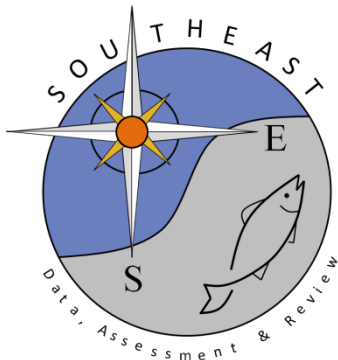# Technical description of operating models in data-limited methods toolkit (DLMtool)

William J. Harford, Skyler R. Sagarese, J. Jeffery Isely, and Matthew W. Smith

SEDAR49-AW-10

30 August 2016

Technical description of operating models in data-limited methods toolkit (DLMtool)

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Table of Contents

Introduction

Data-limited methods toolkit (DLMtool) is a collaboration between the University of British Columbia and the Natural Resources Defense Council that has produced a software library for evaluating the performance of data-limited management procedures (MPs; Carruthers and Hordyk 2015). This software library is implemented in the R statistical computing environment and is maintained by its principal developers T. Carruthers and A. Hordyk (R Development Core Team 2012, Carruthers and Hordyk 2015). DLMtool simulates the performance of data-limited MPs using a framework known as management strategy evaluation (MSE; Butterworth and Punt 1999, Punt et al. 2014). MSE requires linkages to be specified between a fish stock, its fisheries, and a MP. These linkages are used to simulate a dynamic sequence of events that reflects the regulatory effects of a MP, fishery operation responses to regulatory changes, and stock responses to fishing. This approach is otherwise known as closed-loop simulation (Sainsbury et al. 2000, Walters and Martell 2004).

This document is not intended as an exhaustive summary of DLMtool or its wide variety of capabilities or applications. As it pertains to SEDAR 49, we focus on key aspects of the operating model (OM) that contribute to MSE through simulation of stock dynamics, fishery operations, and observation of simulated data. We also focus on the translation of user inputs into OM parameters. This report is separated into three parts. The first part summarizes key OM components of DLMtool v3.2 that were implemented in their standard configurations. The second part details OM components that were modified for use in SEDAR 49. The third part explores the role of uncertainty in decision-making and the use of MSE to evaluate the consequences of uncertainty for achieving management objectives.

Additional technical resources

Carruthers TR, Punt AE, Walters CJ, MacCall A, McAllister MK, Dick EJ, Cope J. 2014. Evaluating methods for setting catch limits in data-limited fisheries. Fisheries Research 153: 48–68.

Carruthers TR, Punt AE, Walters CJ, MacCall A, McAllister MK, Dick EJ, Cope J. 2014. Evaluating methods for setting catch limits in data-limited fisheries [Supplemental information]. Fisheries Research 153: 48–68.

Carruthers TR, Hordyk AR. 2015. DLMtool: data-limited methods toolkit. Available at: https://cran.r-project.org/web/packages/DLMtool/index.html.

Carruthers TR, Kell LT, Butterworth DDS, Maunder MN, Geromont HF, Walters C, McAllister MK, Hillary R, Levontin P, Kitakado T, Davies CR. 2015. Performance review of simple management procedures. ICES Journal of Marine Science: Journal du Conseil fsv212.

Newman D, Carruthers TR, MacCall A, Porch CE, Suatoni L. 2014. Improving the science and management of data-limited fisheries: An evaluation of current methods and commended approaches. Natural Resources Defense Council, NRDC Report R:14-09-B, NY.

Sagarese, S.R., J.F. Walter III, M.D. Bryan, and T.R. Carruthers. 2016. Evaluating Methods for Setting Catch Limits for Gag Grouper: Data-Rich versus Data-Limited. In: T.J. Quinn II, J.L. Armstrong, M.R. Baker, J.D. Heifetz, and D. Witherell (eds.), Assessing and Managing Data-Limited Fish Stocks. Alaska Sea Grant, University of Alaska Fairbanks.

SEDAR. 2016. SEDAR 46: U.S. Caribbean Data-Limited Species. SouthEast Data, Assessment, and Review (SEDAR). 373 pp. Available from: http://sedarweb.org/sedar-46.

Part 1: Operating model (OM)

An OM is a mathematical representation of (1) fish stock dynamics, (2) a fishery that harvests the stock, and (3) an observation process that specifies how the simulated collection of data will occur (Punt et al. 2014). Implementation error is not incorporated in DLMtool and catches specified through an MP are removed without error. In DLMtool, stock dynamics are age-structured for ages 1 (recruitment age) to a maximum age at which $\leq 1\%$ of the cohort survives. Natural mortality is age- and sex-invariant, spawning stock biomass consists of both sexes combined, and maturity is a logistic function of age. DLMtool v3.2 simulates a single fishery operating on a fish stock. Vulnerability at age is calculated through a user-specified double normal distribution, which offers the flexibility to simulate a variety of patterns including dome-shaped and asymptotic vulnerability. Data inputs to MPs are simulated through an observation sub-model that introduces imperfect information into the specification of harvest decisions.

As a numerical simulation, DLMtool can incorporate variation in parameters that represent a variety of biological, fishery, and observation processes. It is important to distinguish between these sources of variation as *inter-annual* stochastic events that reflect natural variability and *inter-simulation* variation that allows MP performance to be evaluated across plausible parameter ranges. When multiple MPs are compared using DLMtool, simulated variation in elements of stock dynamics, observation sub-models, and historical fishing effort are generated and retained. Each MP is then subjected to exactly the same sets of simulated conditions, thus ensuring performance is measured against equivalent sequences of ecological and observation events (Carruthers et al. 2014). In the subsequent sections, the mathematical specification of OM components is summarized, including the specification of deterministic and stochastic elements.

3

1.1 Natural mortality

Stock dynamics

$$M_i \sim Uniform(a,b)$$
$$Msd_i \sim Uniform(c,d)$$
$$Mgrad_i \sim Uniform(f,g)$$

$$dev_{t,i} = \exp(\varepsilon_{i,t} - 0.5Msd_i^2)\left(1 + Mgrad_i/100\right)^{(t-1)}$$
$$\varepsilon_{t,i} \sim Normal\left(0, Msd_i\right)$$
$$Marray_{t,i} = M_i dev_{t,i} / \left(\frac{\sum_t dev_{t,i}}{n} \right)$$

Subscripts *t*, *age*, and *i* denote year, fish age, and simulation run, respectively.

Observation process

$$\varepsilon Obs_i \sim Normal\left(0, Mcv\right)$$
$$DLM\_data@Mort_i = \exp(\varepsilon Obs_i - 0.5Mcv^2)M_i$$

User inputs

OM@M=c(*a, b*) bounds on range of natural mortality used to simulate stock dynamics

OM@Msd=c(*c, d*) bounds on inter-annual process variation in M, used to simulate stock dynamics

OM@Mgrad=c(*f, g*) bounds on slope of M through time, used to simulate stock dynamics

OM@Mcv=*Mcv* observation bias for nsims for in observation of natural mortality

Notes

　　User inputs (*a* and *b*) define the inter-simulation range of natural mortality considered in simulation of stock dynamics. Unique values of *M, Msd, Mgrad* are drawn from uniform distributions for each of nsims. For a given simulation, *Marray* is an nsim by nyears+proyears array that specifies year-specific values of natural mortality according to corresponding values of *M, Msd,* and *Mgrad*.

