

# Unnecessary hyperparameter search

Laurie Kell

*Henstead, UK*

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## Abstract

*Keywords:* Science, Publication, Complicated

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### **1. Introduction**

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

The International Council for the Exploration of the Sea (ICES) categorises stocks in to classes *data-rich*, (categories 1 and 2) i.e those that have a quantitative assessment based on conventional methods that require large

26 amounts of data that include a long historical time series of catches and  
27 sound biological information [2]; or *data-limited* [3](categories 3 and 4) (of-  
28 ten called data poor) those without assessment, forecasts and have limited  
29 funding for research. For data-rich stocks ICES uses two types of reference  
30 points for providing fisheries advice;

- 31     1. Precautionary Approach (PA) reference points (those relating to stock  
32         status and exploitation relative to precautionary objectives) and  
33     2. MSY reference points (those relating to achieving MSY)

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

45     To test the performance of candidate management procedures often re-  
46 quires evaluation of alternative hypothesis about the dynamics of the system  
47 e.g. population dynamics (life history dynamics such as growth parameters  
48 which are an indication of fishery exploitation levels and management) and  
49 the behaviour of the fishery (e.g range contraction and density dependence)  
50 etc.. Due to the nature of conflicting objectives, stakeholder interests and the  
51 uncertainty in the dynamics of the resource and/or the plausibility of alter-  
52 native hypotheses can lead to poor decision making and can be problematic  
53 when defining management policy.

54     An intense area of work being researched over the last 2 decades is Man-  
55 agement Strategy Evaluation (MSE), which focuses on the broader aspects  
56 of fishing (the Ecosystem) whereby different management options are tested  
57 against a range of objectives (see [9] (i.e. biological, social, economic)). The  
58 approach is not to come up with a definitive answer, but to lay-bare the trade  
59 offs associated with each management objective, along with identifying and  
60 incorporating uncertainties in the evaluation and communicating the results  
61 effectively to client groups and decision-makers. MSE is not intended to

62 be complex but to provide a robust framework that account for conflicting  
63 poorly defined objectives and uncertainties that have been absent in conven-  
64 tional management [9].

65 MSE methods rely on simulation testing to assess the consequences of  
66 a range of management options and to evaluate each performance measure  
67 across a range of objectives, requiring the use of an operating model (OM)  
68 to simulate the actual system (observation model) which are then fed into an  
69 management procedure (MP) to provide catch advice. To assess case specific  
70 harvest strategies (via simulation) within the MSE, we will implement a man-  
71 agement procedure based on a empirical HCR that adjusts yield depending  
72 on stock status for a given set of tunable parameters for each of the harvest  
73 strategies and to test their robustness to uncertainty. This approach could  
74 also help identify similar conditions across species where particular advice  
75 rules are likely to work well, and where they perform poorly for a given a set  
76 of parameters.

77 Often empirical harvest control rules require extensive exhaustive param-  
78 eter searches to tune or optimise 'hyper-parameters' (external parameters to  
79 a model) that aren't directly learnt from estimators. This requires a tech-  
80 nique known as a grid search that extensively searches for all combinations of  
81 all parameters. In contrast, and some what less time consuming alternative  
82 and efficient parameter search strategies can be considered for a given range  
83 of parameter space and a known distribution. As such a random sample  
84 can be obtained and used to perform the different experiments for parameter  
85 optimisation.

86 This paper describes a generic method to simulate differing life history pa-  
87 rameters for 5 commercially important european fish species (sprat; *Sprattus*  
88 *prattus*, ray; *Rajidae*, pollack; *Pollachius pollachius*, turbot; *Psetta max-*  
89 *ima* and brill; *Scophthalmus rhombus* and to assess the performance of each  
90 empirical HCRs. Asessment is made via a set of utility functions that in-  
91 dicate where the stock is in relation to ICES limit reference points, target  
92 reference points and economics. Our approach is to show the benefits and  
93 advance management procedures by using an emprical approach for data lim-  
94 ited stocks in comparison to a constant catch HCR strategy i.e one where  
95 catches are kept constant and low to ensure no lasting damage is done in  
96 periods of low stock productivity or whereby the stock is highly variable year  
97 on year, therefore the empirical approach can help optimise catch by setting  
98 a precautionary TAC.

