

Unnecessarily Complicated Research Title

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Abstract

Keywords: Science, Publication, Complicated

1. Introduction

- Risk and uncertainty
- One rule for all?
- Impact of life histories
- Comparison of constant catch v changing catch based on trends in an empirical index.
- catch only - need good catch data if you havent got this how can you set catch limits

Sustainability and risks to non target exploited marine fish stock populations requires both estimates of current stock status, the effects of fishing pressure (catchability and fishing effort) and the effects of management measures on target populations, however these data are often lacking. Subsequently there is increasing concern and a growing need for the development of innovative approaches so that management of all marine stocks not just those of high commercial value can be included into the Common Fisheries Policy (CFP [1]) framework. Under the CFP management objectives are to recover stocks and to maintain stocks within safe biological limits to levels that can produce Maximum Sustainable Yield (MSY), including by-catch species by 2015 (Implementation Plan adopted at the World Summit on Sustainable Development, Johannesburg in 2002) and no later than 2020. These conservation objectives are currently being achieved by introducing

22 biological target (can fluctuate around targets) and limit (i.e must not be
 23 exceeded) reference points e.g. population size (stock biomass) and/or yields
 24 (catches) and/or long-term yields and fishing mortality against which the
 25 preservation of stocks within such limits are assessed. These targets or limit
 26 reference points are often referred to as harvesting strategies which include
 27 an operational component called a harvest control rule (HCR) that are based
 28 on indicators (e.g. monitoring data or models) of stock status and to prevent
 29 overfishing.

30 The International Council for the Exploration of the Sea (ICES) cate-
 31 gorises stocks in to classes *data-rich*, (categories 1 and 2) i.e those that have
 32 a quantitative assessment based on conventional methods that require large
 33 amounts of data that include a long historical time series of catches and
 34 sound biological information [2]; or *data-limited* [3](categories 3 and 4) (of-
 35 ten called data poor) those without assessment, forecasts and have limited
 36 funding for research. For data-rich stocks ICES uses two types of reference
 37 points for providing fisheries advice;

- 38 1. Precautionary Approach (PA) reference points (those relating to stock
 39 status and exploitation relative to precautionary objectives) and
- 40 2. MSY reference points (those relating to achieving MSY)

41 In contrast for data limited stocks MSY *proxy* reference points are used to
 42 estimate stock status and exploitation. Often many of the methods used to
 43 estimate MSY proxy reference points require length based inputs as they are
 44 cheap, easy to collect [4] and are related to life history parameters such as
 45 fish size, mortality and fecundity as well as fishery selectivity. For example
 46 many methods are being developed to estimate MSY, but currently only 4 are
 47 approved by ICES, these include, Surplus Production model in Continuous
 48 Time (catch based) (SPiCT; [5], Mean Length Z (MLZ; [6]), Length Based
 49 Spawner Per Recruit (LBSPR; [7]) and Length Based Indicators (LBI; e.g.
 50 [8]). The aforementioned data limited procedures have differing data require-
 51 ments, intended uses and obviously have their own strengths and weaknesses.

52 To test the performance of candidate management procedures often re-
 53 quires evaluation of alternative hypothesis about the dynamics of the system
 54 e.g. population dynamics (life history dynamics such as growth parameters
 55 which are an indication of fishery exploitation levels and management) and
 56 the behaviour of the fishery (e.g range contraction and density dependence)
 57 etc.. Due to the nature of conflicting objectives, stakeholder interests and the
 58 uncertainty in the dynamics of the resource and/or the plausibility of alter-

native hypotheses can lead to poor decision making and can be problematic when defining management policy.

An intense area of work being researched over the last 2 decades is Management Strategy Evaluation (MSE), which focuses on the broader aspects of fishing (the Ecosystem) whereby different management options are tested against a range of objectives (see [9]). The approach is not to come up with a definitive answer, but to lay-bare the trade offs associated with each management objective, along with identifying and incorporating uncertainties in the evaluation and communicating the results effectively to client groups and decision-makers. MSE is not intended to be complex but to provide a robust framework that account for conflicting poorly defined objectives and uncertainties that have been absent in conventional management [9].

