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Evaluating a prior on relative stock status using simplified age-structured models

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ABSTRACT

Fisheries management aimed to support sustainable fisheries typically operates under conditions of limited data and analytical resources. Recent developments in data-limited analytical methods have broadened the reach of science informing management. Existing approaches such as stock reduction analysis and its extensions offer simple ways to handle low data availability, but are particularly sensitive to assumptions regarding relative stock status. This study develops and introduces a prior on relative stock status using Productivity-Susceptibility Analysis vulnerability scores. Data from U.S. west coast groundfish stocks ($n = 17$) were used to develop and then test the performance of the new relative stock status prior. Traditional simulation testing via an operating model was not possible because vulnerability scoring could not be simulated; we instead used the "best available scientific information" (BASI) approach. This approach uses fully-realized stock assessments (deemed the best available scientific information by management entities) and reduces data content available to simpler models. The Stock Synthesis statistical catch-at-age framework was used to nest within the full assessment two simpler models that rely on stock status priors. Relative error in derived estimates of biomass and stock status were then compared to the BASI assessment. In general, the new stock status prior improved performance over the current application of stock status assumed at 40% initial biomass. Over all stocks combined, stock status showed the least amount of bias, while initial biomass was better estimated than current biomass. The BASI approach proved a useful and possibly complimentary approach to simulation testing with operating models in order to gain insight into modelling performance germane to management needs, particularly when system components (e.g., susceptibility scoring) cannot be easily simulated.

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1. Introduction

Scientifically-motivated analyses and subsequent communication of findings underpin effective and sustainable resource management (Fleishman et al., 2011). The properties of available data greatly drive this capacity of science to inform management. In fisheries, the enormous diversity of data types (e.g., quality and quantity) and impacted stocks, and complexity of management systems necessitates a multitude of approaches to best negotiate the needs of decision-makers in a variety of management contexts. In addition to increasing our understanding of how data affects complex stock assessment models (Magnusson and Hilborn, 2007), many alternative approaches to providing catch limits and relative population reference points under resource limitations have been developed (Cope and Punt, 2009; Wiedenmann et al., 2013; Carruthers et al., 2014).

One particular area of development has been in the use of stock reduction analysis (SRA) to gain insight into sustainable removal levels (Kimura and Tagart, 1982; Kimura et al., 1984). Modifications to the standard SRA (Walters et al., 2006; Dick and MacCall, 2011; Cope, 2013; Martell and Froese, 2013; Thorson and Cope, 2015) have gained wider application and relevance as alternative methods to inform management for stocks with limited data (Dick and MacCall, 2010). Such approaches have the common need of a time-series of catches and some measure of relative stock status to scale the historical removals to current biomass and define sustainable removals in relation to management reference points. These two inputs (removals and relative stock status) are also common to other data-limited methods being applied in management (MacCall, 2009; Berkson et al., 2011), highlighting their general importance.

While a removal time-series in some form may be reconstructed (Vasconcellos and Cochrane, 2005; Berkson et al., 2011), prior

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knowledge of stock status is almost always unknown. Current practice often uses the same prior for relative stock status that assumes the stock is currently at the target status level (e.g., 40% of unfished conditions) and is applied universally to all stocks in question (Dick and MacCall, 2011). Simulation studies have subsequently demonstrated that the above models are highly sensitive to the treatment of the stock status prior (Wetzel and Punt, 2011; Wiedenmann et al., 2013; Carruthers et al., 2014). Developing a stock-specific relative stock status prior could greatly improve our application of these data-limited approaches.

This study developed and evaluated the performance of a prior on relative stock status via application to data-limited stock assessment approaches. The relative stock status prior is predicated on a relationship between stock vulnerability (as defined in the Productivity-Susceptibility Analysis by Patrick et al., 2010) and stock status as established in management-approved stock assessments. This predictive relationship, as well as the default prior (currently assumed to equal 40% of initial stock biomass), is then used to test the performance of these stock status priors in data-reduced applications conducted within a common age-structured framework. This framework serially reduces the data content within the full stock assessment to that of the SRA-type analyses that use either catch-only or catch and biomass index data. Model performance is compared against the fully-specified assessment (e.g. including biomass indices, and length and age data) results, considered the best available scientific information (BASI), for several model-derived outputs under different stock status prior assumptions. This approach is different than the commonly used simulation testing approach, and the pros and cons of using the BASI approach rather than simulation testing are discussed.

2. Methods

2.1. Data, modelling and management context

We used the U.S. Pacific Fishery Management Council (PFMC) Groundfish Fishery Management Plan (FMP) (PFMC, 2011) and stock assessments as the basis for the stocks, data, and comparisons in this study. The PFMC groundfish FMP contains 90+ stocks managed under the reauthorized Magnusson-Stevenson Fishery Conservation and Management Act of 2006. Under the National Standard Guidelines (U.S. Office of the Federal Register, 2009) of this Act, NOAA Fisheries via the PFMC decision-making process is mandated to provide annual catch limits (ACLs) and overfishing limits (OFLs) for each stock. The stock state of nature relative to overfishing (a fishing mortality reference point) and an overfished state (a relative biomass reference point) are additional important quantities required for sustainable management. Currently, the PFMC recognizes three categories[1] of modelling approaches providing all or some of the above information:

Category 1: statistical catch-at-age/length model containing, at minimum, a time series of removals fit to biomass indices and biological composition data (e.g., age or lengths). This is often referred to as a "full stock assessment";
Category 2: models that use a time series of removals and fit to biomass indices. Referred to asa "data-moderate" model;
Category 3: catch-only models not fit to any data. Referred to as a "data-poor" model.

