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 F

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. You can see this in Figure 2.

Growth	
L_∞	120
k	0.192
$maxage$	25
Maturity	
$mat95$	6
SRR	
s	0.75
v	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

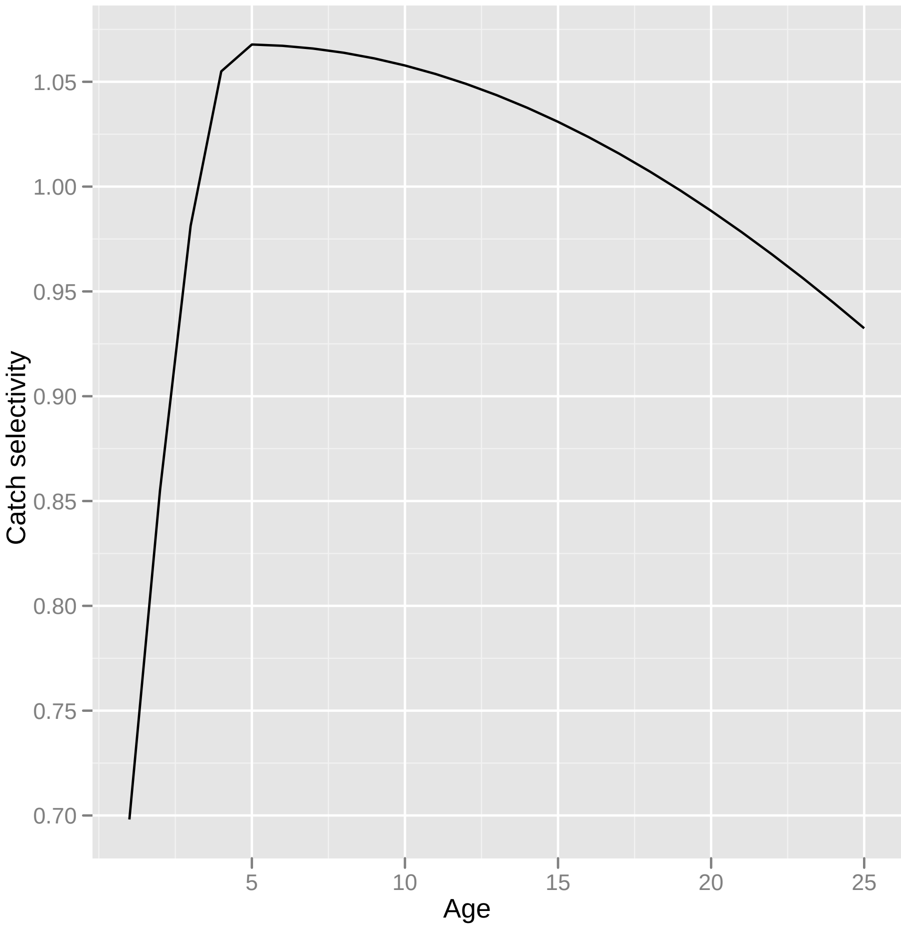

Figure 1: Double normal catch selectivity curve for the generic stock with parameters $a1 = 0.5$, $sL = 0.5$ and $sR = 5$.

