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JABBA-Select: Incorporating life history and fisheries' selectivity into surplus production models

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ABSTRACT

Age-structured production models (ASPMs) are often preferred over biomass aggregated surplus production models (SPMs) as the former can track the propagation of cohorts and explicitly account for the effects of selective fishing, even in the absence of reliable size- or age data. Here, we introduce 'JABBA-Select', an extension of the JABBA software (Just Another Bayesian Biomass Assessment; Winker et al., 2018), that is able to overcome some of the shortcomings of conventional SPMs and allows a direct comparison to ASPMs. JABBA-Select incorporates life history parameters and fishing selectivity and distinguishes between exploitable biomass (used to fit indices given fishery selectivity) and spawning biomass (used to predict surplus production). Applying JABBA-Select involves using an age-structured equilibrium model to convert the input parameters into multivariate normal priors for surplus-production productivity parameters. We illustrate the main elements of JABBA-Select using the stock parameters of South African silver kob (*Argyrosomus inodorus*, Scienidae) as a case study. This species is exploited by multiple fisheries and was selected as an example of a data moderate fishery that features strong contrast in selectivity over time and across fleets. For proof-of-concept, we use an age-structured simulation framework to compare the performance of JABBA-Select to: 1) a conventional Bayesian state-space model using a Pella-Tomlinson (PT) production function, 2) an ASPM with deterministic recruitment; and 3) an ASPM with stochastic recruitment. The PT model produced biased estimates of relative and absolute spawning biomass trajectories and associated reference points, which by contrast could be fairly accurately estimated by JABBA-Select. JABBA-Select performed at least as well as the ASPMs in accuracy for most of the performance metrics and best characterized the stock status uncertainty. The results indicate that JABBA-Select is able to accurately account for moderate changes in selectivity and fleet dynamics over time and to provide a robust tool for data-moderate stock assessments.

1. Introduction

For over 50 years Surplus Production Models (SPMs) have been used to analyze catch and fishing effort data to determine biomass and exploitation levels of marine populations in relation to biological reference points (BRPs) based on the Maximum Sustainable Yield (*MSY*) (Fox, 1970; Pella and Tomlinson, 1969; Schaefer, 1957), and biomass (B_{MSY}) levels associated with it. SPMs are age-, size-, and sex-aggregated models that approximate changes in biomass as a function of the biomass of the preceding year, the surplus production in biomass and the removal by the fishery in the form of catch (in biomass) and are therefore often referred to as Biomass Dynamics Models (Hilborn and Walters, 1992) to distinguish them from age-structured production models (ASPMs; Hilborn, 1990). Somatic growth, reproduction, natural

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mortality and associated density-dependent processes are simultaneously captured in the surplus production function, and the slope of this function as biomass approaches zero is the termed intrinsic rate of population increase r. An important conceptual bridge between SPM and ASPMs are delay difference models (Deriso, 1980; Schnute, 1985). Although we do not discuss them further (for a review, see e.g. Hilborn and Walters, 1992), future research could extend delay-difference models along similar lines to what we develop for SPMs in this study.

Over the last two decades there have been considerable improvements in developing and estimating parameters for SPMs (McAllister, 2014; Meyer and Millar, 1999; Pedersen and Berg, 2017; Punt, 2003; Thorson et al., 2014). Recently the user-friendly, open source Bayesian state-space SPM framework JABBA (Just Another Bayesian Biomass Assessment; Winker et al., 2018) has been applied to assess a number of international data moderate stocks, including Atlantic bigeye tuna (*Thunnus obesus*) (ICCAT et al., 2018a), Mediterranean albacore (*Thunnus alalunga*) (ICCAT, 2017), South Atlantic swordfish (*Xiphias gladius*) (ICCAT, 2017b), Atlantic blue marlin (*Makaira nigricans*) (ICCAT, 2018b), Indian Ocean black marlin (*Istiompax indica*) and striped marlin (*Kajikia audax*) (IOTC, 2018), North and South Atlantic mako shark (*Isurus oxyrinchus*) (ICCAT, 2017c) and Indian Ocean blue shark (*Prionace glauca*) (IOTC, 2017). Despite the renaissance of SPMs in data moderate assessments, a major shortcoming of the SPM framework remains that by ignoring the stock's size/age-structure, SPMs fail to explicitly account for changes in gear selectivity (Wang et al., 2014) and lag effects of spawning biomass on recruits in the population (Aalto et al., 2015). Many stock assessment scientists retain strong reservations about SPMs (Maunder, 2003; Punt and Szuwalski, 2012; Wang et al., 2014) and age-structured assessment models are now the default for most of the major stock assessments globally.

ASPMs can be viewed as a simplified, less data demanding version of an age-structured integrated model (ASIM), such as Stock Synthesis (Methot and Wetzel, 2013). Just like SPMs, ASPMs require catch time series and abundance indices and are therefore widely used in data-moderate stock assessments, where catch size or age composition data is inadequate or absent (Booth and Quinn, 2006; Thorson et al., 2019; Wetzel and Punt, 2015). In contrast to SPMs, ASPMs distinguish between spawning-biomass (*SB*) and exploitable biomass (*EB*). *SB* is the fraction of the biomass that is made up of mature fish (or females) in the population, and *EB* is the fraction of the biomass that is vulnerable to be selected by the fishing gear. The distinction between *SB* and *EB* allows accounting for important age-specific processes, such as size- (or age) dependent fishing mortality and lags between spawning and the recruitment into the fishery. However, this requires many stock parameters to explicitly model the population dynamics[1], where these parameters are either estimated (with or without Bayesian priors) or fixed at values a priori. Density-dependent processes are then typically limited to the spawner-recruitment relationship (SRR), as natural mortality (*M*) is often assumed to be age- and time invariant (Thorson et al., 2012). Moreover, the form and steepness (*h*) of the SRR and estimates of *M* are highly uncertain and it is seldom possible to estimate *h* and *M* from the data with any certainty. Values for one, or both parameters in age-structured stock assessments are therefore commonly fixed (Lee et al., 2012; Mangel et al., 2013), thereby making strong assumptions about a stock's resilience/productivity and BRPs (Mangel et al., 2013).

A critical component of ASPMs is the estimation of recruitment. Early applications of ASPMs assumed that recruitment was a deterministic function of spawning output. Restrepo and Legault (1998) were the first to extend the ASPM formulation to account for stochastic recruitment. More recently, Thorson et al. (2019) highlighted that besides extensive evidence that marine fishes have substantial variation in recruitment; to this day many applications of ASPMs assumed that recruitment is a deterministic function of spawning output. Thorson et al. (2019) argue that estimating annual variations in recruitment in age-structured assessment models, including ASPMs, is important to reduce bias and to better characterize uncertainty in in biomass trends.

Bayesian state-space formulations for SPMs could provide a more parsimonious alternative to ASPMs in data moderate situations. State-space SPMs can be used to account for both process and observation error (Ono et al., 2012; Punt, 2003). In addition, the choice of fixing key parameters, often adopted in age-structured models, can be overcome in Bayesian SPMs through the formulations of adequate priors (McAllister et al., 2001). However, even when such formulations are considered, SPMs are still likely to introduce bias to the BRPs where introductions of new gears, mesh size restrictions or minimum size limits causes changes in selectivity (Wang et al., 2014).

Here we introduce JABBA-Select, a novel Bayesian state-space surplus production modelling framework that overcomes many limitations common to conventional SPMs. JABBA-Select can account for known differences in selectivity and associated fishing mortality over time and across different fleets. It enables the inclusion of life history parameters common to ASPMs in the form of priors and can distinguish between *EB* and *SB*, making its results directly comparable to those of ASPMs. JABBA-Select derives two key parameters (the harvest rate at MSY, H_{MSY}, and shape parameter m of the production function) from the many age-structured parameters that are explicitly included in ASPM, and then uses these two derived parameters to implicitly capture the net effect of these age-structured processes. JABBA-Select is implemented as an extension of the JABBA open source software for fitting generalized Bayesian State-Space SPMs (Winker et al., 2018), and is freely available online on the global open-source platform GitHub (https://github.com/JABBAmodel/JABBA-Select). We illustrate the key concepts of JABBA-Select based on stock parameters and catch- and abundance time series for silver kob (*Argyrosomus inodorus*) caught by the South African boat-based handline and inshore trawl fisheries. We argue that JABBA-Select performs at least as well as, and often better than, alternative ASPMs commonly used in data-moderate cases. To support this claim, we use an age-structured simulation-estimation framework in the R package *CCSRA* (Thorson et al., 2019; Thorson and Cope, 2015) to compare the performance of JABBA-Select against a deterministic and stochastic implementation of an ASPMs and a comparable Pella-Tomlinson SPM.

2. Materials and methods

2.1. JABBA-Select model

We formulate JABBA-Select by extending the Bayesian state-space SPM estimation framework JABBA (Winker et al., 2018). With JABBA-Select, we seek to improve model performance of Bayesian state-space surplus production models when estimating stock status by accounting for selectivity-induced distortion of biomass indices and stock productivity. Central to JABBA-Select is the integration of prior information from spawning biomass- and yield-per-recruit models (Sissenwine and Shepherd, 1987) with integrated Beverton-Holt SRR from here forth referred to as age-structured equilibrium models (ASEMs). The ASEM is used in conjunction with age-structured assessment models to derive *MSY*-based BRPs from estimated stock parameters by searching iteratively for the fishing mortality that produces *MSY*, F_{MSY}, from the corresponding spawning biomass SB_{MSY} at MSY (Punt et al., 2013). The required ASEM inputs are parameters describing length-at-age (l_a), weight-at-age (w_a), maturity-at-age (ψ_a) and selectivity-at-length (s_a) for fisheries operating with selectivity function *s*, natural mortality *M* and the steepness parameter *h* of the BH-SRR. For convenience, the acronyms that are commonly referred to in the following sections are summarized in Table 1.

[1] Effective length at birth (t_0), maximum length (L_∞), relative growth rate (κ), mortality rate (M), weight-at-length parameters (ϖ, δ), spawner-recruit parameters (R_0, h), age-at-maturity (a_{mat}) and selectivity-at-age (S_a),.

Table 1
List and description of symbols used throughout the main text.

Symbols	Description
y	subscript for year
a	subscript for age
s	subscript for fishing selectivity
i	subscript for abundance indices
k	subscript of simulation permutations
SB_0	unfishing spawning biomass
SB_y	spawning biomas
P_y	ratio of SB_y / SB_0
$EB_{y,s}$	exploitable biomass
$C_{y,s}$	catch
$F_{y,s}$	instantaneous rate of fishing mortality
$H_{y,s}$,	harvest rate, here: $H_{y,s} = C_{y,s} / SB_y$
MSY_s	maximum sustainable yield
SB_{MSY}	spawning biomas that produces MSY
H_{MSY_s}	harvest rate at MSY, here $H_{MSY_s} = MSY_s/SB_{MSY}$
SB_{MSY}/SB_0	inflection point of the JABBA-Select surplus production function
m	shape parameter of the surplus production function
r	intrinsic rate of population increase
ψ	initial depletion of SB_1/SB_0
M	natural mortality
h	steepness of the Beverton and Holt Spawner recruitment relationship
q_i	catchabilitiy coefficient
F	instantaneous rate of fishing mortality
$I_{i,s}$	abundance index
σ^2_η	process variance
$\sigma^2_{\varepsilon i}$	observation variance
Y_{40_s}	yield at 0.4 SB/SB_0
SB_{40}	spawning biomass at 0.4 SB/SB_0
H_{40_s}	harvest rate at 0.4 SB/SB_0
P_F	ratio of $SB(F)$ / SB_0 over iterative steps F at equilibrium
$\upsilon_{1\text{-}5s}$	parameter describing the EB_P/SB_P at equilibrium
L_a	length-at-age
L_∞, k, t_0	parameters of the Von Bertalanffy Growth Function (VBGF)
$s_{a,s}$	selectivity-at-age
$s_{L50,s}$	length-at-50%-selectivity
$s_{L95,s}$	length-at-95%-selectivity
ω, δ	weight-length parameters
w_a	weight-at-age
a_{mat}	age-at-maturity (assumed knife-edge)
φ_a	maturity-at-age
a_{min}	minimum age considered in assessment
a_{max}	maximum age or Plus group (optional)

JABBA-Select has four novel components compared to conventional state-space SPMs:

1 The model uses the expression of harvest rate at *MSY* (H_{MSY}), which we define here as $H_{MSY} = MSY / SB_{MSY}$, as a reparameterization for the intrinsic rate of population increase at low population size *r*, and derives the shape parameter *m* of the surplus production curve as a function of SB_{MSY}/SB_0 (Fig. 1a). This provides a means to generate prior distributions of likely values of H_{MSY} and *m* from the ASEM using life history and selectivity function parameter inputs.
2 The parameter H_{MSY_s} is specific to fishing operations that fish with selectivity function *s* and is used to estimate the mean annual sustainable harvest rate H_{MSY_y} (see Eq. 11) to account for selectivity-induced changes of the stock's surplus production (Fig. 1b).
3 The model distinguishes between exploitable biomass EB_s and spawning biomass *SB;* the former is used to fit indices given selectivity function *s*, and the latter as input to the surplus production function to predict annual production. The parameters used to describe the ratio of $EB_{s,y}$ and SB_y, as a function of spawning biomass depletion relative to average unfished levels are inferred from the ASEM (Fig. 1c)
4 The model accounts for the underlying correlation structure between generated values H_{MSY} and *m* through the formulation of a multivariate normal (MVN) prior, which allows for estimating both parameters jointly within the model (Fig. 1d).