Category 1 and 2 models usually provide catch recommendations and biological reference points. Category 3 had previously only been considered for informing catch recommendations (e.g. OFLs). Overfishing may be determined in all three modelling categories depending on the policy treatment of the OFLs. This study focused on whether spawning biomass and relative stock status can be accurately estimated in Category 2 and 3 models, given an informative prior on stock status derived from Category 1 stocks.

Stock Synthesis (SS; Methot and Wetzel, 2013) is the prevailing statistical catch-at-age modelling framework used in PFMC groundfish stock assessments. Cope (2013) demonstrated the SS framework was flexible enough to conduct category 3 (catch-only) models (deemed "Simple" Stock Synthesis or SSS). Subsequent work (Cope et al., 2013) has also applied the SS framework to category 2 models (following, e.g., Hilborn, 1990). This approach is referred to as "extended Simple Stock Synthesis" or "XSSS". Both the category 2 and 3 extensions of SS use sampling of priors on natural mortality, steepness (the Beverton–Holt recruitment compensation parameter; Mace and Doonan, 1988), and relative stock status to estimate initial recruitment. XSSS, by fitting biomass indices, also estimates an additional variance parameter for each index, representing variance for the biomass index in excess of the variance estimated from inputted variance and hence representing potential variation in catchability for the index (see Wilberg et al., 2010). SSS and XSSS also differ in the way variance of derived model outputs are determined: SSS uses Monte Carlo sampling, while this XSSS implementation uses an adaptive importance resampling approach (Wetzel and Punt, 2015) that applies weighted sampling to update the priors based on fits to the indices. Detailed methods for SSS and XSSS can be found in Cope (2013) and Wetzel and Punt (2015). This full complement of SS modelling extensions was used in the BASI comparisons (described below) to test the performance of the vulnerability-based relative stock status prior.

2.2. Building the relative stock status prior

Previous applications of the relative stock status prior to SRA type models made two assumptions: (1) stock status was defined in the terminal (i.e., final available) year of the time-series and (2) it was set at 40% the initial stock biomass (Dick and MacCall, 2010). The proposed new stock status prior frees up both of these assumptions. Defining the prior earlier in the time-series, at a point in time when there is information on stock status, allows subsequent removals and biomass indices (if any are available) to inform terminal stock status (an important management reference point). By setting stock status at the terminal year, one has pre-determined status and disqualified any opportunity to inform current stock status. The first steps, then, in determining a relative stock status prior were to identify a measure related to stock status and a time before the terminal year that stock status should be estimated. We used the PSA vulnerability measure and the PFMC management history to accomplish these respective tasks.

2.2.1. Defining "retrospective" vulnerability

The PSA-derived vulnerability measure (Patrick et al., 2010) uses productivity and susceptibility to define a stock's vulnerability to overfishing (Patrick et al., 2009). The relationship of vulnerability to stock status assumes that a long period of relatively consistent vulnerability (and thus fishing mortality) has occurred. For this reason, a year was chosen that represented the most recent year before management had significant impact on removals. Stocks in the PFMC groundfish FMP generally experienced large reductions in fishing mortality post-2000 due to management changes, thus vulnerability also changed. Each stock had at least 20 to 30 years (with 50–75 years being more typical) of significant removals prior to year 2000.

All stocks with a category 1 stock assessment less than 5 years old were considered when building the stock status prior ($n = 17$;

[1] http://www.pcouncil.org/wp-content/uploads/I2b_SUP_SSC_APRIL_2010_BB.pdf.

Table 1
Retrospective vulnerability score (from highest to lowest), stock status in year 2000, and the results from the Type C meta-analysis, (i.e. excluding each stock sequentially and re-fitting the model) for 17 groundfish stocks with full stock assessments. Values for both the lognormal and the beta parameterizations are provided. Stocks in gray were not used in the subsequent assessment comparisons (see Section 3.2 for details). Full stock assessments (and thus the stock status values) for each species can be found at http://www.pcouncil.org/groundfish/stock-assessments/.

Stock	Scientific name	Vulnerability v_i	Stock status$_{2000}$	$E[D_i]$	beta *SD*	$E[\ln(D_i)]$	ln *SD*
Yelloweye rockfish	*Sebastes ruberrimus*	2.53	0.17	0.17	0.12	0.73	0.70
Canary rockfish	*Sebastes pinniger*	2.52	0.11	0.23	0.18	0.80	0.78
Bocaccio	*Sebastes paucispinis*	2.43	0.12	0.21	0.15	0.68	0.66
Darkblotched rockfish	*Sebastes crameri*	2.38	0.13	0.22	0.17	0.66	0.66
Blackgill rockfish	*Sebastes melanostomus*	2.17	0.18	0.33	0.19	0.68	0.61
POP	*Sebastes alutus*	2.08	0.14	0.36	0.20	0.64	0.57
Widow rockfish	*Sebastes entomelas*	2.05	0.32	0.34	0.22	0.64	0.61
Aurora rockfish	*Sebastes aurora*	2.01	0.70	0.31	0.17	0.51	0.52
Splitnose rockfish	*Sebastes diploproa*	1.95	0.36	0.39	0.25	0.66	0.62
Petrale sole	*Eopsetta jordani*	1.94	0.09	0.39	0.18	0.45	0.44
Shortspine thornyhead	*Sebastolobus alascanus*	1.8	0.78	0.41	0.25	0.56	0.56
Lingcod	*Ophiodon elongatus*	1.71	0.41	0.50	0.29	0.63	0.62
Cabezon	*Scorpaenichthys marmoratus*	1.69	0.36	0.51	0.28	0.62	0.62
Sablefish	*Anoplopoma fimbria*	1.67	0.53	0.50	0.29	0.63	0.63
Pacific whiting	*Merluccius productus*	1.62	0.38	0.54	0.28	0.62	0.67
Dover sole	*Microstomus pacificus*	1.54	0.70	0.54	0.28	0.65	0.63
Longspine thornyhead	*Sebastolobus altivelis*	1.53	0.46	0.58	0.27	0.63	0.68

