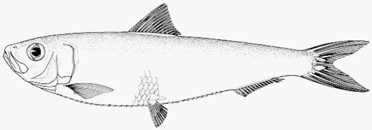
Assessment For All (a4a)

The stock assessment model



Whitehead, P.J.P., 1985. FAO Species Catalogue.

FAO

The a4a team
European Commission
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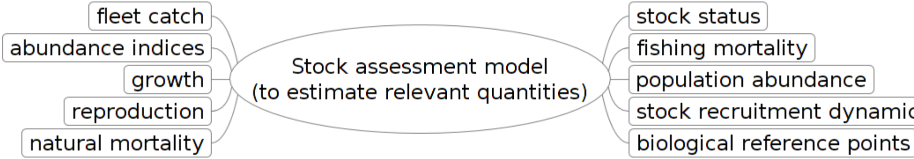
What is it ?

Stock assessment is the synthesis of information on life history, fishery monitoring, and resource surveys for estimating stock size and harvest rate relative to sustainable reference points.

Stock assessment is usually carried out by applying mathematical models that fit available information to provide simplified representations of population and fishery dynamics.

Cadrin, S. and Dickey-Collas, M. 2015. Stock assessment methods for sustainable fisheries. ICES J. Mar. Sci. 72 (1): 1-6

How ?


fleet catch
abundance indices
growth
reproduction
natural mortality
Stock assessment model
(to estimate relevant quantities)
stock status
fishing mortality
population abundance
stock recruitment dynamic
biological reference points

The a4a stock assessment framework

- The a4a stock assessment framework is a statistical catch-at-age model written in R and ADMB (maximum likelihood fit with automatic differentiation).
- It was written with the aim of quickly developing stock assessment models for stocks with limited time series.

Model detail

The famous Baranov equation:

$$e^{\mathrm{E}\left[\log C_{ay}\right]} = \frac{F_{ay}}{F_{ay} + M_{ay}} \left(1 - e^{-(F_{ay}+M_{ay})}\right) R_y e^{-\sum(F_{ay}+M_{ay})}$$

and the survey catchability equation:

$$e^{\mathrm{E}\left[\log I_{ays}\right]} = Q_{ays} R_y e^{-\sum(F_{ay}+M_{ay})}$$

So what are we going to model ?

Each model is defined by submodels, which specify the different parts of the statistical catch-at-age model.

There are 5 submodels in operation:

- a model for F-at-age
- a (list) of model(s) for abundance indices catchability-at-age
- a model for recruitment
- a list of models for the observation variance of catch-at-age and abundance indices.
- a model for the initial age structure

Submodels (variables in red)

$$e^{\mathrm{E}[\log C]} = \frac{F}{F+M}\left(1 - e^{-(F+M)}\right) Re^{-\sum(F+M)}$$

and

$$e^{\mathrm{E}[\log I]} = QRe^{-\sum(F+M)}$$

and

$$C \sim LogNormal(\mathrm{E}\left[\log C\right], \sigma^2) \qquad I \sim LogNormal(\mathrm{E}\left[\log I\right], \tau^2)$$

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The likelihood

A composite lognormal likelihood with

$$\ell = \ell_C + \ell_I + \ell_{SR}$$

If there's not a S/R model it's likelihood is zero $\ell_{SR} = 0$.

... and how ?

- The submodels use R formulas for linear models
- which opens the possibility of using the linear modelling tools available in R.
- for example the mgcv gam formulas, or factorial design formulas using lm().

... and how ?

- For example a constant model is coded as

$$\sim 1$$

while a intercept + slope model would simply be

$$\sim x$$

- We can write a traditional year/age separable F model like

$$\sim factor(age) + factor(year)$$

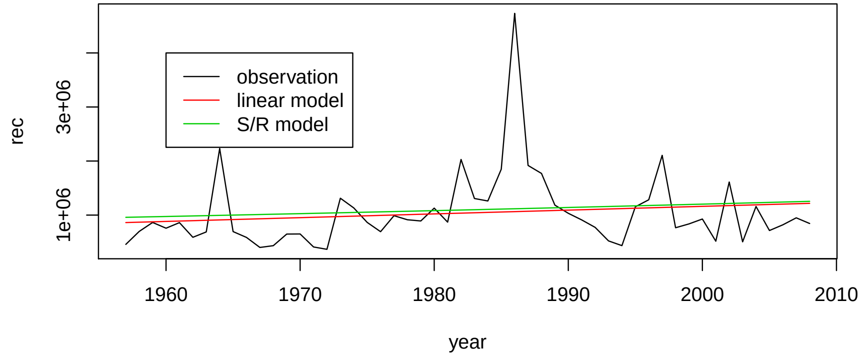
Examples: starting ...

```r
library(FLa4a)
data(ple4)
data(ple4.indices)
data(ple4.index)
```

Examples: linear model for recruitment

```r
# linear model of recruitment
rec <- c(rec(ple4))
year <- as.numeric(dimnames(rec(ple4))[[2]])
# linear stock-recruitment model
rlm <- lm(rec~year)
scafit <- sca(ple4, ple4.indices, srmodel=~year)
```

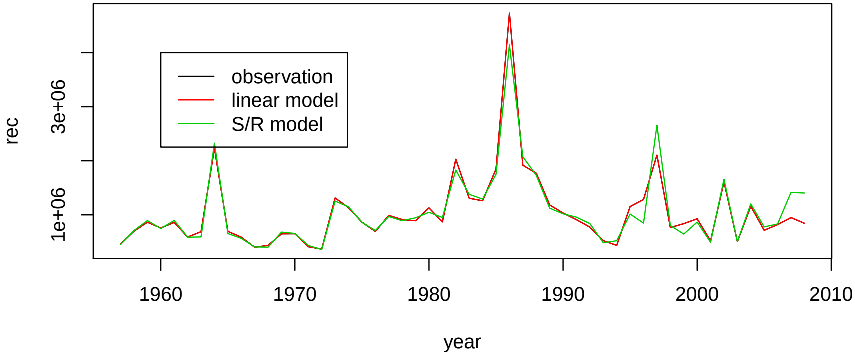
Examples: linear model for recruitment



Examples: factor model for recruitment

```r
# factor model of recruitment
rlm <- lm(rec~factor(year))
# factor stock-recruitment model
scafit <- sca(ple4, ple4.indices,
  srmodel=~factor(year))
```

Examples: factor model for recruitment



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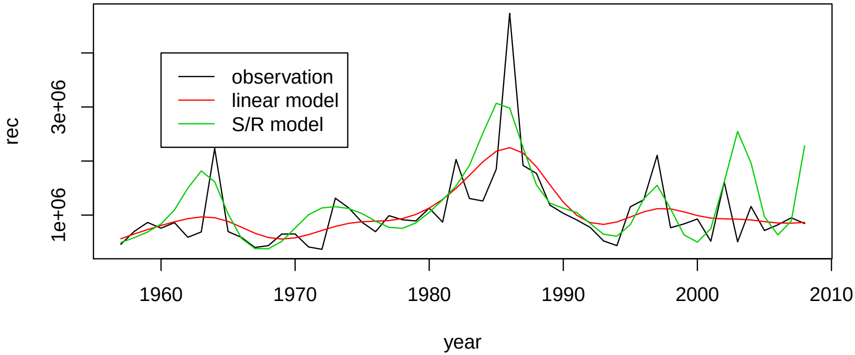
linear model examples

```
# thin plate spline model for recruitment
rlm <- gam(rec~s(year, k=20))
# thin plate spline model for stock recruitment
scafit <- sca(ple4, ple4.indices,
        srmodel=~s(year, k=20))
```

linear model examples



Model detail: a bit more on recruitment

Recruitment is modelled as a fixed variance random effect with linear models for

- log a
- log b

where relevant.

Models available: Ricker, Beverton Holt, smooth hockeystick, geometric mean.

The FLa4a types of stock assessments

There are two types of assessment, '**MP**' and '**assessment**'. Which return different types of information.

- **MP** - was set for quick runs, like those used in MSE algorithms, and returns stock abundance (stock.n), catch at age (catch.n), fishing mortality at age (harvest) and indices. It does not require ADMB to compute the hessian, which may result in fits that did not converge.

- **assessment** - was set for full assessments like those required by working groups or during operating model conditioning. It returns the same information as 'MP' plus all the coeficients and the hessian. If the fit didn't converge a warning is issued and the results are all NA.

The FLa4a methods for stock assessment

There are two methods that implement the stock assessment framework, ’**sca**’ and ’**a4aSCA**’.

- **sca** - It’s simpler and has more robust default values. It hides from the user the most cryptic submodels, the vmodel and n1model. By **default** the type of assessment is ’**MP**’.

- **a4aSCA** - It allows the user to set all possible arguments. It’s more complex to use but gives access to more interesting features. However the default values are not so robust. By **default** the type of assessment is ’**assessment**’.

What can’t do

- estimate random effect variance
- estimate smoothing parameters
- estimate growth parameters

What we can do

- predict missing values: missing at random
- use multiple surveys
- estimate variables Q, F and their variance
- use splines (fixed degreed of freedom)
- estimate stock-recruit relationships (fixed variance)
- simulate from the distribution of model params
    - normal approx
    - avoids the need for delta approx
    - can use MCMC if desired (not implemented yet)
- we can approximate the (joint) distribution of
    - terminal year Fs and Ns
    - terminal year Fbar and Fmsy
    - F / Fmsy

The likelihood

$$\hat{\ell}_C = \sum_{ay} (w^c_{ay}\ \hat{\ell}_N(log\hat{C}_{ay}, \hat{\sigma}^2_{ay};\ \log C_{ay}))$$

$$\hat{\ell}_I = \sum_{s} \sum_{ay} (w^s_{ays}\ \hat{\ell}_N(log\hat{I}_{ays}, \hat{\tau}^2_{ays};\ \log I_{ays}))$$

$$\hat{\ell} = \hat{\ell}_C + \hat{\ell}_I$$

If there's a S/R model it's likelihood will be added

$$\hat{\ell}_{SR} = \sum_{y} (\hat{\ell}_N(log\tilde{R}_y, \phi^2_y;\ \log \hat{R}_y))$$

where $\hat{\ell}$ is the negative log-likelihood of a normal distribution.