99    **2. Material and Methods**

100    *2.1. Materials*

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

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

118    The equilibrium relationships can then be turned into a forward dynamic  
119    model and projected forward.

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

127    *2.2. Methods*

128    Individual Growth

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

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

130    where  $k$  is the rate at which the rate of growth in length declines as  
131    length approaches the asymptotic length  $L_\infty$  and  $t_0$  is the hypothetical time  
132    at which an individual is of zero length.

<sup>133</sup> Length is converted to mass using the length-weight relationship

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

<sup>134</sup> where  $a$  is the condition factor and  $b$  is the allometric growth coefficient.

<sup>135</sup> Maturity-at-age

<sup>136</sup> Proportion mature-at-age is modelled by the logistic equation with 2 pa-  
<sup>137</sup> rameters: age at 50% ( $a_{50}$ ) and 95% ( $a_{95}$ ) mature.

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

<sup>138</sup> Selection Pattern

<sup>139</sup> By default the fishery is assumed to catch mature fish and so the selection  
<sup>140</sup> pattern is based on the maturity ogive. It is modelled by a double normal  
<sup>141</sup> curve, however, to allow scenarios to be implemented where older fish are  
<sup>142</sup> less vulnerable to the fisheries.

<sup>143</sup> The double normal has three parameters that describe the age at maxi-  
<sup>144</sup> mum selection ( $a1$ ), the rate at which the left-hand limb increases ( $sl$ ) and  
<sup>145</sup> the right-hand limb decreases ( $sr$ ) which allows flat topped or domed shaped  
<sup>146</sup> selection patterns to be chosen, i.e.

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

<sup>147</sup> Stock Recruitment Relationship By default a Beverton and Holt stock  
<sup>148</sup> recruitment relationship [13] was assumed, This relationship is derived from  
<sup>149</sup> a simple density dependent mortality model where the more survivors there  
<sup>150</sup> are the higher the mortality. It is assumed that the number of recruits ( $R$ )  
<sup>151</sup> increases towards an asymptotic level ( $R_{max}$ ) as egg production increases i.e.

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

<sup>152</sup> The relationship between stock and recruitment was modelled by a Bev-  
<sup>153</sup> erton and Holt stock-recruitment relationship [13] reformulated in terms of  
<sup>154</sup> steepness ( $h$ ), virgin biomass ( $v$ ) and  $S/R_{F=0}$ . Where steepness is the propor-  
<sup>155</sup> tion of the expected recruitment produced at 20% of virgin biomass relative  
<sup>156</sup> to virgin recruitment ( $R_0$ ). However, there is often insufficient information

157 to allow its estimation from stock assessment [14] and so by default a value  
 158 of 0.8 was assumed. Virgin biomass was set at 1000 Mt to allow comparisons  
 159 to be made across scenarios.

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

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

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

163 where fecundity-at-age is assumed proportional to biomass and the sex  
 164 ratio to be 1:1. Proportion mature is 50% at the age that attains a length of  
 165  $l_{50}$ , 0% below this age and 100% above.

### 166 2.2.1. Operating Model

#### 167 Age based Equilibrium Analysis

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

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

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

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

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

183     Forward Projection

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

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

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

191     2.2.2. Management Procedure

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

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

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

202        The TAC is then the average of the last TAC and the value output by  
203        the HCR.

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

204        *2.2.3. Random Search*

205        When running an MSE commonly a set of MP scenarios are run to tune  
206        the MP, this requires running the MSE for each OM scenario for a range of  
207        fixed values in the HCR and then choosing the rule that best meets manage-  
208        ment objectives. If there are a lot of parameters to tune then a grid search  
209        may become unfeasible. An alternative is random search [16] as randomly  
210        chosen trials are more efficient for parameter optimisation than trials based  
211        on a grid. The random parameter search is performed where random combi-  
212        nations of hyperparameters k1 and k2 are used to find the optimal solutions  
213        for the MSE model in terms of performance measures: a) safety, (recruit-  
214        ment in relation to virgin recruitment), b) yield (catch/MSY), c) proportion  
215        of years in the kobe green zone i.e  $B/B_{MSY} > 1$  and  $F/F_{MSY} < 1$  and d)  
216        Average annual variation in a TAC from one year to the next (expressed as  
217        a proportion of the average annual catch). For instance as the process is  
218        random at each iteration its likely that the whole of the grid space would be  
219        covered in the simulation providing that there are enough iterations, there is  
220        a greater chance of finding the optimal parameter pairs.

