Additional material for the 2014 MSC assessment of N.Z. orange roughy fisheries: supplement 2

P.L. Cordue, ISL
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Introduction

This document contains supplementary material which was produced in response to queries by the MSC assessment team. The results contained within were produced using either the 2014 orange roughy stock assessments (Cordue 2014a) or the Management Strategy Evaluation (Cordue 2014b).

For the three orange roughy stocks being considered against the MSC standard, the limit reference point (LRP) is 20% B_0 and the target biomass range is 30–50% B_0.

Stock status trajectories and snail trails

New plots have been produced for the three base model assessments presenting the MCMC estimates of stock status trajectories and the snail trails. These new plots include the LRP and the target biomass range (Figures 1–6).

Fixed *M* versus estimation of *M*

For many years there has been debate between stock assessment scientists in New Zealand on whether *M* should be estimated within stock assessment models or estimated externally and fixed within the models (with sensitivity runs using lower and higher values of fixed *M*). Both approaches are used in New Zealand stock assessments.

Estimation of *M* within a stock assessment model may reduce estimation bias but may also increase estimation variance. The choice of whether to fix or estimate *M* is a classic example of the "bias-variance tradeoff". This is usually demonstrated by the fact that Mean Squared Error (MSE) is the sum of variance and squared bias. For example, suppose we estimate, *p*, the probability of success for a Bernoulli trial, using an estimator $\hat{p}$. MSE is the expected value of the squared difference between the estimator and the true value:

$$\mathrm{MSE} = \mathrm{E}[(\hat{p} - p)^2] = \mathrm{Var}(\hat{p}) + \mathrm{Bias}(\hat{p})^2$$

There is no uniformly best estimator in terms of MSE (ideally we want MSE low for all values of p). Instead, estimators form a continuum from those with low variance and high bias through to those with low bias and high variance. Generally, the more information that is available the better it is to use a low bias estimator rather than a low variance estimator.

For example, suppose we have n independent Bernoulli trials: $X_1, \ldots, X_n$. A low variance estimator of p is a given constant k:

$$\mathrm{Var}(k) = 0$$
$$\mathrm{Bias}(k)^2 = (k - p)^2$$

Alternatively, the lowest bias estimator is $\bar{X}$:

$$\mathrm{Var}(\bar{X}) = \frac{p(1-p)}{n}$$
$$\mathrm{Bias}(\bar{X})^2 = 0$$

The choice of which estimator to use (to "minimize" MSE) comes down to how much information on p is contained in the available data, how biased k is, and the value of p. For example, if $p = ½$ and there is a 20% bias on k then a sample size of $n \geq 26$ is required before $\mathrm{MSE}(\bar{X}) < \mathrm{MSE}(k)$. For $p = ¼$, the threshold on the sample size is 76 and if $p = ¾$ the threshold is only 9.

The estimation of M within a stock assessment model is far more complex than the Bernoulli example given. However, the conclusion is the same: it is not clear whether it is better to fix M at a plausible value or to estimate M within the model (because it depends on many factors). Certainly if M is to be estimated within the model then an informed prior should be used – this will reduce variance and increase bias compared to an uninformed prior, but should give lower MSE. However, any level of variance may allow the MSE of the estimator to generally exceed that which would be achieved by fixing M.

In the case of the three orange roughy assessments it is difficult to see where the models are obtaining genuine information on M (in the "estimate M" models, the posterior medians range from 0.037–0.041, see Cordue 2014a, Table 13). It seems very likely that the signals are coming from the age frequencies (i.e., more "old" fish than expected with $M = 0.045$), but it is not clear whether the signals are driven by "information" or the assumption of average recruitment for the cohorts that appear in the right-hand tails. It is not sensible to estimate year class strengths for cohorts that are poorly represented (e.g., only appear in the right hand tails of age distributions) but a "surplus" of old fish can be explained by above average year class strengths, sampling vagaries, errors in selectivity, as well as a lower M. Because of the low information content with regard to M in the available stock assessment data, it is better to fix rather than estimate M at this stage.

