Using management strategy evaluation to design harvest control rules under decreasing survey effort

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1 Introduction

2 The generic stock

We start by generating a single stock using the FLH generic life history generator. The parameters are given in Table 1 and the resulting reference points in Table 2.

3 Historic stock trajectory

3.1 Historic fishing scenarios

When Magnusson & Hilborn (2007) where investigating how information content of the catch and index histories affected the assessment they used four different scenarios of fishing mortality:

1. one-way trip, harvest rate gradually increases
2. no change, constant at a somewhat low harvest rate
3. good contrast, stock is fished down to less than half its initial size, then allowed to rebuild
4. rebuild only, stock begins at low abundance and is allowed to rebuild under low fishing mortality

We begin by looking at scenario 3 only: starting from 0, F will increase to $2F^{MSY}$ before decreasing slightly over a period of 40 years (Figure 2).

Growth	
L_∞	120
k	0.192
$maxage$	25
Maturity	
$mat95$	6
SRR	
Steepness h	0.75
Virgin Biomass $B0$	1000

Table 1: Parameters for generating the generic stock with FLH

Reference points	
MSY	30.1924
B^{MSY}	380.989
F^{MSY}	0.0858183

Table 2: Reference points for the generic stock with FLH

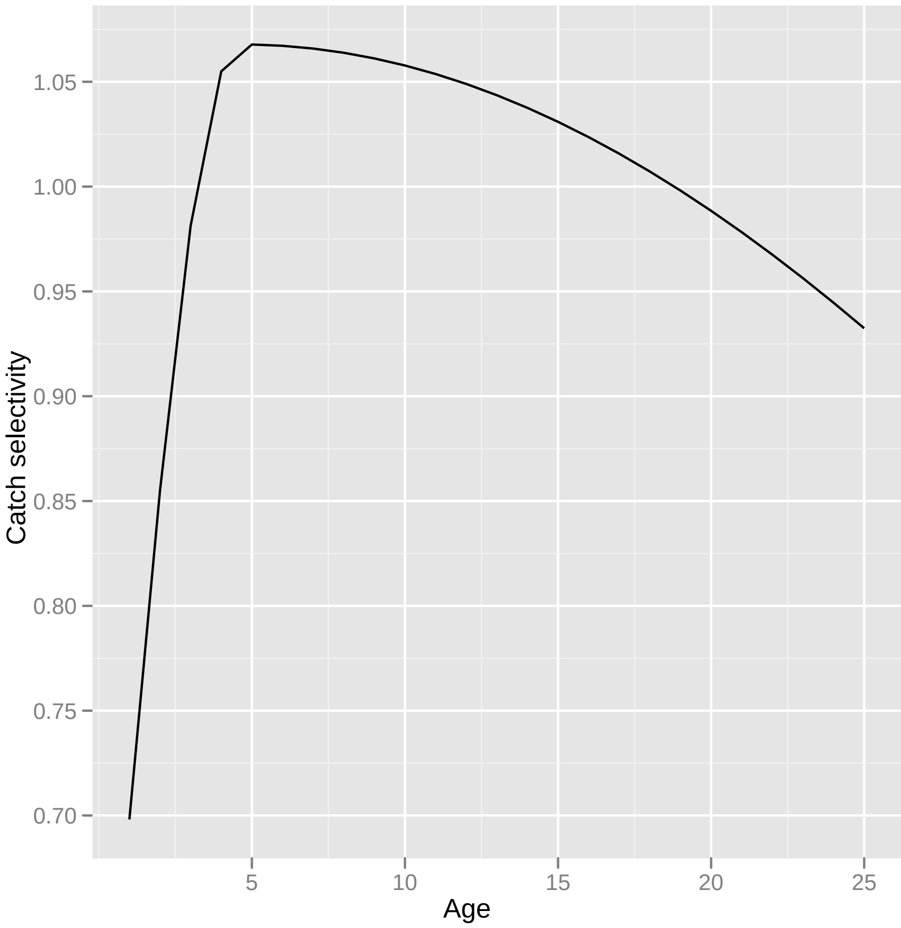

Figure 1: Double normal catch selectivity curve for the generic stock with parameters $a1 = 0.5$, $sL = 0.5$ and $sR = 5$.