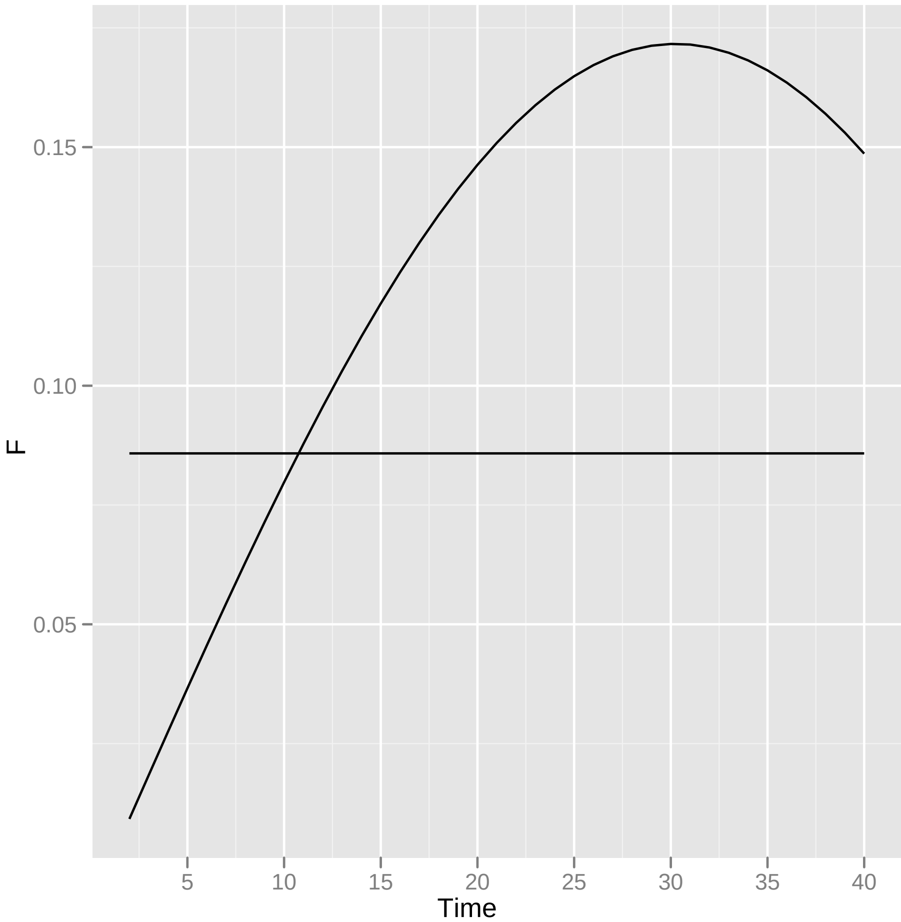

Figure 2: Fishing mortality scenario. F increases from 0 to $2F^{MSY}$. The horizontal line is F^{MSY}.

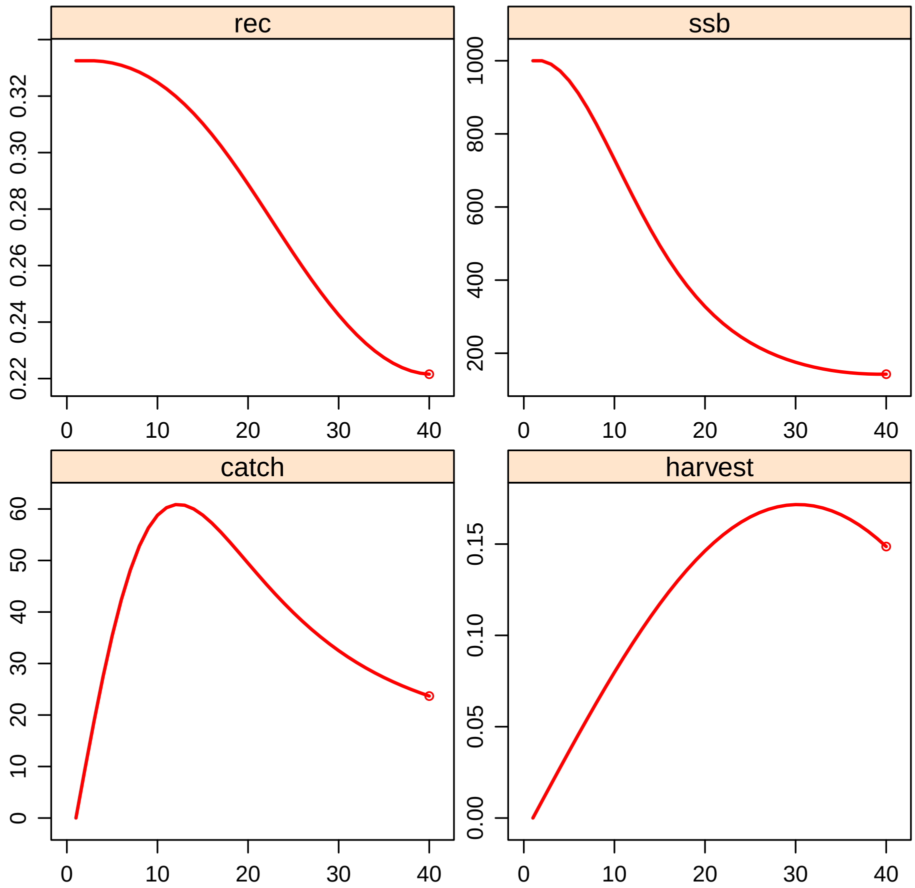

Figure 3: Historic stock dynamics

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:

```
> stk1 <- as(gen1, "FLStock")
> stk1 <- window(stk1, end = maxt)
> ctrl_F1 <- fwdControl(data.frame(year = 2:maxt, quantity = "f", val = F1))
> sr_resid <- FLQuant(1, dimnames = list(age = 1, year = dimnames(stock.n(stk1))$year, iter = dimnames(stock.n(stk1))$iter)
> stk1 <- fwd(stk1, ctrl = ctrl_F1, sr = list(model = model(gen1), params = params(gen1)), sr.residuals = sr_resid)
```

The resulting stock object can be seen in Figure 3.

4 Management scenarios

We compared three different managment scenarios:

- perfect knowledge
- model based control rule
- empirical control rule

Management objectives are utilitarian, specified as both a target catch C^{TAR} and catch rate I^{TAR}. Given that $MEY < MSY$, these are specified arbitarily as $C^{TAR} = 0.9C^{MSY}$ and $I^{TAR} = 0.9qB^{MSY}$ with $q = 1e-4$. 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

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

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

- $G(B_y) = qB_y$
- $G(B_y) = \hat{q}\hat{B}_y$
- $G(B_y) = I_y$

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.

Performance was measured as the probability of $C > C^{TAR}$ and $I > I^{TAR}$ after a 20 year projection period. Managment scenarios will be compared by a regression of performance against survey effort.

5 Management strategy projection

5.1 Getting the index data for the control rule

We're going to assume the index comes from a survey vessel so we need to set up a catch selectivity for the survey. It's going to be sigmoid that is fully selected at age 4 (Figure 4).

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 5).

We are going to generate historic survey data assuming the selectivity in Figure 4. We now apply this selectivity to the population, and sum to get the index of abundance. We assume that the survey takes place half way through the year and we'll scale the abundance down by a 1000 (i.e. catchability $q = 1e{-}4$). There is no observation error. The index is asssumed to be perfectly known.

```
> index <- apply(sweep(stk2@stock.n * exp(-stk2@m/2) * stk2@stock.wt, 1:5, sselq, "*"), 2:6, sum) *
+     1e-04
```

6 Management simulation

6.1 Scenario 1: perfect knowledge

```
> hcr <- function(catch, index, year) {
+     CTAR <- 0.9 * as.numeric(refpts(gen1)[, "yield"][4])
```