Estimation of growth parameters

The von Bertalanffy growth parameters were fixed at historical estimates in the assessments. They were estimated outside the model some years ago primarily using ESCR age-length data (see recent Plenary reports for references). For the NWCR and ESCR assessments, the CVs of length at mean-length-at-age were estimated within the model because these assessments included some length frequencies (ORH 7A did not have any length frequencies to fit). Two parameters were estimated for the CVs: CV at mean length at age 1; and CV at mean length at age 100. A linear relationship was assumed for mean lengths at age between ages 1 and 100. The median estimates ranged from 5–9% with larger CVs at age 1 than 100 (Table 1).

Table 1: MCMC estimates of the CVs of length at mean-length-at-age for the two base models that included some length frequencies.

	CV at age 1 (%)		CV at age 100 (%)	
	Med.	95%CI	Med.	95% CI
NWCR	9	3–15	6	3–14
ESCR	7	4–9	5	3–7

The von Bertalanffy parameters were not estimated within the models because there is no reason to believe this would result in better assessments. The models are age based and the results will not be sensitive to small-moderate changes in growth parameters. The model results are driven by biomass indices with some influence from age data and little influence from length frequencies. The length frequencies are included, where needed, to provide information on selectivities. The length frequencies are adequately fitted so the growth parameters are almost certainly adequate. We would only estimate growth in the model if there was concern about variation in growth across time (cohort specific or otherwise) and/or length frequencies were not adequately fitted with external growth estimates (e.g., if selectivity on young fish was confounded with growth to some extent).

Estimated proportionality constants when there were informed priors

In each of the three stock assessments there were a number of proportionality constants (*q*s) for acoustic and/or trawl surveys which were estimated with informed priors. When the posterior means are compared with the prior means we see that 8 of the posterior means are lower than the prior means, 7 are higher, and there is one case where they are the same (Table 2). This is a balanced result in terms of numbers higher and lower. However, the largest percentage changes are all downwards with a 21% decrease in two of the mean *q*s for ESCR and a 27% and 33% decrease in two of the ORH 7A mean qs.

As a diagnostic this result has no value as it is simply an example of Bayes Theorem at work. The best *a priori* information available was put into the priors and the best data available were used to update the priors (through the application of Bayes Theorem given the structure and assumptions of each model). The fact that some of the posterior means are up to 33% different from the prior means is unremarkable given the CVs of the priors. The diagnostics to look at are the posteriors of the *q*s compared to the priors (the comparisons are presented in Cordue 2014a) – and they produce no cause for concern.

A detailed analysis of which data tend to shift certain *q*s in certain directions has not been performed. The sensitivity analysis was concentrated on stock status.

Table 2: The means of the priors and posteriors for the proportionality constants (*q*s) which were estimated with informed priors in the three stock assessments.

Stock	Method	Year(s)	Mean q prior	Mean q posterior	Posterior mean lower?
ESCR	Acoustics	2011 & 2013	0.80	0.63	Yes
		2012	0.70	0.55	Yes
		2002	0.70	0.78	No
		2003	0.65	0.55	Yes
		2004	0.60	0.57	Yes
		2005	0.55	0.56	No
		2006	0.50	0.60	No
		2007	0.45	0.45	No
		2008	0.40	0.41	No
		2009	0.35	0.37	No
		2010	0.30	0.27	Yes
ORH 7A	Acoustics & trawl	2010 & 2013	0.77	0.56	Yes
	Trawl	2006, 9, 11, 12	1.27	0.85	Yes
	Acoustics	2009	0.80	0.81	No
NWCR	Acoustics	1999 & 2012	0.80	0.71	Yes
		2013	0.30	0.31	No

Correlation between successive assessments

The formulation of the correlated estimators of stock status and vulnerable biomass is detailed in Cordue 2014b, Appendix A. The correlation between successive estimators of an annual biomass time series $B_1, \ldots, B_y$ is pB_{y-1} / B_y (provided the expression is not greater than 1). **A value of $p = 0.95$ was used in all of the simulations.** This gives a correlation between successive annual estimators that is close to 1 (because annual biomass does change much in a single year).

The correlations vary from year to year and depend on the HCR used and the values of h and M. The correlations were not stored during the simulations. However, to provide an example, the simulations were rerun for dynamic HCR10 using $h = 0.75$, $M = 0.045$, with assessments every 3 years. The estimated 1-year lag correlation for the annual estimators of stock status was 0.96. The estimated 1-lag correlation between successive 3-year assessments was 0.87.

The choice of such a high p was based on the principle that the addition of a single year of new data to a very large existing data set would produce a very high correlation between annual estimators. Any given HCR can be expected to perform better if a lower value of p is used in the simulations. An extreme value of $p = 0.99$ would be problematic as it would often contradict the requirement of $pB_{y-1} / B_y \leq 1$ (see Cordue 2014b, Appendix A).

MPD sensitivities: extra tables

Cordue 2014a, Appendix 2 included MPD sensitivity results. They were in tabular form for ESCR but ORH 7A and NWCR results were only presented as plots for stock status. The results from which those plots were produced are tabulated below (Tables 3 and 4).

Table 3: ORH 7A: estimates of virgin biomass (B_0), current biomass (B_{2014}), and stock status (B_{2014}/B_0) for MPD sensitivity runs: the base model without recent biomass indices; alternative effective sample sizes for the age frequency data (N = 150, 20, 1); deterministic recruitment with or without recent biomass indices (YCS1, YCS1-recent); recent biomass indices halved or doubled; decreasing *M* by 20% while also increasing the mean of the informed *q* priors by 20% (LowM-Highq); and increasing *M* by 20% while also decreasing the mean of the informed *q* priors by 20% (HighM-Lowq).

	B_0 (000 t)	B_{2014} (000 t)	B_{2014} (%B_0)
Base	89	29	32
Base – recent	88	25	28
N 150	92	30	33
N 20	85	28	33
N 1	79	26	33
YCS 1	91	45	49
YCS 1 – recent	100	55	54
Recent × 0.5	82	15	18
Recent × 2.0	106	55	52
LowM-Highq (20%)	88	23	26
HighM-Lowq(20%)	93	37	40

Table 4: NWCR: estimates of virgin biomass (B_0), current biomass (B_{2014}), and stock status (B_{2014}/B_0) for MPD sensitivity runs: low and high values of *M*; low and high values for the mean of the acoustic *q* prior ("low *p*", "high *p*"); low and high values for the CV of the acoustic *q* prior; all YCS equal to 1 (YCS 1); and estimating *M*.

	B_0 (000 t)	B_{2014} (000 t)	B_{2014} (%B_0)
Base	68	24	35
Low *M*	77	22	28
High *M*	61	24	39
Low *p*	73	30	42
High *p*	66	21	33
Low CV	67	23	35
High CV	68	24	35
YCS 1	64	22	35
Estimate *M*	69	24	34

References

Cordue, P.L. 2014a. The 2014 orange roughy stock assessments. *New Zealand Fisheries Assessment Report 2014/50*. 135 p.

Cordue, P.L. 2014b. A management strategy evaluation for orange roughy. ISL Client Report for Deepwater Group Ltd. 42 p.