1.2   Growth parameters

$$\text{Linf}_i \sim Uniform(c, d)$$

$$\text{Linf}sd_i \sim Uniform(f, g)$$

$$\text{Linf}grad_i \sim Uniform(j, k)$$

$$dev_{t,i} = \exp(\varepsilon_{t,i} - 0.5\text{Linf}sd_i^2)\left(1 + \text{Linf}grad_i / 100\right)^{(t-1)}$$

$$\varepsilon_{t,i} \sim Normal\left(0, \text{Linf}sd_i\right)$$

$$\text{Linf}array_{t,i} = \text{Linf}_i dev_{t,i} / \left(\frac{\sum_t dev_{t,i}}{n}\right)$$

Subscripts *t*, *age*, and *i* denote year, fish age, and simulation run, respectively.

Observation process

$$\varepsilon Obs_i \sim Normal\left(0, \text{Linfcv}\right)$$

$$\text{DLM\_data@vbLinf}_i = \exp(\varepsilon Obs_i - 0.5\text{Linfcv}^2)\text{Linf}_i$$

User inputs

OM@Linf=c(*c, d*) bounds on range of von Bertalanffy *Linf* parameter used to simulate stock dynamics

OM@Linfsd=c(*f, g*) bounds on inter-annual process variation in *Linf*, used to simulate stock dynamics

OM@Linfgrad=c(*j, k*) bounds on slope of *Linf* through time, used to simulate stock dynamics

OM@Linfcv=*Linfcv* observation bias for nsims for *Linf* parameter

Notes

Calculations are shown for the von Bertalanffy *Linf* parameter. Unique values of *Linf, Linfsd,* and *Linfgrad* are drawn from uniform distributions for each of nsims. For a given simulation, *Linfarray* is an nsim by nyears+proyears array that specifies year-specific values according to *Linf, Linfsd, Linfgrad*. In application, the same approach is taken for the von Bertalanffy K parameter. von Bertalanffy t0 does not have inter-annual variation, but all other calculations apply. Length-at-age is calculated: $L_{t,age,i} = \text{Linf } array_{t,i}\left(1 - \exp\left(-Karray_{t,i}\left(age - t0_i\right)\right)\right)$.

Length-to-weight parameters are user inputs as constants and correspond to the function: $W_{t,age,i} = aL_{t,age,i}^b$. There is no observation error on length-to-weight conversion parameters.

1.3 Stock-recruitment relationship

$h_i \sim Uniform(a,b)$, where h is steepness of the Beverton-Holt stock recruitment function

$procsd_i \sim Uniform(c,d)$, where $procsd$ is standard deviation of log normal recruitment deviation

$AC_i \sim Uniform(f,g)$, where AC is autocorrelation in recruitment deviations

$$\eta_{t,i} \sim Normal\left(0, procsd_i\right)$$

$$\varepsilon_{t,i} = AC_i \varepsilon_{t-1,i} + \eta_{i,t}\sqrt{1+AC_i^2}$$

$$Perr_{t,i} = \exp(\varepsilon_{t,i} - 0.5\, procsd_i^2)$$

$$R_{t,i} = N_{t,1,i} = Perr_{t,i}\left(\frac{0.8R_0 h_i}{0.2SSB_0\left(1-h_i\right)+\left(h_i-0.2\right)\sum_{age} SSB_{t-1,age,i}}\right)\sum_{age} SSB_{t-1,age,i}$$

$R_{t,i}$ is number of age-1 fish, SSB_0 is unfished spawning stock biomass, $SSB_{t-1,i}$ is spawning stock biomass in year $t-1$.

Subscripts t, age, and i denote year, fish age, and simulation run, respectively.

Observation process

$$\mathrm{Re}\, ccv_i \sim Uniform(j,k)$$

$$\varepsilon R_{t,i} \sim Normal\left(0, \mathrm{Re}\, cv_i\right)$$

$$DLM\_data@Rec_{t,i} = \exp(\varepsilon R_{t,i} - 0.5\,\mathrm{Re}\, cv_i^2)R_{t,i}$$

$hObs_i \sim Beta$ with h_i as measure of central tendency, and hcv as measure of spread. Beta distribution is scaled to produce values between 0.2 and 1.0.

$$DLM\_data@steep_i = hObs_i$$

User inputs

OM@h=c(*a, b*) bounds on range of steepness parameter

OM@Perr=c(*c, d*) bounds on inter-annual process variation in recruitment

OM@AC=c(*f, g*) bounds on autocorrelation of inter-annual recruitment variation

OM@Reccv=c(*j, k*) bounds on log-normal observation error on annual recruitment for each nsim

OM@hcv=*hcv* observation bias for nsims for steepness parameter

Notes:

Calculations are shown for the Beverton-Holt stock recruitment function, which was selected for all 8 species under assessment for SEDAR49. Other stock-recruitment functions are also available within DLMtool.

1.4 Reproductive biology

$lenM_i \sim Uniform(a,b)$, where *lenM* is length at 50% maturity

$len95_i \sim Uniform(c,d)$, where *len95* is the growth increment from *len50* length at 95% maturity

$ageM_i = \left(\left(\log\left(1 - len50_i / L\inf_i\right)\right)/ K_i\right) + t0_i$, where *ageM* is age at 50% maturity

$age95_i = \left(\left(\log\left(1 - len95_i / L\inf_i\right)\right)/ K_i\right) + t0_i$, where *age95* is age increment from *ageM*

$Mat\_age_{age,i} = \dfrac{1}{\left(1 + \exp\left(\left(ageM_i - age\right)/\left(ageM_i \kappa_i\right)\right)\right)}$, where κ is the logistic curvature parameter and is calculated using *ageM* and *age95*.

Subscripts *t*, *age*, and *i* denote year, fish age, and simulation run, respectively.

Observation process

$\varepsilon len_i \sim Normal\left(0, LenMcv\right)$

$DLM\_data@L50_i = \exp(\varepsilon len_i - 0.5LenMcv^2)lenM_i$

$DLM\_data@L95_i = \exp(\varepsilon len_i - 0.5LenMcv^2)len95_i$

User inputs

OM@L50=c(*a, b*) bounds on *len50* parameter used to simulate stock dynamics

OM@L50_95=c(*c, d*) bounds on *len95* parameter used to simulate stock dynamics

OM@LenMcv=*LenMcv* observation bias for nsims for *len50* and *len95*

Notes

User inputs of maturity parameters are in terms of lengths and these values are subsequently converted to age-based maturity criteria. For each of nsim simulations, coding ensures that $lenM_i$ does not exceed $0.8Linf_i$ and that $len95_i$ does not exceed $0.9Linf_i$.

1.5 Cohort equations

$N_{t,age,i} = N_{t-1,age-1,i} \exp\left(-Z_{t-1,age-1,i}\right)$, where *N* is abundance and *C* is catch numbers

$Biomass_{t,age,i} = N_{t,age,i}W_{t,age,i}$, where *B* is biomass and *W* is weight

$VBiomass_{t,age,i} = Biomass_{t,age,i}V_{t,age,i}$, where *VBiomass* is vulnerable biomass according to vulnerability *V*.

$SSB_{t,age,i} = N_{t,age,i}W_{t,age,i}Mat\_age_{age,i}$, where *SSB* is spawning stock biomass and *Mat_age* is maturity at age.

$$Depletion_{t,i} = \frac{\sum_{age} Biomass_{t-1,age,i}}{B_0}$$, where *Depletion* is stock reduction relative to unfished state

Subscripts *t*, *age*, and *i* denote year, fish age, and simulation run, respectively.

