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Model performance for the determination of appropriate harvest levels in the case of data-poor stocks

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ABSTRACT

The determination of harvest limits for data-poor and data-limited stocks poses unique challenges for traditional complex stock assessment methods. Simulation is used to examine the performance of two new data-poor assessment methods, Depletion Corrected Average Catch (DCAC) and Depletion-Based Stock Reduction Analysis (DB-SRA), and a more complex catch-at-age method, Stock Synthesis (SS), in terms of estimating harvest levels for two life-history types (U.S. west coast flatfish and rockfish) under varying mis-specifications of parameter distributions. DCAC and DB-SRA are fairly robust to mis-specification of the distributions for natural mortality and the productivity parameter (the fishing mortality rate that corresponds to maximum sustainable yield relative to natural mortality) for the flatfish life-history, but led to greater error for the rockfish life-history when estimating harvest levels that would not result in overfishing. SS estimates of the harvest level increased when natural mortality was set to a higher value than the true value for both life-histories. Both DCAC and DB-SRA were highly sensitive to the assumed distribution for the ratio of the current to starting biomass and provided overestimates of the harvest level when based on an overly optimistic value for this ratio.

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1. Introduction

Developing and implementing appropriate harvest strategies that avoid overfishing has proven challenging for even the most data-rich marine fishes (Walters and Maguire, 1996). Hence, data-poor stocks pose a particularly difficult task for fishery managers. The 2006 reauthorization of the Magnuson-Stevens Fishery Conservation and Management Act (MSRA) included new requirements for the management of federal fisheries, including the implementation of annual catch limits (ACLs) for all exploited fish stocks within a fishery management plan, even the most data-poor un-assessed stocks.

A stock can be data-poor due to a number of factors: (a) little to no commercial value, resulting in a high frequency of discarding at sea, (b) infrequently encountered by fishing/survey gear, or (c) occurrence of small sub-populations that have limited or no mixing. On the U.S. west coast, the Pacific Fishery Management Council (PFMC) often manages data-poor and un-assessed stocks by forming them into groups termed stock complexes, based on spatial distributions (PFMC, 2010). Previously, stock complexes have been managed using an Overfishing Level (OFL; a level of harvest that if exceeded would constitute overfishing) and an Acceptable Biological Catch (ABC; a level of harvest that accounts for scientific uncertainty in the estimate of the OFL, and thus is less than the OFL) that was determined for the entire complex without consideration of individual stocks. The MSRA now requires ABCs and OFLs for all species. For stock complexes, the PFMC must now determine ABCs and OFLs on an individual species basis and combine the species specific values todefine the ABC and the OFL for the complex as a whole (PFMC, 2008). This shift in management has created the need to determine appropriate harvest limits for un-assessed and data-poor stocks that will avoid overfishing and are based upon the best available science.

Data-poor stock management in the past has largely focused on the use of harvest limits based on proxies (e.g. setting harvest rate equal to natural mortality) or average catches, due to the inability to apply traditional data-dependent stock assessment methods (Restrepo et al., 1999). The development of methods that incorporate some aspects of traditional assessment techniques and direct or indirect information on a stock has created alternatives for the management of data-poor stocks. For example, the "Robin-Hood" method borrows information from data-rich stocks to inform the assessments of data-poor stocks and hence catch limits (Smith et al., 2009; Punt et al., 2011). Alternative methods that allow for an "assessment-free" estimation of reference points using biological parameters to directly calculate biological reference points and

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relative abundance have also been proposed to provide harvest advice (Brooks et al., 2010).

Harvest limits for un-assessed data-poor groundfish stocks off the U.S. west coast (West Coast groundfish) have been computed using Depletion-Corrected Average Catch (DCAC) (MacCall, 2009) and the Depletion-Based Stock Reduction Analysis (DB-SRA) (Kimura et al., 1984; Walters et al., 2006; Dick and MacCall, 2010). DCAC and DB-SRA are data-poor methods that estimate either a sustainable yield (DCAC) or an OFL (DB-SRA). Each method requires the analyst to specify probability distributions for various biological parameters. Both methods use catch histories. However, each method uses this information differently. DCAC is based on the mean catch over a specified time-period, while DB-SRA uses each year's catch in a delay-difference production model. An advantage of these two methods is the limited amount of data required to apply them.

It is important to understand when it is most appropriate to apply DCAC and DB-SRA and when should a more complex statistical catch-at-age model, with the ability to incorporate all available data, be applied for harvest determinations. Stock Synthesis (SSv.3, referred to henceforth as SS, Methot, 2009, model description Methot, 2005), an age-length structured population dynamics model, forms the basis for most West Coast groundfish stock assessments. However, the amount of data provided to SS in a data-limited or a data-poor case may result in poor model performance in comparison to methods that are based only on catch data (and some assumptions).

Simulation (see Butterworth and Punt, 1999 for an overview) was used to evaluate the performance of DCAC, DB-SRA, and SS for determining the harvest that would not result in overfishing given data-limited situations for two life-histories common on the U.S. west coast, a flatfish (medium-lived fast growing species) and a rockfish (long-lived slow growing species). Each estimation method was used to estimate a harvest level (HL) (generically, since DCAC estimates a sustainable yield while DB-SRA and SS estimate OFLs) that was compared to the true OFL that occurred at the associated PFMC-selected target fishing mortality rate for each life-history (PFMC current harvest policy is $F_{30\%}$[1] for flatfish and $F_{50\%}$ for rockfish).

2. Methods

2.1. The operating model

The population dynamics with a continuous fishing mortality, where the numbers of fish of gender γ in age group a, at the start of each year t, are calculated as:

$$N_{\gamma,a,t+1} = \begin{cases} N_{\gamma,0,t+1} & a = 0 \\ N_{\gamma,a-1,t}e^{-M-S_{\gamma,a-1}F_t} & a \geq 1 \text{ to } A-1 \\ (N_{\gamma,A-1,t} + N_{\gamma,A,t})e^{-M-S_{\gamma,A}F_t} & a = A \end{cases} \quad (1)$$

where $N_{\gamma,a,t+1}$ is the number of fish of age a and gender γ at the start of the year t, $S_{\gamma,a}$ is the gear selectivity by age and gender, A is the plus group for age, F_t is the instantaneous fishing mortality rate during year t, and M is the instantaneous rate of natural mortality. The number of age-0 fish is related to spawning biomass according to the Beverton–Holt stock recruitment relationship:

$$N_{\gamma,0,t} = \frac{4hR_0S_t}{S_0(1-h)+S_t(5h-1)}e^{-0.5\sigma_R^2+\tilde{R}_t}\,\tilde{R}_t{\sim}N(0;\sigma_R^2) \quad (2)$$

[1] $F_{x\%}$ is the fishing mortality rate that reduces spawning output-per-recruit to x% of its unfished level.

where R_0 is the number of age-0 fish at unfished equilibrium, S_0 is the unfished equilibrium spawning biomass (corresponding to R_0), S_t is the spawning biomass at the start of the spawning season during year t, h is the recruitment compensation (also known as steepness) parameter, σ_R is the standard deviation of recruitment in log space, and $\tilde{R}_t$ is the lognormal recruitment deviation for year t. A non-equilibrium starting population was created by applying Eqs. (1) and (2) for a pre-specified number of years prior to the start of fishing with F = 0 and with random recruitment deviations. The value of spawning biomass at the start of the fishery defines the virgin spawning stock biomass (SSB_0). This value varied among the 100 simulations depending on the random recruitment deviations generated for the years prior to the year with the first catch.

The operating model was projected forward for 50 years with fishery removals. The catch of fish of age a and gender γ during year t in numbers was determined using the Baranov catch equation:

$$C_{\gamma,a,t} = \frac{S_{\gamma,a}F_t}{M+S_{\gamma,a}F_t}N_{\gamma,a,t}(1-e^{(-M-S_{\gamma,a}F_t)}) \quad (3)$$

The specified final depletion is implemented by finding the value for the R_0 that would result in the selected final depletion based on the randomly drawn vector of annual recruitment deviations and the catch history. Selectivities for both the fishery and survey take the form of a logistic curve, with larger fish being fully selected. Selectivity for smaller fish is greater in the survey than in the fishery.

Two life-history types (flatfish and rockfish) with the appropriate biological parameters are simulated (Table 1). A full description of the operating model is provided in Appendix A.

2.2. DCAC

DCAC (MacCall, 2009) was developed as a means to estimate a sustainable yield for data-poor stocks. DCAC uses a catch history, the length of the catch history, a user-defined relative stock depletion status, along with biologically based parameters to calculate a yield that would likely be sustainable:

$$\text{DCAC} = \frac{\sum C_t}{n + \Delta[B_{peak}(F_{MSY}/M)M]^{-1}} \quad (4)$$

where C_t is the catch during year t, n is the length of the catch time-series in years, Δ is the relative stock status (i.e. $1 - B_{current}/K$), B_{peak} is the biomass that corresponds to maximum sustainable yield relative to carrying capacity (B_{MSY}/K), M is the instantaneous rate of natural mortality, and F_{MSY}/M is the ratio between the fishing mortality rate that corresponds to B_{peak} and M. A Monte Carlo approach is used to account for the uncertainty regarding the four input parameters (Δ, B_{peak}, F_{MSY}/M, and M). 10,000 random draws from pre-specified prior distributions (Table 2) are made for this paper and Eq. (1) applied to each.