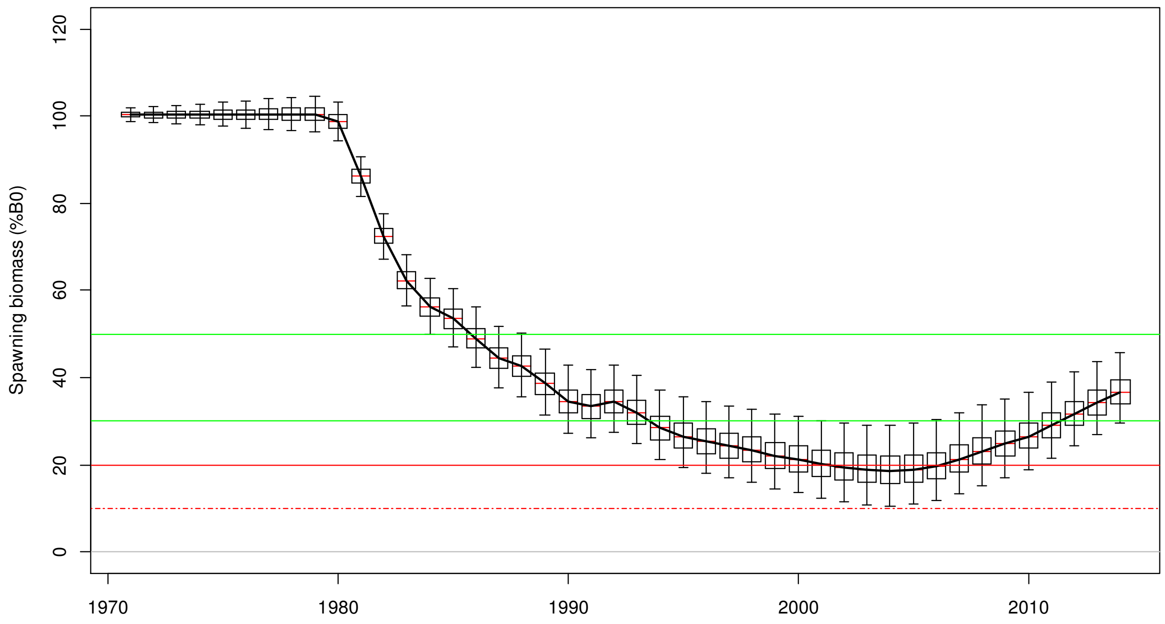


Figure 1: NWCR, base, MCMC estimated spawning-stock biomass trajectory. The box in each year covers 50% of the distribution and the whiskers extend to 95% of the distribution. The LRP (red, solid), NZ HSS hard limit (red, dashed), and biomass target range (green) are marked by horizontal lines.

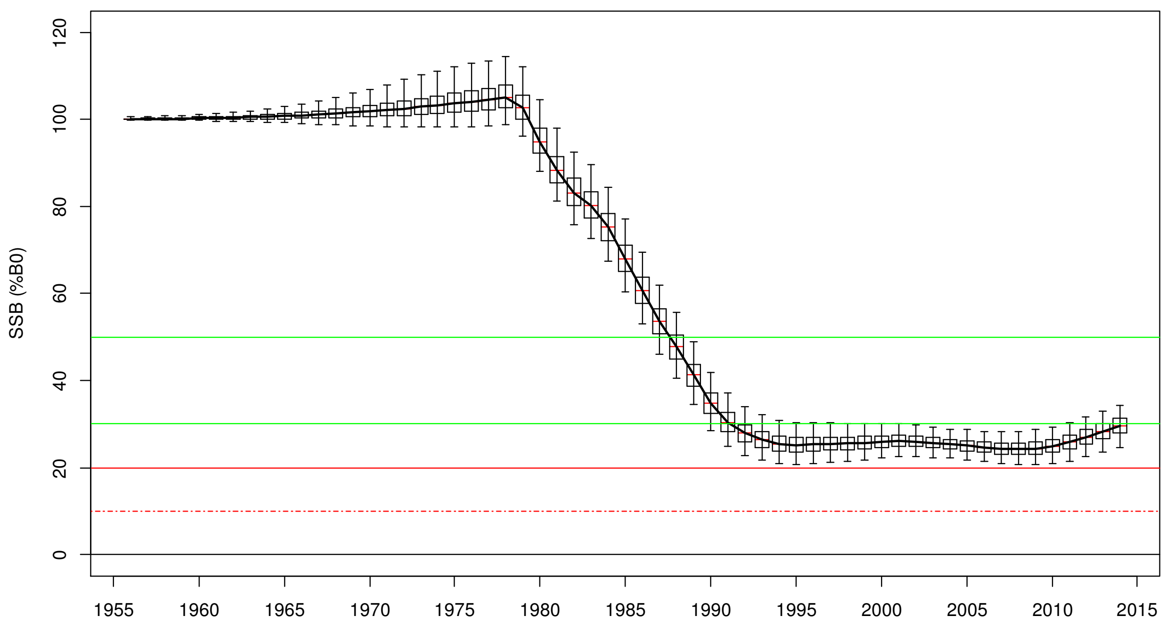
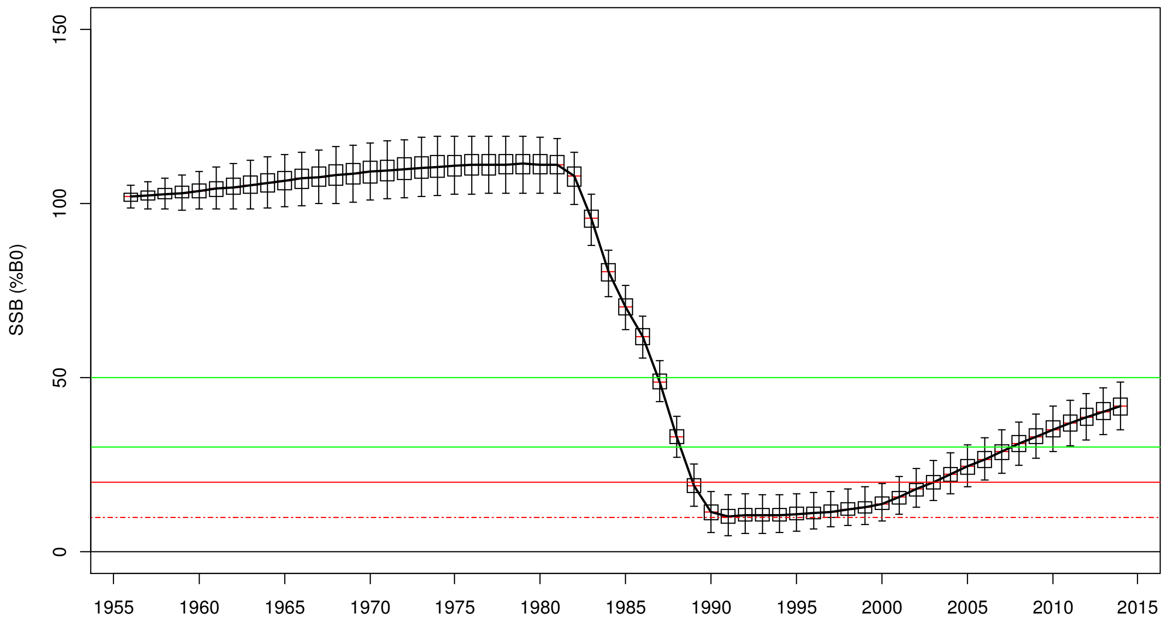


Figure 2: ESCR, base, MCMC estimated spawning-stock biomass trajectory. The box in each year covers 50% of the distribution and the whiskers extend to 95% of the distribution. The LRP (red, solid), NZ HSS hard limit (red, dashed), and biomass target range (green) are marked by horizontal lines.



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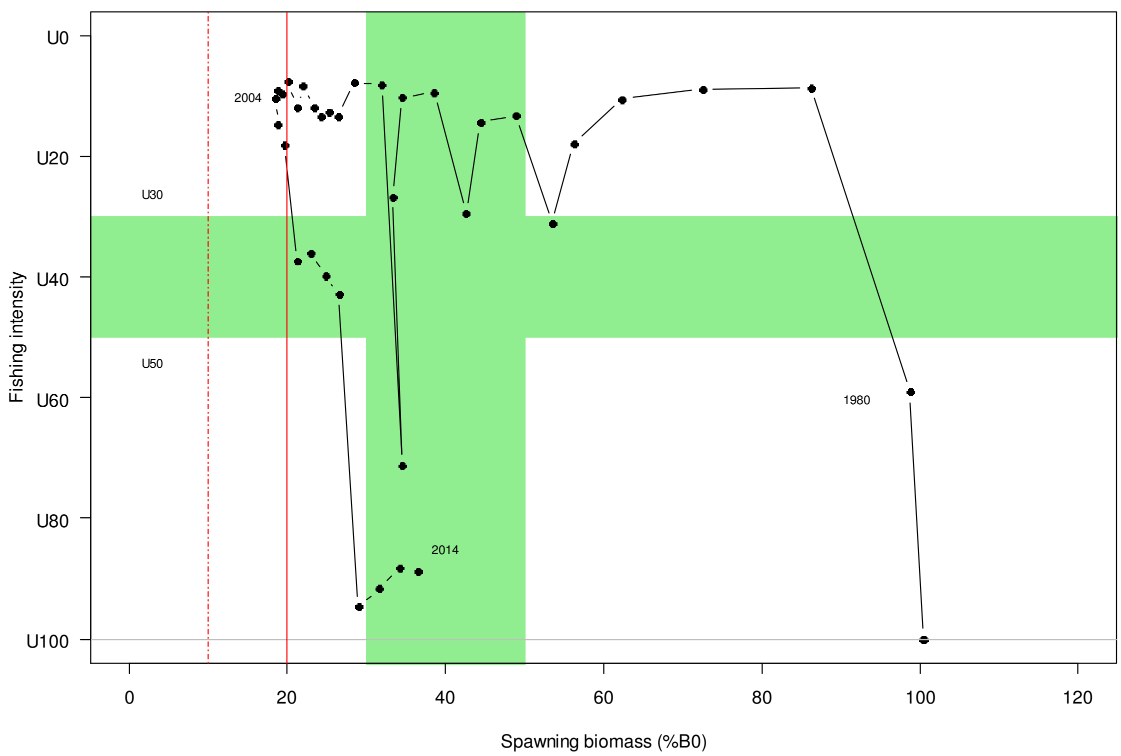

Figure 4: NWCR: historical trajectory of spawning biomass (%*B_0*) and fishing intensity (%) (base model, medians of the marginal posteriors). The biomass target range of 30–50% *B_0* and the corresponding fishing intensity range are marked in green. The LRP (20% *B_0*) is marked in red (solid) and the NZ HSS hard limit (10% *B_0*) in red (dashed).

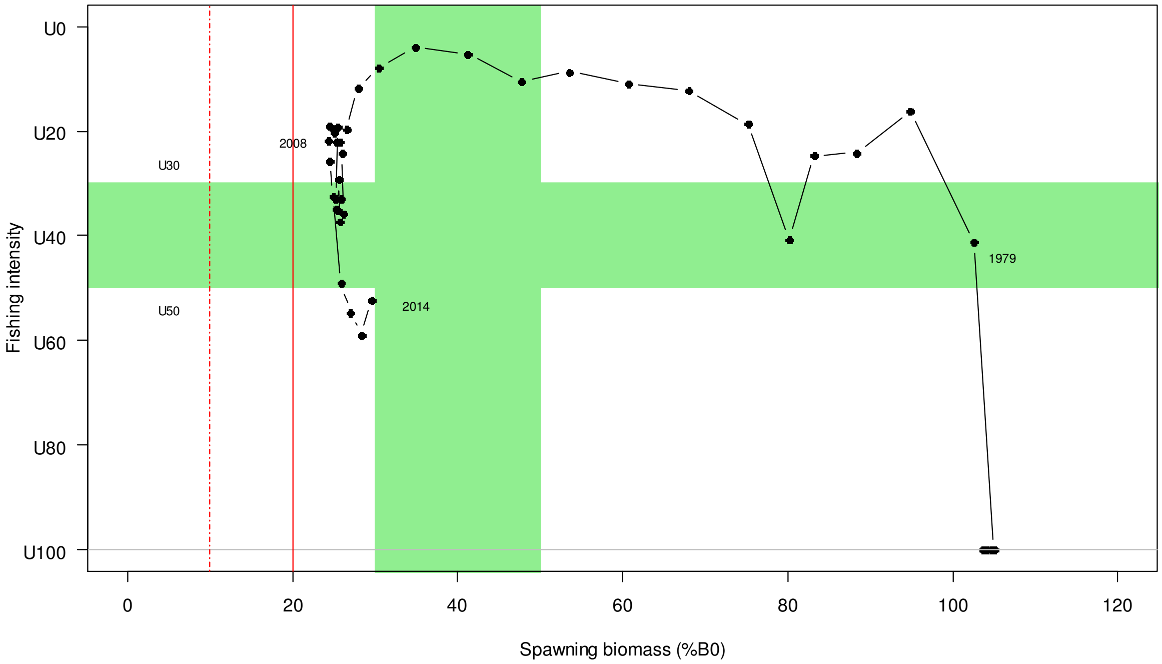

Figure 5: ESCR: historical trajectory of spawning biomass (%B_0) and fishing intensity (%) (base model, medians of the marginal posteriors). The biomass target range of 30–50% B_0 and the corresponding fishing intensity range are marked in green. The LRP (20% B_0) is marked in red (solid) and the NZ HSS hard limit (10% B_0) in red (dashed).

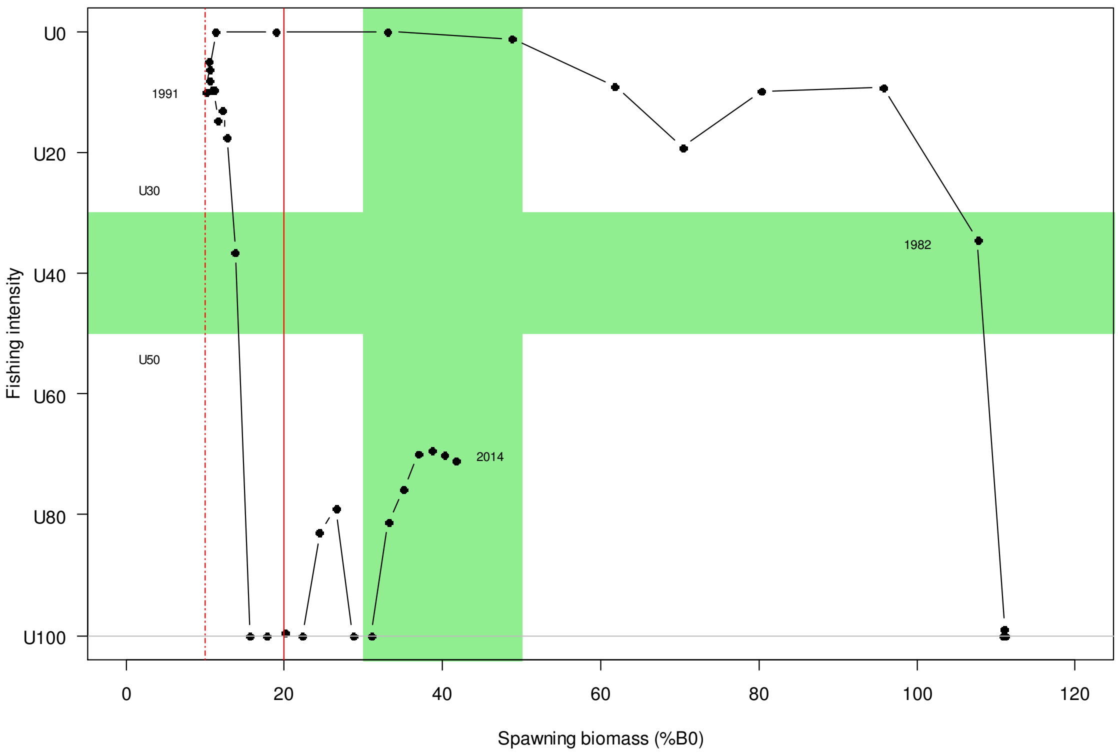

Figure 6: ORH 7A: historical trajectory of spawning biomass (%B_0) and fishing intensity (%) (base model, medians of the marginal posteriors). The biomass target range of 30–50% B_0 and the corresponding fishing intensity range are marked in green. The LRP (20% B_0) is marked in red (solid) and the NZ HSS hard limit (10% B_0) in red (dashed).