221        *2.2.4. Utility function*

222        Utility is based on economic theory and as such a decision-maker is faced  
223        with making a choice among a number of alternative options, obtaining dif-  
224        fering levels of utility from each alternative option, and tending to choose  
225        one that maximizes utility. To evaluate the HCRs from the range of per-  
226        formance measures described above it is possible to collectively group the  
227        measures to suit different stakeholders and/or objectives. Here we provide  
228        visual isopleths as decision support tools to show the net benefit of making  
229        one decision over another with the inclusion of the sources of uncertainty  
230        with the objective of showing where where the stock is in relation to ICES  
231        limit reference points, target reference points and economics.

232        **3. Results**

233        Results from our simulated life histories illustrate the diversity in relation  
234        to growth, size and maturity and are presented in Fig.1. These plots show

235 that for fast growing species which are small in size  $l_\infty$  (asymtopic length  
236 parameter - maximum attainable length) species such as sprat, the growth  
237 parameter  $k$  is high. There are also inherent relationships between length at  
238 maturity and the maximum attainable length. For instance sprats length-at-  
239 50%-maturity  $l_{50}$  are low, in contrast to a slower growing larger species  $l_\infty$   
240 such as ray or pollack.

241 Observations in Fig.2 shows the resulting trends of the vectors from the  
242 OM for natural mortality, selectivity, maturity and length in relation to age.  
243 Selectivity is derived from maturity and results show that the faster growing  
244 species (Fig.1 i.e. sprat) are more selective to fishing, have a high natural  
245 mortality at lower ages and thus length. However for the slower growing  
246 larger (here represented by length) species (e.g. pollack or ray) have a higher  
247 natural mortality rate at lower ages, are more selective/mature with age  
248 increases. Interestingly the most significant natural mortality rate increases  
249 are associated with turbot at lower ages, however in contrast for the similar  
250 flatfish brill, the rate isn't as steep.

251 Fig.3 displays the equilibrium relationships of the OM. Comparisons of  
252 reference points estimates can be made across species. The  $m/k$  plot shows  
253 interesting trends with lower values for sprat where the growth rate  $k$  is  
254 considerably higher than the natural mortality rate  $m$  with little uncertainty  
255 around the estimate. In contrast to a slower growing species such as pollack  
256 where natural mortality is higher, as is the uncertainty around the estimate.  
257 The aforementioned relationships when compared with the proxy for fishing  
258 pressure  $f/m$  show that the estimate is considerably higher in sprat than  
259 pollack.

260 The intrinsinc population growth rate  $r$  shows that sprats reproductive  
261 capacity is higher than all of the species. However the long term average  
262 biomass (if fishing at  $f_{msy}$ ) to deliver MSY  $b_{msy}$  is slightly less in comparison  
263 to all other species although has a higher MSY. Nevertheless the catch size  
264 relative to the stock size  $f_{msy}$  is  $> 1$  thus suggesting this species is susceptible  
265 to overfishing.

266 The dynamics of the forward projection to go from equilibrium (Fig.3) to  
267 time series dynamics are presented in Fig.4. As an example we show that by  
268 changing the fishing mortality  $F$  time series so that it represents a time series  
269 where the stock was originally lightly exploited and then increase  $F$  until the  
270 stock was overfished, and show by reducing fishing to ensure spawning stock  
271 biomass was greater than  $b_{msy}$ .

272 The outputs from the MSE and hyperparameters relative to performance

measures are displayed in Fig.5. For the proportion of years where  $B/B_{MSY} > 1$  and  $F/F_{MSY} < 1$  here represented by "kobe.p" it is evident that if the desired objective is to increase the proportion of years of staying in the kobe green zone then the hyperparameter  $k_1$  must be increased while  $k_2$  must be decreased for all species. Observations for safety (recruitment relative to virgin recruitment) expectedly show the same patterns as for kobe.p. In contrast, for yield it has an opposite trend especially pronounced for brill and ray, i.e. by decreasing  $k_1$  and increasing  $k_2$  the yield would increase. While for sprat, turbot and pollack the relationship is particularly different in that the dynamics are highly variable, more so for sprat. Turbot and pollack show similar relationships whereby keeping  $k_2$  high solely increases yield and that  $k_1$  has very little effect when the parameter is decreased/increased. In contrast sprats isopleths depict that the best yields are obtained when  $k_2$  are at 25% when  $k_1$  is at zero or both  $k_1$  and  $k_2$  are at 100%.

#### 4. Discussion

Fisheries management is often faced with multiple conflicting objectives e.g social, biological and economic, and it is widely recognised that there is a need to incorporate these objectives into management plans. However such an experiment on large scale fish stocks is nearly impossible to perform. Therefore performing computer simulations to develop robust management procedures is particularly valuable in data poor situations where knowledge and data are limited, but also in data rich situations as simulation testing an assessment procedure using a model conditioned on the same assumptions is not necessarily a true test of robustness.

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

305 **5. Conclusions**

306 **6. References**

307 **References**

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359 **7. Figures**

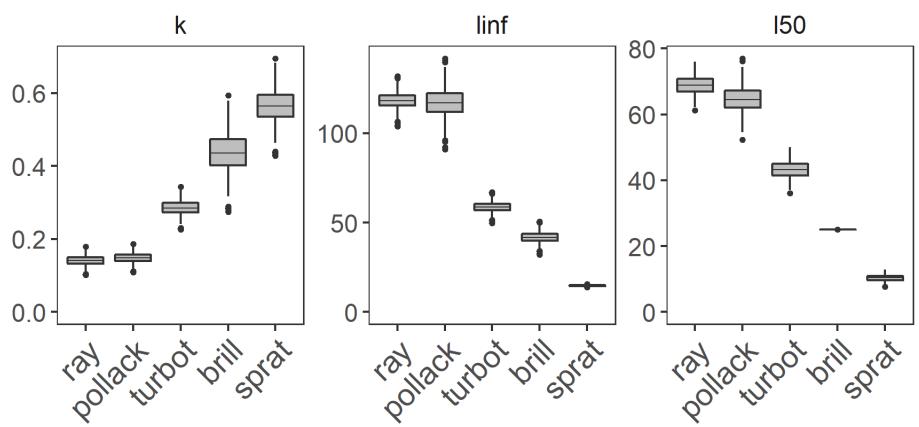


Figure 1:

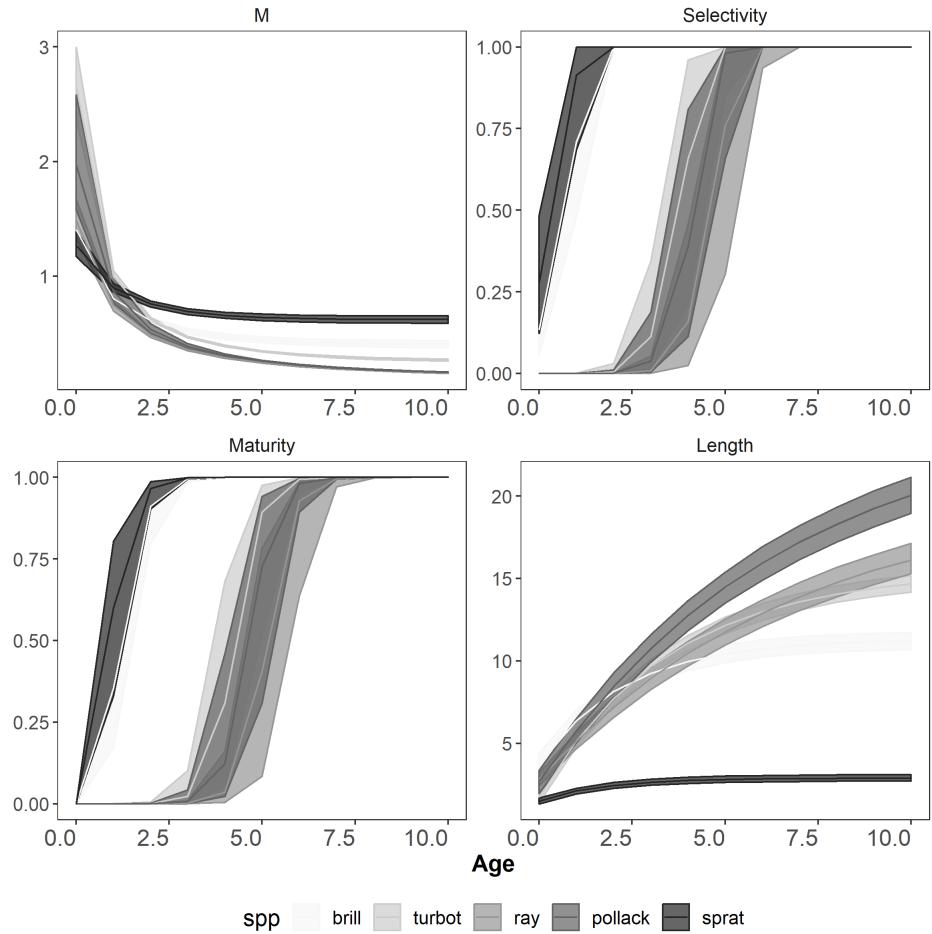


Figure 2:

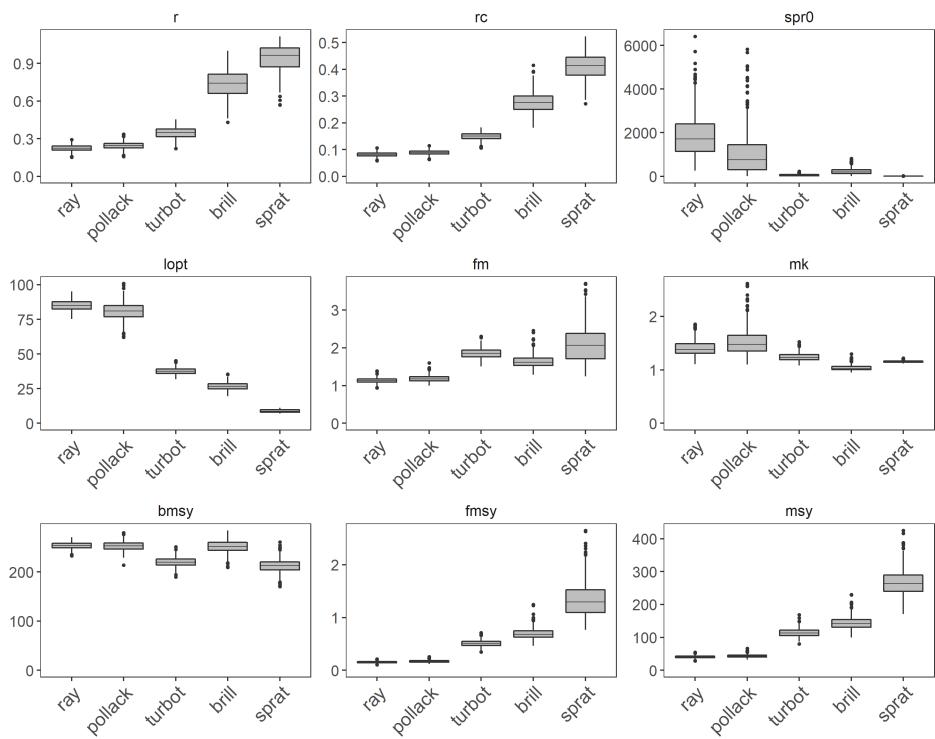


Figure 3:

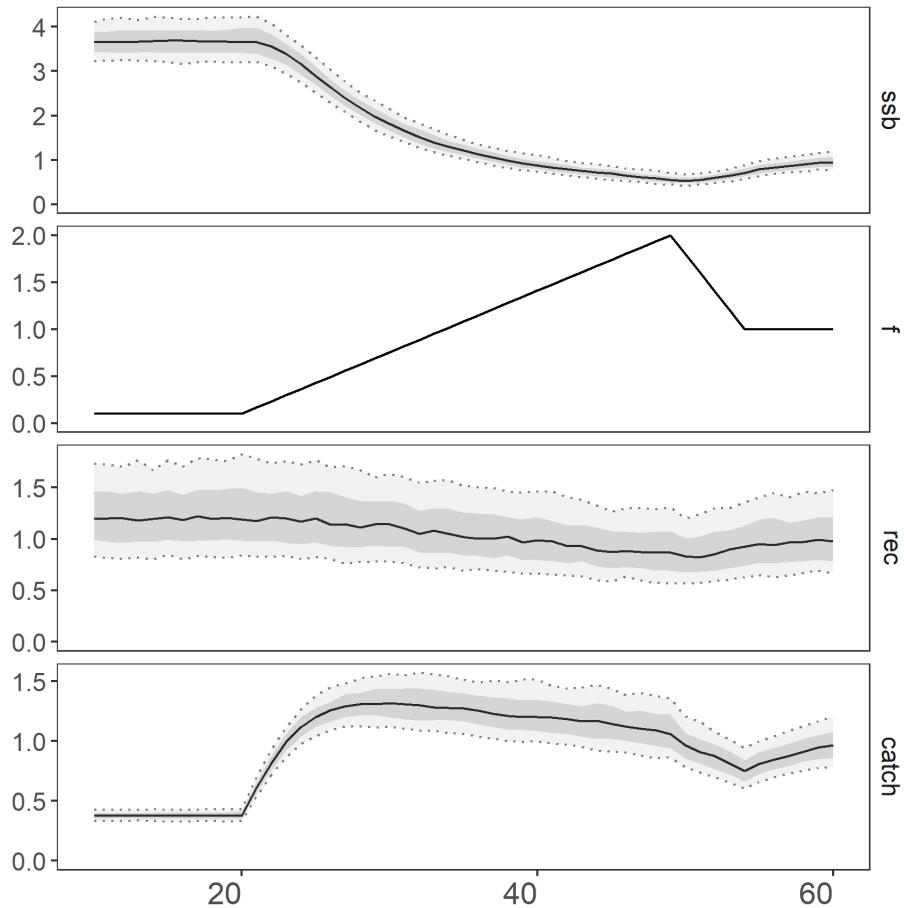


Figure 4:

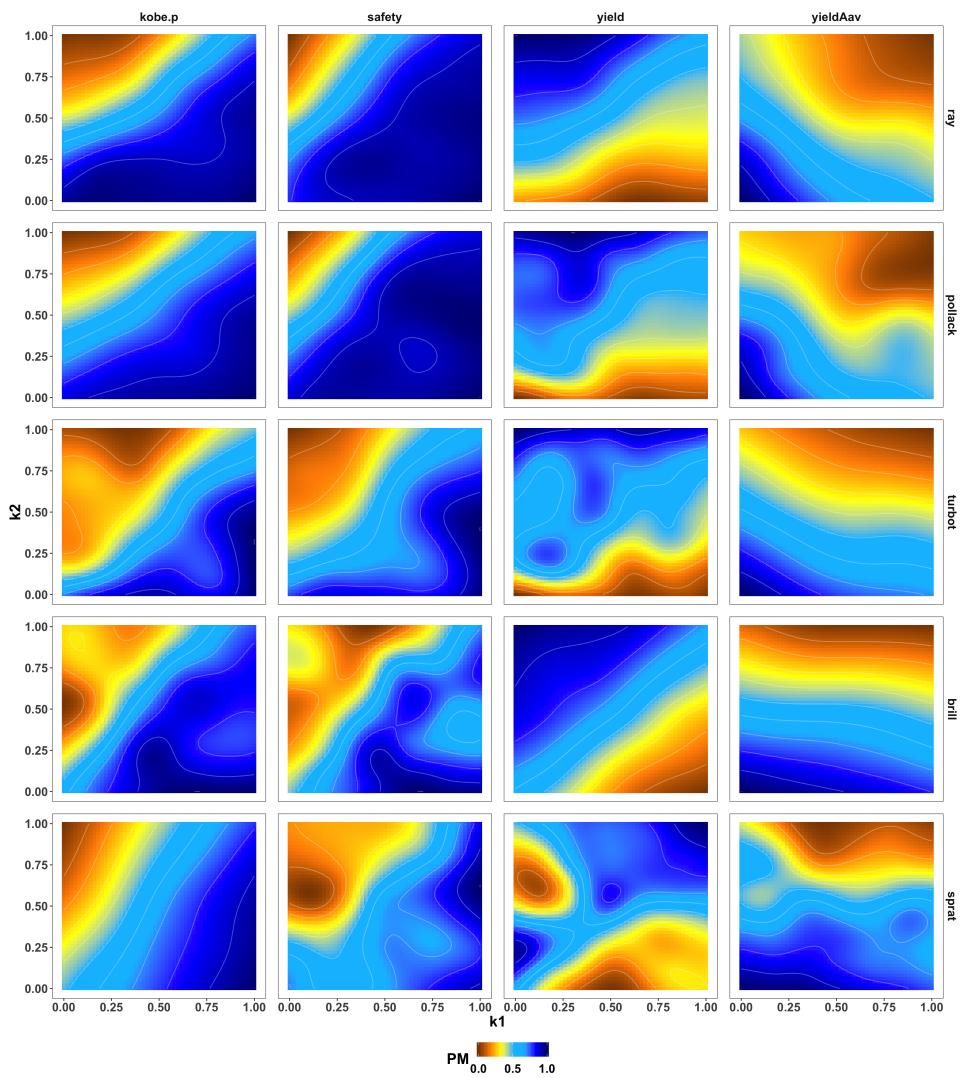


Figure 5:

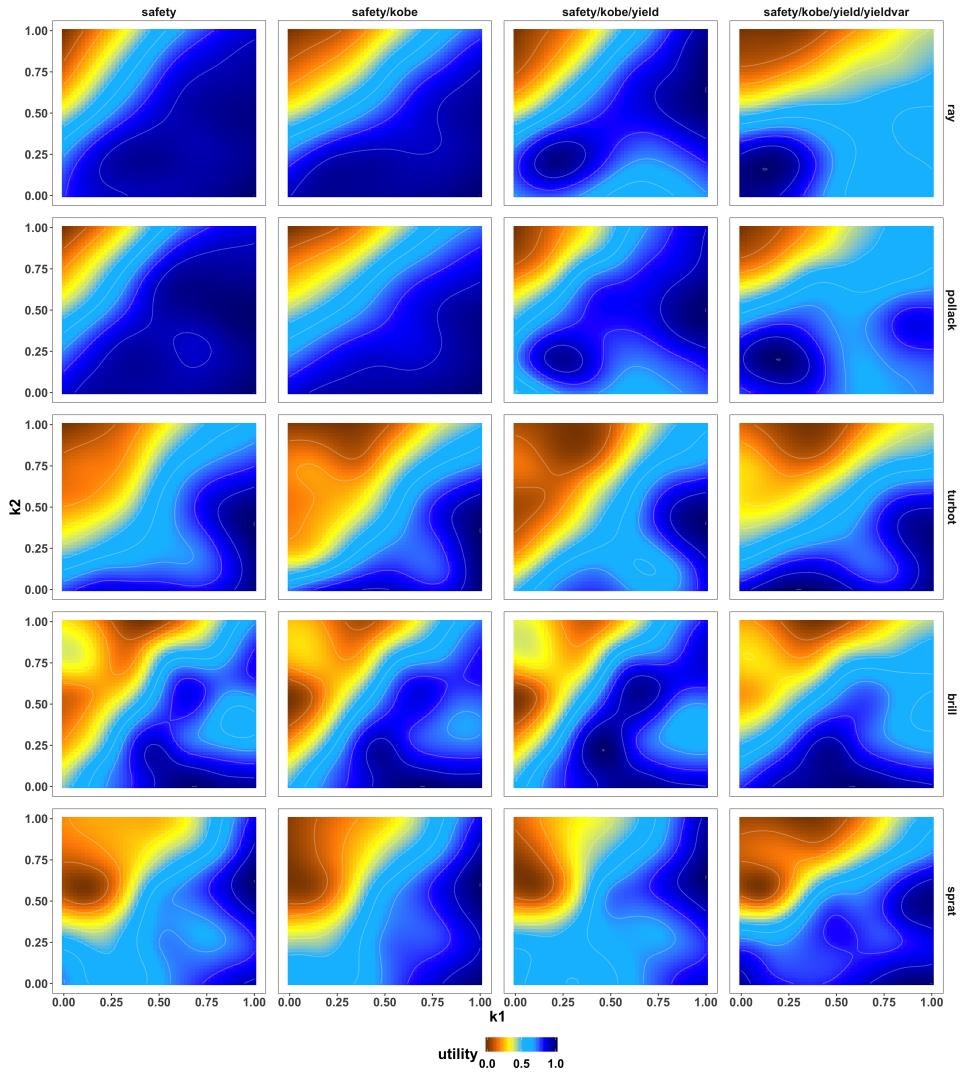


Figure 6: