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Implementing a statistical catch-at-age model (Stock Synthesis) as a tool for deriving overfishing limits in data-limited situations

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ABSTRACT

Stock Synthesis (SS) is a likelihood-based statistical catch-at-age modeling environment allowing multiple data sources to be used to characterize population dynamics through time. While it is typically applied in data-rich circumstances, its suitability in data-limited situations is investigated in this work. Two "Simple Stock Synthesis" (SSS) approaches are outlined, each developed to mimic the Depletion-Based Stock Reduction Analysis (DB-SRA) estimation of overfishing limits (OFLs) currently applied to data-limited U.S. west coast groundfish species. SSS-MC uses Monte Carlo draws of natural mortality, steepness, and stock depletion and estimates initial recruitment, while SSS-MCMC estimates natural mortality, steepness, and initial recruitment while fitting to an artificial abundance survey representing stock depletion with an error distribution equivalent to the stock depletion prior used in DB-SRA. These approaches are applied to 45 species of unassessed groundfishes in the Pacific Fishery Management Council Groundfish Fishery Management Plan, and the OFL estimates are compared to corresponding DB-SRA estimates. Despite model structure and parameter specification differences, SSS led to results comparable to DB-SRA over a wide range of species and life histories. SSS models with sex-specific life history parameters and growth variability are also presented as examples of how the inherent flexibility of SS can be used to account for more uncertainty in derived quantities. SSS-MCMC, while exhibiting statistically undesirable traits due to the inclusion of the artificial survey, readily includes data-informed abundance surveys into an assessment framework consistent with more complex, data-informed assessments. Establishment of viable data-limited approaches in SS is a convenient first steps in "building-up" stock assessments towards fuller implementation in SS when additional data become available, while also providing a way to inform management in data-limited situations.

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1. Introduction

The long recognition that excessive removals of marine resources can lead to undesirable consequences to populations and ecosystems has motivated many management systems worldwide to examine ways to halt future resource deterioration (Smith et al., 2009; Worm et al., 2009; Villasante et al., 2011). For example, the reauthorization of the U.S. Magnuson-Stevens Fishery Conservation and Management Act (MSA) mandates the immediate ending of overfishing of all stocks within a fishery management plan (FMP), while continuing to maintain optimal catch. The MSA requires annual catch limits (ACLs) for all FMP species to obtain this balance of sustainable and economically viable removals. The National Marine Fisheries Service National Standard guidelines define ACLs in relation to two other metrics—the overfishing level (OFL) and the acceptable biological catch (ABC)—wherein OFL ≥ ABC ≥ ACL. The first step in this chain, the OFL, is defined as exploitation at maximum sustainable yield (U_{MSY}) of the current year's exploitable biomass (B_{EX}) (OFL = $U_{MSY} \times B_{EX}$). Exploitable biomass and U_{MSY} are typically derived from statistical catch-at-age models that require information on catch histories, life history parameters, abundance indices, and size- and/or age-compositions of catch. When U_{MSY} is not reliably estimable, proxies are used instead (Ralston, 2002).

Continuing with the U.S. example, the Pacific Fishery Management Council (PFMC) groundfish FMP contains 90+ species of fish of which only ~1/3 have stock assessment-derived OFLs. The remaining stocks have not been formally assessed because of insufficient data or other resources. Given data and resource limitations are ongoing issues, alternative ways to fulfill the MSA mandates of setting catch limits for all FMP species are needed.

Average catch has long been a suggested fall back to devising catch recommendations in the U.S. (Restrepo et al., 1998). MacCall (2009) proposed an improvement to average catch

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(Depletion-Corrected Average Catch or DCAC) by introducing a Monte Carlo derived correction to average catch based on probability distributions for current stock depletion levels, natural mortality (M), the ratio of the fishing mortality at MSY (F_{MSY}) to M, and the ratio of biomass at maximum sustainable yield (B_{MSY}) to initial biomass (B_0). DCAC returns a distribution for sustainable catch that could be used to derive an OFL. Dick and MacCall (2010, 2011) built on the tenants of DCAC and developed the Depletion-Based Stock Reduction Analysis (DB-SRA), a method that uses the same approach as DCAC, but links it to a simple population dynamics model. This step allows production and biomass to be explicitly connected and leads to derived quantities (MSY, B_0, and B_{MSY}) similar to those from stock assessments, as well as an OFL distribution. DB-SRA can be updated yearly with new catch information and offers insight into the probability of catch exceeding the OFL through time. It currently serves as the primary method providing OFLs estimates for most unassessed U.S. west coast groundfishes.

In recognition that OFLs derived from differing data availability and analytical approaches warrant different treatments when used for management decision making (Smith et al., 2009), three categories of species are distinguished by the PFMC: (A) Category 3: species with OFLs calculated using only historical catch and life history information ("data-poor"); (B) Category 2: species with OFLs calculated with the addition of indices of abundance ("data-moderate"); (C) Category 1: species with OFLs calculated using traditional stock assessment approaches ("data-rich"; Ralston et al., 2011). OFLs derived from more data-limited situations are discounted to a greater extent when calculating ABCs (Ralston et al., 2011). There is thus a need to not only have the ability to derive OFLs in data-limited situations, but to also graduate species towards more data-rich assessments at less discounted future catches (Smith et al., 2009). A common framework to achieve both goals is desirable.

Stock Synthesis (SS; Methot and Wetzel, submitted for publication) is a likelihood-based statistical catch-at-age modeling package allowing multiple data sources to be used to characterize population dynamics through time. It is used for most U.S. west coast groundfish stock assessments. While it is typically applied when data such as indices of abundance and length- and/or age-compositions are available, its suitability in data-limited environments is the subject of this paper, which aims to demonstrate how SS can be applied in data-limited situations using the established theoretical foundation of DB-SRA. The approach is referred to as "simple" Stock Synthesis (SSS). Two variants of SSS are presented and compared to DB-SRA. The pros and cons of these variants are presented, as well as the main differences between the assumptions of SSS and DB-SRA. Examples are also provided to demonstrate the flexibility of SSS to represent additional uncertainty related to parameters and model specification (e.g., incorporating growth variability and sex-specific differences in life history), thus providing a consistent and generalized framework to inform resource management.

2. Methods

Dick and MacCall (2010) applied DB-SRA to calculate OFLs for 50 species in the groundfish FMP (Table 1). OFLs are used here as the primary metric to compare SSS and DB-SRA. DB-SRA assumes females and males have the same life history parameters (usually using female values; Table 1), so the same assumptions are initially made for SSS. The catch histories used by Dick and MacCall (2010) are used in SSS, assuming one fleet with selectivity equal to the maturity curve.

SSS is implemented in two ways: (1) using the same Monte Carlo approach as DB-SRA that requires drawing values for each of the input parameter from probability distributions, calculating any derived quantities and repeating this many times to obtain probability distributions for model outputs (SSS-MC); and (2) using the DB-SRA distributions as prior distributions for the parameters and a Markov chain Monte Carlo (MCMC) approach to calculate posterior distributions for all model outputs (SSS-MCMC). All SSS models use SS version 3.11c. Example SSS model files are provided in Supplementary material.

2.1. Matching DB-SRA inputs

DB-SRA uses four parameter inputs: (1) Relative Stock Status (Δ; equivalent to 1-stock depletion); (2) natural mortality (M); (3) F_{MSY}/M and (4) B_{MSY}/B_0. Each of these is assigned a distribution from which the Monte Carlo draws are taken. In the SSS applications, each is treated in the following manner:

2.1.1. Relative Stock Status (Δ)

This input represents the prior belief on the status of the stock in the current year, measured as 1-stock depletion. In DB-SRA, a beta distribution bounded at 0.01 and 0.99 is assumed, with a mean $\Delta = 0.6$ (thus, stock depletion = 0.4) and standard deviation (SD) = 0.1. In SSS, stock depletion is treated as two "observed" survey value entries in the data file (Supplementary material: SSS File 3). The first entry value is 1, representing no stock depletion in the modeled first year (before fishing); the second is the stock depletion in the current year. The mean and standard deviation (SD) of this second entry is determined differently for each SSS variant.