For illustration of these key elements of JABBA-Select, we use the stock parameter estimates for South African silver kob (Table 1). This species is exploited by the South African boat-based hook and line fishery ('linefishery') and the demersal inshore trawl fishery. With multiple abundance indices, available information on life history, but without any size composition or length-at-age data since 2010, it provides a data moderate example with strong contrast in selectivity regimes across fisheries as well as temporal changes in selectivity. The endemic silver kob is the most abundant sciaenid species in South Africa and is predominantly caught along the temperate south coast between Cape Point and East London. The species' legal minimum size limit for the linefishery was increased from 400 mm to 500 mm in 2003, which effectively resulted in an instant reduction of *EB* (Winker et al., 2013). Furthermore, an increasing proportion of the total catch has been landed by the inshore trawl, particularly after a drastic reduction in linefishing effort in 2003, which occurred concomitantly with the new minimum size regulations. In contrast to the linefishery, there are no minimum size limits for the trawl fishery and selectivity is dependent on mesh size. As a result this fishery catches a larger proportion of smaller silver kob (S_{L50} = 334 mm; Winker et al., 2014a).

2.1.1. Estimating surplus production from an Age-Structured Equilibrium Model (ASEM)

To directly link the generalized three parameter SPM by Pella and Tomlinson (1969) to the ASEM, we assume that surplus production is a function of spawning biomass (Thorson et al., 2012), so that:

$$\mathrm{SP} = \frac{r}{(m-1)}\mathrm{SB}\left(1-\left(\frac{\mathrm{SB}}{\mathrm{SB}_0}\right)^{m-1}\right) \tag{1}$$

where *r* is the intrinsic rate of population increase, SB_0 is the unfished biomass and *m* is a shape parameter that determines at which SB/SB_0 ratio maximum surplus production is attained. The shape parameter *m* can be directly translated into the SB_{MSY}, via the ratio SB_{MSY}/SB_0 (Brodziak and Ishimura, 2012; Winker et al., 2018):

$$\frac{SB_{MSY}}{SB_0} = m^{\left(-\frac{1}{m-1}\right)} \tag{2}$$

H_{MSY} is a function of *r* and *m*:

$$H_{MSY} = \frac{r}{m-1}\left(1-\frac{1}{m}\right) \tag{3}$$

and the corresponding *MSY* is the product of $MSY = B_{MSY}H_{MSY}$. Solving Eq. (3) for *r* (see Eq. (7) in Winker et al., 2018) then allows expressing surplus production as a function of our formulation of H_{MSY} instead of the intrinsic rate of population increase:

$$\mathrm{SP} = \frac{H_{\mathrm{MSY}}}{(1-m^{-1})}\mathrm{SB}\left(1-\left(\frac{\mathrm{SB}}{\mathrm{SB}_0}\right)^{m-1}\right) \tag{4}$$

The functional links between the ASEM and Pella-Tomlinson SPM are illustrated in Fig. 2, which also provides a means to translate typical input parameters of age-structured models into the key SPM parameters *r* and *m* (Maunder, 2003; Thorson et al., 2012; Wang et al., 2014). Accordingly, it is possible to generate $H_{MSY} = MSY/SB_{MSY}$ and SB_{MSY}/SB_0 from the ASEM.

The ASEM formulation is based on deterministic age-structured population dynamics at equilibrium. The numbers at age per-recruit ($\widetilde{N}_a$) are given by:

$$\widetilde{N}_a = \begin{cases} 1 \; if \; a = 0 \\ \widetilde{N}_{a-1}\exp(-s_aF - M) \; if \; a > 0 \end{cases} \tag{5}$$

where s_a is the selectivity at age *a* (Eq. A.4)*, F* is the instantaneous rate

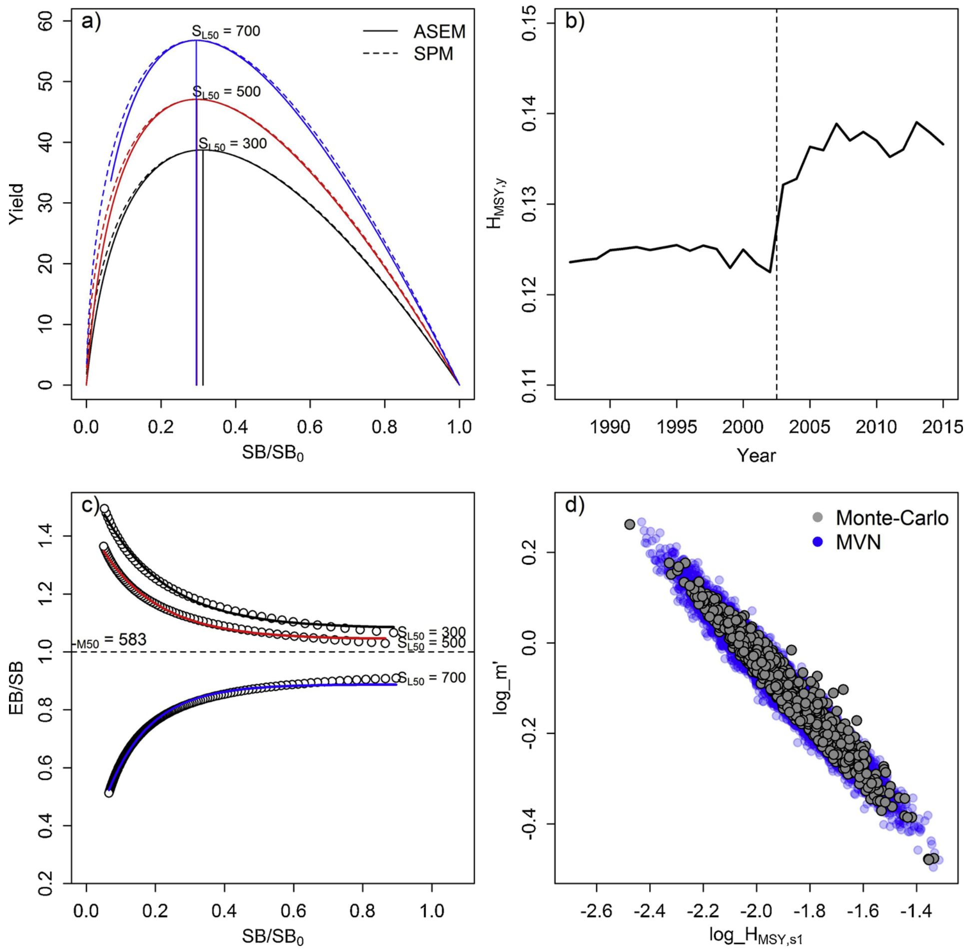

Fig. 1. Illustration of the four novel elements of JABBA-Select based on the stock parameters for silver kob: (a) Comparison of the functional forms of the yield curves produced from the Age-Structured Equilibrium Model (ASEM) with the approximation by the JABBA-Select surplus production function (Eq. 4) as a function of spawning biomass depletion (SB / SB_0), using the life history parameter input values and a range of length-at-50%-selectivity values; (b) JABBA-Select model estimates of time-varying average annual $H_{MSY,y}$(Eq. 11). The dashed line denotes the increase in minimum size limit. 11);(c) ASEM-derived selectivity-dependent distortion in the exploitable biomass (EB) relative to the spawning biomass (SB) over a wide a range of SB / SB_0 iterations, which were fitted by Eq. 10, presented for three lengths-at-50%-selectivity ; and (d) Multivariate normal (MVN) approximation of $\log(H'_{MSY_{s,k}})$ and $\log(m'_{s,k})$ random deviates generated from the ASEM via Monte-Carlo simulations (Eq. 12).

of fishing mortality and M is the instantaneous rate of natural mortality. For ease of presentation, we assumed M is constant and omitted the plus group.

The Spawning-biomass-per-recruit ($\widetilde{S}$) is obtained as function of F, such that:

$$\widetilde{S}(F) = \sum_a w_a \varphi_a \widetilde{N}_a \tag{6}$$

where w_a is the weight at age a (Eqs. A.1-A.2), φ_a is the proportion of mature fish in the population at age a (Eq. A.3) and $\widetilde{N}_a$ is the number of survivors-at-age per-recruit. The corresponding yield-per-recruit is given by:

$$\widetilde{Y}(F) = \sum_a \frac{w_a s_a F}{s_a F + M} \widetilde{N}_a (1 - e^{-s_a F - M}) \tag{7}$$

Under steady state conditions, the yield (Y) can then be expressed as a function of recruitment R and yield-per-recruit ($\widetilde{Y}$):

$$Y(F) = \widetilde{Y}(F) \times R(F) \tag{8}$$

The corresponding equilibrium spawning-biomass SB is:

$$SB(F) = \widetilde{S}(F) \times R(F) \tag{9}$$

Assuming a BH-SRR, reparameterized as a function of steepness h and virgin spawning-biomass-per- recruit ($\widetilde{S}_0$), the equilibrium recruitment at F is given by:

$$\widetilde{R}(F) = R_0 \frac{4h\widetilde{S} - (1-h)\widetilde{S}_0}{\widetilde{S}(5h-1)} \tag{10}$$

where the steepness parameter h is defined as the ratio of the average unfished recruitment R_0 when spawning biomass is reduced to 20% of unfished levels, SB_0 (Mace and Doonan, 1988). MSY and the corresponding fishing mortality F_{MSY} is obtained through iterative maximization of Eq. 6 over a range of plausible F values, which then allows the calculation of SB_{MSY} by inputting F_{MSY} into Eq. (9).

2.1.2. Accounting for fisheries selectivity effects on stock productivity

It can be shown that the selectivity-specific yield curves from the ASEM (generated through iterations of fishing mortality F) can closely approximate the shape of a selectivity-specific surplus production curve from the SPM (Eq. 1) over a wide range of logistic selectivity curves (Fig. 1a). For example, if two fleets catching the same quota but fish with different selectivity patterns, this will result in different quantities of H_{MSY} and MSY (Wang et al., 2009), but SB_{MSY} and thus the shape parameter m, is affected less. Therefore, if there are two or more fisheries that operate with different selectivity patterns, and their relative contribution to the total catch varies over time, H_{MSY} will inherently

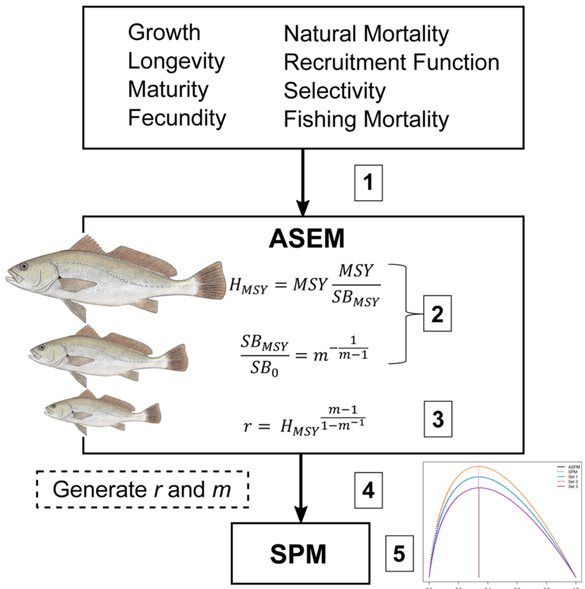

Fig. 2. Schematic of functional relationships between the productivity parameter r and the shape parameter m of the surplus production function and the Age-Structured Equilibrium Model (ASEM; i.e. yield- and spawning biomass-per-recruit models with integrated spawner recruitment relationship). Numbers in boxes denote the sequence of deriving deviates of r (H_{MSY}) and m from life history and selectivity parameter inputs into the ASEM.

become time-varying. This would equally apply to r in conventional SPM formulations.

