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Modelling time-varying growth in state-space stock assessments

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State-space assessment models (SSMs) have garnered attention recently because of their ability to estimate time variation in biological and fisheries processes such as recruitment, natural mortality, catchability, and selectivity. However, current SSMs cannot model time-varying growth internally nor accept length data, limiting their use. Here, we expand the Woods Hole Assessment Model to incorporate new approaches to modelling changes in growth using a combination of parametric and nonparametric approaches while fitting to length and weight data. We present these new features and apply them to data for three important Alaskan stocks with distinct data and model needs. We conduct a "self-test" simulation experiment to ensure the unbiasedness and statistical efficiency of model estimates and predictions. This research presents the first SSM that can be applied when length data are a key source of information, variation in growth is an essential part of the dynamics of the assessed stock, or when linking climate variables to growth in hindcasts or forecasts is relevant. Consequently, the state-space approach and growth estimation can be applied to more fish stocks worldwide, facilitating real-world applications and implementation of simulation experiments for performance evaluation of SSMs for the many stocks whose assessments rely on length data.

Keywords: growth, random effects, size-at-age, weight-at-age, Woods Hole Assessment Model (WHAM).

Introduction

Variation in biological (e.g. recruitment, natural mortality, growth) and fishery (e.g. selectivity, fishing pressure) processes has frequently been documented for fish stocks (Thorson *et al.*, 2015b; Aeberhard *et al.*, 2018). Somatic growth ("growth" hereafter) is the increase in the size or weight of a fish throughout its lifespan. Growth may vary among fish, time, and space, and this variability is evident for several fish stocks and is a critical driver of fluctuations in population biomass (Stawitz and Essington, 2018). Some important factors driving growth variability are (1) conditions during early life stages (Ciannelli *et al.*, 2020): larval size variability (which affects the size of older stages), (2) genetic effects (Berg *et al.*, 2018: slow-growing females will produce slow-growing offspring), (3) density-dependence (Rijnsdorp and van Leeuwen, 1996: higher abundance will increase competition and potentially decrease growth rates), (4) fishing pressure (Lester *et al.*, 2014; Wilson *et al.*, 2019: fishing may remove fast-growing fish, therefore, decrease population size-at-age over time), and (5) environmental conditions (Kreuz *et al.*, 1982; Baudron *et al.*, 2014: temperature, prey density, and quality are factors impacting growth rates). Growth in stock assessment models is modelled as changes in mean size- or weight-at-age at the population level. Historically, variability in mean size-at-age has been ignored in models based on the integrated analysis paradigm. Nevertheless, increasing evidence shows that this practice may lead to biased model estimates (Correa *et al.*, 2021; Punt *et al.*, 2015; Lee *et al.*, 2018), and the modelling of growth variability in fishery assessment models based on the integrated analysis paradigm has become more common in recent years.

Currently, there are two common strategies to account for temporal variability in growth in a stock assessment: (1) prespecifying weight-at-age based on empirical data (empirical weight-at-age; EWAA), or (2) modelling temporal variability in the parameters of a growth equation. The former strategy is more accurate in data-rich situations and does not require additional parameters to be estimated (Kuriyama *et al.*, 2016). However, EWAA is assumed to be perfectly known and does not separate changes in mean length-at-age and the morphometric condition of the length–weight relationship. How to handle missing weight observations (e.g. a missing survey) is unclear, and any uncertainty in EWAA is ignored. The second approach models variation in mean length-at-age and uses the length–weight relationship to estimate the population mean weight-at-age. Estimating growth parameters requires informative data such as marginal length compositions or conditional age-at-length (CAAL; Lee *et al.*, 2019) and may be computationally demanding and challenging since model predictions of size-specific data are also affected by other model components such as selectivity. Traditionally, modelling temporal variability in growth parameters has been performed using the "penalized maximum likelihood" (PML) approach, which estimates penalized deviations $\epsilon_y(0, \sigma_\epsilon^2)$ from the mean parameter while subjectively fixing or iteratively tuning the penalty term σ_ϵ^2 (e.g. Methot and Taylor, 2011), or

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approximating it (Thorson *et al.*, 2015a). In some cases, an environmental index, commonly assumed to be known without error, is included in the stock assessment allowing growth parameters to vary over time through a linking equation (Lee *et al.*, 2018).

State-space assessment models (SSMs) are a type of stock assessment that separate and estimate the process error in the population dynamics and the observation error in the data (Aeberhard *et al.*, 2018). Stochastic processes affecting the unobserved temporal dynamics of a stock are accounted for by the introduction of random effects. In SSMs, the penalty terms are estimated as variance parameters that constrain the associated random effects, while parameter estimation involves maximizing the marginal likelihood (Skaug and Fournier, 2006; Aeberhard *et al.*, 2018). The state-space approach produces more realistic levels of uncertainty compared to the PML approach, and the resulting assessments exhibit smaller retrospective patterns (Miller and Hyun, 2018; Stock *et al.*, 2021). The origin of these models is not recent (Sullivan, 1992; Gudmundsson, 1994); however, their use has been limited due to the computational burden when using the common modelling platform ADMB (Fournier *et al.*, 2012). The development of Template Model Builder (TMB; Kristensen *et al.*, 2016), which performs the Laplace approximation efficiently and automatically, has allowed more extensive use of SSMs during the last decade. Currently, more than 20 official fish stock assessments by the International Council for the Exploration of the Sea are conducted using a state-space framework (Nielsen and Berg, 2014; Aeberhard *et al.*, 2018), and its use is growing on the east coast of North America (Cadigan, 2016; Miller *et al.*, 2016; Miller and Hyun, 2018; Stock *et al.*, 2021). Some common SSM platforms are SPiCT, which relies on indices of abundance (Pedersen and Berg, 2017), and SAM and the Woods Hole Assessment Model (WHAM), which use indices of abundance and age data (Nielsen and Berg, 2014; Stock and Miller, 2021).

WHAM is a state-space age-structured assessment model coded in TMB (Stock and Miller, 2021; Stock *et al.*, 2021) and has been applied to data for several stocks off the U.S. east coast (Stock *et al.*, 2021; du Pontavice *et al.*, 2022; Legault *et al.*, 2023), where extensive age data (e.g. age compositions) are available for many years. WHAM currently accounts for variability in growth by incorporating annual EWAA information, and internal growth modelling using size (e.g. marginal length compositions) or size-at-age information (e.g. CAAL data) for parameter estimation is unavailable. In general, growth modelling in SSMs has not been thoroughly explored (but see Miller *et al.*, 2018), and research is needed to understand the performance of these SSMs when growth variability is estimated. Furthermore, the absence of growth modelling approaches and the inability to include size-specific information have limited the use of SSMs in other fishery jurisdictions where age information is not extensive.

In this study, we aimed to (1) document how parametric and nonparametric modelling of growth can be included in state-space age-structured stock assessment models, (2) apply these approaches to three case studies in Alaska: walleye pollock (*Gadus chalcogrammus*) in the Gulf of Alaska (GOA), Pacific cod (*Gadus macrocephalus*) in the GOA, and Pacific cod in the eastern Bering Sea (EBS) based on a WHAM implementation, and (3) for each of the models in the case studies, conduct a "self-test" simulation to assure the unbiasedness of growth model estimates. To our knowledge, this is the first study that presents an SSM that accounts for growth variation and uses size data for parameterization. The new extension of stock assessment will allow assessment analysts to apply SSMs to a broader set of species, including data-moderate fish stocks with few or no years of age compositions. It will also allow stock forecasts to propagate climate impacts and uncertainty about future growth scenarios.

Methods

Section "Growth modelling" outlines how parametric growth can be modelled in a state-space stock assessment, Section "Overview of the Woods Hole Assessment Model" briefly overviews some key features of WHAM, Section "Case studies" describes the case studies, and Section "Simulation experiment" outlines the simulation experiment. The source code of the implemented modelling features can be found at https://github.com/timjmiller/wham/tree/growth (tested version, used in this study) and https://github.com/GiancarloMCorrea/wham/tree/growth (in-development version). The code to replicate the case studies and simulation experiments can be found at https://github.com/GiancarloMCorrea/AKWHAM. The software R (R Core Team, 2022) and the *ggplot2* package (Wickham, 2016) were used for analyses and to produce figures.

Growth modelling

Variation in growth is one mechanism that can explain changes in population mean length- or weight-at-age. The sections below outline how we model the mean length- and weight-at-age and include random effects on model parameters (Figure 1). Online Appendix A describes the data inputs that are used to inform growth estimation, and online Appendix B the likelihood components. Additionally, linking these growth parameters to environmental variables is also possible, as described by Stock and Miller (2021) for processes other than growth.

Parametric modelling of mean length-at-age

We first introduce the feature used to specify a parametric model of mean length-at-age. The basic growth equation is the Richards' equation (Richards, 1959), with linear growth below a reference age ($\tilde{a}$), based on the Schnute parameterization (Schnute, 1981). For the first year ($y = 1$), the mean length-at-age a at the start of the year ($\tilde{L}_{y,a}$) is calculated as

$$\tilde{L}_{y,a} = \begin{cases} L'_{min} + ba & for\ a \le \tilde{a} \\ \left(L_\infty^\gamma + \left(L_{\tilde{a}}^\gamma - L_\infty^\gamma\right) \exp\left(-k\left(a - \tilde{a}\right)\right)\right)^{1/\gamma} & for\ a > \tilde{a} \end{cases}, \quad (1)$$

where $b = (L_{\tilde{a}} - L'_{min})/\tilde{a}$, $L_{\tilde{a}}$ is the mean length-at-age $\tilde{a}$, L'_{min} is the lower limit of the smallest length bin in the population assumed in the model, L_∞ is the asymptotic length, and k is the growth rate. The linear growth below age $\tilde{a}$ is because, in most cases, there is little information about the actual size-at-age trajectory for very young animals (Methot and Wetzel, 2013).

The von Bertalanffy equation is Equation (1) with $\gamma = 1$. For $y > 1$, $\tilde{L}_{y,a}$ is calculated as

$$\tilde{L}_{y,a} = \begin{cases} L'_{min} + ba & for\ a \le \tilde{a} \\ \left(\tilde{L}_{y-1,a-1}^\gamma + \left(\tilde{L}_{y-1,a-1}^\gamma - L_\infty^\gamma\right)\left(exp\left(-k\right) - 1\right)\right)^{1/\gamma} & for\ a > \tilde{a} \end{cases}. \quad (2)$$

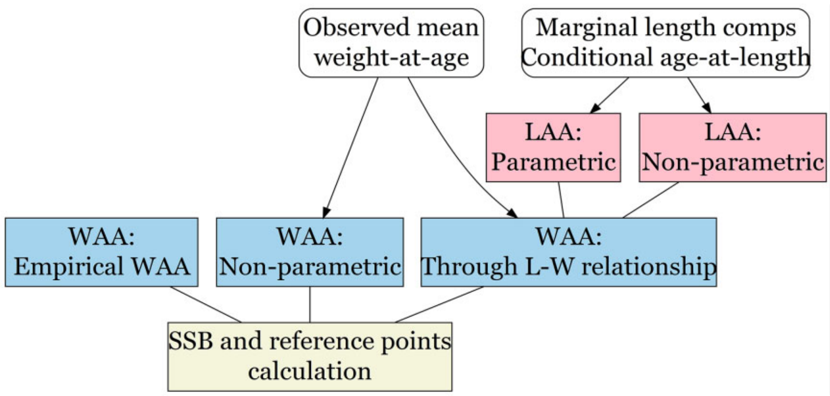

Figure 1. Data (white blocks) used to estimate growth. Population mean length-at-age (LAA, red blocks) can be modelled using a parametric (von Bertalanffy or Richards equation) or nonparametric LAA approach. Population mean weight-at-age (WAA, blue blocks) can be modelled using an empirical weight-at-age (nonparametric WAA) approach or using a length–weight (L-W) relationship (which uses mean length-at-age information).

Mean length-at-age a at any fraction $\theta \in [0, 1]$ of year y ($\tilde{L}_{y,a+\theta}$) is calculated according to:

$$\tilde{L}_{y,a+\theta} = \left(\tilde{L}^{\gamma}_{y-1,a-1} + \left(\tilde{L}^{\gamma}_{y-1,a-1} - L^{\gamma}_{\infty}\right)\left(exp\left(-k\theta_y\right) - 1\right)\right)^{1/\gamma}. \quad (3)$$

Random effects (δ) can be predicted on the mean parameters (μ) in logarithmic scale in Equations (1–3). They are assumed to be normally distributed with zero mean but autocorrelated over the years or cohorts:

$$log(L_{\infty_t}) = \mu_{L_\infty} + \delta_{1,t}, \quad (4a)$$

$$log\left(k_t\right) = \mu_k + \delta_{2,t}, \quad (4b)$$

$$log(L_{\tilde{a}t}) = \mu_{L_{\tilde{a}}} + \delta_{3,t}, \quad (4c)$$

where t represents years or cohorts. The random effects, on a given growth parameter, can be first-order autoregressive AR(1):

$$\delta_t|\delta_{t-1} \sim N\left(\rho\delta_{t-1}, \sigma^2_G\right) \quad (5)$$

with initial condition:

$$\delta_1\left(0, \frac{\sigma^2_G}{1-\rho^2}\right) \quad (6)$$

The covariance is

$$Cov\left(\delta_t, \delta_{\tilde{t}}\right) = \frac{\sigma^2_G \rho^{|t-\tilde{t}|}}{\left(1-\rho^2\right)}, \quad (7)$$

where σ^2_G and ρ are the AR(1) variance and correlation coefficient over years or cohorts, respectively. Including first-order autocorrelation in the model formulation has been shown to improve forecast skill in other demographic processes (Johnson *et al.*, 2016), but has not, to our knowledge, been explored for growth parameters.

Nonparametric modelling of mean length-at-age

We also introduce a nonparametric approach to model mean length-at-age. This approach does not use conventional parametric growth equations. Instead, we assume the average population mean length-at-age ($\tilde{L}_a$) on January 1st are parameters (i.e. fixed effects). To model time variation, a random effect ($\delta_{a,y}$) can be predicted on $\tilde{L}_a$ for each age a in logarithmic scale ($\mu_{\tilde{L}_a}$) to allow for a correlated (smoothed) process by age and year:

$$log\left(\tilde{L}_{y,a}\right) = \mu_{\tilde{L}_a} + \delta_{a,y}. \quad (8)$$

The random effects matrix $\mathbf{\Delta}$ has a two-dimensional (2D) stationary AR(1) structure distributed as

$$\text{vec}\left(\mathbf{\Delta}\right) \sim MVN\left(0, \mathbf{\Sigma}\right), \quad (9)$$

where $\text{vec}(\mathbf{\Delta}) = (\delta_{1,1}, \ldots, \delta_{1,Y}, \ldots, \delta_{A,1}, \ldots, \delta_{A,Y})'$ is the vector of random effects, such that A and Y are the number of ages and years, respectively. The covariance matrix ($\mathbf{\Sigma}$) of $\text{vec}(\mathbf{\Delta})$ is

$$\mathbf{\Sigma} = Cov\left(\delta_{a,y}, \delta_{\tilde{a},\tilde{y}}\right) = \frac{\sigma^2_G \rho^{|a-\tilde{a}|}_{age} \rho^{|y-\tilde{y}|}_{year}}{\left(1-\rho^2_{age}\right)\left(1-\rho^2_{year}\right)}, \quad (10)$$

where σ^2_G, ρ_{age}, and ρ_{year} are the estimated AR(1) variance and correlation coefficients by age and year, respectively. The mean length-at-age a at any fraction θ of year y ($\tilde{L}_{y,a+\theta}$) is based on linear interpolation between $\tilde{L}_{y,a}$ and $\tilde{L}_{y+1,a+1}$:

$$\tilde{L}_{y,a+\theta} = \tilde{L}_{y,a} + \left(\tilde{L}_{y+1,a+1} - \tilde{L}_{y,a}\right)\theta. \quad (11)$$

This parametrization is identical to the M-at-age available in WHAM (see Stock and Miller, 2021) and acts like a smoother across the mean length-at-age matrix with the constraints estimated from the data. This approach has three noteworthy features: it can predict negative changes in the size-at-age of a cohort (resulting from processes affecting size-at-age besides growth), naturally accounts for missing data, and can be projected into the future as in other processes in an SSM. Because the smoother complexity is related to the information contained in the data, and there is no parametric growth equation, we refer to this as "nonparametric," recognizing that this term is not consistently defined in the statistical literature.

Parametric modelling of mean weight-at-age

Next, we introduce a parametric model of mean weight-at-age. This approach uses the allometric length–weight relationship to calculate the weight (w) in kg for a given population length (l) in cm:

$$w_l = \Omega_1 l^{\Omega_2}, \quad (12)$$

where Ω_1 and Ω_2 are the weight coefficient and exponent, respectively. Random effects (δ) can also be predicted on these parameters by year or cohort, and follow the structure shown in Equations (4–7). The population mean weight-at-age can then be predicted using the age-length transition matrix:

$$W_{y,a} = \sum_{l} \varphi_{y,l,a} w_l, \tag{13}$$

where the age-length transition matrix ($\varphi_{y,l,a}$) represents the variability in fish length within an age (Methot and Wetzel, 2013) (online Appendix C).

Nonparametric modelling of mean weight-at-age

Last, we introduce a nonparametric approach for mean weight-at-age. As for the nonparametric modelling of mean length-at-age, the parameters are the population mean weight-at-age $\tilde{W}_a$ (January 1st) with random effects (δ) to allow for temporal variability:

$$log\left(\tilde{W}_{y,a}\right) = \mu_{\tilde{W}_a} + \delta_{a,y}. \tag{14}$$

Random effects have the same structure as shown in Equations (9) and (10). The mean weight-at-age a at any fraction θ of year y ($\tilde{W}_{y,a+\theta}$) can be calculated as

$$\tilde{W}_{y,a+\theta} = \tilde{W}_{y,a}(G_{y,a})^{\theta}, \tag{15}$$

where $G_{y,a}$ is the growth rate and is calculated as $G_{y,a} = \tilde{W}_{y+1,a+1}/\tilde{W}_{y,a}$. This parametrization approximates the seasonal non-linearity of the weight–age relationship without requiring extra parameters. The calculation of predicted quantities is described in online Appendix D. Additionally, we also added selectivity-at-length functions given their importance when modelling growth (online Appendix E). As discussed by Francis (2016), size-based selectivity would make a sample random at size, while an age-based selectivity would be random at age (i.e. only the sizes of age a are considered random), impacting the predicted age–size data by the assessment model and the estimation of growth parameters. Moreover, size-based selectivity also influences the variation in mean size-at-age, which can be confounded with variation in growth (Francis, 2016).

Overview of the WHAM

WHAM was built based on the structure of the Age-Structured Assessment Program (ASAP; Miller and Legault, 2015) and uses landings, indices of abundance, age compositions, environmental covariates, and EWAA data for parameter estimation. It implements the prediction of random effects on inter-annual transitions in numbers-at-age, natural mortality, catchability, selectivity, and environmental covariates. Input environmental covariates are treated as observations (with error), while true (unobserved) latent states can be treated as random effects. Several options are available to model the structure of random effects, including independent, AR(1) or random walk, and a 2D first-order autoregressive 2DAR(1) (Cadigan, 2016). These options can be applied to annual effects and different model configurations can be compared using the Akaike information criterion (AIC, Burnham and Anderson, 2002). WHAM assumes the separability of fishing mortality-at-age into annual fully selected fishing mortalities (estimated as fixed effects) and selectivity-at-age (several random effects structures available). Short-term projections and one-step-ahead residual calculations (Trijoulet *et al.*, 2023) can be conducted using WHAM. Projections are especially useful for models with random effects because the temporally correlated process can continue into the future. WHAM is implemented in TMB and is available as an R package (Miller and Stock, 2020).

Case studies

The new approaches to modelling growth presented in Section "Growth modelling" were applied to three stocks in Alaska, USA, with distinct size data and assumptions about growth (see Figure 2 and Table 1 for a summary of data and model configurations). We compared the spawning stock biomass (SSB) and other relevant quantities between the official assessments (i.e. those adopted by the North Pacific Fishery Management Council) and the WHAM versions.

Walleye pollock in the GOA

We used the data and model configuration of the 2021 stock assessment (Monnahan *et al.*, 2021) for a case study of walleye pollock in the GOA. The official assessment was implemented in ADMB (Fournier *et al.*, 2012) and contained information for one fishery and four surveys. Selectivity was age-based for all fleets (fishery and surveys), and the parameters controlling the initial slope and inflection point in the fishery double-logistic selectivity varied annually (Monnahan *et al.*, 2021). The Shelikof Strait age 3+ pre-spawner survey and Alaska Department of Fish and Game bottom trawl survey had autocorrelated catchability over time. For all other surveys, catchability was constant but estimated. EWAA was used to account for growth variation and compute expected indices and SSB.

We used the same data and configuration as in the original assessment and constructed 3-year projections based on the fishing mortality (F) in the terminal year for the projection period. We implemented three configurations in WHAM to account for growth variation:

1) *wham_ewaa*: uses EWAA information assumed to be known perfectly (as in the original assessment). In the projection, we use the average EWAA from the last 5 years of the assessment.
2) *wham_iid*: nonparametric modelling of the population mean weight-at-age (independent random effects by year and age). The random effects structure was used in the projection period to calculate the population mean weight-at-age.
3) *wham_2dar*1: nonparametric modelling of population mean weight-at-age (2DAR(1) random effects by year and age). The random effects structure was used in the projection period to calculate the population mean weight-at-age.

Models *wham_iid* and *wham_2dar*1 used the EWAA data from the Shelikof Strait survey as observations, where the observation error was calculated externally and then provided to the model (see online Appendix B). We used AIC to compare the two configurations.

Pacific cod in the GOA

We used the data and model configuration for the 2022 stock assessment (Model 19.1a, Hulson *et al.*, 2022) for this case study. The official assessment was implemented in Stock Synthesis 3 (SS3) (Methot and Wetzel, 2013) and included three fisheries and two surveys (bottom trawl and longline). Selectivity was length-based and double-normal for all fleets and

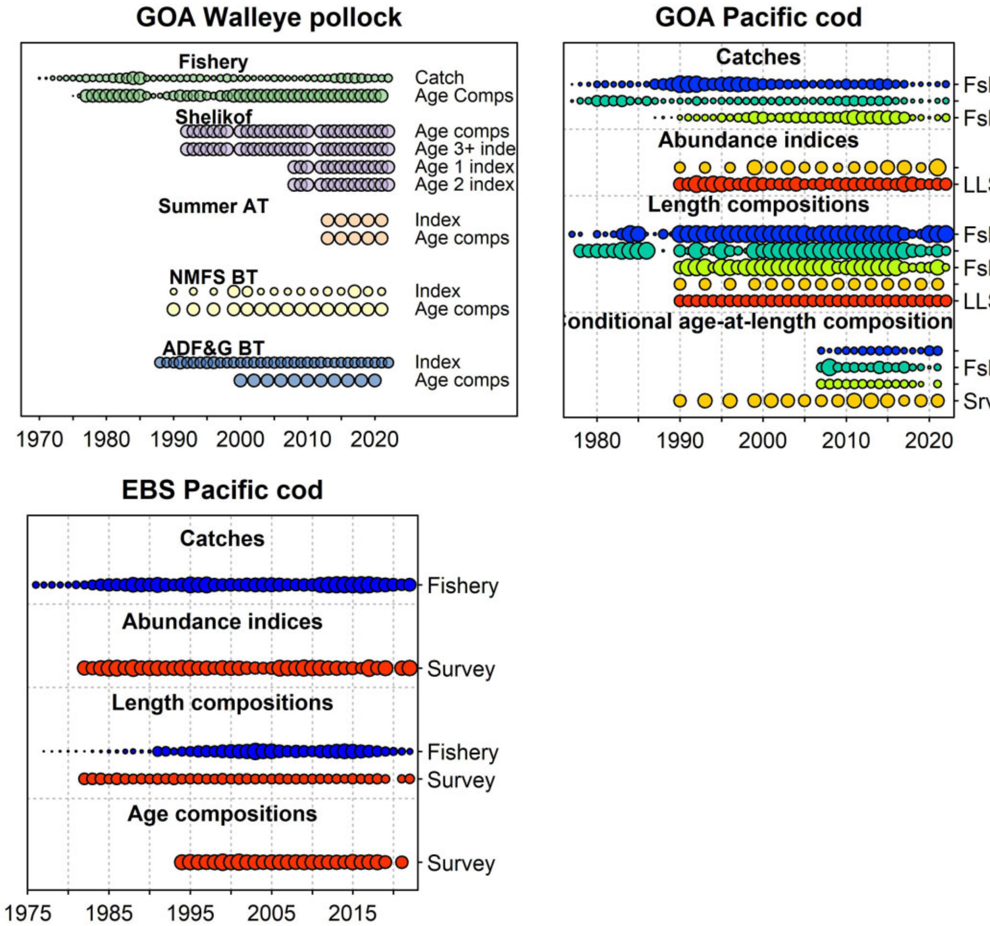

Figure 2. Data included in the official assessment models and WHAM configurations presented in this study. Circles indicate that data were present for a given year, and the circle size is proportional to input sample size, index precision, or catch size for a given row. Each fleet (fishery or survey) is represented by a different colour.