Table 1). Cope et al. (2011) conducted a PSA on all PFMC groundfish species for the year 2010 and also used retrospective vulnerability scores to define vulnerability reference points. The vulnerability scoring excluded any susceptibility attributes informed by stock assessments so as to avoid contamination of assessment-influenced susceptibility scoring. We followed that approach to obtain a vulnerability measure in year 2000 for each of the 17 groundfish stocks. Susceptibility scores from Cope et al. (2011) were rescored to reflect how vulnerability would have been scored in the year 2000 (i.e. only using information available at that time). Productivity scores were not changed because they are not expected to change over such short time periods relative to the maximum expected ages of these stocks. These retrospective vulnerabilities were then compared to category 1 stock assessment estimates of relative stock status (specifically, SB_{2000}/SB_0, where SB is spawning biomass) for the year 2000. A standard error for each stock assessment estimate of relative spawning biomass was also recorded.

Both vulnerability and relative stock status of the 17 stocks considered demonstrated good contrast in values used in the predictive model. The vulnerability scores ranged from low to major vulnerability (Fig. 1) based on the Cope et al. (2011) vulnerability reference points. While absolute vulnerability scores theoretically range from 0 (highest productivity and lowest susceptibility) to 2.83 (lowest productivity and highest susceptibility), such a range is not uniformly expected or observed. Patrick et al. (2009) considered 150 stocks throughout the U.S. and found only 1 with a higher vulnerability score than the highest used in this study, while 30% of the stocks they considered were below the lowest vulnerability score of this study (but less than 2% with $V<1.0$). Relative stock status generally ranges between 0 and 1, and the minimum and maximum stock status values in year 2000 were 0.11 and 0.78.

2.2.2. Formulating the stock status priors

We sought to estimate parameters for a model that predicts relative spawning biomass estimates for the year 2000 from the most recent assessment for each species, using retrospective PSA scores for year 2000. A regression model was used that satisfies the following four principles:

The expected value of predictions for relative stock status is between 0 and 1 for each stock. This arises from the knowledge that stocks cannot have negative spawning biomass, and assume they will not sustain spawning biomass above SB_0 for prolonged periods and hence will not have an expected relative value above 1.

An increase in vulnerability is associated with a decreasing expectation for relative stock status.

Realized values of relative stock status are bounded to be above 0, but has no theoretical upper limit. This follows from the recognition that natural variation in recruitment can result in spawning biomass being above SB_0 (e.g., Pacific hake, Pacific halibut).

The distribution for realized values of relative stock status around its expected value is lognormal. This arises because recruitment variability is considered lognormally distributed, and hence the sum of spawning biomass from different cohorts has larger tails than expected under a normal distribution.

The simplest model that satisfies these four principles is a logit-linear model for the expected value of relative stock status μ_i for each stock i as a function of retrospective vulnerability v_i for that stock:

$$\mu_i = \frac{1}{1+\exp\left[-\beta_0+\beta_v v_i\right]}$$

where β_0 controls the level of vulnerability that results in expected value of relative stock status $\mu_i = 0.5$, and β_v controls the strength

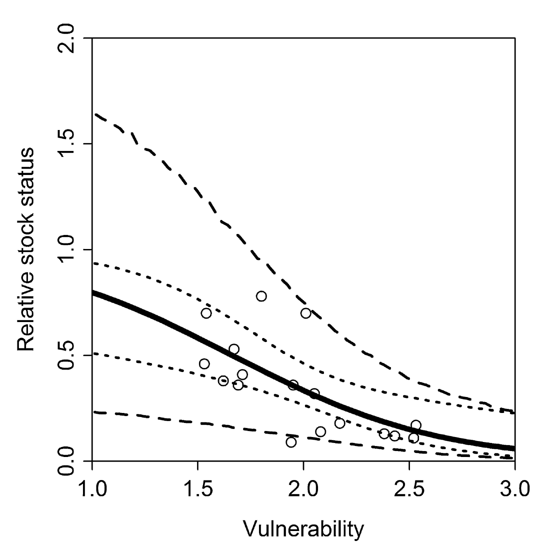

Fig. 1. Expected value (solid black line), 90% credible interval for this expectation (dotted lines), and 90% predictive interval (dashed lines) for relative stock status in year 2000 (SB_{2000}/SB_0) as a function of vulnerability for each species used in this analysis.

of the relationship with vulnerability (where $\beta_v = 0$ corresponds to the null hypothesis that retrospective vulnerability has no ability to predict subsequent values of relative stock status). Realized values of relative stock status from category 1 stock assessments are then distributed around their expected values:

$$D_i \sim \text{Lognormal}\left(\ln(\mu_i) - \frac{s_i^2 + \sigma^2}{2}, s_i^2 + \sigma^2\right)$$

where s_i is the stock assessment estimate of standard error for relative stock status for stock i, and σ represents variability in spawning biomass in excess of that expected based on each standard error. This equation includes bias correction to ensure that μ_i represents the expected value (and not predictive median) for relative stock status.

