



## Evaluation of a simple harvest control rule for the Bounty southern blue whiting management area (SBW6B)

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I.J. Doonan

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## EXECUTIVE SUMMARY

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For the Bounty Platform southern blue whiting stock, a simple harvest control rule (HCR) was evaluated using a model that simulated long-term single-species stock dynamics, monitored using an industry acoustic survey, and management decisions that modified the Total Allowable Commercial Catch (TACC). Uncertainty in model parameters and acoustic surveys was allowed for. The principle performance measure for the HCR was that the mid-year  $B_{\text{current}}$  should not fall below 20%  $B_0$  more than 10% of the time over a 120 year projection period.

The HCR tested set a TACC for year  $t+1$  as  $\xi (B_t - C_t / 2)$ , where,  $B_t$  is acoustic abundance from a survey,  $C_t$  is the catch, and  $\xi$  is a fixed factor. For a given  $\xi$ , performance depended mainly on assumed natural mortality rate and the catchability distribution. Given an assumed natural mortality, a method is suggested to find the  $\xi$  that gives a 10% probability that mid-year  $B_{\text{current}}$  is below 20%  $B_0$  for 10% of the time.

## 1. INTRODUCTION

Fisheries for southern blue whiting were developed in the early 1970s by the Soviet fleet. Landings have fluctuated considerably, peaking at 75 000 t in the 1991/92 fishing year. Southern blue whiting was introduced into the Quota Management System (QMS) in 1999 with separate Total Allowable Commercial Catches (TACCs) for each of the four main stocks within FMA 6.

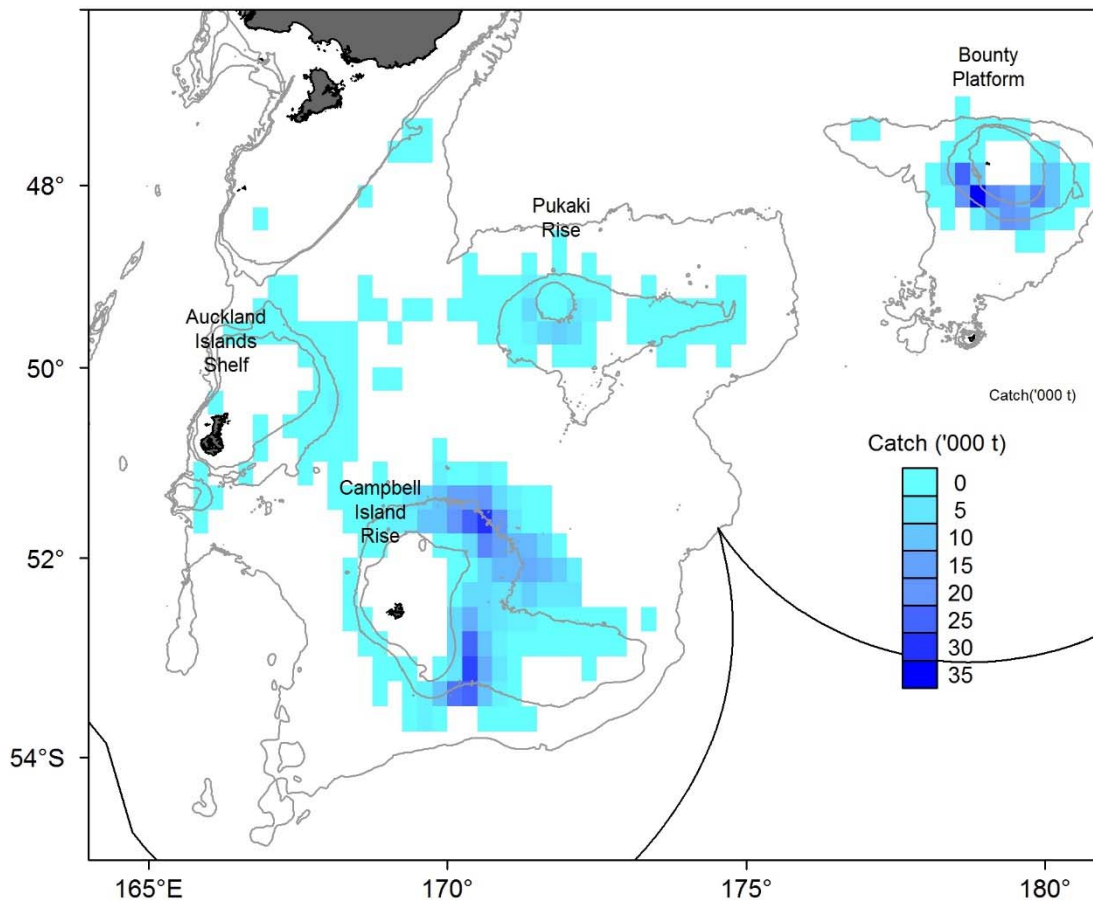
The Bounty Platform stock is the second largest of the four southern blue whiting stocks, with a current TACC of 2940 t (Figure 1). Southern blue whiting abundance on the Bounty Platform has been monitored using acoustic biomass surveys on spawning fish aggregations. Surveys are on a local area aggregation, taken opportunistically by an industry vessel using a random stratified survey design that encompasses an aggregation of southern blue whiting (Dunn et al. 2015). The surveys have been carried out every year since 2004. Dunn et al. (2015) reported that “the proportions of the population covered by the aggregation surveys were likely to have been different in each year” so the series entered the assessment model with annually varying catchability.