The majority of the prior distributions for DCAC were selected for consistency with previous DCAC work that focused on West Coast groundfish stocks (Dick and MacCall, 2010); (a) the mean for the prior for MSY was assumed to occur when B/K is 0.30 for flatfish and 0.40 for rockfish, and (b) the stock is close to the target depletion of 30% for flatfish and 40% for rockfish (Δ = 0.70 and 0.60, respectively). The mean value for the ratio between F_{MSY} and M_w asset equal the true ratios from the operating model (flatfish 1.18 and rockfish 0.64), while in previous applications this value has been assumed to be 0.8 (based on available information for West Coast groundfish species; Walters and Martell, 2004). The distribution of M differs from previous applications of DCAC and was specified as uniform rather than lognormal to be consistent with the treatment of M in SS, with bounds selected at 20% above and below an assumed value.

Table 1
List of the parameter values for the rockfish and flatfish life-histories used when generating the simulated data sets. The parameters applied were based upon assumed biological values for U.S. west coast Petrale soleand Splitnose rockfish.

Parameter	Equation form	Flatfish life-history		Rockfish life-history	
		Males	Females	Males	Females
Natural mortality, m	M = constant	$M = 0.20$ (year^{-1})		$M = 0.05$ (year^{-1})	
Steepness, h		$h = 0.875$		$h = 0.50$	
Fishing rate at B_{MSY}, F_{MSY}		$F_{MSY} = 0.24$		$F_{MSY} = 0.032$	
Recruitment deviation, σ_R		$\sigma_R = 0.50$		$\sigma_R = 0.50$	
Mean length at age, $L_{\gamma,a}$ (cm)	$L_{\gamma,a} = L_{\infty,\gamma} + (L_{1,\gamma} - L_{\infty,\gamma})e^{-K(a-a_3)}$				
Mean asymptotic size, $L_{\infty,\gamma}$ (cm)	$L_{\infty,\gamma} = L_{1,\gamma} + \frac{L_{2,\gamma} - L_{1,\gamma}}{1 - e^{-K_\gamma(a_4 - a_3)}}$	$a_3 = 2.833$ (year)	$a_3 = 2.833$ (year)	$a_3 = 1$ (year)	$a_3 = 1$ (year)
		$a_4 = 17.833$ (year)	$a_4 = 17.833$ (year)	$a_4 = 80$ (year)	$a_4 = 80$ (year)
Reference ages, a_3, a_4					
		$L_{1,\gamma} = 24.6210$ (cm)	$L_{1,\gamma} = 24.6210$ (cm)	$L_{1,\gamma} = 6.64$ (cm)	$L_{1,\gamma} = 6.64$ (cm)
Mean length at a_3, $L_{1,\gamma}$					
		$L_{2,\gamma} = 40.6664$ (cm)	$L_{2,\gamma} = 55.4099$ (cm)	$L_{2,\gamma} = 59.7094$ (cm)	$L_{2,\gamma} = 59.844$ (cm)
Mean length at a_4, $L_{2,\gamma}$					
		$K_\gamma = 0.299488$ (year^{-1})	$K_\gamma = 0.14375$ (year^{-1})	$K_\gamma = 0.2579$ (year^{-1})	$K_\gamma = 0.1314$ (year^{-1})
Growth coefficient, K_γ					
Body weight, $w_{l,\gamma}$	$(w_{l,\gamma}) = \Omega_1 L_l^{\Omega_2}$	$\Omega_1 = 7.17 \times 10^{-6}$	$\Omega_1 = 3.42 \times 10^{-6}$	$\Omega_1 = 1.55 \times 10^{-6}$	$\Omega_1 = 1.55 \times 10^{-6}$
Length, L_l (cm)		$\Omega_2 = 3.346$	$\Omega_2 = 3.134$	$\Omega_2 = 3.03$	$\Omega_2 = 3.03$
Fraction mature, φ_l'	$\varphi_l' = (1 + e^{\Omega_3(L_l - \Omega_4)})^{-1}$				
Maturity slope, Ω_3	$f_a = \sum_{l=1}^{A_l} \varnothing_{al} \varphi_l' w_l'$		$\Omega_3 = -0.734$		$\Omega_3 = -0.25$
Length at 50% maturity, Ω_4			$\Omega_4 = 33.10$ (cm)		$\Omega_4 = 40.5$ (cm)
Fecundity at age, f_a					
Fishery selectivity			$\beta_1 = 43$, $\beta_2 = 3$, $\beta_3 = 5.05$		$\beta_1 = 43$, $\beta_2 = 3$, $\beta_3 = 5.05$,
			$\beta_4 = 6$, $\beta_4 = -12$, $\beta_6 = 70$		$\beta_4 = 6$, $\beta_5 = -12$, $\beta_6 = 70$
Survey selectivity			$\beta_1 = 33$, $\beta_2 = 3$, $\beta_3 = 5.05$,		$\beta_1 = 33$, $\beta_2 = 3$, $\beta_3 = 5.05$,
			$\beta_4 = 6$, $\beta_5 = -12$, $\beta_6 = 70$		$\beta_4 = 6$, $\beta_5 = -12$, $\beta_6 = 70$
Coefficient of variation of length-at-age, $\sigma_{0\gamma a}$	$\sigma_{0\gamma a} = \tilde{L}_{\gamma a} * CV$		$CV = 0.08$		$CV = 0.08$
Catchability coefficient, Q_f			$Q_f = 1.0$		$Q_f = 1.0$

Table 2
The distribution type with mean and standard deviation (SD) used to generate random samples for each parameter in each of the five cases. Values in bold differ from the true values in the operating model.

		Flatfish				Rockfish			
		True value	Assumed value	SD	Distribution	True value	Assumed value	SD	Distribution
All cases	B_{peak}	0.30	0.30	0.05	Beta	0.40	0.40	0.05	Beta
Case 1	M	0.20	[0.16, 0.24]		Uniform	0.05	[0.3,0.07]		Uniform
	F_{MSY}/M	1.18	1.18	0.40	Lognormal	0.64	0.64	0.40	Lognormal
	Δ	0.70	0.70	0.10	Beta	0.60	0.60	0.10	Beta
Case 2	M	0.20	[0.16, 0.24]		Uniform	0.05	[0.3,0.07]		Uniform
	F_{MSY}/M	1.18	**0.80**	0.40	Lognormal	0.64	**0.80**	0.40	Lognormal
	Δ	0.70	0.70	0.10	Beta	0.60	0.60	0.10	Beta
Case 3	M	0.20	[**0.18**, **0.28**]		Uniform	0.05	[**0.06**, **0.10**]		Uniform
	F_{MSY}/M	1.18	1.18	0.40	Lognormal	0.64	0.64	0.40	Lognormal
	Δ	0.70	0.70	0.10	Beta	0.60	0.60	0.10	Beta
Case 4	M	0.20	[**0.18**, **0.28**]		Uniform	0.05	[**0.06**, **0.10**]		Uniform
	F_{MSY}/M	1.18	**0.80**	0.40	Lognormal	0.64	**0.80**	0.40	Lognormal
	Δ	0.70	0.70	0.10	Beta	0.60	0.60	0.10	Beta
Case 5	M	0.20	[0.16, 0.24]		Uniform	0.05	[0.3, 0.07]		Uniform
	F_{MSY}/M	1.18	1.18	0.40	Lognormal	0.64	0.64	0.40	Lognormal
	Δ	0.85	**0.70**	0.10	Beta	0.80	**0.60**	0.10	Beta

MacCall (2009) cautioned against the application of DCAC when M exceeds 0.20 year^{-1} because the depletion correction value becomes small and the DCAC is simply the average catch value as M increases to higher values. The true M for the flatfish life-history in this paper was 0.20 year^{-1}(Table 1). The distribution about M applied to DCAC therefore includes some values that exceeded the recommend threshold value. The violation was done to test DCAC at the extremes of its potential application range and this violation was accounted for when the results for the flatfish life-history were interpreted.