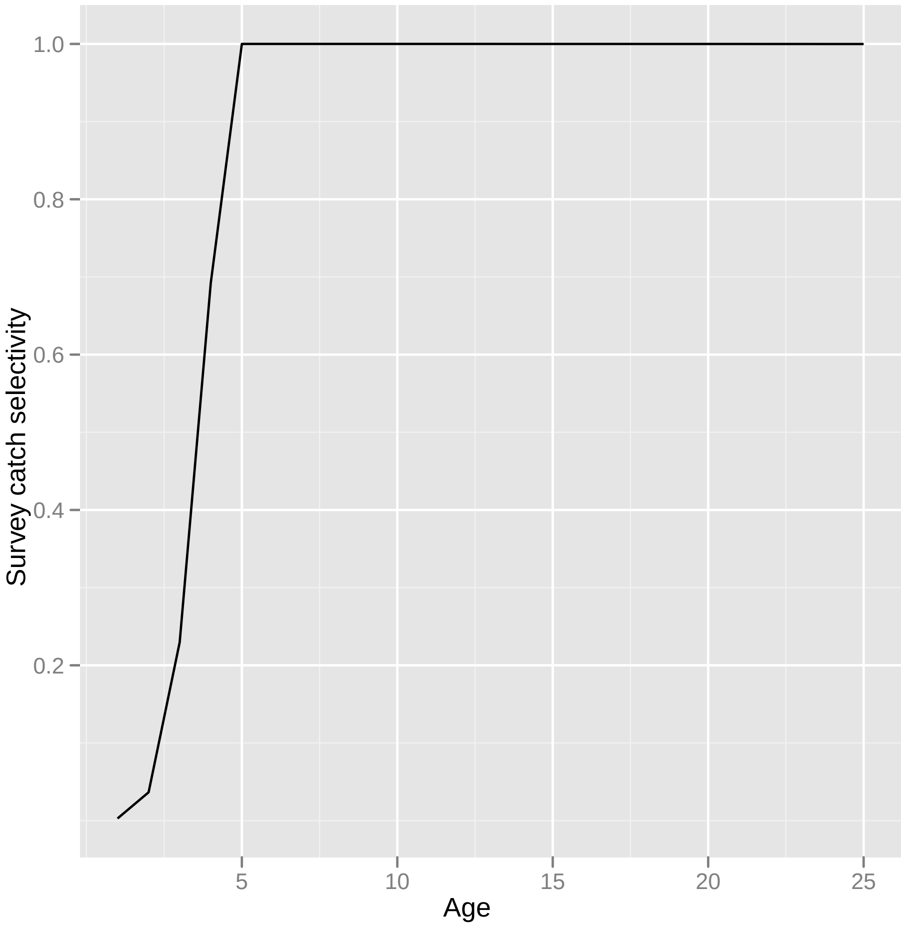

Figure 4: The selectivity curve of the survey vessel

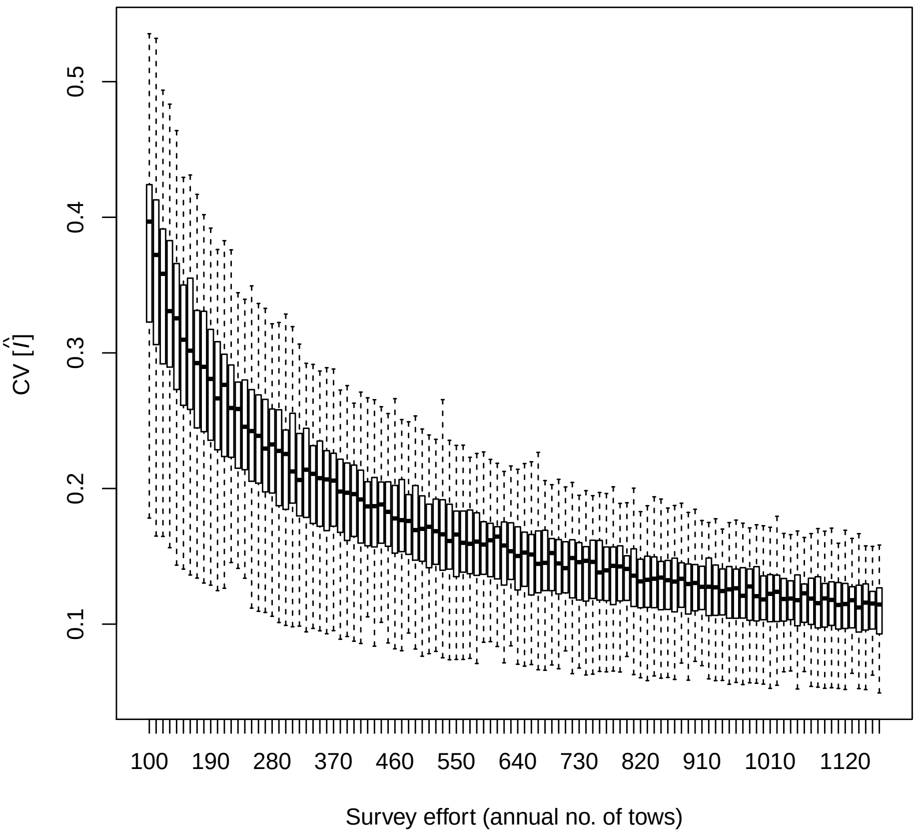

Figure 5: Estimated relationship between CV of the estimated catch rate and survey effort. Boxplots represent the variation across years.

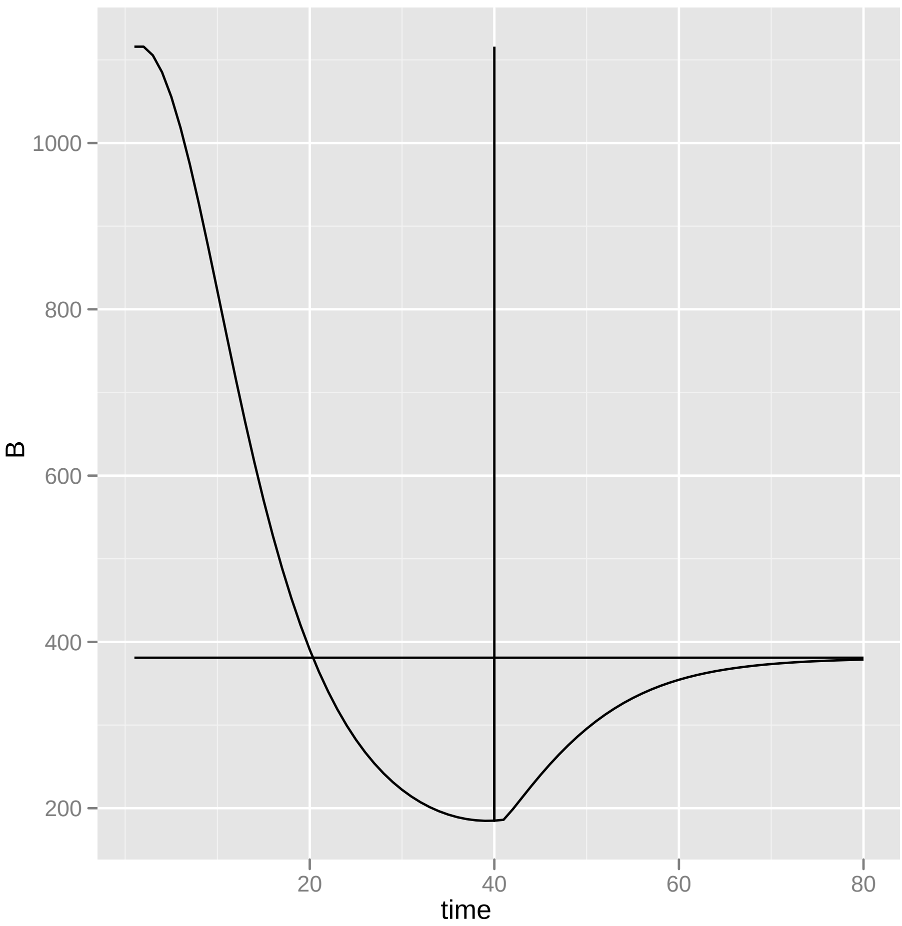

Figure 6: The results of the projection

```
+     ITAR <- 0.9 * as.numeric(refpts(gen1)[, "biomass"][4]) * 1e-04
+     ILIM <- 0
+     GB <- as.numeric(quantSums(stock.n(stk2)[, year - 1] * stock.wt(stk2)[, year - 1] * catch.sel(gen1))) *
+         1e-04
+     if (GB <= ILIM) {
+         TAC <- 0
+     }
+     else {
+         if (GB > ILIM & GB < ITAR) {
+             TAC <- (CTAR * (GB - ILIM))/(ITAR - ILIM)
+         }
+         else {
+             if (GB >= ITAR) {
+                 TAC <- (CTAR * GB)/ITAR
+             }
+         }
+     }
+     ctrl <- fwdControl(data.frame(year = year, val = TAC, quantity = "catch"))
+ }
```

6.2 Scenario 3: empirical control rule

```
> hcr <- function(catch, index, year) {
+     CTAR <- 0.9 * as.numeric(refpts(gen1)[, "yield"][4])
+     ITAR <- 0.9 * as.numeric(refpts(gen1)[, "biomass"][4]) * 1e-04
+     ILIM <- 0
```

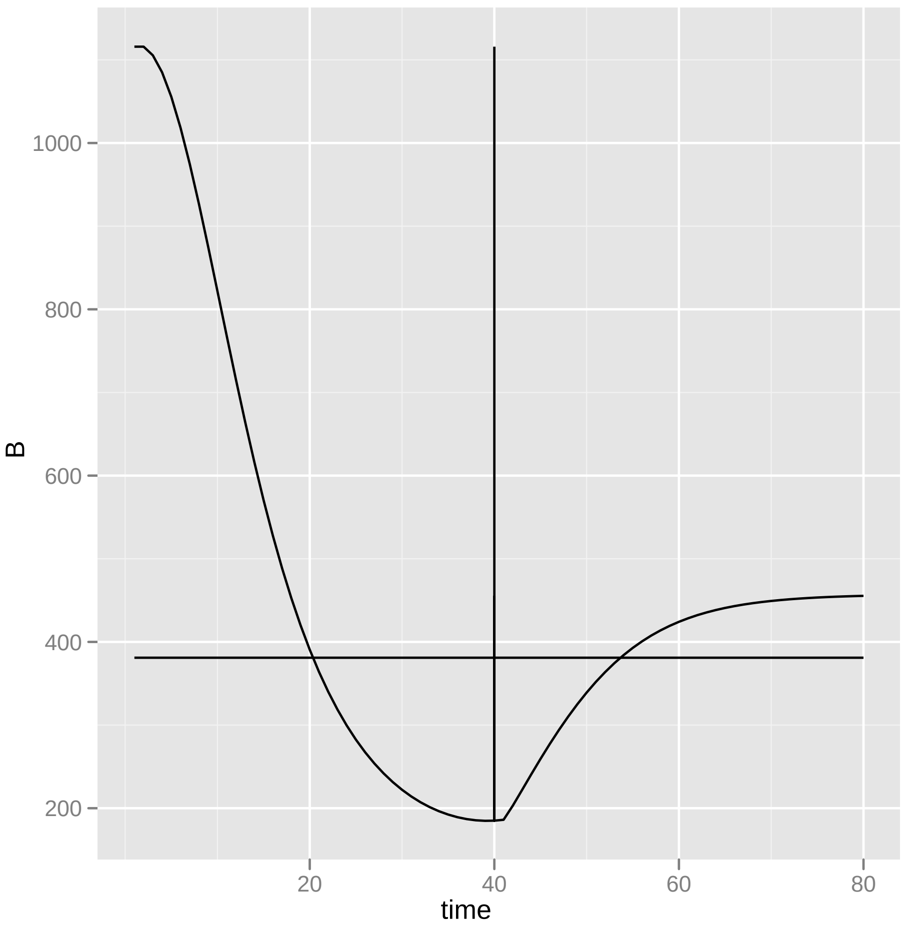

Figure 7: The results of the projection

```
+     GB <- as.numeric(index[, year - 1])
+     if (GB <= ILIM) {
+         TAC <- 0
+     }
+     else {
+         if (GB > ILIM & GB < ITAR) {
+             TAC <- (CTAR * (GB - ILIM))/(ITAR - ILIM)
+         }
+         else {
+             if (GB >= ITAR) {
+                 TAC <- (CTAR * GB)/ITAR
+             }
+         }
+     }
+     ctrl <- fwdControl(data.frame(year = year, val = TAC, quantity = "catch"))
+ }
```

References

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

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