Biomass estimates from the aggregation surveys have been variable, with a large increase in 2007 and 2008 followed by a large drop in 2009, and have remained at lower levels since then. Stock assessment models have been unable to fit these observations, and so the results of recent stock assessments have been very uncertain (Dunn et al. 2015). To fit the acoustic data, a separate catchability for each survey was needed, resulting in a model that was over-parameterized. Consequently, the model results are not thought to be reliable for setting the TACC.

In recent years, the TACC for next year,  $t+1$ , have been set using an ad-hoc harvest control rule based on the estimated biomass from the acoustic survey in year  $t$ ,

$$M * (B_t - C_t / 2)$$

where  $M$  is the natural mortality which was set to  $0.2 \text{ y}^{-1}$ ,  $C_t$  is the annual catch in year  $t$ , and  $B_t$  is the acoustic abundance, assuming that the survey was conducted at the start of the fishery for that year. When surveys occurred at other times, the  $C_t / 2$  term was adjusted to reflect the survey timing relative to the fishery. However, this ad-hoc harvest control rule has not been formally evaluated.



**Figure 1: Relative total density of the commercial catch of southern blue whiting by location, derived from TCEPR data 1989–90 to 2013–14.**

The aim of this paper is to identify a simple harvest control rule (HCR), such as the product of  $M$  and acoustic biomass rule used above, that can be demonstrated to lead to a sustainable fishery over a range of plausible values of relevant population parameters, and covering processes that are known or potentially could occur.

This report fulfils the reporting requirements for Objective 3 of Ministry for Primary Industries (MPI) funded Project DEE2016-11.

## 2. METHODS

The performance of the HCR is tested using a simulation model. The model simulates long-term single-species SBW stock dynamics, acoustic surveys, and management decisions. We allow for uncertainty

in model parameters and acoustic surveys. To evaluate the suitability of the candidate HCR, we used MPI's performance criterion: that there is a less than 0.1 (10%) chance of mid-year  $B_{\text{current}}$  being below 20%  $B_0$ .

## 2.1 Overview of simulations

Each HCR was tested with 1000 model simulations. In some cases, these were replicated to test simulation error. The simulations were completed using a simple age-structured stock model (Beverton & Holt, 1957) that mimicked the Bounty's southern blue whiting stock assessment structure (Dunn et al. 2015).

The assessment model had a single species, one sex, ages from 1 to 30, with age 30 including all fish aged 30 or older (a plus group). The stock was assumed to reside in one homogeneous area. In reality, mature fish migrate to the spawning area on which the fishery operates. To account for this, the fishing selectivity was set to the maturity ogive. There were two time periods modelled: the first was non-spawning in which 90% of natural mortality occurred, followed by the spawning period. Age was incremented at the start of spawning, then fish recruited into age 1, followed by fishing along with the rest (10%) of natural mortality. Catch was assumed to be taken in the middle of spawning. The maximum exploitation rate was set at 0.8. There was no skip spawning or catch under-reporting.

Some demographic parameters were assumed to be constant across all simulations. The constant parameters were the size of the unfished stock ( $B_0$ ), maturity ogive, and the fish growth rate. We thereby assumed that the carrying capacity of the environment was fixed, productivity was determined primarily by recruitment levels, not by individual growth or age at first maturity or spawning, and that the fishery exploitation pattern was constant.

The simulations were specified such that the HCR started 20 years after the start of the fishery, consistent with an HCR starting in 2016. The choices of grid parameters and distributions for random draws was decided by the MPI Deepwater Fisheries Assessment Working Group in a meeting on 5 December 2016 (DWWG-2016-51), and updated later at an informal meeting (see later).

In each simulation run, the un-fished stock was simulated for 40 years, then a constant fishing mortality was applied over 20 years to reduce the biomass to a selected level of depletion by the start of the HCR period. In this way, the fishing mortality during the first 20 years varied for each simulation depending on the selected level of depletion and the pattern of recruitment. There followed a period of 120 years simulated under the HCR. The annual acoustic survey estimates were used to modify the TACCs, according to the HCR, for each following year. We assumed that the catch indicated by the HCR was taken exactly, except when the fishing exploitation was greater than 80% of the mature stock, in which case the catch was reduced so that 20% of the mature stock remained. Stock size and other parameters were recorded for the last 120 years so that performance criteria could be calculated.

Simulations were performed on two recruitment scenarios: using "usual" recruitment, seen in 19 of the 20 years of the fishery, and adding a single very large recruitment YCS 10 years into the HCR period. The latter also included a large mortality event in year 15 before the fishery started. A very large recruitment had been observed in the Bounty stock in 2002, and the mature stock was severely depleted two years after the 2002 cohort matured. In reality, the 2002 cohort matured about one year later than usual. This has not been modelled here, since it is the maturation of the large cohort (entry into the fishery) and its depletion two years later that had the largest impact.