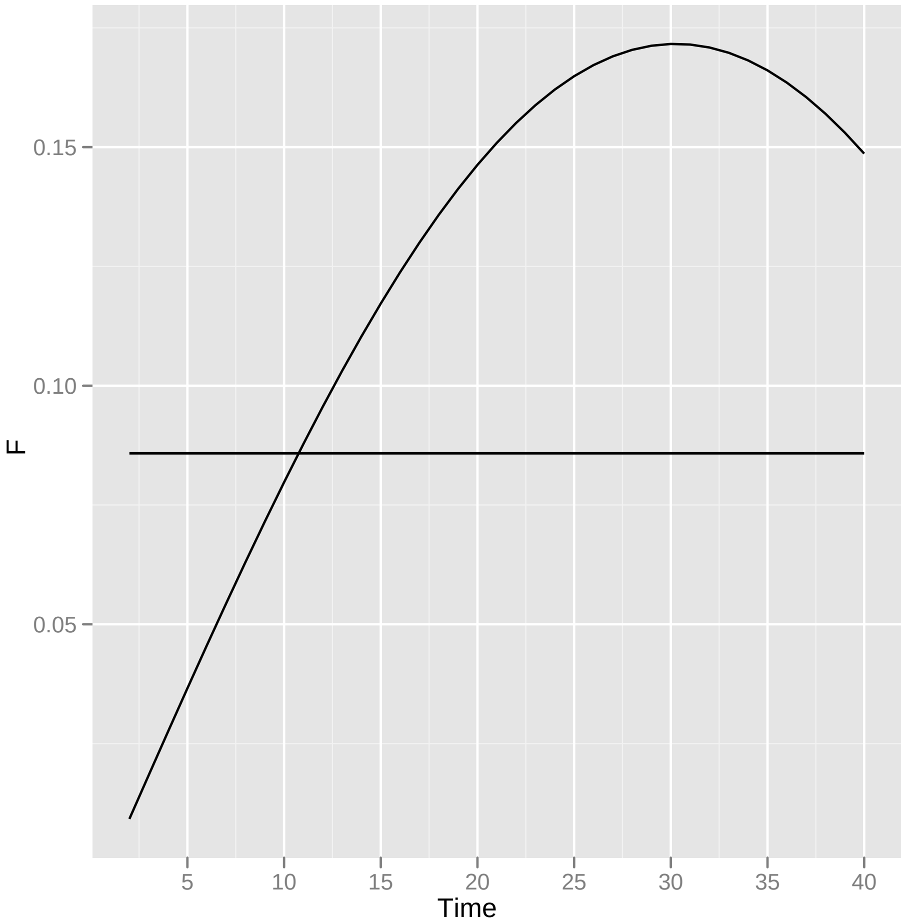

Figure 2: Fishing mortality scenario. F increases from 0 to $2F^{MSY}$. The horizontal line is F^{MSY}.

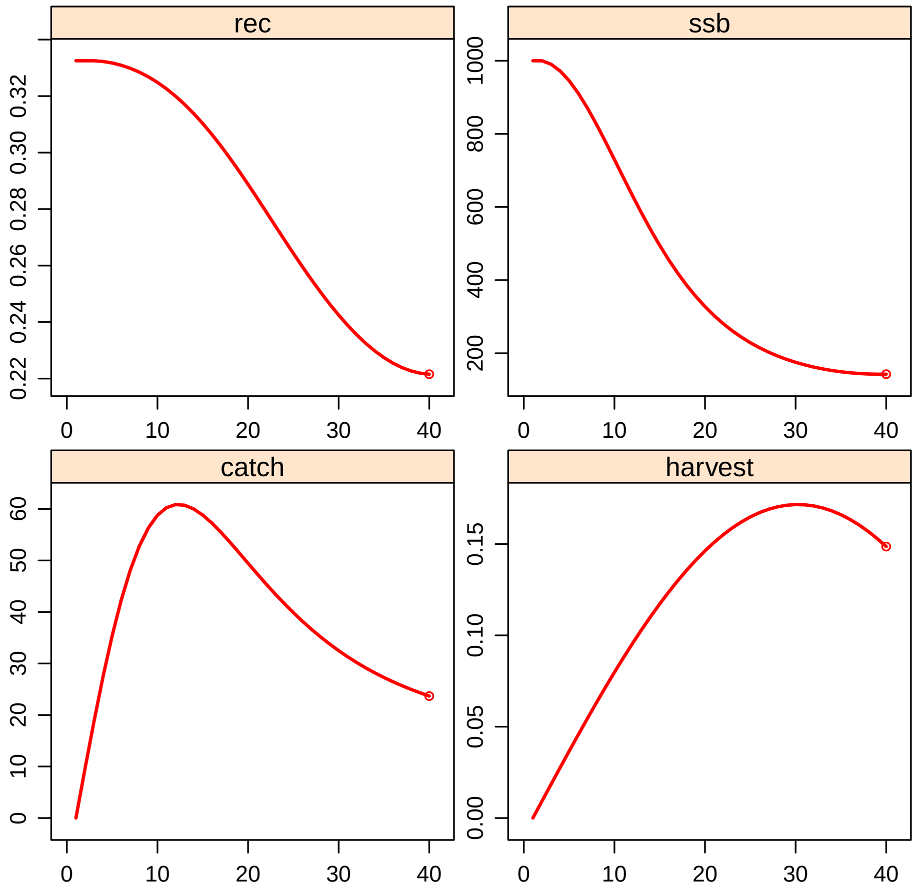

Figure 3: Historic stock dynamics

3.2 Historic biomass trajectory

Using the glory of *FLash* we can now project the stock forward from time $t = 0$ to $t = 40$ under this fishing scenario. To perform our projection we convert our generic stock (currently a *FLBRP* object) into an *FLStock* object, define an *FLQuant* containing the recruitment residuals, setup a control object and then project forward:

The resulting stock object can be seen in Figure 3.

4 Management strategy projection

4.1 Management scenarios

We compared three different managment scenarios:

1. perfect knowledge
2. model based control rule
3. empirical control rule

Management objectives were specified as a target catch $C^{TAR} = C^{MSY}$ and biomass $B^{TAR} = B^{MSY}$. Note that both targets are consistent with each other (i.e. it is feasible to achive both simultaneously).

The harvest conrol rule defines the catch per year

$$C_{y+1} = \frac{C^{TAR} G(B_y)}{G(B^{TAR})}$$

where $G(B)$ is our observation of the resource. For the scenarios listed above:

1. $G(B) = B$
2. $G(B) = \hat{B}$
3. $G(B) = I$

To ensure comparibility of results, for all scenarios the values of C^{TAR} and B^{TAR} were assumed known. For scenario 3, we observe the survey catch rate I only. Since the survey and commercial catches are obtained under differing selectivity assumptions $G(B^{TAR}) = I^{TAR} \neq qB^{TAR}$. Instead we calculate I^{TAR} directly from the numbers vector N_a^{TAR} associated with B^{TAR} and assuming a constant survey catchability. Thus $I^{TAR} = q \sum_a w_a N_a^{TAR}$.

Since scenario 2 requires an estimation step, we predict that as survey effort declines performance of this control rule will deteriorate. Specifically it will deteriorate at a faster rate than the control rule in scenario 3, which is empirical. Performance was measured as the probability of $C \geq C^{TAR}$ and $B \geq B^{TAR}$ after a 40 year projection period. Managment scenarios will be compared by a regression of performance against survey effort.

4.2 Getting the index data for the control rule

We assume the index comes from a survey vessel, and that the resource is fully selected by the gear. We use empirical survey data to estimate the relationship between uncertainty in our catch rate index and the survey effort. Specifically, data were extracted from the ICES International Bottom Trawl Survey (IBTS) database for the North Sea, and filtered for *Gadus morhua* and the GOV gear type. For each year from 1983 to 2011, bootstrap samples of individual trawls were taken, from which a mean catch rate in numbers per tow ($\hat{I}$) could be estimated. The number of bootstrap samples represented the hypothesised survey effort. For each year and survey effort, we sampled 1000 values of $\hat{I}$ from the data, from which we obtained the coefficient of variation (Figure 4).

We assume that the survey takes place at the beginning of the year (before any catches have been taken) and with a constant catchability $q = 1e-04$.

4.3 Stochasticity

Sources of stochasticity were as follows:

1. recruitment: multiplicative log-normal noise around the predicted recruitment
2. observation: the survey catch rate was subjected to a degree of noise equivalent to that given in Figure 4 for a specified level of effort

5 Preliminary runs

We ran deterministic projections for all three management scenarios to ensure that they are behaving as expected (i.e. converging on B^{TAR} and C^{TAR}). These are shown in Figures 5, 6 and 7.

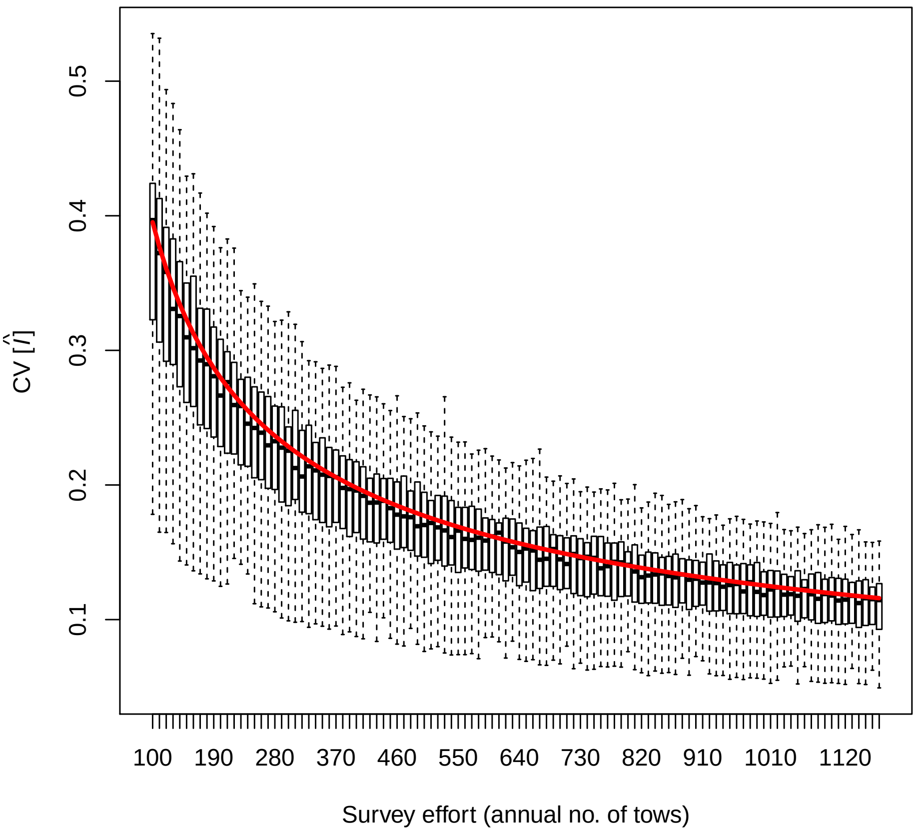

Figure 4: Estimated relationship between CV of the estimated catch rate and survey effort. Boxplots represent the variation across years. The mean across years is represented by the fitted red line $\hat{CV}[\hat{I}] = \alpha E^{\beta}$, where E is the survey effort, $alpha = 3.93$ and $\beta = -0.5$.

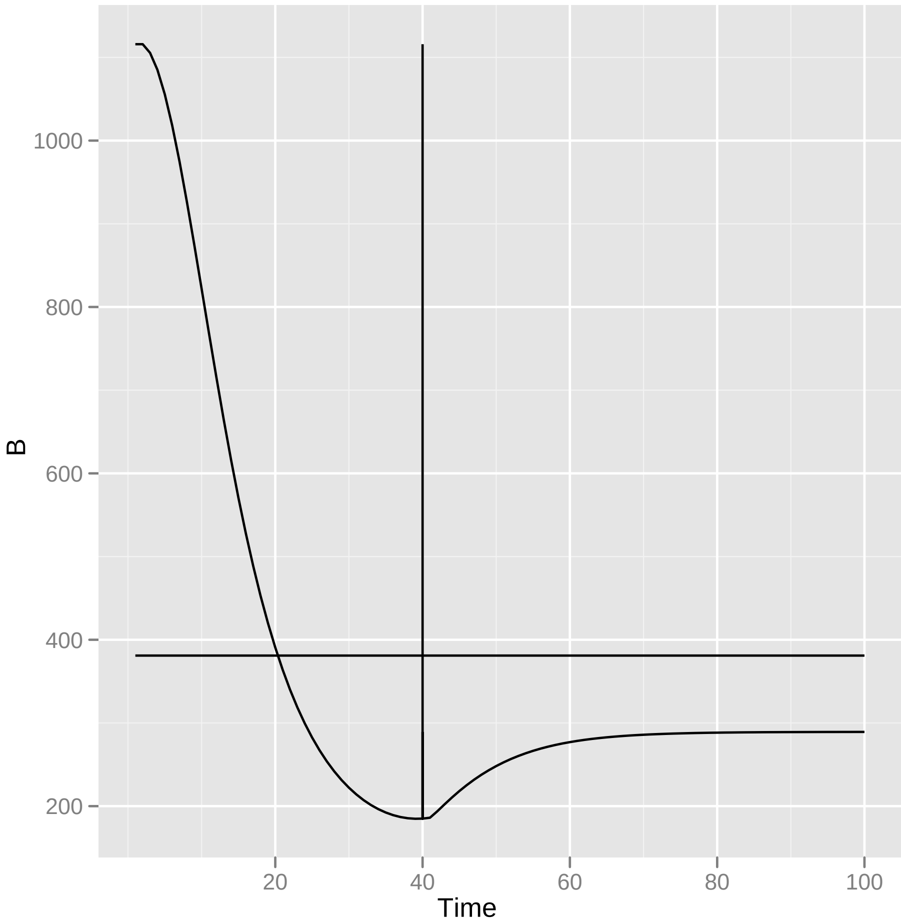

Figure 5: Scenario 1: Performance of control rule assuming perfect knowledge of resource status. Vertical line represents start of projection period. Horizontal line represents the target biomass B^{TAR}.

```
> source("../cde/sra.r")
> index <- quantSums(sweep(stock.n(stk2) * stock.wt(stk2), 1, catch.sel(gen1), "*"))
> fit <- optim(SSB0, fn = logl, catch = catch(stk2)[, 1:maxt], index = index[, 1:maxt], hh = slope,
+     M = m(gen1), mat = mat(gen1), sel = landings.sel(gen1), wght = stock.wt(gen1), amin = range(gen1)["min"],
+     amax = range(gen1)["max"], method = "L-BFGS-B", lower = c(800), upper = c(1500), hessian = T)
> out <- pdyn(B0 = fit$par, catch = catch(stk2)[, 1:maxt], index = index[, 1:maxt], hh = slope,
+     M = m(gen1), mat = mat(gen1), sel = landings.sel(gen1), wght = stock.wt(gen1), amin = range(gen1)["min"],
+     amax = range(gen1)["max"])
> msy <- msy.sra(B0 = fit$par, catch = catch(stk2)[, 1:maxt], index = index[, 1:maxt], hh = slope,
+     M = m(gen1), mat = mat(gen1), sel = landings.sel(gen1), wght = stock.wt(gen1), amin = range(gen1)["min"],
+     amax = range(gen1)["max"])
> CTAR <- msy$MSY
> BTAR <- msy$MSY/msy$F
```

5.1 Scenario 1: perfect knowledge

5.2 Scenario 2: model based control rule

5.3 Scenario 3: empirical control rule

6 Stochastic results

6.1 Scenario 1

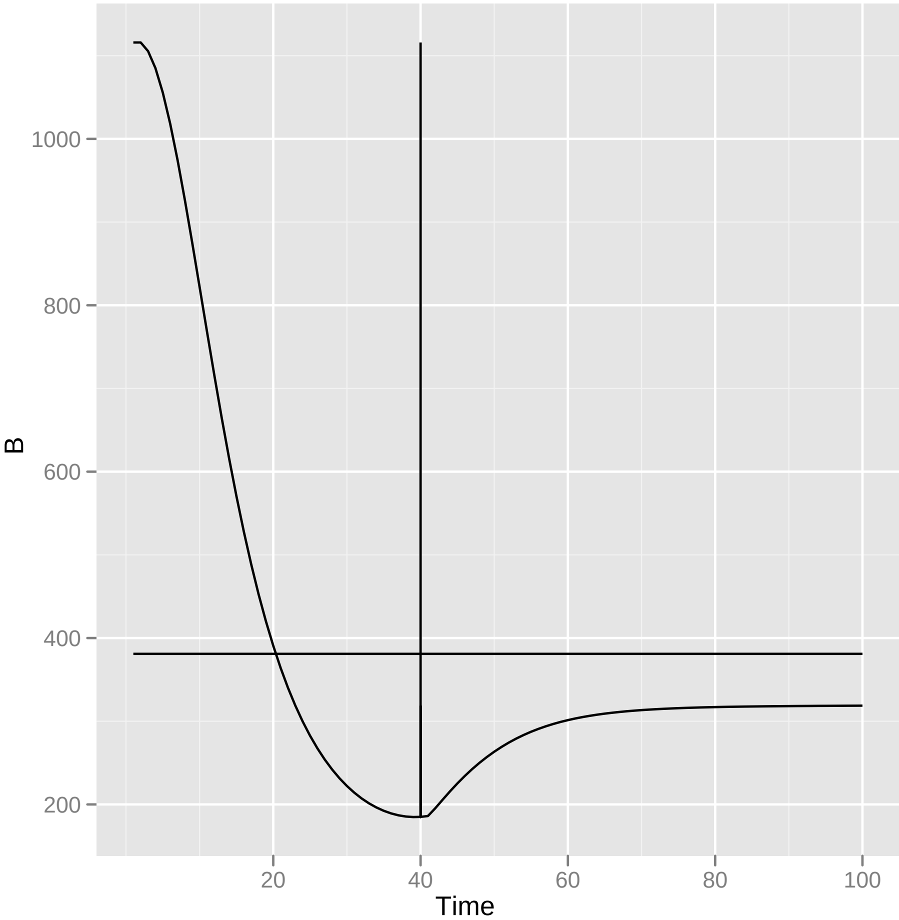

Figure 6: Scenario 2: Performance of model-based control rule. Vertical line represents start of projection period. Horizontal line represents the target biomass B^{TAR}.

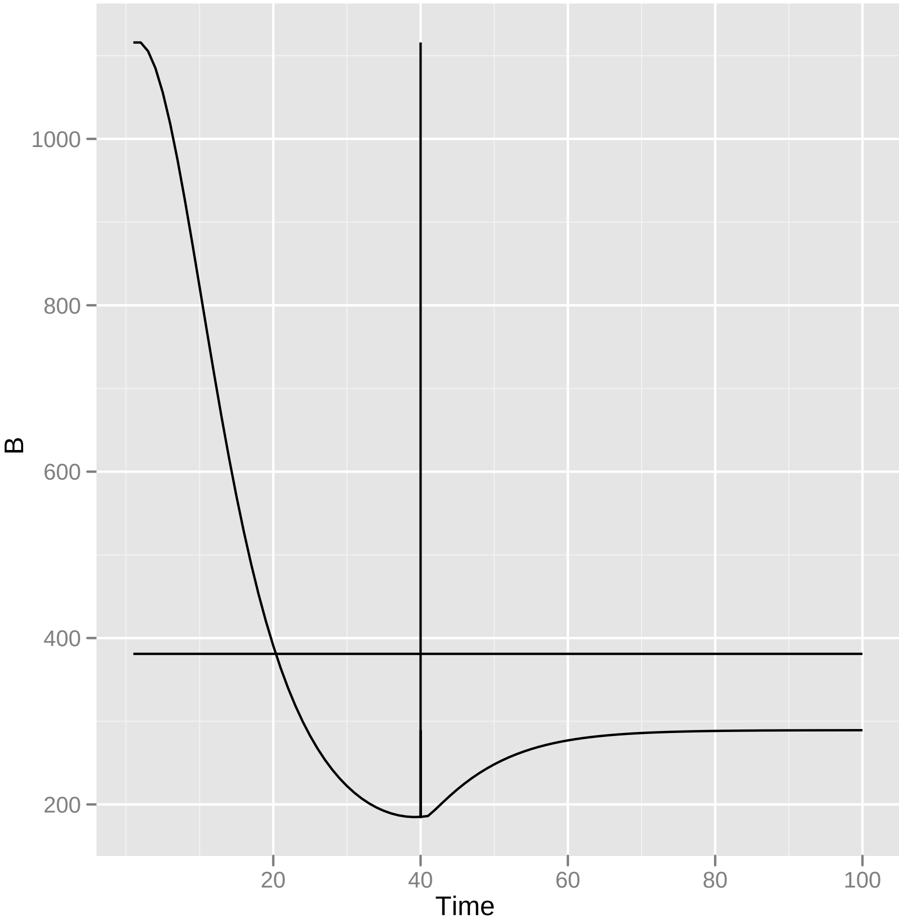

Figure 7: Scenario 3: Performance of empirical control rule. Vertical line represents start of projection period. Horizontal line represents the target biomass B^{TAR}.

References

Magnusson, A. & Hilborn, R. (2007). What makes fisheries data informative. *Fish and Fisheries*, 8, 337–358.

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