Observation process

$Derrcv_i \sim Uniform(a,b)$

$\varepsilon Derr_{t,i} \sim Normal(0, Derrcv_i)$

$\varepsilon Dbias_i \sim Normal(0, Dbiascv)$

$\text{DLM\_data@Dt}_{t,i} = Depletion_{t,i} \exp(\varepsilon Derr_{t,i} - 0.5Derrcv_i^2)\exp(\varepsilon Dbias_i - 0.5DBiascv^2)$

$Aerrcv_i \sim Uniform(c,d)$

$\varepsilon Aerr_{t,i} \sim Normal(0, Aerrcv_i)$

$\varepsilon Abias_i \sim \exp(Uniform(f,g))$

$\text{DLM\_data@Abun}_{t,i} = VBiomass_{t,i} \exp(\varepsilon Aerr_{t,i} - 0.5Aerrcv_i^2)\varepsilon Abias_i$

$Isd_i \sim Uniform(j,k)$

$\varepsilon Ierr_{t,i} \sim Normal(0, Isd_i)$

$betas_i \sim \exp(Uniform(\log(u), \log(v)))$

$Index_{t,i} = \left(Biomass_{t,i} \exp(\varepsilon Ierr_{t,i} - 0.5Isd_i^2)\right)^{betas_i}$

$$\text{DLM\_data@Ind}_{t,i} = Index_{t,i} / \left(\frac{\sum_t Index_{t,i}}{n}\right)$$

$\varepsilon IrefBias_i \sim Normal(0, Irefcv)$

$betas_i \sim \exp(Uniform(\log(u), \log(v)))$

$$\text{DLM\_data@Iref}_{t,i} = \left(Biomass_{t,i}\right)^{betas_i} / \left(\frac{\sum_t \left(Biomass_{t,i}\right)^{betas_i}}{n}\right) Bmsy\_B0_i \exp\left(\varepsilon IrefBias_i - 0.5Irefcv^2\right)$$

where *Bmsy_B0* is biomass producing MSY as fraction of unfished biomass.

User inputs

OM@Dcv=c(*a, b*) bounds on annual observation error for depletion observation

OM@Dbiascv=*Dbiascv* observation bias for nsims for depletion

OM@Btcv=c(*c, d*) bounds on annual observation error for observation of vulnerable biomass

OM@Btbias=c(*f,g*) observation bias for nsims for vulnerable biomass

OM@Iobs=c(*j,k*) bounds on annual log-normal observation error on biomass index for nsim

OM@beta=c(*u,v*) bound on hyperstability/hyperdepletion of index for nsim

OM@Irefcv=*Irefcv* observation bias for nsims for biomass index

1.6 Catches and selectivity

$$C_{t,age,i} = N_{t,age,i}\left(1-\exp\left(Z_{t,age,i}\right)\right)\frac{F_{t,age,i}}{Z_{t,age,i}}$$

$$CB_{t,age,i} = Biomass_{t,age,i}\left(1-\exp\left(Z_{t,age,i}\right)\right)\frac{F_{t,age,i}}{Z_{t,age,i}}$$

$$Z_{t,age,i} = Marray_{t,i} + F_{t,age,i}$$
$$F_{t,age,i} = q_i E_{t,i} V_{t,age,i}$$

where *C* is catch in numbers, *CB* is catch in weight, *Z* is total mortality, *F* is fishing mortality, *q* is catchability, *E* is effort and *V* is vulnerability.

Subscripts *t*, *age*, and *i* denote year, fish age, and simulation run, respectively.

$$L\_msel_i \sim Uniform(a,b)$$
$$L\_sel1_i \sim Uniform(c,d)$$
$$L\_sel2_i \sim Uniform(f,g)$$

Length-based selectivity is inputs, and converted to age-based selectivity within the model, where $msel = f\left(L\_msel\right)$, $sel1 = f\left(L\_sel1\right)$, and $sel2 = f\left(L\_sel2\right)$. Vulnerability is calculated as a double normal:

$$A_{age,i} = \frac{1}{\sqrt{2\pi sel1_i^2}}\exp\left(-\frac{\left(age-msel_i\right)^2}{sel1_i^2}\right)$$

$$D_{age,i} = \frac{1}{\sqrt{2\pi sel2_i^2}}\exp\left(-\frac{\left(age-msel_i\right)^2}{sel2_i^2}\right)$$

$$V_{t,age,i} = \begin{cases} A_{age,i}/\max(A_i) & age \leq msel_i \\ D_{age,i}/\max(D_i) & age > msel_i \end{cases}$$

Observation process

$$\varepsilon L\_msel_i \sim Normal(0, LFScv)$$

$$\text{DLM\_data@}LFS_i = L\_msel_i \exp(\varepsilon L\_msel_i - 0.5LFScv^2)$$

$$\varepsilon Cbias_i \sim Normal(0, Cbiascv)$$

$$Csd_i \sim Uniform(j, k)$$

$$\varepsilon Csd_{t,i} \sim Normal(0, Csd_i)$$

$$\text{DLM\_data@}Cat_{t,i} = \sum_{age} CB_{t,age,i} \exp(\varepsilon Cbias_i - 0.5Cbiascv^2) \exp(\varepsilon Csd_{t,i} - 0.5Csd_i^2)$$

$$CAA\_nsamp_i \sim Uniform(l, m)$$

$$CAA\_ESS_i \sim Uniform(p, r)$$

$$CAA_{t,age,i} \sim Multinomial(prob = C_{t,age,i}, N = CAA\_ESS_i)$$

$$\text{DLM\_data@}CAA_{t,age,i} = CAA_{t,age,i} / CAA\_ESS_i \times CAA\_nsamp_i$$

$$CAL\_ESS_i \sim Uniform(u, v)$$

$$tmpCN_{t,age,i} \sim Multinomial(prob = C_{t,age,i}, N = CAL\_ESS_i)$$

tmpCN is used to create a vector of observed lengths, each observed with 10% obsevation CV

The length vector is then binned according to bins of size 0 to $Linf_{t,i} + 2 \times 0.1 \times Linf_{t,i}$

Bin width is $0.03 \times (Linf_{t,i} + 2 \times 0.1 \times Linf_{t,i})$

$\text{DLM\_data@}CAL\_bins_{t,Lbins,i}$ is length bins

$\text{DLM\_data@}CAL_{t,Lbins,i}$ is numbers per length bin

User inputs

OM@LFS= *a* and *b* are bounds on length at maximum selectivity specified as a fraction of length at 50% maturity

OM@L5= *c* and *d* are bounds on length at 5% selectivity specified as a fraction of length at 50% maturity

OM@Vmaxlen= *f* and *g* are bounds on selectivity at maximum length.

OM@LFScv=*Dbiascv* observation bias for nsims for length at maximum selectivity

OM@Cbiascv=*Cbiascv* observation bias for nsims for total catch

OM@Cobs=c(j, *k)* bounds on annual observation error for catch

OM@CAA_nsamp=c(*l,m*) range of actual sample sizes for catch at age

OM@CAA_ESS=c(*p,r*) range of effective sample sizes for catch at age

OM@CAL_ESS=c(*u,v*) range of effective sample sizes for catch at length

1.7   Simulating historic stock dynamics

Temporal trends are divided into a historical time period and a projection time period. The

historical time period constructs plausible biological and fishery trends prior to the start of the

projection time period. At the beginning of the historical time period, the fish stock is initiated in

an unfished equilibrium state. A user-specified time series of fishing effort provides the basis for

natural mortality trends during the historical time period. Fishing mortality rates are calculated

by adjusting a catchability parameter such that corresponding mortality trends produce a user-

specified level of stock depletion at the end of the historic time period. Four user inputs are

required to describe a temporal effort pattern during the historical time period. Here we use a

built-in fleet sub-model named "Generic Fleet" to illustrate effort simulation; however, note that

custom effort trends were used in SEDAR 49. Input parameters using the "Generic Fleet" are:

OM@EffYear=c(0.0, 0.3, 0.6, 1.0)
OM@EffLower=c(0.0, 0.4, 0.4, 0.25)
OM@EffUpper=c(0.0, 0.6, 0.6, 1.00)
OM@Fsd=c(0.1, 0.4)

OM@EffYear indicates the relative size of each segment of the effort time series. For example, a

50 year historical time period would have effort segments breaks of 1, 16, 31, and 50. For each

segment break, a value is drawn from a uniform distribution with minimum and maximum

values corresponding to OM@EffLower and OM@EffUpper. Linear interpolation is used to

calculated effort values for years between segment breaks. Finally, inter-annual variation in

effort is produced from a log-normal distribution with standard deviation corresponding to OM@Fsd. For each simulation run, a unique effort time series is constructed from deterministic and stochastic elements (Fig. 1-1).

1.8   Spatial considerations

Spatial population dynamics can be simulated in a two-area spatial model. User-defined movement between areas allows spatial management strategies to be investigated (Carruthers et al. 2014). In SEDAR 49, spatial stock structure was not simulated. Spatial parameter values were specified to reflect a fully mixed stock that is equivalent to a single-area operating model.

1.9   The observation process

The "true" simulated values of an OM are connected as inputs to a management procedure through an observation sub-model. In proceeding from "true" simulated values to values used in management procedures, error is introduced to reflect user-specified levels of imperfect knowledge. Imperfect knowledge is introduced in the forms of imprecision and bias. Imprecision refers to random inter-annual variation in observable quantities around respective "true" simulated values. Bias refers to inaccuracy in a given quantity that occurs for the duration of a simulation (i.e. for a unique realization of a historic and projection simulation sequence). Simulating bias and imprecision allow measurement of the effects of imperfect information on management procedure performance (Carruthers et al. 2014). Error can be specified for several parameter types, including natural mortality, the ratios F_{MSY}/M and B_{MSY}/B_0, current stock depletion, biomass, and catches. Details regarding simulation of imperfect information is found throughout the preceding sections.

As an example, log-scale bias in estimation of stock depletion is shown for two built-in observation sub-models: "Precise-unbiased" and "Imprecise-biased" (Fig. 1-2A). In each simulation run, i, and year, t, estimated depletion is calculated as (see Part 1; section 1.5):

$$\text{DLM\_data@Dt}_{t,i} = Depletion_{t,i} \exp(\varepsilon Derr_{t,i} - 0.5 Derrcv_i^2) \exp(\varepsilon Dbias_i - 0.5 DBiascv^2).$$

Imperfect information is introduced through log-normal error structure, specified as:

$$Derrcv_i \sim Uniform(a,b)$$
$$\varepsilon Derr_{t,i} \sim Normal\left(0, Derrcv_i\right)$$
$$\varepsilon Dbias_i \sim Normal\left(0, Dbiascv\right).$$

In the "Precise-unbiased" scenario, precision ($Derrcv_i \sim Uniform(a,b)$) is specified as $a=0.025$ and $b=0.100$ and bias is specified as $Dbiascv = 0.20$. In the "Imprecise-biased" scenario, the log-normal distribution is modified with $a=0.050$ and $b=0.200$ and $Dbiascv = 0.75$. Introducing errors into an MP allows the effects of imperfect information to be propagated into performance measures, thus revealing the consequences of data quality on achievement of management objectives (Fig. 1-2B). Misspecification of data inputs can also reveal the direction of effects on performance measures (Fig. 1-2C).
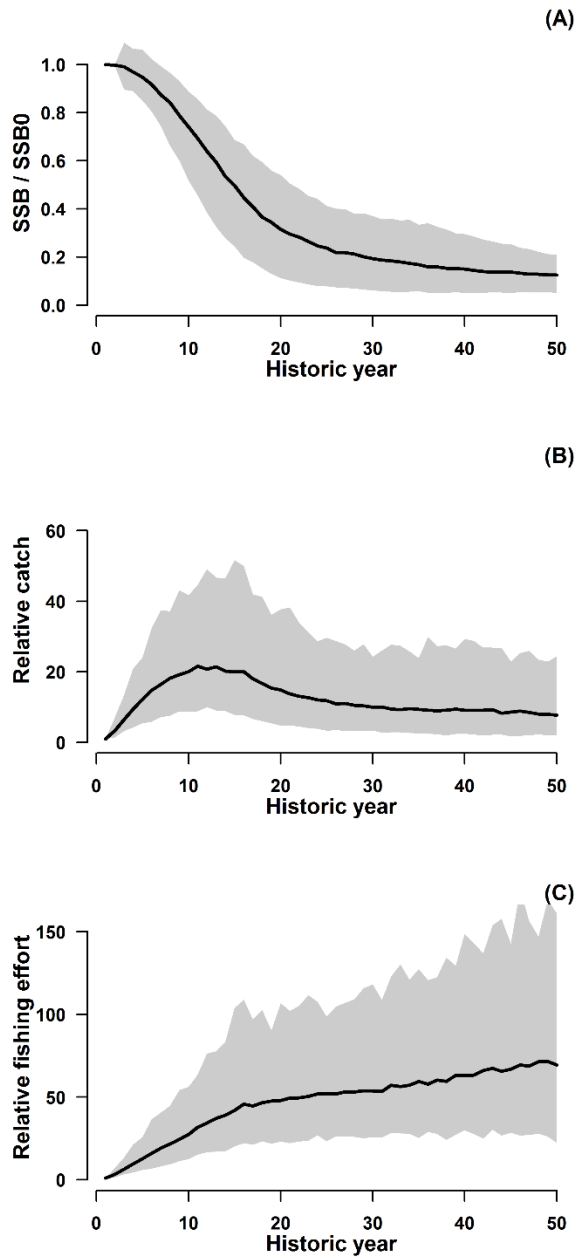
Fig. 1-1. Simulated historical dynamics using the "Generic Fleet" sub-model. (A) Declining trend in spawning stock biomass reflects specified depletion range at year 50 of the historic time period. (B) Resultant catch relative to year 1 catch. (C) Fishing effort pattern scaled relative to year 1 of the historic time period. Solid line is median trend and shaded area is centered 95% of simulations.
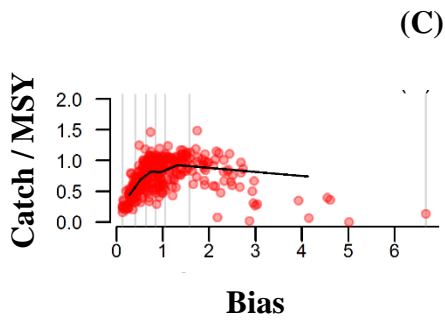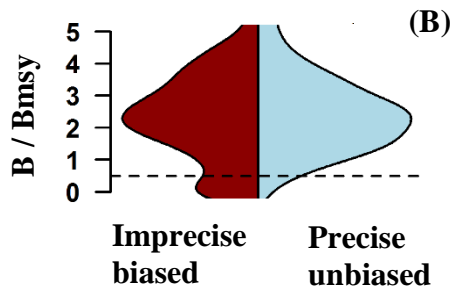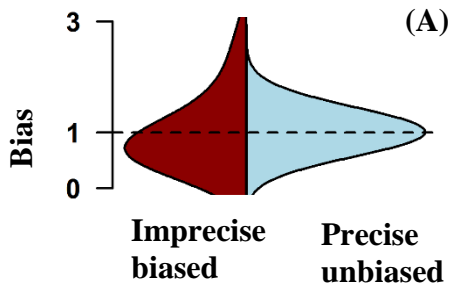
Fig. 1-2. Example distributions of bias (A), management procedure performance in terms of biomass relative to biomass associated with MSY (B), and the directionality of the effect of bias on long-term catch relative to MSY (C).

Part 2: SEDAR 49 operating model modifications

2.1   Incorporating von Bertalanffy correlation structure

In DLMtool, OM inputs for inter-simulation variation in von Bertalanffy growth parameters are specified by the user as uniform distributions. In generating unique sets of growth parameters for a given simulation run, values are drawn from these user specified uniform distributions of K, Linf and t0. In building upon this existing framework, it was desirable to enable correlated uniform draws for the von Bertalanffy parameters. The OM in DLMtool was modified to allow correlated uniform distributions to be simulated using copulas. Copulas are functions that join together multiple univariate distributions to form multivariate probability distributions (Weisstein). The utility of copulas is that separate univariate distributions (like each of the growth parameters) can be joined together though functions that specify dependence between these variables, thus enabling simulation of multivariate probability distributions. Copulas are used in economics and finance, and credit is provided here to a web source for R coding on which the modification to DLMtool was based (Schumann, Embrechts et al. 2001). An example of correlated uniform distributions for K and Linf is provided (Fig. 2-1).

In DLMtool, runMSE is a wrapper function that carries out MSE. An alternative version of this function, named runMSE_LVBcor was coded to allow von Bertalanffy growth parameters to be drawn from a multivariate uniform distribution, based on user specified correlations between parameters. Verification testing was carried out to check for errors in modified R code. First, the performance of runMSE was compared to runMSE_LVBcor when LVB correlation parameters were set to 0. The comparison confirmed the expectation that both functions would produce equivalent results, suggesting that errors were not inadvertently introduced during coding (Fig. 2-2). Second, verification tests were performed to ensure that specified levels of correlation between variables were indeed produced in modeling outputs (e.g. Fig. 2-1).
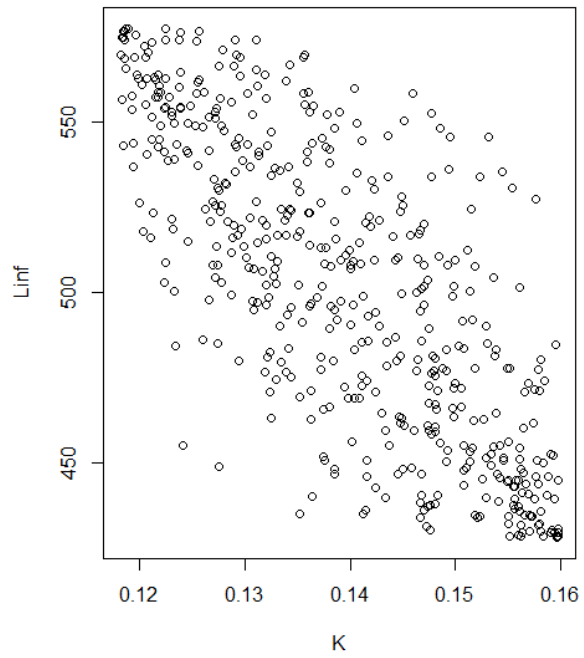
Figure 2-1. Example of simulated correlated uniform distribution between K and Linf. Specified correlation is -0.76.
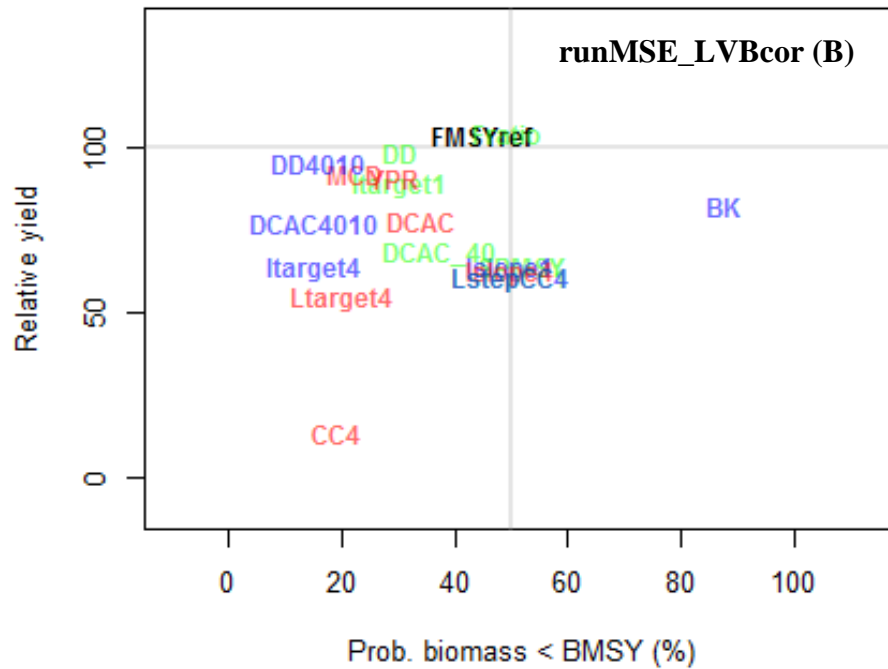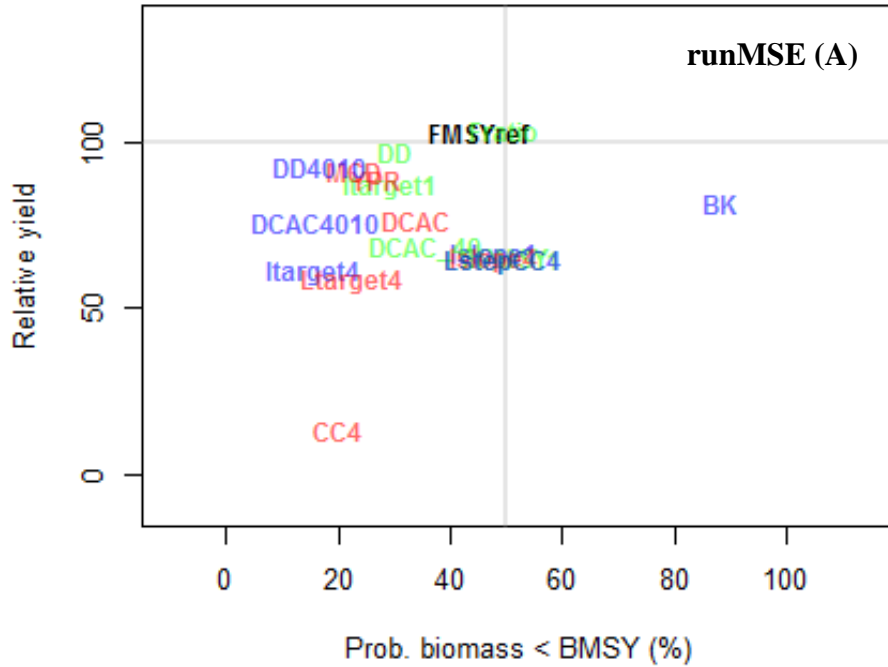
Figure 2-2. Comparison of MP performance between runMSE (A) and runMSE_LVBcor (B). In this verification test, all correlation parameters are set to zero to ensure runMSE_LVBcor produces equivalent results to runMSE. nsim=500, reps=1, proyears=40, interval=4, Stock=Snapper, Fleet=Generic_fleet, observation=Perfect_info.

18

Part 3: Overview of the role of uncertainty in MSE

Butterworth (2007) uses the terms management procedure (MP) and traditional approach (TA) to setting total allowable catches (TAC) as a means to explain the role of MSE in the provision of management advice. The TA may involve the use of "best available science", probably through stock assessment, to estimate current stock biomass and productivity. These quantities are translated into TAC recommendations. A MP provides a formula to produce a TAC recommendation, and in this context, a MP is similar to the TA (Butterworth 2007). However, these two constructs differ in that a MP (consisting of (i) information collection, (ii) data analysis, and (iii) a harvest control rule) is subjected to simulated performance testing (Butterworth and Punt 1999, Sainsbury et al. 2000, Butterworth 2007). Importantly, performance testing (via MSE) is typically aimed at illuminating trade-offs between the achievement of fishery management objectives (Butterworth 2007, Punt 2015).

Central to formulation of MPs is understanding the consequences of uncertainty for achieving management objectives (Punt et al. 2014). For instance, it may be useful to identify circumstances under which management objectives may fail to be achieved. It is well established that the TA has moved beyond "best fit" or point estimation as the basis for provision of management advice, and embraced the evaluation of uncertainty through confidence envelopes, sensitivity analysis, and stochastic projections (Hilborn and Liermann 1998, Peterman 2004, Butterworth 2007). As a corollary, subjecting MPs to simulation testing enables the consequences of management decisions to be evaluated across a broad array of uncertainties, and with outcomes evaluated across a variety of management objectives (Butterworth 2007, Punt et al. 2014). The following is a non-exhaustive list of some uncertainties that can be incorporated into OMs used in MSE:

1. Process uncertainty that arises from random variation in ecological systems. Example: annual recruitment variability;

2. Model uncertainty associated with incomplete understanding of the correct structure and parameter values used in describing stock dynamics. Examples: natural mortality rate or steepness of stock-recruitment function;

3. Observation uncertainty that arises through imperfect sampling, recording, and measurement of data streams. Example: underreporting of catches.

4. Estimation uncertainty that is typically associated with quantities that are determined through statistical analysis. Estimation error arises from observation error and process error in data and from structural assumptions associated with statistical analysis. Example: total mortality estimation from mean length data.

Several literature sources provide more extensive lists of scientific uncertainties (Smith 1993, Fogarty et al. 1996, Francis and Shotton 1997, Peterman 2004, Haddon 2011, Punt et al. 2014).

In the context of data-limited fishery management, scientific uncertainties will be a substantial consideration in MP formulation (Carruthers et al. 2014, 2015). In DLMtool, uncertainties can be represented through specification of alternative OMs using discrete sets of parameter values, through Monte Carlo simulation across plausible parameter ranges, or through some combination thereof. Developing alternative OMs enables identification of MPs that are robust to plausible OM scenarios (Butterworth and Punt 1999, Butterworth et al. 2010). By iteratively generating plausible sets of parameter values for one or multiple parameters via a Monte Carlo approach, corresponding biological trajectories are produced along with probability distributions of performance measures. A combination of discrete scenarios and integration across uncertainty in some parameters appears to be a useful approach for precipitating effective

management advice about MP selection (Butterworth et al. 2010, Carruthers et al. 2014, 2015, Geromont and Butterworth 2015).

3.1 An example management procedure

As a demonstration, we implement a MP that calculates a TAC based on an estimate of a target harvest rate and current stock biomass (Fig. 3-1). In the discussion of the role of uncertainty in MSE that follows, we provide neither a definitive nor exhaustive example and recognize that there are alternative approaches to analyzing and interpreting MSEs. This demonstration is intended as a simple introduction to MSE within a more complex process of providing fishery management advice. The MP we introduce may not be truly "data-limited" in any strict sense because biomass estimates are used to calculate TACs. Biomass estimates are unlikely to be available in most data-limited circumstances. However, the example is used to illustrate some aspects of explicitly considering scientific uncertainties in MP evaluation. In addition, actual applications of MSE are most commonly focused on relative performance contrasts between several MPs (Smith et al. 1999, Butterworth et al. 2010). For simplicity of this demonstration, we focus on a single MP named "Fdem" that is available in DLMtool.

The Fdem MP is a demographic approach that approximates intrinsic rate of increase using estimates of life history parameters and expert judgement about steepness of the Beverton-Holt stock recruitment function (Fig. 3-1). The harvest rate associated with MSY (HR_{MSY}) is then approximated as ½ of the estimated intrinsic rate of increase. Using an additional input of current biomass, a TAC is calculated as: $TAC = B \times HR_{MSY}$. TACs are held constant for five years between subsequent decisions. This MP is intended to guide stock size towards B_{MSY} and to sustain long-term catches in proximity to MSY.

3.2   Defining key uncertainties

In our demonstration, we simulate a generic fish stock that is of concern to resource managers because fishing effort continues to increase. In defining key uncertainties, we limit this demonstration to model uncertainty and observation and estimation uncertainty.

Model uncertainty

The life history of this generic stock is well studied; however the stock-recruitment relationship is highly uncertain, including the value of the steepness parameter. In addition, the current state of stock depletion is highly uncertain and managers have asked whether long-term achievement of management objectives can be obtained using Fdem, regardless of current stock status. As a generic approach to data-limited MSE, categorizing uncertainties into scenarios reflecting their plausible extents is commonplace (Smith et al. 2009, Carruthers et al. 2014, 2015, Geromont and Butterworth 2015). Here, we categorize OM scenarios using a factorial design with two levels of depletion (rebuilding status and non-rebuilding status) and three discrete levels of steepness that encompass a range of values from 0.4 to 0.99 (Table 3-1). Our plausible range for steepness should be assumed to reflect the hypothetical plausibility of this parameter.

Observation and estimation uncertainty

By introducing reasonably realistic levels of observation imprecision and bias into parameter inputs, we evaluate whether shifts in MP performance occur as a consequence of imperfect information. Since steepness is considered uncertain for our generic stock, there is a real possibility that steepness inputs to the Fdem MP would also be highly inaccurate. We use the observation sub-model to generate biased inputs to the MP, which enables the influence of bias on MP performance to be calculated.

3.3   A generic fish stock

Dynamics for the generic fish stock are age-structured for ages 1 to a maximum age of 19 years. Natural mortality is 0.18 year^{-1} and maturity occurs at approximately ½ of maximum fish length. A single fishery operates on the stock with full vulnerability occurring at approximately ½ of maximum fish length. Recruits are generated according to a Beverton-Holt stock-recruitment function with random recruitment variation specified using a log-normal standard deviation SD~U[0.2, 0.4]. Recruitment is the only source of random inter-annual variation (i.e. process uncertainty).

3.4   Understanding management procedure robustness to uncertainty

Model uncertainty

To evaluate the effects of model uncertainty on MP performance, different OM configurations are simulated (Table 3-1). Perfect information about "true" simulated value is provided to the MP, so that performance measures capture only the effect of different OM configurations. Comparison of different steepness scenarios reveals a greater probability of the biomass being below B_{MSY} for higher steepness stocks than for lower steepness stocks (Fig. 3-2). This lack of robustness to "true" steepness value is explained by recognizing that a positive bias between "true" HR_{MSY} and the estimate of HR_{MSY} produced by the Fdem MP appears to be magnified at higher steepness values. These discrete scenarios allow performance consequences to be teased apart based on current depletion level (minimal) and steepness (potentially problematic) (Fig. 3-2). For the rebuilding scenario, we also plot the distributions of terminal biomass estimates relative to B_{MSY} to illustrate differences between the use of discrete sets of parameter values and the use of Monte Carlo integration across plausible parameter ranges (Fig. 3-3). The top panel in Figure 3-3 provides a means to calculate the probability of biomass falling

below an undesirable threshold as an integrated combination of all plausible steepness values, while the lower panels reveal the principle cause of low biomass levels (Fig. 3-3).

Observation and estimation uncertainty

When performance of Fdem is contrasted between a scenario that involves perfect information and one that involves imprecise and biased quantities, performance measures demonstrate the negative effects of data quality (Fig. 3-4). The built-in "Imprecise-biased" observation model in DLMtool produces errors on several parameters including a log-normal steepness bias that is specified with a standard deviation of 0.3. The distinction between perfect information and the imprecise-biased alternative is that observed quantities will no longer retain their "true" simulated values when they are used in MP steps that involve analysis or the harvest control rule. Demonstrating that an MP can provide satisfactory achievement of management objectives even when observed or estimated quantities are in error can be an essential criteria for MP selection (Butterworth 2007). As a simple demonstration, our simulated performance under imperfect information raises questions about whether the Fdem MP (as currently formulated) offers sufficient allowance for scientific uncertainty. The directionality of bias can also be of interest (Fig. 3-5). Our simulations suggest that systematic over-estimation of steepness leads to biomass decline, which is commensurate with our observation that steepness has a positive influence on perceived intrinsic rate of increase, and corresponding estimates of HR_{MSY}.

Table 3-1. Operating model scenarios categorized according to current state of stock depletion and plausible steepness of the stock-recruitment function. *h* is steepness, *D* is stock depletion, U is uniform distribution that delineates *inter-simulation* variation.

Depletion scenario	Steepness scenario		
	low	medium	high
Rebuilding phase	$h \sim U[0.4, 0.6]$	$h \sim U[0.6, 0.8]$	$h \sim U[0.8, 0.99]$
	$D \sim U[0.05, 0.2]$	$D \sim U[0.05, 0.2]$	$D \sim U[0.05, 0.2]$
Non-rebuilding phase	$h \sim U[0.4, 0.6]$	$h \sim U[0.6, 0.8]$	$h \sim U[0.8, 0.99]$
	$D \sim U[0.2, 0.6]$	$D \sim U[0.2, 0.6]$	$D \sim U[0.2, 0.6]$
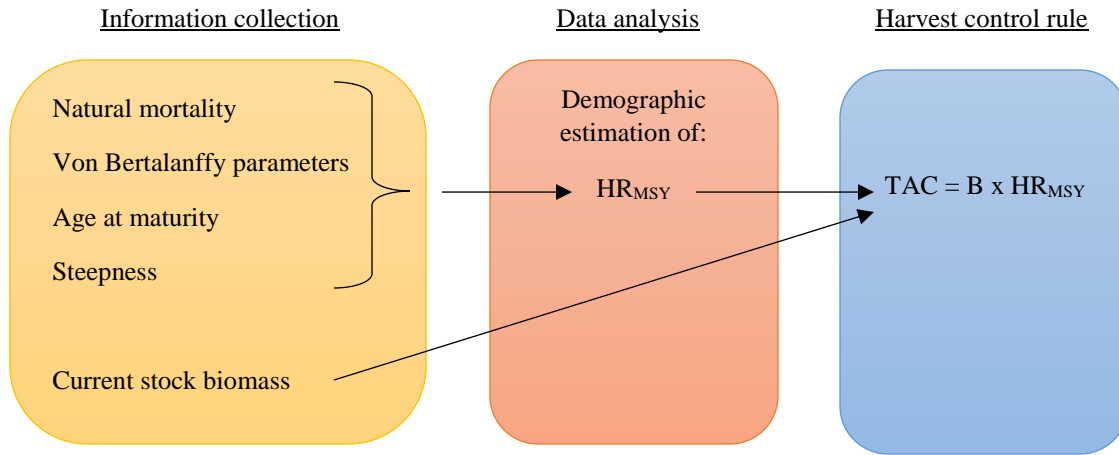
Fig. 3-1. Schematic of a generic management procedure in DLMtool named Fdem.
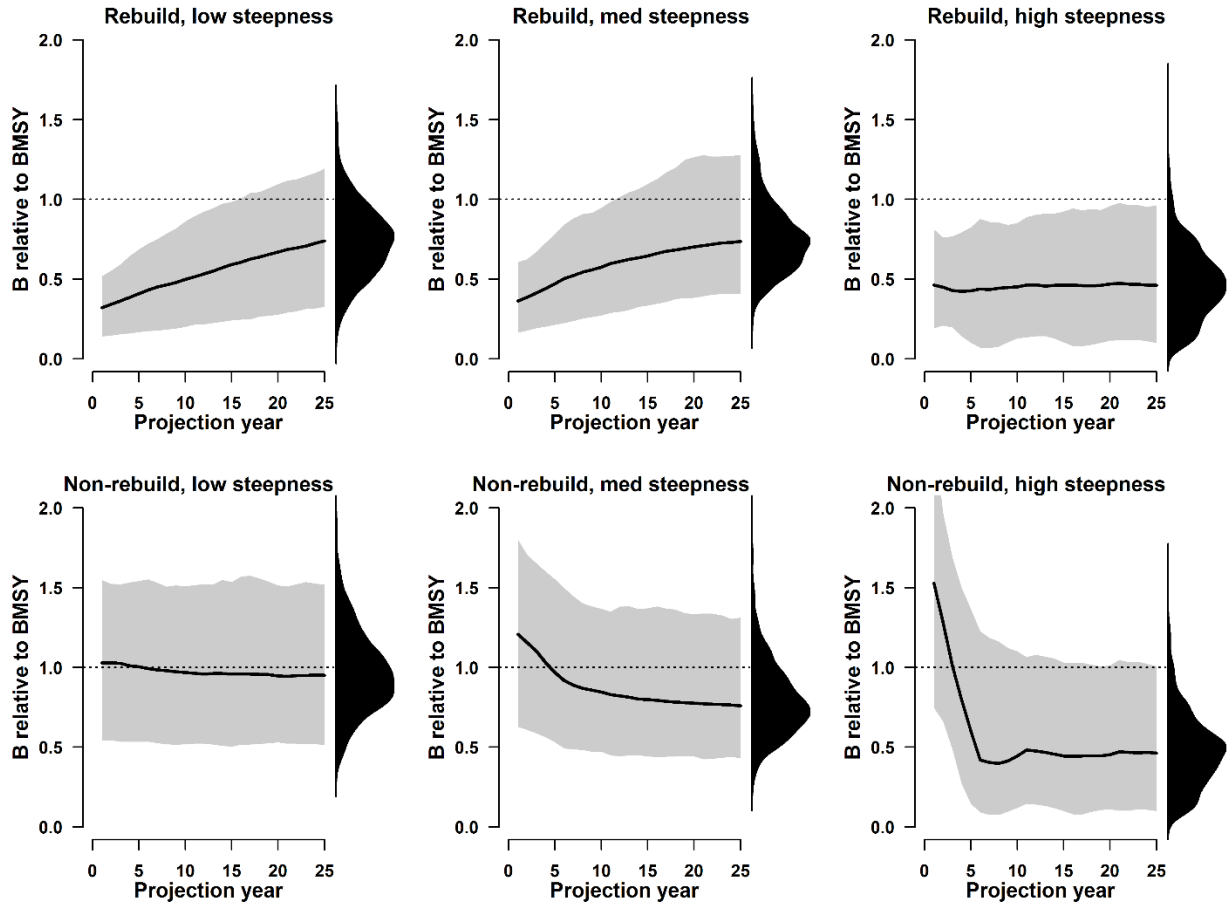
Fig. 3-2. Projected performance of Fdem management procedure in terms of biomass level relative biomass associated with maximum sustainable yield (B/Bmsy). Shown are median trajectories (solid line) and centered 95% of simulation runs. Density plots (solid black) show distribution of terminal B/Bmsy.
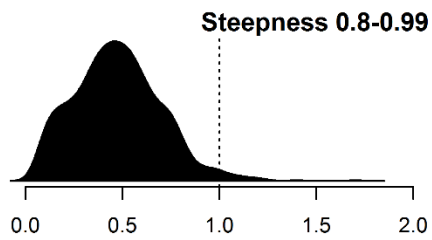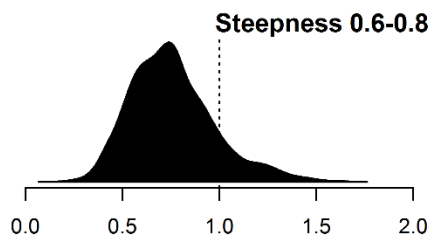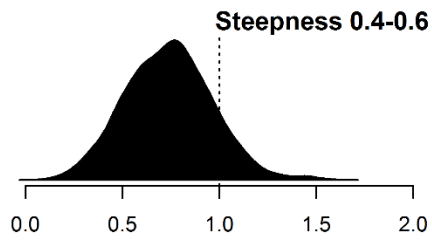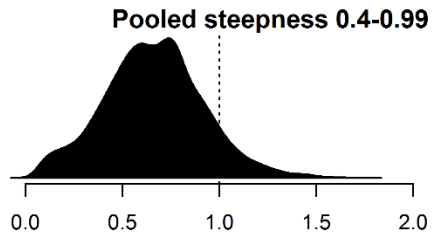
Fig. 3-3. Comparison of terminal B/Bmsy for rebuilding scenario based on different uniform distribution ranges used to generate *inter-simulation* variation in steepness. Contrasted are the approach involving generating discrete scenarios (bottom 3 panels) versus the approach to integrating across the plausible parameter range (top panel).
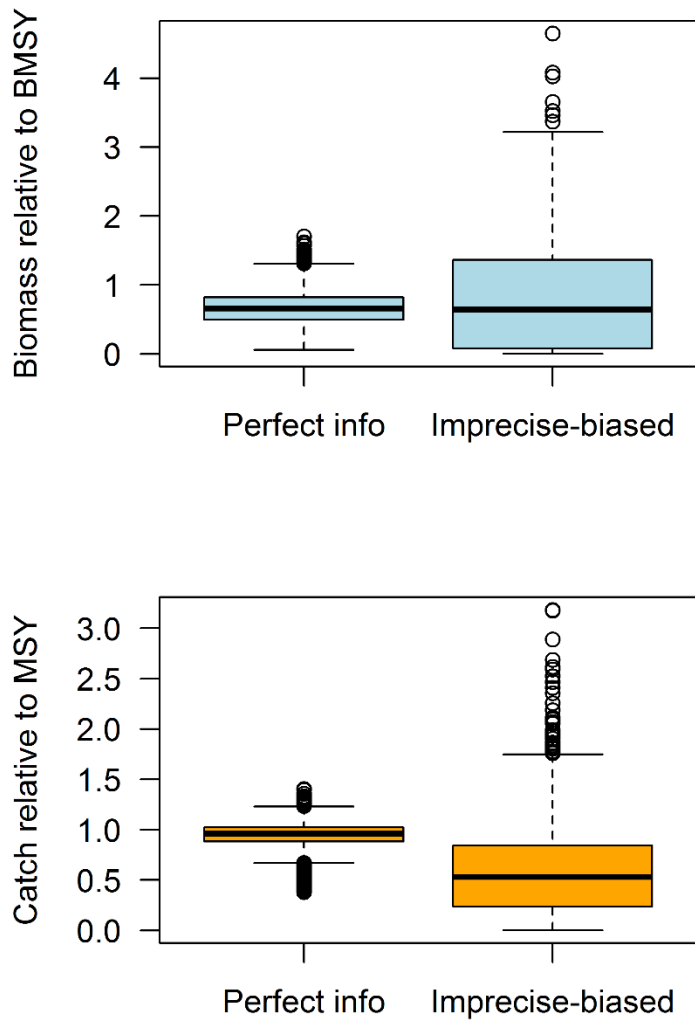
Fig. 3-4. Comparison of MSE performance when imperfect information is introduced to the Fdem management procedure. The rebuilding scenario with steepness integrated across its entire plausible range (0.4-0.99) was used in producing two performance metrics: terminal B/Bmsy (top panel) and catch relative to MSY (bottom panel).
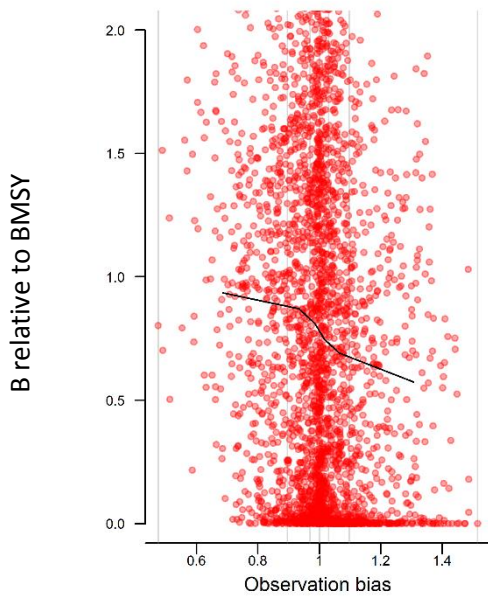
Fig. 3-5. Effect of bias in observed steepness on terminal B/Bmsy Comparison of MSE performance when imperfect information is introduced to the Fdem management procedure. The rebuilding scenario with steepness integrated across its entire plausible range (0.4-0.99) was used in producing two performance metrics: terminal B/Bmsy (top panel) and catch relative to MST (bottom panel).

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