

Potential Effects of HCR Methods on Overfished Status

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The Harvest Control Rule Amendment consists of five options for setting recreational harvest controls. Four of these methods rely on quantitative scoring to assign population status into multiple categories. Example categories include overfished vs not overfished, overfishing occurring vs overfishing not occurring, and so forth. Cut points of the categories are used to create up to 8 different bins of population status. Within each bin, a homogeneous set of recreational effort measures (e.g., bag limit, size limit, season length) is assigned to control fishing mortality. In theory, the measures would exert a constant fishing mortality on the population while it was in a given population state (i.e., bin). When the population changes state, another set of HCRs would be applied. For example, if the population went from not overfished to overfished, allowable effort would be reduced to help restore the population to the “not overfished” bin.

The HCR policies could have important implications for controlling the population and the variability of catch. The simulation study herein examines those possible effects for a population with a constant average recruitment, independent of stock size. This is the assumption used in nearly all of the stock assessments in the Northeast. The hypothesis implies a steepness of 1.0. The basis of this pattern has been the inability to define a parametric stock recruitment relationship in most assessments.

Model

Let B_t represent the stock biomass at time t , Z represent the total mortality on the stock ($Z =$ fishing mortality $F +$ natural mortality M) and R_t equal the recruitment to the stock biomass at time t .

The basic dynamics are thus governed by

$$B_{t+1} = B_t e^{-Z} + R_t \quad (1)$$

Recursive application of Eq. 1 yields

$$\begin{aligned} B_{t+1} &= B_t e^{-Z} + R_t \\ B_{t+2} &= B_{t+1} e^{-Z} + R_{t+1} \\ B_{t+3} &= B_{t+2} e^{-Z} + R_{t+2} \\ &\dots \\ B_{t+T} &= B_{T-1} e^{-Z} + R_{T-1} \end{aligned} \quad (2)$$

The limit of this process as T approaches infinity converges to

$$B_{\infty} = \frac{R}{1 - e^{-Z}} \quad (3)$$

In the absence of fishing, the maximum population size is defined as

$$B_{max} = \frac{R}{1 - e^{-M}} \quad (4)$$

If we apply the usual convention that $B_{msy}=1/2 B_{max}$, a little algebra will show that F_{msy} is defined as

$$F_{msy} = -\ln(2e^{-M} - 1) - M \quad (5)$$

Applying the catch equation give MSY as

$$MSY = \frac{F_{msy}}{F_{msy}+M} (1 - e^{-(F_{msy}+M)}) B_{msy} \quad (6)$$

The behavior of a population governed by Eq. 1 is similar to a population governed by a logistic equation, although the density dependence is not explicit. Note also that the above definition of MSY is determined by the assumption that B_{msy} is $1/2 B_{max}$ ¹.

Harvest control rules, in general terms, are designed to achieve some objective, subject to constraints. If a population is overfished, control rules should allow the population to increase to B_{msy} over some defined time period T . If a population is well above B_{max} , the objective is to allow as much fishing as possible subject to a constraint that $F_t < F_{msy}$. In all other cases, a common objective is to move the population toward B_{msy} . For the sake of this analysis, I assumed that the objective of the HCR was to achieve B_{msy} in some time period T subject to the constraint that $F_t < F_{msy}$.

Under these conditions the optimal fishing mortality is defined as the fishing mortality rate necessary to move the population from its current state to B_{msy} in a time horizon T . This can be written as two-point boundary value problem to find the solution to Eq 2 where $B_{t+T}=B_{msy}$. Thus

$$\begin{aligned} B_{t+1} &= B_t e^{-F_{opt}-M} + R_t \\ B_{t+2} &= B_{t+1} e^{-F_{opt}-M} + R_{t+1} \\ B_{t+3} &= B_{t+2} e^{-F_{opt}-M} + R_{t+2} \\ &\dots \\ B_{msy} &= B_{t+T} = B_{T-1} e^{-F_{opt}-M} + R_{T-1} \end{aligned} \quad (7)$$

The optimal fishing mortality can be found numerically by setting finding F_{opt} such that $B_{msy}-B_{t+T}=0$. Two special conditions apply. First, it may not be possible to achieve B_{msy} even when $F=0$. Second, Council policy and National Standards do not allow F to exceed F_{msy} . Hence F_{opt} has a maximum value of F_{msy} . Under condition 1 the F_{opt} is infeasible; under condition 2, the population will exceed B_{msy} at the end of the horizon $t+T$. An important aspect of Eq. 7 is that the future dynamics are not affected by the current level of F . F_{opt} is a function of B_t , B_{t+T} , R and M only.

See Table 1 for a list of all model parameters.

¹ In a population truly governed by Eq. 1, the maximum sustainable yield would be to harvest the entire recruitment at each time period. No sense letting the biomass degrade in the B_t pool!

Table 1. Summary of model parameters and derived quantities used in simulations.

| Parameter | Variable | Value |
|---------------------------|--------------------------|----------------|
| Natural Mortality | M | 0.2 |
| Initial Biomass | B_0 | 300 |
| Recruitment | R_t | 100 |
| Planning Horizon (years) | T | 5 |
| Range of Recruitment | R_{min}, R_{max} | 50, 150 |
| Derived Quantities | | |
| Maximum Biomass | Bmax | 551.6 |
| Biomass at MSY | Bmsy | 275.8 |
| Fishing Mortality for MSY | Fmsy | 0.2503 |
| Maximum Sustainable Yield | MSY | 55.6 |
| HCR Bins | | |
| Biomass: Very High | $>1.5 B_{msy}$ | 413.7 |
| Biomass: High | $[B_{msy}, 1.5 B_{msy})$ | [275.8, 413.7) |
| Biomass: Low | $[0.5 B_{msy}, B_{msy})$ | [137.9, 275.8) |
| Biomass: Too Low | $<0.5 B_{msy}$ | <137.9 |

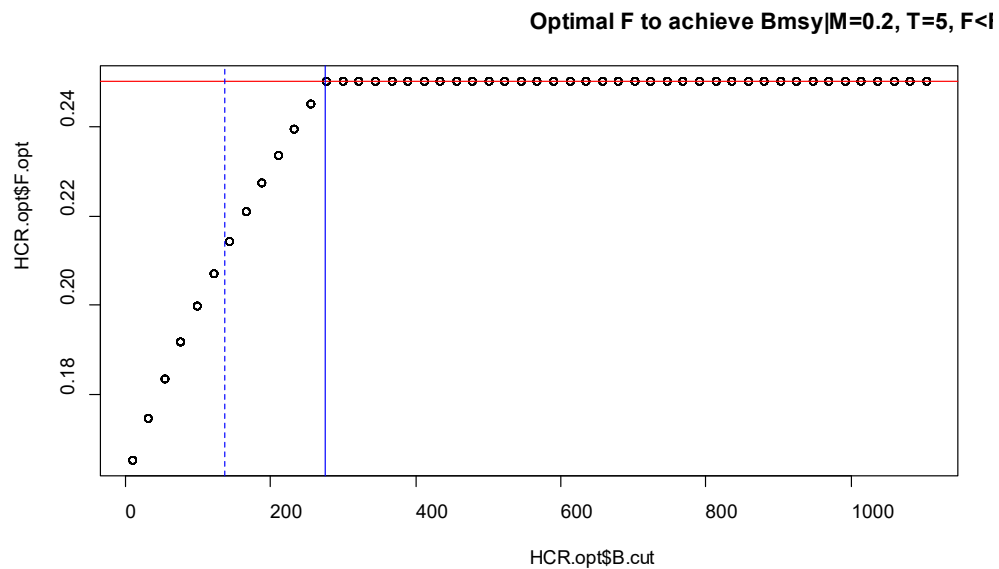


Figure 1. Optimal F to achieve Bmsy given initial biomass level B_t . See Eq. 7. Red line is Fmsy. Solid blue vertical line is Bmsy, dashed vertical line is $\frac{1}{2}$ Bmsy.

As shown in Fig. 1 the optimal policy does not depend on whether fishing mortality is, or is not occurring at time t . However, the magnitude of change in F for a given population state (B_t, F_t) does depend on F_t (i.e., $F_t - F_{opt}$). To illustrate this further, consider the B_t, F_t phase plane used for Option D.

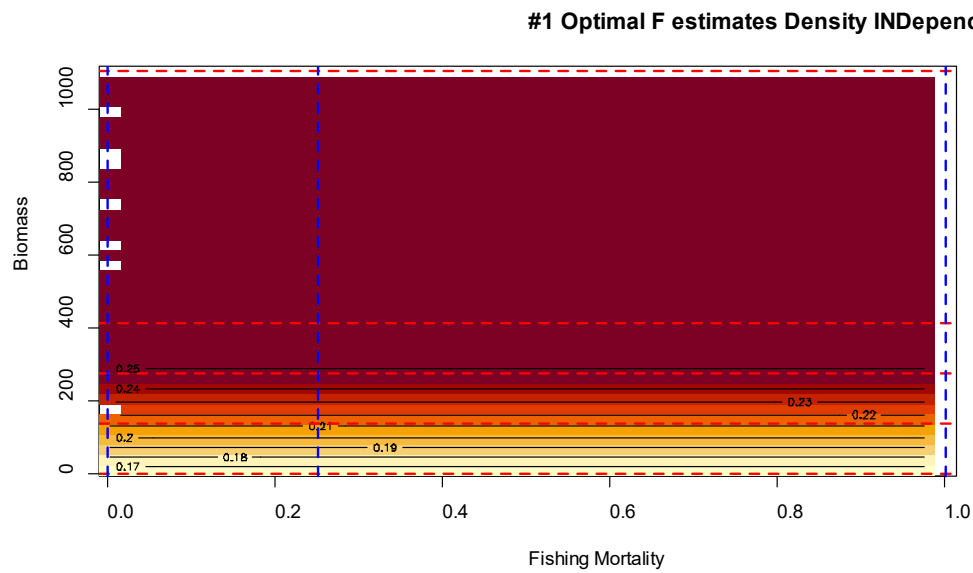


Figure 2. Optimal F response surface vs biomass and fishing mortality.

Effects of Binning

Equation 7 defines an optimal fishing mortality rate for every value of B_t . However, the HCR is based on the use of a common F strategy within bins of population states. These states include intervals of biomass, fishing mortality, biomass rates of change, a linear scoring approach, and expected differences between recent catch and RHL. One way of dealing with this binning is to use a measure of central tendency for all possible observations within the HCR category. For example, one could compute the average F_{opt} for all possible values of B_t in the interval $[B_{msy}, B_{max}]$ or in the interval $[0.5 B_{msy}, B_{msy}]$ etc. This process is illustrated in Fig. 3.

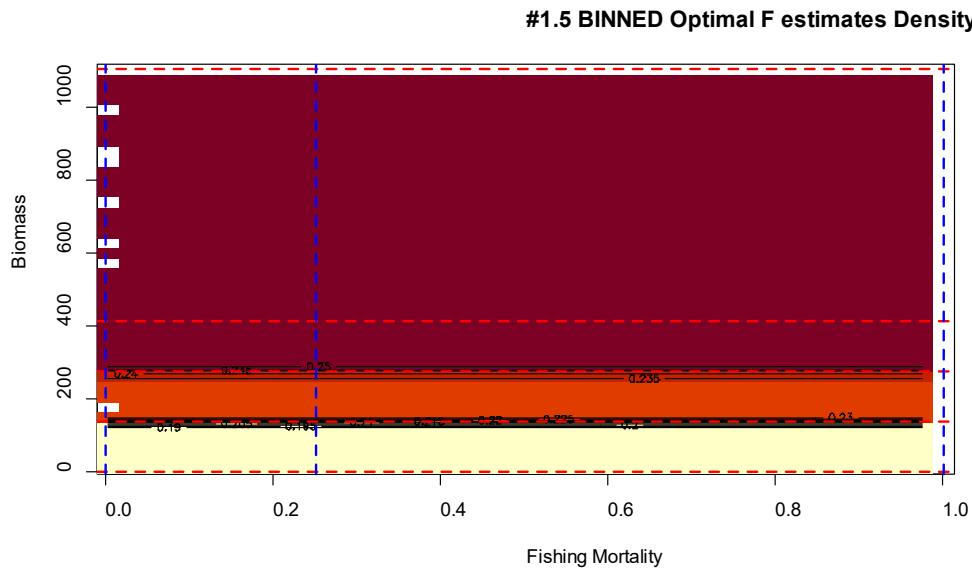


Figure 3. Binned optimal F values representing the average F_{opt} within each population state defined by the horizontal and vertical cut points. Lighter colors represent lower average fishing mortality rates.

Figure 3 illustrates that under a given population state, a common F would be applied. The use of averages of F_{opt} for each bin implies slightly different cumulative catches over the period T. Figure 4 shows the cumulative catches with unique F_{opt} values. Figure 5 shows the same response given average F_{opt} values within bins.

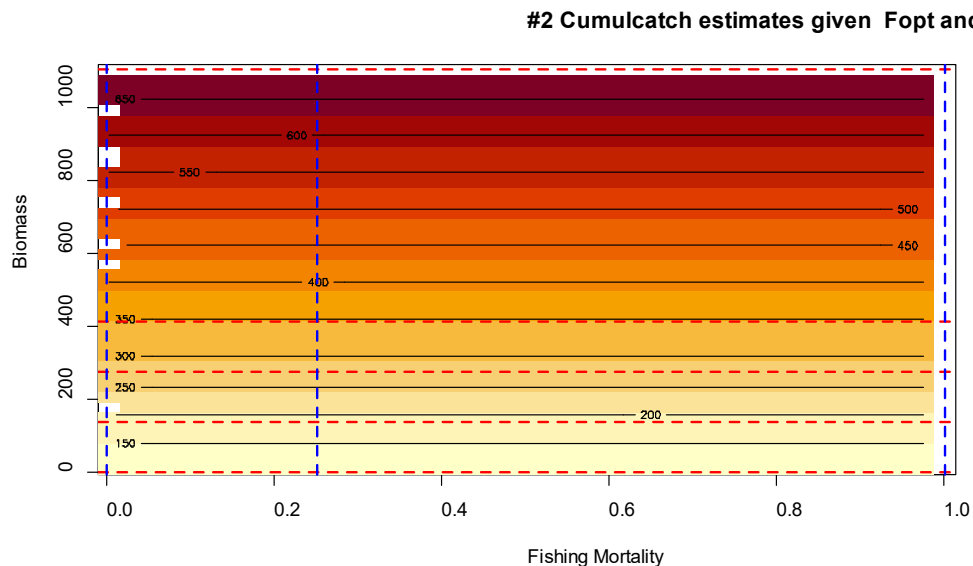


Figure 4. Response surface for cumulative catches over a T=5 yr period give F_{opt} for each level of initial biomass B_t and initial Fishing mortality F_t . See Fig. 2. Note that cumulative catch is unaffected by F_t .

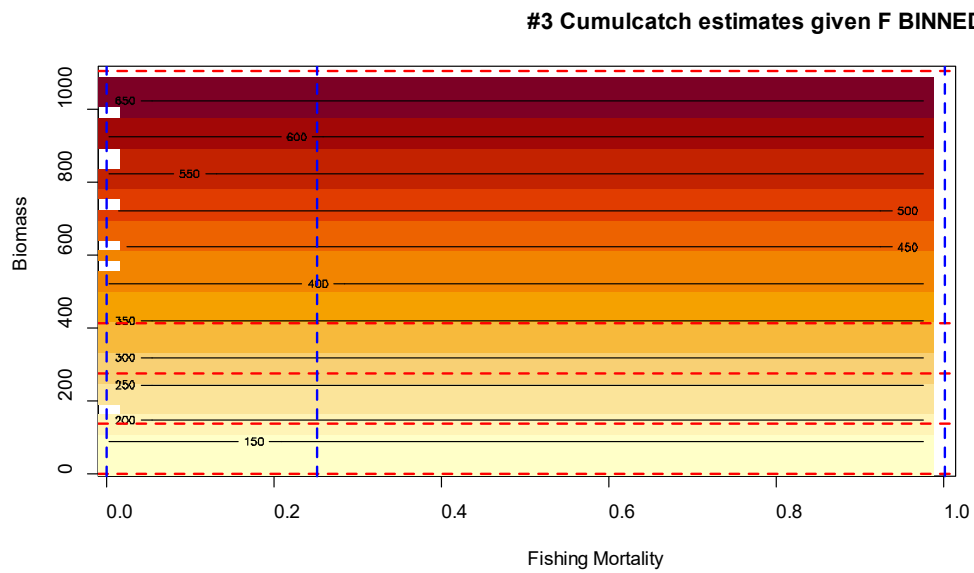


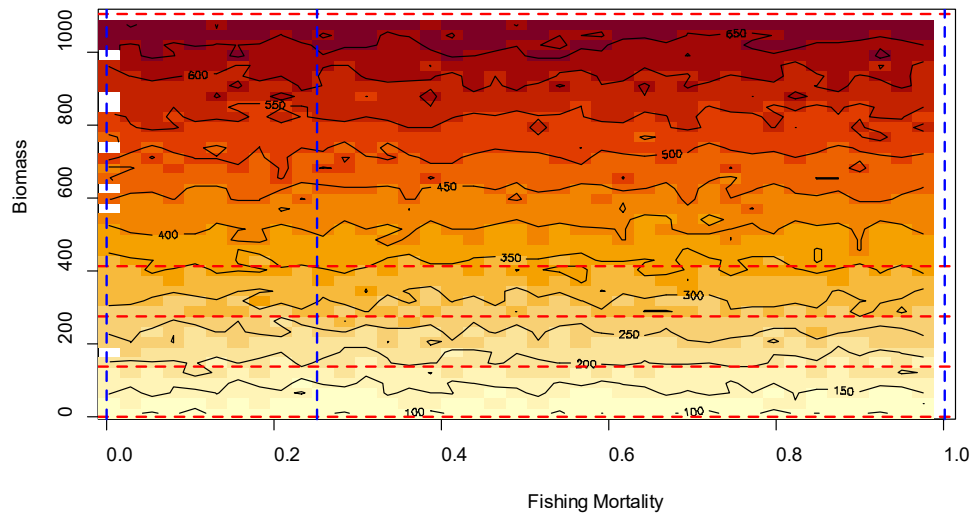
Figure 5. Response surface for cumulative catches over a $T=5$ yr period given BINNED F_t for category. See levels in Fig. 3. Note that cumulative catch is unaffected by F_t .

Effects of Random Recruitment and Binning

Results thus far have considered a deterministic model only. Random recruitment, combined with binned HCR might be expected to increase the variability of the catches. Recruitment was modeled as a uniform random number between R_{\min} and R_{\max} . See Table 1 for list of all model parameters.

First, consider the implications of random recruitment on cumulative catch (Fig. 6 top).

#4.5 Cumulcatch estimates, random, give



#4 Cumulcatch estimates, Random, given F

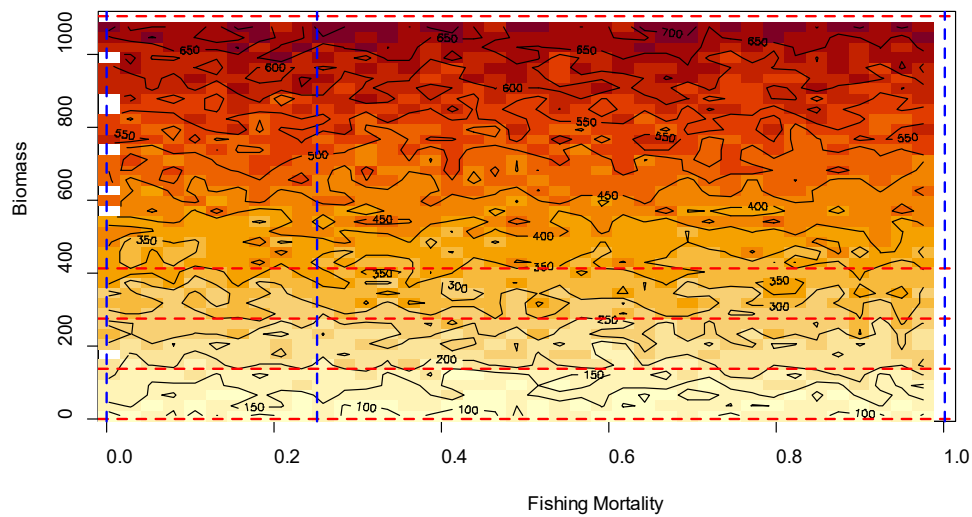


Figure 6. Cumulative catch as a function of initial density with random recruitment only and optimal F based on initial density (top). Cumulative catch with random recruitment AND binned F control (Bottom).

The mean and variance of cumulative catch did not change appreciably under the random Recruitment vs random recruitment with binned controls.

The efficacy of control measures can also be examined with respect to their ability to achieve target biomass levels. In this case the target was defined as being 90% or more of the Bmsy. In other words, successes were defined as outcomes where $B_t > 0.9 B_{msy}$.

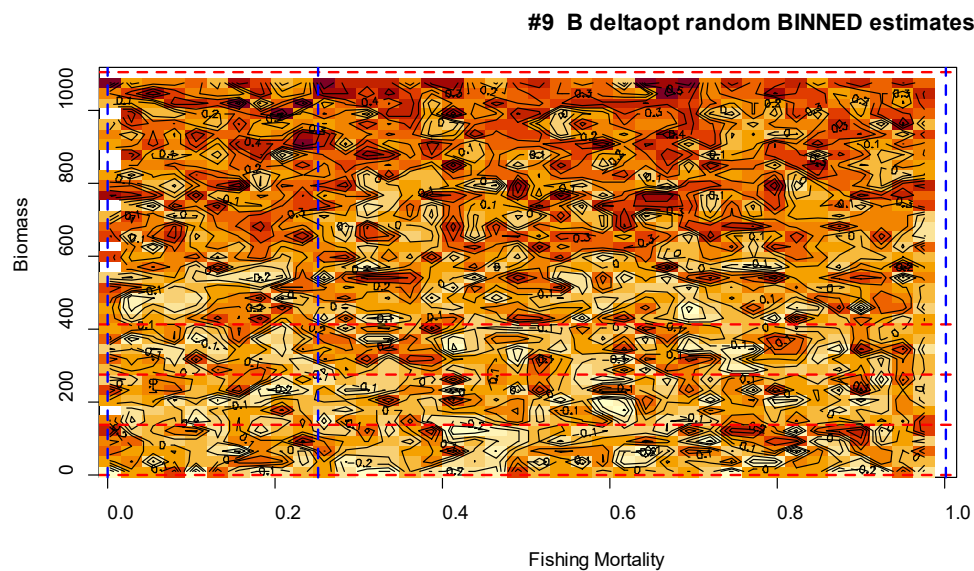
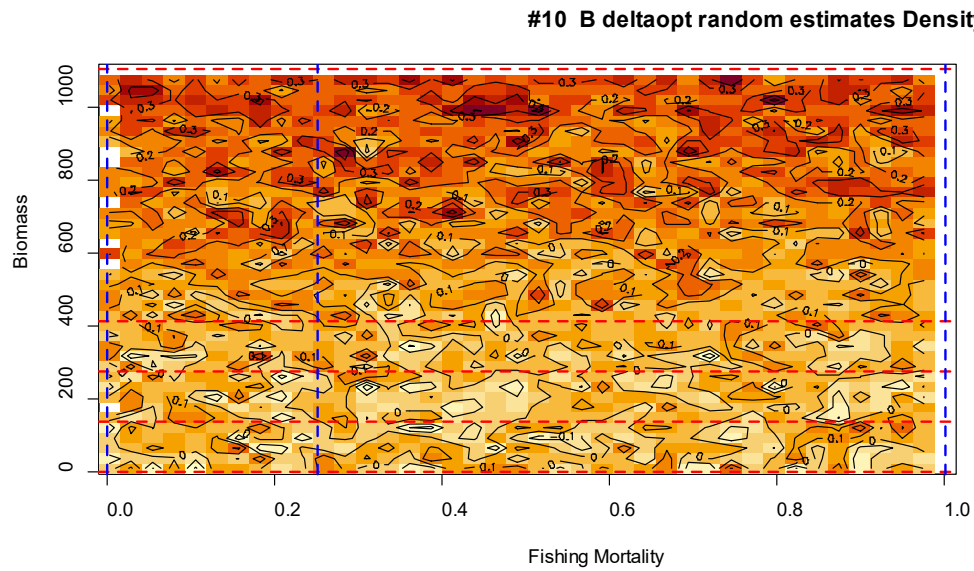


Figure 7. Difference in terminal biomass B_{t+T} and B_{msy} as a function of initial density with random recruitment only and optimal F based on initial density (top). Cumulative catch with random recruitment AND binned F control (Bottom).

Are Binned Measures Sufficient?

One measure of the efficacy of binned controls is whether or not the measures achieve the desired target of achieving B_{msy} over the planning horizon T . This property was tested by comparing the initial state of the population with the final state of the population after 5 years. Ideally, the derived F_{opt}

should be sufficient to achieve B_{msy} irrespective of the binning or magnitude of random recruitment. For the deterministic case, F_{opt} was sufficient to return the population to a not overfished state.

The rows below represent the initial state of the biomass, the columns represent the final state of the population after 5 years of applying F_{opt} for every biomass value or an average F_{opt} depending on the initial bin.

```
> tapply(HCR.opt$F.opt,list(HCR.opt$B.status, HCR.opt$B.poststatus.det),length )
```

| | Not Overfished |
|------------|----------------|
| Overfished | 300 |
| Low | 300 |
| High | 350 |
| Very High | 1550 |

```
> tapply(HCR.opt$F.opt,list(HCR.opt$B.status, HCR.opt$B.poststatus.det.bin),length )
```

| | Not Overfished |
|------------|----------------|
| Overfished | 300 |
| Low | 300 |
| High | 350 |
| Very High | 1550 |

