

## Technical Details of the Management Strategy Evaluation

### Introduction

This document provides the technical details of the MSE. The document has three distinct sections with details that pertain to: 1) Atlantic herring (Deroba), 2) Atlantic herring predators (Gaichas), and 3) economics (Lee). Symbol definitions and terminology may vary among sections. This inconsistency is the outcome of meeting deadlines, but also a lack of standardization in the scientific community such that the same term may be defined differently by a fisheries biologist or an economist. Consequently, each section should be read somewhat independently. The models of predators and economics, however, do rely on outputs from the Atlantic herring simulations, and these dependencies are highlighted in each section. The Atlantic herring section also includes the majority of results, and so some cross-referencing among sections may be necessary to understand the interpretation of some performance metrics.

1     **Technical Details of Operating Models and Harvest Control Rules used in the Georges Bank/Gulf of**  
2                             **Maine Atlantic herring Management Strategy Evaluation**

3   Jonathan J. Deroba

4     **Introduction**

5             Attention has been given to applying a harvest control rule to Atlantic herring *Clupea harengus*  
6     that considers a fishery objective related to their role as a forage fish. The fishery also has other  
7     competing objectives, however, such as attaining relatively high and stable yields. The information  
8     available to evaluate the relative performance of control rules at meeting these competing fishery  
9     objectives is limited to analyses that are not specific to the system (Pikitch et al., 2012; Deroba and  
10    Bence 2008). While “borrowing” control rules from other systems or species might be a valid last resort,  
11    it is not the ideal method (Deroba and Bence 2008). Applying generic control rules may have  
12    unintended consequences, may not achieve fishery objectives, and may not adequately consider  
13    uncertainty in the way in which the control rules were derived (Deroba and Bence 2008). Control rules  
14    and the parameters that define them are best chosen based on stochastic simulations that consider key  
15    uncertainties for the specific system (e.g., management strategy evaluation; MSE; Deroba and Bence  
16    2008). This document describes a system specific MSE for Atlantic herring that may be used by the New  
17    England Fishery Management Council to choose a harvest control rule.

18    **Methods**

19             *Basics.*—An MSE was developed specific to Gulf of Maine – Georges Bank Atlantic herring. The  
20    MSE was a modified version of that used in Deroba (2014), and symbols are largely consistent with  
21    Deroba (2014; Table 1). The MSE was based on an age-structured simulation that considered fish from  
22    age-1 through age-8+ (age-8 and older), which is consistent with the age ranges used in the 2012 and  
23    2015 Atlantic herring stock assessments (NEFSC 2012; Deroba 2015). The abundances at age in year one  
24    of all simulations equaled the equilibrium abundances produced by the fishing mortality rate that would

25 reduce the population to 40% of  $SSB_{F=0}$ . Abundance in each subsequent age and year was calculated  
 26 assuming that fish died exponentially according to an age and year specific total instantaneous mortality  
 27 rate:

$$28 \quad N_{a+1,y+1} = N_{a,y} e^{-Z_{a,y}} ;$$

$$29 \quad Z_{a,y} = F_{a,y} + M_a.$$

30 Recruitment followed Beverton-Holt dynamics:

$$31 \quad R_{1,y+1} = \frac{\left(\frac{SSB_{F=0}}{R_{F=0}} \frac{1-h}{4h}\right) SSB_y}{1 + \left(\frac{5h-1}{4hR_{F=0}}\right) SSB_y} e^{\varepsilon_{Ry} - \frac{\sigma_R^2}{2}} ;$$

$$32 \quad \varepsilon_{Ry} = \omega \varepsilon_{Ry-1} + \sqrt{1 - \omega^2} \chi_y ; \chi_y \sim N(0, \sigma_R^2) ;$$

$$33 \quad SSB_y = \sum_{a=1}^{8+} N_{a,y} m_a W_a ;$$

34 (Francis 1992). The variance of recruitment process errors ( $\sigma_R^2$ ) equaled 0.36 and the degree of  
 35 autocorrelation ( $\omega$ ) equaled 0.1, which are values consistent with recruitment estimates from a  
 36 recent Atlantic herring stock assessment (Deroba 2015).

37 *Assessment Error.*—A stock assessment was approximated (i.e., assessment errors) similar to  
 38 Punt et al. (2008) and Deroba (2014):

$$39 \quad \hat{N}_{a,y} = [N_{a,y}(\rho + 1)] e^{\varepsilon_{\varphi y} - \frac{\sigma_\varphi^2}{2}} ;$$

40 where:

$$41 \quad \varepsilon_{\varphi y} = \vartheta \varepsilon_{\varphi y-1} + \sqrt{1 - \vartheta^2} \tau_y ; \tau_y \sim N(0, \sigma_\varphi^2).$$

42

43 The variance of assessment errors ( $\sigma_\phi^2$ ) equaled 0.05 and autocorrelation ( $\vartheta$ ) equaled 0.7. Rho ( $\rho$ )  
44 allowed for the inclusion of bias in the assessed value of abundance (see below; Deroba 2014). Assessed  
45 spawning stock biomass ( $\widehat{SSB}_y$ ) was calculated similarly to  $SSB_y$  except with  $N_{a,y}$  replaced with  $\widehat{N}_{a,y}$ ,  
46 and assessed total biomass ( $\widehat{B}_y$ ) was calculated as the sum across ages of the product of  $\widehat{N}_{a,y}$  and  
47  $W_a$ .

48 *Operating Models.*—The stakeholder workshops identified uncertainties about herring life  
49 history traits and stock assessment, and the effect of some of these uncertainties on harvest control rule  
50 performance was evaluated by simulating the control rules for each of eight operating models (Table 2;  
51 Figures 1-2). The uncertainties addressed by the eight operating models included: Atlantic herring  
52 natural mortality and recruitment, Atlantic herring weight-at-age, and possible bias in the stock  
53 assessment beyond the unbiased measurement error ( $\varepsilon_{\phi y}$ ).

54 The specific values used in the operating models for each of the uncertainties were premised on  
55 data used in recent stock assessments or estimates from fits of stock assessment models (Deroba 2015).  
56 Natural mortality in recent stock assessments has varied among ages and years, with  $M$  being higher  
57 during 1996-2014 than in previous years (NEFSC 2012; Deroba 2015). Natural mortality in the stock  
58 assessments also has relatively minor amounts of interannual variation in  $M$  because the  $M$  values were  
59 calculated using a relationship with weights at age (Lorenzen 1996), which vary slightly among years.  
60 Natural mortality, however, has also been identified as an uncertainty in the stock assessments and  
61 sensitivity runs have been conducted without higher  $M$  during 1996-2014, such that  $M$  is nearly constant  
62 among years (NEFSC 2012; Deroba 2015). To capture uncertainty in  $M$  in the MSE, operating models  
63 were run with either relatively high or low  $M_a$  (Table 2; Figure 1). Relatively high  $M_a$  values equaled the  
64 age-specific natural mortality rates averaged over the years 2005-2014 that are inputs to the stock  
65 assessment with higher rates in recent years (i.e., higher  $M_a$  during 1996-2014). Relatively low  $M_a$   
66 values in the MSE equaled the age-specific natural mortality rates averaged over the years 2005-2014

67 that are inputs to the stock assessment with nearly constant natural mortality among years (i.e., the  
68 assessment without higher  $M$  during 1996-2014). In the MSE,  $M_a$  was always time invariant.

69         Uncertainty in estimates of stock-recruit parameters were represented in the MSE by using the  
70 parameters estimated by stock assessments fit with and without the higher  $M$  during 1996-2014. Stock  
71 assessment fits with higher  $M$  during 1996-2014 produced estimates of steepness and unfished  $SSB$  that  
72 were lower than in stock assessment fits without higher  $M$  during 1996-2014 (Table 3; Figure 1). Thus,  
73 operating models with relatively high  $M_a$  always had relatively low steepness and unfished  $SSB$ , and the  
74 opposite held with relatively low  $M_a$  (Table 2).

75         Uncertainty in Atlantic herring size-at-age was accounted for by having operating models with  
76 either fast or slow growth (i.e., weights-at-age; Table 2; Figure 3). Atlantic herring weight-at-age  
77 generally declined from the mid-1980s through the mid-1990s, and has been relatively stable since.  
78 Reasons for the decline are speculative and no causal relationships have been established. Thus, fast  
79 growth operating models had weights-at-age that equaled the January 1 weights-at-age from the most  
80 recent stock assessment averaged over the years 1976-1985, while the slow growth operating models  
81 averaged over the years 2005-2014 (Deroba 2015). In the MSE, weight-at-age was always time  
82 invariant.

83         Differences in  $M$ , stock-recruit parameters, and weights-at-age led to differences in unfished  
84 and  $MSY$  reference points among operating models (Table 3). The effect of  $M$  and stock-recruit  
85 parameters was larger than the effect of differences in weight-at-age (Table 3).

86         To address concerns about possible stock assessment bias, operating models with and without a  
87 positive bias were included. In operating models without bias,  $\rho = 0$  and the only assessment error was  
88 that caused by the unbiased measurement errors ( $\varepsilon_{\phi y}$ ). In operating models with bias,  $\rho = 0.6$ , which  
89 was based on the degree of retrospective pattern in  $SSB$  from the most recent stock assessment (Deroba  
90 2015).

91 *Harvest Control Rules.*—Several basic control rules were evaluated, including a biomass based  
 92 control rule (Katsukawa 2004), a constant catch rule, and a conditional constant catch rule (Figure 3;  
 93 Clark and Hare 2004; Deroba and Bence 2012). The biomass based control rule was defined by three  
 94 parameters: the proportion ( $\psi$ ) of  $F_{MSY}$  that dictates the maximum desired fishing mortality rate ( $\tilde{F}$ ),  
 95 an upper  $SSB$  threshold ( $SSB_{up}$ ), and a lower  $SSB$  threshold ( $SSB_{low}$ ). The  $\tilde{F}$  equaled the maximum when  
 96  $\widehat{SSB}$  was above the upper threshold, declined linearly between the upper and lower thresholds, and  
 97 equaled zero below the lower threshold:

$$\tilde{F}_y \begin{cases} F_{msy}\psi & \text{if } \widehat{SSB}_y \geq SSB_{up} \\ (F_{msy}\psi) \frac{\widehat{SSB}_y - SSB_{low}}{SSB_{up} - SSB_{low}} & \text{if } SSB_{low} < \widehat{SSB}_y < SSB_{up} \\ 0 & \text{if } \widehat{SSB}_y \leq SSB_{low} \end{cases}$$

98 The  $\tilde{F}_y$  was then used to set a quota in year  $y + 1$ :

$$99 \quad Q_{y+1} = \sum_{a=1}^{8+} \frac{\tilde{F}_{a,y}}{\tilde{F}_{a,y} + M} \hat{B}_{a,y} \left( 1 - e^{-(\tilde{F}_{a,y} + M_a)} \right);$$

100 where  $\tilde{F}_{a,y}$  equaled  $\tilde{F}_y$  times  $S_a$ , and  $S_a$  was time and simulation invariant selectivity at age equal to the  
 101 values for the mobile gear fishery reported in Deroba (2015; Table 1).  $\tilde{F}_y$  was used to set a quota in the  
 102 following year to approximate the practice of using projections based on an assessment using data  
 103 through year  $y - 1$  to set quotas in the following year(s). Furthermore, although  $\tilde{F}_y$  was set using  $\widehat{SSB}_y$ ,  
 104 the quota was based on  $\hat{B}_y$  because the fishery selects some immature ages. The fully selected fishing  
 105 mortality rate that would remove the quota from the true population ( $\bar{F}_y$ ) was found using Newton-  
 106 Raphson iterations.

107 Several variations of the biomass based rule were also evaluated. These variations included  
 108 applying the control rule annually, using the same quota for three year blocks such that the control rule  
 109 is applied every fourth year (i.e.,  $Q_{y+1} = Q_{y+2} = Q_{y+3}$ ), using the same quota for 5 year blocks, and  
 110 using the same quota for three year blocks but restricting the change in the quota to 15% in either

111 direction when the control rule was reapplied in the fourth year. Thus, four variants of the biomass  
112 based control rule were evaluated: 1) annual application, 2) three year blocks, 3) five year blocks, and 4)  
113 3 year blocks with a 15% restriction.

114 For each biomass based control rule variant, a range of values for the three parameters defining  
115 the control rule were evaluated. The proportion ( $\psi$ ) of  $F_{MSY}$  that dictates the maximum desired fishing  
116 mortality rate was varied from  $0.1F_{MSY}$  to  $1.0F_{MSY}$  in increments of 0.1, while the upper and lower  $SSB$   
117 threshold parameters ( $SSB_{up}$ ,  $SSB_{low}$ ) were varied from  $0.0SSB_{MSY}$  to  $4SSB_{MSY}$  but with inconsistent  
118 increments (i.e., 0.0, 0.1, 0.3, 0.5, 0.7, 0.9, 1.0, 1.1, 1.3, 1.5, 1.7, 2.0, 2.5, 3, 3.5, 4). The full  
119 factorial of combinations for the three biomass based control rule parameters produced 1,360  
120 shapes (note  $SSB_{low}$  must be  $\leq SSB_{up}$ ) and each of these shapes was evaluated for each of the four  
121 biomass based control rule variants described above. The control rule used to set Atlantic  
122 herring allowable biological catch for the years 2013-2018 (i.e., the status quo control rule used  
123 to set quotas) was defined as a biomass based control rule that used three year blocks with:  
124  $\psi = 0.9$ ,  $SSB_{up} = 0.5$ , and  $SSB_{low} = 0.0$ . This shape was chosen for the status quo because for years 2013-  
125 2018 the quota for herring was set to a constant value for three year blocks (2013-2015; 2016-2018;  
126 NEFSC 2012; Deroba 2015), the average proportion of  $F_{MSY}$  achieved by the quotas over those years  
127 equaled 0.9, the stock enters a rebuilding plan with reduced fishing mortality at  $SSB_{up} = 0.5$  (i.e., half of  
128  $SSB_{MSY}$ ), and the fishery would never entirely close and so  $SSB_{low} = 0.0$ . The linear decline in  $\tilde{F}$   
129 between  $SSB_{up} = 0.5$  and  $SSB_{low} = 0.0$  may not exactly match what would occur in reality because  
130 entering a rebuilding plan may induce non-linear changes in  $\tilde{F}$ , but adding this reality requires short-  
131 term projections be conducted within the MSE and this is not a trivial task and could not be completed  
132 in the given time frame.

133 The constant catch control rule is defined by one parameter, a desired constant catch  
 134 (i.e., quota) amount (Figure 3). The constant catch amounts were varied from 0.1  $MSY$  to  
 135 1.0 $MSY$  in increments of 0.1.

136 The conditional constant catch rule used a constant desired catch amount unless removing that  
 137 desired catch from the assessed biomass caused the fully selected fishing mortality rate to exceed a pre-  
 138 determined maximum, in which case the desired catch was set to the value produced by applying the  
 139 maximum fully selected fishing mortality rate to the assessed biomass (Figure 3). Thus, the conditional  
 140 constant catch rule has two policy parameters: a desired constant catch amount, and a maximum fishing  
 141 mortality rate. The constant catch amounts were varied from 0.1  $MSY$  to 1.0 $MSY$  in increments of  
 142 0.1, while the maximum fishing mortality rate equaled 0.5  $F_{MSY}$ . When the maximum fishing  
 143 mortality rate portion the conditional constant catch rule was invoked, a quota was set in the same  
 144 manner as when  $\widehat{SSB}_y \geq SSB_{up}$  in the biomass based control rule described above.

145 *Implementation Error.*—Implementation errors were also included in a similar way as in Punt et  
 146 al. (2008) and Deroba and Bence (2012):

$$147 \quad F_{a,y} = \bar{F}_y S_a e^{\varepsilon_{\theta y} - \frac{\sigma_{\theta}^2}{2}}; \varepsilon_{\theta} \sim N(0, \sigma_{\theta}^2).$$

148 The variance of implementation errors ( $\sigma_{\theta}^2$ ) equaled 0.001.

149 *Performance metrics.*—For each combination of control rule shape and operating model, 100  
 150 simulations were conducted, each for 150 years. Preliminary simulations suggested that this number of  
 151 simulations and years was sufficient for results to be insensitive to starting conditions and short-term  
 152 dynamics caused by auto-correlated processes. Median  $SSB$ ,  $\frac{SSB}{SSB_{F=0}}$ ,  $\frac{SSB}{SSB_{MSY}}$ , yield,  $\frac{yield}{MSY}$ , biomass of  
 153 herring dying due to  $M$ , and the proportion of the herring population comprised of age-1 fish over the  
 154 last 50 years of each simulation were recorded as performance metrics. Additional performance metrics

155 included the proportion of the last 50 years of each simulation with  $SSB < SSB_{MSY}$ ,  $SSB < \frac{SSB_{MSY}}{2}$  (i.e.,  
156 proportion of the last 50 years that are overfished),  $SSB < 0.3SSB_{F=0}$ ,  $SSB < 0.75SSB_{F=0}$ , fully-selected  
157  $F > F_{MSY}$  (i.e., proportion of the last 50 years that overfishing occurred), and  $Q = 0$  (i.e., proportion of  
158 the last 50 years that the fishery was closed). Interannual variation in yield ( $IAY$ ) was also recorded over  
159 the last 50 years of each simulation:

$$160 \quad IAY = \sqrt{\frac{1}{50} \sum_{y=1}^{50} (Y_{y+1} - Y_y)^2} / \left( \frac{1}{50} \sum_{y=1}^{50} Y_y \right).$$

161 These performance metrics were highlighted to be of interest at the stakeholder workshops.

162 Two types of two-dimensional tradeoff plots for some pairs of performance metrics were used  
163 to graphically summarize results. 1) For comparing large numbers of control rule shapes, tradeoff plots  
164 were generated for individual operating models and were based on the median among simulations, such  
165 that each control rule shape was represented by a single point. These types of plots were generally used  
166 to introduce the broad topic of tradeoffs, convey the extent of performance that each general control  
167 rule could achieve, and to highlight the pairs of metrics with relatively strong tradeoffs. While focusing  
168 on a single operating model and relying solely on the median ignores variation in results, simultaneously  
169 plotting the range of performance among operating models with multiple percentiles for thousands of  
170 control rule shapes was ineffectual. 2) For comparing relatively few control rule shapes (e.g.,  $\sim 6$ ),  
171 tradeoff plots were generated using shaded areas that ranged from the 25<sup>th</sup> to the 75<sup>th</sup> percentile of  
172 each performance metric among all the operating models for each control rule shape. These types of  
173 plots were generally used to introduce the concept of “robustness”, i.e., that some control rule shapes  
174 are more certain to produce a given result or tradeoff than other control rule shapes. These two types  
175 of tradeoff plots are presented in separate Results sections below.

176 Results presented here also include performance metrics for Atlantic herring predators, the  
177 details of which can be found in Gaichas’ technical document. Results for economic metrics are not

178 presented here because some corrections and refinements are being made. The details of the economic  
179 metrics are available, however, in Lee’s technical document. Results for economic metrics may be  
180 presented at the peer review meeting. Some cross-referencing between this document and the other  
181 technical documents may be necessary.

## 182 **Results**

183 The results described here are intended to serve as examples of how various graphics were used  
184 to convey information, and are not comprehensive. Results for control rule shapes that achieve  
185 specified objectives (e.g., achieve 80% of *MSY*) are also not presented because the New England Fishery  
186 Management Council is in the process of selecting preferred control rules, and this process has not yet  
187 identified such preferred objectives or performance.

188 *1) Comparing large numbers of control rule shapes*—Yield relative to *MSY* (i.e.,  $\frac{\text{yield}}{MSY}$ ) generally  
189 exhibited a dome-shaped relationship with  $\frac{SSB}{SSB_{F=0}}$ , and the severity of this relationship varied  
190 among operating models (Figure 4, which occurs on multiple pages). Generally, the biomass  
191 based control rule variants achieved higher levels of yield and maintained higher biomass than  
192 the constant catch or conditional constant catch rules (Figure 4).

193 A broad range of  $\frac{\text{yield}}{MSY}$  could be achieved across a broad range of *IAV*, and while this  
194 relationship varied among operating models, the general pattern held. So for the sake of  
195 brevity, results were only presented for the operating model with a combination of Hi *M*, low  
196 steepness, slow growth, and an unbiased assessment (Figure 5). The biomass based rule  
197 applied with 3 year blocks and a 15% restriction, the constant catch, and the conditional constant catch  
198 rules more consistently achieved low *IAV* than the other biomass based alternatives, but this came  
199 at the cost of fewer alternatives that could achieve relatively high yield (Figure 5).

200 The frequency with which tuna weight was greater than average was driven almost  
201 entirely by whether Atlantic herring grew fast or slow (Figure 6). Results were only presented  
202 for operating models with a combination of Hi  $M$ , low steepness, and an unbiased assessment  
203 (Figure 6).

204 The frequency with which tern production was  $\geq 1$  (i.e., that terns were able to maintain  
205 replacement) was generally  $\sim 85\%$  or higher and Atlantic herring biomass was generally higher  
206 for the biomass based alternatives without the 15% restriction than for the biomass based rule  
207 with three year blocks and a 15% restriction, constant catch, and conditional constant catch  
208 rules (Figure 7). Results were only presented for the operating model with a combination of Hi  
209  $M$ , low steepness, slow growth, and an unbiased assessment (Figure 7).

210 Results for the frequency with which dogfish were  $> 0.5B_{MSY}$  were similar to results for  
211 that of tern production (Figure 8). The frequency with which dogfish were  $> 0.5B_{MSY}$  was nearly  
212 1.0 and Atlantic herring biomass was generally higher for the biomass based alternatives  
213 without the 15% restriction than for the biomass based rule with three year blocks and a 15%  
214 restriction, constant catch, and conditional constant catch rules (Figure 8). Results were only  
215 presented for the operating model with a combination of Hi  $M$ , low steepness, slow growth,  
216 and an unbiased assessment (Figure 8).

217 *2a) Comparing relatively few control rule shapes*—Results in this section pertain to four  
218 specific biomass based control rule shapes (Figure 9). These four shapes were chosen ad hoc  
219 and are for demonstration purposes. Unless otherwise noted, the same colors correspond to  
220 the same biomass based shapes throughout the figures. Whether the control rules were  
221 applied annually, with three year blocks, or with five year blocks was noted in figure captions,

222 as was whether the results cover operating models with unbiased assessments or both biased  
223 and unbiased assessments.

224 Control rules that were more certain to provide relatively high yield were more certain  
225 to produce smaller amounts of herring *SSB*, more frequently resulted in herring becoming  
226 overfished, and were more certain to produce less variation in yield than control rules less  
227 certain to provide relatively high yield (Figure 10). Control rules that resulted in herring  
228 becoming overfished less frequently also produced more frequent fishery closures than other  
229 control rules (Figure 10).

230 The frequency with which tuna weight was greater than average was driven almost  
231 entirely by whether Atlantic herring grew fast or slow, and so results for each control rule  
232 varied from 0-1 in that metric (Figure 11). Control rules less certain to maintain the frequency  
233 of tern production at levels  $\geq 1$  were also more certain to reduce herring *SSB*, although in the  
234 worst case the frequency with which tern production was  $\geq 1$  was still  $> \sim 80\%$  (Figure 11). The  
235 frequency with which dogfish were  $> 0.5B_{MSY}$  did not vary among the four control rule shapes  
236 (Figure 11).

237 *2b) Comparing the sensitivity of relatively few control rule shapes to assessment bias—*  
238 All of the control rules produced less herring *SSB* in biased assessment operating models than in  
239 unbiased assessment operating models (Figure 12). Some control rules, however, were more  
240 certain to generate less yield in the biased than in the unbiased operating models, while other  
241 control rules were actually more certain to produce higher yield in the biased than unbiased  
242 assessment operating models (Figure 12). All of the control rules were more certain to result in  
243 greater frequencies of herring becoming overfished in biased than in unbiased assessment

244 operating models, but control rules that were more certain to produce relatively high yield in  
245 the unbiased operating models were more sensitive to assessment bias(Figure 12). Other  
246 tradeoff plots were not included for the sake of brevity.

247 *2c) Evaluating the effect of applying biomass based control rules annually, in three year*  
248 *blocks, or five year blocks*—The same four control rules analyzed in sections 2a and 2b (Figure  
249 9) were also evaluated for their sensitivity to applying each of the control rules annually, in  
250 three year blocks, or in five year blocks. The four control rules responded similarly to the  
251 various blocks, and so results are only presented for the status quo biomass based shape (see  
252 *Harvest Control Rules* section above).

253 The short-term stability provided by using the same quota in three or five year blocks  
254 resulted in less long-term yield, less herring *SSB*, greater frequencies of herring becoming  
255 overfished, and increases in long-term variation in yield (i.e., *I**AV*) than if quotas were varied  
256 annually (Figure 13). The effects were greatest on the frequency that herring became  
257 overfished (Figure 13).

## 258 **Caveats**

259 This MSE assumed that the reference points used to define the harvest control rules (i.e.,  $F_{MSY}$   
260 and  $SSB_{MSY}$ ) were known without error. The bias and precision of such reference points, however, can  
261 depend on life history characteristics, exploitation history, and autocorrelation in recruitment (Brodziak  
262 et al., 2008; Haltuch et al., 2008; Haltuch et al., 2009). Incorporation of errors in these reference points  
263 into an MSE is not a trivial task (see discussion in Deroba and Bence 2012), but should be a topic of  
264 future research.