For SSS-MC, values for current stock depletion are determined from the beta distribution for Δ used in DB-SRA and converted to stock depletion via $1 - \Delta$. Standard deviations for these "observed" survey values are set to be extremely low (0.00001) so the estimated current depletion matches the inputted survey value. For SSS-MCMC, the beta distribution is not available when fitting survey data, so approximations of the DB-SRA beta distribution were made using both lognormal (the most common error distribution used when fitting abundance index data in SS) and normal distributions. An optimization routine based on 1,000,000 random draws from each distribution is used to solve for the mean and SD values for the lognormal and normal distributions that approximated the DB-SRA beta distribution (Fig. 1). Both the lognormal and normal error distributional assumptions were considered in the SSS-MCMC comparisons to DB-SRA.

2.1.2. Natural mortality

SSS treats M the same as DB-SRA; a species-specific mean M (Table 1) and lognormal standard deviation of 0.4 are used either to form a distribution from which M values are drawn (SSS-MC), or used to form a prior distribution when M is estimated (SSS-MCMC).

2.1.3. Productivity (F_{MSY}/M and B_{MSY}/B_0)

Productivity in DB-SRA is specified in terms of the distributions for F_{MSY}/M and B_{MSY}/B_0. The closest analog to these in SS is steepness (h), though growth parameters also contribute to the translation of production to biomass. No direct mapping of the two DB-SRA production ratios to steepness or growth currently exists, so SSS is not expected to match DB-SRA exactly.

Growth parameters for each species were assumed known (Table 1; an assumption confronted in Section 2.6), while h was assigned prior distributions. Bounds for h were set using a minimum bound of 0.25 based on He et al. (2006), and a maximum of 0.99 (values of $h = 1$ can sometimes lead to unstable model behavior). For rockfishes and flatfishes, mean steepness values were taken from priors formulated by Dorn (pers. comm.; Dorn, 2002; Table 1) and Myers et al. (1999), respectively. Those prior distributions were then converted into bounded beta distributions (Fig. 2). The elasmobranchs and roundfishes ($N = 5$; Table 1) did not have steepness

Table 1
Life history parameter inputs. Females and males were assumed to have the same parameters when sex-specific data were not available. Length at maturity refers to female maturity.

Group	Scientific name	Common name	Species code	A_{MAX}	A_{MAT}	L_{MAX}	M	Growth parameters											Weight (g)–length (cm) relationship				Length (cm) at maturity	
								Female					Male						Female		Male		$L_{50\%}$	Slope
								L_1	L_∞	k	CV_{young}	CV_{old}	M	L_1	L_∞	k	CV_{young}	CV_{old}	a	b	a	b		
Rockfishes	*Sebastes aurora*	Aurora rockfish	ARRA	75	5		0.058	5.91	36.90	0.06	0.10	0.10	0.058	15.04	33.60	0.09	0.10	0.10	2.44E−05	2.83	2.44E−05	2.83	26	−0.62
Rockfishes	*Sebastes rufus*	Bank rockfish	BANK	73	13		0.08	16.26	45.60	0.09	0.10	0.10	0.08	14.73	40.30	0.13	0.10	0.10	7.80E−06	3.15	7.80E−06	3.15	34	−5.39
Rockfishes	*Sebastes chrysomelas*	Black-and-Yellow rockfish	BYEL	30	4		0.157	6.88	25.20	0.22	0.10	0.10	0.157	6.71	24.70	0.24	0.10	0.10	1.38E−05	3.13	1.67E−05	3.07	15	−1.42
Rockfishes	*Sebastes melanostomus*	Blackgill rockfish (N)	BLGL_N	87	20		0.04	11.22	55.39	0.04	0.10	0.10	0.04	9.92	46.71	0.06	0.10	0.10	1.22E−05	3.04	1.22E−05	3.04	34	−0.87
Rockfishes	*Sebastes mystinus*	Blue rockfish (CA)	BLUR_SCB	41	6		0.1	11.85	40.02	0.15	0.10	0.10	0.1	10.64	32.94	0.20	0.10	0.10	2.55E−05	2.87	2.27E−05	2.89	26	−0.60
Rockfishes	*Sebastes mystinus*	Blue rockfish (WA & OR)	BLUR_ORWA	41	6		0.1	6.42	47.20	0.31	0.10	0.10	0.1	10.19	48.40	0.23	0.10	0.10	2.55E−05	2.87	2.27E−05	2.89	26	−0.60
Rockfishes	*Sebastes paucispinis*	Bocaccio (N)	BCAC	37	3		0.15	26.00	67.75	0.22	0.10	0.10	0.15	26.00	58.91	0.26	0.10	0.10	7.36E−06	3.11	7.36E−06	3.11	40	−0.36
Rockfishes	*Sebastes gilli*	Bronzespotted rockfish	BRNZ	89	15		0.037	38.80	63.60	0.04	0.10	0.10	0.037	38.80	63.60	0.04	0.10	0.10	1.77E−05	2.98	1.77E−05	2.98	35	−0.10
Rockfishes	*Sebastes auriculatus*	Brown rockfish	BRWN	34	4		0.137	11.29	51.40	0.16	0.10	0.10	0.137	11.29	51.40	0.16	0.10	0.10	2.30E−06	2.95	2.80E−06	2.87	26	−2.29
Rockfishes	*Sebastes nebulosus*	China rockfish	CHNA	79	5		0.055	5.32	37.30	0.19	0.10	0.10	0.055	7.79	37.50	0.19	0.10	0.10	1.07E−05	3.21	1.25E−05	3.15	27	−5.53
Rockfishes	*Sebastes caurinus*	Copper rockfish	COPP	50	6		0.09	14.48	57.20	0.13	0.10	0.10	0.09	9.42	51.70	0.22	0.10	0.10	1.37E−04	3.10	2.02E−05	2.98	34	−1.33
Rockfishes	*Sebastes levis*	Cowcod (N)	CWCD	55	11		0.055	11.06	85.80	0.06	0.27	0.64	0.055	11.06	85.80	0.06	0.27	0.64	1.01E−05	3.09	1.01E−05	3.09	43	−0.51
Rockfishes	*Sebastes rubrivinctus*	Flag rockfish	FLAG	38	5		0.121	**NA**	**NA**	**NA**	0.10	0.10	0.121	**NA**	**NA**	**NA**	0.10	0.10	8.81E−06	3.20	5.32E−06	3.34	34	−4.09
Rockfishes	*Sebastes carnatus*	Gopher rockfish (S. CA)	GPHR_SCB	30	4		0.2	6.95	34.10	0.25	0.10	0.10	0.2	7.22	32.90	0.28	0.10	0.10	1.97E−05	3.01	1.70E−05	3.03	17	−1.68
Rockfishes	*Sebastes rastrelliger*	Grass rockfish	GRAS	23	4		0.209	16.05	51.30	0.11	0.10	0.10	0.209	16.05	51.30	0.11	0.10	0.10	3.21E−05	2.89	7.31E−05	2.66	24	−1.55
Rockfishes	*Sebastes rosenblatti*	Greenblotched rockfish	GBLC	50	10		0.09	9.24	57.99	0.05	0.10	0.10	0.09	9.52	56.11	0.06	0.10	0.10	1.10E−05	3.11	1.10E−05	3.11	28	−2.69
Rockfishes	*Sebastes chlorostictus*	Greenspotted rockfish	GSPT	51	10		0.088	5.43	44.20	0.13	0.10	0.10	0.088	5.59	44.00	0.14	0.10	0.10	7.70E−06	3.21	5.50E−06	3.29	28	−0.59
Rockfishes	*Sebastes umbrosus*	Honeycomb rockfish	HNYC	31	5		0.151	3.88	24.90	0.11	0.10	0.10	0.151	3.88	24.90	0.11	0.10	0.10	6.70E−06	3.32	6.70E−06	3.32	11	−1.41
Rockfishes	*Sebastes atrovirens*	Kelp rockfish	KLPR	25	4		0.191	7.36	28.50	0.29	0.10	0.10	0.191	7.37	28.19	0.30	0.10	0.10	1.24E−05	3.09	1.45E−05	3.04	26	−3.61
Rockfishes	*Sebastes macdonaldi*	Mexican rockfish	MXRF	22	3		0.219	**NA**	**NA**	**NA**	0.10	0.10	0.219	**NA**	**NA**	**NA**	0.10	0.10	4.46E−05	2.66	4.46E−05	2.66	**NA**	**NA**
Rockfishes	*Sebastes serranoides*	Olive rockfish	OLVE	30	5		0.157	19.22	51.90	0.18	0.10	0.10	0.157	18.66	53.90	0.17	0.10	0.10	1.11E−05	3.06	1.52E−05	2.96	35	−4.06
Rockfishes	*Sebastes eos*	Pink rockfish	PNKR	66	9		0.067	**NA**	**NA**	**NA**	0.10	0.10	0.067	**NA**	**NA**	**NA**	0.10	0.10	1.86E−05	2.96	1.86E−05	2.96	**NA**	**NA**