To assess case specific harvest strategies (via simulation) within the MSE, we will implement a management procedure based on a empirical HCR that adjusts yield depending on stock status for a given set of tunable parameters for each of the harvest strategies and to test their robustness to uncertainty. This approach could also help identify similar conditions across species where particular advice rules are likely to work well, and where they perform poorly for a given a set of parameters.

Often empirical harvest control rules require extensive exhaustive parameter searches to tune or optimise 'hyper-parameters' (external parameters to a model) that aren't directly learnt from estimators. This requires a technique known as a grid search that extensively searches for all combinations of all parameters. In contrast, and some what less time consuming alternative and efficient parameter search strategies can be considered for a given range of parameter space and a known distribution. As such a random sample can be obtained and used to perform the different experiments for parameter optimisation. This approach differs from the simplest constant catch HCR strategy whereby catches are kept constant and low to ensure no lasting damage is done in periods of low stock productivity or whereby the stock is highly variable year on year, therefore the empirical approach can help optimise catch by setting a precautionary Total Allowable Catch (TAC).

Here we describe methods to assess the performance of each empirical HCR via a set of utilities and show the benefits compared to a constant catch strategy across a spectrum of different species: safety (recruitment relative to virgin recruitment), yield ($yield/MSY$), kobe proportion (proportion of years that stay in the green zone of kobe plot ($B/B_{MSY} > 1$ and $F/F_{MSY} < 1$), and Yield Annual Variation (Average annual variation in a TAC from one

97 year to the next (expressed as a proportion of the average annual catch).

98 2. Material and Methods

99 2.1. Materials

100 Life history parameters for growth, natural mortality and maturity were
 101 used to develop an age-based Operating Model. To do this the parameters
 102 were first used to parameterise functional forms for mass (W), proportion
 103 mature (Q), natural mortality (M) and fishing mortality (F) at age. These
 104 were then used to calculate the spawner (S/R) and yield-per-recruit (Y/R)
 105 which were then combined with a stock recruitment relationship [10] to cal-
 106 culate the equilibrium stock size as a function of fishing mortality (F).

107 This analysis allows a variety of reference points such as those based on
 108 Maximum Sustainable Yield (MSY), i.e. B_{MSY} the spawning stock biomass
 109 (S) and F_{MSY} the fishing mortality that produces MSY at equilibrium to be
 110 estimated. Other reference points are $F_{0.1}$ the fishing mortality on the yield
 111 per recruit curve where the slope is 10% of that at the origin, a conservative
 112 proxy for F_{MSY} ; and F_{Crash} which is the fishing mortality that will drive
 113 the stock to extinction since it is equivalent to a R/S greater than the slope
 114 at the origin of the stock recruitment relationship, i.e. recruitment can not
 115 replace removals for a fishing mortality equal to F_{Crash} .

116 The equilibrium relationships can then be turned into a forward dynamic
 117 model and projected forward.

118 A variety of functional forms can be assumed for all of the various pro-
 119 cess, i.e. growth, mortality, maturity, the selection pattern of the fisheries
 120 and the stock recruitment relationship. Commonly processes such as growth
 121 an maturity-at-age are well known while those for natural mortality and the
 122 stock recruitment relationship are poorly known [11]. In the later case as-
 123 sumptions have to be made and to evaluate the sensitivity of any analysis to
 124 those assumptions a variety of scenarios are considered.

125 2.2. Methods

126 Individual Growth

127 Growth in length is modelled by the Von Bertalanffy growth equation [12]

$$L = L_{\infty}(1 - \exp(-k(t - t_0))) \quad (1)$$

128 where k is the rate at which the rate of growth in length declines as
 129 length approaches the asymptotic length L_∞ and t_0 is the hypothetical time
 130 at which an individual is of zero length.