2.3. DB-SRA

DB-SRA incorporates concepts from stock reduction analysis (SRA) (Kimura et al., 1984), and from later work that implemented SRA within a stochastic framework (Walters et al., 2006). Similar to DCAC, Monte Carlo draws from the four parameter distributions (Δ, B_{peak}, F_{MSY}/M, and M) are used to generate probability distributions for current stock status and management reference points. DB-SRA is implemented using a delay-difference production model:

$$B_t = B_{t-1} + P(B_{t-a}) - C_{t-1} \tag{5}$$

where B_t is the biomass at the start of year t, and $P(B_{t-a})$ is the latent annual production based on a function of the biomass in year $t-a$ is:

$$P(B_{t-a}) = gMSY\left(\frac{B_{t-a}}{K}\right) - gMSY\left(\frac{B_{t-a}}{K}\right)^{n} \tag{6}$$

where K is the virgin biomass, MSY is the maximum sustainable yield, n is the shape parameter for the Pella–Tomlinson–Fletcher (PTF) model which determines the skewness of the productivity curve, g is a numerical factor:

$$g = \frac{n^{n/(n-1)}}{n-1} \tag{7}$$

While the PTF production model allows B_{peak} to range from 0 and 1, several authors have observed excessive productivity at low biomass levels when the productivity curve is highly skewed to the right (Fletcher, 1978; McAllister et al., 2000). To correct for this behavior, latent annual production, $P(B_{t-a})$, is calculated using a hybrid between the PTF and Schaefer surplus production functions, originally proposed by McAllister et al. (2000). The hybrid model joins the PTF and Schaefer production models at a join-point (B_{join}) located at B_{peak}. The hybrid model calculates $P(B_{t-a})$ using Eq. (6) when $B_t > B_{join}$. However, when $B_t < B_{join}$ the latent annual production is:

$$P(B_{t-a} < B_{join}) = B_{t-1}\left(\frac{P(B_{join})}{B_{join}} + c(B_{t-a} - B_{join})\right) \tag{8}$$

where c is the PTF production-to-biomass ratio (c) at the join point defined as:

$$c = (1-n)(MSY)gB_{join}^{n-2}K^{-n} \tag{9}$$

The resulting hybrid model prevents the unrealistically high productivity at low biomass sizes, but when compared to the production-to-biomass ratio from the PTF model, the hybrid model results in productivity values that are too low at low biomass levels relative to those expected under the Beverton–Holt stock recruitment relationship (BHSSR) (Dick and MacCall, 2010) that is assumed for many West Coast groundfish stocks. Dick and MacCall (2010) proposed a modification to the calculation of $P(B_{t-a})$ at low biomass levels to create a closer approximation to the BHSSR-driven model at low biomass; when $B_t < B_{join}$. The optimal values for B_{join} were determined by minimizing the sum of the squared difference between the P/B values for the Schaefer and BHSRR models (Dick and MacCall, 2010):

$$B_{join} = \begin{cases} 0.5B_{peak} & \text{for} \quad B_{peak} < 0.3 \\ 0.75B_{peak} - 0.075 & \text{for} \quad 0.3 < B_{peak} < 0.50 \\ B_{peak} & \text{for} \quad B_{peak} > 0.5 \end{cases} \tag{10}$$

F_{MSY} is the product of the parameters M and F_{MSY}/M. The calculated F_{MSY} value is then used to calculate MSY using the equation:

$$MSY = (1 - e^{-(M+FMSY)})\left(\frac{F_{MSY}}{M + F_{MSY}}\right)(B_{peak})K \tag{11}$$

Unfished biomass, K, is calculated separately for each draw from the parameter distributions by solving the equation $B_{current}/K = 1 - \Delta$ for K using a Golden Section Search, which searches for the value of K within a bounded region. The bounds for the searched region are defined by the average catch over the time-series, as the low bound, and the upper bound is determined by 110%($\sum_{i=1}^{N} Catch_i$/minimum (Δ)).

The OFL value for a given year is calculated as:

$$OFL_t = (1 - e^{-(M+F_{MSY})}) \left(\frac{F_{MSY}}{M + F_{MSY}} \right) B_t \quad (12)$$

The same parameter distributions were used for DB-SRA and DCAC (see Section 2.2 and Table 2). DB-SRA applies a delay-difference model that requires one additional parameter, an age-at-maturity value. The value for this parameter was fixed at its true value (flatfish 5 years, rockfish 9 years).

2.4. Stock synthesis (SS)

SS is an integrated statistical catch-at-age model that is commonly used to assess West Coast groundfish and can incorporate data on catches, fishery and survey indices, length-, and age-compositions. For analyses in this paper, R_0 (virgin recruitment), the annual recruitment deviations, and some size-selectivity parameters were estimated using SS. Only the slope parameter for the ascending limb of the selectivity curve was estimated for the fishery. Three selectivity parameters were estimated for the survey: the size at which selectivity is first 1.0 (β_1), the slope of the ascending limb of the selectivity curve (β_3), and the selectivity at minimum size (β_5). M was fixed in SS at a random value drawn from an uniform distribution which was centered about the true value within the operating model for both life-history types: flatfish (U[0.16 year^{-1}, 0.24 year^{-1}]) and rockfish (U[0.03 year^{-1}, 0.07 year^{-1}]). All other biological parameters (i.e. growth, fecundity, steepness) were fixed at their true values in the estimation model when applying SS. Data from the operating model were selected to correspond to each of the data scenarios (described below) and SS was run an initial time. The variance–covariance matrix from this initial estimation call was used to calculate the asymptotic standard errors of the estimated recruitment deviations and hence the appropriate annual recruitment bias adjustment (I. Taylor, NWFSC, pers. commn.):

$$b_t = 1 - \frac{SE(\hat{\varepsilon}_t)}{\sigma_R^2} \quad (13)$$

where $SE(\hat{\varepsilon}_t)$ is the asymptotic standard error of the estimated recruitment deviation for year t. SS was run three additional times with the estimated bias adjustment values to ensure the best model fit was selected and used as the basis for the estimated model outputs.

SS was used to estimate stock status (ratio of current to virgin biomass) and the OFL, for two data scenarios (Fig. 1) to assess how a more complex model (SS) would perform compared to data-poor methods (DCAC and DB-SRA) when there are limited data. The data scenarios examined were meant to be representative of a data-limited situation where there is limited survey information and no fishery data except for landings, as is common for West Coast groundfish. The only data that were always available to SS for the entire modeled period were annual catches. Each data scenario contained length-composition data from the survey, and survey indices. However, the period with data differed between the scenarios; with data scenario 1 having data on a triennial basis for the last 20 years of the modeled period, and with data scenario 2 having survey indices for each of the last 20 years of the modeled period and survey lengths for the last 10 years of that period.

2.5. Scenarios

Four cases were created to explore the effect of knowledge about M and F_{MSY}/M for both life-histories for DCAC and DB-SRA (Table 2 and Fig. 2):

- Case 1: The M and F_{MSY}/M distributions were assumed to be centered about the true values.
- Case 2: The distribution for M was centered about the true value, but that for F_{MSY}/M was centered about an incorrect value.
- Case 3: The distribution for F_{MSY}/M was centered about the true value, but that for M was centered about an incorrect value.
- Case 4: The M and F_{MSY}/M distributions were each centered about incorrect values.

  An additional fifth case was included to examine the impact of assuming the current stock status incorrectly (Table 2):

- Case 5: The M and F_{MSY}/M distributions were assumed to be centered about the true values (similar to Case 1), but the distribution for Δ was centered about an incorrect value which underestimated final depletion.

The cases examined using DCAC and DB-SRA differed slightly from those examined for SS. SS estimates F_{MSY} as model output rather than as an input (as for DCAC and DB-SRA). This difference results in the model estimates for SS in cases 1 and 2 being identical (same for cases 3 and 4) based on the specification of M. In case 5, the final depletion in the operating model was either 15% (flatfish) or 20% (rockfish), with DCAC and DB-SRA assuming overly optimistic depletion values for each life-history (Table 2), while SS estimated a final depletion value. Three catch histories: constant, ramp up, and a ramp and decline (Fig. 3) were examined to explore the effect of catch history on estimation performance.

DCAC only uses the mean catch over a pre-specified period to estimate a sustainable yield. Many groundfish species off the U.S. west coast have been subject to recent management restrictions that have resulted in substantial declines in harvest levels. Using the mean catch over the entire period of exploitation to determine a harvest level may therefore lead to a biased estimate. Consequently, the part of the catch history that includes the recent decline in catches has been ignored when applying DCAC to date (Dick and MacCall, 2010). Three analyses specific to DCAC were therefore conducted that used only selected portions of the catch history when there was a ramp up or ramp and decline in historical catches to explore the implications of truncating a catch history: (1) only use the years where the catches were at least 10% of the maximum catch (ramp up years 15–50, ramp and decline years 16–50), (2) 20% of the maximum (ramp up years 17–50, ramp and decline years 17–49), and (3) 30% of the maximum (ramp up years 18–50, ramp and decline years 18–45) (Fig. 3).

2.6. Performance

The median HL was calculated from the 10,000 parameter draws for DCAC and DB-SRA. The median value was then compared with each of the 100 operating model OFL values to estimate the probability of setting HLs above the true OFL at the associated PFMC selected F_{SPR} rate (flatfish $F_{30\%}$ and rockfish $F_{50\%}$). Estimates from each of the SS runs were compared with the corresponding operating model value to calculate the probability of overfishing. In addition, the relative errors of the estimates from SS were calculated as:

$$RE = \frac{E - T}{T} \quad (14)$$

where E is the estimated OFL and T is the true value OFL from the operating model. REs were also calculated for DCAC and DB-SRA, but the calculations were made comparing the median value from the 10,000 estimates with each of the 100 operating model values.