This large recruitment could have been considered part of normal recruitment. However, its frequency is poorly estimated and due to its large impact needed to be characterised on its own. To do this, performance was also assessed from years 13 to 23 which covers the period when the large cohort enters the fishery, and the seven years after the large mortality event.



## 2.2 Model parameters

Parameters were divided into two groups: (1) grid parameters, which were those that were specified by a pre-determined set of fixed values; and (2) other parameters, which were specified with a distribution. All parameter bounds were set to encompass available and relevant estimates, and allow for the ‘range of uncertainty’ of the real world. A simulation was completed for each combination of grid parameters, and for each of these simulations, 1000 runs were done with the other parameter values chosen from their respective distributions (i.e., total number of simulations was the number of grid parameter combinations x 1000).

### (1) Grid parameters

Natural mortality,  $M$ , was assumed at values of 0.1, 0.15, 0.2, 0.25, and 0.3  $y^{-1}$ , which were considered by the Deepwater Working Group to bound the likely true value. The value used in previous stock assessments of southern blue whiting has been 0.2  $y^{-1}$  (Dunn et al. 2015).

The values for steepness in the Beverton-Holt stock-recruitment model,  $h$ , were 0.9 and 0.84. The Markov-Chain Monte-Carlo (MCMC) estimates of  $h$  from the Bounty stock assessment (Dunn et al. 2015) had a median of 0.95, so 0.9 was considered plausible whilst being more conservative than the median. Shertzer & Conn (2012) in a meta-analysis on  $h$  covering many species obtained a mode at 0.84, which is in the tail of the Dunn et al. (2015) MCMC distribution and serves as a lower bound on  $h$ .

The process error assumed for industry acoustic surveys was an additional CV of 0, 0.1, or 0.2. The latter (0.2) was recommended by Francis et al. (2003) for surveys in stock assessments.

The values of these grid parameters ( $M$ ,  $h$ , and process error) would give 30 combinations. To speed up the analyses, two sets of grid combinations were used: using the M grid in combination with

- (1) Case-1: steepness = 0.84; process CV, 0.20
- (2) Case-2: steepness = 0.90; process CV, 0.0

Preliminary model runs indicated that these two cases represent combinations of steepness and process error that bracketed the risk from all combinations, Two sets of 1000 random draws were then used to evaluate reproducibility and simulation error for each combination.

### (2) Other parameter distributions

The year-to-year variability in recruitment (the year class strength, YCS), was assumed to be autocorrelated, with a lag of 1 year. YCS in log space ( $\zeta$ ) was given by:

$$\zeta_t = \eta + \alpha (\zeta_{t-1} - \eta) + Z_t$$

where  $\alpha$  is the autocorrelation,  $Z$  is an independently random normal variable with mean 0 and variance  $\sigma_R^2 (1 - \alpha^2)$ , and  $\eta$  is  $-\sigma_R^2/2$  (Chatfield 1996). When the  $\zeta$  are back-transformed to get YCS, the YCS has a mean of 1 in the original scale. The parameterisation YCS variability was therefore via  $\alpha$  and  $\sigma_R$ , in log space. The distribution of auto-correlations was normal with mean 0.15 and standard deviation 0.06 which were derived from the MCMC chains for Campbell SBW stock, an assessment that has been accepted by the Deepwater Working Group (Dunn & Hanchet, 2017).

For the usual recruitment part, the  $\sigma_R$  for YCS in log space was fixed at 0.83, the value for YCS from the Bounty assessment MCMC when the large 2002 YCS was not used to normalise the mean of the YCS to 1 (Dunn et al. 2015).

The depletion in Phase 2 (fish-down) had a uniform distribution between 20 and 30%  $B_0$ .

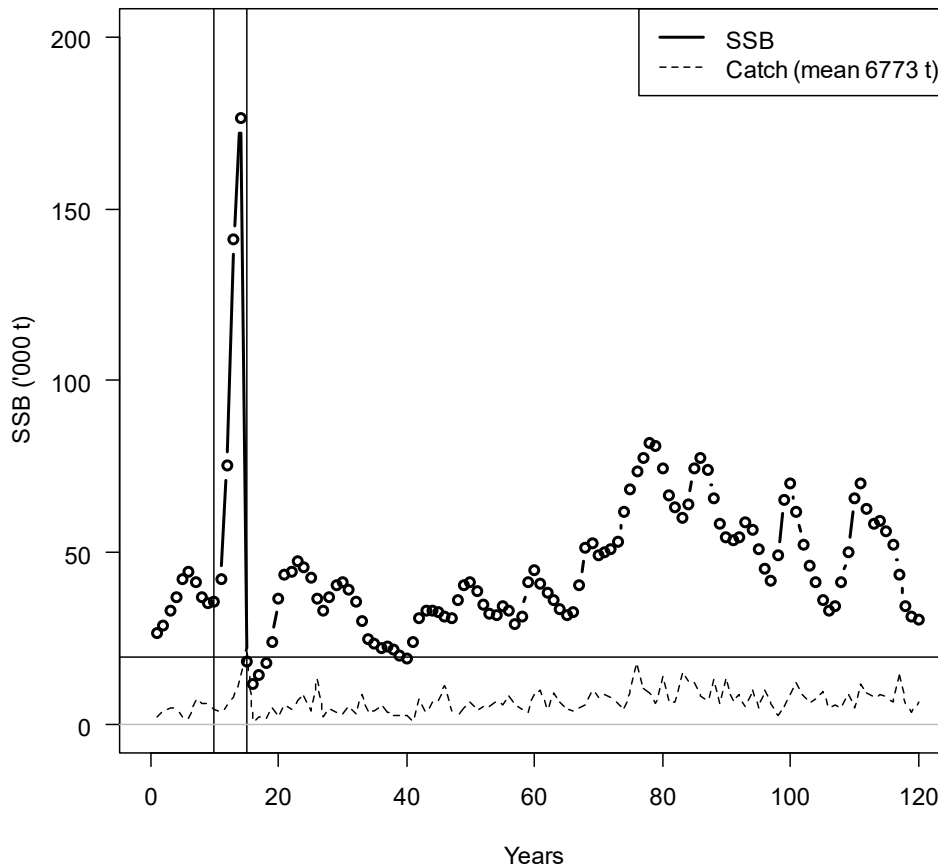
### 2.3 Adding a large recruitment event

A limited number of simulations were completed using Case-1 and Case-2 parameter combinations (restricted to  $M = 0.10, 0.20, \text{ and } 0.30 \text{ y}^{-1}$ ). These simulations incorporated a large recruitment in year 10 of the projection phase, without considering effects from auto-correlation. A large mortality event was applied in year 15, before the fishery started, which partially mimicked two years with high mature abundance. The effect is shown in Figure 2 (an example realisation). The interesting scenario is not the large recruitment, as such, but the observed accompanying large mortality after the second year that this cohort was in the fishery, and the following fishing season. This introduced a lag in the information flow and the application of the HCR, since there is now a TACC determined by the large abundance, which is severely depleted before the fleet can attempt to catch the derived TACC.

The large YCS was set to 15 (i.e., 15 times average YCS for normal recruitment). This was the same as that estimated in the 2012 stock assessment using 2011 data when the YCS for the large cohort was not included in the standardisation of YCS (Dunn & Hanchet, 2015).

The exploitation rate to apply for the large mortality event was derived from the acoustic abundances that covered the large reduction. Each abundance estimate was adjusted to account for catch so that they represented the abundance at year end in the year before the reduction, and the abundance at the start of the fishery in following year, i.e., bracketing the large reduction in abundance. The two years with high acoustic abundances (2007 and 2008) were averaged to give about 78 000 t for 2008, and 17 000 t for 2009, both taken to represent mid-fishery abundances (Dunn et al. 2015). The catch in 2008 was 10 000 t, and in 2009 it was 15 000 t, so the abundance for the end of 2008 was approximately  $78\,000 - 10\,000 / 2 / 2$  with the 2<sup>nd</sup> “/2” term to approximately convert the catch into “acoustic abundance” terms (i.e., 0.54 from the mean catchability  $q$  distribution). For the start of the fishery in 2009, the abundance was  $17\,000 + 15\,000 / 2 / 2$ . This gave an exploitation rate of about 0.75.

The performance measure, hereafter referred to as risk, was calculated from the stock abundance over the 120 projection years and also over a shorter timeframe, years 13 to 23 which covered the seven years after the large mortality year.



**Figure 2: Example plot of one realisation showing SSB and catch in which there was a large recruitment (YCS 15) in year 10 (left hand side, vertical line) and an exploitation rate ( $U$ ) of 0.75 in year 15 prior to the fishery (2<sup>nd</sup> vertical line).  $M = 0.2$ ,  $h = 0.84$ , survey process CV = 20%, HCR-p = 0.2. Horizontal line is  $0.2 \text{ SSB}_0$ .**

## 2.4 Stock monitoring

The stock monitoring used to inform the HCR in the simulations was the annual acoustic survey of spawning fish. The survey was simulated to be at the start of the fishery. The survey assumed a constant lognormal observation error coefficient of variation (CV) of 27%, the median CV over the series (Dunn et al., 2015). Process error was also added (as above).

There were additional errors in converting the abundance into an absolute one (i.e., catchability,  $q$ ), e.g., in the target strength (TS) of southern blue whiting used to convert acoustic backscatter to absolute biomass. The  $q$  is made up of several sources of error: target strength uncertainty and fish tilt angle, target identification, vertical availability, areal availability, and system calibration (Dunn et al., 2015). Here, the contribution from areal availability was ignored since it was thought its exclusion would make the HCR more conservative.

The observed acoustic abundance,  $B_{\text{obs}}$ , was drawn from a lognormal distribution with a mean equal to the true abundance (from the model) with sampling CV 27% and multiplied by  $q_i$ , where  $q_i$  is a random draw from the catchability distribution. For use in the HCR,  $B_{\text{obs}}$  is divided by the  $q_{\text{assumed}}$ , i.e., not the simulated catchability, but what the management rule has assumed catchability to be.