265 Assessment errors in this MSE were induced by applying multiplicative error to the underlying  
266 true abundance, but incorporation of a full stock assessment model (e.g., statistical catch-at-age) into

267 MSEs can affect control rule performance (Cox and Kronlund 2008). Incorporation of the assessment  
268 models intended for use in making management recommendations should be the goal of this MSE.

269 While some life-history parameters varied among operating models, they were all treated as  
270 time invariant within each operating model. Time varying life history parameters can affect control rule  
271 performance (Walters and Parma 1996; Deroba and Bence 2008; Hawkshaw and Walters 2015),  
272 however, and this should also be a topic of future research.

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314

Figure 1.—Hi and lo natural mortality rates and stock-recruit relationships used in Atlantic herring MSE operating models. Hi natural mortality was always used with lo steepness in the operating models, and the opposite also held true.

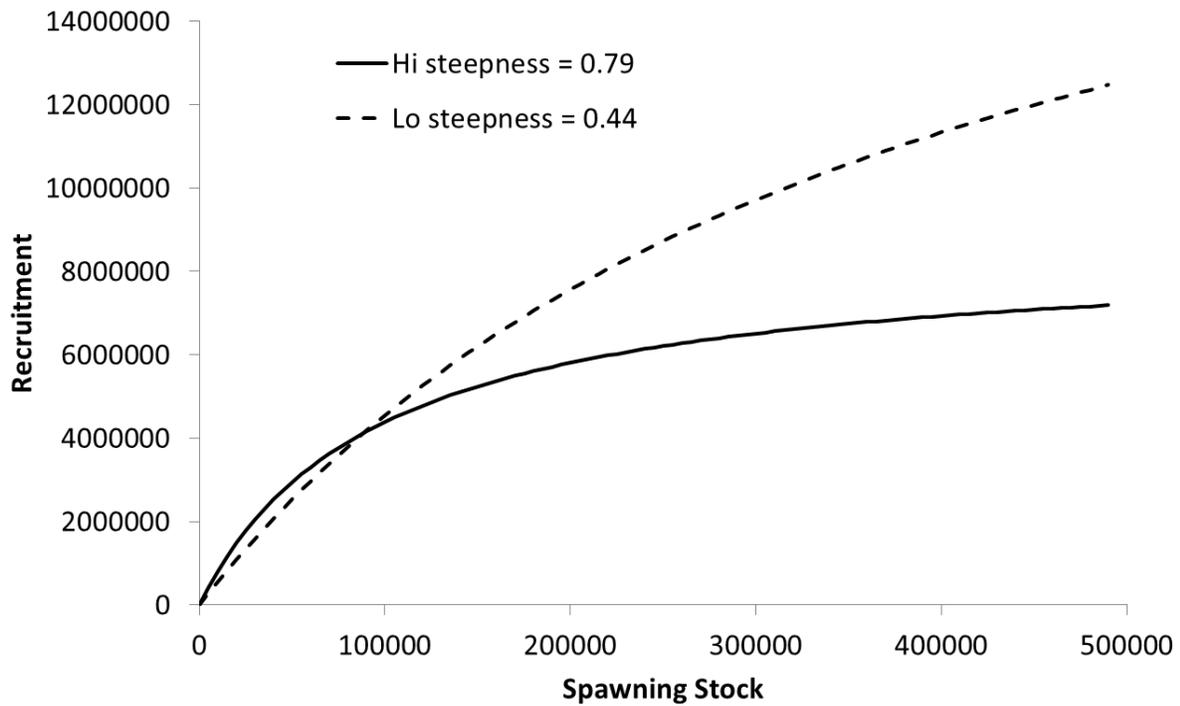
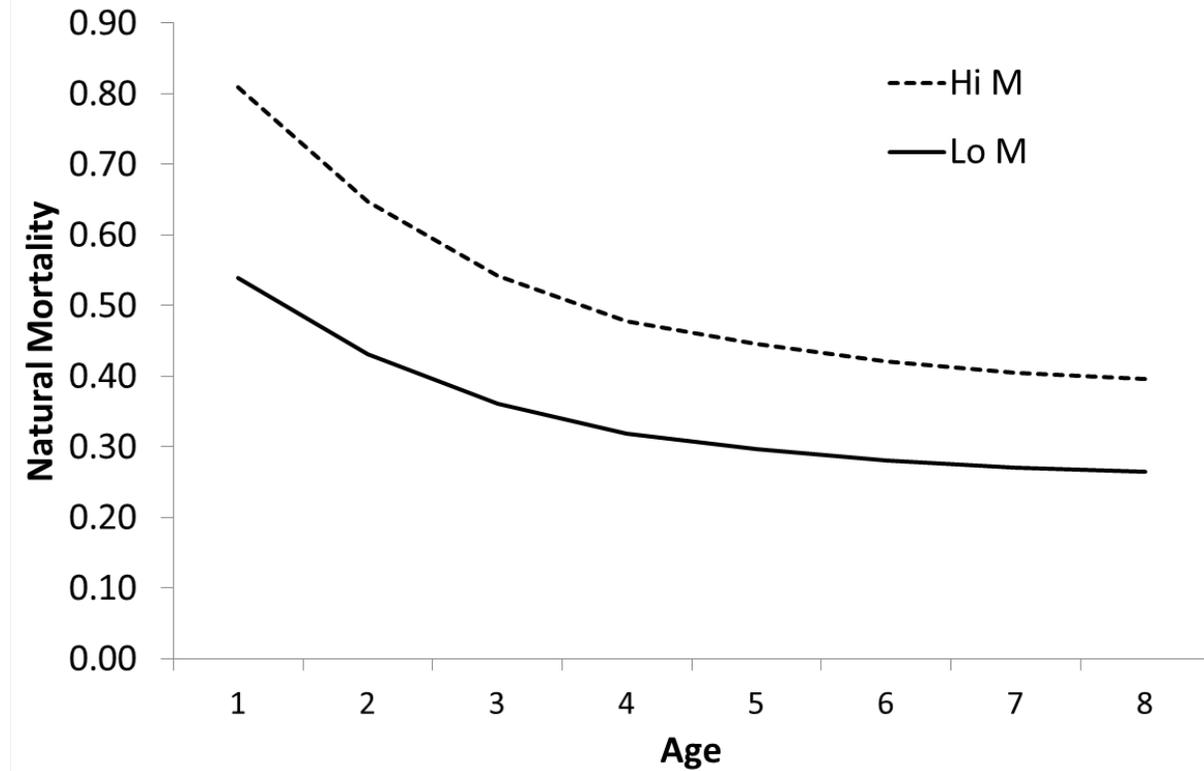


Figure 2.—Fast and slow growth values used in Atlantic herring MSE operating models.

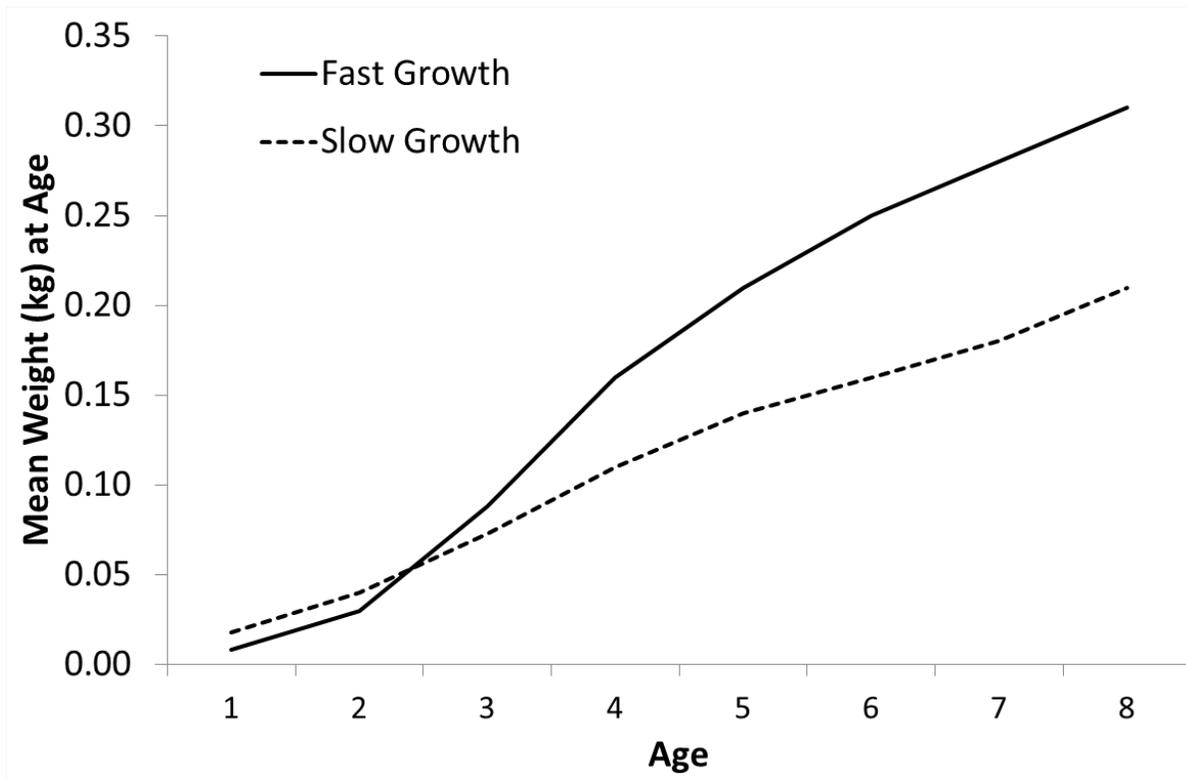


Figure 3.—Example relationships between fishing mortality or catch and biomass for each basic type of control rule evaluated.

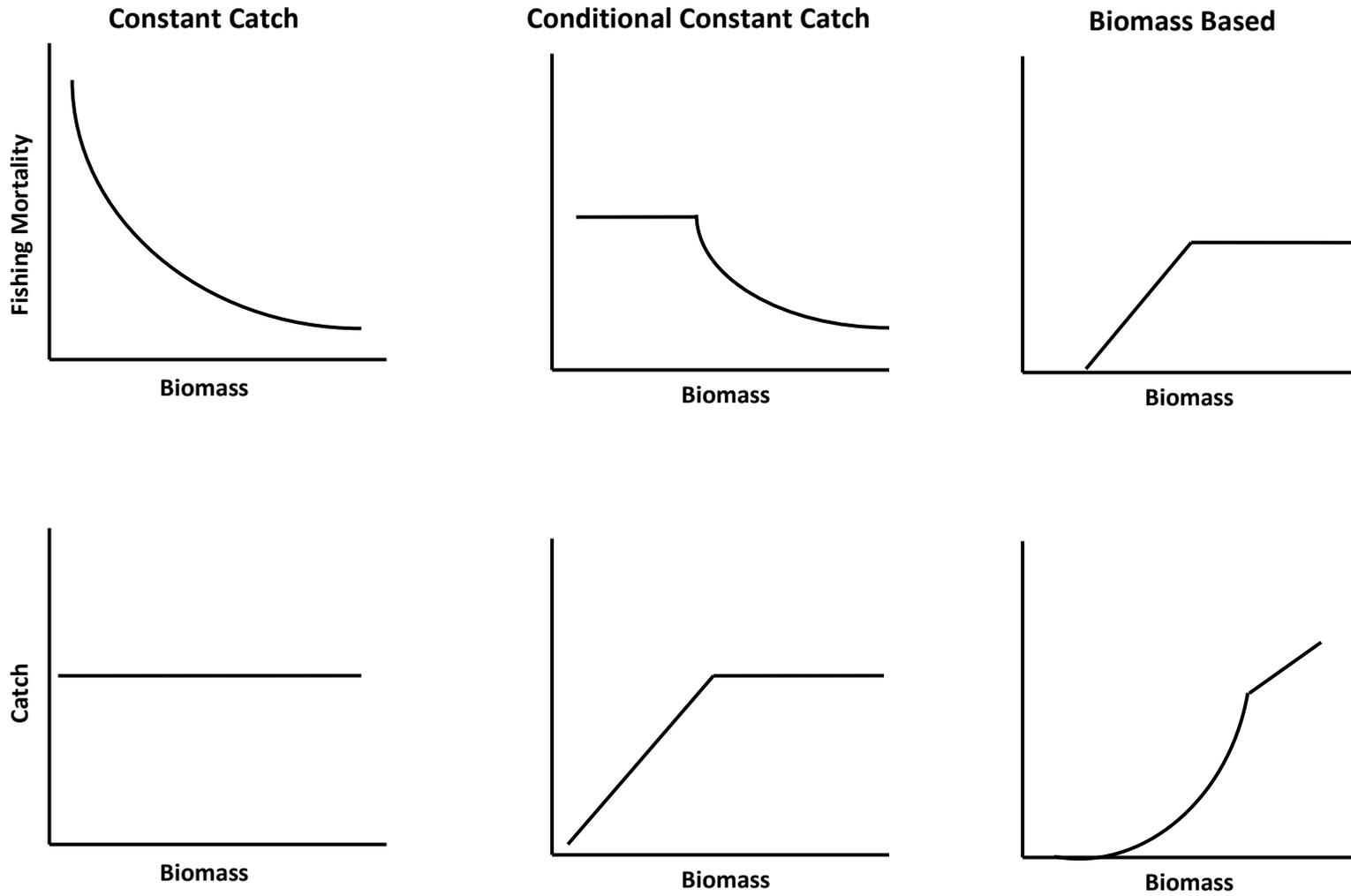
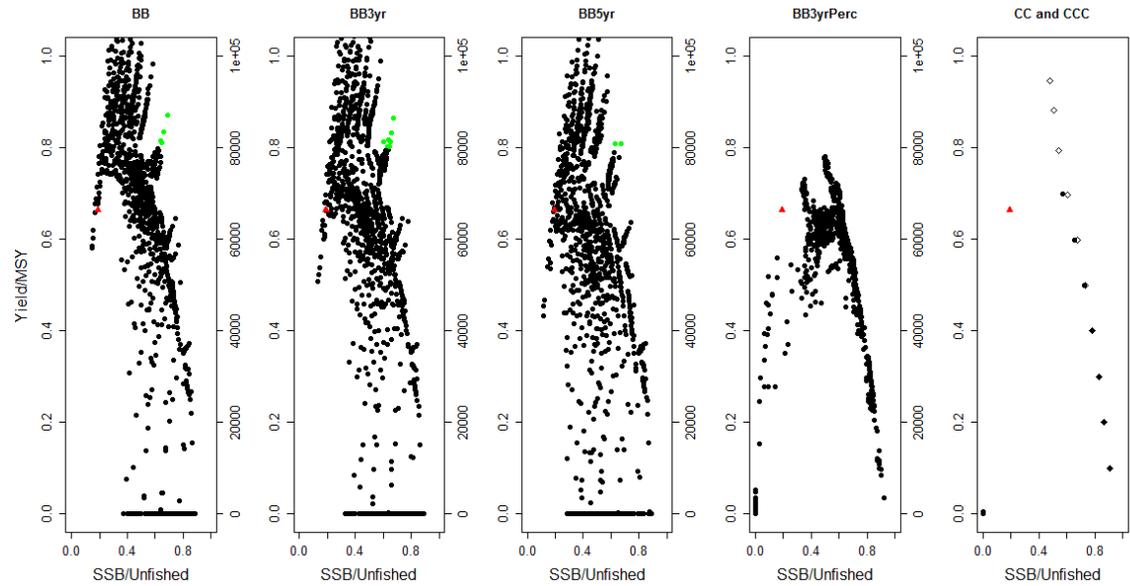


Figure 4.—Tradeoff plot for median yield relative to  $MSY$  versus  $SSB$  relative to unfished  $SSB$ . BB is the annually applied biomass based control rule, BB3yr is the biomass based policy with 3 year blocks, BB5yr is the biomass based policy with 5 year blocks, BB3yrPerc is the biomass based three year block policy with a 15% restriction, CC is constant catch (filled dots in far right panel) and CCC is conditional constant catch (open circles in the far right panel). The red triangle is the performance of the status quo shape (see main text). The green dots simultaneously achieve 80% of  $MSY$  and 65% of unfished  $SSB$ .

Hi  $M$ , low steepness, fast growth, biased assessment



Hi  $M$ , low steepness, slow growth, biased assessment

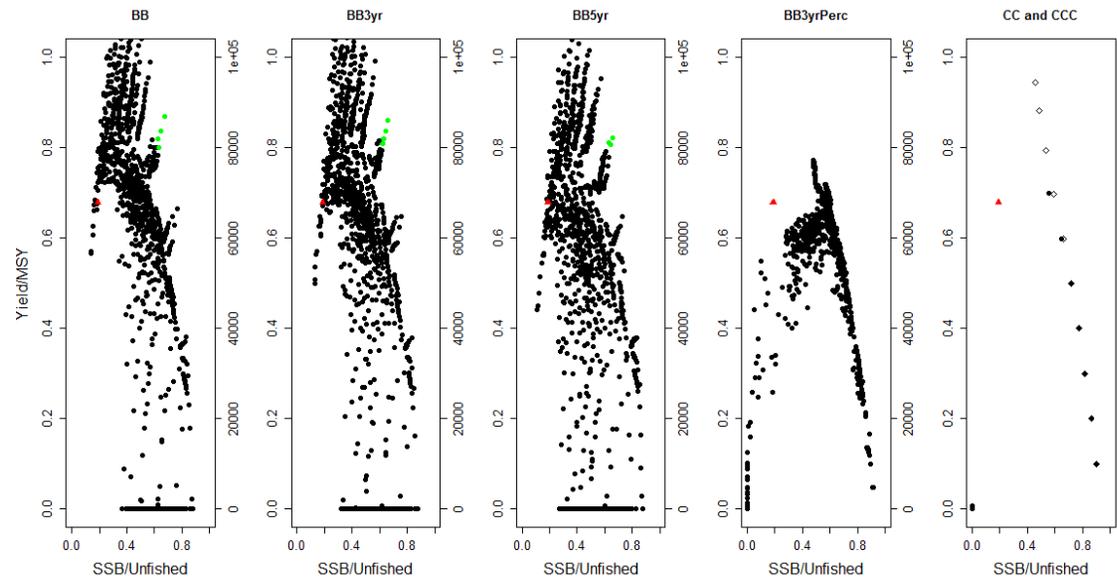
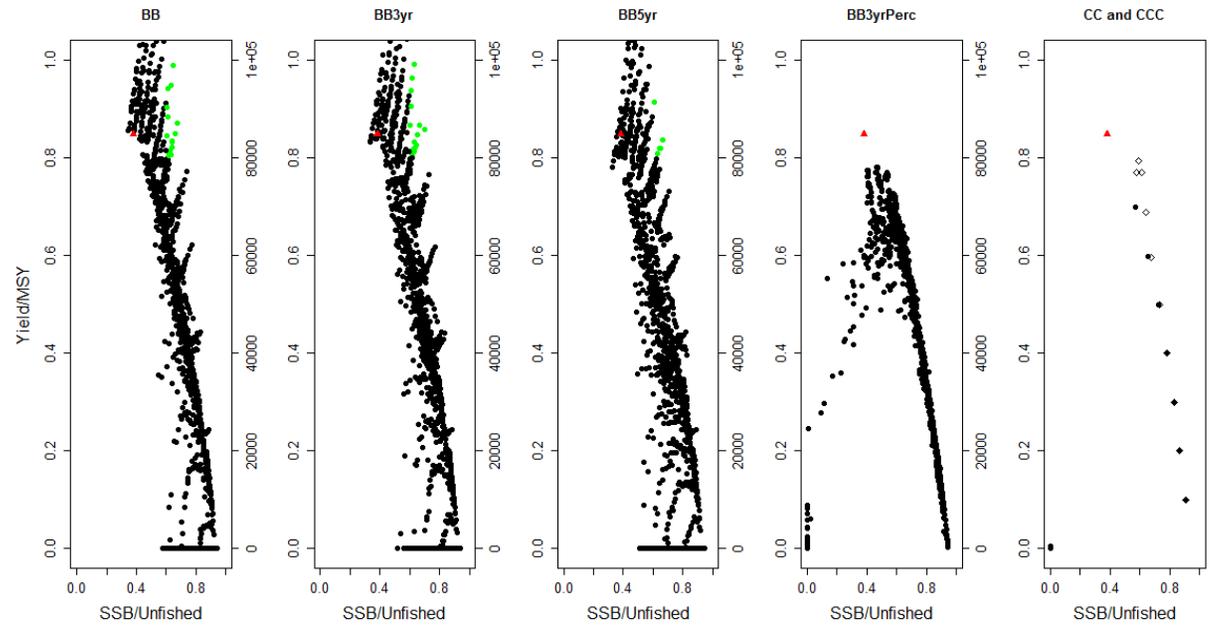


Figure 4 (continued).—

Hi  $M$ , low steepness, fast  
growth, unbiased assessment



Hi  $M$ , low steepness, slow  
growth, unbiased assessment

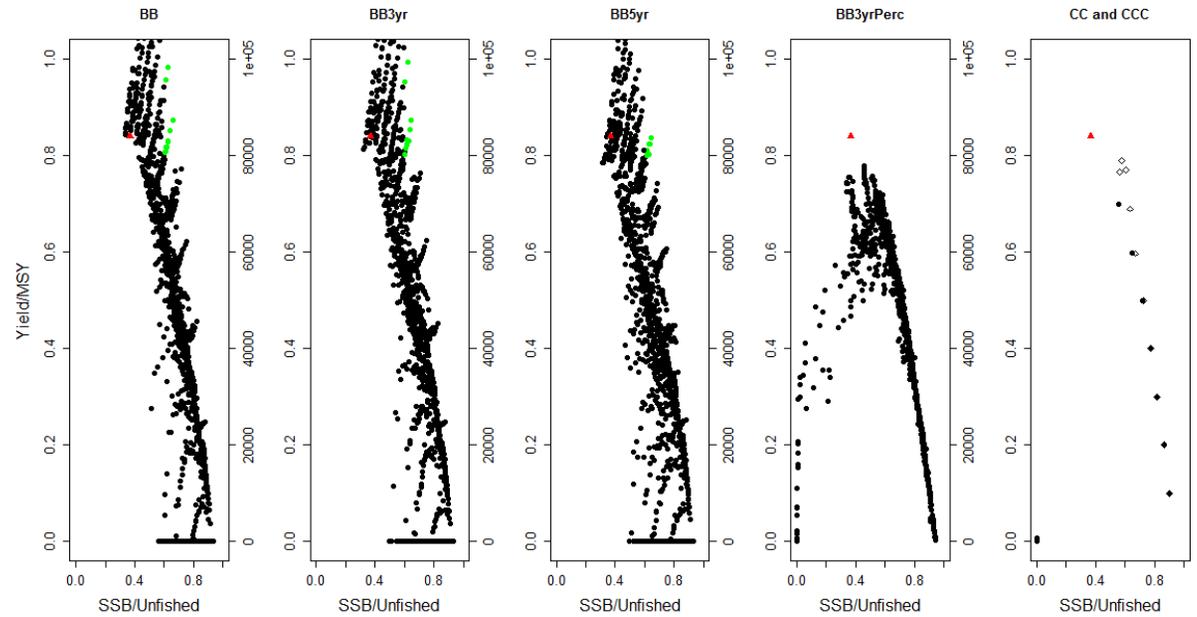
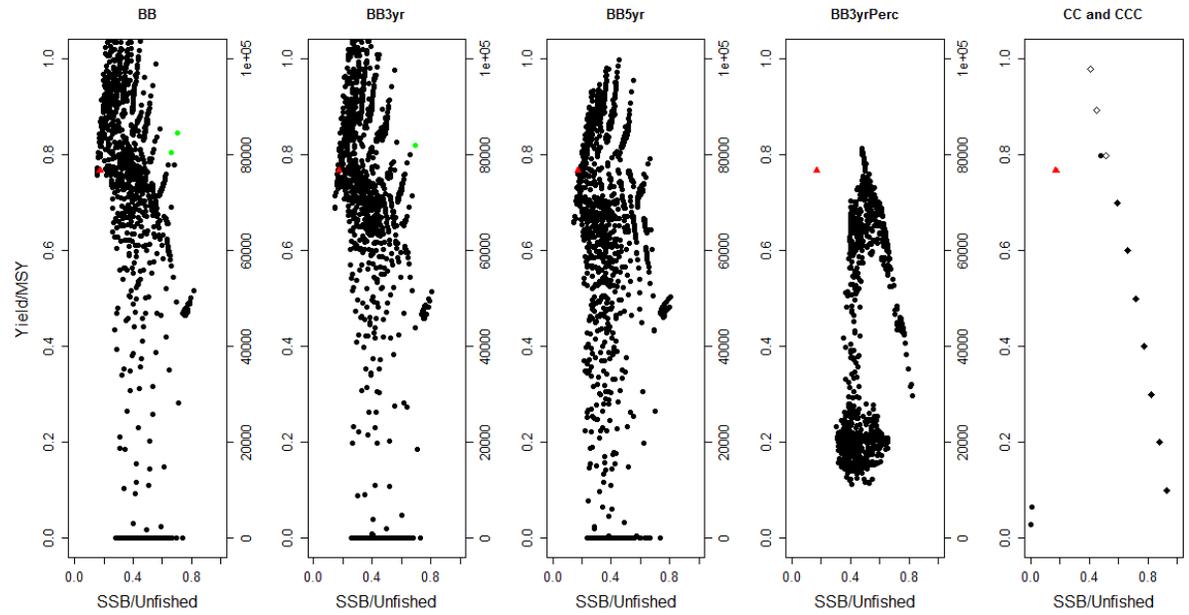


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Lo  $M$ , Hi steepness, fast growth, biased assessment



Lo  $M$ , Hi steepness, slow growth, biased assessment

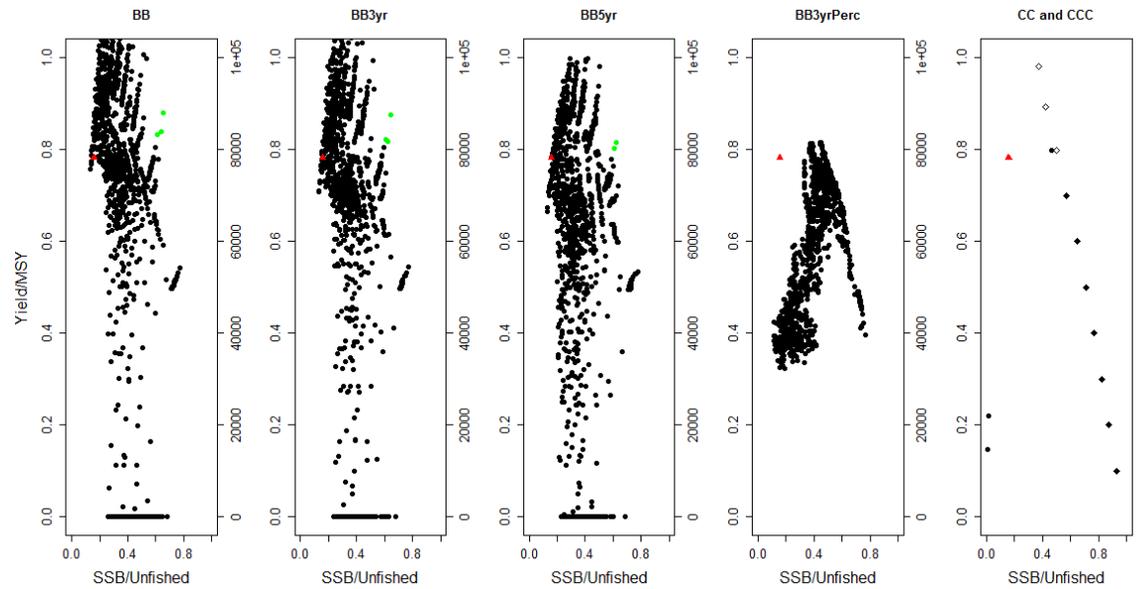
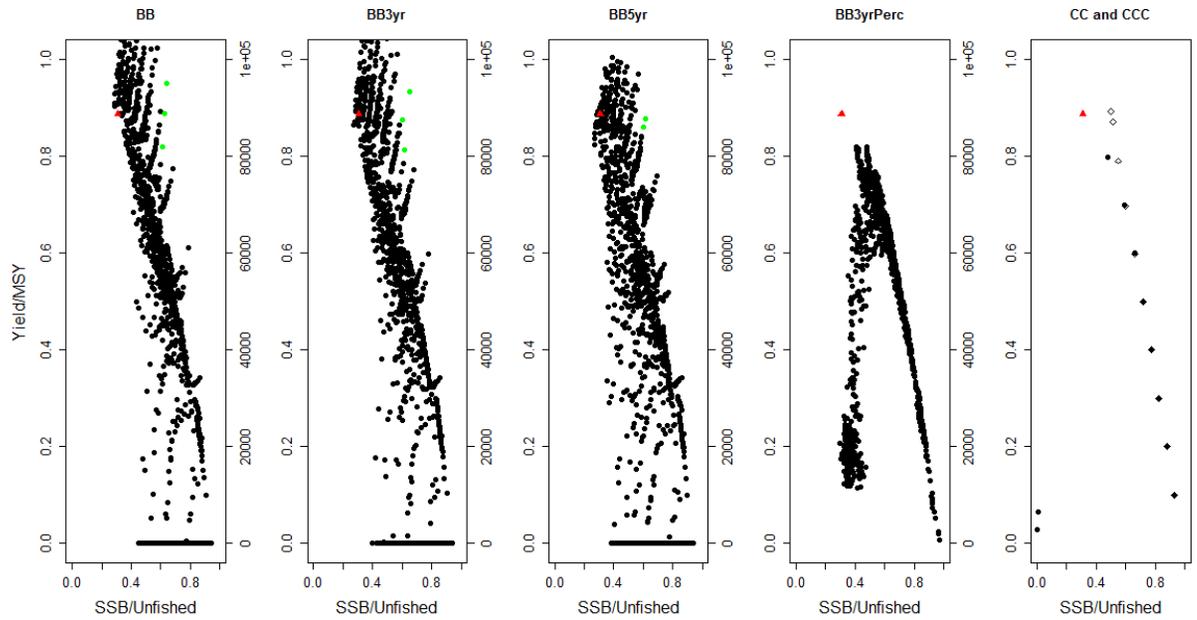


Figure 4 (continued).—

Lo  $M$ , Hi steepness, fast growth,  
unbiased assessment



Lo  $M$ , Hi steepness, slow  
growth, unbiased assessment

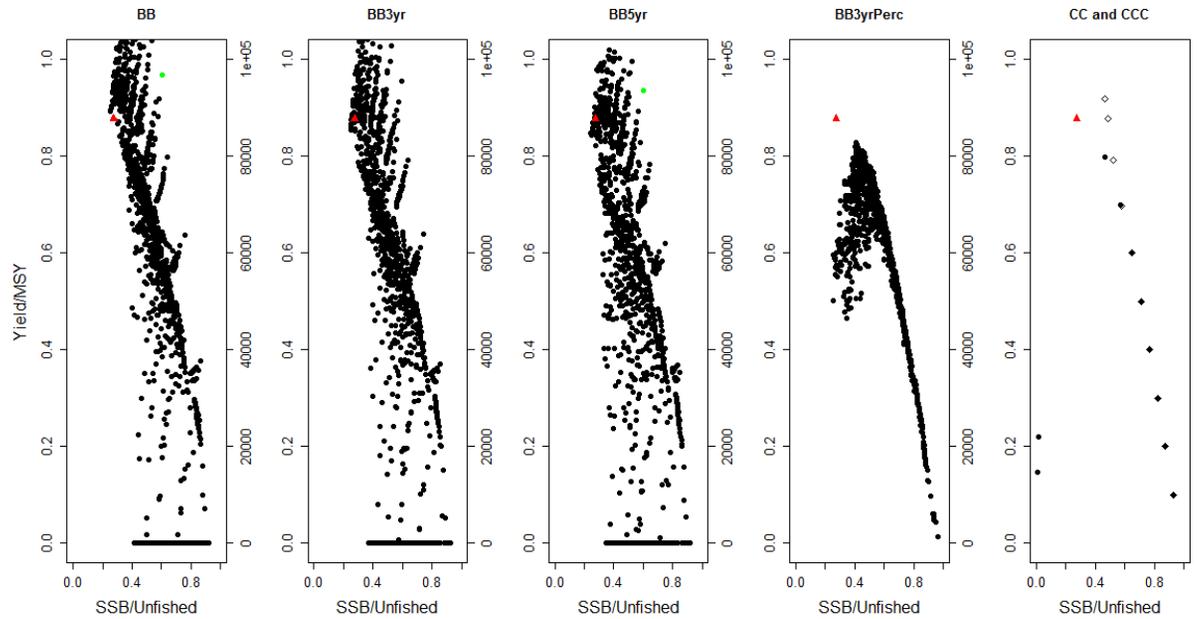


Figure 5.—Tradeoff plot for median yield relative to  $MSY$  versus  $IAV$  (Variation in Yield) for the operating model with Hi  $M$ , low steepness, slow growth, and an unbiased assessment. All else is as in Figure 4.

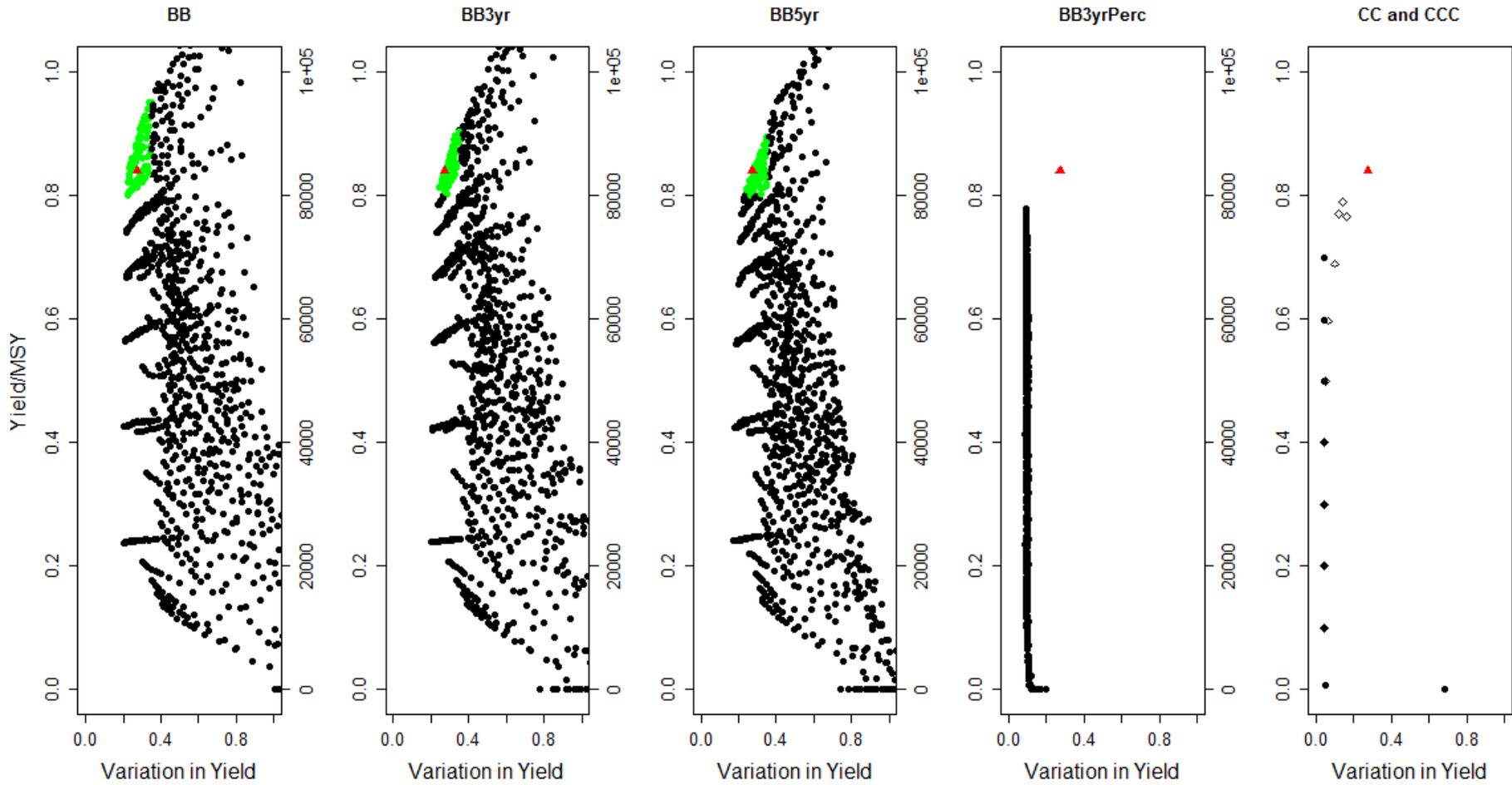
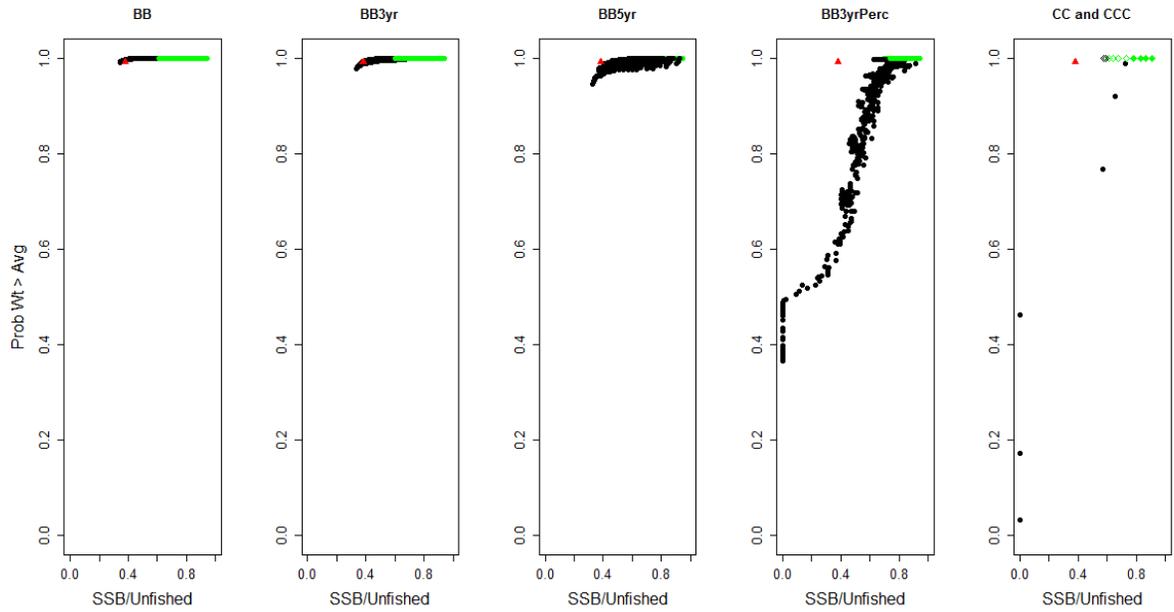


Figure 6.—Tradeoff plot for median frequency with which tuna weight was greater than average (Prob Wt>Avg) versus SSB relative to unfished SSB for the operating model with Hi *M*, low steepness, and an unbiased assessment. All else is as in Figure 4.

Hi *M*, low steepness, fast growth, unbiased assessment



Hi *M*, low steepness, slow growth, unbiased assessment

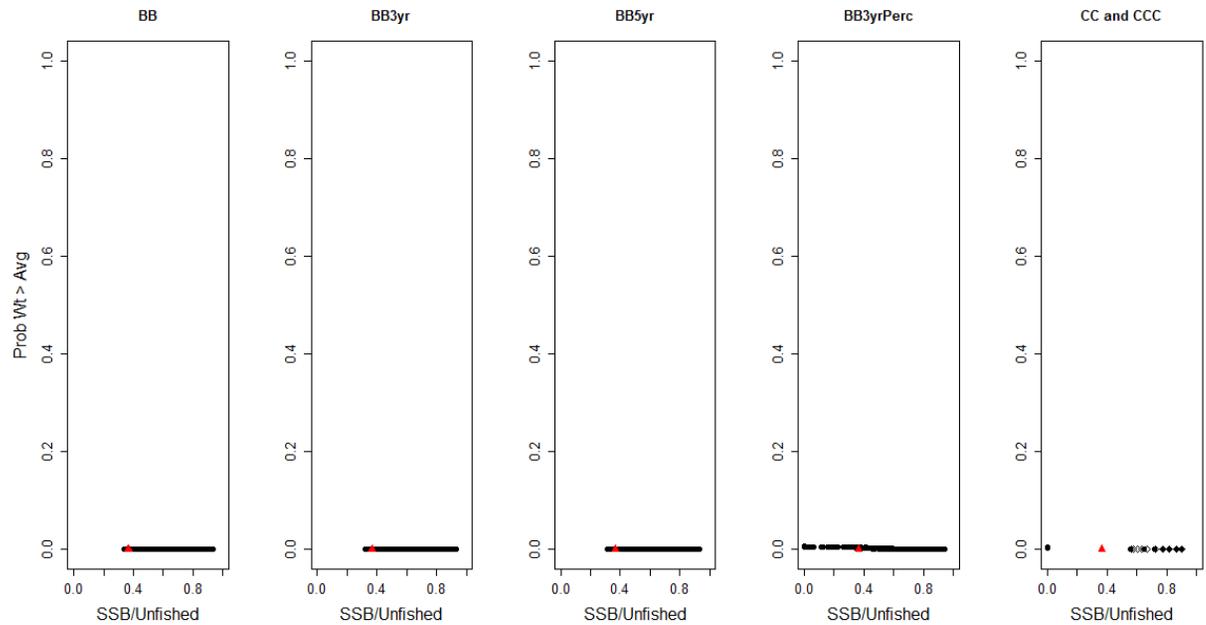


Figure 7.—Tradeoff plot for median frequency with which tern production was  $\geq 1$  (Prob Tern Produ $>1$ ) versus *SSB* relative to unfished *SSB* for the operating model with Hi *M*, low steepness, slow growth, and an unbiased assessment. All else is as in Figure 4.

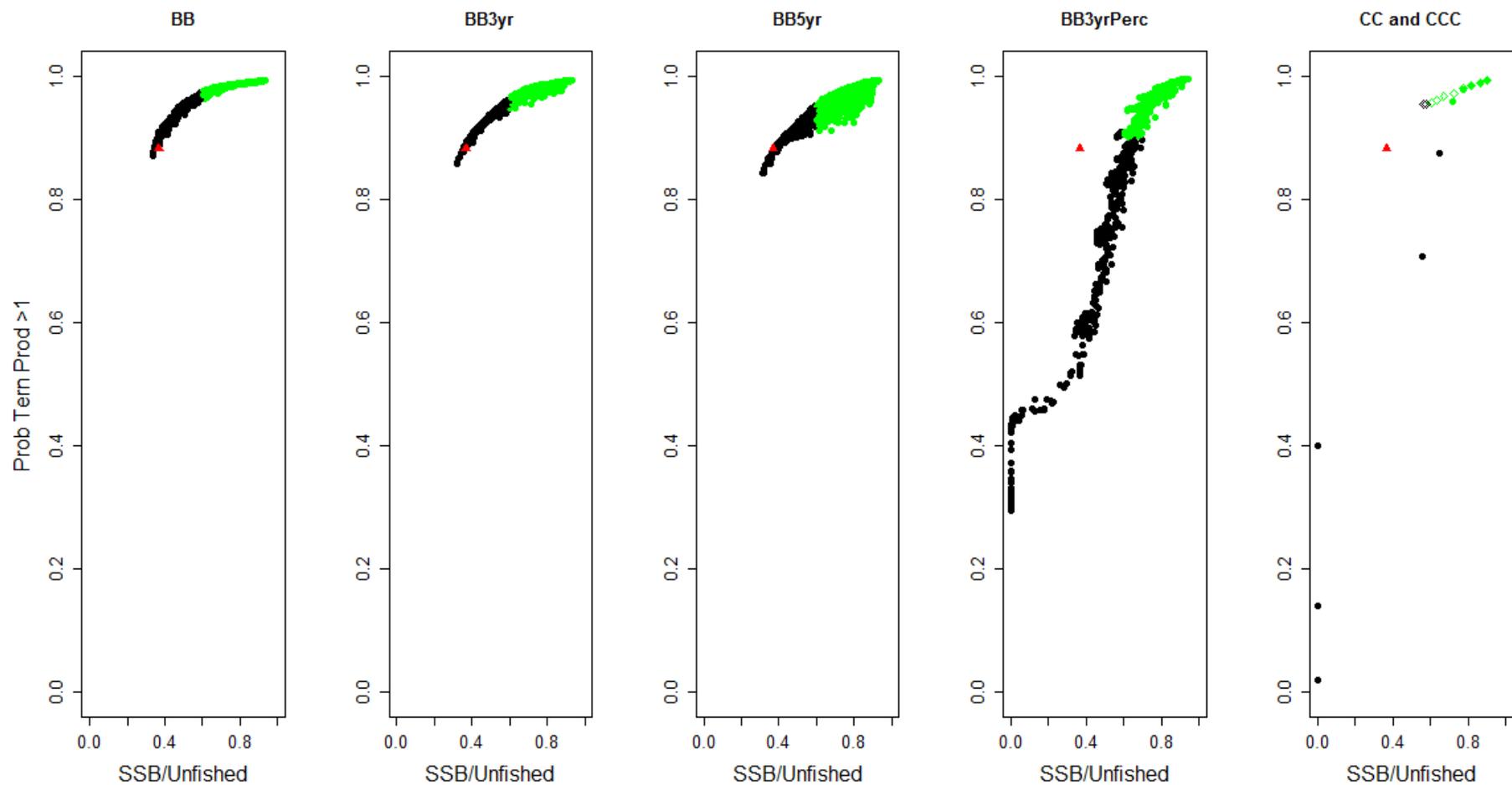


Figure 8.—Tradeoff plot for median frequency with which dogfish biomass was  $> 0.5B_{MSY}$  (Prob GF $>0.5B_{msy}$ ) versus SSB relative to unfished SSB for the operating model with Hi  $M$ , low steepness, slow growth, and an unbiased assessment. All else is as in Figure 4.

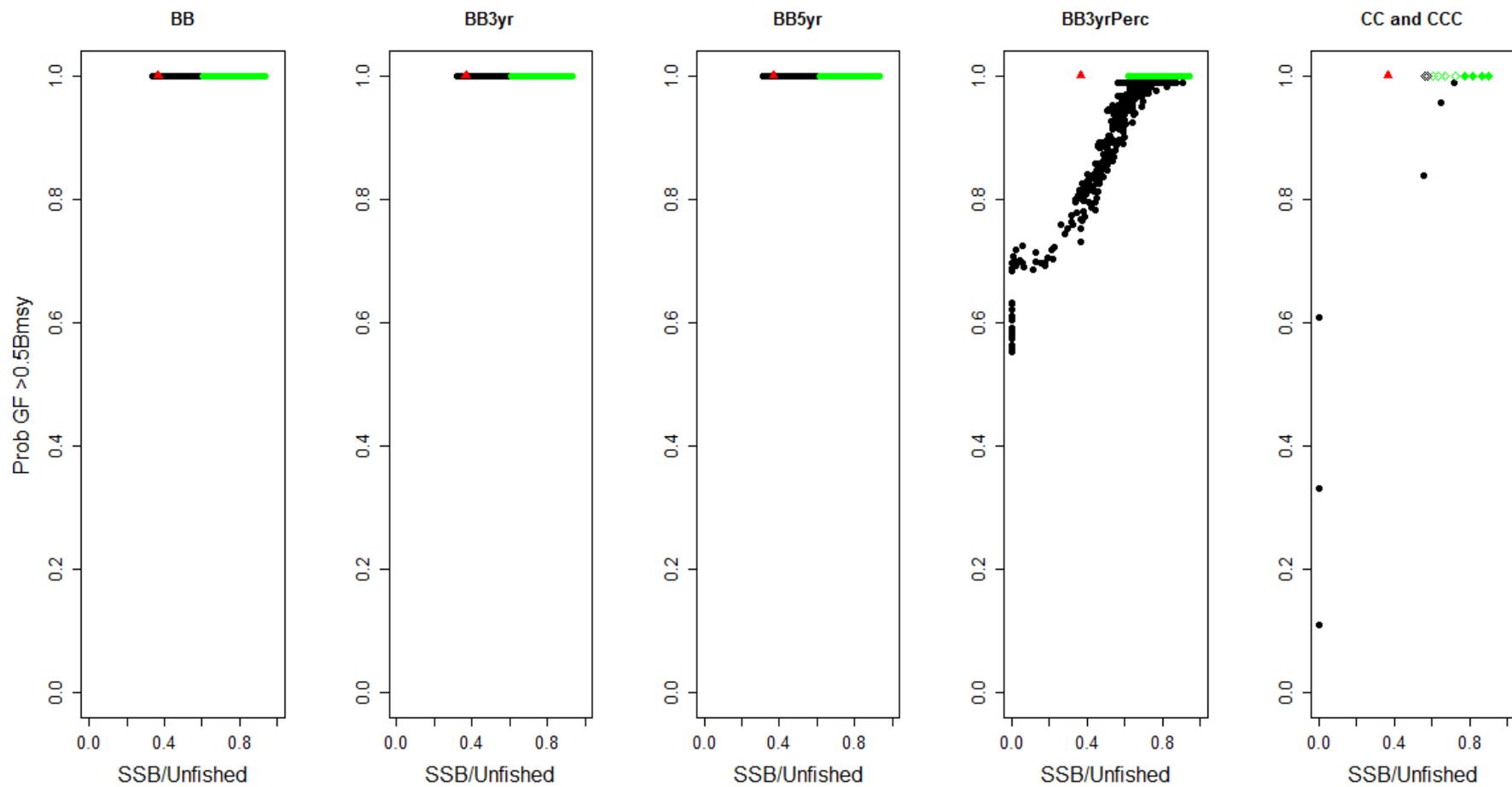


Figure 9.—Four biomass based control rule shapes, the results for which will be presented in Figures 10-12.

