

# *biodyn*

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August 13th, 2014

## *Introduction*

THIS PACKAGE implements a biodyn biomass dynamic stock assessment model. Methods are including for fitting, checking of diagnostics and goodness of fit, estimating uncertainty in stock status relative to reference points, running projections and Harvest Control Rules (HCRs) and conducting Management Strategy Evaluation (MSE).

## *Equations*

The Russell equation <sup>1</sup> summarises the key processes influencing the dynamics of exploited populations where biomass  $B_2$  is a function of the biomass in the previous year ( $B_1$ ) plus gains due to growth (G) and recruitment (R) and losses due to fishing (F) and natural mortality (M).

Since Russel originally formulated his equation two other processes have been recognised, i.e. gains due to immigration (I) and losses due to emigration (E) thus modifying the original equation

The knowledge about these processes affects our ability to provide robust scientific advice. In a biomass dynamic stock assessment the dynamics of recruitment, growth and natural mortality are simplified into a single production function.

$P$  can be modelled by a variety of surplus production functions e.g. Pella-Tomlinson ? ].

The dynamics i.e. productivity and reference points and the response of the stock to perturbations, are determined by  $r$  and the shape of the production function  $p$ ; if  $p = 1$  then MSY is found halfway between 0 and  $K$ , as  $p$  increases MSY shifts to the right.

<sup>1</sup>

$$f(B_2) = B_1 + (G + R) - (F + M) \quad (1)$$

Figure 1: The Russell equation

$$f(B_2) = B_1 + (G + R + I) - (F + M + H) \quad (2)$$

Figure 2: Russell equation with migration

$$B_{t+1} = B_t - C_t + P_t \quad (3)$$

Figure 3: Biomass dynamic

$$\frac{r}{p} \cdot B \left(1 - \left(\frac{B}{K}\right)^p\right) \quad (4)$$

Figure 4: An equation

## Fitting

FITTING TO DATA can be done using either maximum likelihood or by running Monte Carlo Markov Chain (MCMC) simulations.

For fitting we simulate a stock with know parameters and exploitation history. This makes it easier to evalaute fits.

simBiodyn generates a stock

```
bd = simBiodyn()
```

```
plot(bd)
```

The model uses a time series of catch per unit effort (CPUE) are a proxy of stock abundance, we therefore generated this from the stock biomass by taking the mid year biomass and adding an error term.

Before fitting best guesses for the parameters needed to be provided as starting values and add any constraints or fix parameters.

An object of class "FLPar"

params

	r	k	p	b0
	0.50000	1000.00000	1.00000	1.00000
	q1	sigma1		
	1.03258	0.20685		

units: NA

The params slot will hold the fitted parameters, while the control slot takes the best initial guess, sets upper and lower bounds (min and max) and allows parameters to be fixed (i.e. setting phase=-1) or estimated sequentially (i.e. by setting phase >0, parameters will be estimated in turn based on the value of phase).

An object of class "FLPar"

	option			
params	phase	min	val	
r	1.0000e+00	5.0000e-02	5.0000e-01	
k	1.0000e+00	1.0000e+02	1.0000e+03	
p	1.0000e+00	1.0000e-01	1.0000e+00	
b0	1.0000e+00	1.0000e-01	1.0000e+00	
q1	1.0000e+00	1.0326e-01	1.0326e+00	
sigma1	1.0000e+00	2.0685e-02	2.0685e-01	
	option			
params	max			
r	5.0000e+00			
k	1.0000e+04			

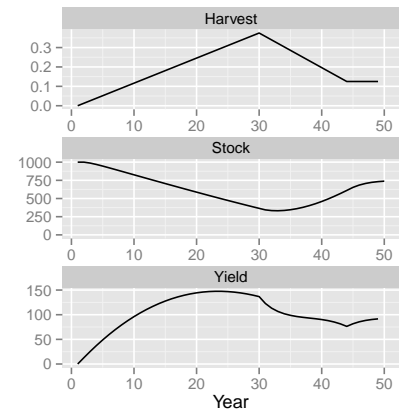


Figure 5: Simulated stock

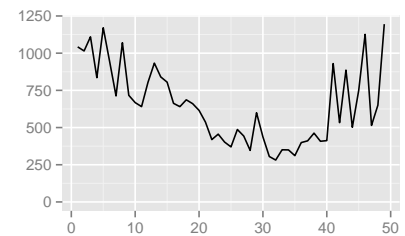


Figure 6: Simulated CPUE series

```

p      1.0000e+01
b0     1.0000e+01
q1     1.0326e+01
sigma1 2.0685e+00
units:  NA

```

To fit using maximum likelihood

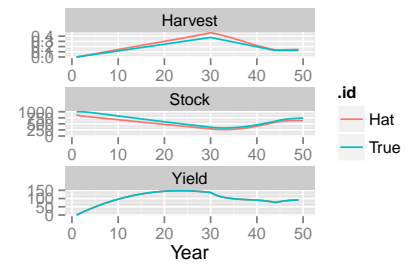


Figure 7: A comparison of the true and fitted time series

## ## Diagnostics

GOODNESS OF FIT diagnostics are important for transparency, replicability and ensuring that a global solution has actually been found, i.e. that when the assessment is repeated that you get the same solution.

Although biomass dynamic models use only catch and effort data and only estimate a few parameters, statistical catch-at-size models with potentially 1000s of parameters are used for the same purpose i.e. to estimate population parameters from fisheries dependent data. However, similar diagnostics are required and helps when comparing fits between stock assessment methods.

Patterns in residuals of the fits to the CPUE and stock abundance may indicate a violation of model assumptions. Residuals and covariates are in the diags slot.

```
rsdl = bdHat@diags
```

```
head(rsdl)
```

	year	stock	catch	index	hat	stockHat
1	1	848.6	0.00	1042.2	1051.3	848.6
2	2	819.8	12.93	1014.9	1015.6	819.8
3	3	798.1	25.53	1109.9	988.7	798.1
4	4	778.0	37.55	835.3	963.8	778.0
5	5	758.4	48.93	1170.6	939.5	758.4
6	6	738.9	59.65	943.7	915.4	738.9

	residual	residualLag	qqx	qqy
1	-0.0086616	-0.0007135	-0.1025	-0.0086616
2	-0.0007135	0.1156681	0.0000	-0.0007135
3	0.1156681	-0.1430870	0.7235	0.1156681
4	-0.1430870	0.2199137	-0.4780	-0.1430870
5	0.2199137	0.0304535	1.1139	0.2199137
6	0.0304535	-0.2236634	0.1025	0.0304535

	qqHat	harvest
1	-0.05546	0.00000
2	-0.03616	0.01555
3	0.10011	0.03158
4	-0.12619	0.04766
5	0.17365	0.06370
6	-0.01685	0.07968

First the observed values are plotted against the fitted values. It is assumed that an index is proportional to the stock so the points should fall around the  $y = x$  line, if they do not then the index may not be a good proxy for the stock trend.

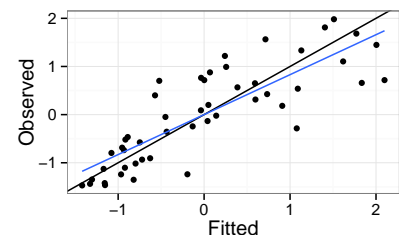


Figure 8: Observed CPUE versus fitted, blue line is a linear regression fitted to points, black the  $y=x$  line.

Next the residuals are plotted against year along with a lowess smoother.

It is also assumed that variance does not vary with the mean, this assumption is evaluated in where the residuals are plotted against the fitted values.

It is assumed that the residuals are normally distributed on the log scale and that there is no autocorrelation between them. Plots of the residuals against each other with a lag of 1 to identify autocorrelation. There are significant autocorrelations particularly for the Japanese and Taiwanese longlines, this could be due to an increase in catchability with time. This may result in a more optimistic estimate of current stock status as any decline in the stock is masked by an increase in catchability.

Q-Q plots compare a sample of data on the vertical axis to a statistical population on the horizontal axis, in this case a normal distribution. If the points follow a strongly nonlinear pattern this will suggest that the data are not distributed as a standard normal i.e.  $X \sim N(0,1)$ . Any systematic departure from a straight line may indicate skewness or over or under dispersion. For example in the panel showing the Taiwanese longline suggests that the negative residuals are much greater in magnitude than expected.

Violation of the assumptions about the may result in biased estimates of estimated parameters, reference points and stock trends. In addition variance estimates obtained from bootstrapping assume that residuals are Independently and Identically Distributed (i.i.d.).

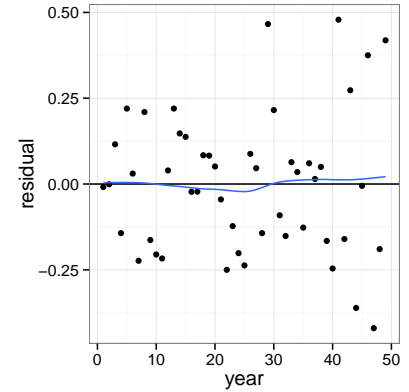


Figure 9: Residuals by year, with lowess smoother and SEs.

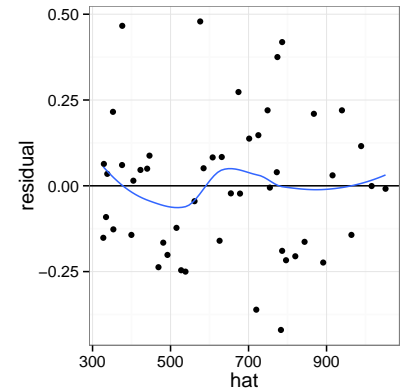


Figure 10: Plot of residuals against fitted value, to check variance relationship.

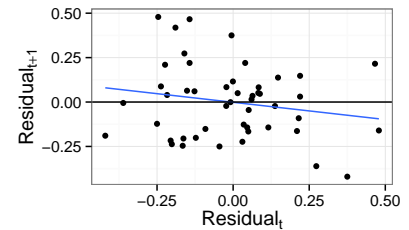


Figure 11: Plot of autocorrelation, i.e.  $residual_{t+1}$  versus  $residual_t$ .

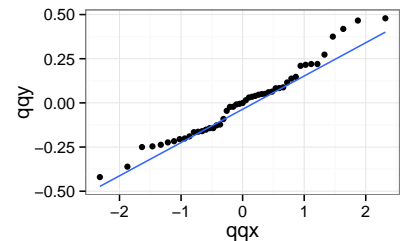


Figure 12: Quantile-quantile plot to compare residual distribution with the normal distribution.

## Stock Status

IN HIS LATER BOOKS<sup>2</sup>, Tufte starts each section with a bit of vertical space, a non-indented paragraph, and sets the first few words of the sentence in small caps. To accomplish this using this style, use the \newthought command as demonstrated at the beginning of this paragraph.

## Projections

IN HIS LATER BOOKS<sup>3</sup>, Tufte starts each section with a bit of vertical space, a non-indented paragraph, and sets the first few words of the sentence in small caps. To accomplish this using this style, use the \newthought command as demonstrated at the beginning of this paragraph.

## MSE

IN HIS LATER BOOKS<sup>4</sup>, Tufte starts each section with a bit of vertical space, a non-indented paragraph, and sets the first few words of the sentence in small caps. To accomplish this using this style, use the \newthought command as demonstrated at the beginning of this paragraph.

## Figures

### Full Width Figures

You can arrange for figures to span across the entire page by using the `fig.fullwidth` chunk option.

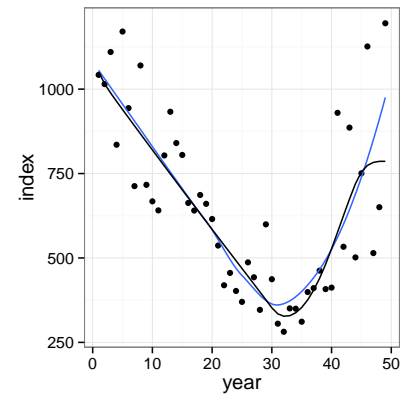
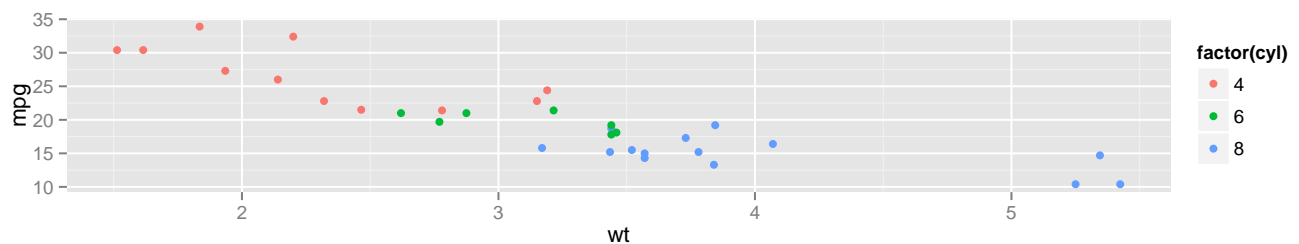


Figure 13: Plot predicted stock trend by

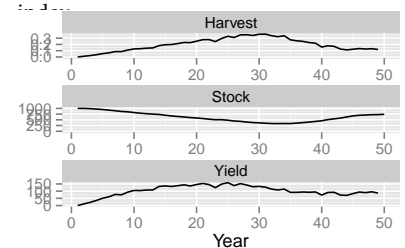


Figure 14:

<sup>2</sup> [http://www.edwardtufte.com/tufte/books\\_be](http://www.edwardtufte.com/tufte/books_be)

<sup>3</sup> [http://www.edwardtufte.com/tufte/books\\_be](http://www.edwardtufte.com/tufte/books_be)

<sup>4</sup> [http://www.edwardtufte.com/tufte/books\\_be](http://www.edwardtufte.com/tufte/books_be)

Figure 15: Full width figure

Note the use of the `fig.width` and `fig.height` chunk options to establish the proportions of the figure. Full width figures look much better if their height is minimized.

### Main Column Figures

Besides margin and full width figures, you can of course also include figures constrained to the main column.

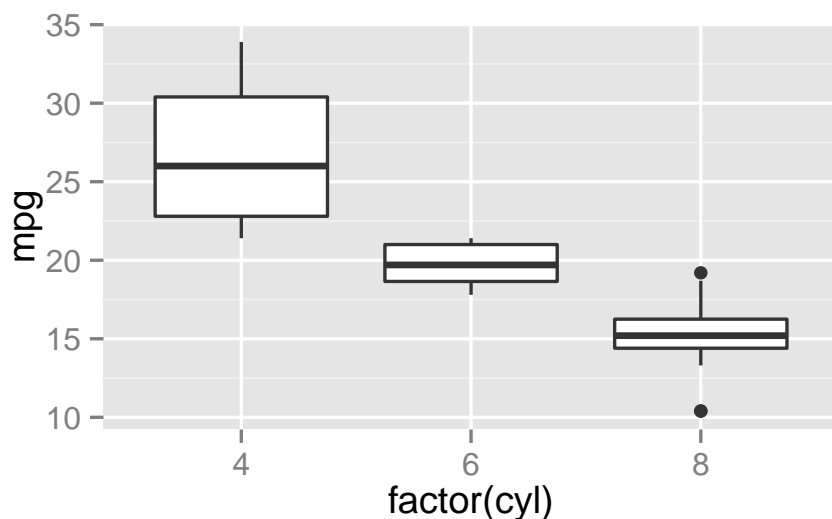


Figure 16: Another figure

### Sidenotes

One of the most prominent and distinctive features of this style is the extensive use of sidenotes. There is a wide margin to provide ample room for sidenotes and small figures. Any use of a footnote will automatically be converted to a sidenote.<sup>5</sup>

If you'd like to place ancillary information in the margin without the sidenote mark (the superscript number), you can use the `\marginnote` command.

Note also that the two footnote references (`tufte_latex` and `books_be`, both defined below) were also included in the margin on the first page of this document.

<sup>5</sup> This is a sidenote that was entered using a footnote.

This is a margin note. Notice that there isn't a number preceding the note.

### Tables

You can use the `xtable` package to format  $\text{\LaTeX}$  tables that integrate well with the rest of the Tufte handout style. Note that it's important to set the `xtable.comment` and `xtable.booktabs` options as shown

below to ensure the table is formatted correctly for inclusion in the document.

	mpg	cyl	disp	hp	drat	wt
Mazda RX4	21.00	6.00	160.00	110.00	3.90	2.62
Mazda RX4 Wag	21.00	6.00	160.00	110.00	3.90	2.88
Datsun 710	22.80	4.00	108.00	93.00	3.85	2.32
Hornet 4 Drive	21.40	6.00	258.00	110.00	3.08	3.21
Hornet Sportabout	18.70	8.00	360.00	175.00	3.15	3.44
Valiant	18.10	6.00	225.00	105.00	2.76	3.46

Table 1: First rows of mtcars