The distribution for  $q$  was lognormal with CV 35% and mean 0.54. The prior for  $q$  used in the Bounty stock assessment was lognormal with a mean of 0.54 and a CV of 68% (Dunn et al. 2015) based on the distributions from the sources listed above. The large CV was used to make a diffuse (uninformative) prior. This large CV had a considerable influence on results, and so it was adjusted downwards since there was no evidence available for the extreme values the prior indicated in any southern blue whiting assessment. The MCMC estimates were considered from three SBW assessments ( $q$  medians in brackets, first run is base case): Campbell (2013 catch, run 1.1 ( $q = 0.09$ )), Bounty (2014 catch, runs 3.11 ( $q = 0.05$ ) and 2.10 ( $q = 0.13$ )), and Pukaki (2013 catch, runs 1.1 ( $q = 0.20$ ), 1.2 ( $q = 0.25$ ), and 1.4 ( $q = 0.30$ )). The “process” error CV was the between-area variance of posterior mean  $qs$  (29%), and within assessment variability, which set to the maximum variability within a base case, 20% (Pukaki 1.1). These combined to give a CV of 35%. The simulation CV was therefore made up of “process” error between the stocks combined with variability seen within MCMC analysis.

We used  $q_{\text{assumed}} = 0.54/0.9$  to get acoustic abundance for the HCR (0.9 is aerial availability in the  $q$  prior for Bounty Plateau assessment).

## 2.5 Fixed parameters

The size of the unfished stock ( $B_0$ ) was assumed to be 100 000 t, which fell between the 62 000 t estimated when the 2002 YCS was not included in the sum-to-1 for the YCS, and 120 000 t when it was (Dunn & Hanchet 2011, Dunn et al. 2015). Growth in length and weight at age was modelled using the von Bertalanffy growth formula ( $k=0.22$ ,  $t_0=-1.3$ ,  $L_\infty=51.3$ ), with a CV of mean length at age of 10%. In the assessment, growth used empirical mean lengths by age for each year, and these were used to estimate the von Bertalanffy parameters averaged over sexes (Dunn et al. 2015). The length (L) to weight (W) relationship was  $W = 4.9 \times 10^{-8} \times L^{3.12}$  which was the average over the sexes (Dunn et al. 2015). The proportion at age that were mature, spawning, and vulnerable to the fishery were all fixed to the same ogive: a logistic curve where the age at 50% mature was 3.45 years, and the difference between the age at 50% and 95% mature was 1.5 years (Dunn et al. 2015). All mature fish were assumed to spawn each year.

## 2.5 Harvest control rules & risk

We assumed that the frequency of applying the HCR was annual. The HCR was applied in year  $t+1$  to give

$$\text{TACC}_{t+1} = \xi (B_t - C_t / 2)$$

where  $B_t$  is the acoustic abundance from a survey,  $C_t$  is the catch, and  $\xi$  is a fixed factor to be estimated.

The acoustic survey was simulated to be at the start of the fishing period. The  $- C_t / 2$  term gives an approximate mid-fishery abundance that takes into account the level of the TACC.

Risk for a simulation run was measured as the proportion of the mid-year  $B_{\text{current}}$  values that were below 20%  $B_0$  over the 120-year projection phase. The risk for the combination of grid parameters was the average of the simulations.

The values of the  $\xi$  investigated were: 0.10, 0.15, 0.20, 0.25, and 0.30.

## 2.6 Stochastic $SSB_0$

We investigated applying a correction factor to the deterministic  $SSB_0$  to account for stochastic effects of recruitment. This was evaluated over a limited set of parameters using simulations without any fishing. There were 12 parameter combinations made up from  $M$  (0.1, 0.2, 0.3),  $h$  (0.84, 0.9), and auto-correlation (0.08, 0.14, and 0.20). A burn-in period of 20 000 years was used, followed by another 30 000 years to estimate the stochastic mean  $SSB_0$ . Simulation error gave inconsistent results over the auto-correlation values and the stochastic mean  $SSB_0$  could be greater than the deterministic  $SSB_0$  (they should be lower) so the mean YCS was forced to be 1.

Preliminary results of this simulation gave a trivial correction factor, and it was not considered again. However, it was a useful check of the model setup, since it can identify misspecifications of timing within the annual cycle.

## 3. RESULTS

### 3.1 “Usual” recruitment

Case-1 results are shown in Table 1. The simulation standard deviation for risk was 0.0038 averaged over the combinations of  $M$  and  $\xi$ , and ranged from 0.0007 ( $M=0.30 \text{ y}^{-1}$ ,  $\xi=0.10$ ) to 0.011 ( $M=0.15 \text{ y}^{-1}$ ,  $\xi=0.30$ ). The standard error for the risk mean over two simulations was  $0.0038 / \sqrt{2} = 0.0027$ , i.e., in general, the results were reliable to two to three decimal places.

**Table 1: Case-1: Risk for a combination of  $M$  and  $\xi$  values with steepness set to 0.84 and survey process CV at 20%. Risk is the probability of  $SSB_0$  being below 0.20  $B_0$  over a 120-year projection). Mean over 2 runs. Simulation standard deviation was about 0.0012. Acceptable risks are those below the thick black border (those less than 0.1).**

M	$\xi$				
	0.1	0.15	0.2	0.25	0.3
0.1	0.052	0.194	0.368	0.530	0.659
0.15	0.014	0.067	0.162	0.274	0.387
0.2	0.005	0.028	0.075	0.143	0.218
0.25	0.003	0.016	0.043	0.087	0.141
0.3	0.002	0.009	0.026	0.053	0.089

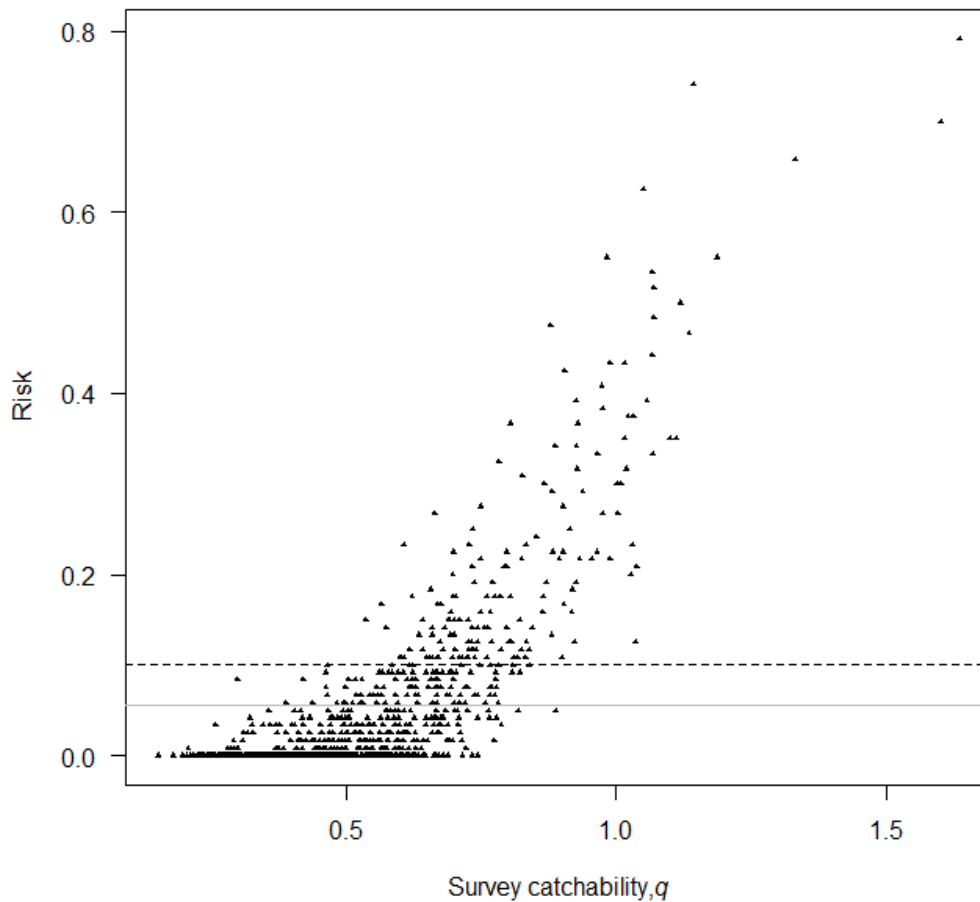
Case-2 results are shown in Table 2. They are consistently lower than those for Case-1 for all combinations, but the absolute difference does depend on the value of the risk. The difference ranged

from 0.001 for  $\xi$  of 0.1 with  $M = 0.3 \text{ y}^{-1}$  to 0.070 for  $\xi$  of 0.3 and  $M=0.01 \text{ y}^{-1}$ . The relative difference is larger for smaller  $\xi$ s. The standard error for the mean was 0.0035.

**Table 2: Case-2: Risk for a combination of  $M$  and  $\xi$  values with steepness set to 0.90 and survey process CV at 0% (probability of  $SSB_0$  being below  $0.20 B_0$  over a 120-year projection). Risk is the probability of  $SSB_0$  being below  $0.2 B_0$  over a 120-year projection. Mean over 2 runs. Standard simulation error was about 0.0025. Acceptable risks are below the thick black border.**

M	$\xi$				
	0.1	0.15	0.2	0.25	0.3
0.1	0.037	0.151	0.305	0.460	0.589
0.15	0.010	0.053	0.131	0.229	0.332
0.2	0.003	0.021	0.058	0.113	0.180
0.25	0.002	0.012	0.035	0.070	0.117
0.3	0.001	0.007	0.020	0.042	0.071

Within a simulation run for one combination of grid parameters, there was generally a wide spread of risk over the 1000 individual simulations, which was mainly caused by the right-hand side of the survey catchability ( $q$ ) distribution (example shown in Figure 3).



**Figure 3: Example showing the effect of the catchability ( $q$ ) on risk for grid parameters  $M=0.15 \text{ y}^{-1}$ ,  $h=0.90$ , survey process CV= 0.2 with  $\xi$  of 0.15. Grey line is the mean risk (0.055); dashed line is at 0.10.**

### 3.2 Add a large recruitment event

Case-1 risks are shown in Table 3. In general, the increase in risk relative to the same simulation for the normal recruitment is from 0.01 to 0.04 (outside the simulation error), and the effect is proportionally greater for lower risks in usual recruitment. For example, when  $M$  is 0.2, then risk increases from 0.005 to 0.018, 0.078 to 0.102, and 0.223 to 0.242 for  $\xi$ s: 0.1, 0.2, and 0.3. Over the 120-year projection the twin events of large recruitment followed by a large mortality has a modest impact on risk when risk is around the 0.1 level.

