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# Harvest control rules for a sustainable orange roughy fishery

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ABSTRACT

Some of the best described examples of unsustainable deep-sea fisheries have been for the orange roughy, *Hoplostethus atlanticus*. Nevertheless, fisheries for orange roughy around New Zealand have persisted for more than 30 years, and some stocks that were overfished and substantially depleted now appear to be recovering. Scientific advice on the status of New Zealand orange roughy stocks has historically used population models fitted to various observational data, but this approach has proved problematic, largely due to uncertainty in recruitment, to the extent that from 2008 these models were replaced by a simple harvest control rule (HCR). The catches taken under this HCR were a fixed proportion of the weight of the mature stock, estimated principally from acoustic surveys. We test the performance of the current HCR, and some alternative HCRs, using a simulation model. The model simulates long-term single-species orange roughy stock dynamics, stock monitoring surveys, and management decisions. We allow for uncertainty in model parameters, but focus on the effects of changes in mean recruitment and recruitment variability, because the latter have been considered the primary source of uncertainty in future stock status. Results show that the current HCR is likely to lead to a sustainable fishery. Nevertheless, there are alternative HCRs that could out-perform the existing HCR. With a reliable series of biomass estimates from acoustic surveys, good knowledge of biological parameters (natural mortality in particular), some revision of a HCR to control catch, and spatial management to control habitat damage, it appears that an orange roughy fishery might achieve best-practice sustainability and environmental standards.



## 1. Introduction

The expansion of the fishing industry into the deep sea was relatively recent, and followed the decline of shallow-water fisheries and the advent of new technology (Morato et al., 2006; Norse et al., 2012; Watson and Morato, 2013). Many deep-sea fisheries have proven to be short-lived, however, and commercial deep-sea fisheries have a worldwide, and often deserved, reputation for being unsustainable (Roberts, 2002; Morato et al., 2006; Norse et al., 2012). This led researchers to call for a stop to deep-sea fishing, and a focus instead on rebuilding and sustainably fishing more resilient and productive coastal species (Norse et al., 2012). The plea to stop deep-sea fishing was echoed by non-governmental organisations and lobby groups worldwide (e.g., Greenpeace, WWF, Deep Sea Conservation Coalition). Despite these opinions, it seems likely that many deep-sea fisheries will persist. In December 2013, the European Parliament rejected a proposal to ban deep-sea trawling in EU waters, and in New Zealand, for example, deep-sea fisheries continue to be a mainstay of the commercial fishing industry (Ministry for Primary Industries, 2013).

Some of the best described examples of unsustainable fisheries have been for the orange roughy, *Hoplostethus atlanticus*, and as a result this species is commonly cited as one of the worst possible purchasing choices for ethical seafood consumers (Roheim, 2009). Nevertheless, a few fisheries for orange roughy have persisted, and some around New Zealand continue after 35 years of fishing (Ministry for Primary Industries, 2013). In addition, the orange roughy stock (population) on the Challenger Plateau (New Zealand) was depleted and then closed to fishing, but surveys show biomass has been rebuilding in the area and it now supports low levels of fishing again (Ministry for Primary Industries, 2013).

The reasons for the collapse of many orange roughy fisheries have already been discussed (Boyer et al., 2001; Bax et al., 2005; Francis and Clark, 2005; Foley et al., 2011; Clark and Dunn, 2012), but briefly it has been because orange roughy (i) are a valuable product in premium international markets, providing incentive for fishing, (ii) form large and predictable aggregations that can be easily found and rapidly depleted by industrial-scale trawlers operating in the deep-sea, (iii) are long-lived and unproductive, meaning sustainable catches are relatively small and recovery from overfishing is slow, and (iv) have proven difficult and

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expensive to study scientifically, such that scientific data and advice are often sparse or acutely uncertain, and consequently science can be a marginal contributor to fishery management.

In this study, we consider how the remaining or rebuilding orange roughy stocks might be managed to support sustainable fisheries. We use a case study of the fishery on the east and south Chatham Rise, New Zealand, but our analyses could, in principle, be applied to any orange roughy stock, or other species having similar population dynamics. The Chatham Rise orange roughy fishery started in the late 1970s, and has proven to be the largest in the world (Clark, 2001; Norse et al., 2012; Ministry for Primary Industries, 2013). Chatham Rise is a relatively large and highly productive area of continental shelf; as such, the east and south Chatham Rise orange roughy stock may be rather special in having been able to support a long-term fishery. Historically, the status and sustainable yield of the stock was scientifically assessed using demographic population (stock assessment) models fitted to various observational data (Sissenwine and Mace, 2007). Stock assessment model results led total allowable commercial catch limits (TACCs) to be reduced in the mid-1990s, to levels estimated to be sustainable and to allow the stock to rebuild. However, over the following decade the expected biomass rebuild was not apparent in scientific observations, nor in fishery performance (Sissenwine and Mace, 2007). The biomass rebuild was predicted by stock assessment models assuming deterministic recruitment, and it was therefore suspected that recruitment had not been deterministic, but a period of reduced recruitment had started at about the time that the fishery started (Ministry for Primary Industries, 2013). In 2008, the credibility of the stock assessment model was questioned to such an extent that it was discarded, and in its place an assessment-model-free stock evaluation was completed (Dunn et al., 2008; Ministry for Primary Industries, 2013). Stock assessment models, although still used to provide scientific advice for some New Zealand orange roughy stocks, continue to be problematic, as they do not always explain observed data well, and are not easily applied where observational data are sparse (Clark and Dunn, 2012; Ministry for Primary Industries, 2013).