To account for relative changes in the catch $C_{s,y}$ among multiple fisheries that operate with different selectivity functions s in year y, we estimate the year-specific H_{MSY_y} as the weighted product of the relative catch (but ignoring lag effects), such that

$$H_{MSY_y} = \sum_s (H_{MSY_s} C_{s,y}) / \sum_s C_{s,y} \tag{11}$$

so that annual estimates of H_{MSY_y} are conditioned on the relative impacts of a fishery-specific selectivity s in year y (Fig. 1c).

2.1.3. Distinguishing between exploitable biomass and spawning biomass

Accounting for selectivity dependence alone would not address additional distortions during the fitting process of any age-aggregated stock assessment model (Maunder, 2003; Wang et al., 2014), which can arise from the non-linear behaviour of the ratio of exploitable- to spawning biomass (*EB/SB*) relative to biomass depletion levels (Fig. 1c). The ratio *EB/SB* would only be constant if the functions describing age-at-selectivity and age-at-maturity were identical, and becomes increasingly disproportionate towards lower biomass levels as age-at-selectivity generally diverges from age-at-maturity (Fig. 1c). To account for this effect, we seek to integrate information about the probable response of EB_{P_s}/SB_P to changes in biomass depletion levels ($P = SB/SB_0$) into the observation equation of the JABBA-Select model (Eqs. 17–18), where EB_{P_s}/SB_P is conditioned on selectivity function s and the stock's life history parameters. Again, we make use of ASEM to obtain expected values of EB_{P_s}/SB_P for different depletion levels of P_F by iteratively changing the fishing mortality F. Initial trials indicated that the functional form of this steady-state relationship can be adequately described by an asymptotic function of the form:

$$\frac{\mathrm{EB}_{P_s}}{\mathrm{SB}_P} = \left(\upsilon_{1_s} + (\upsilon_{2_s} - \upsilon_{1_s}) \frac{1 - e^{-\upsilon_{3s}(P_F - P_1)}}{1 - e^{-\upsilon_{3s}(P_2 - P_1)}}\right) \tag{12}$$

where P_F denotes the relative depletion $SB(F)/SB_0$ as a function of F, υ_{1_s} and υ_{2_s} are parameters describing the ratio of EB_{P_s}/SB_P for the lowest and highest observed depletion P_1 and P_2, respectively, and υ_{3_s} is the rate of change between υ_{1_s} and υ_{2_s} expected for selectivity s (Fig. 3). The values of υ_{1-3_s} are estimated externally for each catch and abundance time series that have a unique selectivity function s by fitting Eq. 3 to vectors of $\mathrm{EB}_{P,s}/SB_P$ and $P_{F,s}$. In the present framework, the non-linear relationship between EB_{P_s}/SB_P and P_F is estimated externally by fixing the ASEM-values M and h to their prior means. Model exploration suggests that the errors arising from the misspecification of externally derived parameters υ_{1-3_s} can be compensated for by the process variance in JABBA-select (Eq. 13), although future research could investigate how to derive a posterior distribution for υ_{1-3_s}.

2.1.4. Multivariate normal (MVN) prior formulation for the H_{MSY} and shape m

In terms of Bayesian model formulations, the ASEM lends itself to deriving informative priors for H_{MSY} and m from Monte-Carlo Simulations to produce a distribution of likely values for MSY/SB_{MSY} and SB_{MSY}/SB_0 (Mangel et al., 2013; McAllister et al., 2001). In the following, we focus on incorporating the uncertainty associated with M and h into an informative MVN prior for H_{MSY} and the shape parameter m.

The Monte-Carlo approach is implemented based on the following steps: (1) randomly generate 1000 permutations of the leading parameters $M_k^{'}$ from a gamma distribution and $h_k^{'}$ from a beta distribution (Michielsens et al., 2004), (2) iteratively maximize Eq. 6 over a wide range of F' values to obtain $MSY_{s,k}^{'}$ given the remainder of life history parameters in Tables 2 and 3 input the corresponding F_{MSY} into Eq. 7 to obtain $SB_{MSY_{s,k}}^{'}$, (4) set $F = 0$ to obtain SB_0, using Eq. 7, (5) calculate $H_{MSY_{F,s,k}}^{'}$ and $m_{F,s,k}^{'}$ as a function of the ASEM output ratios $H_{MSY_{s,k}}^{'} = MSY_{s,k}^{'}/SB_{MSY_{s,k}}^{'}$ and $SB_{MSY_s}^{'}/SB_0^{'}$, respectively. The MVN prior is parameterized with the mean values and covariance matrix of $\log(H_{MSY_{s=1,k}}^{'})$ for selectivity type $s=1$ and $\log(m_k^{'})$ (Fig. 1d), such that:

$$\{\log(H_{MSY_{s=1}}), \log(m)\} \sim MVN(\{\log(\bar{H}_{MSY_{s=1,k}}^{'}), \log(\bar{m}_k^{'})\}, Cov\{\log(H_{MSY_{s=1,k}}^{'}), \log(m_k^{'})\}) \tag{13}$$

where $m_k^{'}$ is taken as the mean across selectivity-specific deviates for each iteration k. The prior expectation for a time-invariant m relies on the assumption that m, and thus SB_{MSY}/SB_0, can be approximated as constant over time. This assumption is also common practice in age-structured stock assessments (Punt et al., 2013), and implies independence of SB_{MSY}/SB_0 to selectivity. As illustrated in Fig. 1a, this assumption holds well for logistic type selectivity curves, but can theoretically produce biased results in the presence of dome-shaped selectivity curves (Wang et al., 2014). To then account for the selectivity effect on $H_{MSY_{s>1,k}}^{'}$ for $s > 1$ (i.e. more than one selectivity), we used the ratios of the simulation vectors $\Delta H_{MSY_{s>1}}^{'} = H_{MSY_{s>1}}^{'}/H_{MSY_{s=1}}^{'}$, where $\Delta H_{MSY_{s>0}}^{'}$ was fitted to a gamma probability density function (Fig. 3). The estimated shape and scale parameters are used to generate informative priors for $H_{MSY_{s>1,k}}^{'}$ as input to the JABBA-Select model in conjunction with the log-MVN prior for $H_{MSY_{s=1}}$ and m (Fig. 1d; Fig. 3).

2.2. Model formulation

The generalized form of the process equation is given by:

$$\mathrm{SB}_y = \mathrm{SB}_{y-1} + \mathrm{SP}_{y-1} - \sum_s C_{s,y-1} \tag{14}$$

where SP_y is surplus production for year y and C_y is the catch in year y for all fishing operations with a common selectivity s. Using Eq. 1 for SP_y and expressing spawning biomass and total catch as a fraction of SB_0, such that $P_y = SB_y / SB_0$, results in the following process equation:

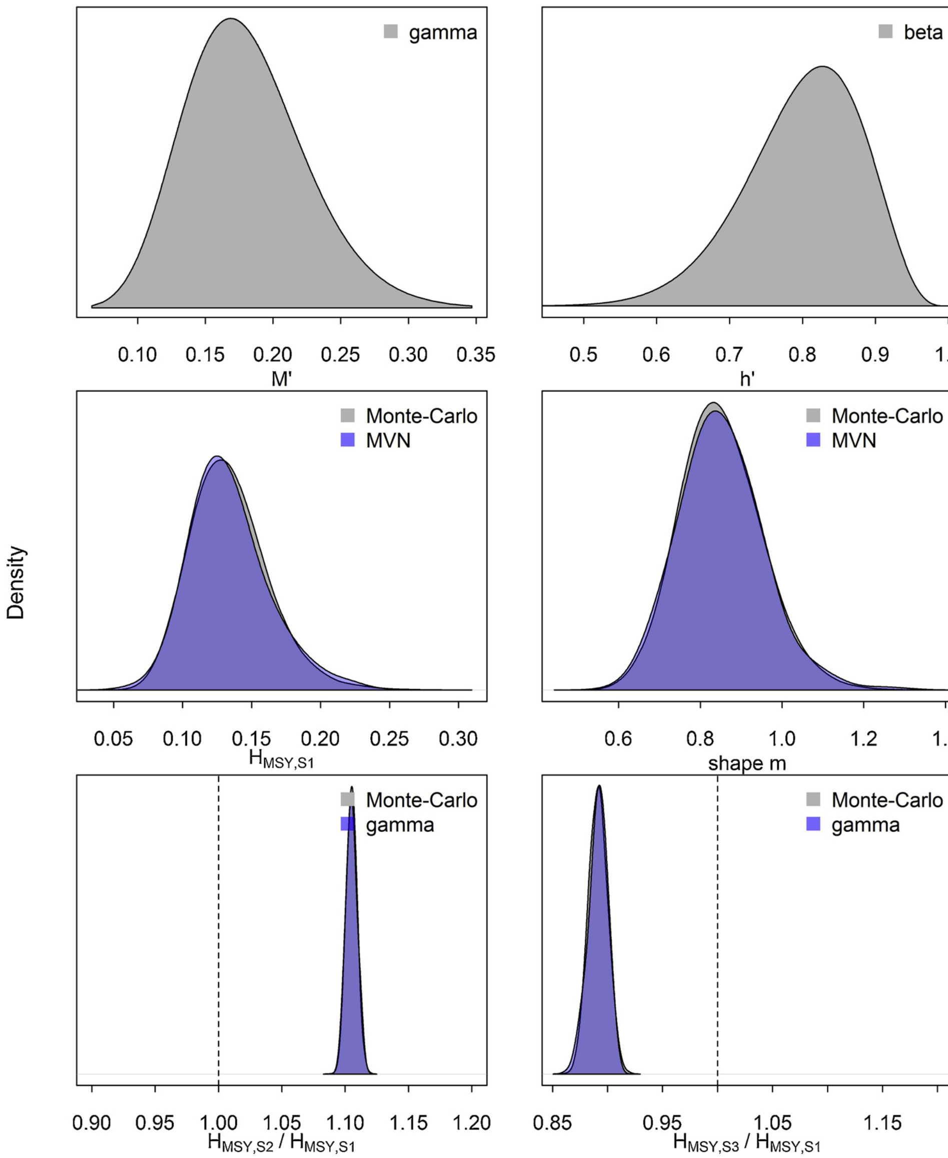

Fig. 3. Assumed distributions for natural mortality M (gamma) and steepness h (beta) deviates used as input for the ASEM to derive an informative Multivariate normal (MVN) priors for silver kob (top panels). The resulting distributions of simulated deviates of $H^{'}_{MSY_{1,k}}$ for selectivity function $s = 1$ and $\bar{m}^{'}_{k}$ and corresponding MVN approximations (middle panels) and ASEM-generated distributions of H_{MSY} ratios for recent linefishery selectivity function $s = 2$ (2004–2015) and inshore trawl selectivity function $s = 3$ to reference selectivity function $s = 1$ for early linefishery (1987–2003), which are approximated by a gamma prior.

$$P_y = \begin{cases} \psi e^{\eta_y - 0.5\sigma_\eta^2} & \text{if } y = y_{init} \\ \left(P_{y-1} + \dfrac{\sum_s \gamma_{s,y-1} H_{MSY_s}}{1 - m^{-1}} P_{y-1}(1 - P_{y-1}^{m-1}) - \dfrac{\sum_s C_{s,y-1}}{SB_0}\right) e^{\eta_y - 0.5\sigma_\eta^2} & \text{if } y > y_{init} \end{cases} \tag{15}$$

where y_{init} is the first year for the catch time series, η_y is the lognormal process error term, with $\eta_y \sim Normal(0, \sigma_\eta^2)$, σ_η^2 is the process variance, ψ is a scaling for initial biomass depletion in the first year P_1, $C_{s,y-1}$ is the catch with selectivity s in year y-1, m is the shape parameter, and $\gamma_s = C_{s,y}/\sum_s C_{s,y}$ is used as a multiplier to weight H_{MSY_s} relative to catch taken with selectivity s (Eq. 9). The corresponding spawning biomass for year y is:

$$\mathrm{SB}_y = P_y \mathrm{SB}_0 \tag{16}$$

The exploitable biomass is expressed as the product of SB in year y and the ratio of EB/SB as a function of $P = SB/SB_0$, such that:

$$\mathrm{EB}_{s,y} = \mathrm{SB}_y\left(\upsilon_{1_s} + (\upsilon_{2_s} - \upsilon_{1_s})\frac{1 - e^{-\upsilon_{3_s}(P_y - P_{1_s})}}{1 - e^{-\upsilon_{3_s}(P_{2_s} - P_{1_s})}}\right) \tag{17}$$

where υ_{1-3_s} are the externally derived parameters to approximate the ratio $\mathrm{EB}_{s,y}/\mathrm{SB}_y$ for a fishery (or survey) with selectivity s within JABBA-Select. The corresponding observation equation is given by:

$$\ln(I_{s,y}) \sim Normal(\ln(q_i \mathrm{EB}_{s,y}), \sigma^2_{\varepsilon,y,i}) \tag{18}$$

where q_i is the catchability coefficient for abundance index *i,* and $\sigma^2_{\varepsilon_{y,i}}$ is the total observation variance in year y for index *i.* Here, we specifically separate index i and selectivity s to accommodate abundance indices from fishing operations that may have comparable selectivity or observations variances but require different catchability scaling estimates. JABBA-Select allows the separation of $\sigma^2_{\varepsilon_{y,i}} = \sigma^2_{SE_{y,i}} + \sigma^2_{fix} + \sigma^2_{est_i}$ into three components: (1) the squared externally estimable observation error $\sigma^2_{SE_{y,i}}$ of the log of the expected values from the abundance index i from the standardization model, (2) a fixed additional input variance σ^2_{fix}, and (3) estimable variance $\sigma^2_{est_i}$, where the default prior option for $\sigma^2_{est_i}$ assumes an uninformative inverse-gamma distribution with both gamma scaling parameters set to 0.001 (Winker et al., 2018). All three variance components are additive and can be switched on or off in any combination to provide flexible data-weighting options to deal with

Table 2
Summary of life history parameters for silver kob used as input for the ASEM to generate priors for JABBA-Select. The following subscripts denote the three different logistic selectivity functions: s1 = linefishery (1987–2002) and s2 = linefishery (2003–2015) and s3 = inshore trawl fishery (1987–2015).

Parameter	Silver kob	Sources
L_∞	1372	Griffiths (1997)
κ	0.115	Griffiths (1997)
a_0	−0.815	Griffiths (1997)
a	0.000006	Griffiths (1997)
b	3.07	Griffiths (1997)
a_{mat}	3	Griffiths (1997)
$a_{\max}$	25	Griffiths (1997)
M	0.18	Winker et al. (2014a)
h	0.8	Winker et al. (2014a)
$a_{\min}$	0	minimum age
$a_{\max}$	20	assumed maximum age
$s_{L50,s=1}$	400	Winker et al. (2014a)
$s_{L95,s=1}$	406	Winker et al. (2014a)
$s_{L50,s=2}$	500	Winker et al. (2014a)
$s_{L94,s=2}$	504	Winker et al. (2014a)
$s_{L50,s=3}$	334	Winker et al. (2014a)
$s_{L95,s=3}$	348	Winker et al. (2014a)

Table 3
Prior specifications used in the illustrated example of silver kob, summarized by their means (μ) and coefficients of variation (CV in %).

Parameter	Distribution	μ	CV	Input
SB_0	log-normal	35000	100%	Prior
q	uniform			Prior
$\psi = SB_{y=1}/SB_0$	beta	0.1	35%	Prior
σ^2_η	inverse-gamma	$1/gamma$(0.001,0.001)		Prior
σ^2_{est}	inverse-gamma	$1/gamma$(0.001,0.001)		Prior
h	beta	0.8	10%	ASEM input
M	log-normal	0.18	25%	ASEM input

data conflicts and model misspecifications in stock assessments (Carvalho et al., 2017; Francis, 2011).

In summary, JABBA-Select is able to accommodate multiple catch time series, changes in selectivity within each fishery (e.g. due to gear regulations), and can be simultaneously fitted to multiple abundance indices with varying selectivity. JABBA-Select reduces to a conventional Pella-Tomlinson model (JABBA-PTM) if $SB = EB$ and then estimates a single H_{MSY} independent of selectivity. This JABBA-PTM can be evoked via an implemented "user option" that sets all selectivity functions associated with the catch time series and abundance indices equal to the asymptotic maturity curve parameterization (c.f. Wetzel and Punt, 2015).

Like JABBA, JABBA-Select is implemented in JAGS (Plummer, 2003), called from the statistical programming environment R (R Core Team, 2017). JABBA-Select retains the core features of a basic JABBA modelling framework (Winker et al., 2018), including its modular coding structure, a suite of options to fix or estimate process and observation variance components and inbuilt graphics to illustrate model fit diagnostics and stock status results. Its implementation in R facilitates its use alongside other packages, for example to compare assessment results or as part of a Management Procedure when conducting Management Strategy Evaluation with the R package *FLR* (Kell et al., 2007).

2.3. Application to South African silver kob

For illustration, we fitted JABBA-Select to available time series of catch and standardized catch-per-unit-effort (CPUE) data for South African silver kob. The catch time series were grouped according to three selectivity patterns: selectivity 1 ($s = 1$) was assigned to the early linefishery catch time series (1987–2003), which represents the time period before the increase in the minimum size limit in 2004; selectivity 2 ($s = 2$) represents the recent linefishery catch time series (2004–2015); and selectivity 3 ($s = 3$) represents the inshore trawl catch (1987–2015). The external parameter estimates from available size data for the corresponding logistic selectivity functions are provided in Table 2. The increase in the species' legal minimum size from 400 mm to 500 mm TL in 2003 for the linefishery changed the age-at-selectivity from approximately knife-edge selectivity at age-3 to age-4 and effectively resulted in an instant reduction of *EB* (Winker et al., 2013).

JABBA-Select was fitted to two abundance indices, which were standardized using commercial catch and effort datasets from the South African south and south-east coast fishing regions (Winker et al., 2014a, 2014b, 2013). Both early CPUE series (1987–2003) were assigned to have the same selectivity ($s = 1$), while the two most recent CPUE series (2004–2015) were assigned to selectivity 2 ($s = 2$), a single catchability q_i was specified for each of the regional abundance indices i. The standard errors for standardized annual CPUE estimates were typically $\hat{\sigma}_{SE_{y,i}} < 0.1$ and thus considered over-precise (Winker et al., 2013). To address this, an additional variance was included by setting $\hat{\sigma}_{fix_i} = 0.10$, which equates to a fixed variance component corresponding to a CV of around 14% (i.e. $\sqrt{0.1^2 + 0.1^2} = 0.14$). An additional, estimable variance $\sigma^2_{est_i}$ was assigned to each of the regional CPUE series. In this case, admitting a minimum realistic observation variance in the form of $\hat{\sigma}^2_{SE_y} + \sigma^2_{est_i}$, substantially reduced the number of MCMC iterations required to achieve convergence in the JABBA-Select model.

Key input priors approximate those used in previous age-structured stock assessments of silver kob (Winker et al., 2014a) and are summarized in Table 3. Uncertainty admitted about M and h included the ranges of 0.11-0.26 and 0.65-0.91, respectively, both within the 90% credibility intervals (Fig. 3). Considering that linefish catch reporting only commenced fully in 1987, at a time when many linefish species were already severely over-exploited (Griffiths, 2000), it was necessary to formulate priors to estimate initial spawning biomass relative to SB_0 (Table 3). The informative beta prior for ψ (mean = 0.1, CV = 35%) was based on estimates of historical reference levels from around 1900 and per-recruit spawning biomass depletion estimates, which is representative for the early period of the available time 1987–1993 (Griffiths, 2000). This information indicated an initial biomass depletion level to around 10% SB_0.

To determine stock status based on BRPs, we made use of the JABBA-Select user option to specify a target SB/SB_0 in addition to the SB_{MSY} that maximizes *MSY*. Here, we adopted $SB_{40} = 0.4 \times SB_0$ as a precautionary reference *SB* for the stock status in accordance with the South African Linefishery management protocol (Griffiths, 1997). The model was evaluated based on a number of JABBA standard diagnostics: 1) plots showing the fits to the observed abundance indices and predicted trajectories of H_y/H_{40s} and SB_y/SB_{40}; 2) the JABBA residual plot, which is described in Winker et al. (2018); 3) the process error deviates plot, which were calculated by taking the difference between deterministic expectation of $\log(\bar{B}_y)$ and stochastic realization of $\log(B_y)$ at each time step; 4) plot of posterior and prior distributions for all estimable parameters. The JABBA residual plot displays: (i) colour coded lognormal residuals of observed versus predicted CPUE indices, (ii) boxplots indicating the median and quantiles of all residuals available for any given year; the area of each box indicates the strength of the discrepancy between CPUE series (larger box means higher degree of conflicting information), and (iii) a loess smoother through all residuals to assess auto-correlated residual patterns. The plots of posterior and prior distributions were, combined with the following two metrics: (i) the posterior to prior mean ratio (PPMR) to assess the direction in which the posteriors are influenced in relation to the prior by the data and (ii) the posterior to prior variance ratio (PPVR) to further assess which parameters are informed by data.

2.4. Simulation experiment

We used a simulation approach to evaluate the performance of JABBA-select compared to three other data moderate stock assessment models in current use. The simulation procedure first creates 'true' population dynamics from an operating model (OM). The OM is used to generate typical data moderate fisheries data (catch and indices of abundance), which is used in a series of estimation models (EM). The EMs are fitted to the data to estimate the population dynamics and resulting quantities of interest. These results are then compared to the true values from the OM. The first EM is a 'naïve' JABBA-Select implementation of the Pella-Tomlinson model (JABBA-PTM). The intention is to provide contrast between more conventionally parameterized SPMs and JABBA-Select. The other two EMs are a deterministic ASPM (ASPM-det) and a stochastic ASPM (ASPM-stoch). Detailed descriptions of the OM, EM, and sensitivity analysis are given below.

2.4.1. Operating model

For the OM, we used an age-structured simulation model developed by Thorson and Cope (2015). This OM has been used for comparisons of stock assessment model performances in a number of previous studies (Thorson et al., 2019.; Thorson and Cope, 2015; Thorson and Kristensen, 2016) and forms part of the age-structured simulation-estimation tool that is implement in the open-source package *CCSRA* (Thorson and Cope, 2015) within the R statistical software (R Core Team, 2017). The population dynamic equations of the OM correspond to the ASEM formulation (Section 2.1.1) and are provided in Appendix A in Supplementary material. Growth, maturation, natural mortality, and the BH-SRR function were described by the stock parameters for silver kob (see Table 2). Stochastic variation in recruitment was introduced by treating recruitment as a lognormally distributed variable with the expected annual means derived from the BH-SRR function and a log-recruitment standard deviation of $\sigma_R = 0.5$. The unfished mean recruitment R_0 was set to 1.5 which was selected to attain an SB_0 similar to our worked example. Compared to the real-world dynamics of the South African silver kob fishery, the simulation experiment is idealized and simplified to: (1) facilitate adequate convergence of the ASPMs; (2) allow comparison with previous performance evaluations using this framework (Thorson et al., 2019; Thorson and Cope, 2015; Thorson and Kristensen, 2016); and (3) preclude other confounding factors that may not necessarily be attributed to structural differences among the EMs. A simulation horizon of 40 years was adopted (Fig. A1) under the assumption that both catch and abundance indices for a single fishery over this time period were available as input into the EMs (c.f. Thorson et al., 2019). A sharp change in length-at-50%-selectivity from 300 mm FL to 500 mm FL was introduced after 25 years to recreate the change in minimum size regulations and provide contrast between the unobservable, latent SB_y and EB_y, with the latter being proportional to the observed abundance index. This increases the age-at-50% selectivity by approximately two years and effectively results in a 21% increase in *MSY*. The observed abundance index was generated as the product of EB_y and a constant catchability coefficient ($q = 0.05$) with an associated constant lognormal observation error of $\sigma_\varepsilon = 0.2$ (Eq. A.9).

We used the effort-dynamics model by Thorson et al. (2013) to generate unique stochastic realizations k of fishing mortality trajectories that determine the population dynamics and resultant catch data. Accordingly, the instantaneous rate of fishing mortality (F_y) for year y was randomly generated based on a first-order Markov process:

$$\ln(F_{y,k}) \sim Normal\left(\ln\left(F_{y-1,k}\left(\frac{SB_{y-1,k}}{\delta SB_0}\right)^{\lambda}\right) - 0.5\sigma_F^2,\ \sigma_F^2\right) \tag{17}$$

where F_1 determines the initial fishing mortality at the start of the time series, λ is the rate of increase in $F_{y,k}$ in year y for simulation replicate k, σ_F introduces process noise around the underlying trend, and δ determines the spawning biomass depletion level to a 'bioeconomic' equilibrium as a level which is approached by $F_{y,k}$ (see Thorson et al., 2013 for further details). We conditioned the simulation model so that stock biomass decreased to low levels ranging between 5% and 20%. At these biomass levels varying strength of recovery signals were observed following the increase in size-at-selectivity from year 26 onwards (Fig. A1). This was achieved by setting $F_1 = 0.01$, $\lambda = 0.14$, $\delta = 0.17$, and $\sigma_F = 0.15$.

2.4.2. Surplus production estimation models

The JABBA-Select and the JABBA-PTM-models were fitted to the simulated abundance index I_y, and annual catch C_y (in weight) time series, where C_y was assumed to be known without error. Both I_y and C_y were split into $I_{y,1}$ and $C_{y,1}$ for the early years 1–25 and $I_{y,2}$ and $C_{y,2}$ for the recent years 26-40. For JABBA-Select, the early and recent time series were assigned to selectivity $s = 1$ ($l_s = 300$ mm) and $s = 2$ ($l_s = 500$ mm), respectively. As in the case study, a common catchability q and process variance σ_{est}^2 were estimated for the combined time series, therefore covering the entire model period (i.e. years 1–40). The fixed observation error was set to $\sigma_{fix} = 0.1$ to mimic a constant $\hat{\sigma}_{SE_i} = 0.1$ for the input time series. The priors were those used in the case study (Table 3), except that the CV for SB_0 prior was doubled (CV = 200%) and, because the stock was unfished at the start of the time series, the prior for $\psi = SB_{y=1}/SB_0$ was assumed to follow a lognormal distribution with a mean of log(1) and a CV of 30%. For the JABBA-PTM model, we assigned only selectivity $s = 1$, with the choice of $l_s = 400$ mm representing mean of the early and late size-at-selectivity that also closely approximated length-at-maturity (*i.e.* $SB_y \sim EB_y$). To still account for the selectivity change, we introduced a so called "change-point" in catchability (Carvalho et al., 2014) by estimating separate $q_{i,s}$ for the early (years 1–25) and recent years (26–40). This approach is considered to account for events that are likely to cause changes in catchability, including changes in selectivity (Winker et al., 2018). Stock parameters, process and observation variance were treated the same as for JABBA-Select EM.

2.4.3. ASPM estimation models

The two ASPMs were structurally identical to the simulation model, except that ASPM-det predicts recruitment as the expected mean from the BH-SRR. The ASPMs were fitted to the simulated abundance index I_y, and annual catch C_y (in weight) time series, where C_y was assumed to be known without error. For the reference case, we assumed perfect knowledge of parameters, except for the four estimable parameters q, M, R_0 and an estimable variance component σ_{est}^2, given a fixed input of $\hat{\sigma}_{SE_y} = 0.1$. To improve comparability, we imposed the same gamma distribution on M as for the ASEM Monte-Carlo simulation (Fig. 3). Similarly, we imposed the same vaguely informative prior on SB_0 that we used for both JABBA-Select and the JABBA-Schaefer models (Table 3). However, we resolved to fix steepness h to its 'true' value in the ASPMs after initially attempts to estimate both h and M simultaneously had caused convergence issues. ASPM parameters were estimated with Template Model Builder (TMB; Thorson and Kristensen, 2016) using the R package CCSRA (Thorson and Cope, 2015). In ASPM-stoch, the recruitment variation was estimated as random effect using the epsilon bias-correction estimator to implement bias-correction for recruitment deviations as is necessary using a maximum-likelihood estimator for this model (Thorson et al., 2019; Thorson and Kristensen, 2016).

2.4.4. Performance metrics

For JABBA-Select and JABBA-PTM, convergence of the posterior distribution was monitored by recording if all estimable parameters had passed the Heidelberger and Welch diagnostic test (Heidelberger and Welch, 1992) and the Geweke convergence test (Geweke, 1992). Convergence was consistently achieved by running three parallel Markov chains, each with 10,000 iterations, of which every second iteration was saved, and a burn-in period of 4000 iterations per chain. For the ASPMs, we assumed that a model has converged if the hessian matrix was positive definite and the absolute value of the gradient of the marginal likelihood was within < 0.0001 for each estimated fixed effect (Thorson et al., 2019). For the performance evaluation, only simulation runs where all models achieved convergence were included until 100 runs successfully converged .

For each converged simulation run, we recorded the errors in estimates relative to the 'true' value for SB_y, SB_y/SB_0 and the reference points H_{MSY_s} and MSY_s for selectivity s = 1, 2, and 3. The relative error $RE_{i,j,k}$ was recorded as:

$$RE_{i,j,k} = (\hat{X}_{i,j,k} - X_{i,j,k})/X_{i,j,k} \quad (19)$$

where $\hat{X}_{i,j,k}$ is the estimated quantity of interest i for EM j and replicate k and $X_{j,k}$ is the corresponding 'true' value. The accuracy of the estimates compared to the 'true' values was evaluated using the Median Absolute Relative Error (MARE):

$$MARE = Median(|RE_{i,j,k}|) \quad (20)$$

Bias was evaluated using the Median Relative Error (MRE):

$$MARE = Median(RE_{i,j,k}) \quad (21)$$

To assess if the models accurately capture uncertainty, we also computed the 'confidence interval coverage', by calculating the proportion of iterations out of 100 where the true value of a population parameter in the terminal year is within the 50%, 80% and 95% confidence intervals (Rudd and Thorson, 2017).

2.4.5. Sensitivity analysis

A sensitivity analysis was conducted to evaluate EM performances against a total of four OMs. The first OM is the correctly specified model (CSM), where all fixed values and prior means correspond to the EM parameterization. To introduce model misspecifications, we altered the OM input parameters and kept the EM parameterization the same as for the CSM EMs. These altered OMs are referred to as Incorrect Specified Models (ISM) and are modified as follows:

- ISM1: Increasing M from 0.18 to 0.23 and decreasing h from 0.8 to 0.65 (Figs. A2–A3)
- ISM2: Changing the selectivity curves from logistic to dome-shaped functions (Fig. A4), which creates a "cryptic" biomass of older fish that experience minimal fishing mortality (Butterworth et al., 2014).
- ISM3: A "one-way trip" (Hilborn, 1979) with constantly declining trend in abundance (Fig. A5) that contains little information about the stock's productivity (Butterworth et al., 2003).

3. Results

3.1. Case study

Linefish and trawl catches show a declining pattern over the available the available assessment horizon, which becomes more pronounced after 2010 (Fig. 4a). The model provided a fairly good fit to both abundance indices (Fig. 4b–c). However, noticeable conflicts between the two abundance indices can be seen during the years 2000–2003, and 2010-2015. Similarly, the estimated process error deviates were relatively stationary until 2003, when they started showing a systematic negative trend, which further exacerbated from 2010 through 2015 (Fig. 4d). This trend coincides with a decrease in both total landings (4a) and the abundance index (4b) over this period. Deterministically, biomass is expected to increase as a result of the substantial decrease in catches. However, the information in abundance indices shows no evidence of a positive response to the continuous decrease in catch and harvest rates relative to H_{MSY} (Fig. 4e). This appears to be partially compensated by the observation variance (Fig. 4c), and mostly by the process error (Fig. 4d). As a result, the silver kob stock is predicted to have remained in collapsed state (SB_{2015}/SB_{40} < 0.5) in accordance with the South African Linefishery management protocol (Griffiths, 1997)

A comparison of prior and marginal posterior distributions showed notable updates of the posteriors for SB_0, $H_{MSY_{s1}}$, m and the initial depletion scaling parameter φ (Fig. 5). The small posterior to prior variance ratio (PPVR = 0.063) for SB_0 suggests that the estimated SB_0 posterior is largely informed by the data. By contrast, the data holds relatively little information about $H_{MSY_{s1}}$ and m as judged by the high PPVR > 0.9, suggesting that the prior is informative about stock's productivity. The shift in central tendency towards lower productivity (low $H_{MSY_{s1}}$ and high m) is therefore likely a result of the interaction between priors and catch history in relation to the fitted abundance indices. We suspect the inference about the stock status particularly relies on the correctly specified prior for the initial spawning biomass depletion level at the start of the catch time series (φ).

3.2. Simulation-estimation experiment

A total of 115 simulation iterations were conducted for the CSM scenarios to achieve 100 replicates for which all four EMs converged. The limiting models in this regard were the two ASPMs, with convergence rates of 95% for ASPM-det and 90% for the ASPM-stoch. For the ISM runs based on OMs with misspecified M and h, dome-shaped selectivity and a one way trip, convergence of the ASPM-stoch decreased to less than 80% of runs, whereas the ASPM-det maintained a convergence rate of around 95%.

The predicted spawning biomass trajectories and associated confidence intervals differed among EMs, as illustrated for the first four CSM runs in Fig. 6. In the CMS scenario, the JABBA-PTM showed the poorest performance for accurately predicting the final year's $SB_{y=40}/SB_0$ (MARE = 0.230) and $SB_{y=40}$ (MARE = 0.224) of the age-structured stock (Fig. 7). The JABBA-PTM accuracy of SB_y and SB_y/SB_0 started to decrease relative to the three other EMs in years after the change point in selectivity (year 25), which was associated with an increasingly positive bias of SB_y and SB_y/SB_0 in recent years (Fig. 7). This indicates that re-estimating q by the JABBA-PTM for the recent period was insufficient to compensate for the selectivity induced bias. By comparison, it was possible to recover SB_y/SB_0 and SB_y more accurately with the JABBA-Select CSM (Fig. 7). For the JABBA-Select CSM the differences in accuracy of $SB_{y=40}/SB_0$ (MARE = 0.123) and $SB_{y=40}$ (MARE = 0.169) were generally small when compared to the ASPM-stoch and ASPM-det (Fig. 7). The ASPM-det performed notably poorer than JABBA-Select in estimating the absolute quantities of SB_y, while the ASPM-stoch performed more similar to JABBA-Select in terms of accuracy of SB_y, albeit associated with a systematically positive bias (Fig. 7). For all CSMs, but the ASPM-det, SB_y/SB_0 showed some positive bias during the simulation years 18–26, coinciding with the induced selectivity change after year 25. JABBA-Select produced the lowest MARE of SB_y for most years, which were similar to those of the ASPM-stoch CSM over large parts of the time series (Fig. 7). The ASPM-stoch CMS resulted in the most accurate selectivity-specific estimates of H_{MSY_s} and MSY_s (Fig. 8), while the ASPM-det CSM estimated H_{MSY_s} less accurately but performed similarly well for MSY_s. JABBA-Select estimates of H_{MSY_s} were more accurate than those by the ASPM-det, but the MSY_s estimates showed a small, but noticeable negative bias. The selectivity independent estimates of H_{MSY} and MSY from the JABBA-PTM CSM showed the poorest accuracy and positive bias relative to the selectivity-specific 'true' values of $H_{MSY_{s=1}}$ and $MSY_{s=1}$, but performed comparably well relative to $H_{MSY_{s=2}}$ and $MSY_{s=2}$, and thus the BRPs relevant to determining the current stock status (Fig. 8).

Among the ISM scenarios, incorrectly specifying M and h (ISM1) produced similar performance results of SB_y and SB_y/SB_0 when compared the CSMs (Figs. 7). Notable differences were that the JABBA-Select was the only EM that produced unbiased estimates of H_{MSY_s},

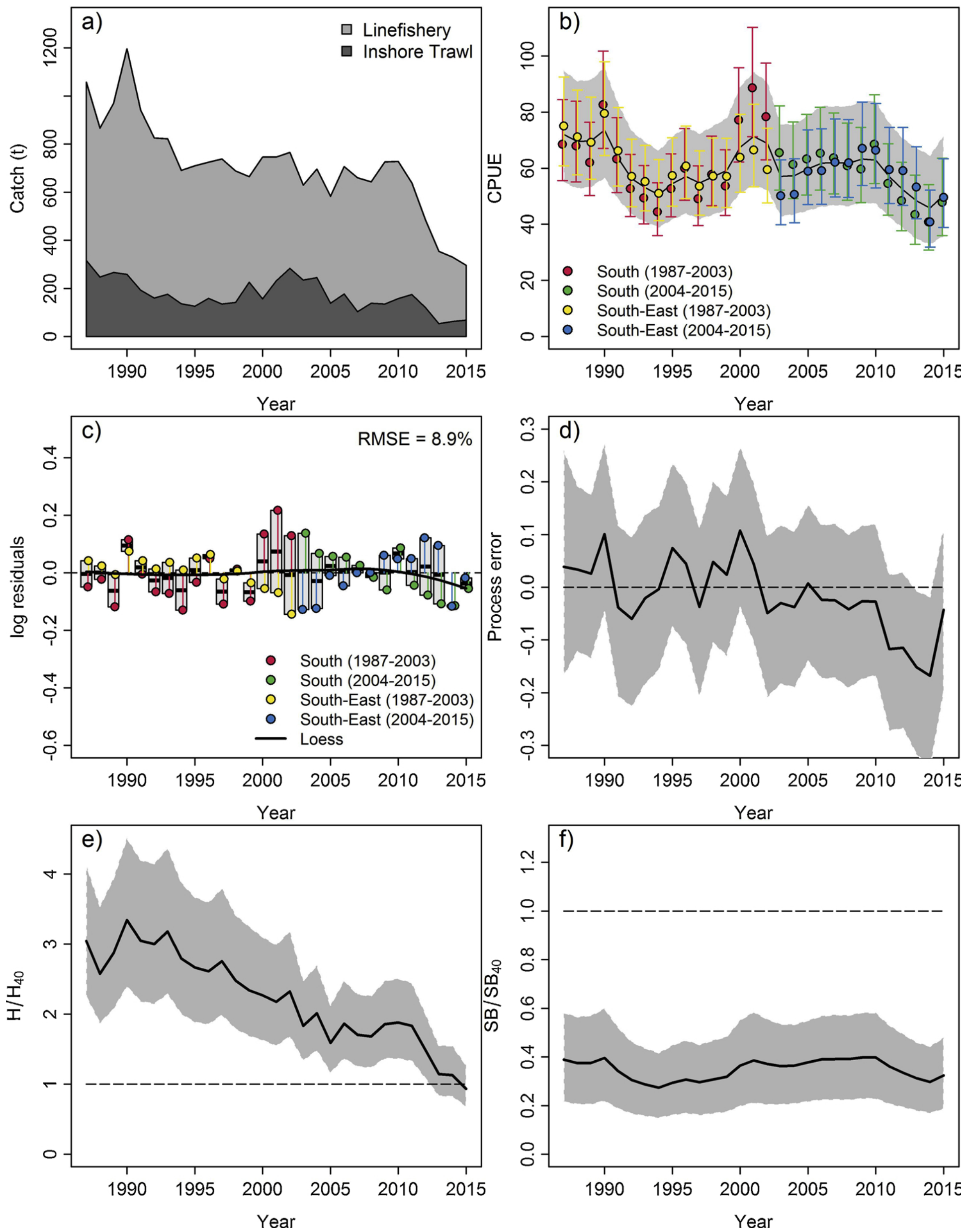

Fig. 4. JABBA-Select results for the silver kob case-study, showing (a) Cumulative catch time series of the inshore and handline fishery (1987–2015), (b) fits to two standardized abundance indices split into two periods with different selectivity, (c) JABBA residual plot boxplots of combined color-coded residual and a loess smoother fitted through all residual (black line), (d) process error deviates on log-scale; and predicted trajectories of (e) H_y/H_{40_y} and (f) SB_y/SB_{40_y}.

under ISM1, and that the two ASPMs showed a decrease in the accuracy of MSY_s compared to the CSMs (Fig. 8).. In addition, the ASPM-det ISM1 showed a relatively stronger decrease in accuracy for SB_y in the final year when compared to CSM (Fig. 7).

The dome-shaped selectivity ISM2 produced systematically biased SB_y and SB_y/SB_0 for all four EMs, which resulted in sharp, systematic increases in MAREs of SB_y/SB_0 over the time series (Fig. 7). Patterns in accuracy and bias for SB_y and SB_y/SB_0 were similar between JABBA-Select and the two ASPMs, showing an increasing positive bias towards the change point in selectivity in year 25, which remained high thereafter. The one-way trip ISM3 scenarios mostly resulted in reduced accuracy of the absolute quantities SB_y and MSY, but showed less effect on the relative quantity SB_y/SB_0 compared to the CSM scenario (Figs. 7 and 8). Interestingly, the JABBA-PTM ISM3 accuracy improved compared to the CSM. In contrast to JABBA-Select and ASPM-det, the ASPM-stoch ISM4 introduced positive bias on the MSY_s estimates. Consistent across the three ISM settings was that JABBA-Select could produce unbiased and relatively accurate estimates of its productivity parameter H_{MSY_s} (Fig. 8).

The confidence interval coverage (CIC) of $SB_{y=40}$ and $SB_{y=40}/SB_0$ for the final assessment year from JABBA-PTM and JABBA-Select were the best across all scenarios (Table 4). The ASPM-stoch model performed reasonably well in comparison to the poor confidence interval coverage of ASPM-det. The high CIC of JABBA-PTM and JABBA-Select indicates that uncertainty is adequately estimated. In the case of JABBA-PTM, this comes, however, with the trade-off of reduced accuracy and precision in stock status estimates and BRPs by not explicitly accounting for systematic changes in selectivity.

4. Discussion

In this study we have introduced JABBA-Select; a novel Bayesian modelling approach to account for changes in selectivity and relative mortality from multiple fisheries in surplus production models. By way

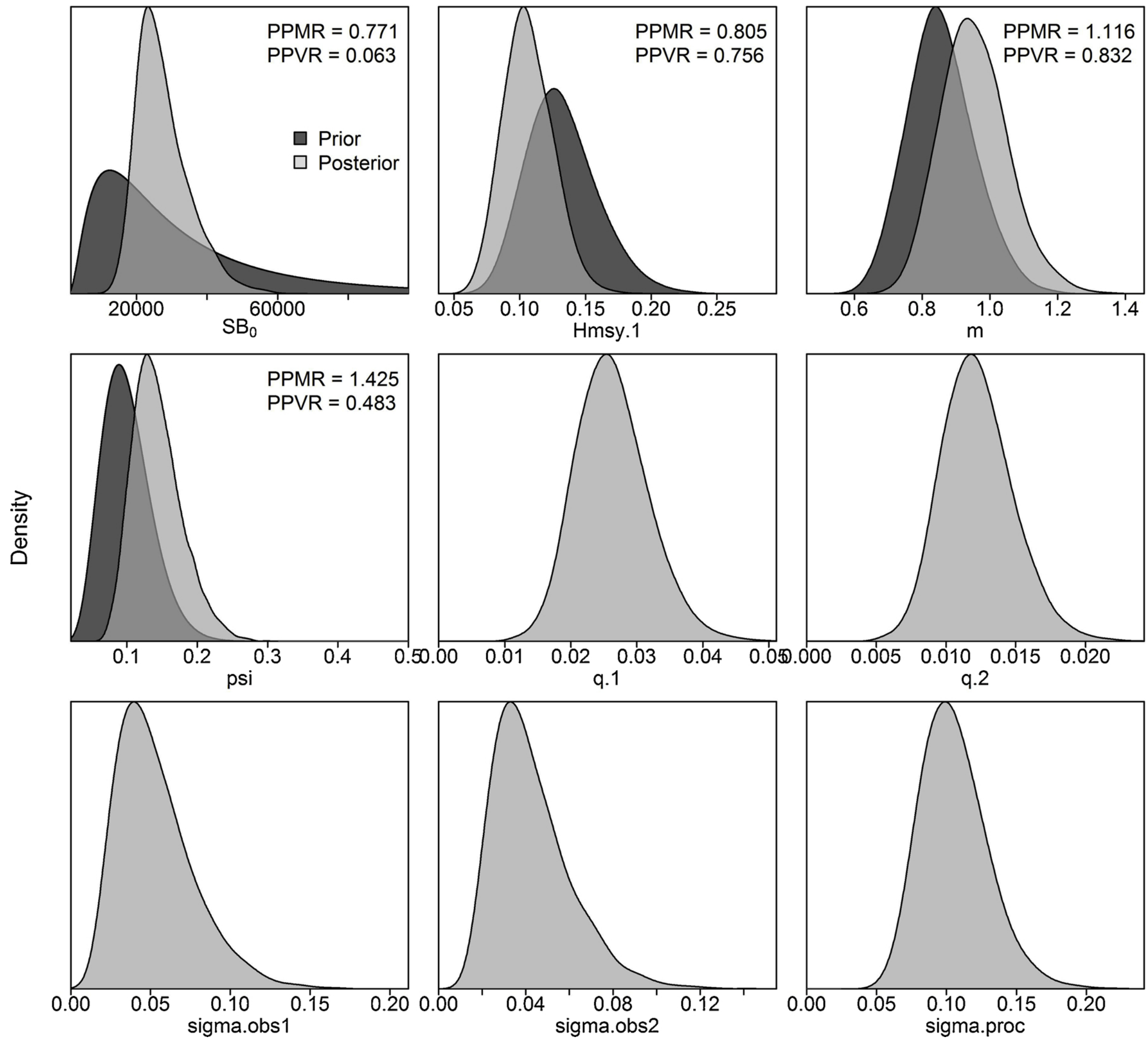

Fig. 5. Posterior and prior distributions for all parameters estimated by JABBA-Select model fitted to catch and abundance data for silver kob. PPRM: Posterior to Prior Ratio of Means; PPRV: Posterior to Prior Ratio of Variances.

of simulation testing, we found that JABBA-Select performs at least as well as ASPMs in predicting spawning biomass and the stock's productivity in situations where a comparable Bayesian state-space SPM that did account for changes in selectivity failed. Despite the similar estimation accuracy, JABBA-Select captured the uncertainty about the stock status more accurately than the ASPMs.

The real-world application of JABBA-Select to the South African silver kob data highlighted a number challenges that are commonly encountered in data-moderate stock assessments, such as incomplete historical catch time series and conflicts among trends in observed abundance indices. Conflict between data within an assessment model should be considered as a diagnostic of model misspecification (Carvalho et al., 2017). JABBA-Select provides a set of diagnostic tools that quickly allows the analyst to evaluate model fits (Winker et al., 2018). In our case study, the residual plot indicated that the model fit the silver kob abundance indices reasonably well, but the systematic pattern in the process error deviates indicates a conflict between data and model assumptions. Possible reasons for this could be systematic trends in under reporting of catches, unreliable indices of abundance, misspecified model parameters or natural stochasticity. These results also emphasize that goodness-of-fit alone may provide little inference about the prediction ability of the assessment model, which would be a prerequisite for robust projections under alternative quota or effort limits. Evaluating this further would require additional diagnostic approaches. For example, recent stock assessments conducted with JABBA routinely applied retrospective analysis (Cadigan and Farrell, 2005) to evaluate the reliability of parameter and reference point estimates (ICCAT, 2018b; Winker et al., 2018). To compare the predictive ability of alternative model specifications hindcasting with cross-validation (Kell et al., 2016) was applied in the recent JABBA assessments of Atlantic bigeye tuna (*Thunnus obesus*) (ICCAT, 2018a), and in the Indian Ocean yellowfin tuna (*Thunnus albacares*) (Sharma, 2018). Due to the similarity in the modular coding structure between JABBA and JABBA-Select, these diagnostics can be readily implemented in JABBA-Select models. Forecasts could likely be improved by incorporating autocorrelated process errors, as has been shown previously for the case of age-structured integrated models (Johnson et al., 2016).

As a novel feature, JABBA-Select summarizes the common input parameters for age-structured models via the ASEM into the productivity parameter H_{MSY} and the shape parameter *m*. In its essence, JABBA-Select reduces several correlated stock parameters into two dimensions, where the first component is H_{MSY} and the second is *m*. The underlying correlation structure between H_{MSY} and *m* is accounted for by the formulation of multivariate normal (MVN) prior, which allows estimating both parameters jointly within the model. The idea of developing a joint prior to estimate productivity and shape of the surplus production function is not new, as it was first proposed by McAllister et al. (2000), as part of a Bayesian surplus production model application

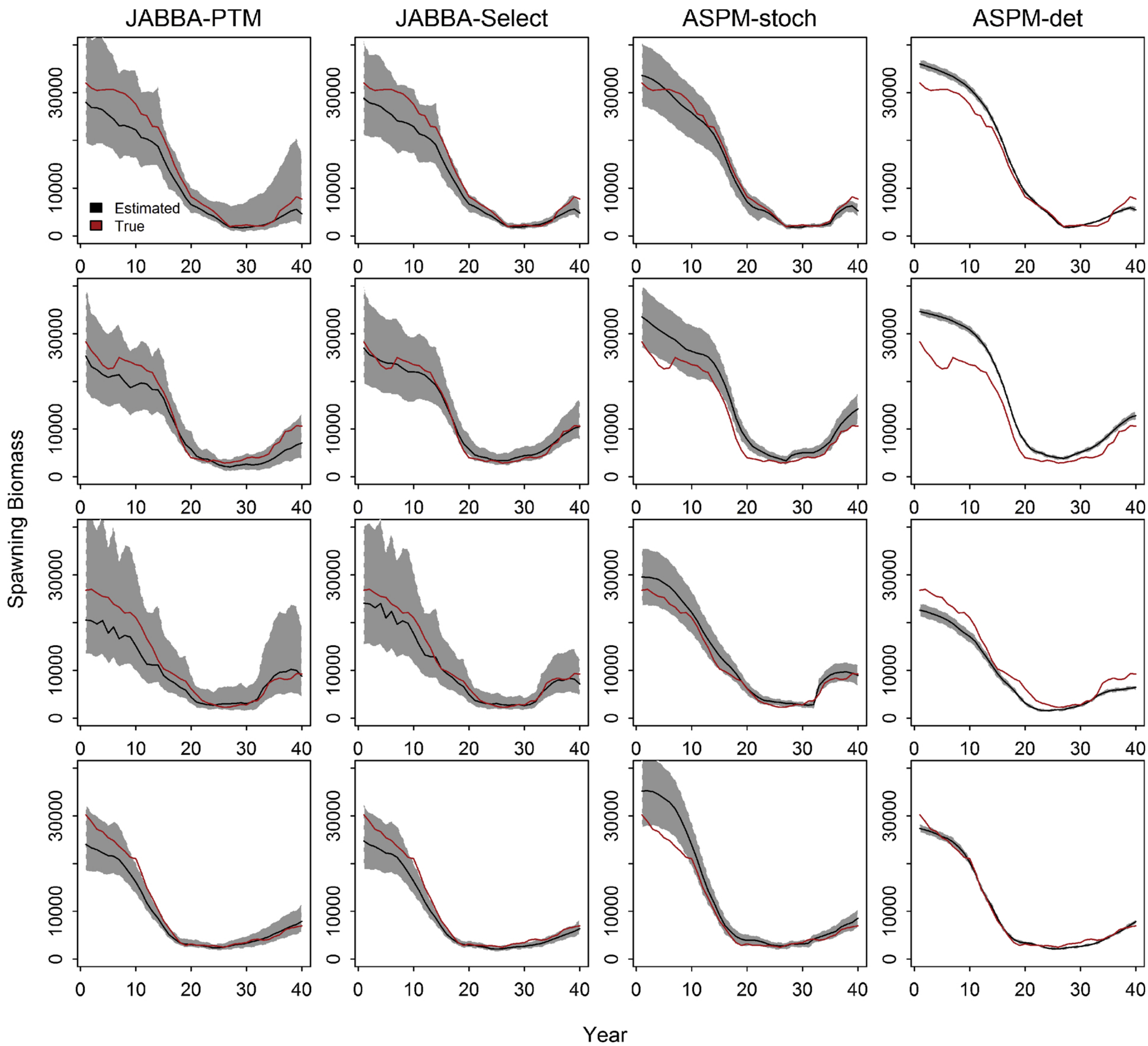

Fig. 6. Simulated trajectories of 'true' and estimated spawning biomass and associated 95% Confindence Intervals from the first 4 converged simulation runs (out of 100) from the correctly specified estimation models (CSM) for the JABBA-PTM, JABBA-Select, ASPM-det, and ASPM-stoch models.

to North Atlantic swordfish. McAllister et al. (2000) proposed a Monte-Carlo simulation approach for developing a joint MVN prior for r and m, which involves generating random deviates of r and generation times T from a Leslie matrix model (see Appendix B in Supplementary material for further details), and then predicting m from an empirical relationship between log(rT) and B/K (Fowler, 1998). There are key differences between our ASEM approach and the one proposed by McAllister et al. (2000): our ASEM incorporates the effect of selectivity on surplus production curve as well as the ratio of between exploitable biomass (*EB*) and spawning biomass (*SB*), and the parameter m is directly derived from the ASEM output of SB_{MSY}/SB_0, which omits the need of an empirical relationship. The choice of the Beverton and Holt SRR is coherent with other age-structured methods for data poor and data moderate stock assessments (Carruthers et al., 2014; Rudd and Thorson, 2017; Thorson et al., 2019; Thorson and Cope, 2015; Wetzel and Punt, 2015). The negative correlation between H_{MSY} and m is a direct consequence of specifying a Beverton-Holt stock recruit function; while this specification may simplify parameter estimation, it also constrains the production function used by JABBA-Select. Future research could explore the implementation of higher parameter SRR functions (Mangel et al., 2013; Punt and Cope, 2019) as an alternative to preserve the flexibility of the Pella-Tomlinson model, for example, by building on published meta-analyses to develop a prior distribution (Foss-Grant et al., 2016).

An advantage of JABBA-Select compared to conventional SPMs is that the separation of exploitable biomass and spawning biomass enables direct comparisons to the results from age-structured assessment frameworks, such as Stock Synthesis. The simulation results indicate that approximating the relationship between exploitable biomass and spawning biomass can accommodate moderate changes in selectivity, which could be caused, for example, by changes in target species, gear modifications (e.g. changes in mesh sizes), and the introduction of new fishing methods. Conventional SPM formulations imply that the modelled biomass represents the exploitable part of biomass EB_y, which can be conceptually calculated as catch/harvest rates (Pedersen and Berg, 2017). Absolute estimates of SB_y are therefore only comparable when the fishery selectivity curve is similar to the maturity ogive, so that $EB_y \sim SB_y$. A common thought is that differences between EB_y and SB_y are less problematic when comparing relative biomass estimates such as B_y/B_0 or B_y/B_{MSY}. However, our simulation results for the JABBA-PTM CSM suggest that changes in fisheries selectivity can cause bias in relative biomass estimates, which could not be accounted for by introducing a change-point in catchability, for example. Globally there is a growing number of stock assessments that include fishery-

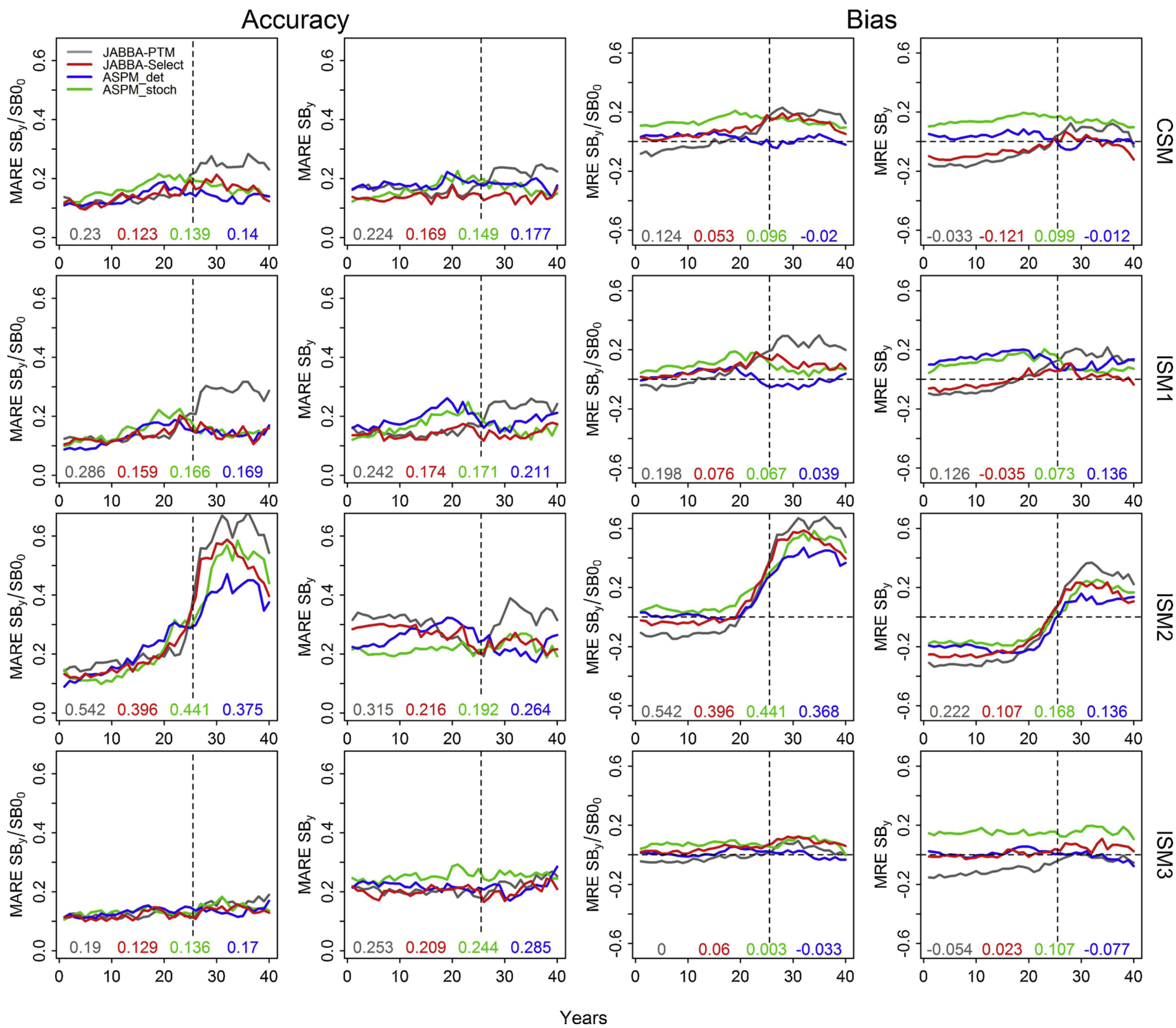

Fig. 7. Trends in annual Median Absolute Relative Error (MARE) as a measure of accuracy and Median Relative Error (MRE) as a measure of bias for relative spanwing biomass SB_y/SB_0 and absolute SB_y for the four esimation models: JABBA-PTM, JABBA-Select, ASPM-det and ASPM-stoch for the correctly specified models (CSM), incorrectly specified steepness and natural mortality (ISM1), incorrectly specified dome-shaped selectivity (IMS2), and fishing-down "one way trip" (ISM3). The vertical dashed lines denote the change point in selectivity after year 25. Color-coded MAREs for the final year are displayed above x-axis in the plots of first left (accuracy) panels and and MREs for the final year are displayed above x-axis in the plot of the 3rd and 4th panels (bias) to the right.

independent estimates of abundance (Thorson, 2019). Although such indices are crucial to successfully complete stock assessments and help management of fish stocks, Pederson and Berg (2017) pointed out the implications of fitting indices from scientific surveys with biomass-dynamic models, when fishery and survey selectivity differ. In such cases, they recommend including fish that are also targeted by the fishery in the survey index calculations. In JABBA-Select this can be achieved instead by assigning different selectivity functions to the surveys and catch indices, while setting the corresponding survey catch to zero (or an otherwise low number).

Similar to ASPMs, JABBA-Select relies on externally estimated biological parameters describing growth, maturity, natural mortality and the spawning-recruitment relationship of the stock. However, in contrast to ASPMs, in JABBA-Select these parameters are treated as latent effects that are captured by the MVN prior means and covariance that informs the estimable parameters H_{MSY} and m. Our difficulties to achieve ASPM convergence when attempting to estimate M and h simultaneously have also been observed in other studies (Cope et al., 2013; Cope, 2015). This difficulty can pose the challenge to determine which of the ASPM parameters need to be fixed or estimated, due to the lack of information in the data or parameter correlations (Wetzel and Punt, 2015). To capture uncertainty about these key parameters in the form of plausible prior distributions, Adaptive Importance Sampling (AIS; McAllister et al., 1994) has been used in a number of recent data-moderate assessments (Cope et al., 2013; Cope, 2015; Wetzel and Punt, 2015). A caveat is the added computational intensity to attain adequate convergence of the generated AIS posteriors (Wetzel and Punt, 2015). In such situations, JABBA-Select could provide an efficient alternative to capture uncertainty about key productivity parameters, while admitting process error and also enabling exploring explicit assumptions about selectivity. On a personal desktop, computing time of JABBA-Select may range from just over one minute for a single fleet scenario to about four minutes for a complex multi-fleet model. The Bayesian implementation is a good alternative to express uncertainty about stock status quantities from readily available posteriors, which can be translated directly into probabilistic statements about the stock status, and future projections.

In this study, we have exclusively focused on incorporating the uncertainty of M and h into informative joint prior of JABBA-Select parameters H_{MSY} and m. Although admitting uncertainty about M may also indirectly capture uncertainty about the growth, maturation and longevity in the form of the H_{MSY} prior variance, this simplification

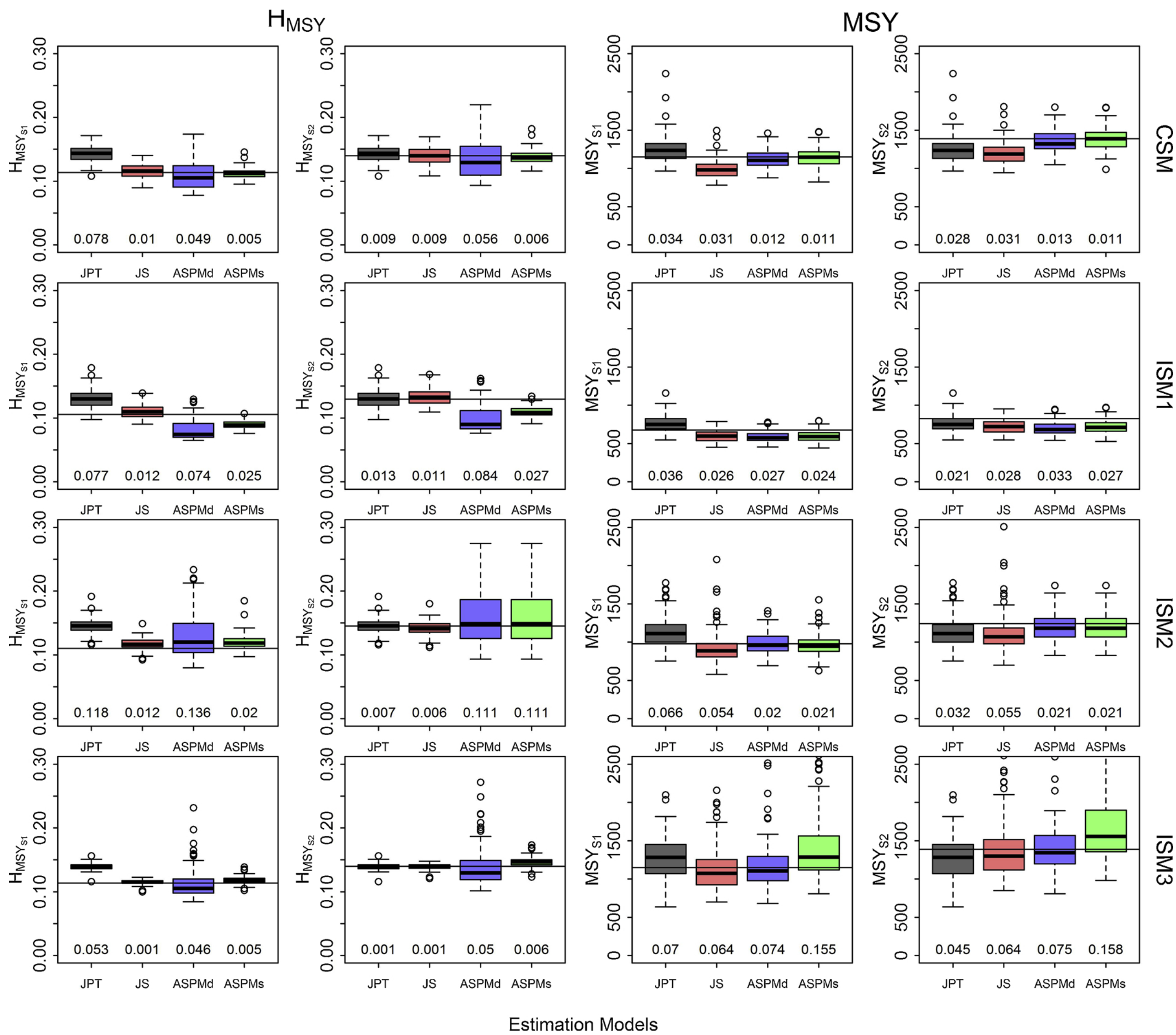

Fig. 8. Estimated stock reference points H_{MSY_s} and MSY_s for selectivity functions $s=1$ and $s = 2$ in comparison to the 'true' values (solid horizontal lines) for for the four esimation models: JABBA-PTM (JPT), JABBA-Select (JS), ASPM-det (ASPMd) and ASPM-stoch (ASPMs) for the correctly specified models (CSM), incorrectly specified steepness and natural mortality (ISM1), incorrectly specified dome-shaped selectivity (IMS2), and fishing-down "one way trip" (ISM3). Median Absolute Relative Errors (MAREs) are displayed above the x-axis for H_{MSY_s} and MSY_s.

should not preclude extending ASEM to incorporate uncertainty about additional stock parameters as well as selectivity. For example, hierarchical meta-analysis analysis of all life history parameters from *FishBase* (www.fishbase.org) has produced a promising predictive modelling tool for objectively generating joint MVN prior distributions of key input parameters for the ASEM, using the R package *FishLife* (Thorson et al., 2017). Such approach could enable JABBA-Select to further relax common ASPM assumptions that incorporate most (if not all) input parameters describing growth, maturity and natural mortality without error.

The sensitivity analysis conducted in this study improved the ability to understand the generic behaviour of the JABBA-Select model under incorrect assumptions about the stocks productivity (M and h) and selectivity. The results of our simulation experiment suggest that JABBA-Select can perform at least as well as the ASPMs, and that JABBA-Select has the best confidence interval coverage of the four tested EMs evaluated. A caveat is that, in JABBA-Select, the relationship between EB_y and SB_y, which is estimated externally, is not updated by the data. We had initially anticipated that our external approximation approach would be sensitive to misspecifications of M, which appear most influential on the increasing divergence between EB_y and SB_y at lower biomass levels. Yet, the accuracy of the SB_y and SB_y/SB_0 estimates appeared to be only slightly affected by the incorrectly specified M in the sensitivity analysis. Under incorrect assumptions about the selectivity, JABBA produced biased BRPs, just like the ASPMs, while the Pella SPM still performed substantially worse. Another caveat is that JABBA-Select does not explicitly account for the lag effect between selectivity and maturation (i.e. EB and SB). Our simulation results indicate that JABBA-Select performs reasonable well for moderate lags compared to a conventional Pella-Tomlinson formulation. However, if extreme lags are expected in certain situations, such as when CPUE is only comprised of immature (e.g. juvenile) individuals, and the mature individuals are largely cryptic to the sampling gear, poor estimation performance of BRPs is somewhat expected. A closed-loop simulation approach (Wetzel and Punt, 2015) could be used to assess how well alternative model structures can provide robust estimates of reference points. As indicated by our results, estimation bias maybe evident in earlier parts of the time series but corrects as the time series extends. However, using robust feedback control rules based on either empirical (e.g. CPUE) or model based control rules, would probably not create any issues for management and decision making if a closed loop simulation is adopted. Although this is beyond the scope of the current paper the use of JABBA-Select in MSE frameworks with adequate feedback control could support more robust and management advice in

Table 4
Confidence interval coverage (CIC) denoting the proportion of iterations where the 'true' values $SB_{y=40}$ and $SB_{y=40}/SB_0$ for the final assessment year (y = 40) fell within the predicted 50%, 80% and 95% confidence interval (CI), showing the results from a Pella-Tomlinson model (JABBA-PTM), JABBA-Select, a deterministic age-structured surplus production model (ASPM-det) and a stochastic age-structured model (ASPM-stoch) for (a) the correctly specified reference case (CSM) and the three incorrectly specified (operating) models (IMS).

	SB (terminal year)			SB/SB_0 (terminal year)		
CSM	50%	80%	95%	50%	80%	95%
JABBA-PTM	0.46	0.79	0.95	0.5	0.77	0.94
JABBA-Select	**0.54**	**0.77**	**0.94**	**0.42**	**0.71**	**0.92**
ASPM-det	0.12	0.25	0.37	0.09	0.17	0.25
ASPM-stoch	0.39	0.73	0.86	0.35	0.63	0.84
ISM1 (low h,high M)	50%	80%	95%	50%	80%	95%
JABBA-PTM	0.41	0.67	0.89	0.41	0.73	0.86
JABBA-Select	**0.4**	**0.71**	**0.9**	**0.41**	**0.67**	**0.88**
ASPM-det	0.05	0.16	0.29	0.03	0.09	0.19
ASPM-stoch	0.35	0.62	0.82	0.3	0.54	0.69
ISM2 (dome-selectivity)	50%	80%	95%	50%	80%	95%
JABBA-PTM	0.27	0.47	0.68	0.38	0.66	0.81
JABBA-Select	**0.24**	**0.44**	**0.62**	**0.31**	**0.65**	**0.86**
ASPM-det	0.02	0.07	0.16	0.06	0.1	0.14
ASPM-stoch	0.09	0.23	0.44	0.27	0.49	0.69
ISM3 (one-way trip)	50%	80%	95%	50%	80%	95%
JABBA-PTM	0.55	0.82	0.95	0.47	0.78	0.94
JABBA-Select	**0.5**	**0.76**	**0.94**	**0.52**	**0.79**	**0.93**
ASPM-det	0.13	0.26	0.39	0.08	0.13	0.33
ASPM-stoch	0.43	0.67	0.93	0.38	0.66	0.88

the long run.

It is well documented that the decision between asymptotic and dome-shaped of selectivity can be very influential on estimates of fishing mortality, absolute abundance and stock status (Punt et al., 2014). In data-rich ASIM assessments, estimation of selection curves is already a major challenge, because selectivity is typically confounded with recruitment, natural mortality and growth and can be affected by changes in availability and non-random sampling, which can all lead to biased assessment results (Carruthers et al., 2017; Minte-Vera et al., 2017; Punt et al., 2014). In data-moderate ASPM assessments, selectivity has to be fixed and is usually assumed to be asymptotic (Booth and Punt, 1998; Cope et al., 2013; Wetzel and Punt, 2015), unless comparisons to an asymptotic reference selectivity suggests otherwise (Punt and Japp, 1994). For example, the data-moderate assessment framework "Extended Simplified Stock Synthesis (XSSS)" relies on the simplified assumption that selectivity is equal to the asymptotic maturity curve (Cope et al., 2013; Wetzel and Punt, 2015). Alternatively, selectivity can be externally estimated from available size or age composition data (Booth and Punt, 1998). The recent development of length-based per-recruit models, such as LBB (Froese et al., 2018) and LBSPR (Hordyk et al., 2016), could aid to improve the reliability of estimated selectivity parameters for the ascending limb of the selectivity curve from available length data (Huynh et al., 2018). However, obtaining reliable estimates for dome-shaped selectivity will always be difficult. To provide additional flexibility for exploring alternative assumptions about selectivity, JABBA-Select provides the user an option to specify a 5-parameter piece-wise dome-shaped selectivity curve (Fig. A4), with a logistic function for the ascending limb and the descending limb described by the mean and CV of a half-normal distribution (Huynh et al., 2018). More detailed documentations on dome-shaped selectivity as well as further user options, such as the sex-structure setting, are also available on the repository site (https://github.com/JABBAmodel/JABBA-Select) and illustrated by replicating a sex-structured, multi-fleet Stock Synthesis model for Atlantic swordfish (ICCAT, 2017b) with JABBA-Select.

The number of ASPMs for data-moderate situations has been continuously increasing over the last three decades (Thorson et al., 2019), with Stock Synthesis having taken a leading role in this development in recent years (Dichmont et al., 2016; Methot and Wetzel, 2013). On the other hand, SPMs persist as an assessment tool, particularly within their traditional realm of large pelagic tuna, billfish and shark assessments (Carvalho et al., 2014; Prager, 1994; Punt et al., 2015; Winker et al., 2018). As a result of these developments, SPMs and Stock Synthesis models are increasingly run in parallel during stock assessments. In some instances the results on stock status are even simplistically averaged across these two model types despite the fact that *SB* seldom equates *EB* and the choice of parameterization for these two models is rarely fully compatible, violating the validity of model comparison and consequently inference about the stock status. For example, Maunder (2003) highlighted this issue by pointing out that the Schaefer model, in predicting MSY at 50% unfished biomass, rarely matches the typical range of steepness values of h = 0.6 – 0.95 considered in age-structured stock assessments for most tuna and billfishes, which would imply MSY at biomass depletion levels that are notably below 50%.

By unifying the parameterization between age-structured assessment models and biomass-aggregated SPMs, JABBA-Select not only provides a robust tool for data-moderate stock assessments, but also provides an important opportunity to compare the respective assessment results directly. This way JABBA-Select can also serve as a diagnostic tool for data-rich ASIMs to evaluate if variations in predicted population dynamics are mainly informed by the relative abundance indices and catches, and governed by the underlying surplus production function and process error. We conclude that this study is an important first step in testing the performance of JABBA-Select, but we recommend further simulation analyses in the future to explore its limits and possibilities.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.fishres.2019.105355.

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