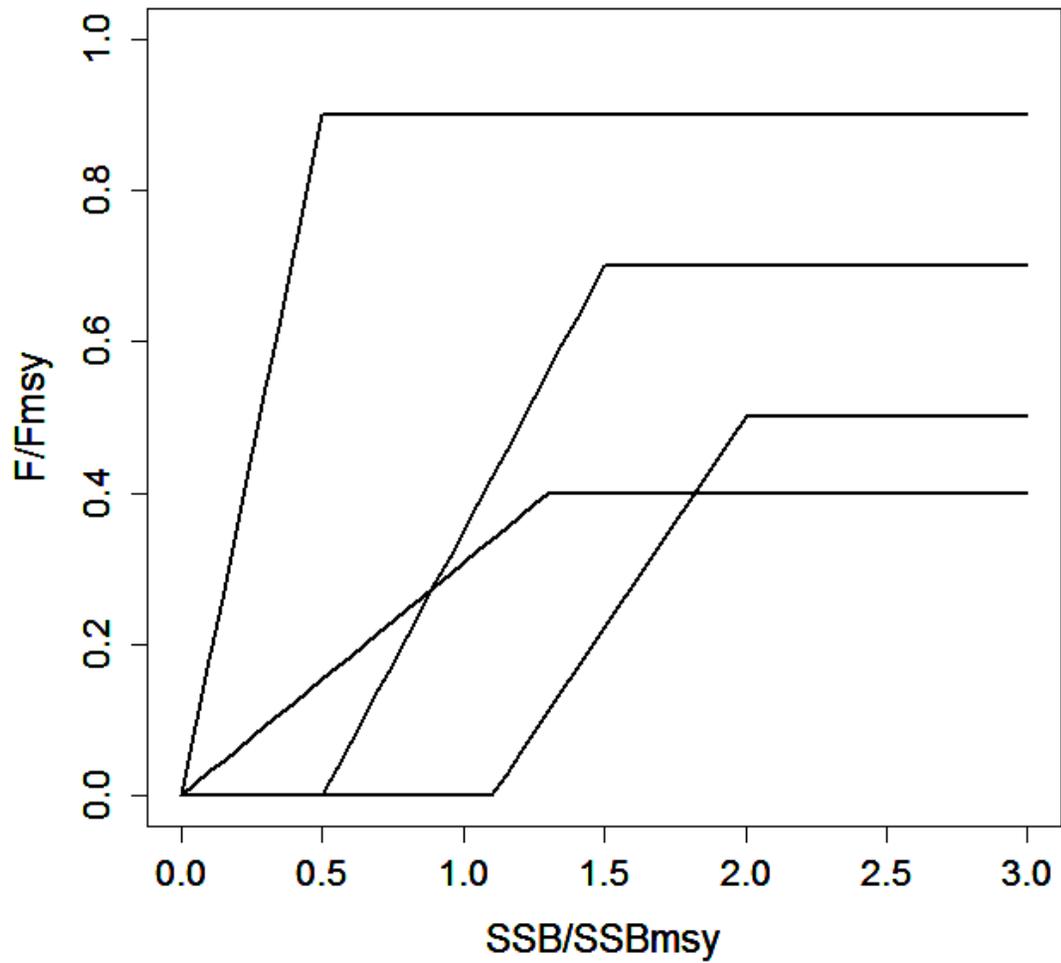


Figure 10.—Tradeoff plots for yield relative to *MSY* versus *SSB* relative to unfished *SSB*, yield relative to *MSY* versus frequency herring become overfished, yield relative to *MSY* versus *IAV* (Variation in Yield), and frequency herring become overfished versus the frequency of fishery closure. The range of colors cover the extremes of the 25<sup>th</sup> and 75<sup>th</sup> percentiles for all operating models except those with biased stock assessments, and pertain to four biomass based control rule shapes applied with three year blocks. Triangles are the median of operating models with low *M* and hi steepness, while circles are medians for operating models with hi *M* and low steepness.

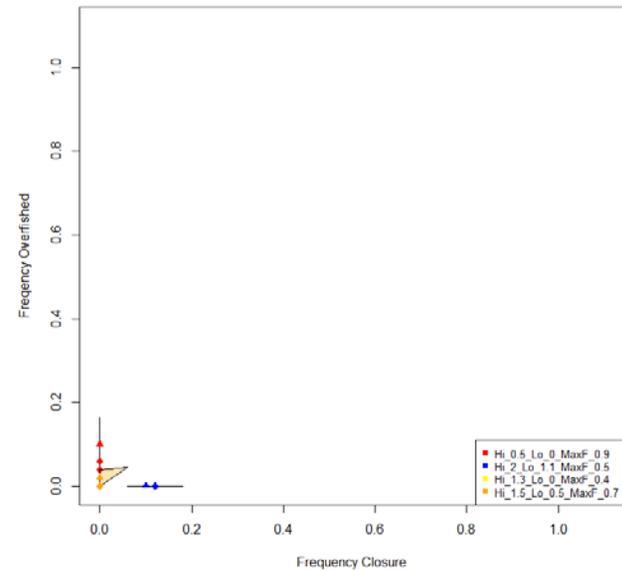
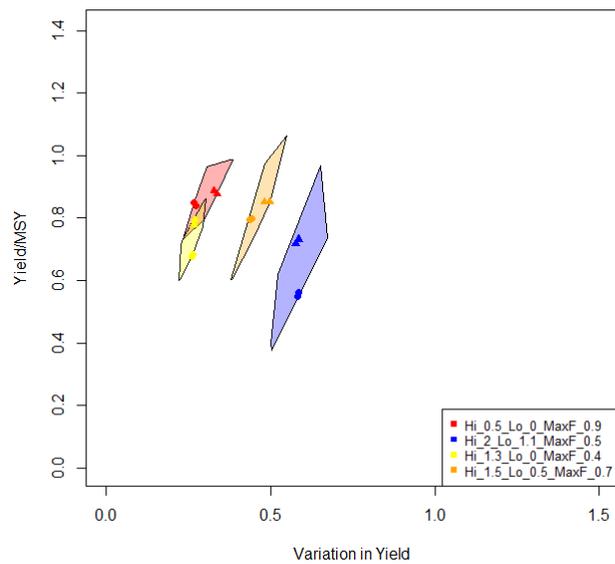
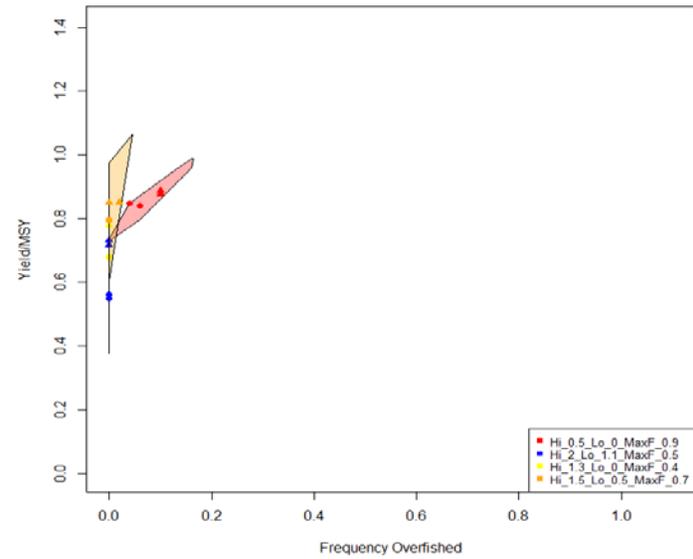
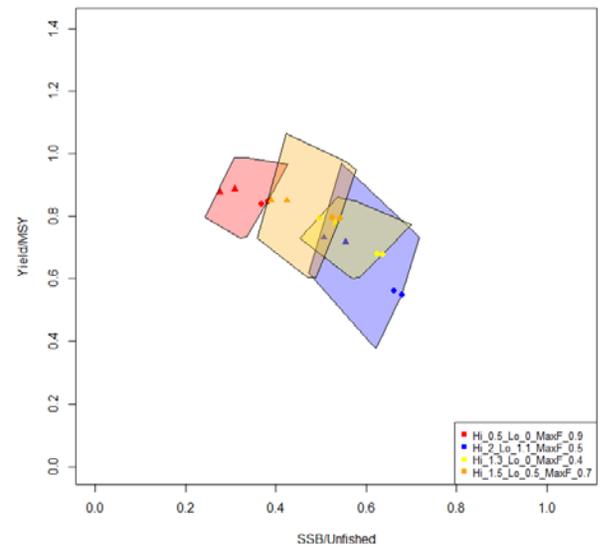


Figure 11.—Tradeoff plots for frequency with which tuna weight was greater than average, frequency with which tern production was  $\geq 1$ , and frequency with which dogfish biomass was  $> 0.5B_{MSY}$  versus herring  $SSB$  relative to unfished  $SSB$ . All else is as in Figure 10.

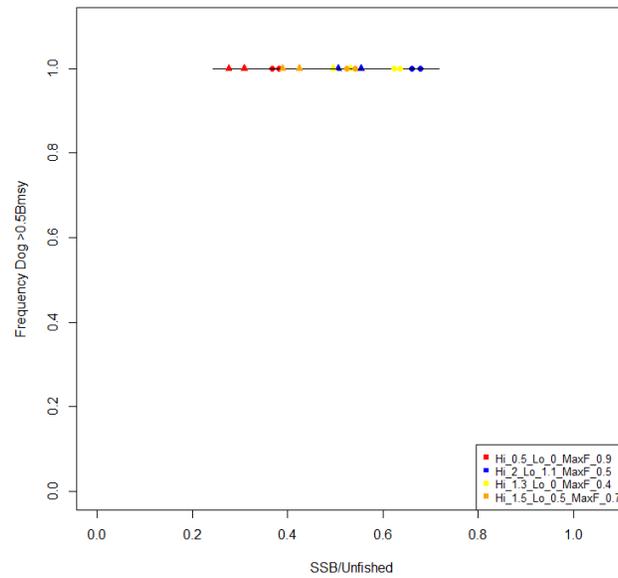
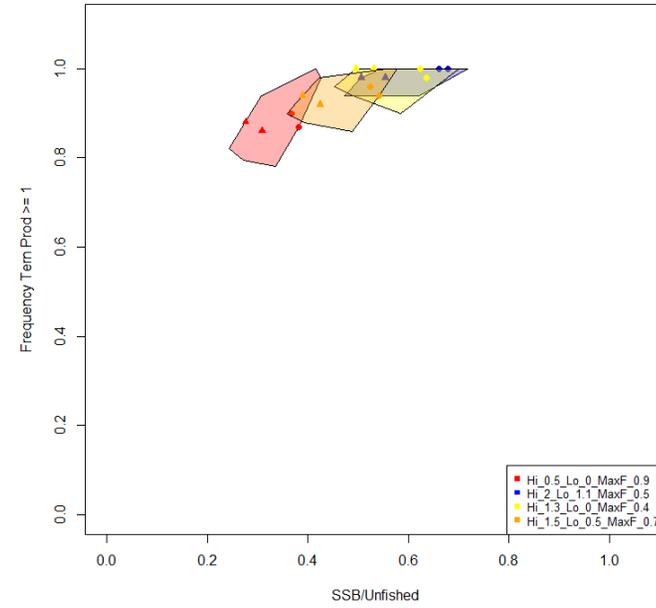
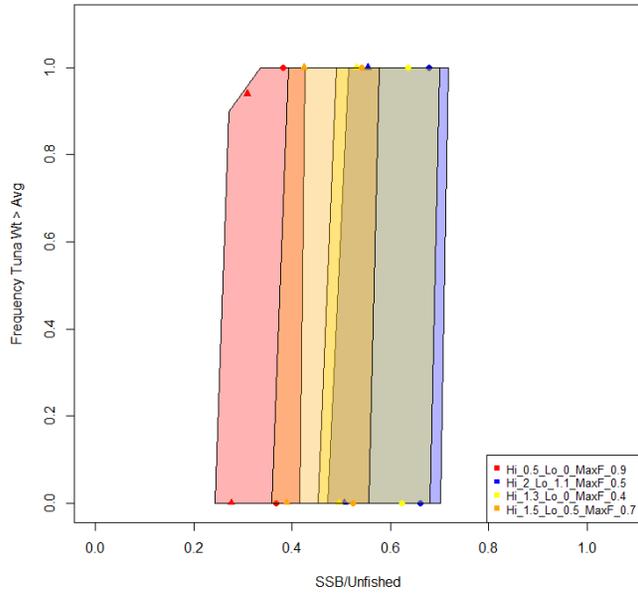


Figure 12.—Tradeoff plots for yield relative to *MSY* versus *SSB* relative to unfished *SSB* and yield relative to *MSY* versus frequency herring become overfished. The solid colors cover the extremes of the 25<sup>th</sup> and 75<sup>th</sup> percentiles for operating models with unbiased assessments (i.e., as in Figure 10), while the hatched colored ranges are for operating models with biased assessments. All else is as in Figure 10.

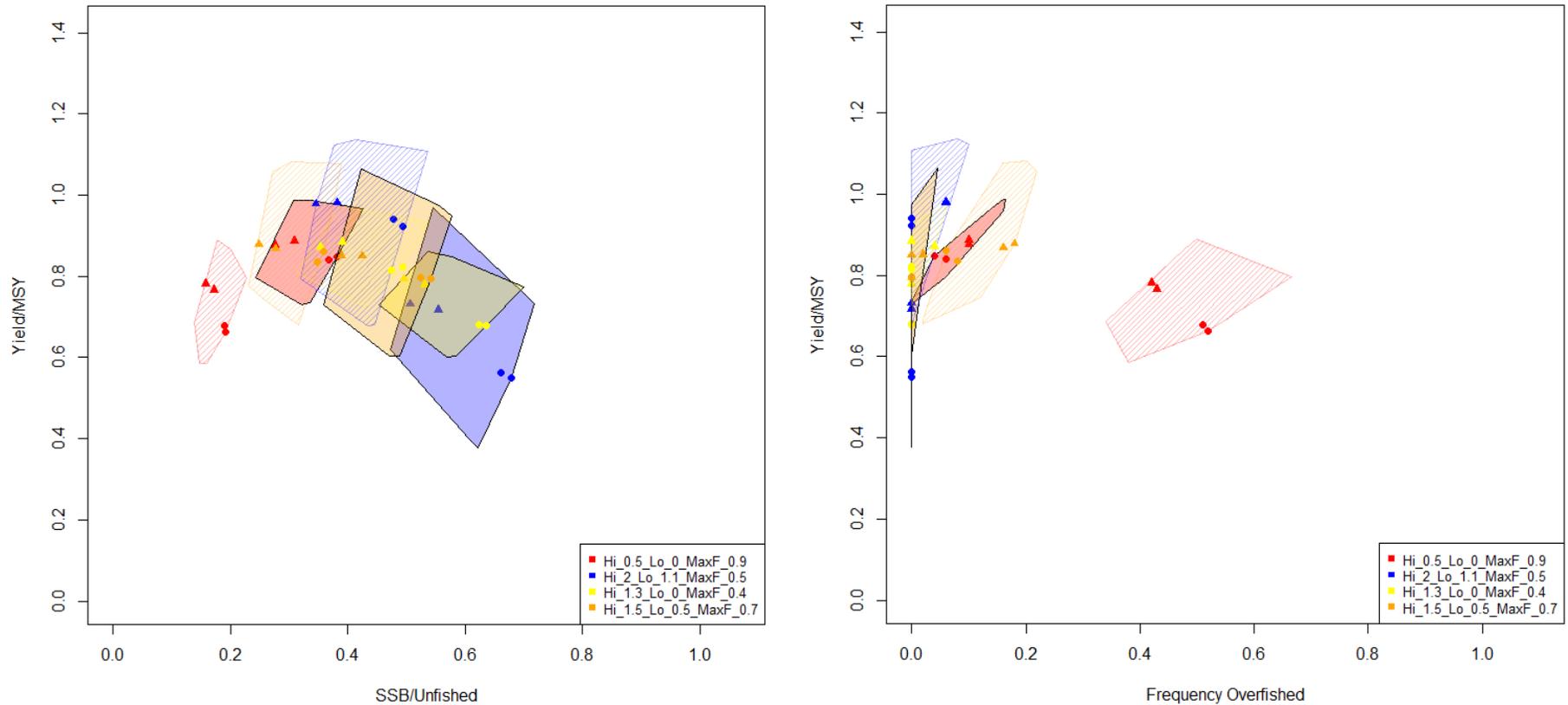
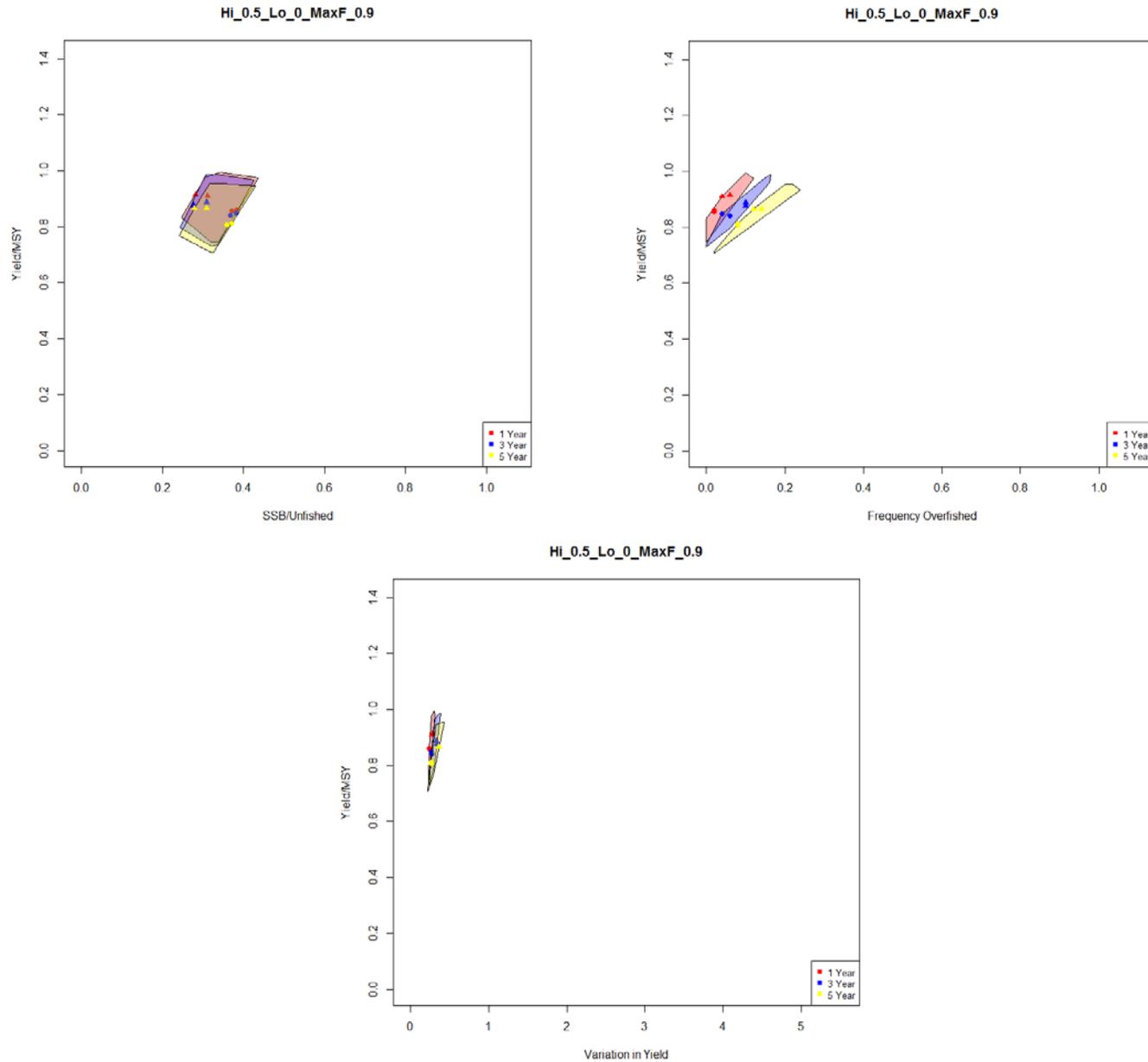


Figure 13.—Tradeoff plots for yield relative to *MSY* versus *SSB* relative to unfished *SSB*, yield relative to *MSY* versus frequency herring become overfished, and yield relative to *MSY* versus *I**AV* (Variation in Yield). Results are only for the status quo biomass based control shape and for operating models with unbiased assessments, and the colors are indicative of whether quotas were varied annually (red), using three year blocks (blue), or five year blocks (yellow). Colors are not indicative of different control rule shapes as they were in Figures 10-12. All else is as in Figure 10.



**Table 1.**

Symbols and descriptions of parameters or variables used in the simulation model

Symbol	Description
$y$	Year
$a$	Age
$N$	True abundance
$F$	Actual fishing mortality rate applied to the population
$M$	Natural mortality
$Z$	Total mortality
$R$	Recruitment
$h$	Steepness of the stock-recruitment relationship
$SSB$	Spawning stock biomass
$\varepsilon_R$	Process error for the stock-recruitment relationship
$\sigma_R^2$	Variance of the stock-recruitment process errors
$\omega$	Autocorrelation coefficient for stock-recruitment process errors
$\chi$	Errors for $\varepsilon_R$
$SSB_{F=0}$	Unfished spawning stock biomass
$R_{F=0}$	Unfished recruitment
$\hat{N}$	Assessed abundance
$\rho$	Degree of bias in assessed abundance
$\varepsilon_\varphi$	Assessment errors
$\sigma_\varphi^2$	Stationary variance of assessment errors
$\tau$	Errors for $\varepsilon_\varphi$
$\vartheta$	Autocorrelation coefficient for assessment errors
$\widehat{SSB}$	Assessed spawning stock biomass
$m$	Maturity
$W$	Weight
$\hat{B}$	Assessed total biomass
$MSY$	Maximum sustainable yield
$SSB_{MSY}$	Spawning stock biomass at maximum sustainable yield
$\tilde{F}$	Desired fishing mortality rate
$S$	Selectivity
$Q$	Desired quota
$\bar{F}$	Fishing mortality rate that would produce the desired quota when applied to the true population
$\varepsilon_\theta$	Implementation errors
$\sigma_\theta^2$	Variance of implementation errors
$\psi$	Proportion of $F_{MSY}$ used to define a parameter of the biomass based control rule
$SSB_{up}$	Upper biomass parameter of the biomass based control rule
$SSB_{low}$	Lower biomass parameter of the biomass based control rule
IAV	Interannual variation in yield

Table 2.—General properties of the eight Atlantic herring operating models.

Steepness		Natural Mortality		Growth		Assessment bias	
Hi	Low	Hi	Low	Fast	Slow	Biased	Unbiased
	x	x			x		x
x			x		x		x
	x	x		x			x
x			x	x			x
	x	x			x	x	
x			x		x	x	
	x	x		x		x	
x			x	x		x	

Table 3.—Unfished and *MSY* reference points for the Atlantic herring operating models.

<b>Steepness</b>	<b>Natural Mortality</b>	<b>Growth</b>	<b>Unfished SSB</b>	<b>SSB<sub>MSY</sub></b>	<b>MSY</b>	<b>F<sub>MSY</sub></b>
0.44	High	Slow	845176	324977	66061	0.31
0.44	High	Fast	845176	335849	60969	0.28
0.79	Low	Slow	1347080	369089	129171	0.54
0.79	Low	Fast	1347080	405485	120360	0.45

# Herring MSE: Predator Models

*Sarah Gaichas and Jonathan Deroba, Northeast Fisheries Science Center*

*February 23, 2017*

## Introduction

This document explains the predator modeling component of the Herring Management Strategy Evaluation (MSE). Predator modeling balanced the New England Fishery Management Council (Council) scope and timeline specified for the Herring Amendment 8 ABC control rule analyses with the objectives identified for predators during the first stakeholder workshop. The Council required evaluation of an annual, stock-wide Atlantic herring harvest control rule that considered herring's ecological role as forage, to be completed within less than one year. Stakeholders were interested in evaluating potential effects of herring harvest control rules on multiple predator types including highly migratory species (tuna), groundfish, seabirds, and marine mammals.

## Herring's ecological role as forage

The food web of the Northeast US continental shelf large marine ecosystem is characterized by many diverse predators and prey (Fig. 1). Atlantic herring is group 37 in the figure, sharing the role of forage with other groups such as sand lance (36), river herring (38), Atlantic mackerel (39), and butterfish (40) (Jason Link 2002).

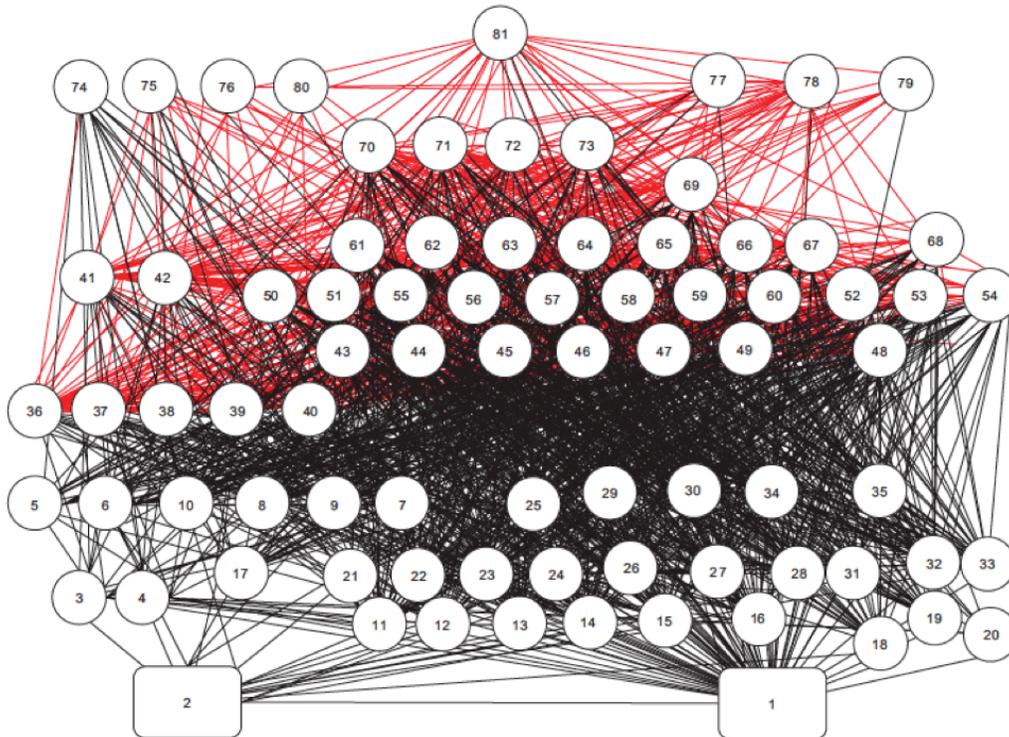


Figure 1: US Northeast shelf food web from Link 2002

In the Northeast US, there is wealth of scientific information to characterize predator-prey relationships, including feeding ecology data for fish predators (e.g., B. E. Smith and Link 2010), seabirds (Hall, Kress, and Griffin 2000), bluefin tuna (Chase 2002; W. J. Golet et al. 2013; Logan, Golet, and Lutcavage 2015; W. Golet et al. 2015), and marine mammals (L. A. Smith et al. 2015). Consumption of herring by predators has been extensively studied in this ecosystem (W. J. Overholtz, Link, and Suslowicz 2000; W. J. Overholtz and Link 2007), and multiple methods were evaluated to include this consumption within the most recent herring benchmark stock assessment (NEFSC 2012). Much of this information was presented at the first stakeholder workshop in May 2016.

## Predator modeling objectives for the herring MSE

We note that the general objective for the Council was to answer “how do changes in herring population abundance affect predator populations?” This is a different and more complex question than that addressed in the 2012 herring assessment “how much herring is consumed by predators?” Council specifications and time constraints did not permit development of integrated multispecies models (existing models account for predation mortality on herring, but not “bottom up” herring impacts on predators), nor spatial or seasonal models accounting for migrations of wide-ranging predators into or out of the Northeast US shelf ecosystem. At the initial stakeholder workshop, it was agreed that separate “general predator” models linked to herring would be a reasonable approach, with the goal of developing one model for each of the four predator categories: highly migratory fish, groundfish, seabirds, and marine mammals.

Predators were therefore modeled with fairly simple delay-difference population dynamics that allowed different predator population processes to be dependent on some aspect of herring population status, following (Plagányi and Butterworth 2012). Each predator model takes output from the herring OM as input, and outputs performance metrics identified at the stakeholder workshop as in Fig. 2. While this allows “bottom up” effects of herring on predators to be examined, this configuration does not consider “top down” effects of predators on herring, or simultaneous interactions of multiple predators with herring.

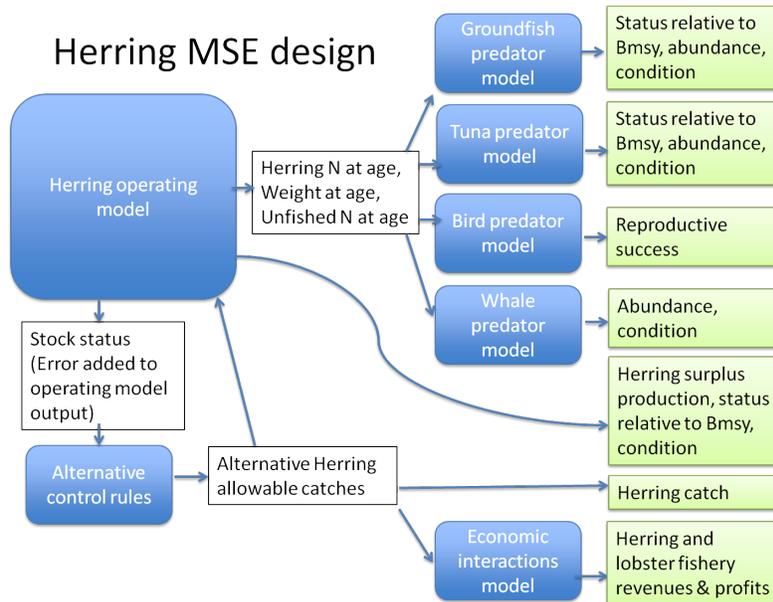


Figure 2: Herring MSE information flow

## Summary of herring MSE predator modeling objectives

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### **Predator models ARE:**

- \* Focused on evaluating stock-wide herring ABC harvest control rules applied annually
- \* Developed balancing Council/ stakeholder specifications and time constraints of MSE
- \* Based on information from the Northeast US shelf and most recent stock assessments

### **Predator models ARE NOT:**

- \* Spatial, do not address local scale or seasonal dynamics
  - \* New or full stock assessments
  - \* Accounting for any impacts on predators other than changes due to herring control rules
  - \* Intended to predict actual predator population dynamics
- 

## Methods

There are two components of predator modeling for the herring MSE: a predator population model, and a herring-predator relationship model to link herring with predator populations. Here, we give an overview of the modeling process, and we describe the decisions made in parameterizing individual predator models and herring-predator relationships in the following sections. The overall population in numbers for each predator each year  $N_y$  is modeled with a delay-difference function:

$$N_{y+1} = N_y S_y + R_{y+1}, \quad (1)$$

where annual predator survival  $S_y$  is based on annual natural mortality  $v$  and exploitation  $u$

$$S_y = (1 - v_y)(1 - u), \quad (2)$$

and annual recruitment  $R_y$  (delayed until recruitment age  $a$ ) is a Beverton-Holt function:

$$R_{y+a} = \frac{\alpha B_y}{\beta + B_y}. \quad (3)$$

Predator recruitment parameters are defined with steepness =  $h$ , unfished recruitment  $R_{F=0}$ , and unfished spawning biomass  $B_{F=0}$  as

$$\alpha = \frac{4hR_{F=0}}{5h - 1}, \text{ and} \quad (4)$$

$$\beta = \frac{(B_{F=0}/R_{F=0})((1 - h)/(4h))}{(5h - 1)/(4hR_{F=0})} \quad (5)$$

.

Predator population biomass is defined with Ford-Walford plot intercept ( $FWint$ ) and slope ( $FWslope$ ) growth parameters

$$B_{y+1} = S_y(FWintN_y + FWslopeB_y) + FWintR_{y+1} \quad (6)$$

Parameterizing this model requires specification of the stock-recruitment relationship (steepness  $h$  and unfished spawning stock size in numbers or biomass), the natural mortality rate, the fishing mortality (exploitation) rate, the initial population size, and the weight at age of the predator (Ford-Walford plot intercept and slope parameters). For each predator, population parameters were derived from different sources (Tab. 1).

Table 1. Predator population model specification and parameter sources

	Highly migratory	Seabird	Groundfish	Marine mammal
Stakeholder preferred species	Bluefin tuna	Common tern	not specified	not specified
Species modeled	Bluefin tuna (western Atlantic stock)	Common tern (Gulf of Maine colonies as defined by the GOM Seabird Working Group)	Spiny dogfish (GOM and GB cod stocks also examined)	none, data limited (Minke & humpback whales, harbor porpoise, harbor seal examined)
Stock-recruitment	Current assessment and literature	Derived from observations	Current assessment and literature	No time series data for our region
Natural mortality	Current assessment	Literature	Current assessment	Derivable from assessment?
Fishing mortality	Current assessment	n/a	Current assessment	Derivable from assessment?
Initial population	Current assessment	Derived from observations	Current assessment	Derivable from assessment?
Weight at age	Literature	Literature	Literature	Literature

Predator population models were based on either the most recent stock assessment for the predator or from observational data from the Northeast US shelf. Herring-predator relationships were based on either peer-reviewed literature or observational data specific to the Northeast US shelf. We did not include process or observation error in any of these modeled relationships. This is obviously unrealistic, but the primary objective of the herring MSE is to evaluate the effect of herring management on predators. Leaving out variability driven by anything other than herring is intended to clarify the effect of herring management.

To develop the herring-predator relationship model, specific herring population characteristics (e.g. total abundance or biomass, or abundance/biomass of certain ages or sizes) were related to either predator growth, predator reproduction, or predator survival. Our aim was to use information specific to the Northeast US shelf ecosystem, either from peer-reviewed literature, from observations, or a combination.

In general, if support for a relationship between herring and predator recruitment was evident, it was modeled as a predator recruitment multiplier based on the herring population ( $Hpop_y$ ) relative to a specified threshold  $Hthresh$ :

$$R_{y+a} = \frac{\alpha B_y}{\beta + B_y} * \frac{\gamma(Hpop_y/Hthresh)}{(\gamma - 1) + (Hpop_y/Hthresh)}, \quad (7)$$

where  $\gamma > 1$  links herring population size relative to the threshold level to predator recruitment.

If a relationship between predator growth and herring population size was evident, annual changes in growth were modeled by modifying either the Ford-Walford intercept ( $AnnAlpha$ ) or slope ( $AnnRho$ ):

$$B_{y+1} = S_y(AnnAlpha_y N_y + FWslope B_y) + AnnAlpha_y R_{y+1}, \text{ or} \quad (8)$$

$$B_{y+1} = S_y(FWint N_y + AnnRho_y B_y) + FWint R_{y+1}. \quad (9)$$

Finally, herring population size  $Hpop_y$  could be related to predator survival using a multiplier on constant predator annual natural mortality  $v$ :

$$v_y = v e^{-\left(\frac{Hpop_y}{Hpop_{F=0}}\right)\delta}, \quad (10)$$

where  $0 < \delta < 1$  links herring population size to predator survival.

After specifying the population model parameters and herring-predator relationship, we applied the (Hilborn and Walters 2003) equilibrium calculation for the delay difference model with  $F=0$  to get the unfished spawners per recruit ratio. This ratio was then used in a new equilibrium calculation with the current predator exploitation rate to estimate Beverton-Holt stock recruitment parameters, equilibrium recruitment and equilibrium individual weight under exploitation. Then, each model was run forward for 150 years with output from the herring operating model specifying the herring population characteristics.

## Highly migratory species

Bluefin tuna were identified at the stakeholder workshop as the recommended highly migratory herring predator.

### Tuna population model

Western Atlantic bluefin tuna population parameters were drawn from the 2014 stock assessment (ICCAT 2015), the growth curve from (Restrepo et al. 2010), and recruitment parameters from a detailed examination of alternative stock recruit relationships (Porch and Lauretta 2016). Ultimately, the “low recruitment” scenario was selected to represent bluefin tuna productivity in the Gulf of Maine, which defines  $Bmsy$  as 13,226 t and therefore affects measures of status relative to  $Bmsy$ . Continuation of the current tuna fishing strategy ( $F < 0.5Fmsy$  under the low recruitment scenario) is assumed. All predator population model parameters are listed in Table 2.

### Herring-tuna relationship model

Tuna diets are variable depending on location and timing of foraging (Chase 2002; W. J. Golet et al. 2013; Logan, Golet, and Lutcavage 2015; W. Golet et al. 2015), but for the purposes of this analysis, we assumed that herring is an important enough prey of tuna to impact tuna growth in the Northeast US shelf ecosystem. A relationship between bluefin tuna growth and herring average weight was implemented based on information and methods in W. Golet et al. (2015). The relationship between tuna condition anomaly (defined as proportional departures from the weight-at-length relationship used in the assessment) and average weight of tuna-prey-sized herring ( $Havgwt_y$ , herring  $> 180$  mm collected from commercial herring fisheries) was modeled as a generalized logistic function with lower and upper bounds on tuna growth parameters:

$$AnnAlpha_y = (0.9FWint) + \frac{(1.1FWint) - (0.9FWint)}{1 + e^{(1-\lambda)*(100(Havgwt_y - T)/T)}}, \quad (11)$$

where  $\lambda > 1$  links herring average weight anomalies to tuna growth.

The inflection point of  $T = 0.15$  kg average weight matches the 0 tuna weight anomaly in W. Golet et al. (2015) (p. 186, Fig 2C), and upper and lower bounds were determined by estimating the growth intercept with weight at age 10% higher or lower, respectively from the average weight at age obtained by applying the length to weight conversion reported in the 2014 stock assessment (ICCAT 2015) to the length at age estimated from the Restrepo et al. (2010) growth curve (Fig 3). When included in the model with  $\lambda = 1.1$  in equation 11, the simulated variation in tuna weight at age covered the observed range reported in W. Golet et al. (2015).

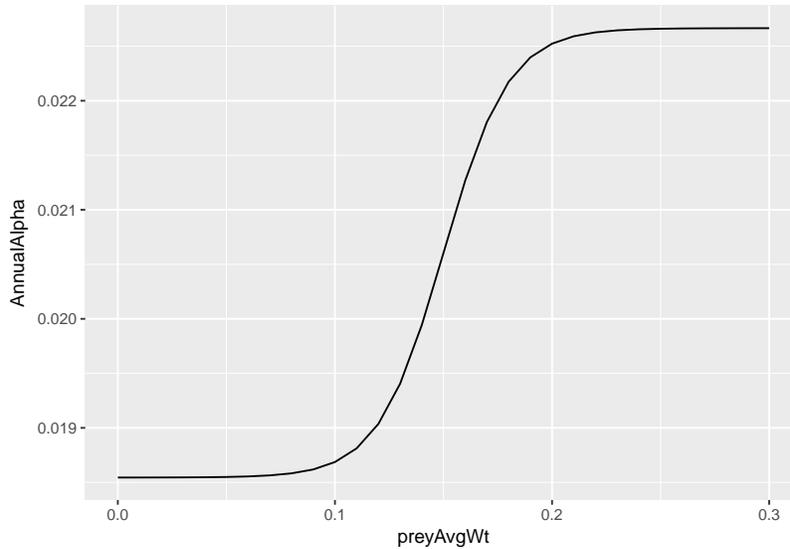


Figure 3: Modeled herring average weight-tuna growth relationship

## Seabirds

Common terns were identified at the stakeholder workshop as the recommended seabird herring predator.

### Tern population model

There is no published stock assessment or population model for most seabirds in the Northeast US. Therefore, Gulf of Maine Common and Arctic tern population parameters were drawn from accounts in the Birds of North America (Hatch 2002; Nisbet 2002) and estimated from counts of breeding pairs and estimates of fledgling success summarized by the Gulf of Maine Seabird Working Group (GOMSWG; data at <http://gomswg.org/minutes.html>), as corrected and updated by seabird experts from throughout Maine. While we analyzed both Arctic and Common tern information, the stakeholder workshop identified Common terns as the example species for modeling, and this species has more extensive data and a generally higher proportion of herring in its diet based on that data. Therefore, the model is based on common terns in the Gulf of Maine.

Adult breeding pairs by colony were combined with estimated productivity of fledglings per nest to estimate the annual number of fledglings for each year. A survival rate of 10% was applied to fledglings from each year to represent “recruits” to the breeding adult population age 4 and up (Nisbet 2002). This “stock-recruit” information was used to estimate steepness for the delay difference model based on common tern information only. Fitting parameters with R nls (R Core Team 2016) had variable success, with the full dataset unable to estimate a significant beta parameter (cyan line, Fig. 4) for common terns, and a truncated dataset resulting in low population production rates inconsistent with currently observed common tern trends (bright green line overlaid with black, Fig. 4). Therefore, steepness was estimated to give a relationship (black line, Fig. 4) falling between these two lines. The resulting stock recruit relationship set steepness at 0.26, a theoretical maximum breeding adult population of 45,000 pairs (Nisbet (2002), 1930’s New England population), and a theoretical maximum recruitment of 4,500 individuals annually (reflecting approximately a productivity of 1.0 at “carrying capacity” resulting in a stable population). Average common tern productivity is 1.02 (all GOM colony data combined). Adult mortality was assumed to be 0.1 for the delay difference model (survival of 90% (Nisbet 2002) for adults).

Tern stock and recruitment assuming 10% fledgling→adult survival

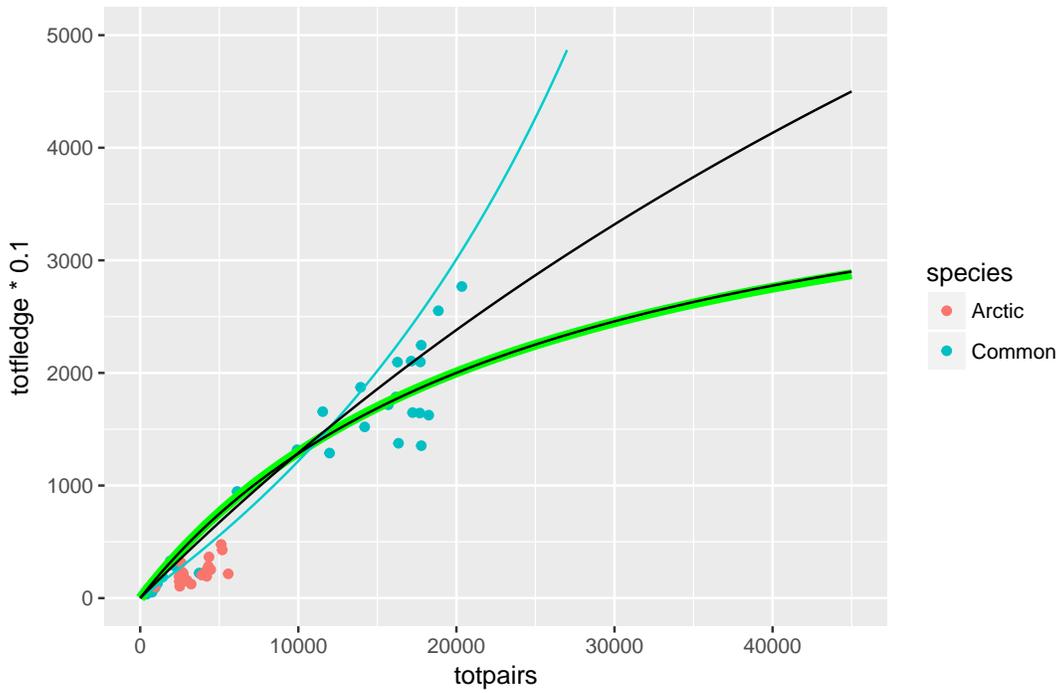


Figure 4: Stock-recruitment function for Gulf of Maine common terns

The resulting model based on common tern population dynamics in the Gulf of Maine (with no link to herring) predicts that the population will increase to its carrying capacity under steady conditions over a 150 year simulation. The actual population has increased at ~2% per year between 1998 and 2015 (Fig. 5). Given the lack of detailed demographic information in the delay-difference model, this was considered a good representation of the average observed trend in current common tern population dynamics.

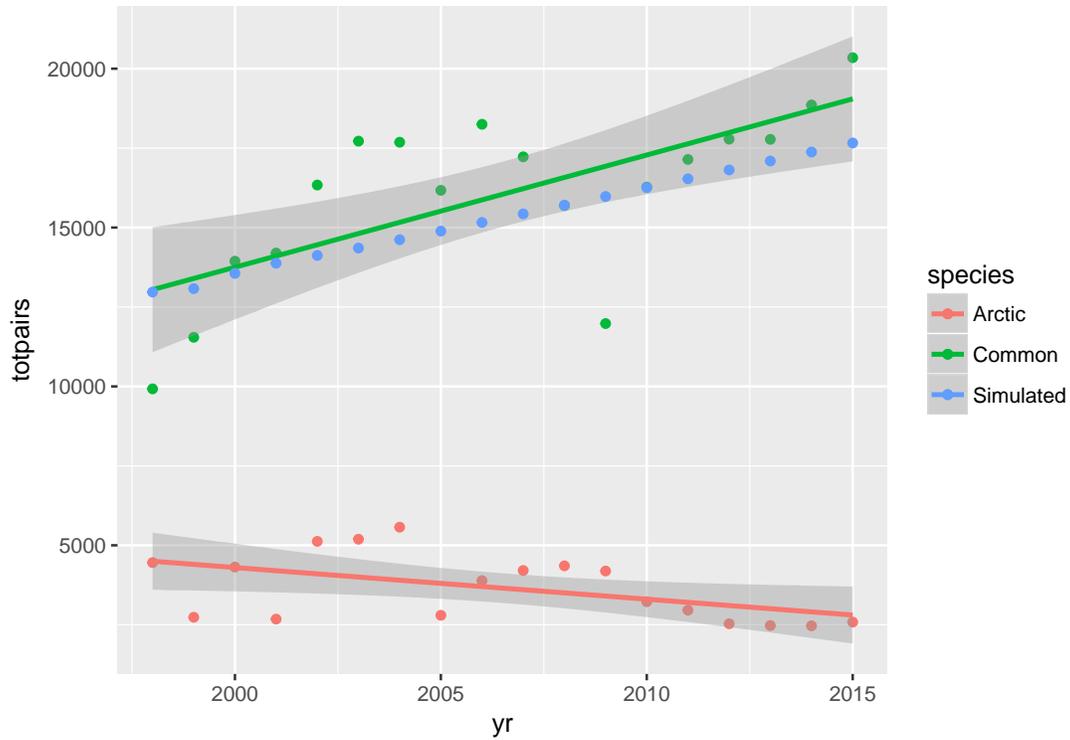


Figure 5: Population trends for Gulf of Maine terns, no herring link

### Herring-tern relationship model

The relationship between herring abundance and tern reproductive success was built based on information from individual colonies on annual productivity, proportion of herring in the diet, and amount of herring in the population as estimated by the current stock assessment. Since little of this information has appeared in the peer-reviewed literature, we present it in detail here. First, productivity information was evaluated by major diet item recorded for chicks over all colonies and years. In general, common tern productivity was higher when a streamlined fish species was the major diet item relative to invertebrates, but having herring as the major diet item resulted in about the same distribution of productivities as having hake or sandlance as the major diet item for these colonies (Fig. 6).

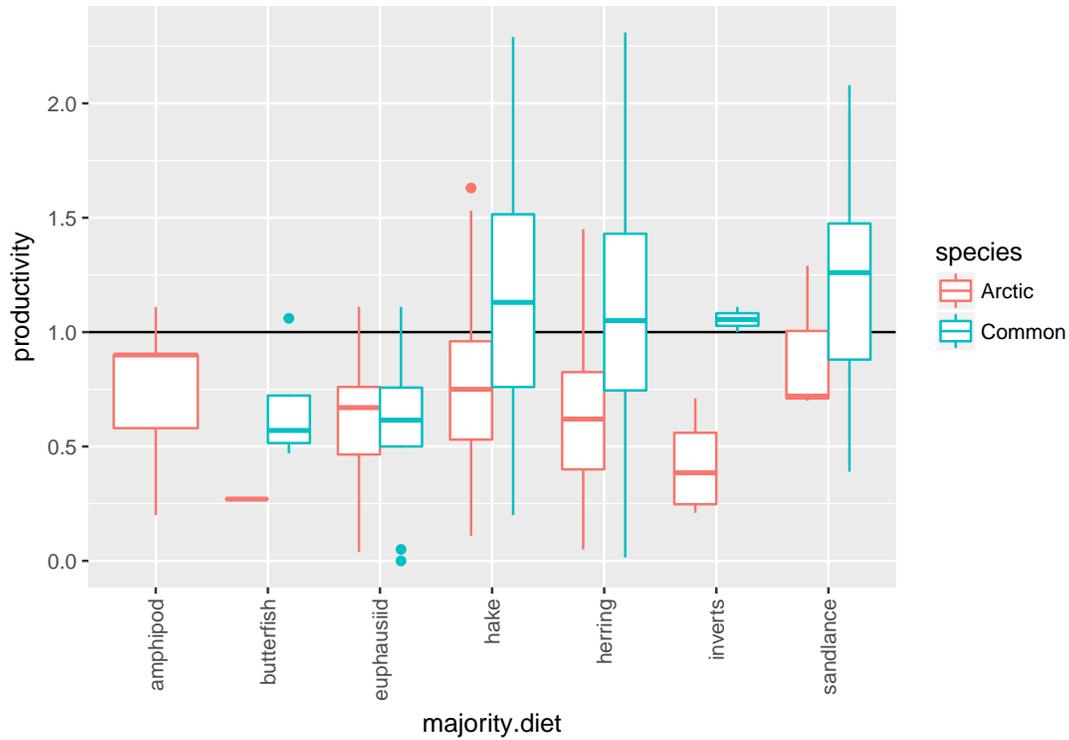


Figure 6: Major diet items for Gulf of Maine tern fledgelings

Individual colonies showed different trends in number of nesting pairs, productivity, and proportion of herring in the diet (plots available upon request). When both Arctic and Common terns shared a colony, interannual changes in productivity were generally similar between species, suggesting that conditions at and around the colony (weather, predation pressure, and prey fields) strongly influenced productivity rather than species-specific traits. Only two colonies (Machias Seal Island near the Canadian Border and Stratton Island in southern Maine) showed a significant positive correlation between the proportion of herring in the chick diet and productivity. Other islands showed either non-significant (no) relationships, or in one case (Metinic Island) a significant negative relationship (Fig. 7).



Figure 7: Herring proportion in diet and tern productivity by colony

The estimated population size of herring on the Northeast US shelf had some relationship to the amount of herring in tern diet at several colonies (4 of 13 common tern colony diets related to herring Age 1 recruitment, 6 of 13 common tern colony diets related to herring total B, and 4 of 13 common tern colony diets related to herring SSB; detailed statistics and plots available upon request). However, statistically significant direct relationships between herring population size and tern productivity were rare, with only Ship Island productivity increasing with herring total B, and Eastern Egg Rock, Matinicus Rock, Ship, and Monomoy Islands productivity increasing with herring SSB. Given that Monomoy Island tern chicks consistently received the lowest proportion of herring in their diets of any colony (0-11%), we don't consider this relationship further to build the model.

Based on tern feeding observations, we would expect the number of age 1 herring in the population to be most related to tern productivity since that is the size class terns target, but this relationship was not found in analyzing the data. Herring total biomass was positively related to tern diets at nearly half of the colonies, and reflects all size classes including the smaller sizes most useful as tern forage, but was only directly related to tern productivity at one colony. Herring SSB was not considered further as an index of tern prey because it represents sizes larger than tern forage.

To represent the potential for herring to influence tern productivity, we parameterized a tern "recruitment multiplier" based on herring assessed total biomass and common tern productivity across all colonies (except Monomoy where terns eat sandlance). This relationship includes a threshold herring biomass where common tern productivity would drop below 1.0, and above that threshold productivity exceeds 1.0 (Fig. 8). The threshold of ~400,000 tons is set where a linear relationship between herring total biomass and common tern productivity crosses productivity=1 (black dashed line in Fig. 8). However, the selected threshold is uncertain because there are few observations of common tern productivity at low herring total biomass (1975-1985). The linear relationship does not have a statistically significant slope; a curve was fit to represent a level contribution of herring total biomass to common tern productivity above the threshold. The curve descends below the threshold, dropping below 0.5 productivity at around 50,000 tons and representing the extreme assumption that herring extinction would result in tern productivity of 0. Although the relationship

of tern productivity to herring biomass at extremely low herring populations has not been quantified, control rules that allow herring extinction do not meet stated management objectives for herring, so this extreme assumption for terns will not change any decisions to include or exclude control rules.



Figure 8: Modeled influence of herring total biomass on tern reproductive success

When included in the model using  $\gamma = 1.09$  in equation 7, this relationship adjusts the modeled common tern population increase to match the current average increase in common tern nesting pairs observed in the data (Fig. 9). There is still considerable uncertainty around this mean population trajectory which cannot be reflected in our simple model.

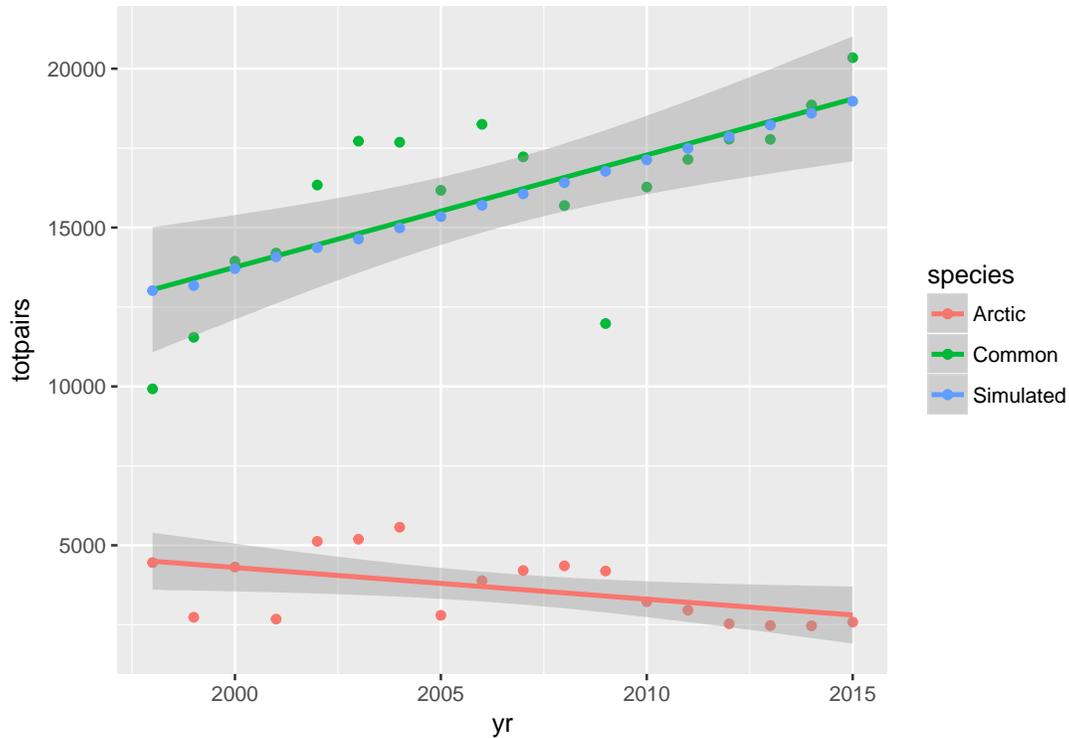


Figure 9: Population trends for Gulf of Maine terns with simulated herring-common tern productivity relationship

## Groundfish

Because no specific groundfish was identified as a representative herring predator during the stakeholder workshop, the first decision was which groundfish to model. Annual diet estimates (based on sample sizes of ~100+ stomachs) are available for the top three groundfish predators of herring (those with herring occurring in the diets most often in the entire NEFSC food habits database): spiny dogfish, Atlantic cod, and silver hake. Cod and spiny dogfish were considered first because their overall diet proportions of herring are higher, and because silver hake has the least recently updated assessment. Diet compositions by year were estimated for spiny dogfish, Georges Bank cod, and Gulf of Maine cod to match the scale of stock assessments. Full weighted diet compositions were estimated, and suggest considerable interannual variability in the herring proportion in groundfish diets (filled blue proportions of bars in Fig. 10).

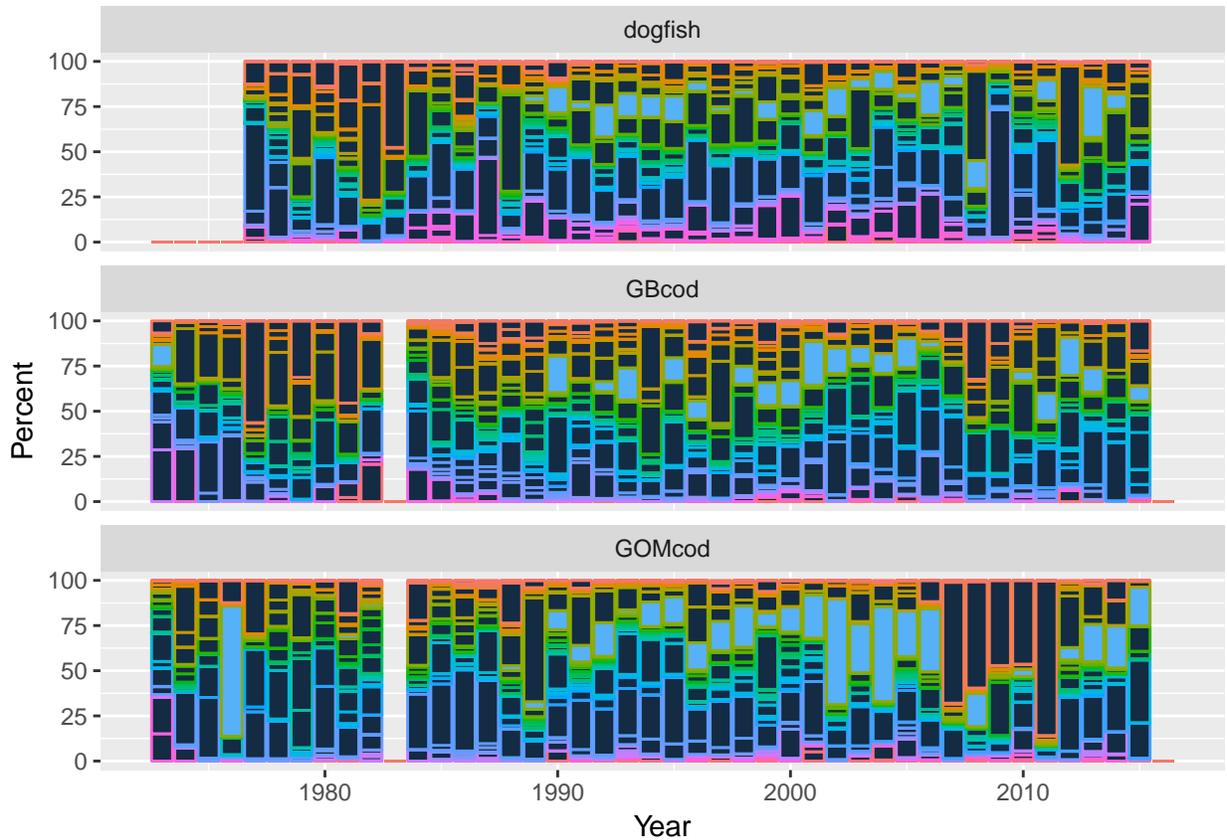


Figure 10: Annual diet compositions for major groundfish predators of herring estimated from NEFSC food habits database

Some interannual variation in diet may be explained by changing herring abundance. Dogfish and both cod stocks had positive relationships between the amount of herring observed in annual diets and the size of the herring population according to the most recent assessment (statistics and plots available upon request). This suggests that these groundfish predators are opportunistic, eating herring in proportion to their availability in the ecosystem. However, monotonically declining cod populations for both GOM and GB cod stocks resulted in either no herring-cod relationship, or a negative relationship between herring populations and cod populations (Fig. 11). Only dogfish spawning stock biomass had a positive relationship with the proportion of herring in dogfish diet. Therefore, we selected dogfish as the groundfish predator for modeling.

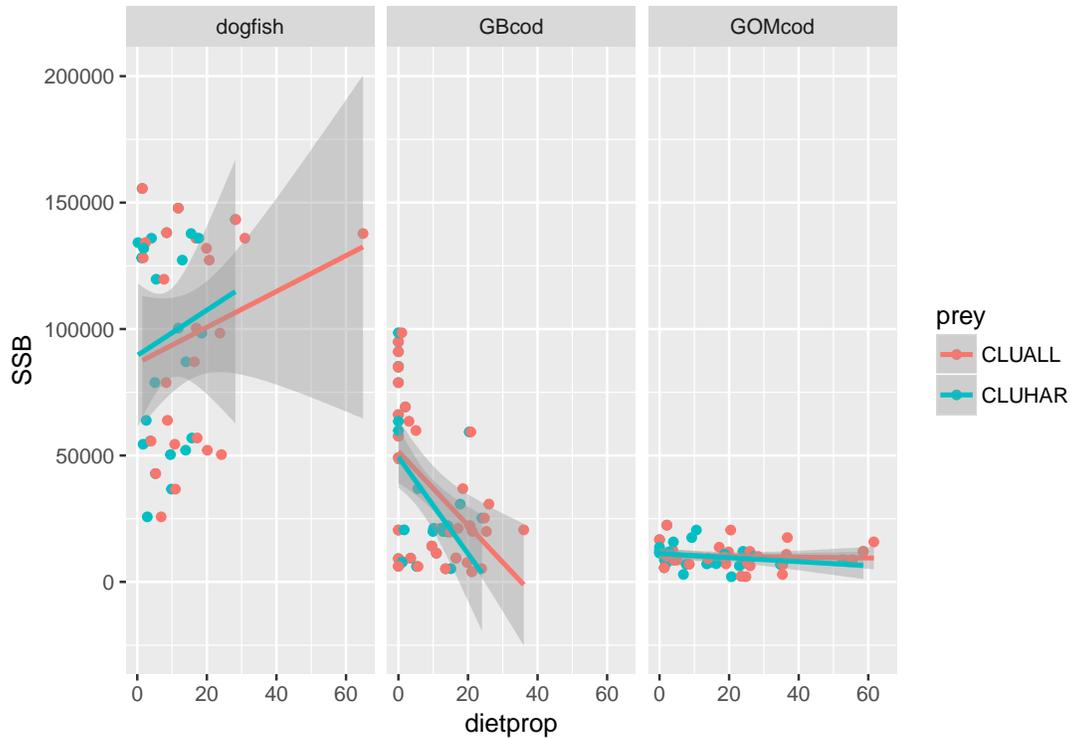


Figure 11: Relationship of assessed groundfish spawning stock biomass (SSB) with the proportion of herring in diet

### Dogfish population model

The dogfish model stock recruitment function, initial population, and annual natural mortality were adapted from information in (P. J. Rago et al. 1998; P. J. Rago and Sosebee 2010; Bubley et al. 2012; P. Rago and Sosebee 2013). Due to differential growth and fishing mortality by sex, our model best represents female dogfish (a split-sex delay difference model was not feasible within the time constraints of this MSE). Further, dogfish stock-recruit modeling to date based on Ricker functions (P. J. Rago and Sosebee 2010) captures more nuances in productivity than the Beverton-Holt model we used. Our recruitment parameterization reflects a stock with generally low productivity and relatively high resilience, which we recognize is a rough approximation for a species such as dogfish. The annual fishing exploitation rate applied is average of the catch/adult female biomass from the most recent years of the 2016 data update provided to the Mid-Atlantic Fishery Management Council (Rago pers comm).

### Herring-dogfish relationship model

There was a weak positive relationship between dogfish total biomass and herring total biomass from the respective stock assessments (Fig. 12), but no clear relationship between dogfish weight or dogfish recruitment and herring population size. During the recent period of relatively low dogfish recruitment (1995-2007), there is a positive relationship between dogfish pup average weight and herring proportion in diet, suggesting a potential growth and or recruitment mechanism; however this relationship does not hold throughout the time series (Fig. 12).

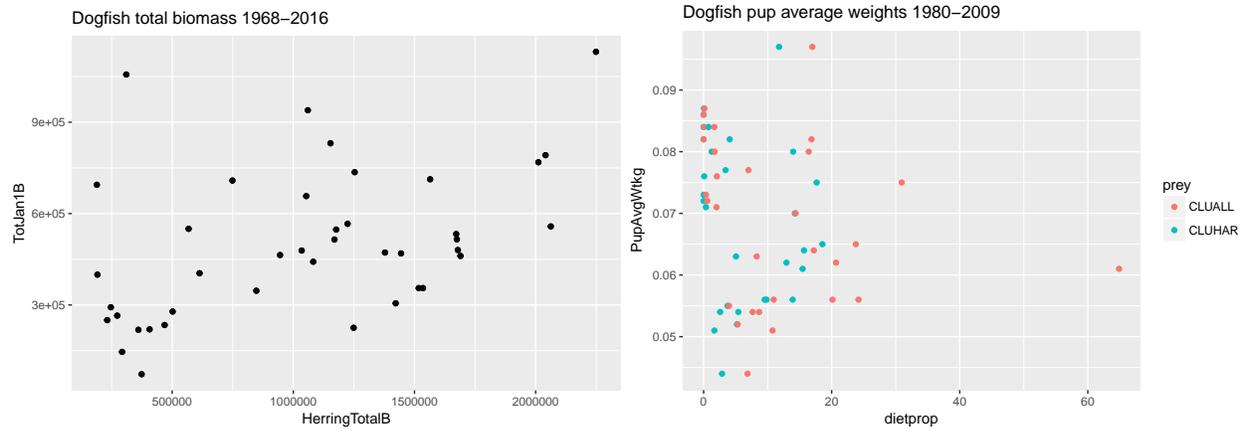


Figure 12: Dogfish population relationships with herring total biomass (left) and herring proportion in diet (right)

Therefore, to simulate a potential positive relationship between herring and dogfish, we assumed that dogfish survival increased (natural mortality was reduced) by an unspecified mechanism as herring abundance increased (Fig. 13). Because dogfish are fully exploited by fisheries in this model, the impact of this change in natural mortality on total survival has small to moderate benefits to dogfish population numbers and biomass. Using a  $\delta = 0.2$  in equation 10 results in weak increases in dogfish biomass with herring abundance consistent with observations.

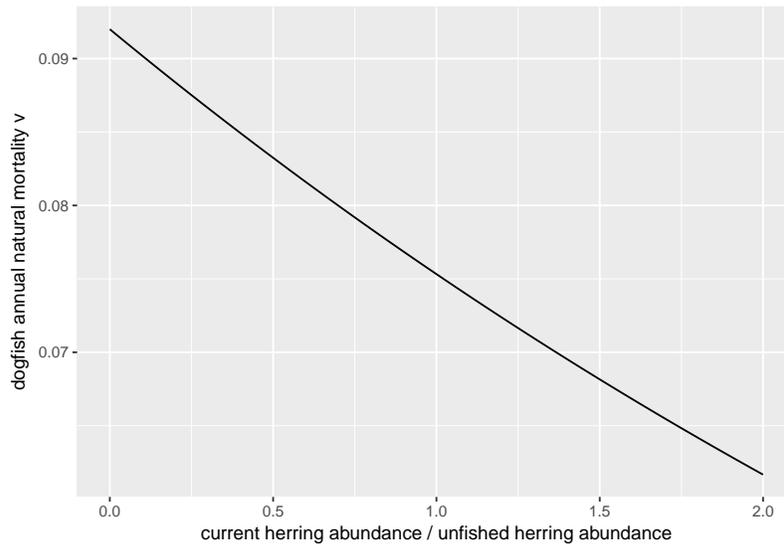


Figure 13: Modeled herring relative population size-dogfish natural mortality relationship

## Marine mammals

Because no specific marine mammal was identified as a representative herring predator in the stakeholder workshop, as with groundfish, the first decision was which marine mammal to model. Diet information for a wide range of marine mammals on the Northeast US shelf suggests that minke whales, humpback whales, harbor seals, and harbor porpoises have the highest proportions of herring in their diets (L. A. Smith et al. 2015), and therefore may show some reaction to changes in the herring ABC control rule.

While some food habits data existed for marine mammals, consultation with marine mammal stock assessment scientists at the Northeast Fisheries Science Center confirmed that no data were available to parameterize a stock-recruitment relationship for any of these marine mammal species in the Northeast US region, and no such information was available in the literature for stocks in this region. Although it may be possible to develop stock-recruitment models for one or more of these species in the future, it was not possible within the time frame of the herring MSE. Therefore, we were unable to model marine mammals within the same framework as other predators.

Potential effects of changes in herring production and/or biomass on marine mammals were instead evaluated using an updated version of an existing food web model for the Gulf of Maine (Jason Link et al. 2008; Jason Link et al. 2009; J.S. Link et al. 2006) and incorporating food web model parameter uncertainty. Overall, food web modeling showed that a simulated increase in herring production in the Gulf of Maine may produce modest but uncertain benefits to marine mammal predators, primarily because increased herring was associated with decreases in other forage groups also preyed on by marine mammals. Please see Appendix 1 of this document for full analyses and results.

## Summary of predator model input parameters

Table 2. Predator model input parameters

Parameter	Tuna	Tern	Dogfish
Numbers or Weight?	Weight	Numbers	Weight
Unfished spawning pop	6.69E+04	45000	300000
Steepness $h$	1.0	0.26	0.97
Annual nat. mortality $v$	0.14	0.1	0.092
Annual exploitation $u$	0.079	0.00	0.092
Growth intercept $FW_{int}$	0.020605	0.00015	0.000278
Growth slope $FW_{slope}$	0.9675	0.0	0.9577
Initial abundance	111864	3000	49629630
Initial biomass	27966	1.5	134000
Recruit delay (age) $a$	1	4	10
Prey-recruitment link	1 (off)	1.09	1 (off)
Prey-mortality link	0 (off)	0 (off)	0.2
Prey-growth link	1.1	1 (off)	1 (off)

## Output metrics

Predator performance metrics included those described at the stakeholder workshop, as well as several others drawn from MSE best practices (Punt et al. 2016). The herring MSE included 8 herring operating models (described fully in Deroba’s Technical Details document); for each operating model 5,460 control rules were tested. For each control rule, 100 replicate simulations reflecting stochastic herring recruitment variability were run for 150 years each. Each of these simulated time series was passed to each predator model, resulting in outputs as described below using the equations above.

All predator performance metrics were calculated based on the final 50 years of each replicate simulation. For all metrics other than “frequency of good status” metrics, we took the median value over the final 50 years of each replicate simulation. Then, the 25th percentile, the median, and the 75th percentile of these 100 medians were calculated to represent the performance metric for a particular control rule. Results reported here focus on the median.

## **Biomass, Abundance, Recruitment**

Population abundance and recruitment in numbers were output for all modeled predators. Population biomass was output for tuna and dogfish. These quantities were directly output by the models.

## **Predator condition**

Stakeholders expressed interest in predator condition for fish and marine mammal predators at the first workshop. While delay difference models do not track individuals or age cohorts, a measure of population average weight (population biomass/population numbers) was output for tuna and dogfish.

## **Predator productivity**

Productivity, the number of fledglings per breeding pair, was output for the tern model. Productivity was calculated as recruitment times 10 (to account for the 10% survival rate of fledglings to adults) divided by tern abundance 4 years earlier in the simulation.

## **Status relative to thresholds**

Stakeholders were interested in different measures of population status depending on the predator. For commercially fished species, status relative to current management reference points was preferred. Tuna and dogfish biomass was divided by a biomass reference point specified in current stock assessments: tuna  $SSB_{MSY}$  was 13226 (ICCAT 2015), and dogfish  $SSB_{MSY}$  was 159288 (P. J. Rago and Sosebee 2010). Because dogfish were fully exploited in our model, they did not reach  $SSB_{MSY}$ , so we also evaluated status relative to  $0.5 SSB_{MSY}$  (“overfished”). Tuna condition status was assessed by dividing the output population average weight with the equilibrium average weight. Common tern colonies are managed to improve productivity, so stakeholders suggested that a common tern productivity level of 0.8 would be a minimum threshold, while a productivity of 1.0 would be a target. In addition, total population status was measured relative to current population numbers using the rationale that maintaining at least the current population was desirable. The average common tern population of nesting pairs (including Monomoy) from 1998-2015 was 16000.

## **Frequency of good status**

Evaluating the frequency of desirable or undesirable states over the course of a simulation is suggested by Punt et al. (2016). We calculated two metrics for each of the status determinations. First, we calculated the minimum number of years in any individual simulation that a metric was above a given threshold. This is a “worst case scenario” metric. Second, we calculated the median proportion of years across all simulations for a control rule that were above the threshold. This is an “average performance” metric addressing how often good status is maintained.

# **Results**

Predator metrics had different levels of sensitivity to herring population changes resulting from different ABC control rules combined with the uncertainties represented in each herring operating model. Here we summarize all predator metric results across all herring operating models and control rules to demonstrate the rationale for keeping only the most sensitive predator metrics in the full MSE results.

## Tuna general results

Simulated tuna biomass, numbers, and recruitment were similar across all herring operating models and control rules. Biomass was the only metric that changed with different herring control rules due to changes in average weight. There was some variation in biomass status, but the median was always above the threshold. Tuna average weight was both above and below the equilibrium weight threshold across all models. Metrics for frequency of good status also reflected the sensitivity of tuna average weight (Fig. 14).

Tuna metrics: median over all operating models and control rules

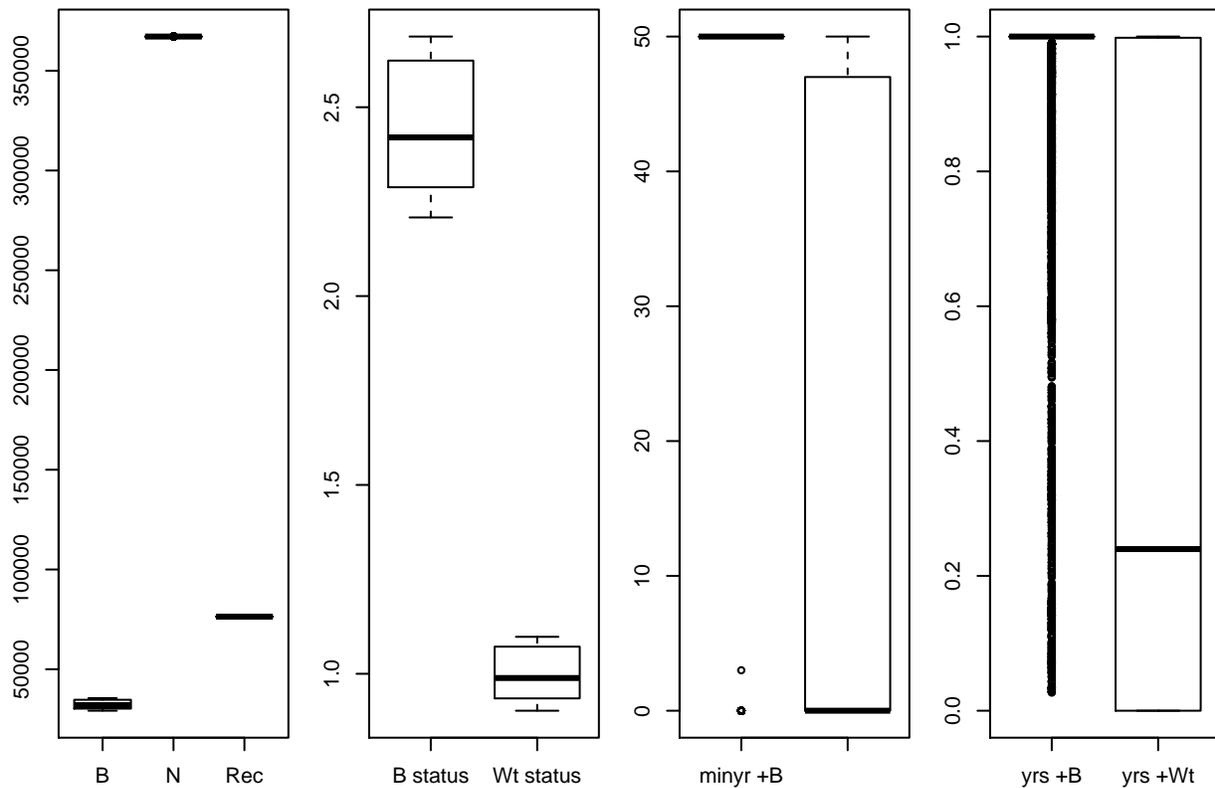


Figure 14: Summary of tuna performance metrics across all herring operating models and control rules

A comparison of the most sensitive tuna metric, average weight status, across herring operating models demonstrates that operating model configuration drives tuna average weight. Separating operating models with historical herring weight at age (OldWt) from those with recent weight at age (RecWt) demonstrates the primary contrast in tuna results. After this difference in operating models is accounted for, there is far less contrast in the median performance of different control rules for tuna (Fig. 15).

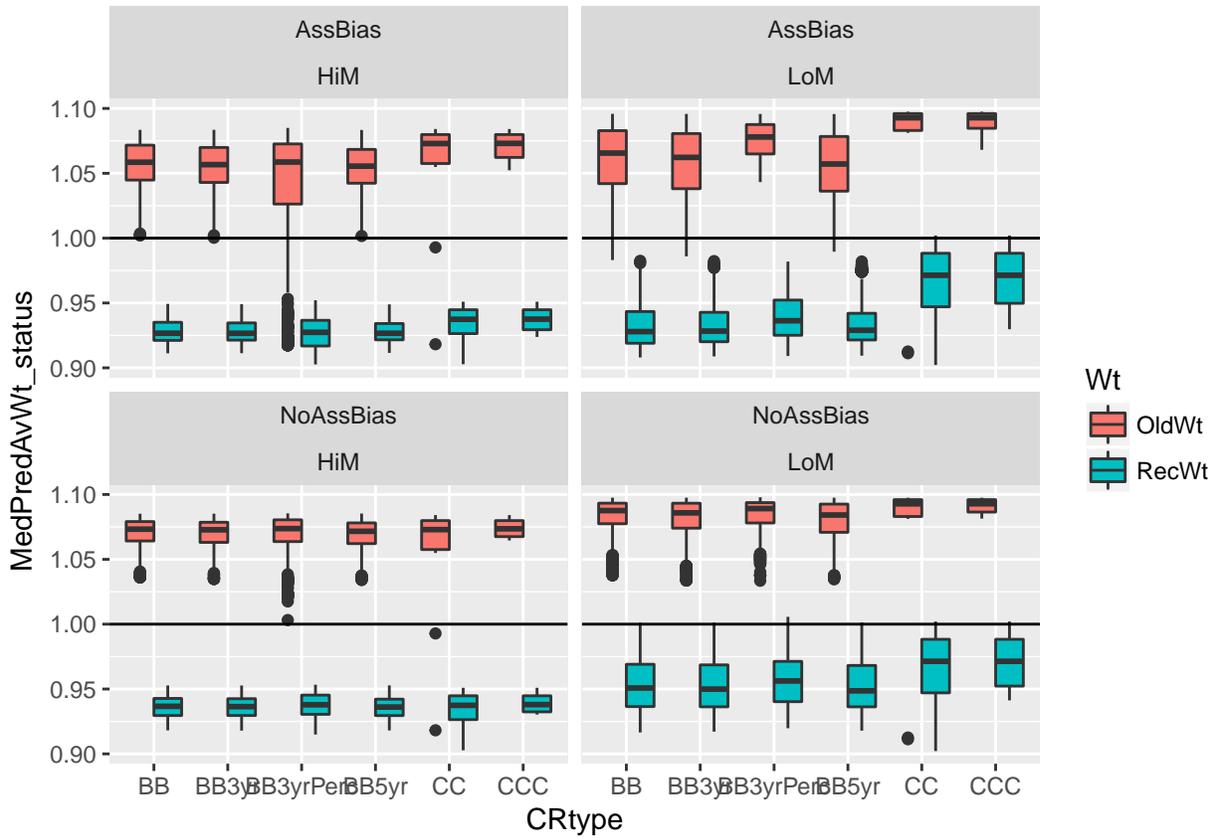


Figure 15: Tuna average weight status by herring operating model group and control rule type

## Tern general results

Simulated tern population metrics were more variable across all operating models and control rules than tuna metrics. However, the median values for these metrics generally indicated relatively high population levels (above current levels), with good recruitment and productivity at or over 1 for most control rules. Summary plots show fairly long tails of median values well below good status for the metrics for some control rules (Fig. 16).

Terns metrics: median over all operating models and control rules

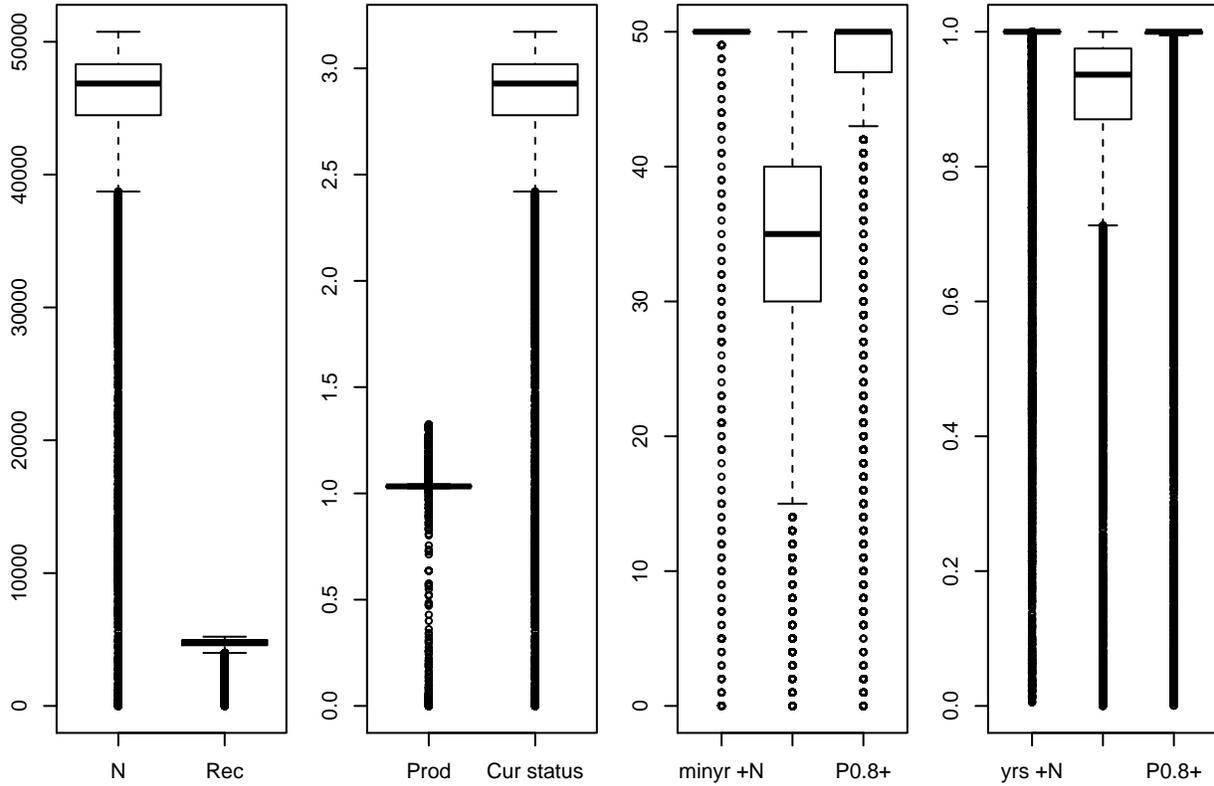


Figure 16: Summary of tern performance metrics across all herring operating models and control rules

Examining tern productivity results by operating model shows little contrast across operating model uncertainties, but differences in performance between control rule types. The biomass-based control rule implemented for 3 years with a constraint of 15% change between specifications (BB3yrPerc) showed a wide range of variability in performance across control rule variants, as did the constant catch (CC) control rules (Fig. 17). For terns, herring weight at age had little effect on results, so those operating models are combined here.

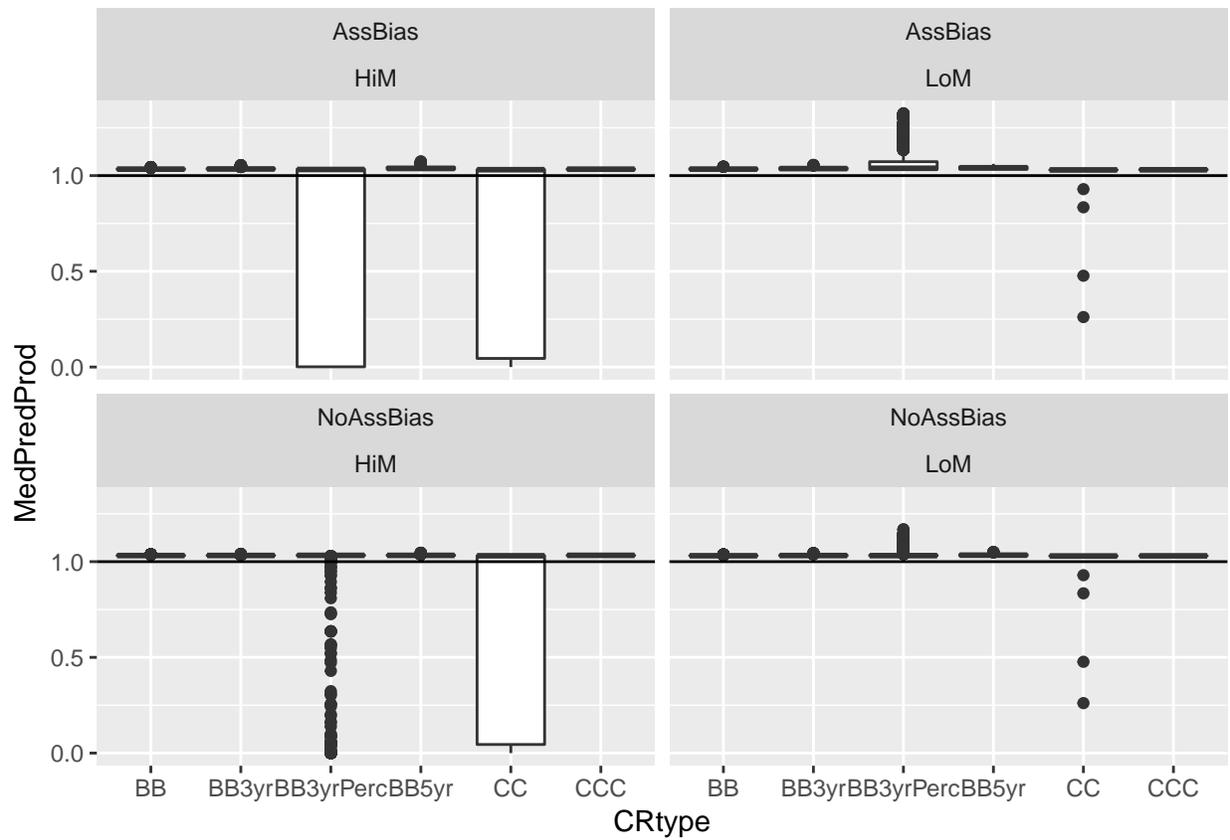


Figure 17: Tern productivity by herring operating model group and control rule type

### Dogfish general results

Simulated dogfish population metrics showed less variation across all herring operating models and control rules combined relative to tuna and terns. Median biomass status never reaches 1 (above  $B_{msy}$ ) but never drops below 0.5 (overfished status; Fig. 18).

Dogfish metrics: median over all operating models and control rules

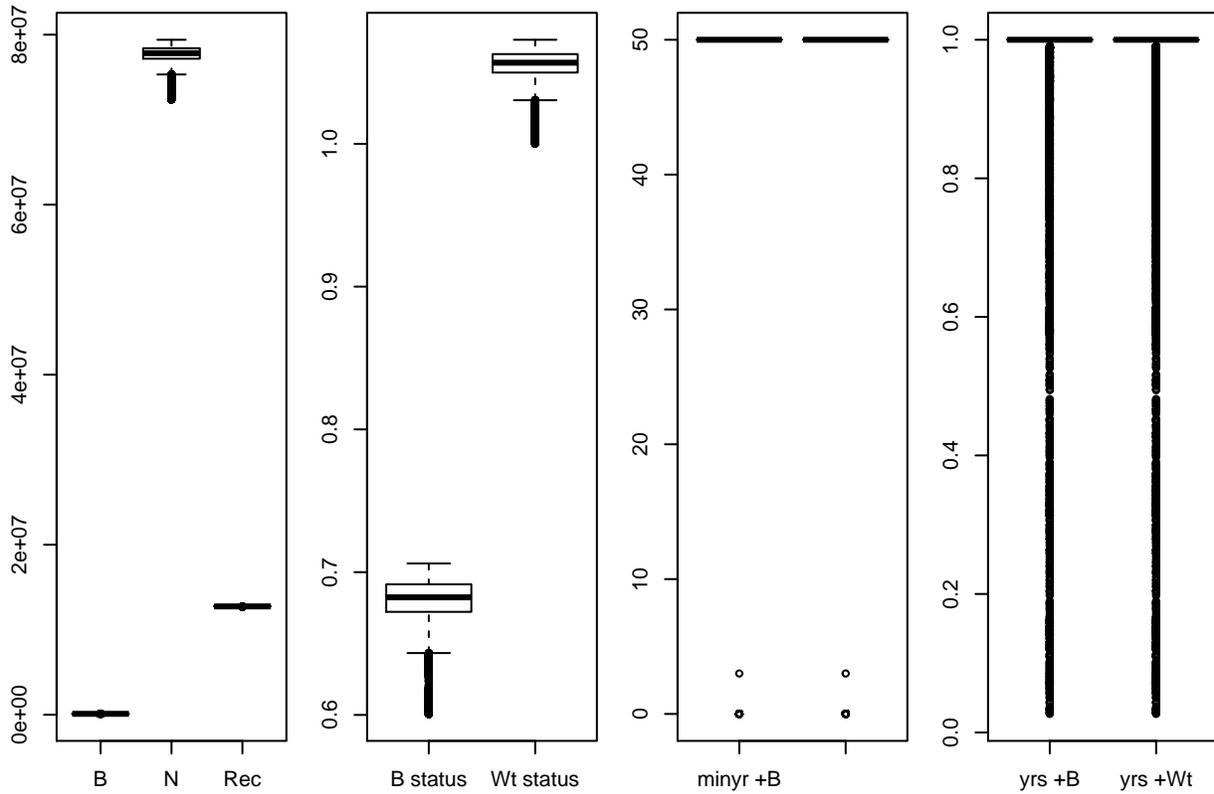


Figure 18: Summary of dogfish performance metrics across all herring operating models and control rules

Cases of poor status observed for dogfish were limited to two control rule types within the herring operating models specified with high natural mortality and low stock-recruit steepness (HiM) representing a poor herring productivity state. The control rule types performing poorly for dogfish under poor herring productivity were the same performing poorly for tern productivity: the biomass-based control rule implemented for 3 years with a constraint of 15% change between specifications (BB3yrPerc) and the constant catch (CC) control rules (Fig. 19). Also similar to terns, herring average weight did not affect these results, so those operating models are combined here.

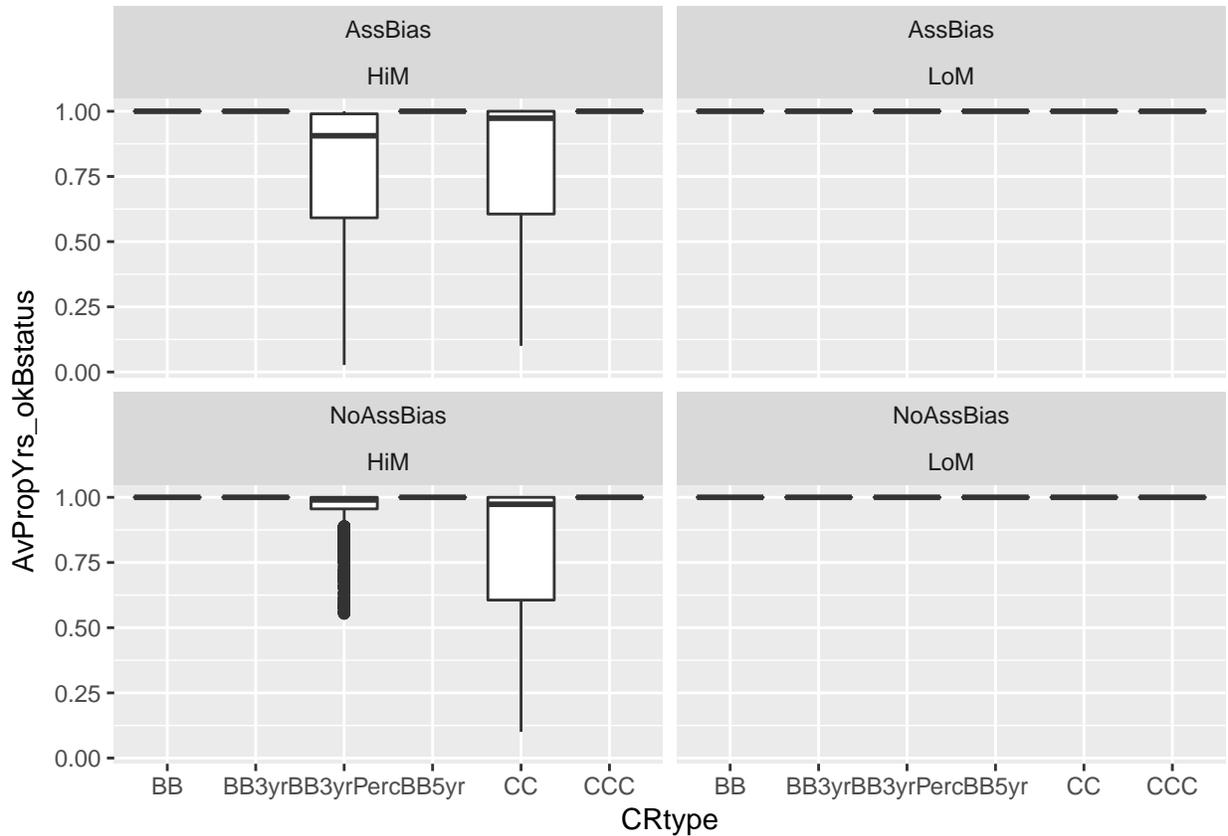


Figure 19: Dogfish proportion of years not overfished across all herring operating models and control rules

## Discussion

This document has explained the predator models used in the herring MSE. These models simulate different predator relationships with Atlantic herring in the Northeast US, and suggest different effects of herring control rules based on these relationships. As has been found in other MSE analyses (Punt et al. 2016), the results may be more useful for eliminating poor control rule options than for optimizing herring control rules to improve predator metrics. There are several reasons for this. First, this is a complex question. Predator populations are affected by many factors, while we attempted to isolate factors associated with prey. Further, in the Northeast US, predators have many prey options, while we attempted to evaluate relationships with just one prey, herring. Finally, time limitation enforced model simplicity for these complex relationships. Our approach was to use the best-supported relationship for each predator based on observations from the Northeast US ecosystem. We discuss the pros and cons of this approach for each predator below.

Western Atlantic bluefin tuna migrate widely and forage throughout North Atlantic; their population footprint is much larger than that of Northeast US Atlantic herring. However, tuna feed seasonally in the Gulf of Maine, exploiting high energy concentrated prey to maximize growth (W. J. Golet et al. 2013). Because tuna growth is key in the Northeast US, and because there is a well-supported relationship between herring weight and tuna growth here (W. Golet et al. 2015), we used this relationship. Other relationships were also investigated. Available data do not support implementing a positive relationship between herring and tuna populations in our models for this MSE; according to assessments, Northeast US shelf herring have increased during a period of bluefin tuna decline (NEFSC 2012; ICCAT 2015). Stakeholder observations and fine-scale analyses (e.g., W. J. Golet et al. 2013) suggest that bluefin tuna follow herring in the Gulf of Maine and likely aggregate around herring while feeding. However, our models designed to address ABC control rules

at the Northeast US shelf scale do not address herring/tuna interactions in a specific place or time, and we can draw no conclusions from our modeling about predator/prey co-occurrence or availability at smaller, local scales. Similarly, without additional observations, we cannot extrapolate local scale co-occurrence to population level relationships.

Common terns, in contrast, are central-placed foragers seasonally near their island breeding colonies in the Gulf of Maine. Their foraging footprint during chick production season is much smaller than the scale of the Northeast US Atlantic herring population. However, because tern productivity is a key management objective for tern colonies in the Gulf of Maine, and with substantial data to explore a relationship between herring and tern reproductive success, we worked to develop this relationship. However, many factors other than herring abundance affect tern production. According to Gulf of Maine Seabird Working Group minutes, predation by mammals, gulls, and other birds is a major factor that most colony management aims to control. Further, timing of weather events and timing of prey availability is important but difficult to quantify from current data. Similarly, the relatively small scale spatial and depth distribution of prey affects tern foraging success as well as the overall abundance of prey. At one colony during the same year, the proportion of herring in tern chick diets was much lower than the proportion of herring in razorbill diets at the same colony; razorbills are capable of deeper dives than terns (GOMSWG minutes). Spatial variability of predation, weather, and prey distribution may drive the high variation in observed herring population-tern productivity relationship among colonies. This high variance in the observations is not considered by the modeled herring tern relationship. Further, the tern model is optimistic about population trajectory because it considers only herring total biomass impacts on terns, and does not model predation, habitat quantity and quality, etc.

Spiny dogfish may have the best spatial footprint match with Atlantic herring in the Northeast US of the three predators modeled. Dogfish forage through same range as herring for most of the year. Considerable information on dogfish diet has been collected over time in the region, and there are adequate data to conduct a stock assessment. However, the dogfish relationship assumes herring abundance improves dogfish survival because no clear relationship was found with recruitment or growth. Increased survival may not be the mechanism for the observed positive influence of herring in diet on the dogfish population.

## Conclusions

Our models are designed for evaluating alternative herring control rules, not predator stock assessment and population prediction. We caution against generalizing results for these particular predators to other predators, as population parameters and herring relationships differ.

Overall lessons from this process can inform future work. First, isolating a clear herring predator relationship from observations is difficult or impossible when other factors dominate predator dynamics (e.g. cod). Second, even with good observations, the modeled herring predator relationship may require strong assumptions and not be statistically significant due to the many other factors affecting predators (e.g. terns). Third, apparent positive herring predator relationships may not arise from the modeled mechanism (e.g. dogfish). Finally, a clear herring predator relationship is not satisfactory when it does not answer the question of interest to stakeholders (e.g. tuna).

Although we selected predators with high herring diet proportions, observed predator population responses to herring alone do not dominate dynamics, and our herring predator relationship models reflect that. Predator responses to aggregate prey dynamics are likely to be much clearer than responses to individual prey in the Northeast US ecosystem given its food web structure. While modeling this is a more complex and time-consuming undertaking, the results may give clearer advice for managers making decisions regarding multiple simultaneously exploited prey and predators within the ecosystem.

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# Herring MSE: Economic Models

Min-Yang Lee, Northeast Fisheries Science Center

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## 1 Introduction

This document explains the economic component of the Herring Management Strategy Evaluation. This was developed during the spring and summer of 2016; the goal of this component is to allow some aspects of economic performance to be included in the MSE. The economic analysis focuses on two revenue metrics and stability of those metrics. Taking cues from the herring dynamics section of the MSE, we report these metrics over the final terminal 50 years of the simulation.

## 2 Background

On an annual basis, the quantity supplied in the herring market is likely to be driven by the TAC, ACL, or sub-ACLs. Sub-ACLs for herring usually limit catch<sup>1</sup>. They are occasionally not constraining; however seems to occur for regulatory reasons (such as a closure for catch of haddock in the Georges Bank fishery<sup>2</sup>) instead of for market reasons.

The fishery is managed spatially, with sub-ACLs for four Herring Management Areas. Herring is caught by purse seine, midwater- and paired-midwater trawls, and small mesh bottom trawls. Purse seine vessels typically fish in the Gulf of Maine (HMA 1A), particularly during the summer. Small-mesh bottom trawl vessels typically fish southern New England and the Mid-Atlantic (HMA 2). Midwater trawl gear fishes in areas 1B, 2, and 3 and is excluded from Area 1A during the summer months. Recently, the purse seine fishery has caught 30% of total landings while the midwater- and bottom-trawl fisheries have caught the remainder.

Herring is often (but not exclusively) used for bait; typically for the lobster fishery. In 2014, approximately 75% of landed herring was utilized as bait. Other uses include animal food and human consumption. From 2010-2015, annual prices were fairly fairly constant (dashed line in figure 1). Prices often spike during the winter months when landings are very low. 2016 is a bit different: large portions of Area 3 were closed due to haddock bycatch until April 30, 2016.

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<sup>1</sup><https://www.greateratlantic.fisheries.noaa.gov/ro/fso/reports/herring/2013/20131231/herr20131231.pdf>;  
<https://www.greateratlantic.fisheries.noaa.gov/ro/fso/reports/herring/2014/20150108/herr20150108.pdf>;  
<https://www.greateratlantic.fisheries.noaa.gov/ro/fso/reports/herring/2015/herr20160107.pdf>

<sup>2</sup>[https://www.greateratlantic.fisheries.noaa.gov/ro/fso/reports/HaddockBycatchReport/2015/hadd\\_20160505.pdf](https://www.greateratlantic.fisheries.noaa.gov/ro/fso/reports/HaddockBycatchReport/2015/hadd_20160505.pdf)

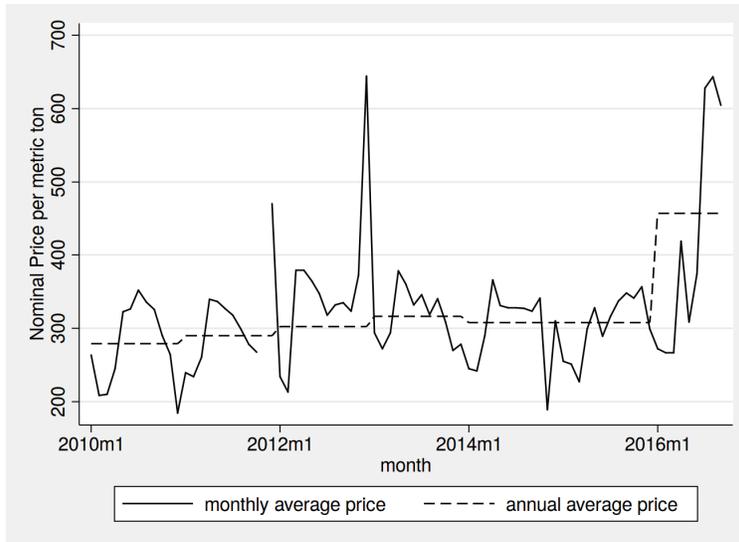


Figure 1: Monthly prices for Atlantic Herring

### 3 Methods

In brief, the economic component of the model converts Yield from the biological component into Gross and Net Operating Revenues. Gross Revenues are simply yield multiplied by price. Net operating Revenues subtract out the variable operating costs. We summarize Gross and Net Revenue metrics by reporting the median of terminal 50-year medians. Variability is captured by using interannual variability over the final 50 years (Amar, Punt, and Dorn, 2009; Deroba, 2014) and reporting the frequency with which Net Revenue metric satisfies the statistical property of stationarity (Dickey and Fuller, 1979).

Real prices, when used, have been normalized to 2015 real dollars using the Bureau of Labor Statistics (BLS) Producer Price Index (PPI) for “Unprocessed and Packaged Fish” (WPU0223)<sup>3</sup>.

The economic component of the model is simple and does not capture aspects of reality that are (likely to be) important, including:

- Herring landings being different from Yield,
- Fixed and quasi-fixed costs,
- Entry- or Exit of participants,
- Effects on fishing communities (both herring and other) or the regional economy,
- The direct and indirect benefits and costs of changes in herring biomass, including
  - economic impacts of changes in predator, biomass on users of those predators, and
  - economic impacts of changes in the location of herring biomass.

We will discuss these caveats and limitations later in the document.

<sup>3</sup>Available at <https://fred.stlouisfed.org/series/WPU0223>

### 3.1 Changes since the second workshop

- We have used real instead of nominal prices for menhaden and herring.
- We have slightly different estimates of cost-per-day based on updated data.
- We have assumed an elasticity of price with respect to quantity supplied of -0.5, instead of -1.

	Workshop 2	Current MSE
menhaden backstop (\$ per mt)	260	275
herring baseline (\$ per mt)	306	324
purse seine (\$ per day)	850	810
Trawl (\$ per day)	2,600	3,000
elasticity of price	-1	-0.5

Table 1: Summary of different parameters

### 3.2 Prices and Gross Revenues

We assume that the elasticity of price with respect to quantities is -0.5.

$$\frac{\partial p}{\partial q} \frac{q}{p} = -0.5 \quad (1)$$

Following Lehuta, Holland, and Pershing (2013), we assume that an unlimited quantity of menhaden is available as a perfect substitute at real price of \$375 per metric ton. Menhaden is likely to be a good substitute in the bait market, but a poor substitute in the human consumption market. \$360 per mt is equal to the average real price over the most recent 5 years (\$242 per metric ton) plus a transportation markup of \$133 per metric ton. This puts an upper bound on the *ex-vessel* price of herring when quantities are low<sup>4</sup>. At the second MSE workshop, we presented results based on an elasticity of  $-1$ . This was not a particularly good choice.

Given an initial value for the price of herring and the quantity of herring, this allows us trace out a demand curve for herring. We average over the same time period to produce a nominal starting price of \$305 per metric ton at a 87,117 mt of landings.

We assume that  $Yield_y$  in year  $y$  is equivalent to quantity supplied in year  $y$  ( $q_y$ ). Therefore, Gross revenues are simply:

$$GR_y = p(q_y)q_y \quad (2)$$

### 3.3 Costs and Net Operating Revenues

We construct costs separately for the purse seine and trawl fleets.

We assume that the purse seine fleet will continue to land 30% of landings and the trawl fishery could land the remainder. We use observer data from 2010-2014 to construct catch-per-day ( $CPUE_p$  and  $CPUE_t$  for the purse seine and trawl fleet respectively). For each fleet, landings are divided by CPUE day to compute days

<sup>4</sup>Preliminary data from 2016 (which was not available when this work was started) suggests that a backstop price of \$375 per mt may not be appropriate (See Figure 1).

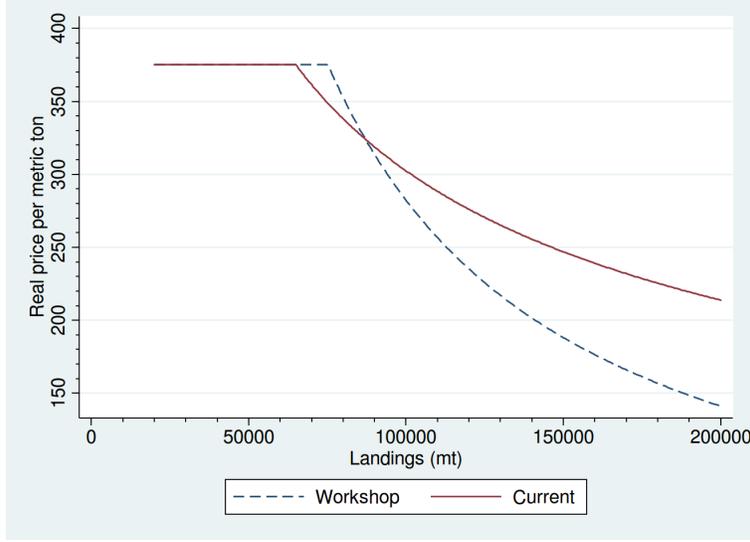


Figure 2: Assumed demand curve for herring

fished. These are multiplied by costs-per-day ( $cost_p$  and  $cost_t$  respectively) to compute variable operating cost. Net Operating revenues are computed by subtracting the variable operating costs from Gross revenues:

$$NR_y = p(q_y)q_y - 0.3q_yCPU E_p cost_p - 0.7q_yCPU E_t cost_t \quad (3)$$

The two fleets have surprisingly similar catch-per-day metrics, although the trawl fleet takes much longer trips than the purse seine fleet and therefore has higher catch-per-trip. We present catch-per-trip in table 2 and 3 because it may be interesting to the reader although they are not used directly in the simulation.

Year	Observed catch (mt)	trips	days	catch per trip	CPUE (mt/day)
2010	8,565	242	283	141	49
2011	17,278	276	338	158	63
2012	19,514	290	342	143	62
2013	23,218	318	355	124	54
2014	27,103	318	355	133	64
Average				66	57

Table 2: Observed herring catch, trips, days, and CPUE metrics for the Purse Seine fishery (2010-2014).

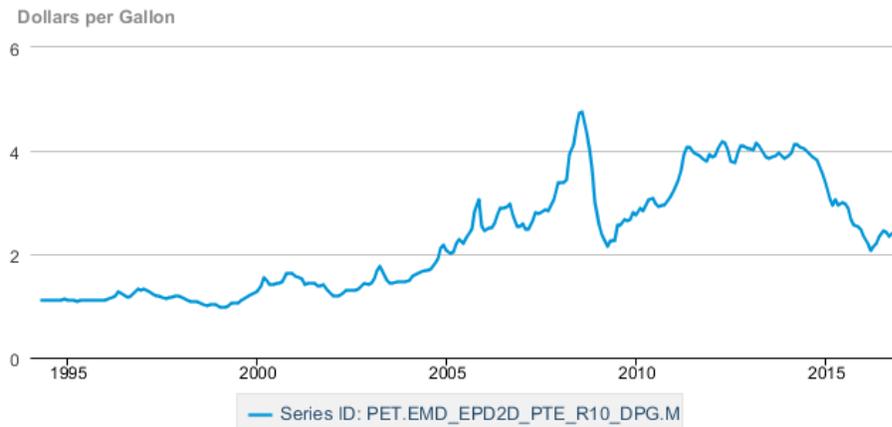
Costs were also extracted from the observer data. These included fuel, damage, supply, water, and oil costs. “Supply” (boots, knives, gear, etc), food, and bait costs were not included in construction of trip costs. Crew pay was also not included. Like many fisheries, fuel expenses are a large portion of total expenses. Fuel prices have changed a bit during the 2010-2015 time period. Average prices were approximately \$3 per gallon in 2010 and 2015 and \$4 per gallon in 2011-2014. Rather than averaging costs over these time periods with very different fuel prices, we used the 2015 cost figures; sensitivity of net revenue metrics under the alternative assumption of \$4 fuel is possible<sup>5</sup>.

<sup>5</sup>For both fleets, daily costs in 2011-2014 are 30-50% higher than in 2015, which roughly corresponds to the fuel price difference over these time periods

Year	Observed catch (mt)	trips	days	catch per trip	CPUE (mt/day)
2010	54,189	385	1,107	141	49
2011	59,932	380	956	158	63
2012	63,122	442	1,016	143	62
2013	62,458	504	1,148	124	54
2014	60,187	454	938	133	64
Average				139	58

Table 3: Observed herring catch, trips, days, and CPUE metrics for the trawl fishery (2010-2014).

### East Coast No 2 Diesel Retail Prices, Monthly



year	Price
2010	3.08
2011	3.98
2012	4.13
2013	4.08
2014	4.01
2015	2.89

(b) Annual Average New England Number 2 Diesel Retail

 Source: Energy Information Administration

(a) Monthly Fuel Prices

Figure 3: Fuel prices from EIA.

year	trips	days	cost per day	cost per trip	days per trip
2011	79	74	1,667	1,562	0.9
2012	40	45	1,290	1,454	1.1
2013	50	40	1,279	1,035	0.8
2014	24	27	1,330	1,510	1.1
2015	14	15	811	864	1.1

Table 4: Observed costs for the purse seine fishery (2011-2015). In the simulation models, the cost of a purse seine day is assumed to be \$810

year	trips	days	cost per day	cost per trip	days per trip
2011	149	387	4,519	11,728	2.6
2012	179	533	4,607	13,711	3.0
2013	103	365	3,955	14,032	3.5
2014	122	298	4,181	10,218	2.4
2015	19	48	3,001	7,633	2.5

Table 5: Observed costs for the Trawl fishery (2011-2015). In the simulation models, the cost of a trawl day was assumed to be \$3,000.

### 3.4 Stability

Stakeholders were interested in understanding “stability” of the herring industry. Following the herring dynamics section, we computed Interannual Variation (IAV) of Net Revenues and report the median (across replicates) of median (across the final 50 years) of IAV. IAV is a summary metric of variability in the time series over a time period, but does not provide insight into stationarity of the time series. We assess stationarity using a Dickey-Fuller, one of many econometric tests of stationarity.

#### 3.4.1 Interannual Variability

Here is the equation for interannual variability over the final 50 years (Amar, Punt, and Dorn, 2009; Deroba, 2014):

$$IAV = \frac{\sqrt{\frac{1}{50} \sum_y^{50} (NR_{y+1} - NR_y)^2}}{\frac{1}{50} \sum_y^{50} NR_y} \quad (4)$$

#### 3.4.2 Stationarity

We assessed stability over the final 50 years using an econometric test for stationarity of Net Revenues (Dickey and Fuller, 1979). In this application, a finding of stationarity implies that the system is in a stable equilibrium. Alternatively, this implies that Net Revenues has a measure of central tendency that does not depend explicitly on time. Yet in another alternative interpretation, it means that shocks or perturbations are not persistent: a “good” year (defined as a year above average) is equally likely to be followed by a “good” or “bad” year.

In contrast, a finding of non-stationarity (or a unit-root process) implies that the system is not in a stable equilibrium. The Net Revenue metric has a measure of central tendency that *does* depend explicitly on time. Alternatively, it can be interpreted as a system in which shocks or perturbations are not persistent: a “good” year more likely to be followed by a good year than a bad year. Similarly, a “bad” year is likely to be followed by another bad year.

$$NR_y = a + \rho NR_{y-1} + \delta y + u_y \quad (5)$$

We are primarily interested in testing for a unit-root or non-stationarity. Econometric evidence that  $\rho = 1$  is evidence of a unit root while statistical rejections of  $H_0 : \rho = 1$  is evidence of stationarity of the time-series.

Equation 5 is difficult to estimate using Ordinary Least Squares because  $u_t$  is often serially correlated ( $E[u_y u_{y-1}] \neq 0$ ), which invalidates inference about  $\rho$ . Instead, equation 5 is typically transformed by differencing. Letting  $\Delta$  be the first difference operator ( $\Delta NR_y = NR_y - NR_{y-1}$ ), the general form of the augmented dickey fuller regression is:

$$\Delta NR_y = a_0 + \beta NR_{y-1} + \delta y + \sum_{j=1}^k \xi_j \Delta NR_{y-j} + \varepsilon \quad (6)$$

In this formulation, econometric evidence that  $\beta = 0$  is evidence of a unit root while statistical rejections of  $H_0 : \beta = 0$  is evidence of stationarity of the time-series. In an homage to Sala-i Martin (1997), we estimate equation 6 for the final 50 years for each simulation. We estimate a version of equation 6 in which  $a$  and

$\xi_j \quad \forall j \geq 4$  are restricted to zero<sup>6</sup>:

$$\Delta NR_y = \beta NR_{y-1} + \delta y + \sum_{j=1}^3 \xi_j \Delta NR_{y-j} + \varepsilon \quad (7)$$

We classify a simulation as stationary if we reject the null  $H_0 : \beta = 0$  at the 10% significance level. We then compute the number of simulation (out of 100) that are stationary for each of the 8 operating models and 5,460 control rules.

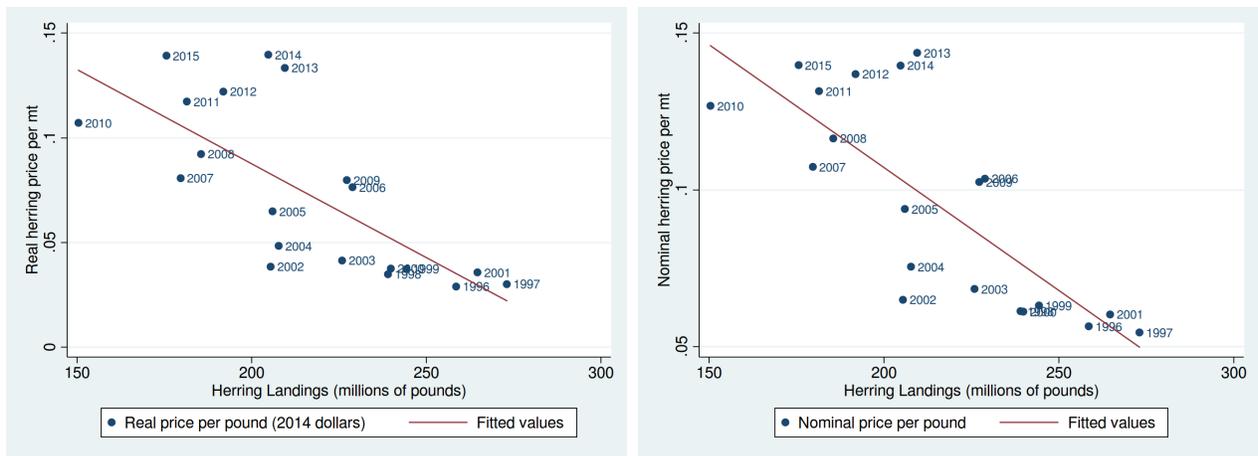
### 3.4.3 Stationarity in Graphical Form

During the second workshop, we presented some illustrative graphics about stationary and non-stationary Net Revenues.



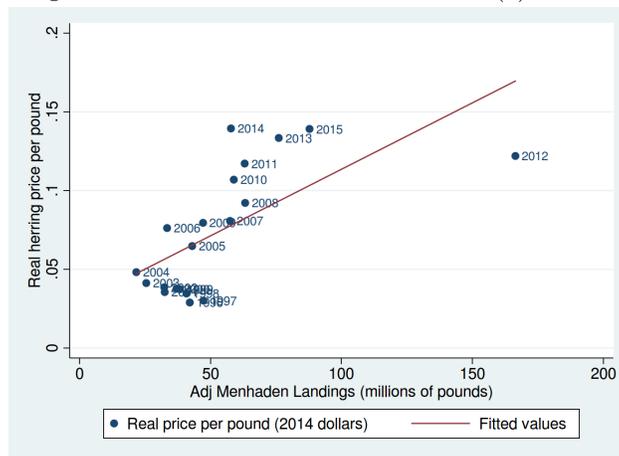
Figure 4: Stationarity is independent of IAV

<sup>6</sup>This is implemented in Stata using `dfuller NR, trend lags(3)`.



(a) Real Herring Prices

(b) Nominal Herring Prices



(c) Real prices and non-Virginia menhaden landings

Figure 5: Some descriptive graphics about the herring fishery

## 4 Methods we tried that didn't quite work out

We attempted to construct a rigorous model of prices for herring. It didn't quite work. This section provides a short overview of those methods. We focused on four species: herring, mackerel, menhaden, and lobster. Mackerel may be jointly produced with herring. Menhaden is a likely substitute for herring in the bait market. The lobster industry is a major consumer of herring (as bait). While other market interactions (for example: squid, redfish racks, and "livestock byproducts") are likely, we focused on a small number to start.

Here are a few summary scatterplots based on annual data.

The relationship between landings and herring prices, particularly real prices, looks like a downward sloping demand curve. The relationship looks stronger for real prices compared to nominal prices. However, all of the high prices and low quantities are recent (2008-2015) while the lower prices and higher quantities are mostly old (1996-2006). This raises the possibility that either (a) structural changes in the underlying market have occurred or (b) something else that is correlated with time is an important determinant of herring prices.

We constructed monthly landings and prices of herring, mackerel, menhaden, and lobster from NMFS’s commercial fisheries database system (1996-2015 calendar years) aggregated at the state level. Herring data was supplemented with the “cleaned” state of Maine database provided by Maine DMR. Menhaden landed in Virginia was treated separately from menhaden landed in other states. Prices were normalized using the Bureau of Labor Statistics (BLS) Producer Price Index (PPI) for “Unprocessed and Packaged Fish” (WPU0223). For this particular exercise, the base year was set to 2014 because the 2015 PPI data were not finalized.

We estimated a bunch of panel (cross-section, time-series) models that attempted to explain the prices of herring as a function of substitute prices or quantities. We also tried to estimate time-series models on data aggregated at the region. We were unable to estimate a model that meets basic goodness-of-fit criteria. Then we ran out of time and just assumed that the elasticity (at the annual level) was -0.5.

## 5 Problems with these methods

### 5.1 Prices

This treatment of prices is not particularly good. It can (charitably) be seen as a sensitivity analysis benchmarked against a “constant price” that can be deduced by comparing Gross revenues with Yield.

### 5.2 Costs

We did not include fixed costs. If firms do not enter or exit, then the exclusion of fixed costs from the model has minimal qualitative effects: the Net Revenue outcomes for all control rules and operating models would shift down by the same amount and the relative rankings would be the same. The stationarity metric would be unaffected; this shift would be differenced out in equation 7. IAV constructed without fixed costs will be smaller than IAV constructed with fixed costs:

$$\begin{aligned}
 IAV &= \frac{\sqrt{\frac{1}{50} \sum_y^{50} ((NR_{y+1} - F) - (NR_y - F))^2}}{\frac{1}{50} \sum_y^{50} (NR_y - F)} \\
 &= \frac{\sqrt{\frac{1}{50} \sum_y^{50} (NR_{y+1} - NR_y)^2}}{-F + \frac{1}{50} \sum_y^{50} NR_y} \tag{8}
 \end{aligned}$$

Because the denominator of 8 is smaller when fixed costs are accounted for, we can deduce that IAV computed when properly accounting for fixed costs is larger than IAV as computed in this simulation.

If firms can enter and exit, then exclusion of fixed costs from the model could result in misleading recommendations. We did not model firm entry and exit; this is a difficult decision to model. Firms should may exit if they anticipate negative profits over a particular planning horizon. The number of active vessels in the herring fishery has declined a bit over, which could provide some data necessary to estimate a model of exit. Properly doing this would probably require accounting for payments to crew (which can readily be done).

Alternatively, we could follow the assumptions of Lehuta, Holland, and Pershing (2013) and include a zero-economic profit condition at the annual level.

### 5.3 Stability

A drawback of the stationary metric is that the “system” can be stable at zero net revenue. This would not be good.

## 6 Caveats, Extensions, and Future Research

Yet another assumption of this model is that herring landings are equal to yield. This is not really likely for many reasons. In particular, if we believe the demand curve described in figure 2, then firms are likely to find landing large amounts of herring at low prices to be unprofitable and will not do this. This will break the link between yield and landings (and therefore net revenue). When this happens, it also implies that biomass in subsequent years will be slightly higher than biomass in the model; the magnitude of this effect depends on the amount of yield that is not converted to landings.

Here is some related literature: Lehuta, Holland, and Pershing (2013) constructs a coupled model of lobster and herring. Kirkley, Walden, and Färe (2011) provides a framework for examining tradeoffs in the herring fishery. Jin et al. (2012) construct an integrated model that examines effects on human communities. Carroll, Anderson, and Martínez-Garmendia (2001) describe another mechanism (product quality) through which changes in prey could be evaluated.

We did not attempt to value *in-situ* herring or compute the social benefits or costs derived from changes in biomass. Brown, Berger, and Ikiara (2005); Finnoff and Tschirhart (2003) describe methods to trace the effects of changes in harvest or biomass of one species on ecosystems or predators. Finally, we note that increases in predator biomass can have negative impacts on prey and harvesters of prey Flaaten and Stollery (1996).

In a more holistic model, with multiple predators, prey, and variability in the “desirability” of predators, it is possible that increases in biomass of a particular prey could be bad for society. For example, biomass of a predator that is low-valued but skilled at consuming herring could result in disproportionate increases in that low-valued predator. If that low-valued predator is not a complete specialist (in consuming herring), it may also drive down the biomass of high-valued predators.

Stated another way, the ability to manipulate the ecosystem with an ABC control rule to achieve desirable outcomes would depend on the rates at which increases in prey are converted into social utility: this depends on the ecosystem “technology” (conversion of prey into additional biomass of valued predators), human technology (conversion of prey and predator biomass into catch or tourism), and human preferences (converting catch or tourism into utility). Many of these technologies are not particularly well understood at this time.

There are undoubtedly more extensions that would increase the realism of this model. However, time is up and our pencils must be put down.

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