**Table 3: Case-1 with large recruitment and mortality events: Risk for a combination of  $M$  and  $\xi$  values with steepness set to 0.84 and survey process CV at 20%. Risk is the probability of  $SSB_0$  being below  $0.2 B_0$  over a 120-year projection. Only one simulation run (1<sup>st</sup> set). Acceptable risks for the normal recruitment are below the thick black border (those less than 0.1).**

M	$\xi$				
	0.1	0.15	0.2	0.25	0.3
0.1	0.090	0.237	0.404	0.557	0.670
0.2	0.018	0.051	0.102	0.170	0.242
0.3	0.011	0.025	0.045	0.073	0.109

Risk was also evaluated for the period from years 13 to 23, i.e., the period when the large recruitment starts to enter the fishery, to seven years past the large mortality event. Table 4 shows that the risks in this period are elevated considerably relative to the full projection.

**Table 4: Case-1 with large recruitment and mortality events: Risk for a combination of  $M$  and  $\xi$  values with steepness set to 0.84 and survey process CV at 20%. Risk is the probability of  $SSB_0$  being below  $0.2 B_0$  over years 13 to 23 in the projection. Results are from one simulation (first thousand shown).**

M	$\xi$				
	0.1	0.15	0.2	0.25	0.3
0.1	0.383	0.525	0.600	0.646	0.674
0.2	0.143	0.255	0.326	0.389	0.427
0.3	0.103	0.174	0.221	0.256	0.285

Case-2 risks are shown in Table 5 and results are similar to Case-1. In general, the increase in risk compared to the same simulation for the normal recruitment is from 0.01 to 0.04 (outside the simulation error), and the effect is proportionally greater for lower risks in usual recruitment. For example, when  $M$  is 0.2, then risk increases from 0.003 to 0.055, 0.078 to 0.0079, and 0.175 to 0.194 for  $\xi$ s: 0.1, 0.2, and 0.3. Again, over the 120-year projection the twin events of large recruitment followed by a large mortality has a modest impact on risk when risk is around the 0.1 level.

**Table 5: Case-2 with large recruitment and mortality events: Risk for a combination of  $M$  and  $\xi$  values with steepness set to 0.90 and survey process CV at 0. Risk is the probability of  $SSB_0$  being below  $0.2 B_0$  over a 120-year projection. One simulation (second set of a thousand). Acceptable risks for the normal recruitment (see above) are below the thick black border.**

M	$\xi$				
	0.1	0.15	0.2	0.25	0.3
0.1	0.068	0.187	0.333	0.475	0.593
0.2	0.014	0.039	0.079	0.132	0.194
0.3	0.010	0.021	0.037	0.058	0.086

Case-2 risk results for years 13 to 23 are shown in Table 6, and as for Case-1, risks in this period are again elevated considerably relative to the risks over the full projection.

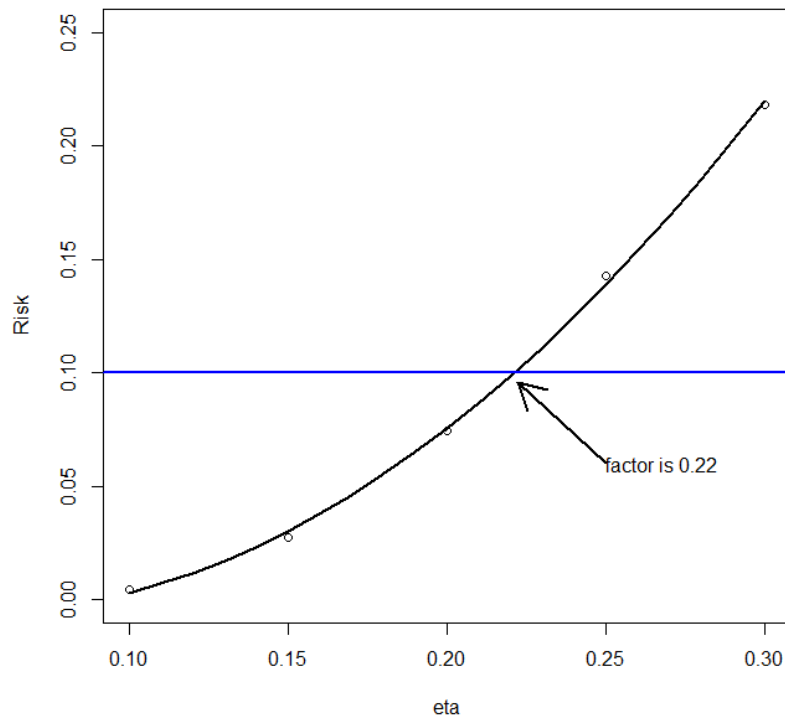
**Table 6: Case-2 with large recruitment and mortality events: Risk for a combination of  $M$  and  $\xi$  values with steepness set to 0.90 and survey process CV at 0%. Risk is the probability of  $SSB_0$  being below  $0.2 B_0$  over years 13 to 23 in the projection. One simulation (second set of a thousand).**