Table 1. Summary of model configurations used in WHAM models (GOA = Gulf of Alaska, EBS = eastern Bering Sea).

	GOA Walleye pollock	GOA Pacific cod	EBS Pacific cod
Model information and compositional data			
Number of ages	10	10	20
Minimum, maximum, and length bin width (cm)	–	0.5 – 116.5 – 1	3.5 – 119.5 – 1
Mean weight-at-age observations	1986–2021	–	–
Compositional data	Marginal age compositions	Conditional age-at-length, marginal length compositions	Marginal age and length compositions
Parameters			
Natural mortality	Age-specific (fixed)	Constant with block in 2014–2016 (estimated)	Constant (estimated)
Growth	EWAA or nonparametric WAA	von Bertalanffy (all parameters estimated)	Richards (all parameters estimated)
Length–weight	–	Fixed	Fixed
Recruitment	Mean recruitment estimated. Annual deviates estimated RE	Mean recruitment estimated. Annual deviates estimated PML	Mean recruitment estimated. Annual deviates estimated PML
Fishing mortality	Estimated	Estimated	Estimated
Catchability	Estimated. Annual deviates estimated RE	Estimated	Estimated
Selectivity	Estimated. Annual deviates estimated PML	Estimated. Annual deviates estimated PML	Estimated. Annual deviates estimated PML
Error distribution for age compositions	Multinomial	Multinomial	Linear-parameterization of Dirichlet-multinomial Estimated
Error distribution for length compositions	Multinomial	Multinomial	Multinomial

PML = penalized maximum likelihood, RE = Random effects. Data are displayed in Figure 2.

time-varying for all fisheries and one survey. Growth was modelled using the classic von Bertalanffy equation and was assumed to be time-invariant. The k and L_∞ parameters were estimated with normally distributed priors. The catchability parameter for the longline survey was linked to an environmental covariate (bottom temperature anomalies), assumed to be known without error, and hence varied over time. Natural mortality, M, was constant across ages and estimated for two time-blocks: 2014–2016 and all other years. A lognormally distributed prior was included for M. Ageing error was prespecified, and ageing bias (pre-2008) was estimated across all fleets.

We implemented the same configuration in WHAM as in the original assessment. The environmental covariate was treated as data, assuming a small observation error variance to approximate the original assessment. The true environmental state was assumed to have an AR(1) structure while estimating process error (see Stock and Miller, 2021). The ageing error matrix from SS3 was included in the WHAM model (see online Appendix A). M, k, and L_∞ were estimated without priors due to the current inability in WHAM to place priors on these parameters.

Pacific cod in the EBS

We used the data and model configuration from the 2022 stock assessment (Model 19.12A, Barbeaux *et al.*, 2022) for a case study of Pacific cod in the eastern and northern Bering Sea. The official assessment was implemented in SS3 and included information for one fishery and one survey. Selectivity was length-based and double-normal, and time-varying for both fleets. Growth was modelled using the Richards equation (Equation 2). SS3 estimated annual deviates on the mean length-at-age 1.5 ($L_{\tilde{a}}$, where $\tilde{a} = 1.5$ is the reference age) parameter using a PML approach (assuming mean zero and a fixed $\sigma^2_{L_{\tilde{a}}} = 1.48$). Ageing error was pre-specified, and ageing bias (pre-2008) was estimated across all fleets.

We included the same information and assumptions as in the original assessment in our WHAM implementation. The ageing error matrix from SS3 was included in the WHAM model. We considered two model configurations to account for variability in $L_{\tilde{a}}$:

1) *wham_ecov*: The mean bottom temperature over the EBS Pacific cod stock area obtained from the Bering10K model (Kearney *et al.*, 2020) was included and treated as data. Since observation error variance was not available, we assumed 0.2 as the observation standard error, but also evaluated the impacts of choosing 0.01 and 0.1. The true state was assumed to have an AR(1) structure and was linked to the $L_{\tilde{a}}$ parameter based on previous evidence (Ciannelli *et al.*, 2020) by

$$L_{\tilde{a}_y} = L_{\tilde{a}} * exp(\beta X_y), \qquad (16)$$

where X_y is the estimated environmental covariate, and β is the linking parameter estimated as a fixed effect.

2) *wham_ar1*: autocorrelated annual random effects were predicted on the $L_{\tilde{a}}$ parameter. The process error ($\sigma^2_{L_{\tilde{a}}}$) and the correlation coefficient (ρ) [see Equations (5)–(7)] were estimated. The mean bottom temperature index was included as in the previous configuration while estimating the true state, but was not linked to any parameter.

We calculated AIC to compare the two configurations, which is valid only due to the inclusion of the environmental data in both models.

Simulation experiment

We used the simulation feature of TMB to conduct a self-test to evaluate the statistical efficiency and quantify any bias in the growth modelling approaches presented here. Using the estimated WHAM models presented in the previous section (case studies) as operating models, we generated 100 new datasets (replicates) without simulating new random effects. For each replicate, we fitted the simulated data using the base configuration as in the operating model. Selectivity parameters were fixed for the EBS Pacific cod case since its estimation led to very low convergence rates. We calculated the relative error in initial abundance, mean recruitment, growth parameters, SSB, and F. Relative error was calculated as $(\hat{\alpha} - \alpha)/\alpha$, where α is the true value in the operating model and $\hat{\alpha}$ is the value estimated in the replicate. We used the median value of relative error across replicates as a measure of bias and the 95% simulation interval as a measure of precision. We confirmed the appropriateness of 100 replicates by analysing the change in bias and precision with increasing the number of replicates (Supplementary Figures S1–S3).

Results

GOA walleye pollock

Annual mean SSB estimates were similar among models (Figure 3a). Larger differences were observed between 1980 and 1985, when SSB estimates from the *wham_iid* and *wham_2dar*1 models were ∼30% larger than the original assessment and *wham_ewaa* models. Uncertainty levels were comparable among models. Projected mean SSB was higher for *wham_iid* and *wham_2dar*1, which also had larger uncertainty than the *wham_ewaa* model (Figure 3b). Predicted random effects over time for population mean weight-at-age were similar for the *wham_iid* and *wham_2dar*1 models (Figure 3c and d). Random effects were very close to zero before 1985 because there were no mean weight-at-age data during that time period. In both models, random effects increased over time until 2010 for older ages and then decreased. Large random effects were predicted in recent years for younger ages. The AIC was 2161.1 for the *wham_iid* model and 1989.1 for *wham_2dar*1 model, suggesting that weight-at-age was represented most parsimoniously using autocorrelation among ages and years.

Selectivity varied similarly over the years among models (Supplementary Figure S4). Catchability estimates were also similar across models, and the largest differences between the original ADMB and WHAM models were for the Shelikof Strait age 1 and age 2 survey indices (Supplementary Table S1). Estimated population mean weight-at-age closely matched observed values in the *wham_iid* and *wham_2dar*1 models, and estimated uncertainty was low when observation errors were small and high when observations were absent, especially for older ages and before 1986 (Supplementary Figures S5–S8). Population mean weight-at-age estimates in projection years were similar for *wham_iid* and *wham_2dar*1, with the latter model exhibiting lower uncertainty, as expected given deviations are informed by adjacent years and ages (Supplementary Figure S9).

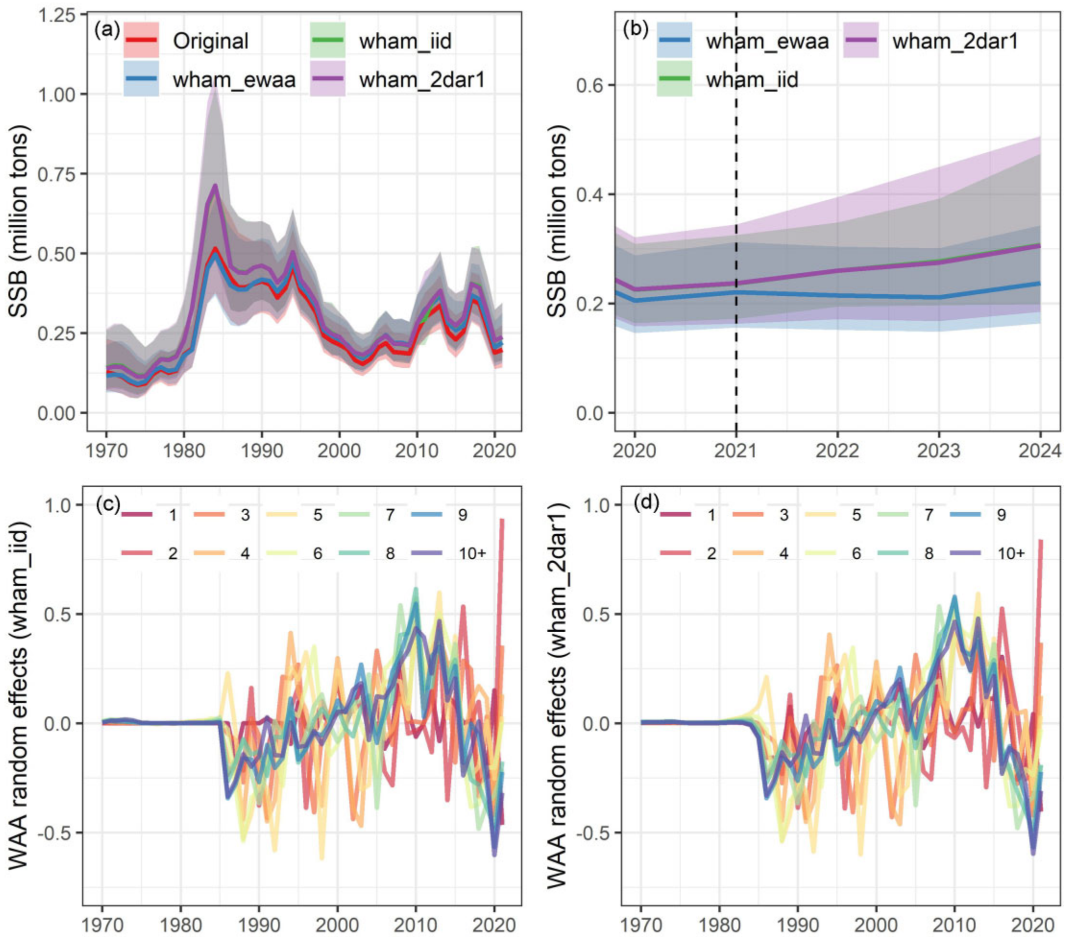

Figure 3. GOA walleye pollock. (a) Mean spawning biomass estimates (SSB) from WHAM configurations and the original assessment) and 95% confidence interval (coloured area). (b) Mean SSB and uncertainty in projection years. The dashed vertical line indicates the last model year (2021). (c) Random effects predicted by the *wham_iid* model by age (colours) and year. (d) Random effects predicted by the *wham_2dar1* model by age (colours) and year.

The initial abundance, mean recruitment, *F*, and SSB were approximately unbiased for all the WHAM configurations (Figure 4). Precision was lower for the *F* and SSB time series during the first model years, while *F* was overestimated (∼ +10%) and SSB underestimated (∼ –10%) during 1980–1990 for all models. The variance of the random effects (σ_{WAA}) was unbiased for the *wham_iid* model but was slightly (∼ –6%) underestimated for the *wham_2dar1* model. The autocorrelation parameters were overestimated (<+10%), and the mean weight-at-age estimates across replicates were unbiased for the *wham_iid* and *wham_2dar1* models (Supplementary Figures S10 and S11).

GOA pacific cod

Annual SSB estimates from the *wham* and SS3 models followed the same trend over time (Figure 5a), although the *wham* models estimated consistently higher (∼ +20%) SSB than SS3 throughout the model period. SSB uncertainty was also equivalent between models. Mean length-at-age estimates and the standard deviations of length-at-age were comparable between models, except for the oldest age/plus group, where the *wham* model estimated a larger mean length than SS3 (Figure 5b). The growth rate and asymptotic length estimated by *wham* were smaller and larger than the SS3 model, respectively (Supplementary Table S2). The estimates of mean catchability were similar between models, and the catchability parameter of the longline survey (LLSrv) varied over time following the estimated environmental covariate (Supplementary Figures S12 and S13). Selectivity varied similarly over the years among models (Supplementary Figure S14).

Moreover, unbiased growth parameter estimates and low precision for the standard deviations of lengths at age 1 and A (SD_1 and SD_A, see online Appendix C, Figure 6) were detected. Initial abundance had a lower precision than mean recruitment, and mean recruitment was estimated with a slight positive bias (∼ +3%). *F* and SSB estimates were unbiased before 2017 and had low precision during the early modelling period. After 2017, there was a small overestimation of SSB and underestimation of *F* (∼8%).

EBS pacific cod

The WHAM models produced larger mean SSB estimates and uncertainty than the SS3 model (∼ +15%; Figure 7a). The mean length-at-age 1 (L_1) calculated using the WHAM models fluctuated over time between 9 and 15 cm, and values from WHAM were slightly larger than the SS3 estimates (∼1.5 cm; Figure 7b). The temporal variability in L_1 followed the same trend among models,

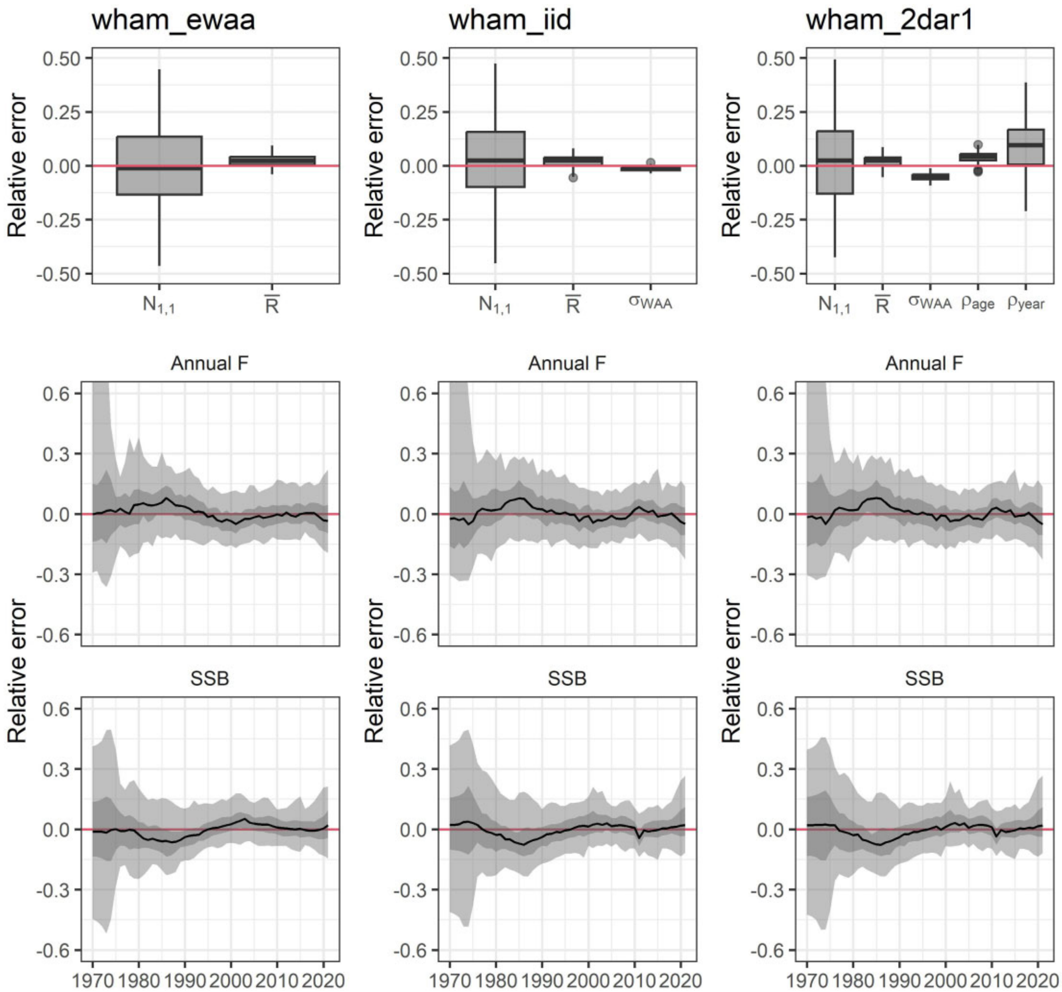

Figure 4. Results of the simulation experiment for GOA Walleye pollock. Relative error of key quantities: initial abundance at age 1 ($N_{1,1}$), mean recruitment ($\bar{R}$), annual fishing mortality, and SSB. Variance and autocorrelation parameters of random effects (population mean weight-at-age) are also displayed for *wham_iid* and *wham_2dar*1. The dark and light areas represent the 50 and 95% quantiles, respectively. The black line is the median.

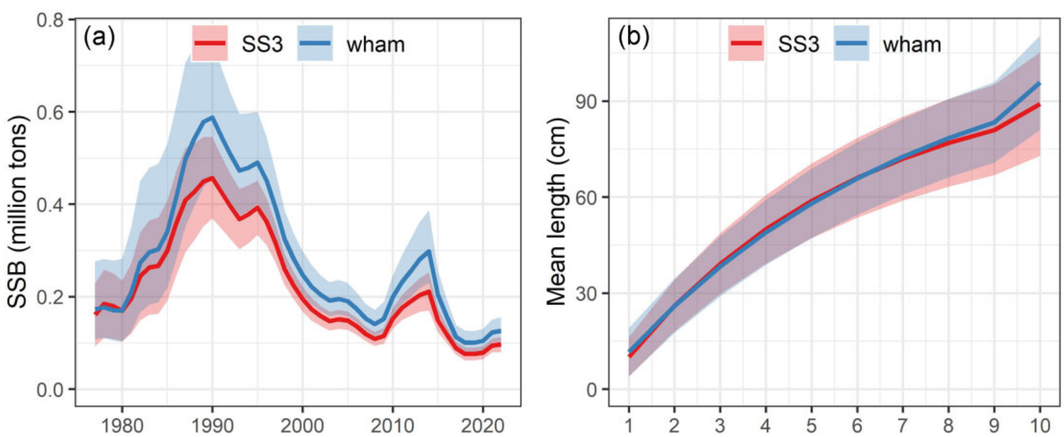

Figure 5. GOA Pacific cod. (a) Mean spawning biomass (SSB) (continuous line) and 95% confidence interval (coloured area) estimated by the original assessment (SS3) and the WHAM model (wham). (b) Mean length-at-age (continuous line) and associated standard deviations (coloured area) estimated by the original assessment (SS3) and WHAM.

especially after 1995. L_1 from the *wham_ecov* model followed a temporal trend similar to the environmental covariate before 1990. The environmental process predicted using the *wham_ar*1 model matched the observations quite well, but the *wham_ecov* did not, especially between 1983 and 1998 (Figure 7c). The catchability parameter was smaller for the WHAM models, which explains the difference in SSB values (Supplementary Table S3). Selectivity varied

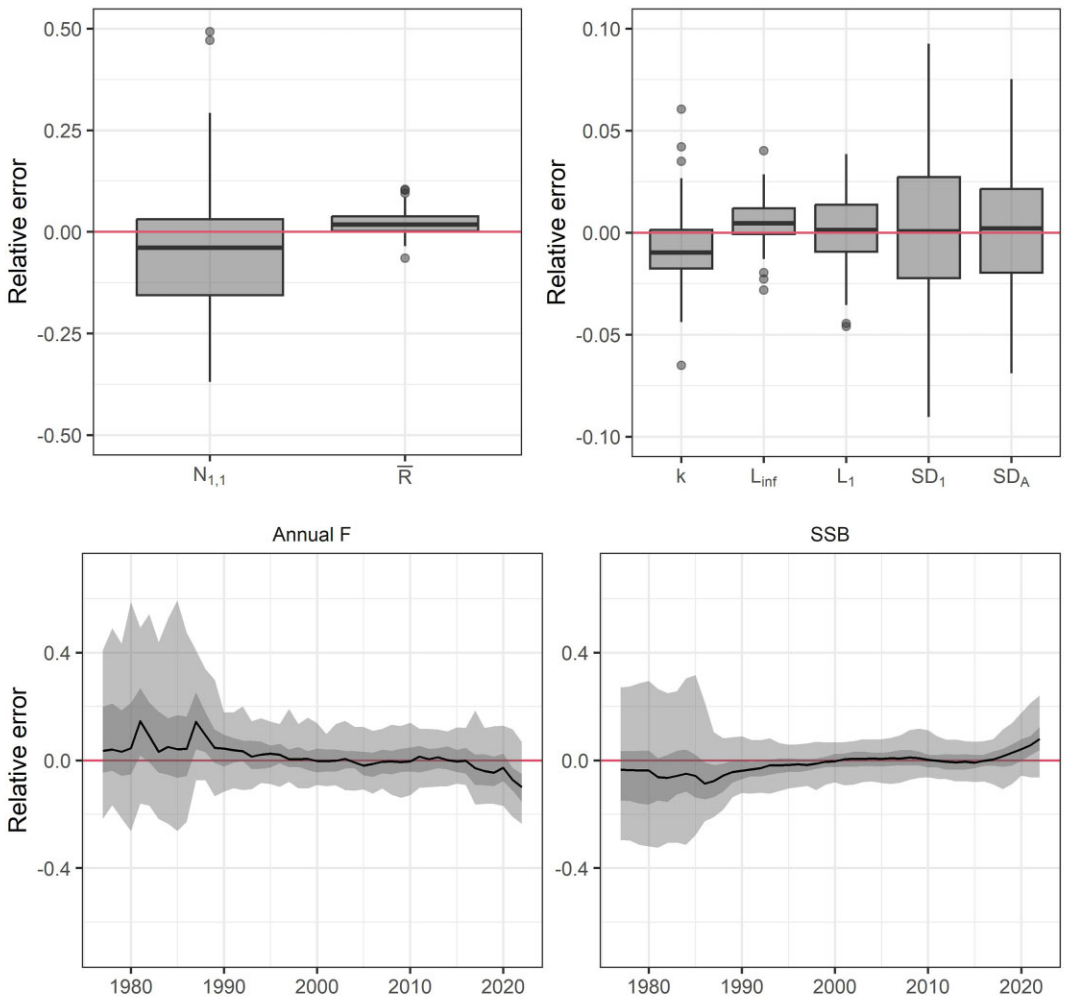

Figure 6. Results of the simulation experiment for GOA Pacific cod. Relative error of key quantities: initial abundance at age 1 ($N_{1,1}$), mean recruitment ($\bar{R}$), annual fishing mortality, and SSB. Relative error for growth parameters is also displayed. The dark and light areas represent the 50 and 95% quantiles, respectively. The black line is the median.

similarly over the years among models (Supplementary Figure S15).

AIC values were generally lower for the *wham_ar*1 model for different values of observation standard error for the environmental time series (Supplementary Table S4). Moreover, a smaller observation standard error increased the AIC for the *wham_ecov* models. We also observed that reducing the observation standard error forced *wham_ecov* to follow the observed environmental time series trend more closely (Supplementary Figure S16).

SSB bias and precision did not change after 45 replicates in the simulation experiment (Supplementary Figure S16), and unbiased and precise growth parameter estimates were observed (Figure 8). Initial abundance and fishing mortality had low precision and positive bias ($\sim +10\%$, Figure 8). *F* and SSB estimates were unbiased in all years but showed low precision during the first years (Figure 8).

Discussion

SSMs have become more popular in recent years, but their use has been limited to fish stocks reliant only on indices of abundance or indices of abundance and age compositions. We present a set of approaches (parametric and nonparametric) to model somatic growth through changes in the population mean length- or weight-at-age and fitted to size-specific data. These features were implemented in WHAM and then applied to three important stocks in Alaska. WHAM can now incorporate size-based information (e.g. marginal length compositions, CAAL data) to estimate growth parameters. Here, we found that WHAM estimates were similar to those from other widely used modelling platforms (SS3 and bespoke ADMB models). The main advantage of using the state-space approach is that random effects can be predicted with multiple structures and multiple process errors can be estimated simultaneously, thus providing an improved characterization of uncertainty (Thorson and Minto, 2015). This extended version of WHAM is the first flexible framework for estimating time-varying length-at-age in a state-space stock assessment framework, and standard WHAM features (e.g. projections, one-step ahead residuals, environmental linkages) are also available.

Growth modelling techniques in an SSM have been limited thus far. Zhang and Cadigan (2022) developed an age- and length-structured statistical catch-at-length model that allowed the inclusion of catch-at-length data and modelled time-invariant growth using a transition matrix. On the other hand, Miller *et al.* (2018) is the only study that modelled

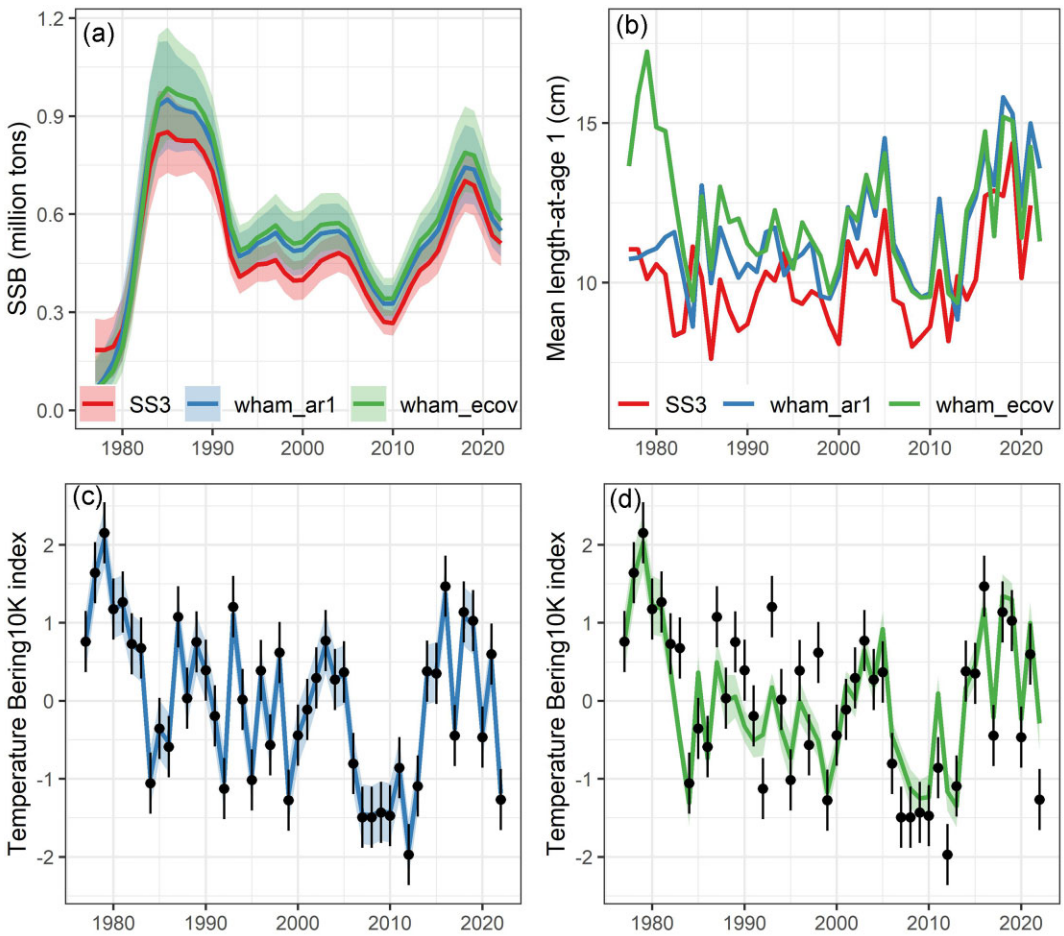

Figure 7. EBS Pacific cod. WHAM models assumed an observation error standard deviation of 0.2 for the environmental time series. (a) Mean spawning biomass (SSB) (continuous line) and 95% confidence intervals (coloured area) estimated by the original assessment (SS3) and the WHAM configurations. (b) Annual variability in the mean length-at-age 1 estimated by the WHAM models. (c) Estimates of the true environmental covariate (continuous line) and 95% confidence intervals (coloured area) from the *wham_ar1* model. Observed environmental covariate and associated observation errors are shown in black points and bars, respectively. (d) Estimates of the true environmental covariate (continuous line) and 95% confidence intervals (coloured area) from the *wham_ecov* model. Observed environmental covariate and associated observation error are shown in black points and bars, respectively.

growth variation in a SSM using an environmental index as a driver of changes in the population mean size-at-age. Marginal length compositions are commonly included in integrated models as a source of information for growth. However, caution should be taken when using these data since they also include the effects of selectivity, fishing mortality, and recruitment (Francis, 2016; Punt, 2023). Size-at-age information can be used for parameter estimation in the form of CAAL data, which are paired age and length observations that are treated as a measure of the age distribution for a specific length class (Lee *et al.*, 2019). CAAL data are particularly useful since they lead to an accurate characterization of growth as long as they are representative of the age structure of the stock (Lee *et al.*, 2019). Another improvement is that ageing error matrices can now be incorporated in WHAM. Ageing error occurs when the age estimated from reading hard structures (e.g. otoliths) differs from the true age, and can have a substantial impact on model estimates and management decisions (Punt *et al.*, 2008; Richards *et al.*, 1992; Reeves, 2003).

The internal modelling of growth variability in assessments has become more frequent in recent years. Stawitz *et al.* (2019) found that the misspecification of growth can result in positive bias in management quantities (e.g. stock depletion), and that this bias is mitigated when growth variability is accounted for. Moreover, they recommended modelling growth variability only in data-rich situations. Likewise, Correa *et al.* (2021) and Lee *et al.* (2018) found a large bias, especially for short-lived species, in SSB estimates when annual or cohort-specific temporal variability in growth was ignored. While the growth modelling framework presented here is similar to those implemented in other modelling platforms (e.g. Stock Synthesis), it is novel in several ways. For example, the process error variance can now be estimated by integrating out the random effects and maximizing the marginal likelihood, which is currently considered as best practice (Punt, 2023). This feature allows us to avoid the PML approach, which usually subjectively fixes the process error variance. In addition, we can now model the population mean length or weight-at-age non-parametrically as is already the case for some model components in similar assessment models (Xu *et al.*, 2019; Stock *et al.*, 2021). Further exploration is necessary to fully understand the performances of these new approaches under diverse circumstances.

Selecting an environmental covariate to drive changes in growth in an assessment model is a crucial decision. WHAM assumes observation error in an environmental covariate such

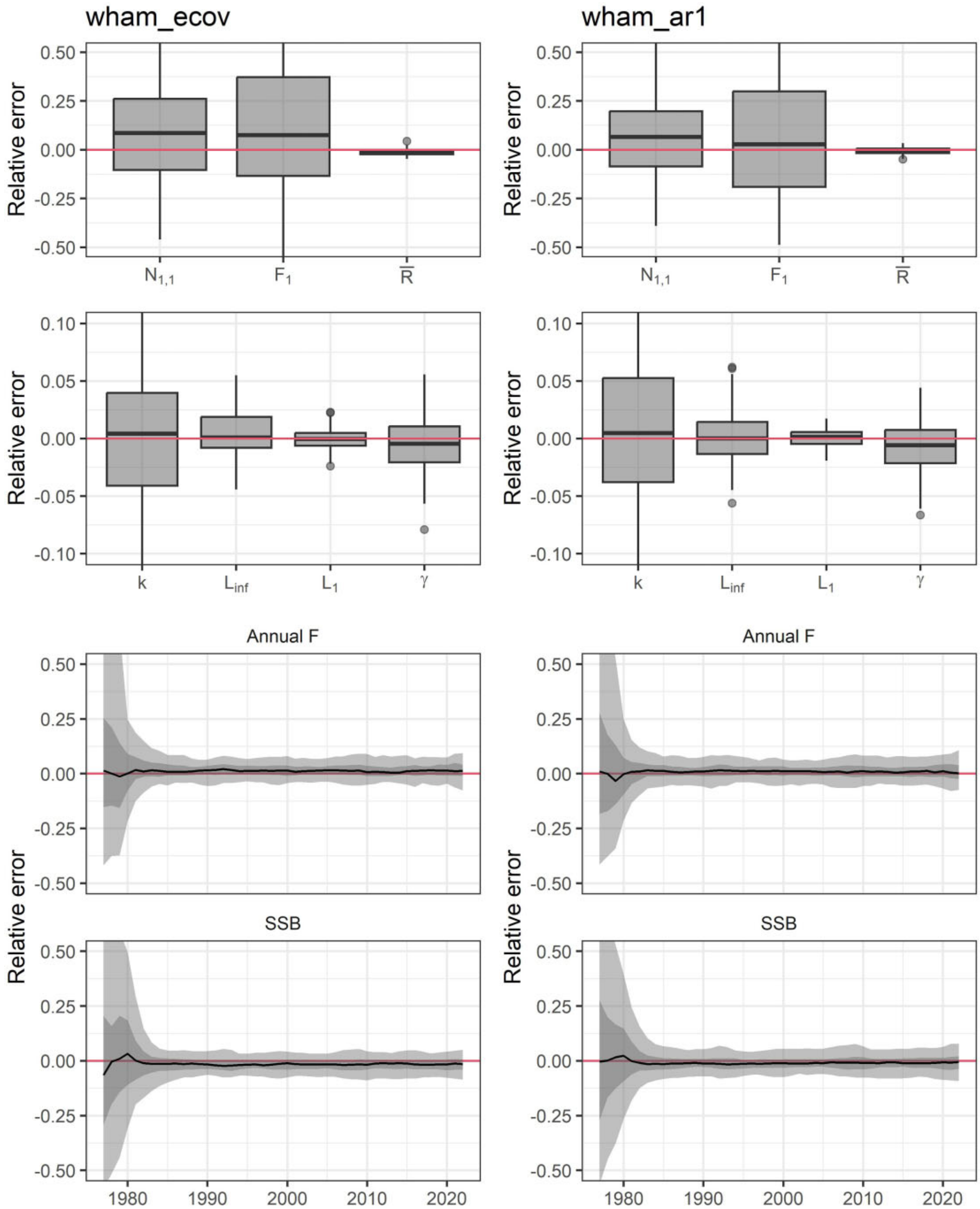

Figure 8. Simulation experiment for EBS Pacific cod. Relative error of key quantities: initial abundance at age 1 ($N_{1,1}$), initial fishing mortality F_1, mean recruitment ($\bar{R}$), growth parameters, annual fishing mortality, and SSB. The dark and light area represent the 50 and 95% quantiles, respectively. The black line represents the median.

that the population parameter (e.g. growth rate) is linked to the predicted latent state of the environmental variable rather than the observed values (Stock and Miller, 2021). Environmental observations and predictions were quite similar in the *wham_ar*1 model for EBS Pacific cod since there were no constraints (i.e. no link to any biological parameter). Conversely, the *wham_ecov* model found differences between environmental observations and predicted states, which could be caused by several factors. First, a temperature index was selected because there is evidence of temperature effects on the growth of Pacific cod. However, there may be other relevant variables (e.g. prey density, oxygen) that we ignored. Second, the calculation of the temperature index, which is an average from the entire eastern Bering Sea, might not be representative of the temperature conditions in the habitat of Pacific cod. Third, the linking equation (Equation (16)) may not be appropriate; therefore, alternative equations need to be explored due to their impacts on model results (du Pontavice *et al.*, 2022). Finally, we observed that the assumed observation standard error impacted the *wham_ecov* model results. A smaller error led to degraded model fits (Supplementary Table S4), which means that the observed environmental covariate conflicted with other data inputs informative to growth (e.g. marginal length compositions). This result was evident after 1985 when the input sample sizes for the length compositions were higher (Figure 7d). Future work could explore estimating the observation standard error as a parameter, which is an option in WHAM.

Based on parametrizations already implemented for other model components in WHAM, we developed a nonparametric approach to model changes in population mean length- or weight- at-age. In our case, the terms $\mu_{\tilde{L}_a}$ or $\mu_{\tilde{W}_a}$ (Equations (8) and (14)) may be externally calculated from a parametric growth function or observed data and then fixed, or internally estimated as fixed effects while predicting $\delta_{a,y}$ as random effects. This approach differs from the semiparametric approach of Thorson and Taylor (2014) and Xu *et al.* (2019). For example, for selectivity, the semiparametric approach is based on a parametric (e.g. logistic equation) and a nonparametric part (e.g. random effects on age and year), and the estimation of the fixed effects parameters and prediction of the random effects occurs simultaneously (Xu *et al.*, 2019). Evidence suggests that semiparametric structures will revert to the parametric form when data are uninformative but will approximate the data-generating process when data are highly informative (i.e. based on a representation theorem, Klein, 1976). We found that the estimated population mean weight-at-age from the nonparametric approach behaved as described for the semiparametric approach for GOA walleye pollock, i.e. reverting to the parametric for ($\mu_{\tilde{W}_a}$) when no observed mean weights-at-age were available and approximating the observed data when there was limited observation error.

A common practice in age-structured assessment models that do not model growth internally is to use EWAA data to calculate biomass-at-age from abundance-at-age. However, this approach assumes that the available weight-at-age information is known without error, an assumption that is not met in most, if not all, cases (Kuriyama *et al.*, 2016). We showed for GOA walleye pollock that the EWAA input could be treated as data while estimating the population mean weight-at-age through the prediction of random effects with two covariance structures (independent and correlated over ages and years). The two configurations led to similar results, but the more complex model with correlated random effects had the lowest AIC ($\Delta AIC = 172$). The improved performance of models with correlated population processes has also been found previously. For example, Stock *et al.* (2021) found that imposing a 2DAR(1) structure on natural mortality improved model fit and reduced retrospective patterns for SSB, *F*, and recruitment for the Southern New England-Mid Atlantic (SNEMA) yellowtail flounder (*Limanda ferruginea*). In addition, Xu *et al.* (2019) and Nielsen and Berg (2014) modelled correlation by age and year in selectivity in age-structured models, leading to an improved model performance. Finally, Stock and Miller (2021) found improved model performance and reduced retrospective bias when predicting 2DAR(1) random effects on abundance-at-age in a simulation experiment for several life histories. Recently, Cheng *et al.* (2023) proposed a parametrization to account for year, age, and cohort autocorrelation in mean weight-at-age and other biological processes. This method offers a new approach to model time variability in weight or length-at-age and could be tested in assessment frameworks in the future.

Forecasting is an important part of the fisheries management process. When forecasting, assessments typically use data and estimates from the last year or an average from recent years for the projection period. This approach assumes that near-future conditions will not vary from the present, an assumption that is hardly ever met. Autoregressive processes in stock assessment models are valuable when forecasting since they can be used to propagate uncertainty in short-term projections. Recruitment is one of the main processes when making projections (Maunder and Thorson, 2019; Van Beveren *et al.*, 2021). However, growth is commonly assumed to be time-invariant despite being an important contributor to stock biomass (Stawitz and Essington, 2018). Stock *et al.* (2021) found an improved consistency of biomass projections for SNEMA yellowtail flounder when survival and natural mortality had a 2D (age and year) autocorrelation structure. Likewise, du Pontavice *et al.* (2022) improved short-term projections and uncertainty representation of recruitment and SSB for the SNEMA yellowtail flounder by accounting for forecast uncertainty of the Cool Pool Index modelled as an autoregressive process. Mean SSB and uncertainty in projection years for GOA walleye pollock were larger in the model with a 2D autocorrelated population mean weight-at-age than in the model that used EWAA. These changes may influence the management advice, as there is considerable interannual variability in size-at-age for this stock.

For all our case studies, we found moderate to minor differences in model estimates, which can partially be explained by the structural dissimilarities between platforms (e.g. SS3 vs. WHAM). For example, the estimation of the initial abundance-at-age is done differently in WHAM and SS3. In WHAM, we estimated an initial abundance-at-age 1 ($N_{1,1}$) and then, using an initial F (F_1), we calculated the initial abundance-at-age a using the exponential decay function from $N_{1,1}$. In contrast, in SS3, the initial abundance-at-age a was calculated using average recruitment from an "early period" (Methot and Wetzel, 2013). This distinction could explain the difference in SSB estimates between WHAM and SS3, especially during the early modelling period. Future studies could explore initializing the WHAM and SS3 models at an earlier year to explore if this results in more similar biomass trajectories by the first year of substantial data. Another dissimilarity is how the process error for selectivity is parametrized. WHAM shares the process error variance across all the selectivity parameters for a given fleet, whereas SS3 assumes a different process error variance for each selectivity parameter. We expect that the extension presented in this study may make WHAM a potential platform to assess the status of a broader range of fish stocks in the future.

Conclusion

We provided a novel framework to model growth and size-at-age in SSMs, implemented it in WHAM, and applied it to three groundfish stocks in Alaska. Our study presents, for the first time, an SSM that is able to model growth using size-specific information (e.g. marginal length compositions, CAAL), in addition to the features already developed in previous studies for SSM (e.g. use of environmental information, projections; Stock and Miller, 2021). These new modelling approaches expand the applicability of SSM and their benefits (e.g. more realistic uncertainty, estimation of process error, reduction of retrospective patterns) to more stocks worldwide. Specifically, our case studies showed that WHAM can now be used as a platform for assessing some fish stocks in Alaska; however, we suggest further examination of the structural differences between WHAM and the assessment platforms currently used for Alaskan fish stocks.

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Supplementary Data

Supplementary material is available at the *ICESJMS* online version of the manuscript.

Conflicts of interest

The authors declare no conflicts of interest.

Data availability

The assessment data used to implement the case studies and the simulation results presented in this article are available in the GitHub repository: https://github.com/GiancarloMCorrea/AKWHAM.

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