131 Length is converted to mass using the length-weight relationship

$$W = aL_t^b \quad (2)$$

132 where a is the condition factor and b is the allometric growth coefficient.

133 Maturity-at-age

134 Proportion mature-at-age is modelled by the logistic equation with 2 pa-
 135 rameters: age at 50% (a_{50}) and 95% (a_{95}) mature.

$$f(x) = \begin{cases} 0 & \text{if } (a_{50} - x)/a_{95} > 5 \\ a_\infty & \text{if } (a_{50} - x)/a_{95} < -5 \\ \frac{m_\infty}{1.0 + 19.0^{(a_{50} - x)/95}} & \text{otherwise} \end{cases} \quad (3)$$

136 Selection Pattern

137 By default the fishery is assumed to catch mature fish and so the selection
 138 pattern is based on the maturity ogive. It is modelled by a double normal
 139 curve, however, to allow scenarios to be implemented where older fish are
 140 less vulnerable to the fisheries.

141 The double normal has three parameters that describe the age at maxi-
 142 mum selection ($a1$), the rate at which the left-hand limb increases (sl) and
 143 the right-hand limb decreases (sr) which allows flat topped or domed shaped
 144 selection patterns to be chosen, i.e.

$$f(x) = \begin{cases} 0 & \text{if } (a_{50} - x)/a_{95} > 5 \\ a_\infty & \text{if } (a_{50} - x)/a_{95} < -5 \\ \frac{m_\infty}{1.0 + 19.0^{(a_{50} - x)/95}} & \text{otherwise} \end{cases} \quad (4)$$

145 Stock Recruitment Relationship By default a Beverton and Holt stock
 146 recruitment relationship [13] was assumed, This relationship is derived from
 147 a simple density dependent mortality model where the more survivors there
 148 are the higher the mortality. It is assumed that the number of recruits (R)
 149 increases towards an asymptotic level (R_{max}) as egg production increases i.e.

$$R = Sa/(b + S) \quad (5)$$

150 The relationship between stock and recruitment was modelled by a Bev-
 151 erton and Holt stock-recruitment relationship [13] reformulated in terms of

152 steepness (h), virgin biomass (v) and $S/R_{F=0}$. Where steepness is the propor-
 153 tion of the expected recruitment produced at 20% of virgin biomass relative
 154 to virgin recruitment (R_0). However, there is often insufficient information
 155 to allow its estimation from stock assessment [14] and so by default a value
 156 of 0.8 was assumed. Virgin biomass was set at 1000 Mt to allow comparisons
 157 to be made across scenarios.

$$R = \frac{0.8R_0h}{0.2S/R_{F=0}R_0(1-h) + (h-0.2)S} \quad (6)$$

158 S the spawning stock biomass, is the sum of the products of the numbers
 159 of females, N , proportion mature-at-age, Q and their mean fecundity-at-age,
 160 G , which is taken to be proportional to their weight-at-age i.e.

$$S = \sum_{i=0}^p N_i Q_i W_i \quad (7)$$

161 where fecundity-at-age is assumed proportional to biomass and the sex
 162 ratio to be 1:1. Proportion mature is 50% at the age that attains a length of
 163 150, 0% below this age and 100% above.

164 2.2.1. Operating Model

165 Age based Equilibrium Analysis
 166 [10], estimated surplus production using an age-based analysis using an
 167 equilibrium analysis that by combining a stock-recruitment relationship, a
 168 spawning-stock-biomass-per-recruit analysis, and a yield-per-recruit analysis.
 169 For any specified rate of fishing mortality, an associated value of spawning
 170 stock biomass (S) per recruit (R) is S/R is defined, based on the assumed
 171 processes for growth, natural mortality and selection pattern-at-age detailed
 172 in the previous sections.

$$S/R = \sum_{i=0}^{p-1} e^{\sum_{j=0}^{i-1} -F_j - M_j} W_i Q_i + e^{\sum_{i=0}^{p-1} -F_i - M_i} \frac{W_p Q_p}{1 - e^{-F_p - M_p}} \quad (8)$$

173 When the value of S/R obtained is inverted and superimposed on the
 174 stock-recruitment function as a slope (R/S), the intersection of this slope
 175 with the stock-recruitment function defines an equilibrium level of recruit-
 176 ment. When this value of recruitment is multiplied by the yield per recruit
 177 calculated for the same fishing mortality rate, the equilibrium yield associ-
 178 ated with the fishing mortality rate emerges [15].

$$Y/R = \sum_{a=r}^{n-1} e^{\sum_{i=r}^{a-1} -F_i - M_i} W_a \frac{F_a}{F_a + M_a} (1 - e^{-F_i - M_i}) + e^{\sum_{i=r}^{n-1} -F_i - M_i} W_n \frac{F_n}{F_n + M_n} \quad (9)$$

179 The second term is the plus-group, i.e. the summation of all ages from
180 the last age to infinity.

181 Forward Projection

182 The stock recruitment relationship and the vectors of weight, natural
183 mortality, maturity and selectivity-at-age allow a forward projection model
184 to be created, which forms the basis of the Operating Model.

$$N_{t,a} = \begin{cases} R_t, & \text{if } a = 0, \\ N_{t-1,a-1} e^{-Z_{t-1,a-1}}, & \text{if } 1 \leq a \leq A-1, \\ N_{t-1,A-1} e^{-Z_{t-1,A-1}} + N_{t-1,A} e^{-Z_{t-1,A}}, & \text{if } a = A, \end{cases} \quad (10)$$

185 where $N_{t,a}$ is the number of fish of age a at the beginning of year t , R_t
186 is the total number of recruits born in year t . Here, A is the so-called plus
187 group age, which is an aggregated age greater than or equal to the actual
188 age A .

189 2.2.2. Management Procedure

190 The management procedure was based on an empirical MP, where an in-
191 crease in an index of abundance resulted in an increase in the TAC, while a
192 decrease in the index results in a decrease in the TAC. This process is per-
193 formed via a derivative control rule (D), and is so called as the control signal
194 is derived from the trend in the signal (abundance), i.e. to the derivative of
195 the error.

$$TAC_{y+1}^1 = TAC_y \times \begin{cases} 1 - k_1 |\lambda|^\gamma & \text{for } \lambda < 0 \\ 1 + k_2 \lambda & \text{for } \lambda \geq 0 \end{cases} \quad (11)$$

196 where λ is the slope in the regression of $\ln I_y$ against year for the most
197 recent n years and k_1 and k_2 are *gain* parameters and γ actions asymmetry
198 so that decreases in the index do not result in the same relative change as
199 an increase.

200 The TAC is then the average of the last TAC and the value output by
 201 the HCR.

$$TAC_{y+1} = 0.5 \times (TAC_y + C_y^{\text{targ}}) \quad (12)$$

202 2.2.3. *Random Search*

203 When running an MSE commonly a set of MP scenarios are run to tune
 204 the MP, this requires running the MSE for each OM scenario for a range of
 205 fixed values in the HCR and then choosing the rule that best meets manage-
 206 ment objectives. If there are a lot of parameters to tune then a grid search
 207 may become unfeasible. An alternative is random search [16] as randomly
 208 chosen trials are more efficient for parameter optimisation than trials based
 209 on a grid. The random parameter search is performed where random combi-
 210 nations of hyperparameters k_1 and k_2 are used to find the optimal solutions
 211 for the MSE model in terms of a) safety, (recruitment in relation to virgin
 212 recruitment), b) yield (catch/MSY), c) proportion of years in the kobe green
 213 zone i.e $B/B_{MSY} > 1$ and $F/F_{MSY} < 1$ and d) Average annual variation in
 214 a TAC from one year to the next (expressed as a proportion of the average
 215 annual catch). For instance as the process is random at each iteration its
 216 likely that the whole of the grid space would be covered in the simulation
 217 providing that there enough iterations, there is a greater chance of finding
 218 the optimal parameter pairs.

219 3. Results

220 Estimates of the simulated life history parameters obtained from Fishbase
 221 (<http://www.fishbase.org>) are presented in Fig.1. These show that for fast
 222 growing species which are small in size l_∞ (asymptotic length parameter)
 223 species such as sprat, the growth parameter k is high. The sprats age-at-
 224 50%-maturity a_{50} are low, in contrast to a slower growing larger longer lived
 225 species l_∞ such as rays or pollack.

226 Observations in Fig.2 shows the relationship of maturity in the OM to
 227 selectivity and that the faster growing species are more susceptible to fishing,
 228 although the slower growing larger (by mass and length) species (e.g. pollack
 229 has a higher natural mortality rate at lower ages) with the most significant
 230 natural mortality rate increases associated with turbot. A levelling off in the
 231 mortality rate is evident for ray just prior to age 4.5. In contrast, there have

232 been less steep declines in natural mortality estimates for brill, but most
233 notably for sprat.

234 Fig.3 displays the equilibrium relationships of the operating model. Com-
235 parisons of reference points estimates can be made across species. The m/k
236 plot shows interesting trends with lower values for sprat where the growth
237 rate k is considerably higher than the natural mortality rate with little un-
238 certainty around the estimate. In contrast to a slower growing species such as
239 pollack where natural mortality is higher, as is the uncertainty around the es-
240 timate. The relationships when compared the proxy for fishing pressure f/m
241 show that the estimate is considerably higher in sprat than pollack, how-
242 ever the intrinsic population growth rate r shows that sprats reproductive
243 capacity is higher and thus its surplus production.

244 **[EXAMPLES TO BE UPDATED]**

- 245 • Figure 3 shows the life history parameters
- 246 • Figure 2 shows the vectors
- 247 • Figure 4 shows the time series relative to reference points
- 248 1.
- 249 2.
- 250 3.
- 251 4.
- 252 5. Figure 5 shows the utility functions for the seven study stocks
- 253 points area
- 254 1.
- 255 2.
- 256 3.
- 257 4.

258 4. Discussion

259 Fisheries management is often faced with multiple conflicting objectives
260 e.g social, biological and economic, and it is widely recognised that there is
261 a need to incorporate these objectives into management plans. However
262 such an experiment on large scale fish stocks is nearly impossible to perform.
263 Therefore performing computer simulations to develop robust management

264 procedures is particularly valuable in data poor situations where knowledge
265 and data are limited, but also in data rich situations as simulation testing an
266 assessment procedure using a model conditioned on the same assumptions is
267 not necessarily a true test of robustness.

268 The main ICES MSY objectives for category 3 and 4 stocks are to max-
269 imise long-term yield, in a manner that is consistent with precautionary prin-
270 ciples; i.e. having a low probability of falling outside biologically sustainable
271 limits. This paper has shown that the desired performance measures can
272 be met via tweaking of the management procedure by adjusting a particular
273 HCR, a specific management objective can be achieved. Here a simplistic
274 utility function was used to evaluate visually how well each HCR performed
275 and the uncertainties associated with the specific combinations.

276 • Bullet point one

277 • Bullet point two

278 5. Conclusions

279 • Bullet point one

280 • Bullet point two

281 6. References

282 References

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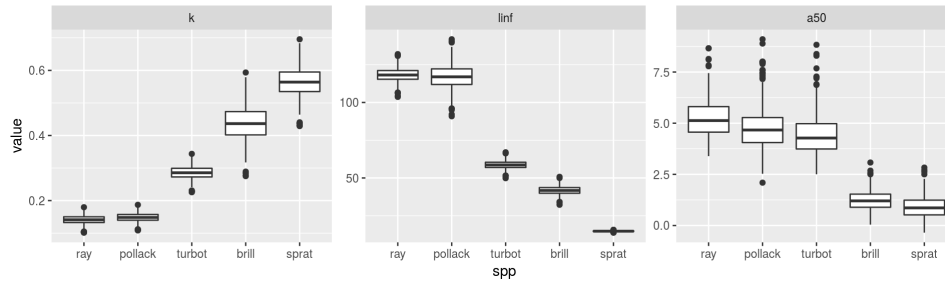


