CAAL data. However, we do offer some initial guidance based on this work. First be specific about the goals of introducing CAAL data. Is it only for estimating growth or is it a measure of the population age-structure? Approaches to structuring and diagnosing a model differ depending on the goal. Use CAAL data in an assessment that are or can be made representative of the population age structure. When there are concerns about the representativeness of the CAAL observations due to factors such as ontogenetic movement (McDaniel et al., 2016), estimating age-based selectivity (or using a spatially structured model) may be appropriate. Because estimating this potentially time-varying observations-modeled process entails many parameters, we further suggest limiting the number of CAAL sources (e.g., fleets or surveys). Instead, it is necessary to carefully select the best fleet for the observations in terms of sampling and coverage of the total population (Goodyear, 2019). If estimation of growth is the primary goal, it may be desirable to limit the number of years with CAAL data as well. Finally, we encourage further research on the usage of this data.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.fishres.2019.04.007.

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