M	$\xi$				
	0.1	0.15	0.2	0.25	0.3
0.1	0.383	0.525	0.600	0.646	0.674
0.2	0.143	0.255	0.326	0.389	0.427
0.3	0.103	0.174	0.221	0.256	0.285

#### 4. DISCUSSION

The HCR,  $TACC_{t+1} = \xi (B_t - C_t / 2)$ , was tested using simulations conducted with a simple population model with parameters set over a range thought to cover their likely values. For management purposes, the  $\xi^*$  that has risk = 0.1 can be found by fitting a regression curve to the relevant simulations data obtained here and interpolating (see example in Figure 4 for  $M = 0.2y^{-1}$ ). This means selecting the relevant grid parameters to integrate across. Results show that  $M$  dominates the other grid parameters in determining the risk and so either  $M$  needs to be specified, or if they are combined then probabilities given to each of the grid  $M$ s. Once  $M$  is specified, the regression would include both CASE-1 and CASE-2 simulation runs for that  $M$  and  $\xi^*$  read off the resultant plot. The choice of  $M$  should be within the range of grid  $M$ s.





**Figure 4: Finding  $\xi^*$  for  $M = 0.2 \text{ y}^{-1}$  by reading off the  $\xi$  where the horizontal line crosses the regression curve:  $\text{risk} = 0.0026 - 0.3560 \xi + 3.6000 \xi^2$  fitted to the mean CASE-1 and CASE-2 risk values for  $M$  of  $0.2 \text{ y}^{-1}$  (or solving the regression for  $\text{risk} = 0.1$ ). For  $M$  of  $0.2$ ,  $\xi^*$  for is  $0.22$ .**

The large YCS simulations show that the HCR has trouble at the time of the large cohort maturing and followed by a large depletion (in reality this might be mortality or migration) two years later, and that this raises risk over the whole 120 projection years. Since these events are easily detected via the acoustic surveys, special management actions can be put into place at the time to manage this effect within the risk performance.

The HCR makes use of the specified  $q_{\text{assumed}}$  and so, at first sight, this may seem like circular logic in proving that the HCR does indeed protect the stock at the specified risk. However, the risk is determined by the population dynamic parameters used, and the catch series. The HCR can be rearranged to explicitly include  $q_{\text{assumed}}$  used to provide the acoustic abundance,  $\text{TACC}_{t+1} = \xi (B_{\text{obs}} / q_{\text{assumed}} - C_t / 2)$ , which shows that  $q_{\text{assumed}}$  and  $\xi$  are negatively correlated (correlation of -1 if the “ $- C_t / 2$ ” is not used) when  $\xi$  is varied to keep risk at 0.1 for different values of  $q_{\text{assumed}}$ . Hence, this analysis depends largely on the parameter’s distributions not the  $q_{\text{assumed}}$  used. Here, the  $M$  specified and the  $q$  distribution are the main factors that determine risk for a given  $\xi$ .

The “ $- C_t / 2$ ” term is fixed in these simulations, but in practice it can vary depending on the time of the acoustic survey. This implicitly selects the mid-fishery point as the reference point. It could be that using the abundance after fishing will be an improvement since all the catch is accounted for in projecting forwards. Since catch should be small relative to survey abundance, this term should have a moderate or minor effect of the TACC from the HCR (note that  $\xi$  will change to adapt to a different reference point for the acoustic survey).

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## 6. REFERENCES

- Beverton, R.J.H.; Holt, S.J. (1957). On the Dynamics of Exploited Fish Populations, Fishery Investigations Series II, vol. XIX. Ministry of Agriculture, Fisheries and Food.
- Chatfield, C. (1996). The analysis of time series, an introduction. Fifth edition. Chapman & Hall, London.
- Dunn, A.; Hanchet, S.M. (2011). Southern blue whiting (*Micromesistius australis*) stock assessment for the Campbell Island Rise for 2009–10. *New Zealand Fisheries Assessment Report 2011/40*. 37 p.
- Dunn, A.; Hanchet, S.M. (2017). Southern blue whiting (*Micromesistius australis*) stock assessment for the Campbell Island Rise for 2016. *New Zealand Fisheries Assessment Report 2017/38*. 20 p.
- Dunn, A.; Hanchet, S.M.; Dunford, A. (2015). Southern blue whiting (*Micromesistius australis*) stock assessment for the Bounty Platform up to and including the 2014 season. Final Research Report to MPI for project DEE201002SBWD. 20 p. (Unpublished report held by MPI Wellington.)
- Francis, R.I.C.C.; Hurst, R.J.; Renwick, J.A. (2003). Quantifying annual variation in catchability for commercial and research fishing. *Fishery Bulletin 101*: 293–304.
- Shertzer, K.W.; Conn, P.B. (2012). Spawner-recruit relationships of Demersal marine fishes: prior distribution of steepness. *Bulletin Marine Science 88*. 39–50.