The effects of random variation in recruitment on the ability to recover the population degraded as shown in the table below. Note that populations that were initially overfished remained overfished in 69 of 300 cases (23% failure rate). A similarly high rate of failure occurred for populations that were low, but not overfished. Perhaps more disturbing, populations that were high had a 21% failure rate. Only 3.6% of the very high abundance populations became overfished.

```
> tapply(HCR.opt$F.opt,list(HCR.opt$B.status, HCR.opt$B.poststatus.ran),length )
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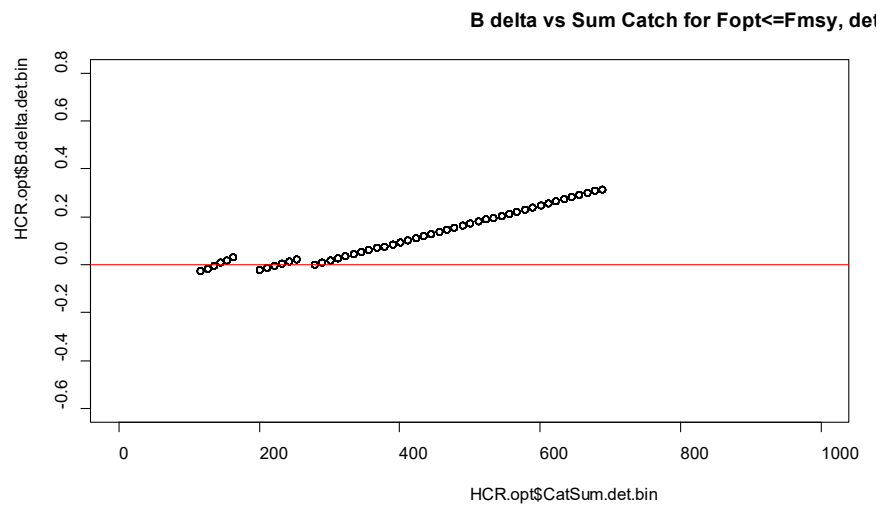
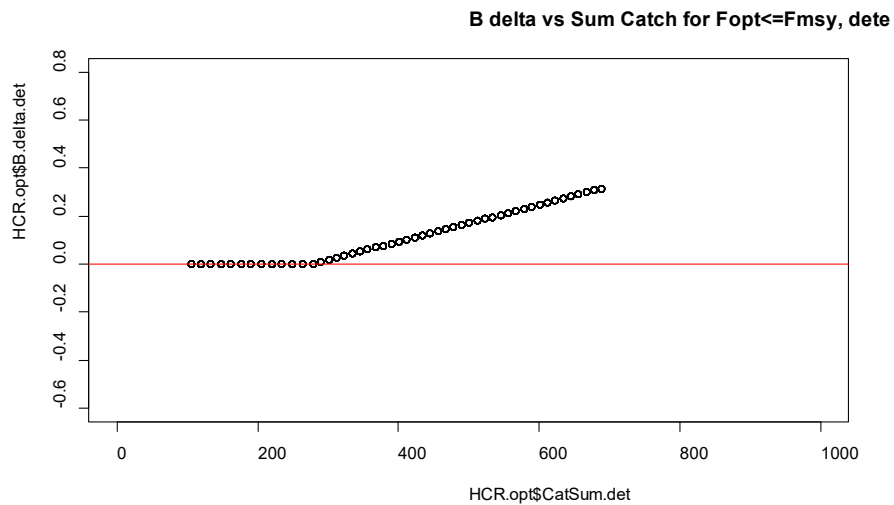
| | Not Overfished | Overfished |
|------------|----------------|------------|
| Overfished | 231 | 69 |
| Low | 231 | 69 |
| High | 287 | 63 |
| Very High | 1494 | 56 |

The joint effects of random variation and binned controls are shown below. The success rate for achieving a not overfish population declined to 61.7% vs 77% when binning did not occur. The failure rate for stocks that were not initially overfished increased significantly with binned controls. For example, 19.1% of the populations initially at very high levels fell into an overfished condition. The ratio of failures when binned to unbinned controls is $296/56=5.3x$. The odds ratio for this comparison is $6.3=(1494*296)/(1254*56)$. The odds ratio for populations initially in a high population state is $2.5=(287*125)/(225*63)$.

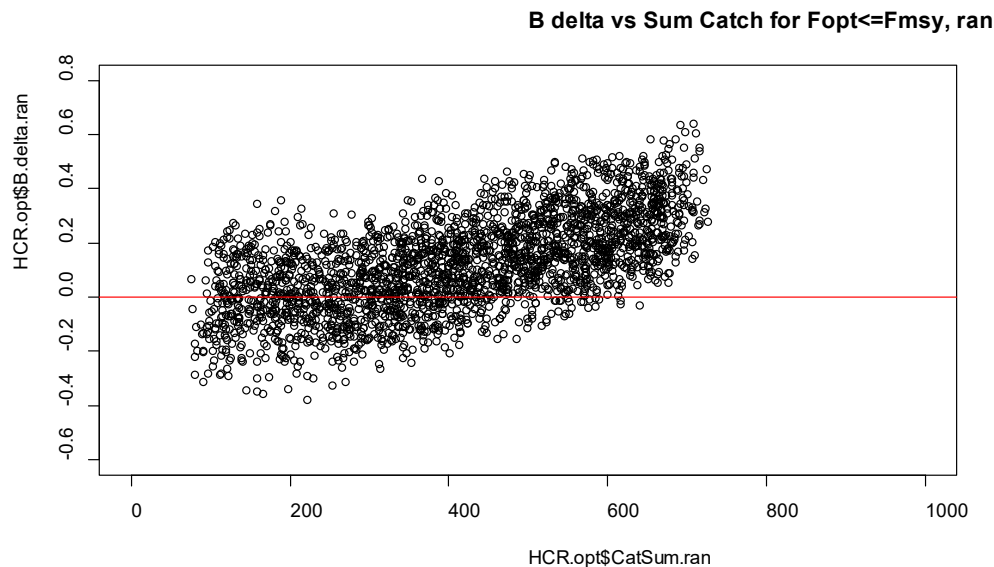
```
> tapply(HCR.opt$F.opt,list(HCR.opt$B.status, HCR.opt$B.poststatus.ran.bin),length )
```

| | Not Overfished | Overfished |
|------------|----------------|------------|
| Overfished | 185 | 115 |
| Low | 186 | 114 |
| High | 225 | 125 |
| Very High | 1254 | 296 |

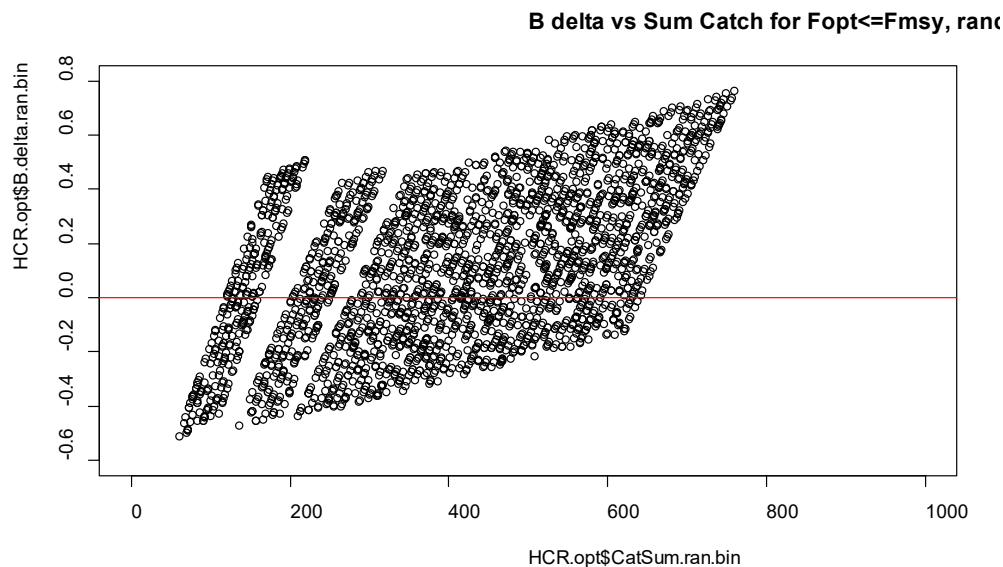
The following graphs illustrate the effects random Recruitment and binning on variation in B_{delta} are shown below. Note that the effect of binning is to result in negative population trends when biomass is low within the bin.



When random variation is added to recruitment, the patterns become more interesting.



Note that the general “lazy J” pattern evident in the deterministic pattern is preserved but the number and magnitude of population declines increases, especially when B is less than B_{msy} . Superposition of binning on top of random variation (shown below) dramatically alters the resulting pattern with more “structure” induced by the bins and more failures.



Preliminary Conclusions

A simple population model was used to characterize the magnitude of uncertainty induced by binning of control rules. When combined with random variation, there was a marked increase in the failure rate of controls. Populations were not rebuilt as frequently as occurred with population specific optimal fishing

mortality rates. Perhaps more importantly, a greater fraction of populations that were previously above B_{msy} fell below $\frac{1}{2} B_{msy}$ when controlled with a binned HCR.

The model used herein, although highly simplified, has properties similar to models used for stock assessments in the Mid Atlantic regions. The HCR implementation is highly simplified and ignores the potential changes in population state that might occur when a population is driven by random recruitment. Specifically, one could adjust the fishing mortality to different population states within the 5-yr projection period. However, it should be noted that neither of the scenarios with random recruitment made such adjustments.

The simulations are indicative but not definitive. I did not evaluate Options B, C or E and the simulation of Option D does not include the additional considerations of whether B or R are increasing or decreasing. Option D includes 13 possible controls rather than the 8 used in this exercise. The simulations may be sufficient to justify the general hypothesis that binning of controls could be problematic if the bins are too wide and the duration between updated of controls is too long.