Figure 1:

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7. Figures

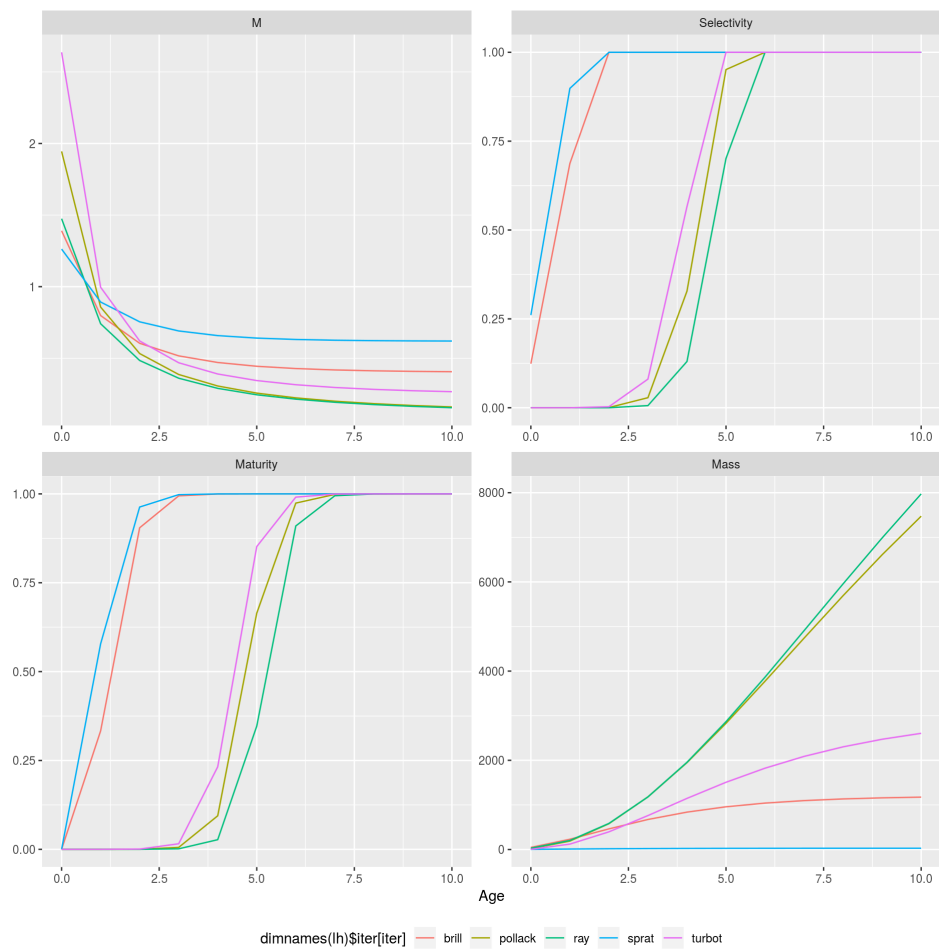


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