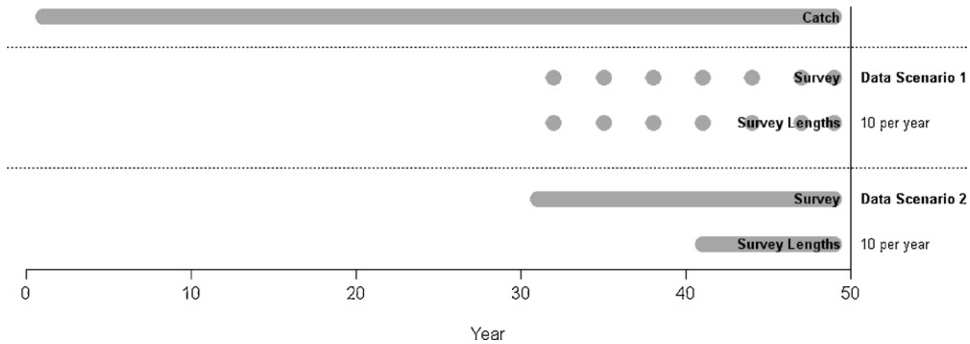

Fig. 1. The data types and data quantity that were provided to SS for the two data scenarios. Catch data were available for the entire modeled period for both scenarios.

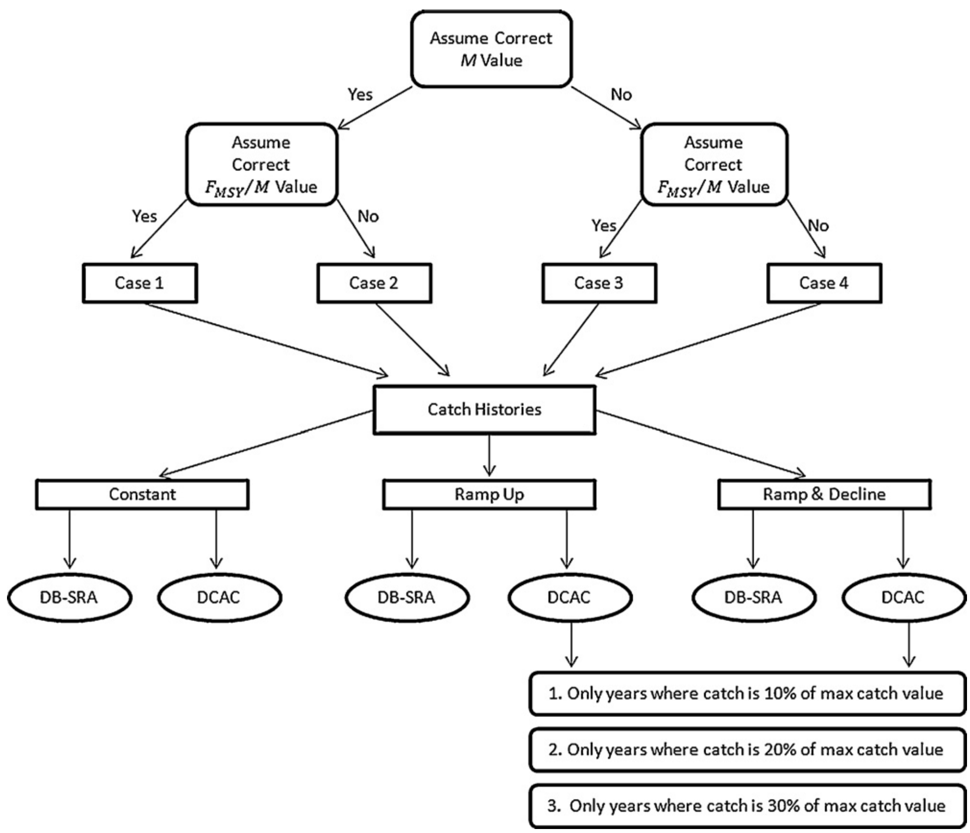

Fig. 2. The process and order of events for the scenarios that examine DCAC and DB-SRA.

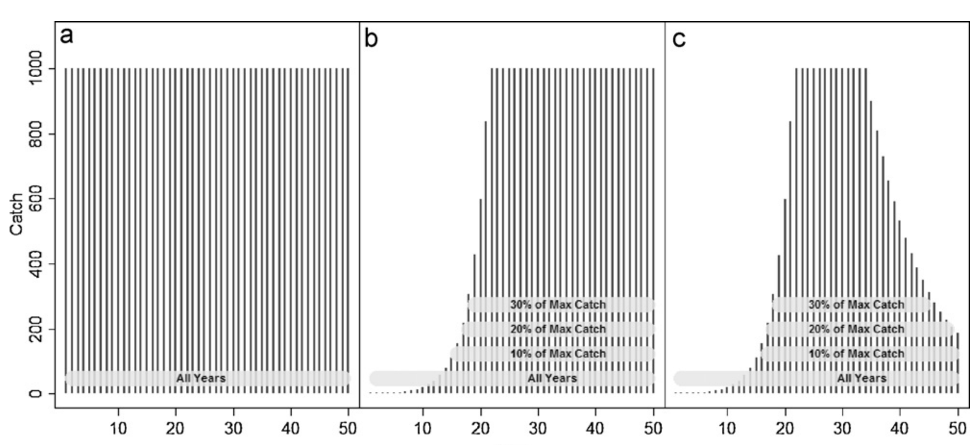

Fig. 3. The three catch histories: constant catch (a), a ramping up of catch (b), and a ramp and decline of catch (c) with the varying catch history segments used by DCAC.

An overall summary statistic was created to describe each estimation method's performance across cases:

$$P_{e,m,l} = \sum_{c=1}^{4} |0.5 - ProbabilityEstimate_{e,m,l,c}| \quad (15)$$

where *ProbabilityEstimate* is the probability of overestimating the HL by each estimation method relative to the true OFL, e is the catch history, c is the case, m is the estimation method, and l is the life-history. This metric was used to summarize results across cases 1–4. It would be difficult, if not impossible, to know which case (1–4) the parameter distributions selected for an actual data-poor species fall within. Eq. (15) therefore summarizes across cases for each life-history, catch history, and estimation method, under the assumption that an underestimate and an overestimate of harvest are both equally undesirable. Perfect performance by an estimation method, 0.50 probabilities for all cases, would result in a value for Eq. (15) of 0.0, while the worst possible performance would result in a value of 2.0. The results for case 5, which examines final depletion mis-specification, were explored independently of the other four cases.

3. Results

3.1. Flatfish life-history

The median of the HL estimates were low relative to the true OFL values for nearly all of the estimation methods and catch-histories when the assumed distributions for M and F_{MSY}/M were centered about the true values (case 1) (Fig. 4 and Table 3a). Median estimates of the HL from DCAC and DB-SRA were lower than each of the true OFL values from the OM runs for all three catch histories, with one exception. The single instance where the probability of overestimating the HL was >0.0 for these two methods was the ramp and decline catch history, when DB-SRA resulted in a probability of overestimation of 0.45 (Table 4a). This occurred because of the catch history (ramp and decline) and the high productivity of the flatfish; DB-SRA is forced to infer a population trajectory that was severely depleted (declines to low biomass levels relative to virgin conditions) during the peak of the harvest to end at a depletion of 0.40 after a period of rebuilding for a highly productive stock. This led DB-SRA to estimate positively biased estimates of virgin biomass which resulted in positively biased estimates of the OFL because of overestimated current biomass. The distribution of estimates by SS were right skewed, with overestimation of the OFL with <0.50 probability for all catch histories and for both data scenarios (0.39–0.47). The HL estimates from each estimation method were negatively biased for nearly all of the catch histories (Table 5a). There was a zero failure rate of SS (estimation of unrealistically high biomass levels) for both data scenarios and each catch history (Table 6a) for cases 1 and 2.

Assuming a lower mean for the distribution for F_{MSY}/M (case 2) resulted in lower median estimates of the HL from DCAC and DB-SRA (Table 3a). This mis-specification did not qualitatively change how frequently the HL is overestimated relative to case 1 (excluding the DB-SRA ramp and decline estimates) (Table 4a). The probabilities of overestimation for DCAC and DB-SRA were 0.0, similar to case 1, which was expected because assuming a distribution for F_{MSY}/M centered about a lower value than the true value should not result in an increase to the HL. The results for the ramp and decline catch history for DB-SRA did change relative to case 1. Assuming a lower mean for the distribution for F_{MSY}/M resulted in a reduced probability of overestimation for this method (0.0). The results from SS were identical for cases 1 and 2 because SS estimated F_{MSY}.

Assuming a positively biased distribution for M (case 3) resulted in increased estimates of median HLs for all estimation methods (Table 3a). The increased estimates led to an increase in the probability of overestimation for SS relative to case 1, while the change in probabilities was minimal for DCAC and DB-SRA (Table 4a). The SS OFL estimates were positively biased in case 3 for all histories (Table 5a). DCAC and DB-SRA resulted in negatively biased estimates of the median HL for all except the ramp and decline catch history for DB-SRA. The failure rate of SS remained at or near zero (0.01) when M was mis-specified for each data scenario and catch history (Table 6a) for cases 3 and 4.

Case 4, which assumed incorrect distributions for M and F_{MSY}/M, resulted in median estimates of the HL and probabilities of overestimating the HL similar to those for case 1 for the majority of estimates from DCAC and DB-SRA (Tables 3a and 4a). The estimates of the HL from DCAC remained below the true value for each catch history and all truncations of the catch history (all, 10%, 20%, and 30%) when both parameters were mis-specified. DB-SRA estimates for the ramp and decline catch history resulted in a low probability of overestimation (0.14).

The performance metric (Eq. (15)) was applied to cases 1 through 4 to summarize each estimation method's performance by catch- and life-history (Table 7). Application of SS for each of the catch histories resulted in the best performance scores (0.20–0.48). DB-SRA resulted in poor performance scores for all catch histories, with this method's best score occurring for the ramp and decline catch history (1.28). DCAC resulted in the worst performance scores (2.0) for all catch histories (except the 30% truncated catch history for the ramp and catch exploitation pattern (1.96)).

Case 5, that examined the potential impact of assuming an incorrect distribution for Δ (a pre-specified parameter distribution in DCAC and DB-SRA), resulted in the greatest frequency of overestimation of the HL for DCAC and DB-SRA (Tables 3a and 4a). Both estimation methods resulted in median estimates for the HLs that were larger than the true OFLs. SS, which estimates final depletion $(1 - \Delta)$, resulted in low probabilities of overestimation of the OFL for both data scenarios and for each catch history ($\leq$0.43). The median HL estimates from DCAC and DB-SRA were highly positively biased, while the SS OFL estimates were negatively biased (Table 5a). SS had zero failure rates for all exploitation patterns (Table 6a).

3.2. Rockfish life-history

The median values of the HL estimates were low relative to the true OFL values for each of the estimation methods and for each catch-history when the assumed distributions for M and F_{MSY}/M were centered about the true values (case 1) (Fig. 5 and Table 3b), similar to the results for the flatfish. DCAC and DB-SRA both resulted in 0.0 probability of overestimating the HL (Table 4b). SS resulted in probabilities of overestimation of the OFL that were approximately risk-neutral for both data scenarios and each catch history (0.38–0.51). The DCAC and DB-SRA median HL estimates and the SS OFL estimates were negatively biased for each catch history (Table 5b). The failure rate of SS was low across exploitation patterns, with the highest frequency of failure occurring for the constant catch history for both data scenarios (0.06 and 0.03) (Table 6b).

Assuming a positively biased value for F_{MSY}/M (case 2) resulted in increased median estimates of the HL for DCAC and DB-SRA (Table 3b). The probability of overestimation of the HL increased for DB-SRA (0.05–0.36), relative to case 1 (Table 4b). The mis-specification of F_{MSY}/M increased the median estimates of the HL from DCAC compared to case 1, but the estimates remained below the true OFLs resulting in 0.0 probability of overestimation in each catch history.

Case 3, that assumed a positively biased distribution for M, resulted in increased estimates of the median HLs from DCAC and

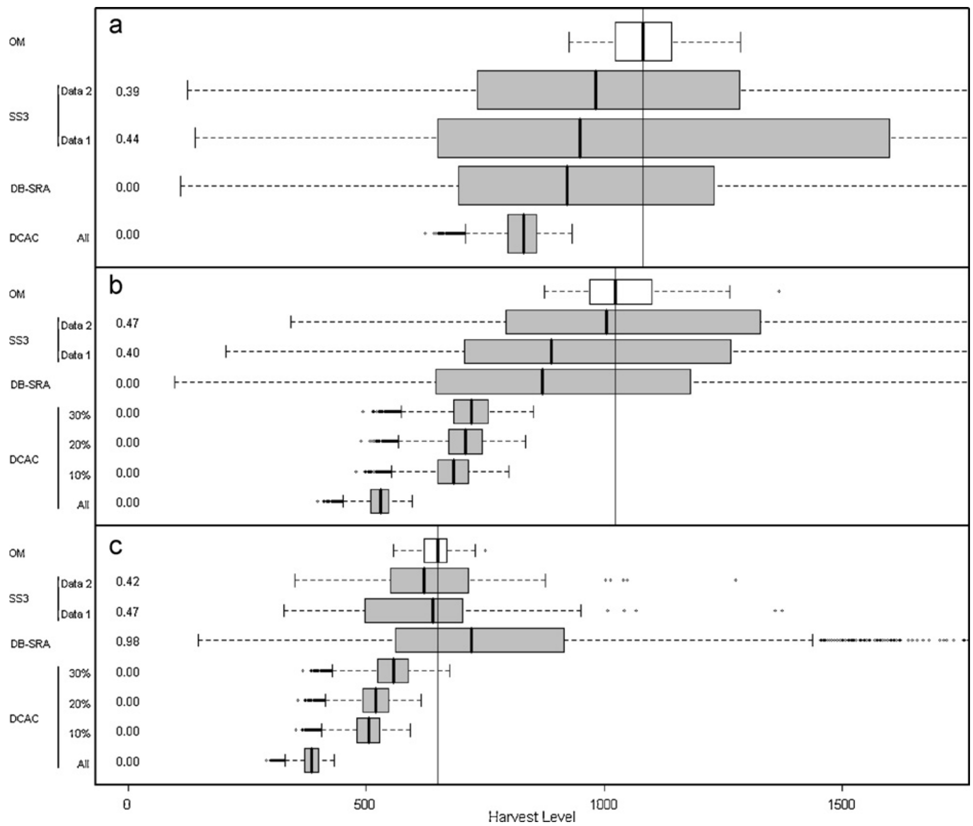

Fig. 4. The distribution for the estimated harvest level (HL) for the flatfish life-history for each estimation method and catch history for case 1. The operating model distribution of true HLs (white) with the median value (vertical solid line) by each catch history; (a) constant catch, (b) ramp, and (c) ramp and decline, plotted with the estimated distribution by each estimation method. The probabilities of overestimating the HL for each estimation method are reported along the left column of each plot.

DB-SRA for each catch history (Table 3b). DCAC median estimates of HL corresponded to a minimal increase in the probability of overestimation for the ramp and decline catch history (Table 4b). The mis-specification of *M* resulted in high probabilities of overestimating the true OFL for each of the exploitation patterns for DB-SRA and SS. The estimates of the OFL from DB-SRA and SS were positively biased (Table 5b). Failure rates for SS were highest for the constant catch history (Table 6b).

Table 3
Median estimates of the HL for each estimation method and catch history; flatfish life-history (a) and rockfish life-history (b) by case with the true OFLs from the operating model for cases 1–4 and case 5.

(a)

Catch history	Constant				Ramp up							Ramp up and decline						
Model	DCAC	DB-SRA	SS3		DCAC				DB-SRA	SS3		DCAC				DB-SRA	SS3	
Data scenario			1	2	All	10%	20%	30%		1	2	All	10%	20%	30%		1	2
Case 1	830	922	949	982	530	685	709	721	870	890	1006	386	506	521	558	647	640	622
Case 2	768	867	949	982	490	619	639	648	787	890	1006	357	456	468	495	553	640	622
Case 3	849	935	1208	1229	542	705	731	744	892	1091	1225	395	521	438	579	678	695	670
Case 4	792	886	1208	1229	506	644	666	675	816	1091	1225	368	475	488	519	582	695	670
True OFL (cases 1–4)		1081							1024							651		
Case 5	830	922	475	497	530	685	709	721	870	452	470	386	506	521	558	647	304	322
True OFL (case 5)		554							526							340		

(b)

Catch history	Constant				Ramp up													
Model	DCAC	DB-SRA	SS3		DCAC				DB-SRA	SS3		DCAC				DB-SRA	SS3	
Data scenario			1	2	All	10%	20%	30%		1	2	All	10%	20%	30%		1	2
Case 1	507	608	752	680	323	374	380	381	465	551	528	236	273	276	278	327	354	358
Case 2	562	687	752	680	359	422	430	433	550	551	528	261	309	313	319	383	354	358
Case 3	623	770	205,676	4712	398	478	489	493	648	1333	1174	290	351	356	367	449	2702	1050
Case 4	674	837	205,676	4712	430	526	439	545	736	1334	1174	314	386	394	409	510	2702	1050
True OFL (cases 1–4)		755							576							392		
Case 5	507	608	287	279	323	374	380	381	465	208	214	236	273	276	278	327	153	1588
True OFL (case 5)		299							226							165		

Table 4
Probability of estimating the HL greater than the true OFL for each estimation method and catch history; flatfish life-history (a) and rockfish life-history (b), where a 0.50 probability would indicate a risk-neutral harvest approach.

(a)

Catch history	Constant				Ramp up							Ramp up and decline						
Model	DCAC	DB-SRA	SS3		DCAC				DB-SRA	SS3		DCAC				DB-SRA	SS3	
Data scenario			1	2	All	10%	20%	30%		1	2	All	10%	20%	30%		1	2
Case 1	0.00	0.00	0.44	0.39	0.00	0.00	0.00	0.00	0.00	0.40	0.47	0.00	0.00	0.00	0.00	0.45	0.47	0.42
Case 2	0.00	0.00	0.44	0.39	0.00	0.00	0.00	0.00	0.00	0.40	0.47	0.00	0.00	0.00	0.00	0.03	0.47	0.42
Case 3	0.00	0.01	0.54	0.63	0.00	0.00	0.00	0.00	0.01	0.57	0.69	0.00	0.00	0.00	0.04	0.82	0.63	0.63
Case 4	0.00	0.00	0.54	0.63	0.00	0.00	0.00	0.00	0.00	0.57	0.69	0.00	0.00	0.00	0.00	0.06	0.63	0.63
Case 5	1.00	1.00	0.33	0.43	1.00	1.00	1.00	1.00	1.00	0.32	0.40	1.00	1.00	1.00	1.00	1.00	0.28	0.35

(b)

Catch history	Constant				Ramp up													
Model	DCAC	DB-SRA	SS3		DCAC				DB-SRA	SS3		DCAC				DB-SRA	SS3	
Data scenario			1	2	All	10%	20%	30%		1	2	All	10%	20%	30%		1	2
Case 1	0.00	0.00	0.51	0.40	0.00	0.00	0.00	0.00	0.00	0.40	0.38	0.00	0.00	0.00	0.00	0.00	0.41	0.40
Case 2	0.00	0.05	0.51	0.40	0.00	0.00	0.00	0.00	0.25	0.40	0.38	0.00	0.00	0.00	0.00	0.36	0.41	0.40
Case 3	0.00	0.62	0.97	0.98	0.00	0.00	0.00	0.00	0.96	0.98	0.96	0.00	0.04	0.06	0.21	0.97	0.93	0.97
Case 4	0.03	0.97	0.97	0.98	0.00	0.10	0.19	0.23	1.00	0.98	0.96	0.00	0.41	0.53	0.73	1.00	0.93	0.97
Case 5	1.00	1.00	0.42	0.46	1.00	1.00	1.00	1.00	1.00	0.44	0.39	1.00	1.00	1.00	1.00	1.00	0.39	0.41

Table 5
Relative errors (REs, %) of harvest level estimates for each data scenario, case, and life-history; flatfish life-history (a) and rockfish life-history (b). REs calculated for DCAC and DB-SRA based on median values compared to each of the 100 true OFL values.

(a)

Catch history	Constant				Ramp up							Ramp up and decline						
Model	DCAC	DB-SRA	SS3		DCAC				DB-SRA	SS3		DCAC				DB-SRA	SS3	
Data scenario			1	2	All	10%	20%	30%		1	2	All	10%	20%	30%		1	2
Case 1	−23	−15	−12	−10	−49	−34	−31	−30	−16	−13	−2	−40	−22	−19	−13	0	−1	−2
Case 2	−29	−20	−12	−10	−53	−40	−38	−37	−24	−13	−2	−45	−29	−27	−23	−14	−1	−2
Case 3	−21	−14	12	14	−48	−32	−29	−28	−14	7	20	−39	−19	−17	−10	5	8	4
Case 4	−27	−18	12	14	−51	−38	−36	−35	−21	7	20	−43	−26	−24	−20	−10	8	4
Case 5	77	97	−13	−10	19	54	60	62	96	−13	−10	34	75	81	94	125	−9	−6

(b)

Catch history	Constant				Ramp up													
Model	DCAC	DB-SRA	SS3		DCAC				DB-SRA	SS3		DCAC				DB-SRA	SS3	
Data scenario			1	2	All	10%	20%	30%		1	2	All	1%0	20%	30%		1	2
Case 1	−33	−19	3	−11	−44	−35	−34	−34	−19	−6	−9	−40	−30	−29	−29	−16	−9	−9
Case 2	−25	−9	3	−11	−38	−27	−25	−25	−4	−6	−9	−33	−21	−20	−18	−2	−9	−9
Case 3	−17	2	23971	508	−31	−17	−15	−14	13	122	105	−26	−10	−9	−6	15	638	168
Case 4	−10	11	23971	508	−25	−9	−6	−5	28	122	105	−20	−1	1	5	30	638	168
Case 5	153	203	−3	−4	113	146	150	151	206	−8	−6	114	148	150	152	196	−5	−5

Table 6
The proportion of runs where the SS-estimated final biomass greater than 10× the true biomass, termeda failed estimated run, for each data scenario and case for the flatfish (a) and rockfish (b) life-histories.

Catch history	Data scenario 1			Data scenario 2		
	Constant	Ramp up	Ramp and decline	Constant	Ramp up	Ramp and decline
(a)						
Cases 1 and 2	0.00	0.00	0.00	0.00	0.00	0.00
Cases 3 and 4	0.00	0.01	0.00	0.01	0.01	0.00
Case 5	0.00	0.00	0.00	0.00	0.00	0.00
(b)						
Cases 1 and 2	0.06	0.02	0.03	0.03	0.00	0.01
Cases 3 and 4	0.58	0.32	0.47	0.45	0.11	0.27
Case 5	0.01	0.00	0.00	0.00	0.00	0.00

Table 7
Summary of performance across cases 1–4 for each estimation method and life-history where performance scores (Eq. (15)) can range from 0.00, indicating perfect estimation of the harvest level, to 2.0, being the worst score possible.

Catch history	Model	Data scenario	Flatfish life-history	Rockfish life-history
Constant	DCAC		2.00	1.97
	DB-SRA		1.99	1.54
	SS3	1	0.20	0.96
		2	0.48	1.16
Ramp up	DCAC	All	2.00	2.00
		10%	2.00	1.90
		20%	2.00	1.81
		30%	2.00	1.77
	DB-SRA		1.99	1.71
	SS3	1	0.34	1.16
		2	0.44	1.16
Ramp up and decline	DCAC	All	2.00	2.00
		10%	2.00	1.55
		20%	2.00	1.47
		30%	1.96	1.52
	DB-SRA		1.28	1.61
	SS3	1	0.32	1.04
		2	0.42	1.14

Assuming incorrect distributions for M and F_{MSY}/M (case 4), resulted in the largest increase in the median HL estimates for DCAC and DB-SRA (Table 3b). The probability of overestimation was highest for DCAC (0.0–0.73) and DB-SRA (0.97–1.0) among cases 1–4, which examined the mis-specification of biological parameter values (Table 4b). The highest probability of overestimation for DCAC occurred in the ramp and decline catch history when the catch history was truncated to only include years that were at least 30% of the maximum recorded catch value (0.73).

The performance metric (Eq. (15)), again suggested that SS performed best (scores 0.96–1.16), independent of data scenario among the three estimation methods (Table 7). The performance

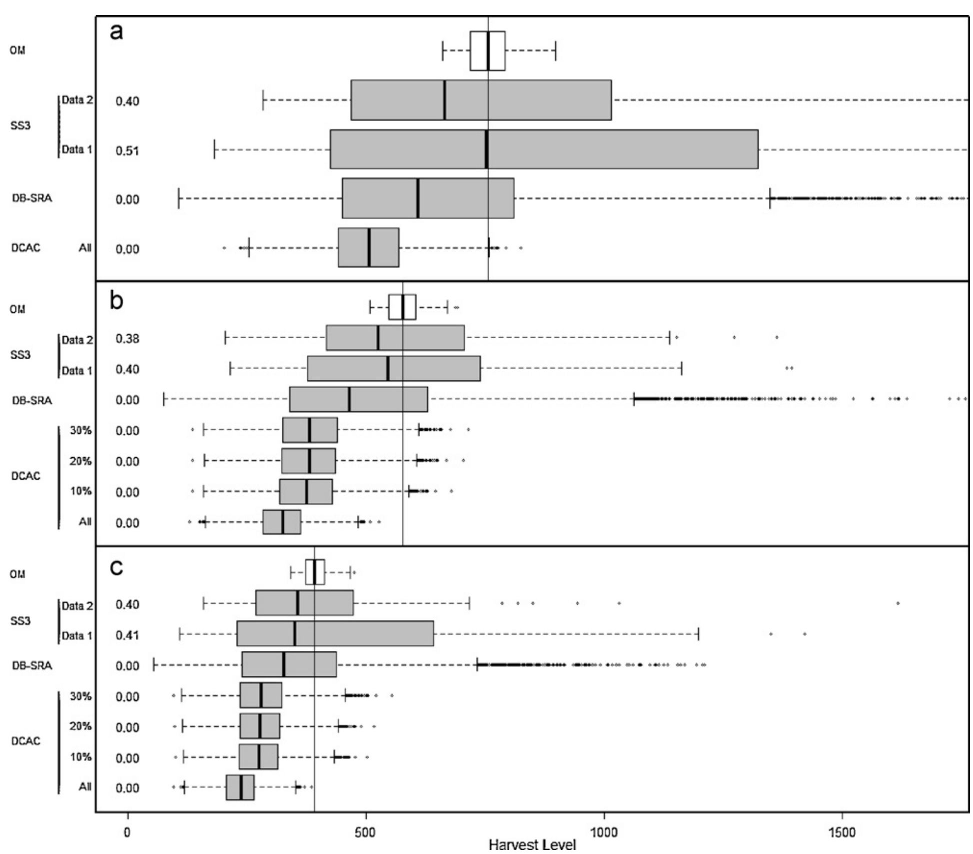

Fig. 5. The distribution for the estimated harvest level (HL) for the rockfish life-history for each estimation method and catch history for case 1. The operating model distribution of true HLs (white) with the median value (vertical solid line) by each catch history; (a) constant catch, (b) ramp, and (c) ramp and decline, plotted with the estimated distribution by each estimation method. The probabilities of overestimating the HL for each estimation method are reported along the left column of each plot.

scores for DB-SRA were poor, ranging from 1.54 (constant) to 1.71 (ramp up). DCAC received the worst performance scores on average (1.52–2.00) of the estimation methods across catch histories.

The median of the HL estimates and the probability of overestimation increased for both DCAC and DB-SRA for case 5 which mis-specified final depletion (Table 3b and 4b). Both DCAC and DB-SRA resulted in a probability of overestimation of 1.0 regardless of the catch history. SS resulted in a probability of overestimation that was $\leq$0.50 for both data scenarios and each catch history (0.39–0.46). The estimates of the OFL from SS were negatively biased (Table 5b) and had nearly zero failure rates for each catch history and data scenario (Table 6b). In contrast, the estimates of HL from DCAC and DB-SRA each were highly positively biased.

4. Discussion

Both DCAC and DB-SRA were highly sensitive to the assumed distribution for Δ (depletion = 1 − Δ). The probability of overestimating the HL greatly increased for DCAC and DB-SRA when the distribution for Δ was assumed incorrectly (case 5). For example, both estimation methods resulted in median estimates of the HL that were greater than the true OFLs in each OM run for the flatfish. Assuming a distribution for the depletion status of a stock is a major drawback to these methods. However, if enough is known about a stock to make inference regarding depletion status, it would likely not be considered data-poor or data-limited. This work shows that this assumption has a large impact on the results, and that multiple runs examining the impact of assumed depletion status should be conducted routinely when these methods are applied to determine the potential range of HLs.

In contrast, SS, which estimates rather than assumes a value for final depletion, estimated lower OFLs for case 5 compared to cases 1–4. SS calculates OFLs by applying a target fishing mortality rate to the estimated ending population age-structure. In a long-lived species, such as a rockfish with slow dynamics, SS was able to estimate OFLs that were approximately risk-neutral, even with limited composition data. The advantage of estimating the final depletion also allowed SS to adjust the target fishing mortality rate according to the PFMC harvest rule when stocks are below the target depletion.

It should be noted that final depletion is not defined in the same terms for all three methods. The final depletion in the operating model and SS is based on the final female spawning biomass relative to the unfished level, while DCAC and DB-SRA respectively define depletion in terms of total biomass and total (males + females) mature biomass. The mismatch in how depletion is defined between the methods could impact the estimates of the HL given sexual dimorphism in growth (Table 1). However, this was not the case because the difference in the operating model depletion of total biomass and total mature biomass were similar to 30% for the flatfish and 40% for the rockfish. This similarity arose because selectivity was independent of sex. However, additional error may have occurred had selectivity been sex-specific.

The impact of assuming biased distributions for the biology-based parameters (M and F_{MSY}/M) varied among the three estimation methods. DCAC and DB-SRA were robust to this mis-specification for the flatfishlife-history with estimates of the HL low relative to the true OFL values, even in the extreme case when both were assumed incorrectly (case 4). However, DCAC and DB-SRA were more sensitive to mis-specification of the distribution for M for the rockfish life-history, especially when the means of the distributions for both biological parameters exceeded the true values. The estimates from SS were sensitive to incorrect assumptions regarding M (cases 3 and 4), with probabilities of overestimation $\geq$0.50, the risk-neutral value, for both life-histories and both data scenarios. Although, these results show that DCAC and DB-SRA can be robust depending on the life-history to mis-specification of M and F_{MSY}/M, these parameter distributions should still be selected carefully regardless of the life-history. Utilizing information from meta-analyses (i.e. Myers and Mertz, 1998; Dorn, 2002; Forrest et al., 2010) to select life-history parameters and distributions provides a good starting point, but the analyst should also examine various parameter distributions for these quantities when applying DCAC and DB-SRA. The selection of M and F_{MSY}/M can be used to inform the analyst what the potential depletion status of a stock might be given the known or assumed historical exploitation based upon these life-history traits. Utilizing prior information from assessed stocks with similar life-history traits can also allow for inferences to be made about Δ.

Simpler assessment methods for data-poor and data-limited stocks have been suggested (Froese, 2004; Hilborn, 2003; Kelly and Codling, 2006) and examined (Cope and Punt, 2009) for data-poor situations with limited success. One of the objectives of this study was to examine the advantages of applying a simple or a more complex assessment method when only limited data (indices and length composition data) were available. The results from both data scenarios applied to SS resulted in similar results. Data scenario 1 with length-composition data for the last 20 (triennial basis) modeled years, typically resulted in higher probabilities of overestimating the true OFL compared to data scenario 2, with length-composition only over the last ten (annual) modeled years.

The estimates from SS reflected a best case scenario because the full range of uncertainty was not accounted for. Specifically, all of the biological parameter values (excluding natural mortality) required by SS were considered known without error. In reality, the application of an age-structured model, such as SS, to a data-poor stock would require the analyst to make assumptions regarding the biological parameters, assuredly resulting in some error.

DB-SRA and DCAC were ranked poorly by the performance statistic. However, Eq. (15) might not be the most appropriate basis to judge the performance of these methods. In an ideal situation the estimation method would provide a risk-neutral harvest (0.50 probability) that management could adjust to implement additional precautionary measures. In a data-limited or data-poor situation, management may prefer to aim for conservative harvests that account for the high uncertainty. Both DCAC and DB-SRA resulted in estimates of harvest that were lower than the true OFLs for the flatfish life-history, even when life-history parameters were mis-specified. Similar results were observed for the rockfish life-history, except for DB-SRA when the mean of the distribution for M exceeded the true M. The conservative estimates of the HL produced by both of these methods could be preferred by management when setting HLs for data-poor stocks when there is a high degree of uncertainty and the preferred course of action is to be risk-adverse.

Although, each estimation method was robust to life-history parameter mis-specification, estimates of harvests were, not surprisingly, highly sensitive to the assumed depletion status. Estimates of the HL were no longer conservative and would result in overfishing if implemented for management when an overly optimistic depletion was assumed. Analysts need to fully explore the potential ranges of harvest results from multiple depletion levels, to better characterize the uncertainty surrounding modeled outputs for to inform managers. In the application of data-poor assessment methods, such as DCAC and DB-SRA, assuming the stock is currently at a higher depletion value relative to the target depletion (high Δ value) will result in lower estimates of the HL that will result in additional precaution for data-poor management.

The methods examined here represent possible tools that can be useful in a range of data-poor scenarios depending on the current knowledge and data available for a stock. Assessing data-poor stocks in a quantitative manner can identify depleted stocks, so that fishery management can initiate timely action, which is critical to eliminate overfishing and potential stock collapse (Schertzer and Prager, 2007). Implementing these methods or any data-poor method should be based on stock-specific issues and management goals. Application of quantitative methods for harvest estimation for data-poor stocks is not only now a required step to comply with the MSRA, but will also pave the way to understand the implications of harvest on data-poor stocks. Finally, the use of simulation to evaluate potential methods, and hence identify when they perform adequately and when they may lead to risk-adverse or less precautionary advice, provides decision makers with some of the information they need to decide how much OFLs should be reduced to set ABCs.

Acknowledgements

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Appendix A. Operating model

The operating model was based on the population dynamics model underlying Stock Synthesis v.3 (Methot, 2009). This model is age-length structured and aims to capture the main biological traits of a targeted species, along with the fishery dynamics of exploitation.

A.1. Basic dynamics

The use of these equations along with biological conditions, allows the population to be modeled over the period of interest to determine its status relative to virgin conditions. The operating model creates the population dynamics with a continuous fishing mortality where the numbers of fish of gender γ in age group a, at the start of each year t is calculated as:

$$N_{\gamma,a,t+1} = \begin{cases} N_{\gamma,0,t+1} & a = 0 \\ N_{\gamma,a-1,t}e^{-M-S_{f,\gamma,a-1}F_t} & a \geq 1 \text{ to } A-1 \\ (N_{\gamma,A-1,t} + N_{\gamma,A,t})e^{-M-S_{f,\gamma,A}F_t} & a = A \end{cases} \tag{A.1}$$

where $N_{\gamma,a,t+1}$ is the number of fish of age a and gender γ at the start of the year t, $S_{f,a,\gamma}$ is the gear selectivity by age and gender, F_t is the instantaneous fishing mortality rate during year t, and M is the instantaneous rate of natural mortality.

The catch of fish of age a and gender γ during year t in numbers is:

$$C_{\gamma,0,t} = \frac{S_{f,\gamma,a}F_t}{M + S_{f,\gamma,a}F_t} N_{\gamma,a,t}(1 - e^{(-M-S_{f,\gamma,a}F_t)}) \tag{A.2}$$

with catch-at-length l calculated as:

$$C_{\gamma,l,t} = \sum_{a=0}^{A} (\varnothing_{\gamma,a,l} S_{f,\gamma,l} F_t)(C_{\gamma,a,t}) \tag{A.3}$$

where $S_{f,\gamma,l}$ is the gear selectivity for the fishery f by length and gender, and $\varnothing_{\gamma,a,l}$ is the proportion of fish of gender γ and age a that are in length bin l:

$$\varnothing_{\gamma,a,l} = \begin{cases} \Phi\left(\dfrac{L'_{\min} - \tilde{L}_{\gamma,a}}{\sigma_{\gamma,a}}\right) & \text{for } l = 1 \\ \Phi\left(\dfrac{L'_{l+1} - \tilde{L}_{\gamma,a}}{\sigma_{\gamma,a}}\right) - \Phi\left(\dfrac{L'_{l} - \tilde{L}_{\gamma,a}}{\sigma_{\gamma,a}}\right) & \\ 1 - \Phi\left(\dfrac{L'_{\max} - \tilde{L}_{\gamma,a}}{\sigma_{\gamma,a}}\right) & \text{for } l = A_l \end{cases} \tag{A.4}$$

where Φ is the standard normal cumulative density function, L'_l is the lower limit of length bin l, $L'_{\min}$ is the lower limit of the smallest bin, $L'_{\max}$ is the lower limit of the largest bin, $L'_{\gamma a}$ is the mean length of fish of gender γ and age a in the middle of year t, and $\sigma_{\gamma,a}$ is the standard deviation of the length of a fish of age a and gender γ (see Table 1 for parameter values).

The catch in weight during year t is calculated as:

$$C_{w,t} \sum_{\gamma} \sum_{l} w_{\gamma,l} C_{\gamma,l,t} \tag{A.5}$$

where $w_{\gamma,l}$ is the weight of fish of gender γ in length bin l (see Table 1 for parameter values).

Asymptotic double-normal selectivity functions with smooth transitions were assumed for the fishery (f) and the survey (s) (denoted f). These functions were composed of three sections: an ascending limb for small fish (asc), a flat-top where selectivity equals 1.0, and a descending limb for large fish (dsc) (forced to equal 1.0 in this analysis). The three sections are joined at two intersections using steep logistic functions j_1 and j_2.

$$S_{f,\gamma,l} = asc_l(1 - j_{1,l}) + j_{1,l}(1 - j_{2,l} + dsc_l j_{2,l}) \tag{A.6}$$

where

$$asc_l = \left(\frac{1}{1+e^{\beta_5}}\right) + \left(1 - \frac{1}{1+e^{-\beta_5}}\right) \times \left(\frac{e^{-((L_l-\beta_1)^2/e^{\beta_3})} - e^{-((L_{i\min}-\beta_1)^2/e^{\beta_3})}}{1 - e^{-((L_{\min}-\beta_1)^2/e^{\beta_3})}}\right) \tag{A6.1}$$

$$dsc_l = 1 + \left(\frac{1}{1+e^{-\beta_6}} - 1\right)\left(\frac{e^{-((L_l-\beta_2)^2/e^{\beta_4})} - 1}{e^{-((L_{\max}-\beta_2)^2/e^{\beta_4})}}\right) \tag{A6.2}$$

$$j_{1l} = (1 + e^{-20(L_l-\beta_1/1+|L_l+\beta_1|)})^{-1} \tag{A6.3}$$

$$j_{2l} = (1 + e^{-20(L_l-\beta_2/1+|L_l+\beta_2|)})^{-1} \tag{A6.4}$$

where l is the index for length bin for $1 \leq l \leq A_l$, L_l is the midpoint of length bin l, $L_{\min}$ is the midpoint of the smallest length bin, $L_{\max}$ is the midpoint of the largest length bin, β_1 is the size at which selectivity = 1.0 begins, β_2 is the size at which selectivity = 1.0 ends, β_3 determines the slope of the ascending limb, β_4 determines the slope of the descending limb, and β_5 is the selectivity at $L_{\min}$.

The quantity β_2 is transformed from a parameter, β_2^*, which determines the end of the peak selectivity section as an offset β_1, according to the function

$$\beta_1 + L_{width} + \frac{0.99L_{\max} - \beta_1 - L_{width}}{1 + e^{-\beta_2^*}} \tag{A6.5}$$

where L_{width} is the width of the length bins in the population.

Selectivity-at-length by gender, $S_{f/s,\gamma,l}$, is converted to selectivity-at-age by gender, $S_{f/s,\gamma,a}$, using the age-length transition matrix $\varnothing_{\gamma,a,l}$.

A.2. Recruitment

The number of age-0 fish is related to spawning biomass according to the Beverton–Holt stock recruitment relationship:

$$N_{\gamma,0,t} = \frac{4hR_0S_t}{S_0(1-h)+S_t(5h-1)}e^{-0.5\sigma_R^2+\tilde{R}_t}\tilde{R}_t \sim N(0;\sigma_R^2) \quad \text{(A.7)}$$

where R_0 is the number of age-0 fish at unfished equilibrium, S_0 is the unfished equilibrium spawning biomass (corresponding to R_0), S_t is the spawning biomass at the start of the spawning season during year t, h is the steepness parameter, σ_R is the standard deviation of recruitment in log space, and $\tilde{R}_t$ is the lognormal recruitment deviation in year t.

The spawning biomass at the start of the spawning season for each year t is calculated by:

$$S_t = \sum_{a=0}^{A} N_{t,fem,a}f_a \quad \text{(A.8)}$$

where f_a is the spawning output for a female fish of age a (see Table 1 for spawning output calculation).

A.3. Initial conditions

The numbers of animals of gender γ in age group a, in a virgin state is calculated as:

$$N_{0,\gamma,a} = R_{0,\gamma}e^{-a,M} \quad \text{for} \quad a=0 \quad \text{to} \quad A-1 \quad \text{(A.9)}$$

with the plus group calculated as:

$$N_{0,\gamma,A} = N_{0,\gamma,A-1}\frac{e^{-M}}{1-e^{-M}} \quad \text{(A.10)}$$

The virgin spawning biomass is calculated as:

$$S_0 = \sum_{a=0}^{A} N_{0,fem,a}f_a \quad \text{(A.11)}$$

A.4. Observation model

The observation model is used to generate the observations of the population obtained from the fishery-independent survey. The biomass that is available for observation at each year t, for the survey by gender γ, at age a, and length l is:

$$\tilde{B}_{t,\gamma,a,l} = \varnothing_{\gamma,a,l}w_{\gamma,l}S_{s,\gamma,a}(N_{t,\gamma,a}e^{(-surveytiming(M_{\gamma,a}+F_{f,\gamma,a}F_t))}) \quad \text{(A.12)}$$

The total retained catch in weight is given by Eq. (A.5). The expected observed biomass by the survey is related to the available population abundance according to:

$$B^{obs}_{t,\gamma,a,l} = Q\tilde{B}_{t,\gamma,a,l}e^{\varepsilon_t^s-((\sigma_s)^2/2)} \quad \varepsilon_t^s \sim N(0;(\sigma_s)^2) \quad \text{(A.13)}$$

where Q is the catchability coefficient for survey and, σ_s is the standard deviation of the survey catchability in log space.

The catch-at-age and length for each year t for the survey s for length l and age a by gender γ is:

$$C_{t,s,\gamma,a,l} = S_{s,\gamma,a}\varnothing_{\gamma,a,l}N_{t,\gamma,a}e^{(-surveytiming(M_{\gamma,a}+S_{f,\gamma,a}F_t))} \quad \text{(A14)}$$

A.5. Length compositions

The observed length compositions of the catch and the survey are assumed to be multinomially distributed. The observations can be compressed at the tails of the length observations using the general formula:

$$p_{1,t,f,l,\gamma} = \begin{cases} 0 & \text{for} \quad l < l_{1\gamma} \\ \sum_{l\le l_{1\gamma}} p_{1,t,f,l,\gamma} & \text{for} \quad l = l_{1\gamma} \\ p_{1tfl\gamma} & \text{for} \quad l_{1\gamma} < l < l_{2\gamma} \\ \sum_{l\le l_{2\gamma}} p_{1,t,f,l,\gamma} & \text{for} \quad l > l_{2\gamma} \\ 0 & \text{for} \quad l > l_{2\gamma} \end{cases} \quad \text{(A.15)}$$

where $p_{1,t,f,l,\gamma}$ is the expected proportion of the catch of fish of gender γ in length bin l during year t for fishery or survey f, $l_{1,\gamma}$ is the accumulator length bin for the lower tail by gender, and $l_{2,\gamma}$ is the accumulator length bin for the upper tail by gender:

$$\hat{p}_{1,t,f,l,\gamma} = \frac{\sum_{a=0}^{A} C_{t,f,\gamma,a,l}}{\sum_{a=0}^{A_l} C_{t,f,\gamma,a,l}} \quad \text{(A.16)}$$

A.6. Age compositions

Similar to the length compositions, the observed age compositions are assumed to be multinomially distributed. The compression of tails of age observations is achieved in a similar fashion as for the length data (Eq. (A.15)).

The expected proportion of the catch in each age bin a for each year t for the surveys and gender γ is:

$$p_{2,t,s,a,\gamma} = \frac{\sum_{l=1}^{A_l} C_{t,s,\gamma,a,l}}{\sum_{\gamma=1}^{A_\gamma}\sum_{a=0}^{A} C_{t,s,\gamma,a,l}} \quad \text{(A17)}$$

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