Table 1 (*Continued*)

Group	Scientific name	Common name	Species code	A_{MAX}	A_{MAT}	L_{MAX}	M	Growth parameters											Weight (g)–length (cm) relationship				Length (cm) at maturity	
								Female					Male						Female		Male		$L_{50\%}$	Slope
								L_1	L_∞	k	CV_{young}	CV_{old}	M	L_1	L_∞	k	CV_{young}	CV_{old}	a	b	a	b		
Rockfishes	*Sebastes maliger*	Quillback rockfish	QLBK	76	9		0.057	17.59	41.80	0.07	0.10	0.10	0.057	17.49	39.50	0.09	0.10	0.10	2.50E−06	2.92	3.40E−06	2.83	26	−8.20
Rockfishes	*Sebastes babcocki*	Redbanded rockfish	RDBD	106	4		0.04	**NA**	**NA**	**NA**	0.10	0.10	0.04	**NA**	**NA**	**NA**	0.10	0.10	2.06E−05	2.94	2.06E−05	2.94	34	−1.33
Rockfishes	*Sebastes proriger*	Redstripe rockfish	REDS	55	7		0.081	9.43	38.28	0.16	0.10	0.10	0.081	9.31	29.52	0.22	0.10	0.10	1.05E−05	3.07	9.80E−06	3.09	30	−0.69
Rockfishes	*Sebastes helvomaculatus*	Rosethorn rockfish	RSTN	87	10		0.049	9.08	28.66	0.10	0.10	0.10	0.049	9.37	27.93	0.13	0.10	0.10	1.15E−05	3.21	5.50E−06	3.26	23	−4.13
Rockfishes	*Sebastes rosaceus*	Rosy rockfish	ROSY	18	4		0.273	6.07	32.90	0.12	0.10	0.10	0.273	4.87	30.20	0.16	0.10	0.10	1.16E−05	3.11	1.34E−05	3.05	20	−2.17
Rockfishes	*Sebastes aleutianus*	Rougheye rockfish	REYE	170	20		0.024	19.01	51.12	0.06	0.10	0.10	0.024	27.32	53.02	0.04	0.10	0.10	7.92E−06	3.18	9.45E−06	3.12	47	−0.34
Rockfishes	*Sebastes zacentrus*	Sharpchin rockfish	SHRP	58	6		0.077	8.25	33.21	0.17	0.10	0.10	0.077	8.23	26.98	0.20	0.10	0.10	1.13E−05	3.07	1.13E−05	3.07	22	−5.01
Rockfishes	*Sebastes borealis*	Shortraker rockfish	SRKR	157	22		0.026	10.95	84.60	0.03	0.10	0.10	0.026	10.95	84.60	0.03	0.10	0.10	9.80E−06	3.13	9.80E−06	3.13	21	−0.75
Rockfishes	*Sebastes brevispinis*	Silvergray rockfish	SLGR	82	9		0.053	7.54	61.38	0.06	0.10	0.10	0.053	34.43	56.46	0.07	0.10	0.10	7.20E−06	3.09	7.20E−06	3.09	46	−0.47
Rockfishes	*Sebastes ovalis*	Speckled rockfish	SPKL	37	4		0.125	12.85	49.99	0.05	0.10	0.10	0.125	17.60	35.86	0.06	0.10	0.10	8.40E−06	3.14	5.20E−06	3.22	25	−2.30
Rockfishes	*Sebastes hopkinsi*	Squarespot rockfish	SQRS	19	5		0.257	13.73	25.25	0.18	0.10	0.10	0.257	12.19	24.71	0.06	0.10	0.10	1.46E−05	2.96	1.46E−05	2.96	18	−5.37
Rockfishes	*Sebastes constellatus*	Starry rockfish	STAR	32	7		0.146	13.91	45.00	0.09	0.10	0.10	0.146	6.47	38.06	0.09	0.10	0.10	1.52E−05	3.01	3.70E−06	3.37	27	−2.30
Rockfishes	*Sebastes saxicola*	Stripetail rockfish	STRK	38	4		0.121	9.47	33.05	0.06	0.10	0.10	0.121	10.37	17.38	0.19	0.10	0.10	2.48E−05	2.80	3.79E−05	2.62	17	−2.30
Rockfishes	*Sebastes ensifer*	Swordspine rockfish	SWSP	43	3		0.106	4.37	17.60	0.14	0.10	0.10	0.106	4.37	17.60	0.14	0.10	0.10	8.06E−05	3.26	8.06E−05	3.26	8	−2.10
Rockfishes	*Sebastes nigrocinctus*	Tiger rockfish	TIGR	116	16		0.036	**NA**	**NA**	**NA**	0.10	0.10	0.036	**NA**	**NA**	**NA**	0.10	0.10	1.13E−05	3.15	1.13E−05	3.15	**NA**	**NA**
Rockfishes	*Sebastes serriceps*	Treefish	TREE	25	5		0.191	12.15	30.64	0.23	0.10	0.10	0.191	12.15	30.64	0.23	0.10	0.10	1.52E−05	3.08	1.42E−05	3.08	21	−8.02
Rockfishes	*Sebastes miniatus*	Vermillion rockfish	VRML	60	5		0.074	16.50	62.40	0.14	0.10	0.10	0.074	12.51	57.50	0.20	0.10	0.10	1.93E−05	2.99	1.90E−05	2.99	38	−0.50
Rockfishes	*Sebastes reedi*	Yellowmouth rockfish	YMTH	99	6		0.043	25.21	46.36	0.25	0.10	0.10	0.043	16.65	45.18	0.22	0.10	0.10	1.87E−05	2.97	1.87E−05	2.97	39	−0.68
Rockfishes	*Sebastes flavidus*	Yellowtail rockfish (S)	YTRK	64	10		0.11	13.44	52.21	0.17	0.10	0.10	0.11	19.04	47.57	0.19	0.10	0.10	3.59E−05	2.75	2.87E−05	2.82	37	−0.47
Flatfishes	*Citharichthys sordidus*	Pacific sanddab	PDAB	11	2		0.465	9.50	30.91	0.31	0.10	0.10	0.465	9.50	25.98	0.46	0.10	0.10	6.29E−08	3.18	6.33E−08	3.17	19	−1.84
Flatfishes	*Glyptocephalus zachirus*	Rex sole	REX	24	5		0.2	13.45	41.82	0.39	0.10	0.10	0.2	13.45	41.82	0.39	0.10	0.10	2.75E−06	3.24	2.75E−06	3.23	35	−0.04
Flatfishes	*Lepidopsetta bilineata*	Rock sole	RSOL	22	5		0.219	20.65	51.60	0.15	0.10	0.10	0.219	19.54	40.20	0.26	0.10	0.10	1.15E−08	3.41	8.79E−08	3.06	30	−0.92

Flatfishes	*Psettichthys melanostictus*	Sand sole	SSOL	10	2	0.516	22.69	37.81	0.79	0.10	0.10	0.516	19.72	31.05	0.60	0.10	0.10	4.85E−06	3.20	4.96E−06	3.17	24	−0.26
Elasmobranchs	*Triakis semifasciata*	Leopard shark	LSRK	25	10	0.191	31.79	160.20	0.07	0.10	0.10	0.191	42.44	149.90	0.09	0.10	0.10	3.05E−06	3.05	3.05E−06	3.05	135	−0.15
Elasmobranchs	*Galeorhinus zyopterus*	Soupfin shark	SSRK	40	12	0.115	45.21	182.90	0.12	0.10	0.10	0.115	45.21	182.90	0.12	0.10	0.10	5.59E−07	4.16	3.80E−06	3.27	159	−0.32
Elasmobranchs	*Squalus acanthias*	Spiny dogfish	DSRK	80	35	0.054	42.28	125.30	0.07	0.10	0.10	0.054	23.89	99.80	0.05	0.10	0.10	1.85E−06	3.70	2.92E−06	3.06	94	−0.31
Roundfishes	*Macrouridae* spp.	Grenadier complex	GRDR	60	20	0.074	2.41	37.20	0.02	0.10	0.10	0.074	0.84	26.80	0.04	0.10	0.10	1.78E−04	2.83	1.89E−04	2.81	65	−0.25
Roundfishes	*Hexagrammos decagrammus*	Kelp greenling (CA)	KLPG_CA	25	4	0.191	25.60	39.51	0.20	0.10	0.10	0.191	21.85	36.23	0.58	0.10	0.10	4.45E−06	3.32	8.28E−06	3.14	35	−1.25

priors available, so a diffuse (standard deviation = 0.05) symmetric beta prior with bounds at 0.25 and 0.99 was used (Fig. 2).

2.2. Additional SSS set-up

In addition to the above parameters, SSS requires weight–length relationships as well as dimensioning of the length and age bins. Length bins were chosen as 2 cm bins up to the maximum reported size, while age bins were defined in one year steps up to 90% of the maximum age (Table 1; Supplementary material: SSS File 3).

2.3. Parameter estimation and model convergence in SSS

Only one parameter, the log of initial recruitment ($\ln R_0$), is estimated in SSS-MC, while $\ln R_0$, M, and h are estimated in SSS-MCMC. In addition, the catchability coefficient (q) for the stock depletion index is derived analytically when stock depletion is lognormal, but estimated when stock depletion is normal.

Maximum likelihood estimation (MLE) is used to obtain the parameter estimates in SSS-MC. When SSS-MC did not converge (i.e. the difference between observed and model-predicted values of the current year index value was >0.01), the non-converged parameter estimates were used as the starting values for a subsequent model run. This approach was repeated until the convergence criterion was met. 1000 Monte Carlo draws were used for SSS-MC to define the probability distributions.

SSS-MCMC uses MCMC to explore parameter space and develop posterior distributions for model outputs. A MCMC chain of 2,200,000 cycles is run for each species, with the covariance matrix rescaled during the first 200,000 iterations to achieve a desirable acceptance rate, after which every 2000th parameter vector is retained. Additional rejection of MCMC draws occurs when estimated current depletion is higher than the 0.999 quantile of the prior distribution for current depletion. This rejection results in fewer than 1000 retained draws for some species, but is consistent with DB-SRA results that do not explore such large population sizes.

2.4. Contrasting SSS approaches

In summary, the main differences between SSS-MC and SSS-MCMC are: (1) M and h are drawn from prior distributions in SSS-MC and not updated, while in SSS-MCMC, M and h are assigned priors that could be updated; and (2) the survey index is fit without error in SSS-MC and with error in SSS-MCMC.

2.5. Differences between SSS and DB-SRA

There are a few notable differences between the population dynamics models used in DB-SRA and SSS. The underlying population dynamics model in SSS is fully age-structured whereas DB-SRA uses a delay-difference model. Therefore, unlike DB-SRA, age and growth estimates are needed in SSS to define age structure and remove catch according to age-/size-based selectivity patterns. Age and growth information was not available for 5 of the 50 species with DB-SRA results; those species were excluded from the subsequent SSS applications (Table 1). Regarding productivity, SSS uses a Beverton–Holt stock–recruitment relationship (BHSRR) that assumes $B_{MSY}/B_0 \leq 0.5$. DB-SRA uses a Schaefer–Pella–Tomlinson–Fletcher (SPTF) hybrid model that allows $B_{MSY}/B_0 \geq 0.5$. This difference in formulations is unlikely to be consequential for the examples of this paper because most of the assumed distributions for B_{MSY}/B_0 in DB-SRA are less than 0.5 (Dick and MacCall, 2010, 2011), and thus behave more like a BHSRR. Finally, the order of operation differs between SSS and DB-SRA. In SSS, recruits are added, followed by catch removal; in DB-SRA, catch is first removed, then recruits are added. The impact of these

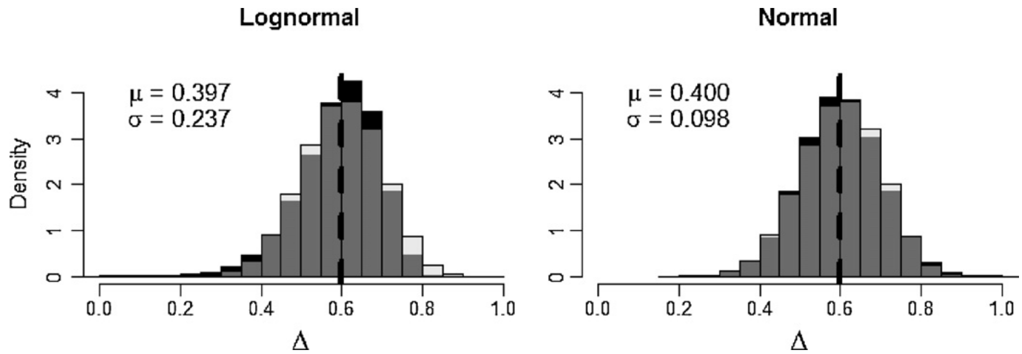

Fig. 1. Best fit approximations to the bounded beta distribution on Δ (1-stock depletion) using either lognormal (left panel) or normal (right panel) distributions. Values for the best-fit mean (μ) and standard deviations (σ) are given in parentheses. Lighter gray bars: beta distribution; black bars c: lognormal or normal distribution; darker gray bars: areas of overlap; broken vertical line: Δ = 0.6.

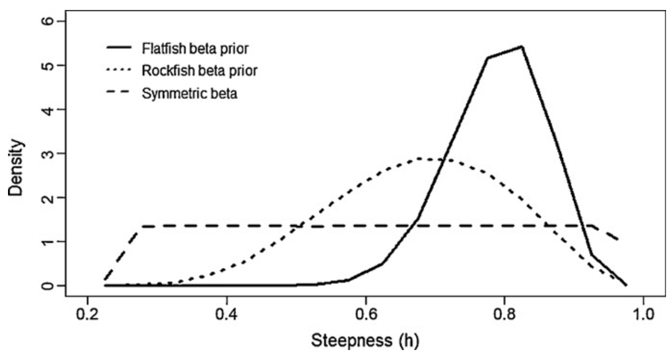

Fig. 2. Beta prior probability density distributions assumed for the steepness parameter used in SSS. The symmetric beta prior was used for species in the elasmobranchs and roundfishes groups.

assumptions has not been formally quantified, but is not anticipated to be great. Biomass (*B*) is measured as sex-combined mature biomass for both SSS and DB-SRA.

2.6. Sensitivity to life history and stock depletion assumptions

The influence on OFL estimates of using sex-specific life history values and including uncertainty in the von Bertalanffy growth parameter *k* (assuming a coefficient of variation of 0.2) was investigated using SSS-MC for copper rockfish (Table 1). Copper rockfish was chosen because it has been shown to be highly vulnerable to overfishing (Cope et al., 2011), lacks a stock assessment, but demonstrates variability in several life history parameters. The sex-specific run of SSS-MC draws *M* for both females and males and includes male-specific values for growth and length–weight parameters (Table 1).

The influence on OFL estimates of different assumptions about mean stock depletion (20% and 60%) was also examined using copper rockfish, as was the ABC value given two different probabilities of overfishing (P^*; Prager and Shertzer, 2010; Ralston et al., 2011): P^* = 0.5 and P^* = 0.4. A P^* of 0.5 is equivalent to setting the ABC to the median of the probability density function for the OFL, whereas a P^* of 0.4 (currently the default P^* value for category 3 (data-limited) U.S. west coast groundfishes; Ralston et al., 2011) is the OFL at a cumulative probability of 0.4.

2.7. Comparing SSS and DB-SRA

OFLs are used to compare SSS variants and DB-SRA for the 45 species, both in terms of central tendency (the median) and variance (the median absolute deviation (MAD)). The MAD was chosen to represent variance because it is comparable across scales and is considered a more robust measure than the interquartile range (Rousseeuw and Crouz, 1993). Although OFLs are the main metric to compare SSS to DB-SRA, results for copper rockfish are used to compare distributions for F_{MSY}, B_{MSY}/B_0, *M*, *h*, and stock depletion.

The 45 groundfishes are organized into three species groupings (Table 1): (1) rockfishes (*N* = 36), (2) flatfishes (*N* = 4), (3) other fishes elasmobranchs (*N* = 3) and roundfishes (*N* = 2). This structure allows for similar steepness prior assumptions to be considered together when reporting results.

3. Results

3.1. Error distribution for stock depletion in SSS-MCMC

The OFLs derived from the converged MLEs were insensitive to whether a normal or lognormal error structure was selected for stock depletion (Fig. 3, upper panel). However, the MCMC results were sensitive to this choice (Fig. 3, lower panels). Specifically, SSS-MCMC using the normal error model exhibits the undesirable behavior that the prior distribution for *M* is not reflected in its posterior. This occurs in SS because the normally distributed survey error requires the estimation of an additional catchability coefficient that demonstrated a high correlation (>0.9) with *M*, constraining the space over which *M* varied, and leading to unrealistically low posterior variation in *M* (Fig. 3, lower left panel). Such behavior makes the assumption of normal error for the stock depletion index questionable. Assuming lognormal error (which does not require estimating a catchability coefficient) shows improved MCMC behavior (Fig. 3, lower right panel) and forms the basis for the remaining comparisons between DB-SRA and SSS-MC.

3.2. Comparing SSS and DB-SRA outputs

SSS-MC and SSS-MCMC led to OFL distributions with relatively larger medians (Figs. 4 and 6) and even larger relative variances (Figs. 5 and 6) than DB-SRA. The differences in medians partly derived from how productivity are parameterized in SSS and DB-SRA, as well as the inclusion of growth parameters in SSS, all affecting the absolute scale of the biomass. Specifically, SSS used group-specific *h* priors, rather than one productivity assumption for all species, thereby accounting for the variability among groups. The species groups with the lowest differences (elasmobranchs and roundfishes) also had the lowest mean *h* values (~0.6). Exploratory model runs with rockfishes and flatfishes confirmed that lowering the mean of the prior for *h* resulted in median OFLs more similar to those from DB-SRA. In general, median OFL values from SSS-MCMC tended to be higher than those from SSS-MC, though variances were similar between the two methods (Figs. 4 and 5).

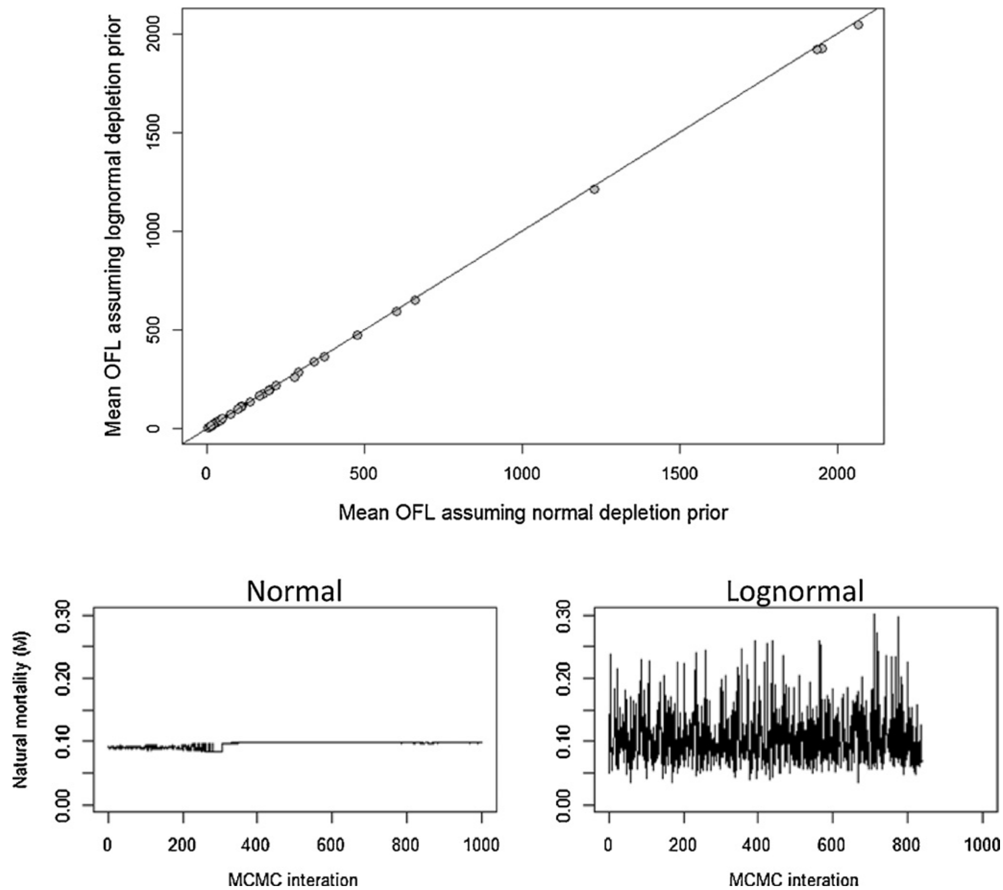

Fig. 3. OFLs for 45 groundfish species from two variants of SSS-MCMC using either the normal or lognormal error distributions for stock depletion (upper panel; solid line is the 1:1 line) and the resultant trace plots for M for copper rockfish (lower panels).

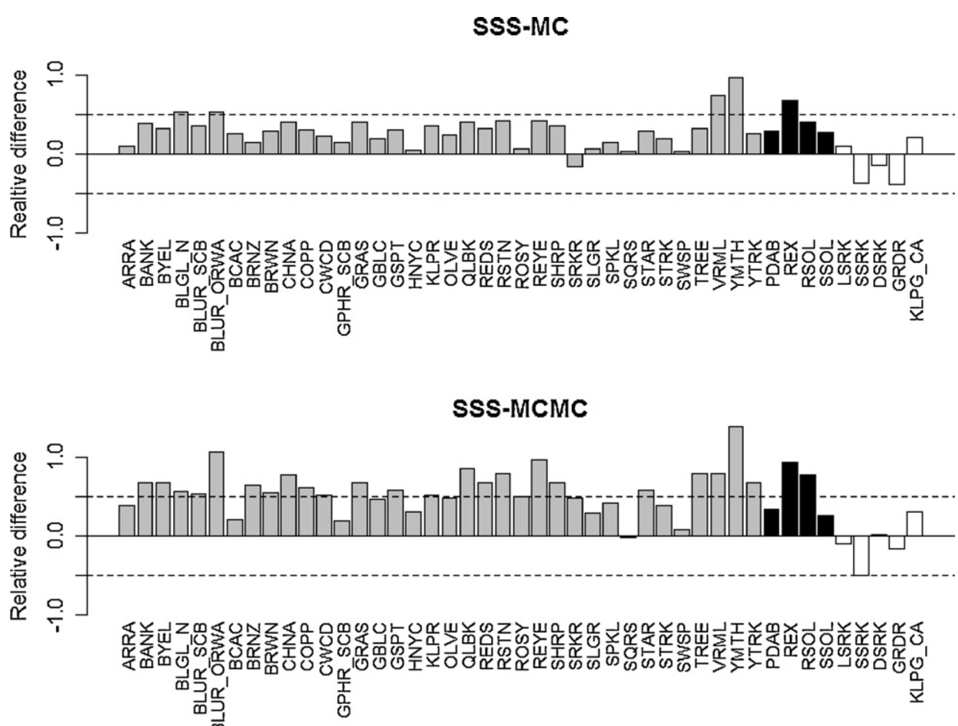

Fig. 4. Differences in median OFL estimates from SSS-MC (upper panel) and SSS-MCMC (lower panel) relative to those from DB-SRA for three species categories: rockfishes (gray bars), flatfishes (black bars), and elasmobranchs and roundfishes (white bars). X-axis labels are species codes found in Table 1. Horizontal broken line indicates a value of 0.5.

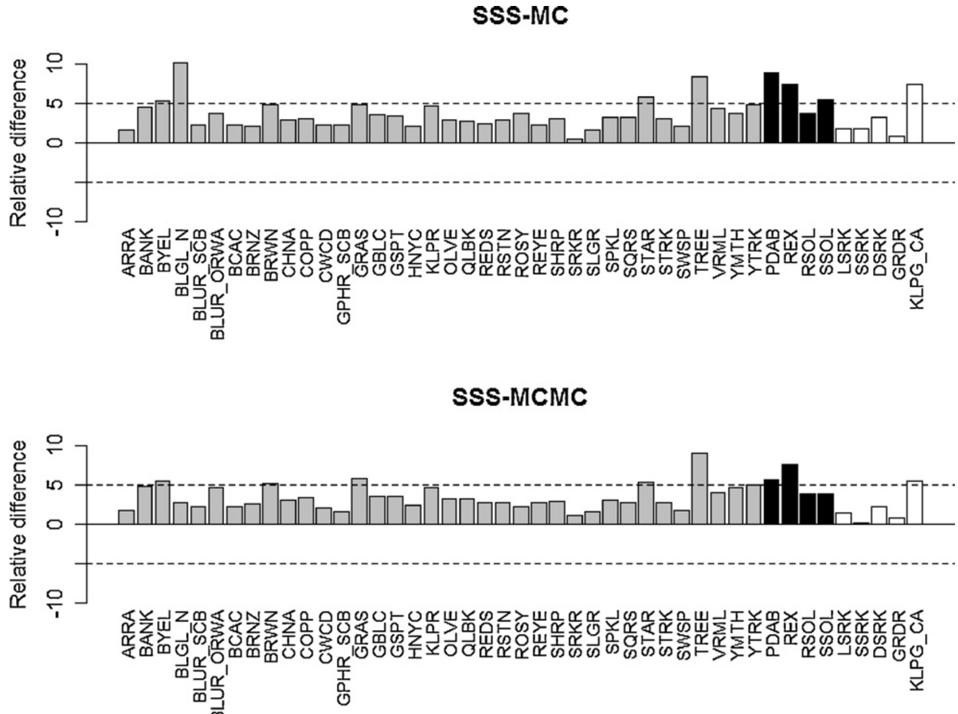

Fig. 5. Differences in median absolute deviations (MADs) of OFL estimates from SSS-MC (upper panel) and SSS-MCMC (lower panel) relative to those from DB-SRA for three species categories: rockfishes (gray bars), flatfishes (black bars), and elasmobranchs and roundfishes (white bars). *X*-axis labels are species codes found in Table 1. Horizontal broken line indicates a value of 5.

A more detailed look using copper rockfish demonstrates a notable overlap in the distributions for OFL and F_{MSY} between SSS and DB-SRA (Fig. 6), while also illustrating the larger medians and fatter tails (most notable for SSS-MCMC). The largest discrepancy relates to the location of B_{MSY} relative to B_0. For example, while the DB-SRA-assumed median B_{MSY}/B_0 was 0.4 for rockfishes, the SSS median B_{MSY}/B_0 estimates for rockfishes ranged from 0.25 to 0.35.

One expectation of SSS is that the resulting probability distributions should reflect the priors because there are no data. This expectation is confirmed for SSS-MC (Fig. 7). However, the posterior distributions for the three parameters from SSS-MCMC, particularly stock depletion, do not match their priors. Further exploratory runs using SSS-MCMC demonstrated that the posterior distributions for stock depletion and h are sensitive to the assumed bounds for $\ln R_0$, (1–31), an extremely wide range compared to values for $\ln R_0$ typically seen in groundfish assessments. This behavior deserves more consideration (see Section 4), so all remaining sensitivity runs are based on SSS-MC.

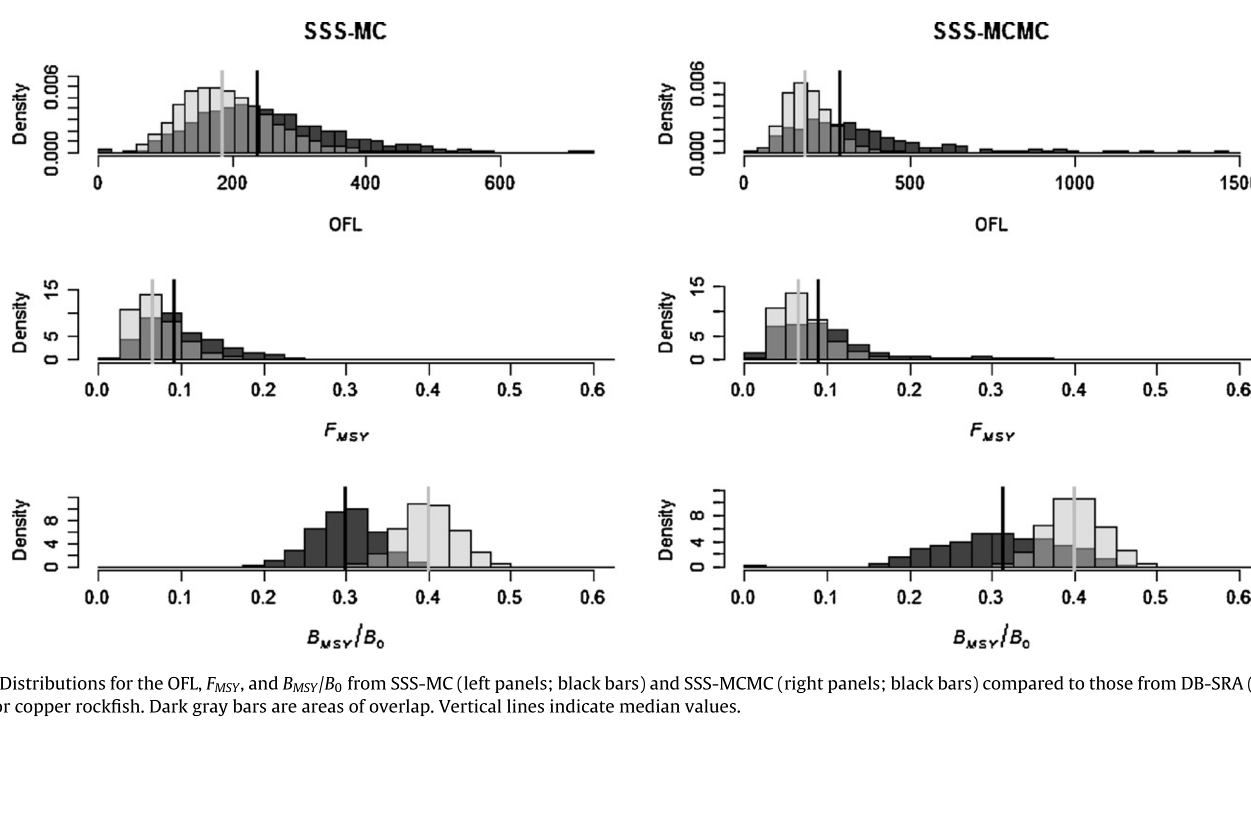

Fig. 6. Distributions for the OFL, F_{MSY}, and B_{MSY}/B_0 from SSS-MC (left panels; black bars) and SSS-MCMC (right panels; black bars) compared to those from DB-SRA (light gray bars) for copper rockfish. Dark gray bars are areas of overlap. Vertical lines indicate median values.

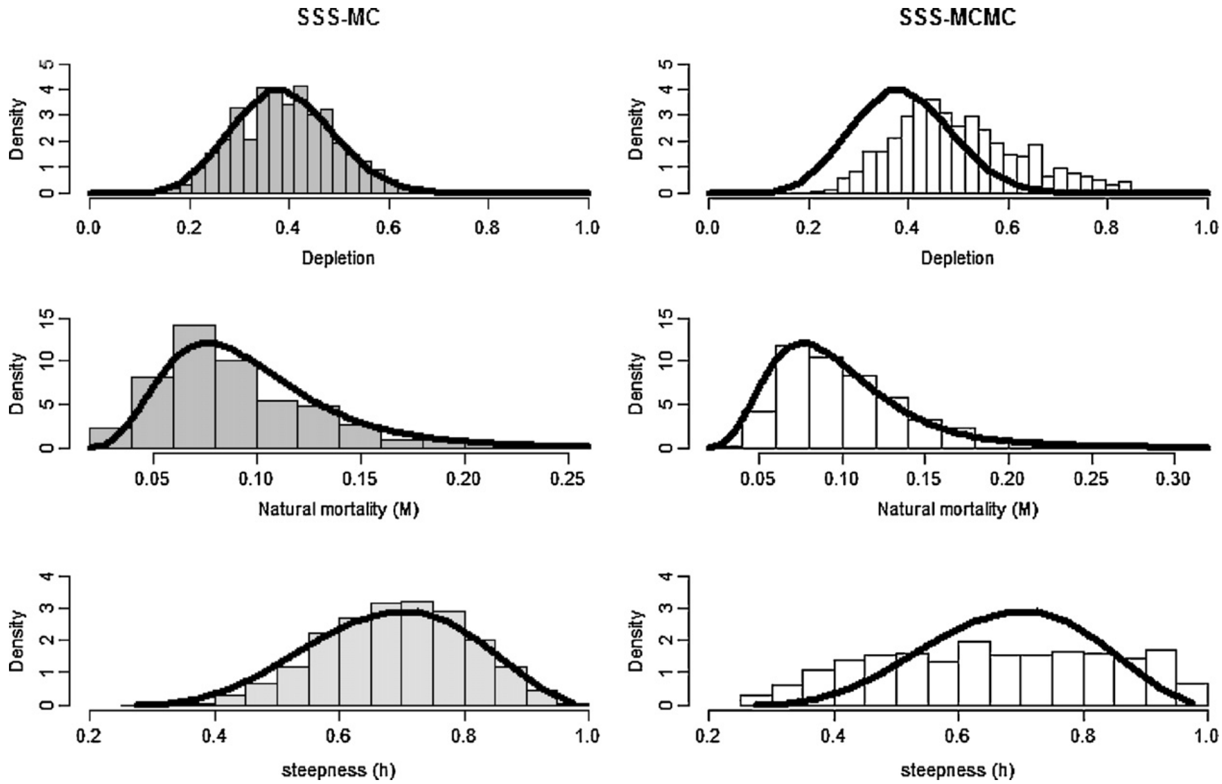

Fig. 7. Posterior distributions for three parameters (stock depletion, natural mortality, and steepness) for copper rockfish from SSS-MC (left panels; gray bars) and SSS-MCMC (right panels; white bars) compared to prior distributions (dark lines).

3.3. Life history and stock depletion sensitivity runs

Allowing for sex-specific parameters (e.g., M, VBGF parameters, length–weight relationships) did not lead to appreciably different estimates of OFL for copper rockfish, although the distribution for OFL was slightly wider (Fig. 8a). Uncertainty in the VBGF growth coefficient k (assuming female life history parameters for both sexes) had a greater impact than sex-specific parameters (Fig. 8b). Combining sex-specific parameters and variability in k for both sexes led to the greatest difference (Fig. 8c).

OFL distributions for copper rockfish were sensitive to the choice of mean stock depletion (Fig. 9; Wetzel and Punt, 2011b). The

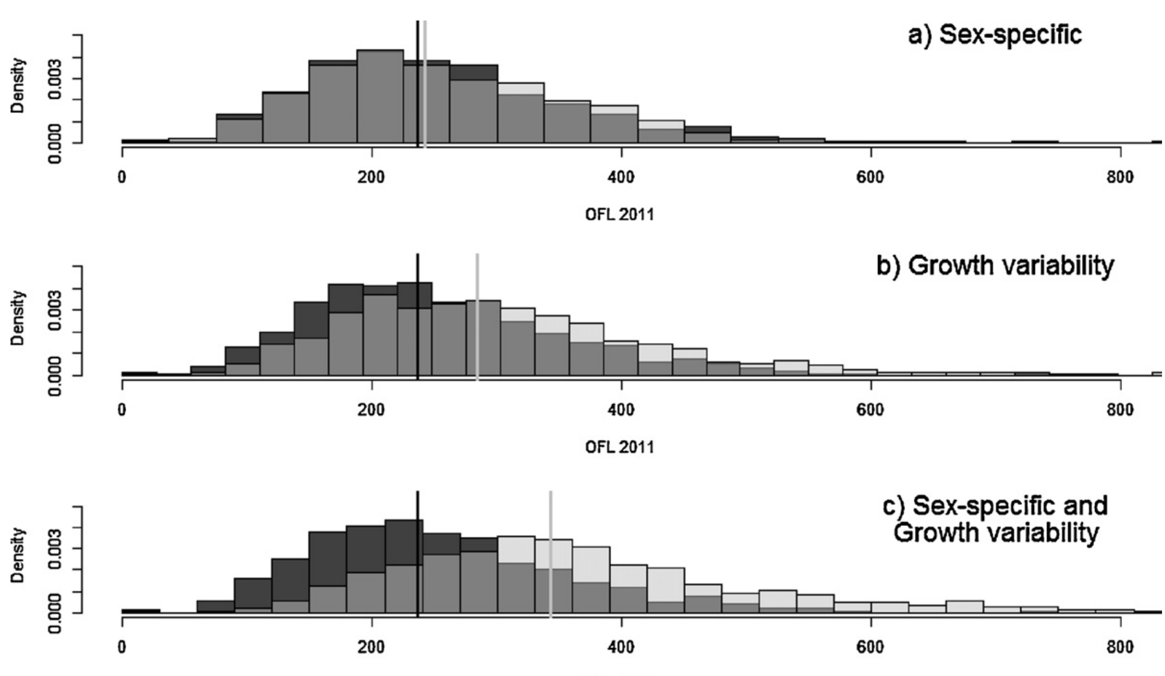

Fig. 8. Distribution of OFLs for copper rockfish from SSS-MC under three different life history parameter assumptions: (a) sex-specific natural mortality, age, growth and weight–length parameters; (b) variability in the female growth parameter k; (c) sex-specific life history parameters and variability in sex-specific growth parameters k.

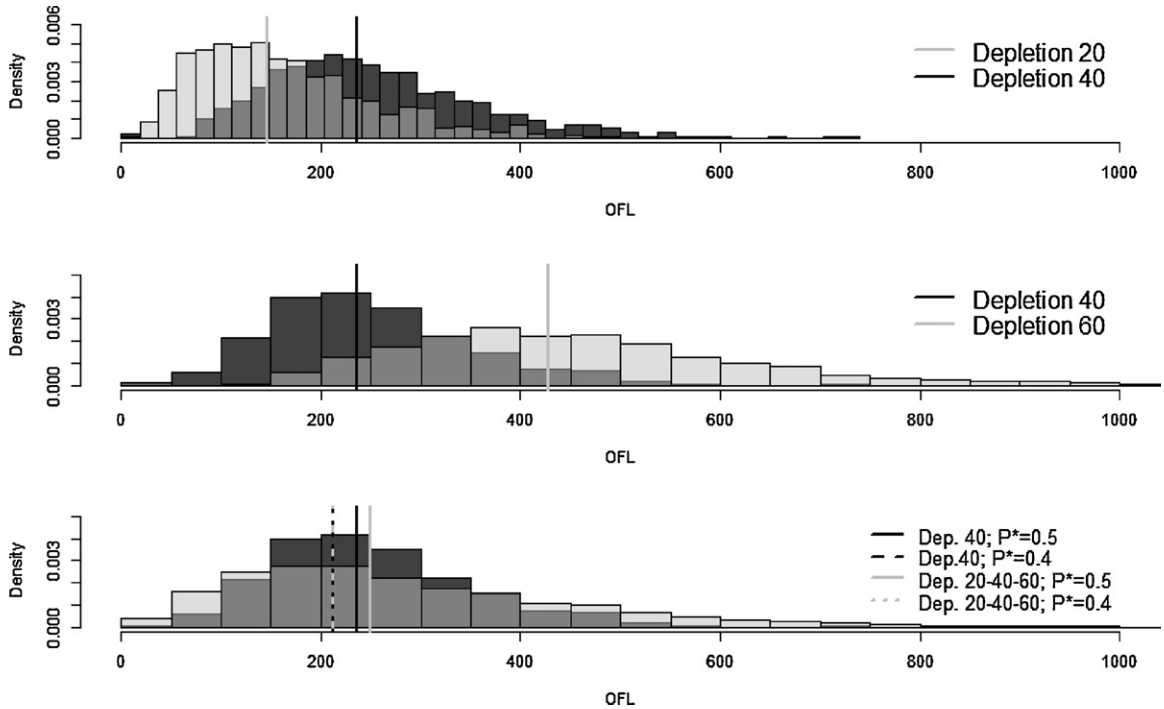

Fig. 9. Distribution of OFLs for copper rockfish from SSS-MC under two different mean stock depletion assumptions compared to the default assumption of 40% stock depletion (black bars): (1) 20% stock depletion (upper panel; light gray bars) and (2) 60% stock depletion (middle panel; light gray bars). Vertical bars are medians. The lower panel compares the OFL distribution using the 40% stock depletion assumption with the blended OFL distribution using 20%, 40%, and 60% stock depletion outputs. Vertical bars are the OFL values at different P^* values.

blended OFL distribution (combining results for multiple depletion assumptions) expectedly led to a larger median OFL with wider variance than when a prior with a mean of only 40% is assumed. These differences in median OFL ($P^* = 0.5$) and variance resulted in similar ABC values ($P^* = 0.4$; Fig. 9, lower panel), a coincidental outcome given the blended distribution has a larger median and variance, and thus by definition has to intersect the OFL values of a distribution with a smaller median and tighter variance somewhere.

4. Discussion

Stock Synthesis has proven a flexible tool for many fisheries management applications, ranging from generalized stock assessment modeling (Methot and Taylor, 2011; Ralston et al., 2011; Methot and Wetzel, submitted for publication), operating models and data generation (Lee et al., 2011; Methot and Taylor, 2011; Maunder, 2012), and as a framework for simulation testing (Cope and Punt, 2011; Piner et al., 2011; Wetzel and Punt, 2011a). This work adds to the list by demonstrating the suitability of SS to perform catch estimation (e.g., overfishing limits) in data-limited situations. It can be argued that SS is so complicated (e.g., many parameters and specification options) that it is inappropriate for simpler, less data-intensive, tasks. The counter argument is that because of its flexibility, SS may be a convenient first step in "building-up" stock assessments of data-limited species towards fuller implementation later. The idea follows that as fisheries information (e.g., population index or composition data) is collected, it can be directly incorporated into a SSS-type model until the model resembles a traditional stock assessment. A common platform that builds up stepwise towards a full stock assessment, while also providing a way to treat the multitude of species that will remain data-limited for the foreseeable future, is consistent with the current U.S. west coast groundfish management tiered system of stock assessment categories based on data availability and uncertainty (Ralston et al., 2011). Both SSS approaches examined here (MC and MCMC versions) show promise as these first steps.

SSS-MC is most similar to DB-SRA, which is already used in west coast groundfish management. Dick and MacCall (2011) note that the population model and stock–recruitment function currently implemented in DB-SRA can be replaced by other models. SSS-MC thus takes the Monte Carlo structure on which DB-SRA is based and applies it to the model structure of SS. Model parameterization therefore becomes an important consideration when selecting between SSS or DB-SRA. Determining whether it is easier to parameterize h (Dorn, 2002; Michielsens and McAllister, 2004) and growth parameters in SSS or F_{MSY}/M and B_{MSY}/B_0 in DB-SRA should be made when selecting among these methods. Informative priors on $\ln R_0$ could also replace the need for an artificial survey representing stock depletion in SSS.

SSS-MC suffers from the same caveats and limitations as DB-SRA, both of which are particularly sensitive to the assumed distribution for stock depletion (Wetzel and Punt, 2011b). Outside of having true prior information on stock depletion, the attempt to construct a blended OFL distribution across multiple stock depletion assumptions is one way to capture this uncertainty for management (simply increasing the uncertainty in the stock depletion prior for the Monte Carlo draws would be another). Other data-limited methods may offer ways to refine stock status input assumptions (Cope and Punt, 2009), whereas Dick and MacCall (2010) presented potential correction factors based on productivity-susceptibility analysis vulnerability scores (Patrick et al., 2010; Cope et al., 2011) that may help reduce the bias in OFL estimates even when the stock depletion assumption is incorrect.

SSS-MCMC applies the same prior structure as DB-SRA, but perpetuates the parameter uncertainty when calculating OFLs in a different way that is most analogous to a typical stock assessment conducted using SS. The inclusion of M and h as estimated parameters, in addition to $\ln R_0$, allows any additional information in the model to influence both maximum likelihood estimation and MCMC exploration. Unfortunately, the simultaneous fitting of an artificial index of stock depletion with error and the prior on $\ln R_0$ effectively places two priors on $\ln R_0$, a discouraged practice in Bayesian statistics and an example of what is known as the Borel paradox (Brandon et al., 2007; Schweder and Hjort, 1996; Wolpert, 1995). This effect likely partially explains the difference between the stock depletion prior and posterior using SSS-MCMC. Unless a more-informed prior is specified for $\ln R_0$ and the artificial index removed, SSS-MCMC may not be a tenable option under catch-only scenarios. However, it may be the next step in building-up data-poor SSS models towards data-rich SS models. The inclusion of a data-informed abundance index and elimination of the artificial depletion index with error also removes the Borel paradox, allowing parameter uncertainty to be characterized using MCMC in a statistically proper way.

There are several advantages to estimating sustainable catch using SSS in data-limited situations. The flexible parameterization of SS can readily allow for the inclusion of additional parameter uncertainty when calculating a distribution for the OFL. As an example, this paper shows how easily sex-specific life history parameters and uncertainty in growth parameters can be accommodated in SSS, and how this changes both the median OFL and increases the width of the OFL distribution. Both the median and width of the OFL distribution are critical components in determining catch limits given a specified probability of overfishing (Ralston et al., 2011). Incorporating these and other sources of uncertainty more fully informs managers. Additionally, alternative life history patterns, such as hermaphroditism (Alonzo et al., 2008), and additional growth morphologies are amendable to modeling using the SS framework.

The SSS approach is one of many ways to guide management decisions when fisheries information is limited. Others examples include catch-based multipliers (Berkson et al., 2011), length-based reference points (Froese et al., 2008; Cope and Punt, 2009), defining trigger points based on trends in catch-per-unit-effort (Dowling et al., 2008; Wilson et al., 2010; Little et al., 2011; Prince et al., 2011), catch-curve-derived decision rules (Wayte and Klaer, 2010), and sharing data from more informed species (Smith et al., 2009; Punt et al., 2011). Recent developments from around the world of many of these methods highlight the increased need for such options to inform management, while the variety reflects different data availabilities, theoretical approaches (empirically derived versus model-based; Prince et al., 2011) and management system needs, underscoring the diversity of situations in which “data-limited/poor” methods are relevant. Also salient in each of these approaches is the numerous ways “data-poor” can be interpreted. Broadly, one can define “data-poor” as any situation where information limitations prohibit one from accomplishing a task (i.e., performing traditional stock assessments; Smith et al., 2009). Realizing that “data-poor” methods form more of a toolbox rather than one or even competing tools is an important conceptual step towards knowing the “when and why” of applying such methods.

The extensive use and development of SS has demonstrated its suitability to complicated, data-intensive situations. However, more commonly, fisheries scientists find themselves lacking the essential data needed to perform stock assessments, and thus are challenged to inform management. Despite the technically complicated and potentially unsettling capacity of SS to consume much disparate data under a multitude of model specifications and output voluminous amounts of derived quantities, its structure is also amenable to simpler tasks. And while due caution should be applied when using any pre-coded modeling software (Martell and Ianelli, submitted for publication), the ability to develop and build up parameter information and data-fitting within a common framework is advantageous. The implementation of SSS offers a foothold in the path towards more fully realized stock assessments in SS, while providing information to advise resource managers along the way.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.fishres.2012.03.006.

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