This model was fitted using a Bayesian statistical paradigm. We therefore specified weakly informative and independent priors, i.e.: $Pr[\sigma] = 1/10$ for all values between 0 and 10; $Pr[\beta_0] = 1/20$ for all values between −10 and 10; and $Pr[\beta_v] = 1/20$ for all values between −10 and 10. This model was fitted with Markov chain Monte Carlo sampling implemented using JAGS (Plummer, 2003) called from the R statistical environment (R Development Core Team, 2013) using the R2jags package (Su and Yajima, 2012). We used three sampling chains, each started at values randomly drawn from the prior distributions. Each chain involved 10,000 samples burn-in, followed by 10,000 monitored samples, while retaining every 10th sample. This resulted in 3000 retained samples when combining across all three chains, and we checked for evidence of non-convergence using trace plots, the Gelman–Rubin R-statistic, and the effective sample size for each parameter.

This model was summarized by predicting relative stock status $\hat{D}_j$ for a hypothetical stock j that was not included in the meta-analysis, given different possible values for vulnerability v_j. We also performed a Type C meta-analysis (Minte-Vera et al., 2005; Thorson et al., 2013), in which we sequentially excluded each stock, re-fit the model, and then estimated relative spawning biomass for the excluded stock. The Type C approach is a type of cross-validation that produces an independent predictive posterior for the stock excluded from the analysis and thus ensures that data from a given stock are not being used when estimating the expected value, credible interval, and predictive interval for relative stock status for that stock.

For this application, we then transformed these priors to conform to current practices for treating stock status priors in data-limited applications, which lack any stochastic process variability (i.e. no recruitment variance) and hence cannot have relative stock status >1. We therefore converted each prior from a lognormal distribution to a beta distribution with an identical mean and standard deviation, for use in this application (where the comparison of parameters for beta and lognormal priors is shown in Table 1). In some cases this required a small ad hoc decrease in the variance to ensure that the beta-distribution was unimodal, although future state-space applications of stock-reduction analyses (i.e., Walters et al., 2006; Thorson and Cope, 2015), e.g., using process variability in recruitment, could use the original lognormally distributed priors.

2.3. "Best available scientific information" comparisons

The implementation and performance of the stock status prior in SSS and XSSS models were conducted as comparisons to the category 1 stock assessment models. For each stock, data was removed from the category 1 assessment until only catch data and biomass indices (XSSS) or only catch data (SSS) remained (Table 2). All biomass indices used in the full stock assessment were retained in the XSSS models. Each of the data-reduced models assumed selectivity was equal to maturity rather than the form estimated or assumed in the full assessment models (Dick and MacCall, 2011; Cope, 2013). Recruitment deviations were not estimated in the data-reduced models (although these could possibly be estimated in future applications of SSS and XSSS). Life history parameters were set to the fixed values or the maximum likelihood estimate (MLE) of the full assessment, except for natural mortality and steepness. The natural mortality prior was assumed lognormal, with the mean taken as the category 1 assessment MLE and the standard deviation = 0.4. Steepness assumed the prior specified in the category 1 stock assessment or those commonly assumed for each groundfish taxa (e.g., rockfishes, flatfishes, or roundfishes). Relative stock status priors were beta-distributed, and two parameterizations were considered for comparison: the commonly applied mean of 0.4 and standard deviation of 0.2 for all stocks, or the new prior determined for each stock (Table 1).

2.4. Performance measures

Performance of the data-reduced models and relative stock status priors were considered using three derived quantities: initial spawning biomass (SB_0), terminal spawning biomass (SB_{term}), and relative stock status (SB_{term}/SB_0). Relative error was used to quantify model and prior performance as

$$RE = \frac{DQ_{\text{DR}} - DQ_{\text{SS}}}{DQ_{\text{SS}}}$$

where RE is relative error, DQ_{DR} is the estimate of a derived quantity from the data-reduced model (either SSS or XSSS), and DQ_{SS} is the estimate of a derived quantity from the full SS (category 1) model.

3. Results

3.1. Vulnerability-based stock status prior

Retrospective vulnerability scores and stock status demonstrated a conspicuous relationship, with higher vulnerability corresponding to lower stock status (Fig. 1). Uncertainty in this relationship was also notably high, resulting in a large range of potential stock status values for a given stock. Sensitivity to the inclusion of any given stock demonstrated general robustness in the median response of the prior, with the higher quantiles of uncertainty showing the most sensitivity to stock exclusion (Fig. 2). The vulnerability-based stock status priors showed appreciable differences across stocks to the default prior mean of 0.4 (Fig. 3). They also demonstrated similar or greater uncertainty than the default value of 0.2 (Table 1), implying that assessed stocks are more dispersed in their assessment estimates of relative stock status in 2000 than previously assumed. Three stocks (cabezon, lingcod, and sablefish) had the most diffuse priors.

3.2. Comparing model inputs

Of the 17 stocks used for the relative stock status prior distributions, 12 of them were deemed useful to the current application of the SSS and XSSS models (Fig. 1). The five stocks not included in the BASI comparisons demonstrated poor MLE convergence over repeated sampling in either the SSS or XSSS implementation, so attempts were abandoned to include those stocks in the present comparisons. For the remaining stocks, the SSS (removals only) and XSSS (biomass indices and removals) models had greatly reduced data types and quantities compared to the full SS models (Table 2). The lack of extensive data underscored the importance of the prior distributions specified for each parameter.

Table 2
Parameterization and data input sample sizes for each of the Stock Synthesis models. Y = yes; N = no.

Model dimensions	Rockfishes																	
	Aurora			Blackgill			Canary			Darkblotched			POP			Splitnose		
	SS	XSSS	SSS	SS	XSSS	SSS	SS	XSSS	SSS	SS	XSSS	SSS	SS	XSSS	SSS	SS	XSSS	SSS
No. of fleets	2	2	0	3	3	3	12	1	1	2	2	2	1	1	1	3	1	1
No. of surveys	4	4	0	7	3	0	6	4	0	4	4	0	6	6	0	4	4	0
No. mean weights	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	7	0	0
No. length comp. years	88	0	0	164	0	0	291	0	0	71	0	0	76	0	0	69	0	0
No. age comp. years	10	0	0	44	0	0	133	0	0	35	0	0	40	0	0	6	0	0
No. time blocks	11	0	0	2	0	0	13	0	0	12	0	0	5	0	0	1	0	0
No. recruitment deviations	51	0	0	111	0	0	49	0	0	52	0	0	57	0	0	47	0	0
Modelled discards?	Y	N	N	N	N	N	N	N	N	Y	N	N	Y	N	N	Y	N	N
M fixed?	Y	N	N	Y	N	N	Y	N	N	Y	N	N	N	N	N	Y	N	N
h Fixed?	Y	N	N	Y	N	N	Y	N	N	Y	N	N	Y	N	N	Y	N	N
Growth estimated?	Y	N	N	Y	N	N	Y	N	N	Y	N	N	N	N	N	Y	N	N
Selectivity estimated?	Y	N	N	N	N	N	Y	N	N	Y	N	N	Y	N	N	Y	N	N

Model dimensions	Rockfish			Flatfishes						Roundfishes								
	Widow			Dover sole			Petrale sole			Cabezon			Lingcod			Sablefish		
	SS	XSSS	SSS	SS	XSSS	SSS	SS	XSSS	SSS	SS	XSSS	SSS	SS	XSSS	SSS	SS	XSSS	SSS
No. of fleets	5	5	5	3	3	3	6	1	1	7	1	1	2	1	1	3	1	1
No. of surveys	8	8	0	4	4	0	3	3	0	7	7	0	3	3	0	5	5	0
No. mean weights	0	0	0	24	0	0	51	0	0	102	0	0	0	0	0	24	0	0
No. length comp. years	144	0	0	163	0	0	294	0	0	134	0	0	78	0	0	124	0	0
No. age comp. years	112	0	0	108	0	0	166	0	0	9	0	0	50	0	0	95	0	0
No. time blocks	4	0	0	10	0	0	18	0	0	3	0	0	1	0	0	8	0	0
No. recruitment deviations	32	0	0	50	0	0	49	0	0	27	0	0	80	0	0	46	0	0
Modelled discards?	N	N	N	Y	N	N	Y	N	N	N	N	N	Y	N	N	Y	N	N
M fixed?	N	N	N	N	N	N	N	N	N	Y	N	N	Y	N	N	N	N	N
h Fixed?	Y	N	N	Y	N	N	N	N	N	Y	N	N	Y	N	N	Y	N	N
Growth estimated?	Y	N	N	Y	N	N	Y	N	N	Y	N	N	Y	N	N	Y	N	N
Selectivity estimated?	Y	N	N	Y	N	N	Y	N	N	Y	N	N	Y	N	N	Y	N	N

3.3. Performance of prior type and modelling approach using BASI reference

Models using the vulnerability-based stock status priors generally produced either less biased or more negatively biased results relative to the full stock assessment (i.e., the BASI baseline) across all derived model outputs when compared to the default prior (Figs. 4 and 5). This translates to better or, when bias was greater, more conservative performance when compared to using one default prior for all stocks. These results are most apparent in stocks with higher vulnerability (based on vulnerability reference points from Cope et al., 2011) or lower relative stock status (Fig. 4). Variance in relative error also tended to decrease when using the vulnerability-based stock status prior. Less vulnerable stocks with higher relative stock status showed little to no improvement in relative error when using the vulnerability-based relative stock status prior (Fig. 5). This is unsurprising as several of those stocks are at (e.g. petrale sole) or near (e.g., lingcod, cabezon, and sablefish) the default prior value by chance, thus the more variable vulnerability prior offers little gain in such circumstances.

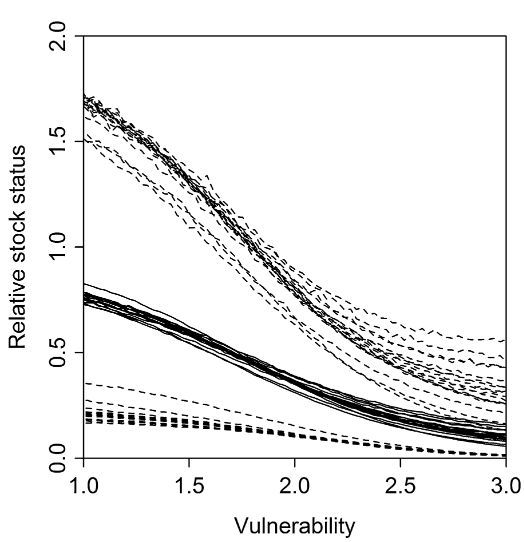

Fig. 2. Expected relative stock status in year 2000 (SB_{2000}/SB_0) and 90% predictive intervals arising from each type C meta-analysis (i.e. excluding each stock sequentially and re-fitting the model).

BASI comparisons also clearly demonstrated the gain in performance across all derived outputs when using XSSS approach over SSS (Figs. 4 and 5). XSSS models typically produced results with less bias and variance in error relative to the SSS models (when comparing both to the full stock assessments). Cases that did not show much difference between the SSS and XSSS models (e.g., widow rockfish) are indicative of models that have uninformative biomass indices, and thus little is gained by applying XSSS. Such cases that eliminated the influence of the model type (e.g., SSS vs XSSS), leaving only the prior type as a variable, supports the conclusion of improved performance of the vulnerability-based stock status prior.

Overall, initial spawning biomass and relative stock status showed less bias and variance compared to the terminal year biomass (Figs. 4 and 5). Relative stock status was the best performing of the derived quantities across all prior types and modelling approaches.

4. Discussion

Using vulnerability-based stock status priors, rather than assuming all stocks were at one pre-specified status level, offered an overall improvement in estimating three important derived model outputs for the groundfish stocks considered in this study.

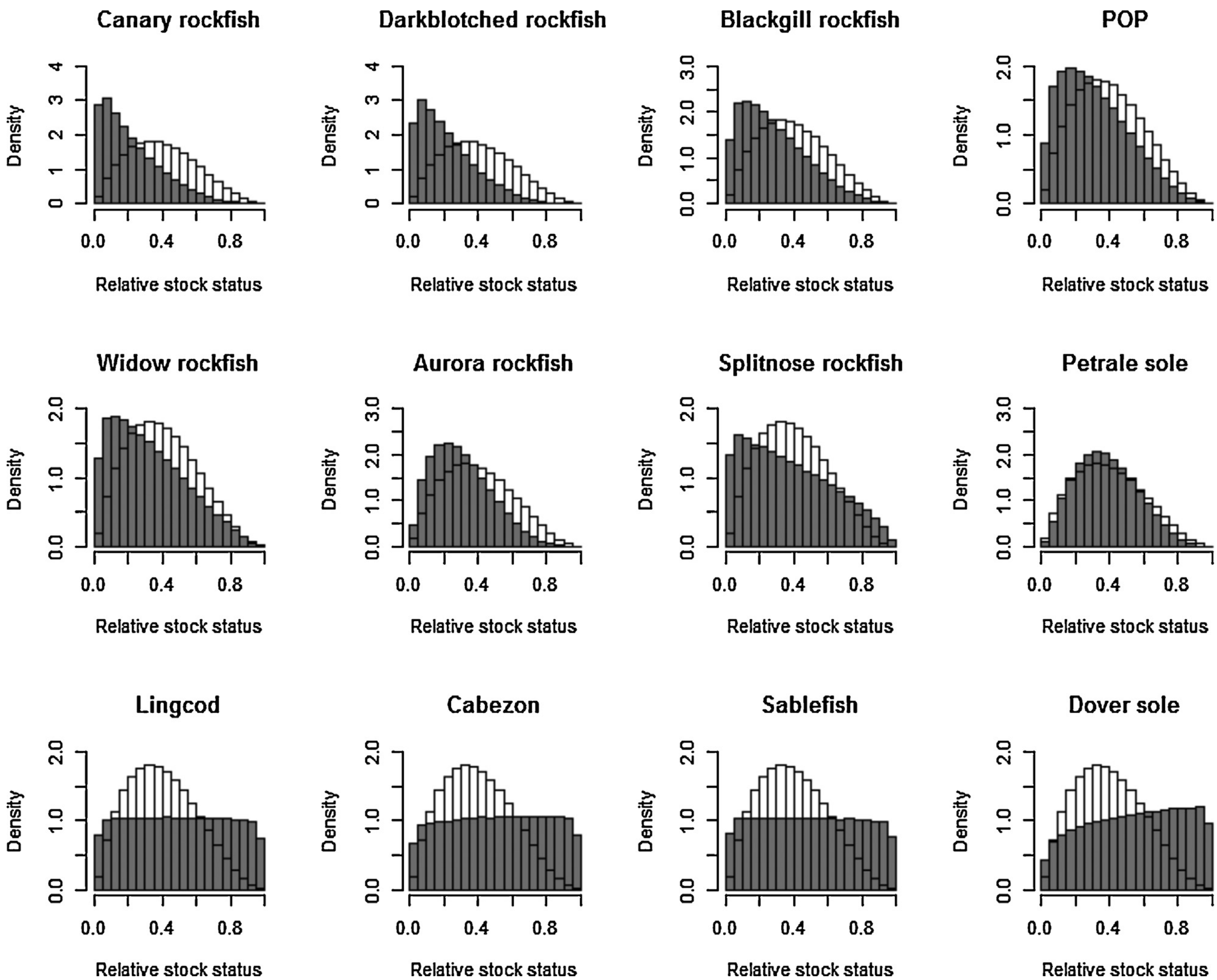

Fig. 3. Comparison of the relative stock status priors for each stock considered. White bars indicate a prior with mean of 0.4 and standard deviation of 0.2. Dark bars indicate priors based on the stock-status and vulnerability relationship (Table 1). Stocks are listed from highest to lowest retrospective vulnerabilities.

The groundfish stocks considered here represented a wide range of vulnerabilities and relative stock statuses (Table 1). However, further exploration of this approach with more taxa is recommended. The derived outputs give important insight into the scale (absolute level of biomass) and status of each population, all of which translate directly to catch recommendations. Gains in performance were particularly prominent in stocks that have suffered the greatest declines. When performance was not improved over the arbitrarily-set common prior (typically in the low vulnerability stocks above target biomass), differences in estimates of derived parameters were relatively small. Aggregate performance across stocks of high and low vulnerability demonstrated improved performance using the new prior when relative stock status is unknown, avoiding the danger of applying a common prior across stocks of variable relative stock status.

We recognize that there may be trepidation to use, for management, stock status estimates from catch-only models (i.e., category 3-type models). While such practice should be done cautiously, our results demonstrate that, at minimum, course stock status determinations (e.g., above or below a status reference point) could guide management action beyond just setting catch limits, while also being used as a tool to prioritize stocks for future full stock assessments. The prior also proved useful in models that included biomass indices (i.e., XSSS). In general, we suggest that the variety of data-limited methods being developed that require some estimate of relative stock status can benefit from the approach presented here.

Given the promising results of this new prior, questions on how best to parameterize it are relevant. In this implementation, we used the beta distribution in order to make a more direct comparison to past applications. The original form of the prior we developed uses a lognormal relationship and could be applied as such in the future. Stock status bins (e.g., high, medium and low stock status) have also been considered[2] for estimating the prior on relative stock status, although we recommend the log-linear model presented here because it was developed to conform to a priori principles (see Section 2.2.2). We also note that future development of the relative stock status prior could include different methods for importing stock status information from Category 1 assessments (used as data known without error in the meta-analysis). Possible improvements include analyzing Bayesian posteriors or likelihood profiles from each assessment, where each of these would be expected to better transmit information from the original assessment (Stewart et al., 2013; Thorson et al., 2014) and employing partially specified models to better manage model assumptions (Wood, 2001). Future research could also involve estimating parameters in the

[2] http://www.pcouncil.org/wp-content/uploads/H3a_ATT1_DATA_MOD_RPT_SEP2012BB.pdf.

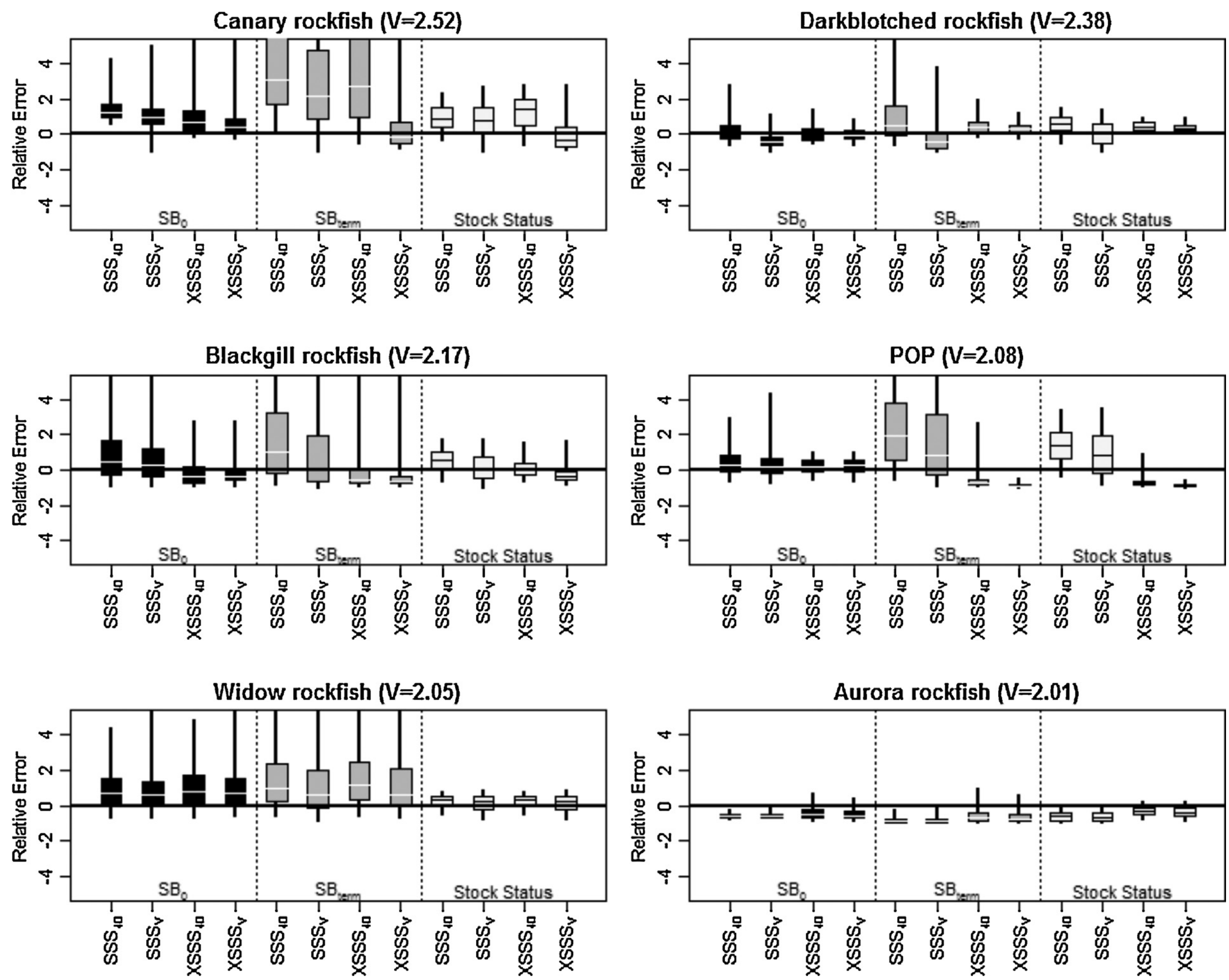

Fig. 4. Boxplot of relative error (RE) for three derived quantities (initial spawning biomass SB_0, terminal spawning biomass SB_{term}, and relative stock status SB_{term}/SB_0) across the four model types (SSS and XSSS with two stock status priors each: subscript 40 = 40%, or subscript V = prior based on vulnerability) for stocks with vulnerabilities >2.0 (high vulnerability). Vertical dotted line separates the derived quantities. Boxes indicate median (middle line) and interquartile range (edge lines); vertical lines off boxes indicate the 2.5% and 97.5% quantiles.

meta-analysis while treating the PSA attributes of productivity and susceptibility separately, rather than combining them to calculate stock vulnerability. Exploratory analysis (not shown) suggested that susceptibility was more informative than productivity in predicting stock status for the stocks considered here, a result that goes beyond the fact that productivity typically does not change retrospectively, only susceptibility does. Future research could also explore more general applications of PSA in a regression-based framework (e.g., to predict productivity (F_{MSY})) or as a means to prioritize the allocation of limited research resources. As more stocks are included in the analysis, and more performance comparisons (via the BASI approach) are made, the vulnerability-based prior may be further refined.

The BASI approach is a different, but ultimately, complimentary approach to traditional simulation testing (Butterworth and Punt, 1999). Open (Wetzel and Punt, 2011) and closed loop (Carruthers et al., 2014) simulation testing provides a controlled environment for experimental design that greatly benefits from knowing the true answers (i.e., the operating model; Peterman, 2004), and is widely used in fisheries research. Given the high level of control the researcher has over these experiments, they are also repeatable (Kelton, 1997). While simulation testing is a fundamental approach to tackling systems that are not otherwise experimentally manipulatable, simulation testing also suffers from limitations. Model misspecification, reduced applicability due to narrow operating model scope, and challenges to characterizing uncertainty (Cope, 2009; Rochet and Rice, 2009) are just some of the larger issues facing simulation studies.

Specific to this study, there was no way to effectively simulate susceptibility scoring, and thus obtaining vulnerability values, in order to simulation-test the proposed PSA-usage to define relative stock status. Using the BASI approach made practical sense given that the goal of this study was to determine if the new prior on stock status provided credible information for fisheries managers to use. It is true that this application of the BASI is neither the true state of nature of the population or the most accurate BASI possible (given a variety of assumptions made when conducting stock assessments). The BASI is instead, by definition, the best scientifically-derived information available to resource managers (e.g., full stock assessment) under the constraints of the analytical system. Thus using BASI in this form as a baseline to compare results of alternative model estimates directly relates to currently applied management uses and decisions, despite lacking a "known" answer from a controlled operating model, and is akin to model sensitivity runs common in stock assessments (Punt and Hilborn, 1997). The BASI approach benefited from the nested modelling framework (here conducted in Stock Synthesis), because internal consistencies in model structure, parameter treatment, and likelihood components/minimization routines decreased the chance that model outcomes were due to changes in modelling framework. BASI

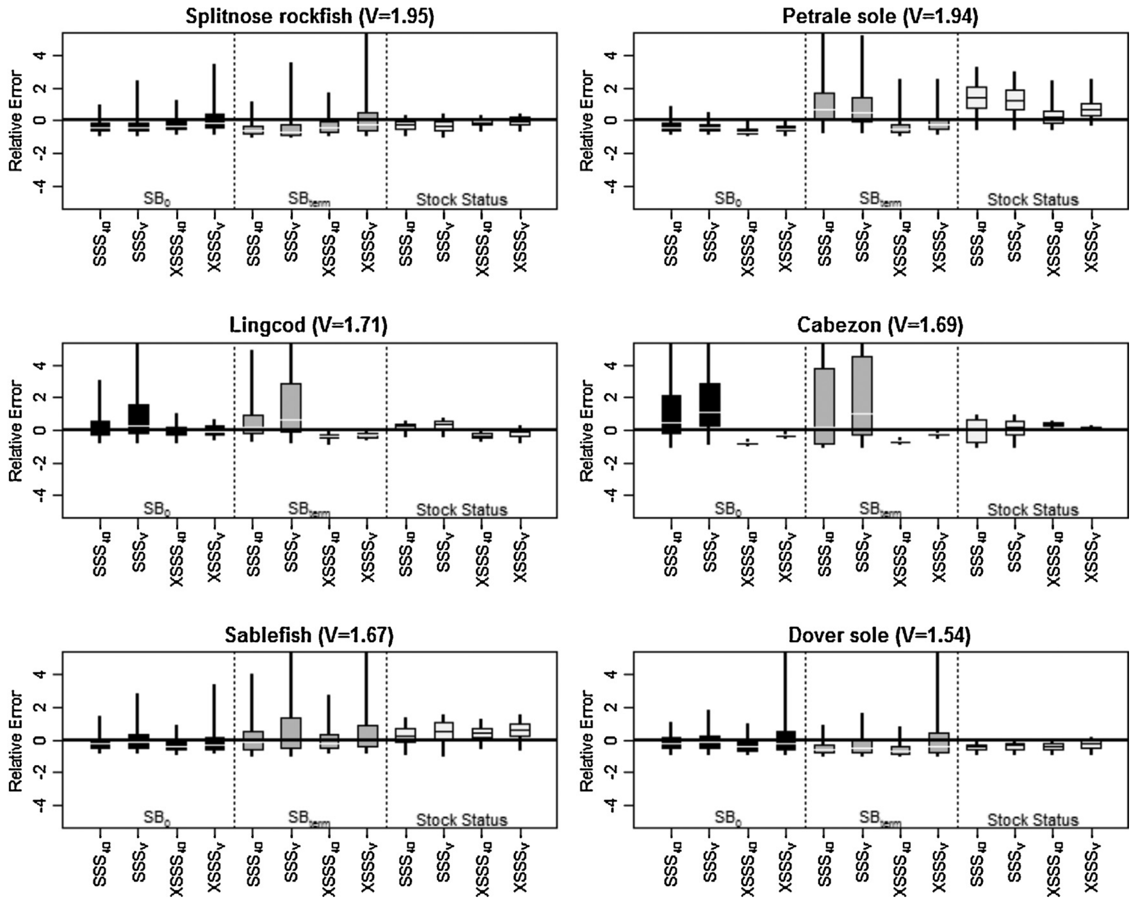

Fig. 5. Repeat of Fig. 4 for stocks with vulnerabilities <2.0 (low vulnerability). See caption to Fig. 4 for further details.

comparisons are not only relevant to fisheries management; we recommend them whenever possible (thus contributing to a larger set of performance results and patterns), something the nested modelling approach readily supports. In general, the BASI approach is another tool useful to gain a more complete understanding of how scientific analysis can help inform decision-making.

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