In the absence of predictions of sustainable yield from a stock assessment model, the TACCs for the east and south Chatham Rise were set using a relatively simple harvest control rule (HCR) (Ministry for Primary Industries, 2013). In essence, the HCR sets the TACC to be a small proportion of the current estimated stock size. The first step in this process is to obtain an estimate of the current size of the spawning stock, primarily from an acoustic survey of the spawning aggregation ('plume') that occurs in early July on flat areas of the northeast Chatham Rise, in an area known as the 'Spawning Box'. Technological advances make acoustic surveys currently the most credible method for estimating orange roughy biomass (Branch, 2001; Hordyk et al., 2011; O'Driscoll et al., 2012; Macaulay et al., 2013). The survey of the Spawning Box plume covers the historical main spawning aggregation, but orange roughy are also known to spawn simultaneously elsewhere within the stock boundaries. This additional spawning biomass has been surveyed less frequently, and the available estimates are added to the Spawning Box plume estimate to give total spawning biomass. It is known that not all mature orange roughy spawn every year, so the total spawning biomass is then scaled up, using a fixed ratio, to give the total mature biomass. Subsequent fishery management decisions about the size of the TACC are made using the estimate of total mature biomass. The simple HCR sets the TACC equal to the total mature biomass multiplied by the estimate of natural mortality ($M$). This is a constant fishing mortality rate ($F$) HCR, where the TACC is equal to $F \times$ current mature biomass, and $F=M$. Setting $F$ equal to $M$ has been suggested as a surrogate for fishing at the rate that produces maximum sustainable yield ($F_{MSY}$; Mace, 1994; Quinn and Deriso, 1999; Gabriel and Mace, 1999; Deroba and Bence, 2008). However, simulation studies have suggested $M$ may be better viewed as an upper bound for $F_{MSY}$ rather than a surrogate, and setting $F$ equal to $M$ may not be sustainable for some stocks (Quinn and Deriso, 1999).

To determine whether the $F=M$ HCR should result in a long-term sustainable fishery for orange roughy, we test this HCR in a simulation model of the east and south Chatham Rise stock. The model simulates the population dynamics, acoustic surveys, and the HCR decisions and resulting fishery catches. Many simulations are conducted, using different model parameter settings, thereby evaluating the HCR across a wide range of uncertainties about stock status and dynamics, which includes changing levels of mean recruitment. The latter was included because of the pronounced uncertainty in orange roughy recruitment. We then use the simulation model to evaluate alternative HCRs, to see if any of these might do better than $F=M$. We evaluate the performance of the HCRs using simple measures, such as the level of fishery yield, stability in yield over time, and the risk of stock biomass being depleted below reference levels. Our performance measures were set without stakeholder consultation, and therefore our study is best described as an evaluation of an empirical management procedure, rather than a management strategy evaluation (Rademeyer et al., 2007).

## 2. Materials and methods

### 2.1. Overview of the simulation model

Each HCR was tested with 1000 model simulations. The simulations were completed using a simple age-structured stock model (Beverton and Holt, 1957). The model was age structured with ages 1–120, with the final age including all fish at that age and older (a plus group), with a single sex, assumed to reside within a single homogenous area. Age was incremented at the start of the year, and recruitment entered at age 1. The fishery was assumed to take the catch at the mid-point of the year. The model was single species, with no species interactions.

Some demographic parameters were assumed to be constant across all simulations. The constant parameters described the initial size of the unfished stock ($B_0$), maturity at age, spawning at age, vulnerability to the fishery at age, and the fish growth rate (weight at age). We thereby assumed that productivity was determined primarily by recruitment levels, not by growth rate or maturity or proportion spawning at age, and that the fishery exploitation pattern (fish vulnerability at age) was constant.

The demographic parameters that varied with each simulation run were $M$, which determined mean productivity, the pattern of annual recruitment variability, the shape of the relationship between spawning stock size and subsequent recruitment, a scaling factor to allow for the proportion of mature fish that were not spawning ($SR$), and the level to which the stock was depleted when the HCR started. The simulations were specified such that the HCR started 30 years after the start of the fishery, consistent with the HCR starting in 2008. In each simulation run, the un-fished stock was simulated for 120 years, then a constant fishing mortality was applied over 30 years to reduce the biomass to the selected level of depletion by the start of the HCR period. This meant that this fishing mortality during the first 30 years varied for each simulation depending on the selected level of depletion and the pattern of recruitment. After this, a period under the HCR was simulated for a further 200 years. Recruitment had stochastic variability around a mean recruitment level ($R_0$). Simulations either assumed a constant $R_0$ throughout, or that $R_0$ halved, or doubled, for the HCR simulation period. This persistent change in $R_0$ is analogous to assuming a regime shift occurred, where the carrying capacity ($B_0$) of the environment halved or doubled. The change in $R_0$ took place in the first year of the HCR simulation period, so the influence of this change on recruitment to the fishery occurred at the age of recruitment (38 years, see below) after the start of the HCR simulation period. Because we chose to simulate each HCR for 200 years under each $R_0$ scenario, the total length of the HCR simulation period when $R_0$ halved or doubled was 238 years (the age at recruitment+200 years).

We simulated annual resource surveys using the acoustic method introduced above, consistent with the surveys that have been completed since 2002 (Doonan et al., 2012). The survey estimates were used to modify the TACCs, according to the HCR, for the following year. In all simulations, the $F=M$ HCR always assumed an $M$ of 4.5% and an $SR$ of 1.5 (Ministry for Primary Industries, 2013), even though these parameters varied for the stock in each simulation run. We assumed that the catch set by the HCR was taken exactly and in full. Stock size and other parameters were recorded for the last 200 years so that performance criteria could be calculated. In these simulations, we did not incorporate correlations between demographic parameters (i.e., joint probability distributions) as these were not available, but we did check that each set of parameters were a reasonable combination by repeating each simulation without fishing, and if the stock failed to rebuild and dropped below 10% $B_0$ after 100 years of the HCR simulation period then we considered this unreasonable (there was only a single simulation run where this occurred, and it was excluded).

## 2.2. Model parameters

For each simulation run, a set of parameter values were randomly chosen from their respective distributions, and distributions were assumed to be independent of each other. Parameter bounds were set to encompass all known estimates, and thereby allow for the 'range of uncertainty' of the real world, as far as we know.

The $M$ assumed for Chatham Rise orange roughy and used in the HCR was 0.045, which was estimated from a lightly-fished stock on Chatham Rise (with 95% CIs 0.030–0.060; Doonan, 1994). A similar estimate was obtained for orange roughy off northern New Zealand ($M=0.037$, 95% CIs 0.025–0.062; Doonan and Tracey, 1997), and from a stock assessment model for the Australian Eastern Zone orange roughy stock ($M=0.042$; Wayte, 2007). Despite the consistency of these estimates, there is still substantial uncertainty in $M$, and recent stock assessment model runs for New Zealand orange roughy assumed $M$ to be either 0.045 or 0.025 with equal probability (Anderson and Dunn, 2011). The lower of these values is close to an estimate for the Australian Cascade Plateau stock ($M=0.02$; Wayte and Bax, 2007). Our assumed distribution of $M$ was therefore uniform, with bounds at 0.015 and 0.075 (symmetrical around 0.045).

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 ($\varsigma$) was given by:

$$\varsigma_t = \eta + \alpha(\varsigma_{t-1} - \eta) + Z_t$$

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 $\varsigma$ are back-transformed to get YCS, the YCS has a mean of 1. The parameterisation of YCS variability was therefore via $\alpha$ and $\sigma_R$ in log space. There were no available estimates of $\alpha$ for orange roughy, so we used estimates from the fisheries literature to inform a distribution. A sand eel stock off Shetland had an $\alpha$ of 0.54 (Poloczanska et al, 2004), in four Bristol Bay sockeye stocks $\alpha$ varied from 0.44 to 0.7 (Pyper and Peterman, 1998), Baltic cod had an $\alpha$ of 0.6, which reduced to 0.2 when other co-variants were included (Sparholt, 1996), Norwegian spring herring had an $\alpha$ of 0.29 (Fiksen and Slotte, 2002), and Dorn (2002) found Pacific rockfish species had an $\alpha$ of about 0.5 and Atlantic rockfish had a weak or negative autocorrelation. Based on these reports, we assumed $\alpha$ to have a uniform distribution, in the log scale, with bounds at 0.2 and 0.8. We assumed $\sigma_R$ to be either 0.4, 0.6, or 0.8, with equal probability, describing low, medium, and high recruitment variability (Francis, 1992). Empirical estimates of $\sigma_R$ for orange roughy have been as low as 0.25 (Wayte and Bax, 2007), but this estimate is likely to be too low because age classes will have been smeared across adjacent cohorts as a result of considerable ageing error (Andrews et al., 2009). Other estimates have been as high as 1.2, but this has been considered too high because it was based upon only 4 cohorts of young fish and natural mortality will probably dampen variability (Francis and Robertson, 1990). However the uncertainty in the parameterisation of $\alpha$ and $\sigma_R$ was not considered to be a key focus, provided that the resulting simulations produced a wide range of different YCS patterns, from near-constant YCS through to highly intermittent peaks in YCS (Fig. 1).

The actual recruitment was the product of YCS and mean recruitment. Mean recruitment was modelled as a function of the size of the spawning stock using the Beverton and Holt (1957) stock–recruit relationship. The steepness parameter ($h$) is unknown for orange roughy, and has been assumed to be 0.75 (Francis, 1992). Shertzer and Conn (2012) found no relationship

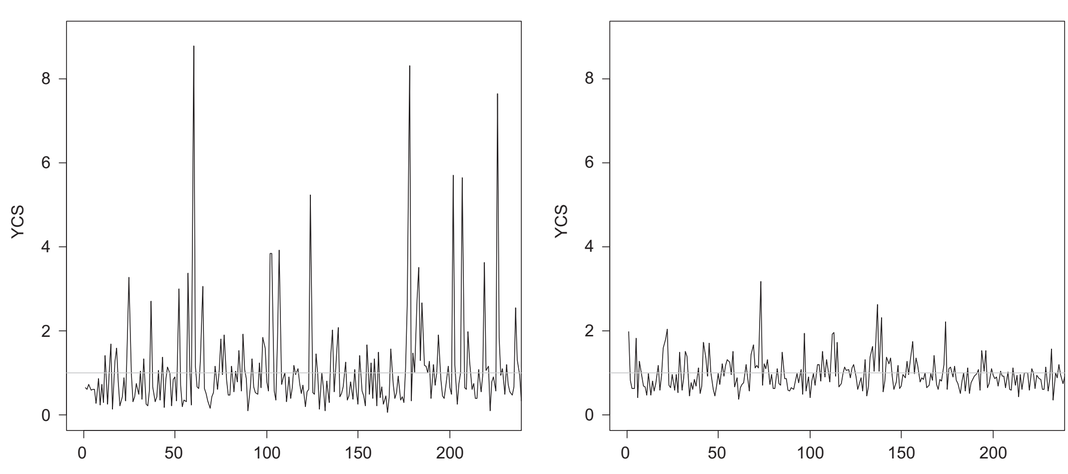


**Fig. 1.** Examples of variability in simulated year class strength (YCS). Left panel ($\alpha=0.64$; $\sigma_R=0.6$); right panel ($\alpha=0.21$; $\sigma_R=0.4$). Both YCS series average to 1 (indicated by the horizontal grey line).

between species life history parameters and $h$, so in our simulations we assumed their general estimated Beta distribution for $h$, with a mode at 0.84, and 95% CIs at 0.42 and 0.96.

The scale-up parameter $SR$ is used to multiply the observed spawning biomass up to the mature biomass. In the existing HCR, the $SR$ was assumed to be 1.5 after a review of available observations and estimates (Dunn et al., 2008). The lowest estimate of $SR$ found was 1.01, and the highest estimate was 1.91, with no obvious mode. We therefore assumed the $SR$ for the stock was uniform, with a lower bound at 1.0 (i.e., all mature fish spawn), and the upper bound at 2.0 (i.e., half of the mature fish spawn). The $SR$ assumed for the HCR was always 1.5.

The most recent published estimate of the level of the depletion of the stock, expressed as a percentage of the estimated stock size before fishing (%$B_0$), was 7–18% and derived from recent acoustic biomass surveys and historical stock assessment model results (Ministry for Primary Industries, 2013). However, a survey in 2011 indicated the spawning biomass could be larger, and therefore less depleted, at 12 to 38% $B_0$. We therefore set %$B_0$ to be uniform, with a lower bound at 7%, and an upper bound at 30%. We assumed that this was uniform since the method to calculate it was *ad hoc* and partly based on the range of $SR$, which we assumed to be uniform.

### 2.3. Stock monitoring

The stock monitoring method used to inform the HCR was a simulated annual acoustic survey of the spawning plume in the Spawning Box. The survey assumed a constant lognormal observation error coefficient of variation (CV) of 10%, consistent with recent surveys (median CV=8%, $n$=17; Cordue, 2014). This CV does not include uncertainty in the acoustic target strength of orange roughy (TS). The TS is used to convert acoustic backscatter to absolute biomass, and the estimation error of TS therefore needs to be added to the survey observation error CV. The TS assumed in the surveys ha a median of -52.0 dB (95% CI $-53.3$ to $-50.9$), for a 33 cm Standard Length orange roughy (Macaulay et al., 2013). The acoustic backscatter is given by abundance (in numbers) $\times\, 10^{(-52.1/10)}$, so the simulated survey result, before applying survey error, is abundance $\times\, 10^{((-52.1\text{-}TS)/10)}$, where TS is drawn from a double normal distribution (mode $=-53.5$, $sd_{left}=0.06$, $sd_{right}=2.15$) (Patrick Cordue, pers.comm.).

Occasional surveys of the spawning grounds outside of the Spawning Box plume led to a best estimate of 12,700 t for this additional spawning biomass (Dunn et al., 2008; Ministry of Fisheries, Science Group (comps.), 2008). From 2011, it was assumed that the Spawning Box plume represented a constant proportion of the total spawning biomass, with the total spawning biomass being the plume biomass multiplied by a scale-up factor of 1.37, i.e., the plume represented about three quarters of the total spawning biomass (Ministry of Fisheries, Science Group (comps.), 2011). We have assumed a constant scale-up factor of 1.37 in all simulations. Because we have assumed no uncertainty in this scale-up factor, we have effectively assumed that the spawning biomass will be fully measured in the simulations, and have an overall CV similar to that for the plume in the Spawning Box.

### 2.4. Fixed parameters

The size of the unfished stock ($B_0$) was assumed to be 375,000 t (Ministry for Primary Industries, 2013). Growth in length and weight at age was modelled using the von Bertalanffy growth formula ($K$=0.065, $L_\infty$=37.63, $t_0$=–0.5), with a CV of mean length at age of 20%, and a length ($L$, standard length in cm) to weight ($W$, total weight in tonnes) relationship of $W=9.21\mathrm{e}-8\times L^{2.71}$ (Anderson and Dunn, 2011). The percentage mature at age was fixed and assumed to be logistic, with the difference between the age at 50% and 95% mature set at 4.56 years (Dunn, 2007), and the age at 50% mature was 38 years (Anderson and Dunn, 2011); this is older than previously assumed, but consistent with current New Zealand best practice where the age at maturity is estimated from the age structure observed in catches from the spawning fishery. The proportion at age vulnerable to the fishery was set equal to the maturity ogive.

### 2.5. Harvest control rules

Four HCRs were investigated. HCR1 is the current HCR, where the TACC is equal to $F\times$ current mature biomass ($B_c$), and $F=M$. The HCR can be expressed in the form TACC=$B_c\times Y$, where $Y$ for HCR1 is given by:

$$Y_i = M \times 1.5 \tag{1}$$

where $M$=0.045 and $Y_i$ is for the current year in which biomass was estimated from surveys. HCR2 starts with $Y_i=0.045\times1.5$ until there are three abundance surveys, then it uses:

$$Y_{i+1} = \begin{cases} Y_i \times 1.1, \text{ 3 consecutive increases in } B_c \\ Y_i \times 0.8, \text{ 3 consecutive declines in } B_c \\ Y_i, \text{ otherwise} \end{cases} \tag{2}$$

where $Y_i$ is for the current year and $i+1$ indexes the following year. HCR2 modifies the TACC based upon the recent biomass gradient, but penalises declines in biomass more than increases, making it arguably a precautionary HCR. HCR3 is HCR1 but it reduces the TACC further when $B_c$ is relatively low ($\leq$20% $B_0$) and increases it when $B_c$ is high ($\geq$40% $B_0$):

$$Y_{i+1} = \begin{cases} 0.5 \times M \times 1.5, B_c \leq 20\% B_0 \\ M \times 1.5,\ 40\% B_0 > B_c < 20\% B_0 \\ 2 \times M \times 1.5, B_c \geq 40\% B_0 \end{cases} \tag{3}$$

we assumed in simulations for HCR3 that $B_0$ is known without error. In simulations where $R_0$ is halved or doubled, the $B_0$ will also halve or double, but the HCR still uses the original $B_0$, which assumes that the change in productivity is unknown to the management system (HCR). This naivety is likely to be the case in a fishery managed using HCRs informed by biomass surveys, where recruitment is not specifically monitored. HCR4 is based upon HCR2, but steeper changes in $B_c$ result in larger changes to the TACC. HCR4 starts with $Y_i=0.045\times1.5$ until there are five abundance surveys, then it uses:

$$\mathrm{TACC}_{i+1} = \mathrm{TACC}_i(1+\lambda b) \tag{4}$$

where $\lambda$ is an adjustment variable for the relative change in TACC to the perceived change in stock size (estimated from initial simulations: $\lambda$=1 or $\lambda$=2), and slope is the unweighted average slope of a log-linear regression line fitted to the last five years of surveys (Shelton, 2011). TACC$i$ is the total allowable catch in the current year and $i+1$ indexes the following year.

HCR3 relies on extra knowledge, as it requires the $B_c$ as a percentage of $B_0$. HCR2 and HCR4 require the least knowledge, as after the initial selection of the TACC they do not need to know $M$. HCR4 does not depend on the absolute value of the survey estimate after the first 5 years, only the rate of change (i.e., TS bias becomes irrelevant).

### 2.6. Performance measures

The performance of HCRs in simulation trials were evaluated against a set of performance measures. The performance measures described catch levels, stability in catch levels, and measures of risk. The catch level performance measures included for each projection period were (1) mean catch, and (2) the percentage of simulations where more than half of the projection years had a catch $<2000$ t (a nominally low catch level below which the economic viability of the fishery might be threatened); the performance measures for stability in catch levels were (3) the mean change in TACC, and the percentage of simulations where more than half of the projection years had a change in TACC of (4) $<15\%$, or (5) $<5\%$; the performance measures for risk were the percentage of simulations where more than half of the projection years had a stock status of (6) within the target depletion level of 20–40% $B_0$, (7) above 40% $B_0$, (8) below 20% $B_0$, and (9) below 10% $B_0$. Performance measures (8) and (9) are not mutually exclusive, but chosen because they refer to depletion levels linked to management action (the "soft limit" and "hard limit", respectively), as specified in the New Zealand Harvest Strategy Standard (Ministry of Fisheries, Science Group (comps.), 2008). When $R_0$ was halved and doubled, the value of $B_0$ used in the risk measures also halved or doubled.

An evaluation of HCR performance in terms of risk was also completed using regression trees. The target variable was the percentage of years where $B_0$ dropped below 20% $B_0$ in each simulation run ($n=1000$). The potential predictors were the model parameters. The analysis was performed using the Recursive Partitioning and Regression Trees function rpart (library rpart, Therneau et al., 2013) in R (R Core Team, 2013) with the parameter maxdepth set to 2. The function is based on the method of Breiman et al. (1984). This analysis allowed us to identify simulation parameter combinations associated with good (above 20% $B_0$) and poor performance of the HCR.

## 3. Results

All HCRs resulted in an initial short-term reduction in catch (Fig. 2) and increase in biomass (Fig. 3), because they all reduced fishing mortality to a more sustainable level. Under the scenario of constant $R_0$, there was little difference in the performance of the HCRs after 10 years, except that HCR3 resulted in slightly fewer depleted ($<20\%$ $B_0$) stocks (Table 1). Over the entire simulation period, HCR4 (with $\lambda=1$) matched the performance of HCR1, but made much smaller changes to the TACC. In simulations using HCR2 the catches declined even though the biomass increased (Figs. 2 and 3). HCR2 did not perform well because the uncertainty in biomass monitoring estimates over each 3-year period was large enough that the trend in the survey biomass estimates could go up, or down, regardless of the trend in the underlying biomass. When upward and downward trends happen with equal regularity, the unbalanced HCR2 drives the catches down. HCR3 was the best rule on the basis of fewest years with stock biomass below 20% $B_0$ combined with highest long term catch. The performance of HCR3 was achieved through relatively large TACC changes, with TACCs doubling or halving as the stock biomass fluctuated around the HCR threshold levels (Fig. 2). Higher levels of $\sigma_R$ resulted in higher variability in catch levels across all HCRs (Fig. 2).

Under scenarios of productivity change ($R_0$ halved or doubled), HCR3 did better than HCR1, in terms of taking higher catches when $R_0$ doubled (Table 2). Under HCR3 with $R_0$ halved, the TACC was in effect reduced strongly when the stock reached $<40\%$ $B_0$ instead of $<20\%$ $B_0$ (the HCR doesn't know the "new" $B_0$ when $R_0$ halves). When $R_0$ doubled, whilst more catch could be taken (the stock grew to $>40\%$ $B_0$ and exceeded the target range, under all HCRs), HCR3 performed materially no worse than the gradient rules, unless the stability of TACC is considered paramount.

The performance of HCR4 with $\lambda=1$ was similar to HCR1, but HCR4 with $\lambda=2$ provided a stronger response to changing biomass, and performed better in terms of avoiding depletion when the $R_0$ halved and achieving high catches when $R_0$ doubled

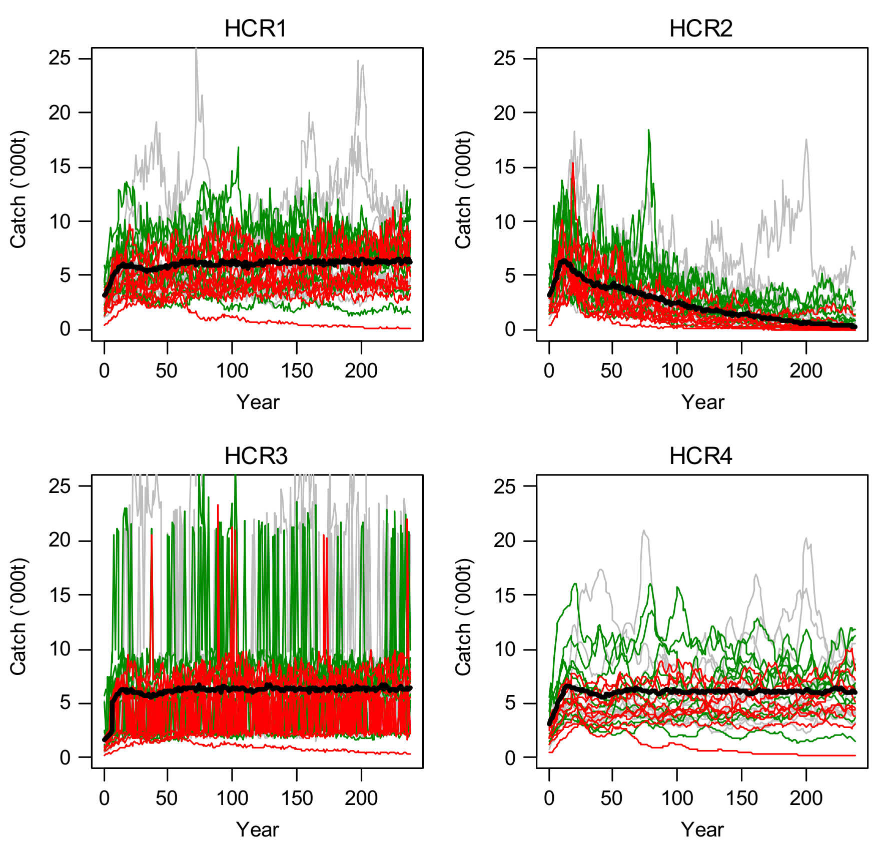


**Fig. 2.** Catches under the four harvest control rules (HCRs) across an example set of simulations having the same set of model parameters (simulated $R_0$ includes those shown in Fig. 1). Gray lines, $\sigma_R=0.8$; green lines $\sigma_R=0.6$; red lines $\sigma_R=0.4$.

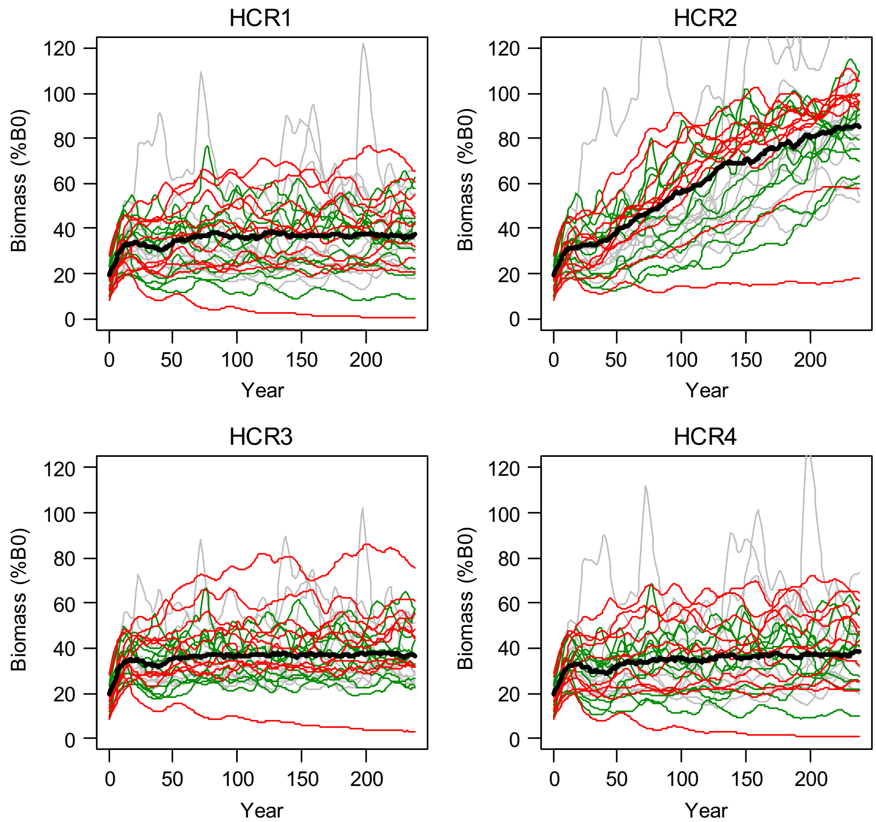


**Fig. 3.** Stock biomass trajectory, as a percentage of initial biomass ($B_0$), under the four harvest control rules (HCRs) across an example set of simulations having the same set of model parameters (same simulations as Fig. 2). Solid black line, mean trajectory; gray lines, $\sigma_R$=0.8; green lines $\sigma_R$=0.6; red lines $\sigma_R$=0.4.

**Table 1**
Performance measures from orange roughy simulation model 1 (constant $R_0$). For each harvest control rule (HCR), the performance measure except for mean catch and mean change in TACC is the percentage of simulations in year 10, and overall, in which more than half of the years met the criteria.

| | HCR 1 | | HCR 2 | | HCR 3 | | HCR 4 ($\lambda$=1) | |
|---|---|---|---|---|---|---|---|---|
| | 10 | Overall | 10 | Overall | 10 | Overall | 10 | Overall |
| Mean catch (t) | – | 6547 | – | 3095 | – | 6705 | – | 6569 |
| Catch <2000 t (%) | 2 | 3 | 2 | 36 | 17 | 5 | 1 | 3 |
| Mean change in TACC (t) | – | 768 | – | 280 | – | 668 | – | 155 |
| Years when change TACC <15% (%) | 0 | 100 | 0 | 28 | 0 | 93 | 0 | 100 |
| Years when change in TACC <5% (%) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 100 |
| SSB 20–40% $B_0$ (%) | 67 | 44 | 70 | 6 | 69 | 53 | 67 | 47 |
| SSB >40% $B_0$ (%) | 23 | 41 | 18 | 85 | 25 | 40 | 22 | 39 |
| SSB <20% $B_0$ (%) | 11 | 13 | 12 | 2 | 6 | 6 | 11 | 14 |
| SSB <10% $B_0$ (%) | 0 | 3 | 0 | 0 | 0 | 1 | 0 | 3 |

(Table 2). Like HCR3, the penalty for avoiding depletion when $R_0$ halved was shown in a relatively high proportion of simulations with catch <2000 t. When $R_0$ doubled, HCR4 provided average catches similar to HCR3 but with smaller changes in TACC. There was an asymmetry between the results for HCR4 with $\lambda$=1 or $\lambda$=2 when productivity changed. When productivity declined ($R_0$ halved), using $\lambda$=2 gave similar results to a $\lambda$=1, but when productivity increased ($R_0$ doubled), using $\lambda$=2 did result in a greater mean catch, but gave a poorer performance in the sense that more simulation runs ended up below 20% $B_0$. The failed recovery of some simulated stocks under HCR4 with $\lambda$=2 and $R_0$ doubled was because of cases where the initial stock status was relatively low and, with a trend of increasing biomass, the HCR allowed too-rapid an increase in catches.

The most important parameter determining stock depletion in the simulations was $M$ (Fig. 4). When $M$ dropped below about 0.02 the chances of a stock being depleted were relatively high. When low $M$ was combined with a spawning scale-up ratio ($SR$) of less than 1.65 (the default value was 1.5), then the chances of HCR1 resulting in stock depletion were high. In simulations assuming constant $R_0$ and using HCR1, when $M$ was >0.02 (a 91.7% probability given our $M$ distribution) and $h$ was >0.51 (an 87.8% probability given our $h$ distribution), the percentage of years where stock biomass remained above 20% $B_0$ was 93.4%. In order to consider research priorities, $h$ was then excluded from the regression analysis, on the basis of being un-estimable in practice. In the revised analysis, $M$ replaced $h$ (Fig. 4), confirming $M$ as a key parameter determining fishery performance.

## 4. Discussion

When HCR1 was introduced on Chatham Rise, it was unknown whether the rule would lead to a sustainable orange roughy

**Table 2**
Performance measures from orange roughy simulation models where $R_0$ is halved or doubled, meaning mean recruitment levels were $R_0 \times 0.5$ and $R_0 \times 2$, respectively. For each harvest control rule (HCR), the performance measure except for mean catch and mean change in TACC is the percentage of simulations in year 10, and overall, in which more than half of the years met the criteria. HCR2 has been excluded from this table.

| | HCR 1 | | HCR 3 | | HCR 4 $\lambda=1$ | | HCR4 $\lambda=2$ | |
|---|---|---|---|---|---|---|---|---|
| | 10 | Overall | 10 | Overall | 10 | Overall | 10 | Overall |
| **$R_0$ halved** | | | | | | | | |
| Mean catch (t) | – | 3,654 | – | 3,165 | – | 3,645 | – | 3,322 |
| Catch $<2000$ t (%) | 3 | 12 | 18 | 29 | 2 | 12 | 7 | 17 |
| Mean change in TACC | – | 462 | – | 264 | – | 82 | – | 214 |
| Years when change TACC $<15\%$ (%) | 0 | 100 | 0 | 90 | 0 | 100 | 0 | 100 |
| Years when change in TACC $<5\%$ (%) | 0 | 0 | 0 | 0 | 0 | 100 | 0 | 46 |
| Years at 20–40% $B_0$ (%) | 27 | 39 | 17 | 25 | 33 | 40 | 42 | 35 |
| Years at $>40\%$ $B_0$ (%) | 0 | 50 | 0 | 74 | 0 | 57 | 2 | 62 |
| Years at $<20\%$ $B_0$ (%) | 69 | 11 | 82 | 1 | 63 | 2 | 51 | 2 |
| Years at $<10\%$ $B_0$ (%) | 4 | 3 | 0 | 0 | 4 | 0 | 4 | 0 |
| **$R_0$ doubled** | | | | | | | | |
| Mean catch (t) | – | 12,296 | – | 14,593 | – | 12,139 | – | 14,357 |
| Catch $<2000$ t (%) | 1 | 2 | 5 | 1 | 1 | 2 | 2 | 2 |
| Mean change in TACC | – | 1,437 | – | 3,981 | – | 394 | – | 1071 |
| Years when change TACC $<15\%$ (%) | 0 | 100 | 0 | 84 | 0 | 100 | 0 | 100 |
| Years when change in TACC $<5\%$ (%) | 0 | 0 | 0 | 0 | 0 | 100 | 0 | 19 |
| SSB 20–40% $B_0$ (%) | 51 | 41 | 57 | 60 | 50 | 43 | 45 | 61 |
| SSB $>40\%$ $B_0$ (%) | 11 | 38 | 6 | 14 | 10 | 38 | 2 | 7 |
| SSB $<20\%$ $B_0$ (%) | 39 | 19 | 37 | 26 | 40 | 17 | 53 | 32 |
| SSB $<10\%$ $B_0$ (%) | 8 | 5 | 3 | 3 | 8 | 6 | 9 | 5 |

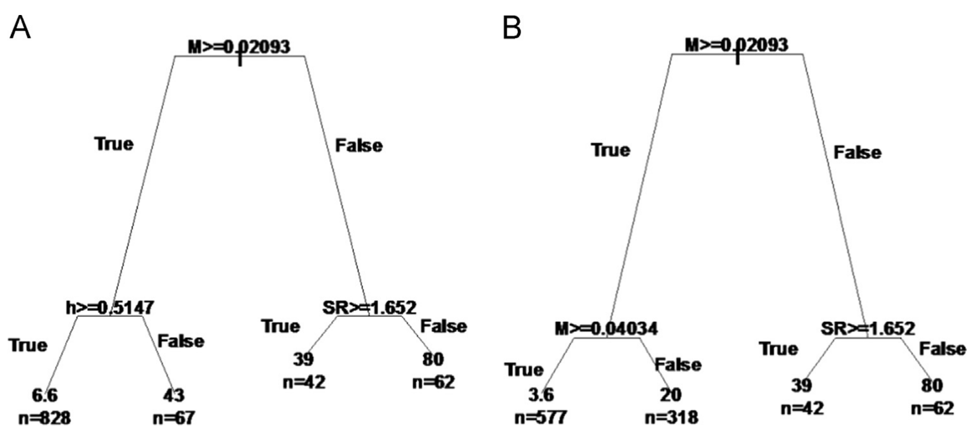


**Fig. 4.** Regression trees of simulation results, where the target variable is the percentage of years where stock biomass was below 20% $B_0$, for constant $R_0$ and HCR1, including (A) all model parameters, and (B) all model parameters except $h$. Each terminal node is labelled with the group mean percentage of years where stock biomass was below 20% $B_0$, and the number of observations ($n$=number of simulations out of 999).

fishery. Given current knowledge and assumptions about orange roughy and fish stock productivity, our simulations indicate that HCR1 would be unlikely to lead to a depleted orange roughy stock. A HCR based upon a biomass gradient or taking a percentage of current biomass will always reach a stock status equilibrium somewhere, and our simulations had long-term modes of 40%, 35% and 50% $B_0$ for HCRs 1, 3 and 4, respectively. These are within or above the current management target range of 30–40% $B_0$ (Ministry for Primary Industries, 2013), with 30% $B_0$ being close to the biomass level estimated to produce deterministic maximum sustainable yield (Francis and Clark, 2005). It is somewhat opportune that HCR1, which has been used to manage the East and South Chatham Rise stock, should lead to a stock status within the target range. But if the target for biomass depletion was different, for example 48% $B_0$ as in Australia (Wayte, 2009), then HCR1 would not achieve this target and would need to be revised.

Simple harvest rules like HCR1 are a promising and tractable approach to achieving sustainable orange roughy fisheries. The approach has the benefit that it is transparent, in that a survey result has an obvious management response (the same is often not true for stock assessment model based approaches), and it can be applied relatively quickly, requiring a biomass survey but not a stock assessment model (except HCR3, which needs $B_0$). If standardised biomass surveys can be done from fishing industry vessels, as they are on Chatham Rise, then the presence of the fishery establishes the stock monitoring capability (Hordyk et al., 2011). The HCR approach does require a representative and sufficiently precise index of abundance, which could preclude its use for some fisheries, for example where spawning aggregations are unpredictable, or incompletely available to the acoustic sampling method (e.g., on steep bathymetry). In addition, our simulations and conclusions were based upon the current situation on Chatham Rise, but they would need to be revised if surveys were completed less frequently, if survey CVs were greater, or if other sources of bias were suspected.

A few on-going fisheries, and some recent stock recoveries, are giving fishery managers an opportunity to achieve demonstrably sustainable orange roughy fisheries. Off New Zealand, substantial orange roughy spawning aggregations have recently been detected on Challenger Plateau and northeast Chatham Rise, consistent with rebuilding of both of these fished stocks (Ministry for Primary Industries, 2013). Off Australia, the Cascade Plateau orange roughy stock continues to be fished (Wayte and Bax, 2007), and the eastern zone orange roughy was depleted and closed to fishing, but is now showing some signs of recovery (Wayte, 2007). However, outside of Australia and New Zealand most territorial orange roughy fisheries remain closed. Orange roughy fisheries off Namibia were put under moratorium in 2008, and remain closed in 2014. The Namibian fishery may be considered for reopening if scientific research surveys can demonstrate that substantial orange roughy spawning aggregations have returned (Paulus Kainge, NatMIRC, pers.comm.). In the northeast Atlantic, the orange roughy catch quota was set to zero from 2010, and although fishing effort has declined the current status of the stocks is unknown (Dransfield et al., 2013). Off Chile, the orange roughy fishery has been closed since 2006 (Nitlitschek et al., 2010). Under the new Chilean Fishery Act 2012, trawling on vulnerable environments, including seamounts, is forbidden until it can be demonstrated that the fishery will not produce negative impacts; this probably precludes the reopening of Chilean orange roughy fisheries for the foreseeable future.

Our simulations found that even when an orange roughy stock experiences a large shift in mean recruitment, which is a concern that has been raised in New Zealand, some HCRs can adapt successfully to the new situation. Although HCR1 might be considered adequate overall, it was not the best performing rule. Using our criteria, HCR3 performed best, although the relatively 'low information' HCR4, using just the rate and direction of biomass change, was a very close second. It may well be that HCR3 does not need to know $B_0$ particularly well, but more work is needed to confirm this. Nevertheless, because assessments of the size and status of orange roughy stocks have been plagued with uncertainties (Sissenwine and Mace, 2007), HCR4 could be considered our best option because it performed well, whilst being relatively robust to uncertainty by requiring relatively little information. Although HCR2 was a relative failure, we included it to illustrate an important point; that uncertainties in biomass estimates can lead to problems in gradient HCRs. The problem is that high uncertainty means the true population trend cannot be detected, and thus the HCR may trigger TACC changes that conflict with the true biomass trajectory. This behaviour becomes most apparent when HCR responses are unbalanced, as in HCR2. One solution, in this case, would be to increase the number of years over which the biomass trend is estimated. But in general, we found that gradient-based rules like HCR2 and HCR4 do need to be carefully tuned and tested. Further HCR testing also needs to allow for variable proportions of the mature stock turning up to spawn in any one year (Dunn et al., 2008), as this variability could also manifest itself as short-term trends in the biomass index. However, one improvement would be to operate a HCR on the spawning plume biomass estimates directly, thereby making *SR* redundant. The rationale for the use of mature biomass in HCR1 rather than spawning stock biomass is not clear (Ministry for Primary Industries, 2013), but it was most likely for consistency with historical stock assessments where all fish above the age at maturity were counted in the spawning stock biomass. A second improvement would be to remove the allowance for additional spawning biomass outside of the monitored areas. This scale-up factor has the potential to create fish that are 'present until proven otherwise'. One of the benefits of the HCR approach is that it could be operated to be inherently precautionary, in that the TACC could be based upon discrete visible fish aggregations only; if the fishers want a higher TACC, then they must find additional fish. The scale-up factors for spawning to mature biomass, and the additional spawning biomass outside of the monitored areas, both weaken a precautionary approach as they could be viewed as being overly optimistic about fish abundance.

Adoption of an HCR for orange roughy should be based upon a Management Strategy Evaluation (MSE), which requires extensive stakeholder engagement (Rademeyer et al., 2007). A MSE for orange roughy has not yet happened in New Zealand. Reluctance to complete a MSE is probably because (a) orange roughy science continues to have considerable uncertainties, and arguably some failures, which have eroded stakeholder trust in science, and (b) a MSE can be time consuming and expensive, which makes MSE unlikely unless the benefits become compelling. The benefit of an MSE for orange roughy may become more apparent as New Zealand stakeholders pursue Marine Stewardship Council certification (www.msc.org) for their fisheries, in a bid to prove their sustainability. In a MSE, the stakeholders would set their own (weighted) performance measures, acceptable HCRs to be tested, and the simulation model might be usefully extended to allow for further uncertainties; for example, variability in the proportion mature at age, and the proportion at age vulnerable to the fishery. Following our regression tree approach, targeted research could also refine knowledge about the parameters that lead to depleted stocks under the HCRs. In the present simulations, we deliberately fixed some of these parameters, and focused our attention on changes in mean recruitment and recruitment variability, as these have been considered the primary source of uncertainty in future stock status (Francis and Clark, 2005).

Whilst orange roughy and other deep sea fisheries have been criticized for overfishing, they have probably received as much criticism for damaging benthic habitats (Roberts, 2002; Morato et al., 2006; Norse et al., 2012). Damage to epibenthic fauna in the path of a deep-sea trawl is unequivocal and often catastrophic, even if the impact to those populations is unclear (the authors know of no assessment of population size and status for deep sea corals, for example). The area fished ('footprint') of orange roughy target fisheries on Chatham Rise was increasing steadily during the early-2000s (Anderson and Dunn, 2008), but the large catch reduction (about 70%) between the mid-2000s and 2011–12 has, anecdotally at least, caused fishers to reduce their footprint and restrict fishing to known areas (i.e., previously impacted areas). As a result, current fisheries are apparently much reduced in both catches and footprint. The Marine Stewardship Council certification includes a 'best practice' environmental standard for sustainable fishing, which is evaluated against the current and future performance of the fishery (see www.msc.org). Whilst damage was done to orange roughy stocks and habitats in the past, using a HCR to control catch, and spatial management to control the fishing footprint and limit habitat damage (Clark and Dunn, 2012), it appears that an orange roughy fishery could achieve best-practice sustainability and environmental standards.

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