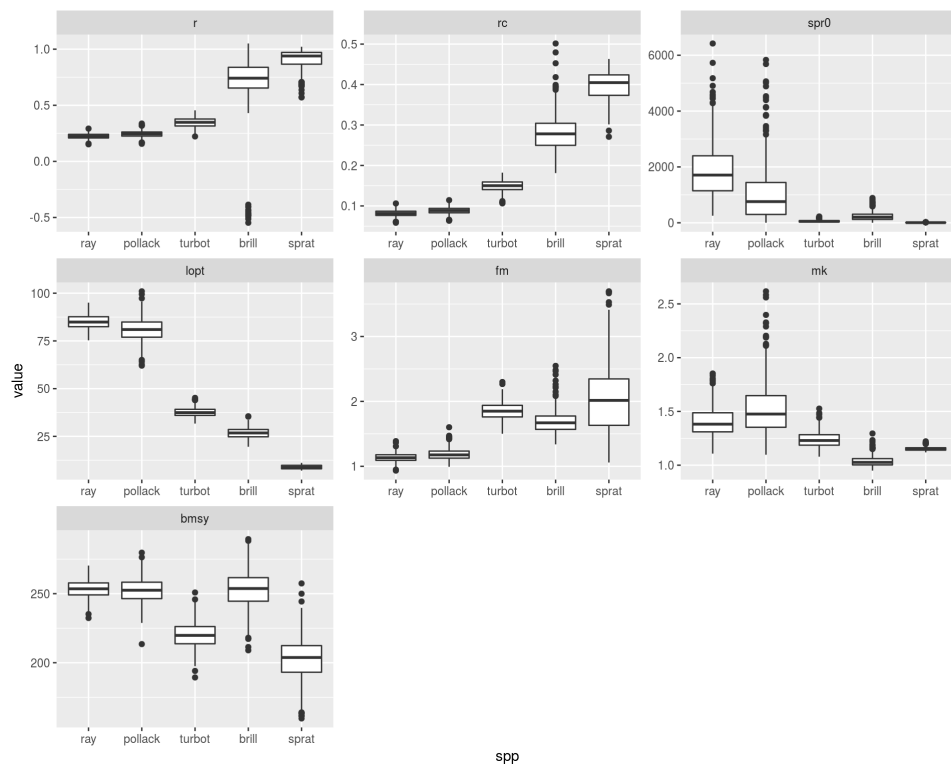


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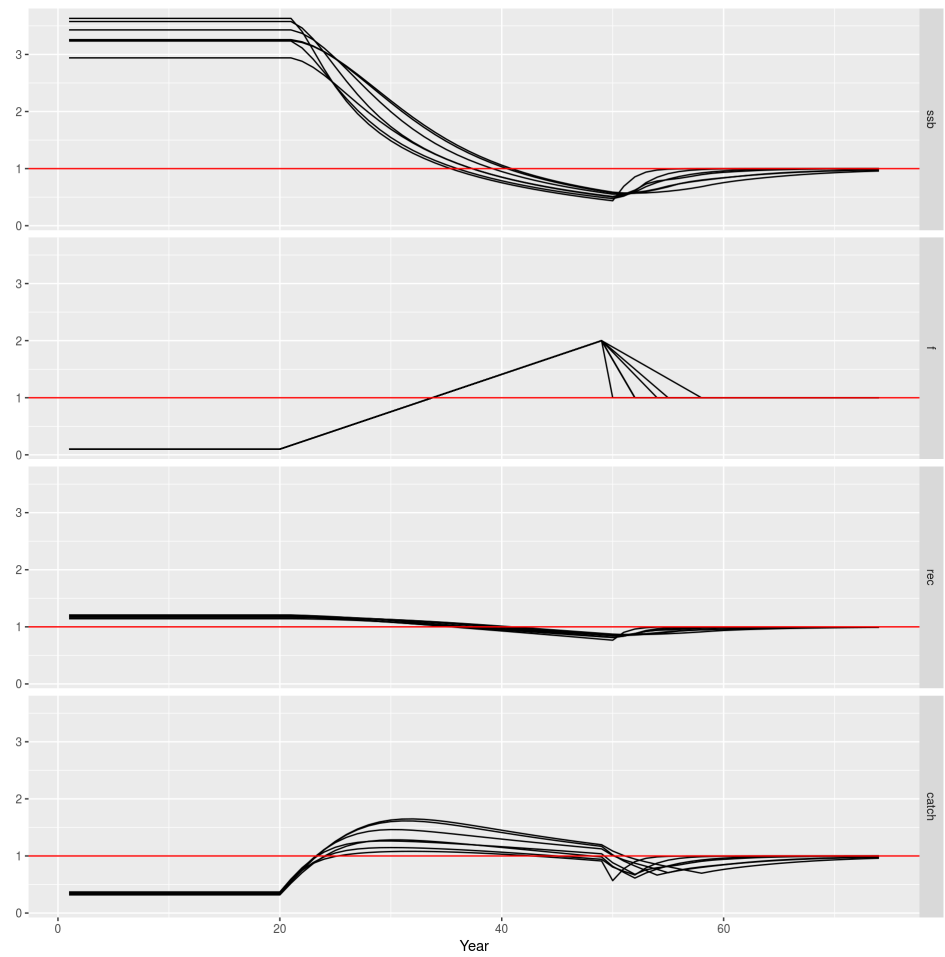


Figure 4:

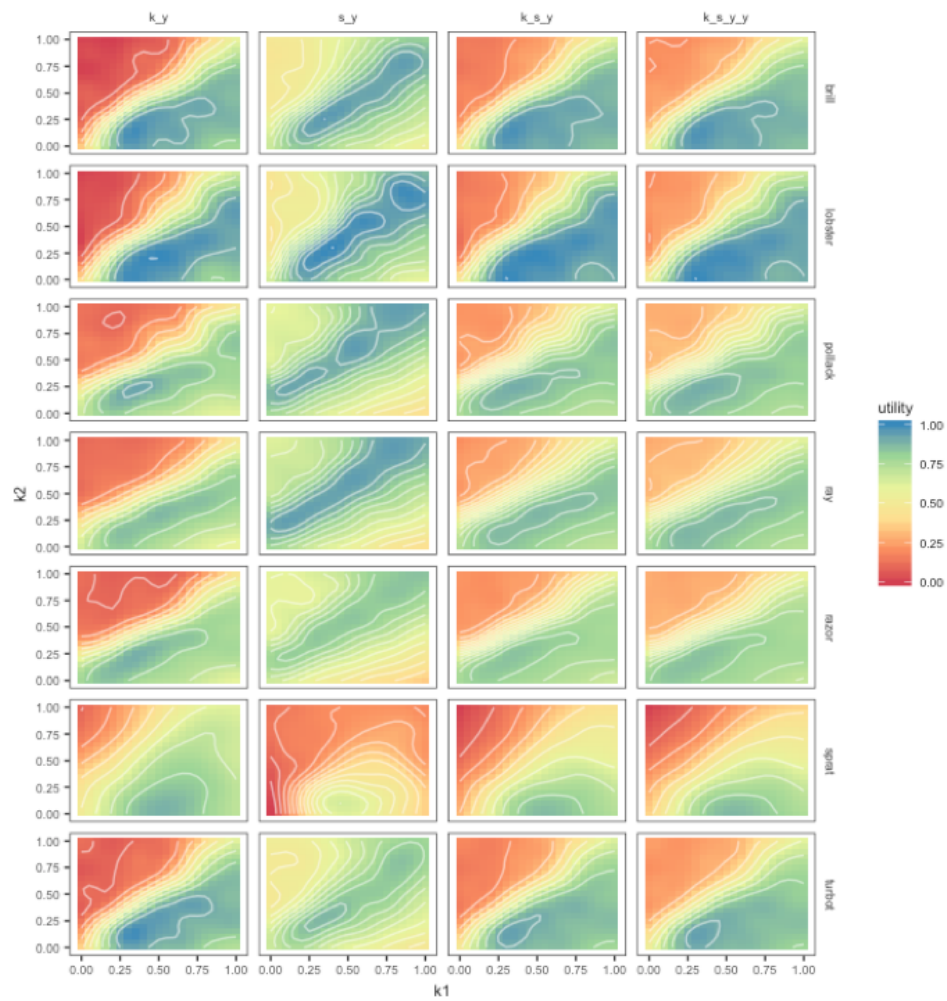


Figure 5: