Stock Reduction Analysis using catch at length data

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Abstract

Last thing to be written

1 Introduction

Modern stock assessments typically attempt to fit population dynamics models to catch at age and catch at length data, in hopes of extracting information from these data about age/size vulnerability and fishing mortality patterns (Methot and Wetzel, 2013; Hilborn and Walters, 1992). In cases where age data are lacking, models like MULTIFAN-CL attempt to obtain estimates of vulnerability and fishing mortality only from size distribution data (Fournier et al., 1998). Combined with a few assumptions regarding the structure and variability in length at age, this procedure can even be used to attempt to recover information about changes in body growth patterns if there is a strong age-class signal in the length frequency data (Fournier et al., 1998). Some assessment methods attempt to put aside the length frequency data, by converting these data to age compositions using age-from-length tables, perhaps using iterative methods to estimate proportions of fish at age for each length interval (Kimura and Chikuni, 1987). It is typical for assessment results from length-based assessment models to show substantial deviations between predicted and observed length distributions of catches, reflecting both sampling variation in the length composition data and incorrect assumptions about stability of growth and vulnerability patterns (Hilborn and Walters, 1992).

The vulnerability process is the combination of two processes: selectivity of the fishing gear and availability of the fished population in the area being fished (Beverton and Holt, 1957). Both processes can vary over time and therefore modify the resulting selectivity. Although selectivity process can often be directly measured through gear experiments, availability is generally harder to measure as it depends on the distribution of the exploited population. Fish movement, changes in fish distribution, and by changes in fleet distribution, can all cause availability changes.Changes in vulnerability are not uncommon (Sampson and Scott, 2012) but are usually difficult to track overtime. This difficulty is associated with an inability to distinguish between changes in fishing mortality and changes in vulnerability in most age and length based stock assessment methods. For this reason, many assessment methods rely on ad hoc parametric vulnerability models that may or may not include changes over time (Maunder et al., 2014). If misspecified, such models might lead to severe bias in fishing mortality estimates, which could result in misleading management advice (Martell and Stewart, 2014).

Here we suggest an alternative approach to assessment modeling that begins by assuming that the assessment model should exactly reproduce the observed catch at length distribution. This approach follows the dynamics of an age structred stock reduction analysis (SRA) (Walters et al., 2006) which follows a "conditioned on catch" format, subtracting observed catches at age from modeled numbers at age in estimation of numbers at age over time. This assumption is analogous to the classical assumption in virtual population analysis that reconstructed numbers at age should exactly match observed catch at age data (Hilborn and Walters, 1992). The suggested approach may have two key advantages over statistical catch at age and/or catch at length models: (1) it does not require estimation of age or size vulnerability schedules, and (2) catch at length data are commonly available for every year, even when age composition sampling has not been conducted.

We demonstrate the performance of this model with a simulation-evaluation analysis and apply it to real fisheries data from the Peruvian jack mackerel (*Trachurus murphyi*) and Pacific Hake (*Merluccius productus*) fisheries.

2 Methods

In this section we describe the stock reduction analysis with catch at length data (Length-SRA), describe the simulation analysis and scenarios used to test the model and provide a description of the real data used to illustrate the model applicability.

2.1 Stock reduction analysis with catch at length data

The stock reduction analysis described here starts by calculating the proportions of individual at length for each age class (Table T1.1-T1.5). The calculation of such proportions (T1.1) relies on three main assumptions regarding the distribution of length at age: (1) The mean length at age follows a von Bertalanffy growth curve (eq.T1.4), (2) The length at age is normally distributed (eqs. T1.1 -T1.3) and (3) The standard deviations of the length at age distributions is defined (e.g. eq.T1.5).

Table 1: population dynamics for Length-SRA and operating model

	Distribution of length given age
(T1.1)	$P_{l\|a} = \int_{z1_{a,l}}^{z2_{a,l}} \Phi(z)dz$
(T1.2)	$z1_{a,l} = \frac{b1_l - \bar{L}_a}{\sigma_{L_a}}$
(T1.3)	$z2_{a,l} = \frac{b2_l - \bar{L}_a}{\sigma_{L_a}}$
(T1.4)	$\bar{L}_a = L_{inf} \cdot (1 - \exp^{(-k\cdot(a-t_o))})$
(T1.5)	$\sigma_{L_a} = \bar{L}_a \cdot cv_l$
	Population dynamics
(T1.6)	$N_{a,t>syr} = \begin{cases} \frac{a_{rec}\cdot SB_{t-1}}{1+b_{rec}\cdot SB_{t-1}} \cdot e^{wt}, & a = 1 \\ N_{a-1,t-1} \cdot S \cdot (1 - U_{a-1,t-1}), & 1 < a < A \\ \frac{N_{a-1,t-1}\cdot S\cdot(1-U_{a-1,t-1})}{1-S\cdot 1-Ua,t}, & a = A \end{cases}$
(T1.7)	$U_{a,t} = \sum_a (P_{l\|a} \cdot U_{l,t})$
(T1.8)	$U_{l,t} = \frac{C_{l,t}}{N_{l,t}}$
(T1.9)	$N_{l,t} = \sum_a (P_{l\|a} \cdot N_{a,t})$
(T1.10)	$SB_t = \sum_a (mat_a \cdot w_a \cdot N_{a,t})$
	Initial year and incidence functions
(T1.11)	$N_{a=1,init} = R_{init} \cdot e^{wt}$
(T1.12)	$a_{rec} = \frac{\kappa}{\phi_e}$
(T1.13)	$b_{rec} = \frac{\kappa - 1}{R_o \cdot \phi_e}$
(T1.14)	$\phi_e = \sum_a lx_a$
(T1.15)	$lx_a = \begin{cases} 1, & a = 1 \\ lx_{a-1} \cdot S, & 1 < a < A \\ \frac{lx_{a-1}\cdot S}{1-S}, & a = A \end{cases}$
	Operating model
(T1.16)	$U_{l,t} = U_t \cdot sel_{l,t}$
(T1.17)	$C_{l,t} = N_{l,t} \cdot U_{l,t} \cdot P_{l\|a}$
(T1.18)	$sel_{l,t} = \frac{1}{1-g} \cdot \left(\frac{1-g}{g}\right)^g \cdot \frac{e^{a\cdot g\cdot(b-l)}}{1+e^{a\cdot(b-l)}}$
(T1.19)	$I_t = q \cdot VB_t \cdot e^{(}\mathcal{N}(0, \sigma_{I_t})$

The proportions of length at age is used to convert the length-based quantities into age based quantities which are used to propagate the age structured population dynamics forward (Table 1 - Population dynamics). We assume that recruitment follows a Beverton & Holt type recruitment curve (eq. T1.6), that harvesting occurs over a short, discrete season in each time step (year or shorter time period) and that natural survival rate is stable over time (eqs. T1.6-T1.10). Differences in the computation of recruitment in the initial year (eq. T1.11) as well as incidence functions (eqs. T1.12-T1.15) are shown in Table 1 - Initial year and incidence functions.

The model estimates three main parameters: average unexploited recruitment R_0, recruitment compensation ratio κ and recruitment in the initial year R_{init}. In addition, the recruitment deviations are estimated for all cohorts observed in the model, that is, the number of recruitment deviations is equal to the number of years in the time series plus the number of age classes greater that recruitment age. The parameters of the model are estimated by fitting to an index of abundance assuming a lognormal distribution with fixed variances. A lognormal penalty is added to the negative log-likelihood function to constrain annual recruitment residuals.

2.2 Simulation evaluation

In order to perform a simulation evaluation of the Length-SRA under various scenarios we used the same model dynamics described in Table 1 - Population dynamics, as an operating model. However we modified the model population dynamics to control annual exploitation rate (eq. T1.16), time varying selectivity (eq. T1.18), and observation and process errors. Selectivity in the operating model was computed with the three parameter selectivity equation described by Thompson (1994) (eq. T1.18). The observation error in the operating model included lognormal error in the index of abundance and logistic multivariate error in the catch numbers at length. Recruitment deviations were assumed to be lognormally distributed.

We considered a total of six different scenarios in the simulation evaluation runs. Three different historical exploitation rate trajectories were used: contrast, one way trip and U ramp. In the contrast scenario the exploitation rate (U_t) starts low and increases beyond U_{msy} and then decreases until $U_t = U_{msy}$. In the one way trip scenario U increased through time until $U = 2 \cdot U_{msy}$. In the U ramp scenario, U_t increases steadily until $U_t = U_{msy}$ and remains constant thereafter. In addition to the exploitation rate scenarios, we considered two selectivity scenarios: constant and time varying selectivity. In the constant selectivity scenario, selectivity was assumed to follow a sigmoid shape. In the time varying selectivity scenario, the selectivity curve was assumed to vary every year, progressively changing form a dome shaped curve to sigmoid and back to dome shaped. The complete list of scenarios and the acronym used for them is presented in Table 3.

Table 2: Indexes, variable definition and values used in simulation-evaluation

Symbol	Value	Description
l	$\{1,2,...L\}$	Central point of length bin, $L = 15$
a	$\{1,2,...A\}$	Age-class, $A = 10$
t	$\{1,2,...T\}$	Annual time step, $T = 50$
$init$	21	Annual time step in which data starts to be reported
Distribution of length given age		
$P_{l\|a}$		Matrix of proportions of length at age
Φ		Standard normal distribution
$z1_{a,l}$		Normalized z score for lower limit length bins
$z2_{a,l}$		Normalized z score for upper limit length bins
$b1_l$		Lower limit of length bins
$b2_l$		Upper limit of length bins
$\bar{L}_a$		Mean length at age
σ_{L_a}		Standard deviation of length at age
L_{inf}	10	Maximum average length
k	0.3	Rate of approach to L_{inf}
t_o	-0.1	Theoretical time in which length of individuals is zero
cv_l	0.08	Coefficient of variation for length at age curve
Population dynamics		
$N_{a,t}$		Numbers of fish at age and time
SB_t		Spawning biomass at time
mat_a		Proportion of mature individuals at age
a_{rec}, b_{rec}		Beverton & Holt stock recruitment parameters
R_o	100	Average unfished recruitment
κ	10	Goodyear recruitment compensation ratio
wt	$\mathcal{N}(0, \sigma_{rec})$	Recruitment deviations
S	0.7	Natural survival
$U_{a,t}$		Exploitation rate at age and time
$U_{l,t}$		Exploitation rate at length and time
$C_{l,t}$		Catch at length and time
$N_{l,t}$		Numbers at length and time
lx_a		Unfished survivorship at age
ϕ_e		Unfished average spawning biomass per recruit
Operating model		
$sel_{l,t}$		Fishing selectivity at length and time
g, a, b		Parameters for selectivity function
U_t		Annual maximum exploitation rate
$C_{l,t}$		Catch at length and time
$N_{l,t}$		Numbers at length and time
I_t		Index of abundance at time
VB_t		Biomass that is vulnerable to the survey at time
q	1.0	catchability coefficient

All simulation runs had 30 years of data and we used 100 simulation runs for each scenario. We evaluated the distribution of the % relative error ($\frac{esimated - simulated}{simulated} \cdot 100$) for the main parameter estimates (R_0, R_{init} and κ) and for four derived quantities (Depletion: $\frac{B_t}{B_0}$, MSY, U_{MSY} and q).

Table 3: Simulation-estimation scenarios

Scenario Code	Selectivity	U trajectory
CC	constant	contrast
CO	constant	one way trip
CR	constant	U ramp
VC	time-varying	contrast
VO	time-varying	one way trip
VR	time-varying	U ramp

2.3 Real data examples

Two species were chosen to illustrate the application of the Length-SRA to real datasets: Chilean jack mackerel and Pacific hake. Both species are believed to be subject to time varying selectivity.

The Pacific hake fishery is believed to exhibit time varying selectivity due to cohort targeting and annual changes fleet spatial distribution. The population is know to have spasmodic recruitment, with high recruitment events occurring once or twice every decade (Ressler et al., 2008). Pacific hake tends to segregate by size during their annual migration(Ressler et al., 2008), allowing the fishing fleet to target the strong cohorts by changing the spatial distribution of fishing effort as the cohort ages.

The movement pattern of jack mackerel is not as well known, although fish appear to move between spawning and feeding areas (Gerlotto et al., 2012). Variability in selectivity patterns for the jack mackerel fishery are believed to be associated both with evolution of fleet capacity and gear utilization and with compression and expansion of the species range associated with abundance changes (Gerlotto et al., 2012).

3 Results

3.1 Simulation-evaluation

The simulation-evaluation showed that the parameters R_0 and R_{init} tend to be underestimated but with very low bias. The median % errors for those parameters were within the $\pm$ 10% interval, with the exception of the U ramp scenarios (CR and VR) in which the median % error for R_o and R_{init} was as high as 25% (Figure

1). The parameter κ was underestimated in all scenarios with higher median % error varying between 9% anf 40%. Once again, the U ramp scenarios (CR and VR) resulted in the highest bias (Figure 1).

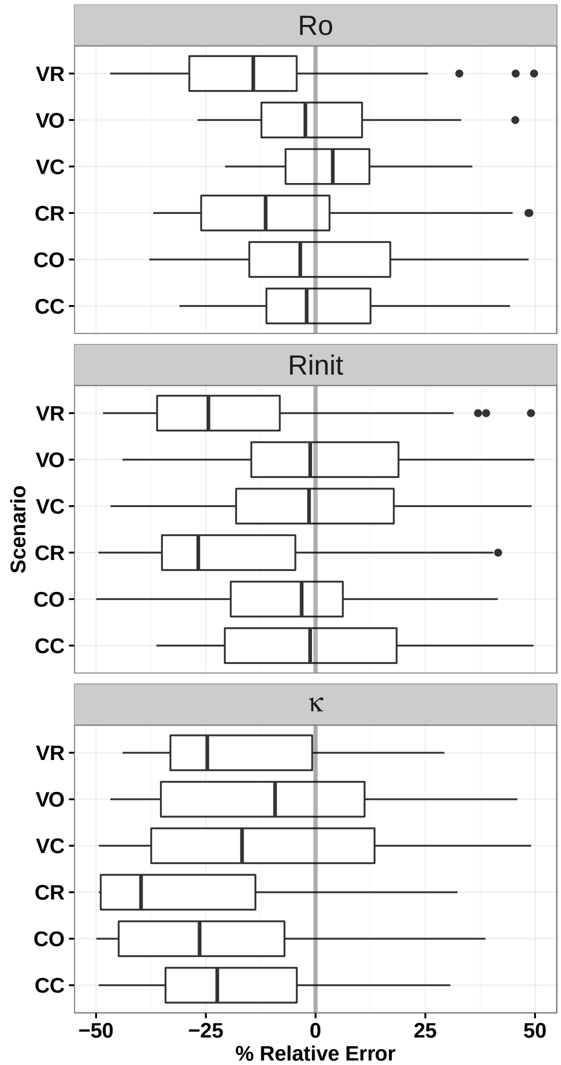

Figure 1: Relative error (%) for main parameters for all scenarios considered in the simulation-evaluation.

In relation to the derived quantities, the Length-SRA tended to underestimate both depletion and MSY estimates with median % errors ranging between -26% and -2% . Once again the U ramp scenarios (CR and VR) yielded the worst bias (Figure 2). The estimates for U_{MSY} showed very low (<5%) median % errors for all scenarios except for the CC scenario (Contrast and constant selectivity) which showed a 13% median % error (Figure 2). The estimates of q tended to be underestimated for the U ramp scenarios an d overestimated for the remaining scenarios, with median % error ranging between -3% and 10% (Figure 2).

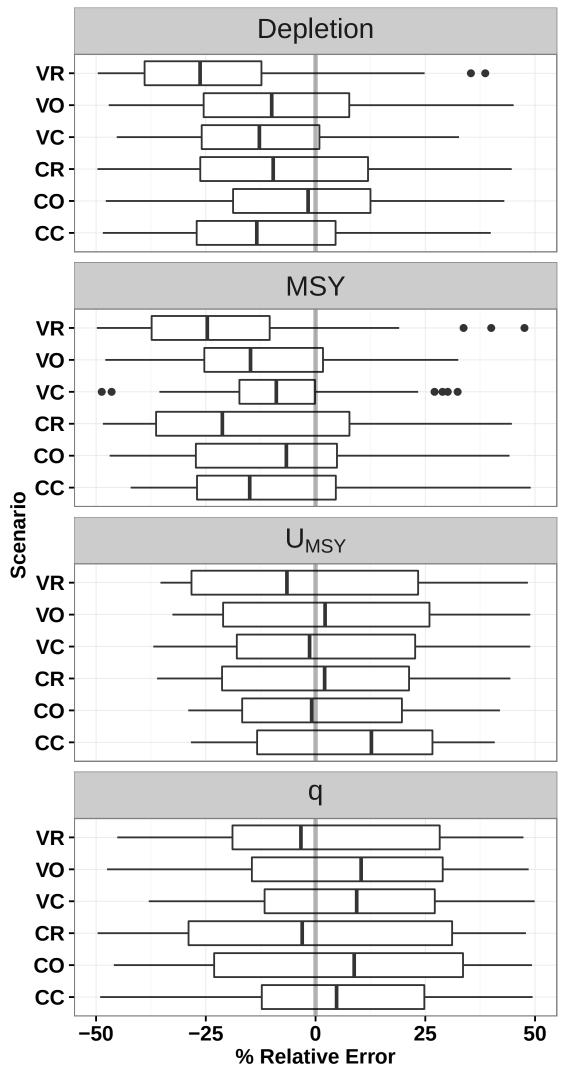

Figure 2: Relative error (%) for main parameters for all scenarios considered in the simulation-evaluation.

The simulation-evaluation exercise showed that the Length-SRA model is able to track selectivity changes over time relatively well. There is a tendency to underestimate selectivity for lower lengths and overestimate it for higher lengths across all scenarios, However, this pattern is particularly prominent for the *U* ramp scenarios (Figure 3).

3.2 Real data examples

show figures with real

4 Discussion

main conclusions: Length-SRA underestimates kappa

Management quantities Depletion and MSY are underestimated - the model tends to produce conservative benchmarks.

UMSY estimates had low bias- good?

U ramp scenario yield very bad results - lack of information in the time series.

Model is able to track selectivity over time, - good

Does the model work? Could it produce useful management advice?

assumption regarding Umsy -¿ changes with selectivity -¿

Time- varying growth might render the model less useful. Suggest estimating cohort-specific growth curves or implementing the density dependent functions shown in multifan-CL.

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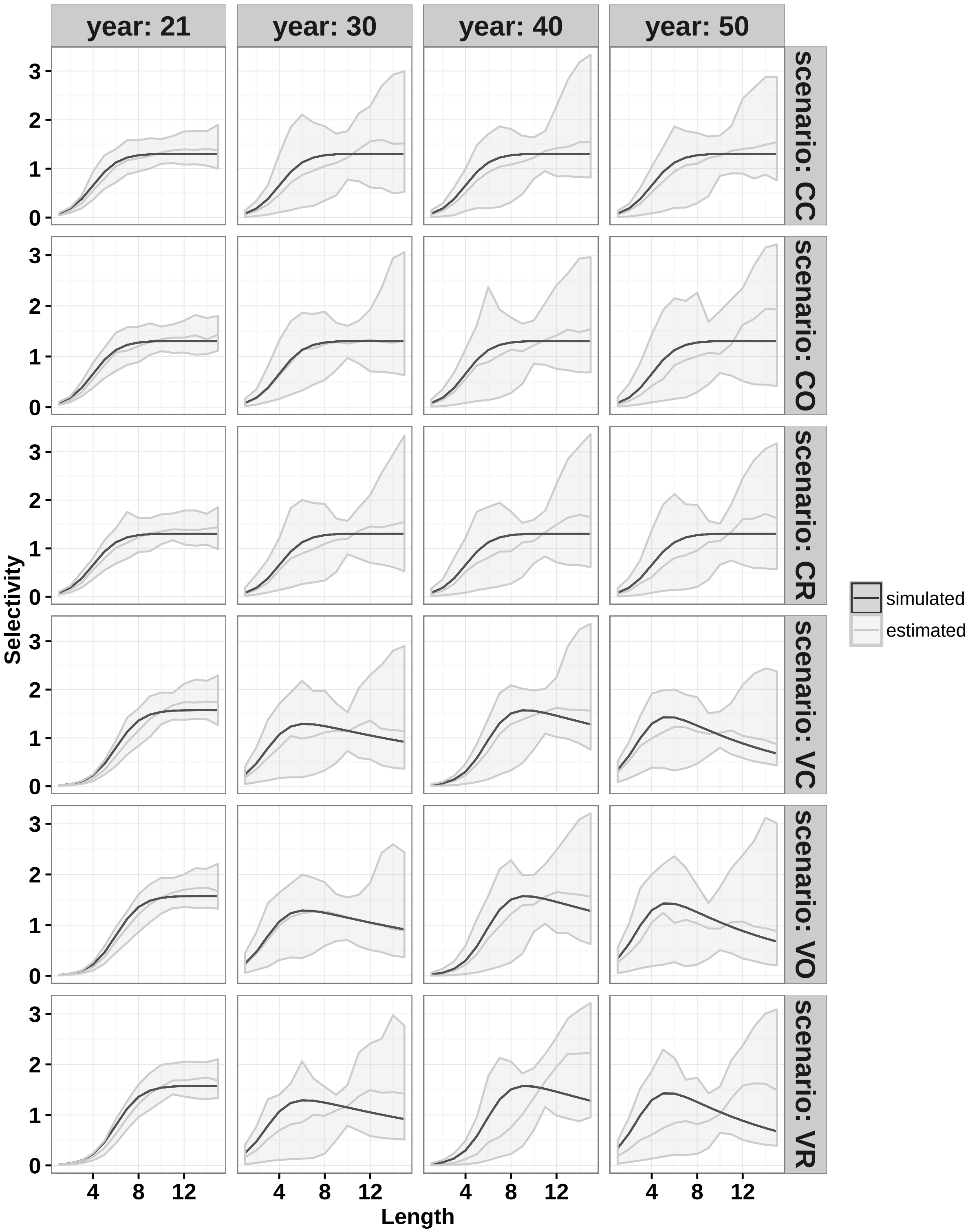

Figure 3: Simulated and realized selectivity estimates for a set of years within simulation-evaluation time series.

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