

Optimising empirical harvest control rules via a random parameter search; A data-poor case study

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Abstract

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1. Introduction

Ensuring sustainability across ecological, social and economic dimensions is a cornerstone of international Sustainable Development policy (United Nations Sustainable Development Goals) and Blue Growth initiatives [1]. However, at least 33% of commercial fish stocks worldwide are being fished at unsustainable levels [2]. A key challenge is how can we rigorously evaluate multifaceted aspects of sustainability and effectively anticipate and avoid risk. It is globally recognised that to improve sustainability a more holistic approach is required so that management of all marine stocks not just those of high commercial value can be included into policy frameworks. Often appropriate data on non target (by-catch) species are lacking [3] both to estimates stock status, the effects of fishing effort and the effects of management measures on these populations.

Under the European Unions Common Fisheries Policy (CFP); [4], management objectives are to recover stocks and to maintain stocks within safe biological limits to levels that can produce Maximum Sustainable Yield (MSY)

¹⁷ - the largest yield that can be taken from a stock over an indefinite period),
¹⁸ including by-catch species by 2015 (Implementation Plan adopted at the
¹⁹ World Summit on Sustainable Development, Johannesburg in 2002) and no
²⁰ later than 2020 [5] [6].

²¹ These conservation objectives are currently being achieved by introducing
²² biological target (e.g. can fluctuate around targets) and limit (i.e must not
²³ be exceeded) reference points e.g. population size (stock biomass) and/or
²⁴ yields (e.g. management of fish stocks under the CFP based on a target
²⁵ exploitation rate achieved by Total Allowable Catch (TAC) management)
²⁶ and/or long-term yields and fishing mortality against which the preserva-
²⁷ tion of stocks within such limits are assessed. These targets or limit refer-
²⁸ ence points are often referred to as harvesting strategies which include an
²⁹ operational component called a harvest control rule (HCR) that are based
³⁰ on indicators (e.g. monitoring data or models) of stock status and to pre-
³¹ vent target, growth and recruitment overfishing. Therefore to achieve MSY
³² requires limit as well as target reference points.

³³ The International Council for the Exploration of the Sea (ICES) cate-
³⁴ gorises stocks in to classes *data-rich*, (categories 1 and 2) i.e those that have
³⁵ a quantitative assessment based on conventional methods that require large
³⁶ amounts of data that include a long historical time series of catches and
³⁷ sound biological information [7]; or *data-limited* [8](categories 3 and 4) (of-
³⁸ ten called data poor) those without assessment, forecasts and have limited
³⁹ funding for research. For data-rich stocks ICES uses two types of reference
⁴⁰ points for providing fisheries advice;

⁴¹ 1. Precautionary Approach (PA) [9] reference points (those relating to

42 stock status and exploitation relative to precautionary objectives) and
43 2. MSY reference points (those relating to achieving MSY)

44 In contrast for data limited stocks MSY *proxy* reference points are used
45 to estimate stock status and exploitation. Often many of the methods used
46 to estimate MSY proxy reference points require length based inputs as they
47 are cheap, easy to collect [10] and are related to life history parameters such
48 as fish size, mortality and fecundity as well as fishery selectivity. For ex-
49 ample many methods are being developed to estimate MSY, but currently
50 only 4 are approved by ICES, these include, Surplus Production model in
51 Continuous Time (catch based) (SPiCT; [11], Mean Length Z (MLZ; [12]),
52 Length Based Spawner Per Recruit (LBSPR; [13]) and Length Based Indica-
53 tors (LBI; e.g. [14]). The aforementioned data limited procedures have differ-
54 ing data requirements, intended uses and obviously have their own strengths
55 and weaknesses.

56 To test the performance of candidate management procedures often re-
57 quires evaluation of alternative hypothesis about the dynamics of the system
58 e.g. population dynamics (life history dynamics such as growth parameters
59 which are an indication of fishery exploitation levels and management) and
60 the behaviour of the fishery (e.g range contraction and density dependence)
61 etc.. Due to the nature of conflicting objectives, stakeholder interests and the
62 uncertainty in the dynamics of the resource and/or the plausibility of alter-
63 native hypotheses can lead to poor decision making and can be problematic
64 when defining management policy.

65 An intense area of work being researched over the last 2 decades is Man-
66 agement Strategy Evaluation (MSE), which focuses on the broader aspects

of fishing (the Ecosystem) whereby different management options are tested against a range of multiple and conflicting biological (i.e. mixed fisheries multispecies interactions [15]), economic (i.e. variability in yield [16]), and social objectives (i.e. full vs part time employment [17]). For instance 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 (see [18]; [19]). 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 [18].

MSE methods rely on simulation testing to assess the consequences of a range of management options and to evaluate each performance measure across a range of objectives, requiring the use of an operating model (OM) to simulate the actual system (observation model) which are then fed into an management procedure (MP) to provide catch advice. 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

92 a model) that aren't directly learnt from estimators. This requires a tech-
93 nique known as a grid search that extensively searches for all combinations of
94 all parameters. In contrast, and some what less time consuming alternative
95 and efficient parameter search strategies can be considered for a given range
96 of parameter space and a known distribution. As such a random sample
97 can be obtained and used to perform the different experiments for parameter
98 optimisation [20].

99 This paper describes a generic method to simulate differing life history pa-
100 rameters for 5 commercially important european fish species (sprat; *Sprattus*
101 *pprattus*, ray; *Rajidae*, pollack; *Pollachius pollachius*, turbot; *Psetta maxima*
102 and brill; *Scophthalmus rhombus* and to simulation test the performance of
103 each empirical HCRs. Assessment is made via a set of utility functions that
104 indicate where the stock is in relation to ICES limit reference points (proba-
105 bility of avoiding limits), target reference points (probability of achieving tar-
106 gets, recovery and long-term) and economics (MSY and variability in yield).
107 Our approach is to show the benefits and advance management procedures
108 by using an empirical approach for data limited stocks in comparison to a
109 constant catch HCR strategy i.e one where catches are kept constant and
110 low to ensure no lasting damage is done in periods of low stock productivity
111 or whereby the stock is highly variable year on year, therefore the empirical
112 approach can help optimise catch by setting a precautionary TAC.

₁₁₃ **2. Material and Methods**

₁₁₄ *2.1. Materials*

₁₁₅ Life history parameters were obtained from Fishbase (<http://www.fishbase.org>)
₁₁₆ for growth, natural mortality and maturity were used to develop an age-based
₁₁₇ Operating Model. To do this the parameters were first used to parameterise
₁₁₈ functional forms for mass (W), proportion mature (Q), natural mortality
₁₁₉ (M) and fishing mortality (F) at age. These were then used to calculate the
₁₂₀ spawner (S/R) and yield-per-recruit (Y/R) which were then combined with
₁₂₁ a stock recruitment relationship [21] to calculate the equilibrium stock size
₁₂₂ as a function of fishing mortality (F).

₁₂₃ This analysis allows a variety of reference points such as those based on
₁₂₄ Maximum Sustainable Yield (MSY), i.e. B_{MSY} the spawning stock biomass
₁₂₅ (S) and F_{MSY} the fishing mortality that produces MSY at equilibrium to be
₁₂₆ estimated. Other reference points are $F_{0.1}$ the fishing mortality on the yield
₁₂₇ per recruit curve where the slope is 10% of that at the origin, a conservative
₁₂₈ proxy for F_{MSY} ; and F_{Crash} which is the fishing mortality that will drive
₁₂₉ the stock to extinction since it is equivalent to a R/S greater than the slope
₁₃₀ at the origin of the stock recruitment relationship, i.e. recruitment can not
₁₃₁ replace removals for a fishing mortality equal to F_{Crash} .

₁₃₂ The equilibrium relationships can then be turned into a forward dynamic
₁₃₃ model and projected forward.

₁₃₄ A variety of functional forms can be assumed for all of the various pro-
₁₃₅ cess, i.e. growth, mortality, maturity, the selection pattern of the fisheries
₁₃₆ and the stock recruitment relationship. Commonly processes such as growth
₁₃₇ an maturity-at-age are well known while those for natural mortality and the

₁₃₈ stock recruitment relationship are poorly known [22]. In the later case as
₁₃₉ sumptions have to be made and to evaluate the sensitivity of any analysis to
₁₄₀ those assumptions a variety of scenarios are considered.

₁₄₁ *2.2. Methods*

₁₄₂ Individual Growth

₁₄₃ Growth in length is modelled by the Von Bertalanffy growth equation [23]

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

₁₄₄ where k is the rate at which the rate of growth in length declines as
₁₄₅ length approaches the asymptotic length L_∞ and t_0 is the hypothetical time
₁₄₆ at which an individual is of zero length.

₁₄₇ Length is converted to mass using the length-weight relationship

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

₁₄₈ where a is the condition factor and b is the allometric growth coefficient.

₁₄₉ Maturity-at-age

₁₅₀ Proportion mature-at-age is modelled by the logistic equation with 2 pa-
₁₅₁ rameters: age at 50% (a_{50}) and 95% (a_{95}) mature.

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

₁₅₂ Natural Mortality

₁₅₃ Natural mortality of exploited fish populations is often assumed to be
₁₅₄ a species-specific constant independent of body size. This assumption has

155 important implications for size-based fish population models and for pre-
156 dicting the outcome of size-dependent fisheries management measures such
157 as mesh-size regulations [24]. Direct estimates of the instantaneous natural
158 mortality made in controlled studies, however, are shown to vary by age [25].
159 Although M can sometimes be estimated within an assessment model for
160 example where data from tagging provide information independent of fishing
161 mortality rates [26]; [27] in most cases M is derived from a variety of life
162 history relationships, e.g. based on size [28]; [29]; [30]; [31]; [32]; [33]. The
163 large and ever increasing literature on this subject is a reflection of the uncer-
164 tainty. [24] in an empirical study showed that M is significantly related to
165 body length, asymptotic length and k . Temperature is non-significant when
166 k is included, since k itself is correlated with temperature, i.e.

$$M = 0.55L^{1.61}L_{\infty}^{1.44}k \quad (4)$$

167 Selection Pattern

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

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

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

176 Stock Recruitment Relationship By default a Beverton and Holt stock
 177 recruitment relationship [34] was assumed, This relationship is derived from
 178 a simple density dependent mortality model where the more survivors there
 179 are the higher the mortality. It is assumed that the number of recruits (R)
 180 increases towards an asymptotic level (R_{max}) as egg production increases i.e.

$$R = Sa/(b + S) \quad (6)$$

181 The relationship between stock and recruitment was modelled by a Bev-
 182 erton and Holt stock-recruitment relationship [34] reformulated in terms of
 183 steepness (h), virgin biomass (v) and $S/R_{F=0}$. Where steepness is the propor-
 184 tion of the expected recruitment produced at 20% of virgin biomass relative
 185 to virgin recruitment (R_0). However, there is often insufficient information
 186 to allow its estimation from stock assessment [35] and so by default a value
 187 of 0.8 was assumed. Virgin biomass was set at 1000 Mt to allow comparisons
 188 to be made across scenarios.

$$R = \frac{0.8R_0h}{0.2S/R_{F=0}R_0(1-h) + (h-0.2)S} \quad (7)$$

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

$$S = \sum_{i=0}^p N_i Q_i W_i \quad (8)$$

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

195 *2.2.1. Operating Model*

196 Age based Equilibrium Analysis

197 [21], estimated surplus production using an age-based analysis using an
 198 equilibrium analysis that by combining a stock-recruitment relationship, a
 199 spawning-stock-biomass-per-recruit analysis, and a yield-per-recruit analysis.
 200 For any specified rate of fishing mortality, an associated value of spawning
 201 stock biomass (S) per recruit (R) is S/R is defined, based on the assumed
 202 processes for growth, natural mortality and selection pattern-at-age detailed
 203 in the previous sections.

$$S/R = \sum_{i=0}^{p-1} e^{\sum_{j=0}^{i-1} -F_j - M_j} W_i Q_i + e^{\sum_{i=0}^{p-1} -F_i - M_i} \frac{W_p Q_p}{1 - e^{-F_p - M_p}} \quad (9)$$

204 When the value of S/R obtained is inverted and superimposed on the
 205 stock-recruitment function as a slope (R/S), the intersection of this slope
 206 with the stock-recruitment function defines an equilibrium level of recruit-
 207 ment. When this value of recruitment is multiplied by the yield per recruit
 208 calculated for the same fishing mortality rate, the equilibrium yield associ-
 209 ated with the fishing mortality rate emerges [36].

$$Y/R = \sum_{a=r}^{n-1} e^{\sum_{i=r}^{a-1} -F_i - M_i} W_a \frac{F_a}{F_a + M_a} (1 - e^{-F_i - M_i}) + e^{\sum_{i=r}^{n-1} -F_n - M_n} W_n \frac{F_n}{F_n + M_n} \quad (10)$$

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

212 Forward Projection

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

$$N_{t,a} = \begin{cases} R_t, & \text{if } a = 0, \\ N_{t-1,a-1} e^{-Z_{t-1,a-1}}, & \text{if } 1 \leq a \leq A-1, \\ N_{t-1,A-1} e^{-Z_{t-1,A-1}} + N_{t-1,A} e^{-Z_{t-1,A}}, & \text{if } a = A, \end{cases} \quad (11)$$

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

220 *2.2.2. Management Procedure*

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

$$TAC_{y+1}^1 = TAC_y \times \begin{cases} 1 - k_1|\lambda|^\gamma & \text{for } \lambda < 0 \\ 1 + k_2\lambda & \text{for } \lambda \geq 0 \end{cases} \quad (12)$$

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

231 The TAC is then the average of the last TAC and the value output by
 232 the HCR.

$$TAC_{y+1} = 0.5 \times (TAC_y + C_y^{\text{targ}}) \quad (13)$$

233 *2.2.3. Random Search*

234 When running an MSE commonly a set of MP scenarios are run to tune
 235 the MP, this requires running the MSE for each OM scenario for a range of
 236 fixed values in the HCR and then choosing the rule that best meets manage-
 237 ment objectives. If there are a lot of parameters to tune then a grid search
 238 may become unfeasible. An alternative is random search [20] as randomly
 239 chosen trials are more efficient for parameter optimisation than trials based
 240 on a grid. The random parameter search is performed where random combi-
 241 nations of hyperparameters k_1 and k_2 are used to find the optimal solutions
 242 for the MSE model in terms of performance measures: a) safety, (recruit-
 243 ment in relation to virgin recruitment), b) yield (catch/MSY), c) proportion
 244 of years in the kobe green zone i.e $B/B_{MSY} > 1$ and $F/F_{MSY} < 1$ and d)
 245 Average annual variation in a TAC from one year to the next (expressed as
 246 a proportion of the average annual catch). For instance as the process is

247 random at each iteration its likely that the whole of the grid space would be
248 covered in the simulation providing that there are enough iterations, there is
249 a greater chance of finding the optimal parameter pairs.

250 *2.2.4. Utility function*

251 Utility is based on economic theory and as such a decision-maker is faced
252 with making a choice among a number of alternative options, obtaining dif-
253 fering levels of utility from each alternative option, and tending to choose one
254 that maximizes utility. To evaluate the HCRs from the range of performance
255 measures described above it is possible to collectively group the measures
256 to indicate potentially conflicting trade-offs to inform different stakeholders
257 and/or objectives. Here we provide visual isopleths as decision support tools
258 to show the net benefit of making one decision over another with the inclu-
259 sion of the sources of uncertainty with the objective of showing where where
260 the stock is in relation to ICES limit reference points, target reference points
261 and economics.

262 **3. Results**

263 Results from our simulated life histories illustrate the diversity in relation
264 to growth, size and maturity and are presented in Fig.1. These plots show
265 that for fast growing species which are small in size l_∞ (asymtopic length
266 parameter - maximum attainable length) species such as sprat, the growth
267 parameter k is high. There are also inherent relationships between length at
268 maturity and the maximum attainable length. For instance sprats length-at-
269 50%-maturity l_{50} are low, in contrast to a slower growing larger species l_∞
270 such as ray or pollack.

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

281 Fig.3 displays the equilibrium relationships of the OM. Comparisons of
282 reference points estimates can be made across species. The m/k plot shows
283 interesting trends with lower values for sprat where the growth rate k is
284 considerably higher than the natural mortality rate m with little uncertainty
285 around the estimate. In contrast to a slower growing species such as pollack
286 where natural mortality is higher, as is the uncertainty around the estimate.
287 The aforementioned relationships when compared with the proxy for fishing
288 pressure f/m show that the estimate is considerably higher in sprat than
289 pollack.

290 The intrinsic population growth rate r shows that sprats reproductive
291 capacity is higher than all of the species. However the long term average
292 biomass (if fishing at $fmsy$) to deliver MSY $bmsy$ is slightly less in comparison
293 to all other species although has a higher MSY. Nevertheless the catch size
294 relative to the stock size $fmsy$ is > 1 thus suggesting this species is susceptible
295 to overfishing.

296 The dynamics of the forward projection to go from equilibrium (Fig.3)
297 to time series dynamics are presented in Fig.4. As an example we show
298 that by changing the fishing mortality F time series so that it represents a
299 time series where the stock was originally lightly exploited and then increase
300 F until the stock was overfished, and show by reducing fishing pressure to
301 ensure spawning stock biomass was greater than b_{MSY} .

302 The outputs from the MSE and hyperparameters relative to performance
303 measures were rescaled by species, measure and are displayed in Fig.5. For
304 the proportion of years where $B/B_{MSY} > 1$ and $F/F_{MSY} < 1$ here repre-
305 sented by "kobe.p" it is evident that if the desired objective is to increase
306 the proportion of years of staying in the kobe green zone then the value of
307 the hyperparameter k_1 must be increased conversely k_2 must be of a lower
308 value for all species. Observations for safety (recruitment relative to virgin
309 recruitment) expectedly show the same patterns as for kobe.p. In contrast,
310 for yield the trend is opposite for all species, i.e by decreasing k_1 and en-
311 suring k_2 is of a high value the yield would increase. While for sprat, the
312 relationship is particularly different in that the isopleths depict that the best
313 yields are obtained when k_2 are at 25% when k_1 is at zero. The variable
314 representing variation in year on year yield, YieldAav, shows that if k_1 and
315 k_2 are reduced to 0 the variability in catch is at its lowest.

316 Fig.6 shows that when combining performance measures a utility function
317 can be derived to indicate how the different components could potentially
318 meet the objectives, i.e. ICES limit reference points, target reference points
319 and in terms of economics. Given that the performance measures are on the
320 same scale it is thus possible to interpret the combined utilities. It can be

321 clearly seen that to achieve managements goals in terms of limit reference
322 points i.e safety, hyper-parameter k1 should be increased and k2 decreased.
323 Meeting both target and limit reference points i.e safety and kobe.p requires
324 similar values of k1 and k2 as mentioned previously when solely observing
325 safety.

326 **4. Discussion**

327 Fisheries management is often faced with multiple conflicting objectives
328 e.g social, biological and economic, and it is widely recognised that their is
329 a need to incorporate these objectives into management plans [37]. However
330 such an experiment on large scale fish stocks is nearly impossible to perform.
331 Therefore performing computer simulations to develop robust management
332 procedures is particularly valuable in data poor situations where knowledge
333 and data are limited, but also in data rich situations as simulation testing an
334 assessment procedure using a model conditioned on the same assumptions is
335 not necessarily a true test of robustness [38].

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

344 **5. Conclusions**

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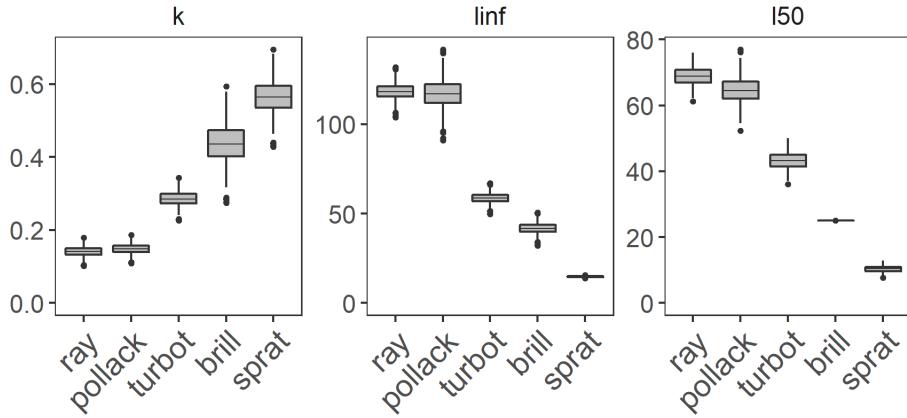


Figure 1:

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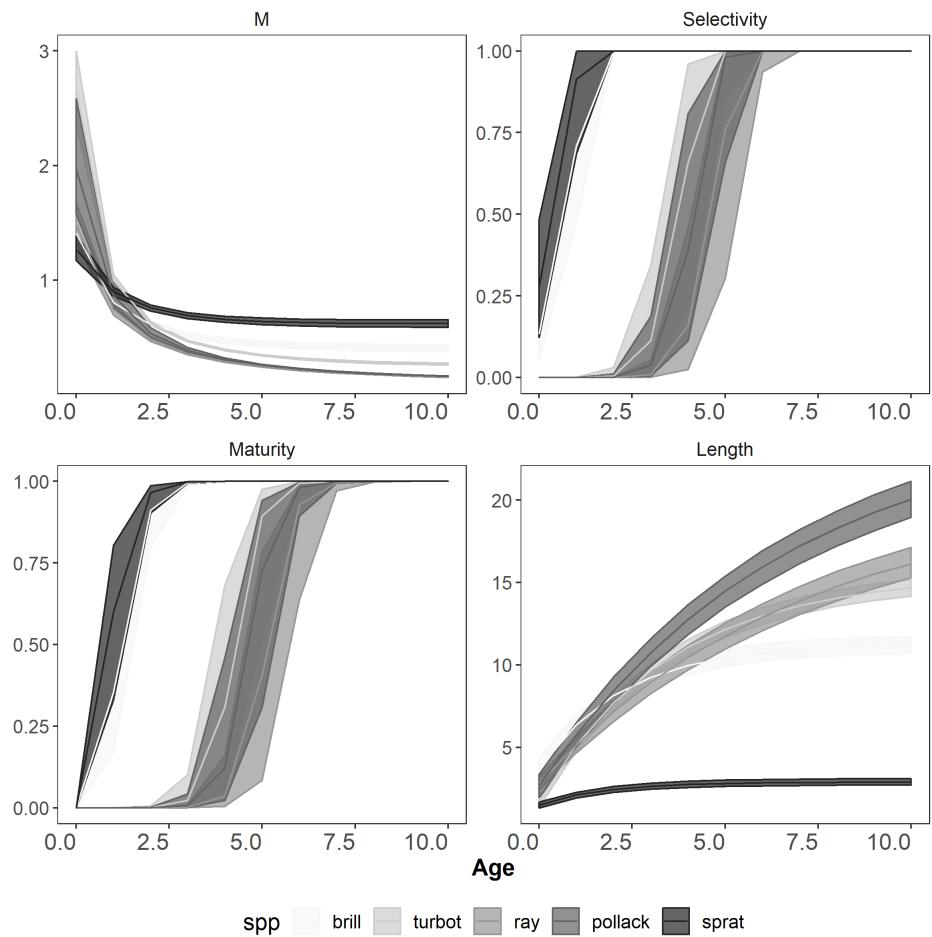


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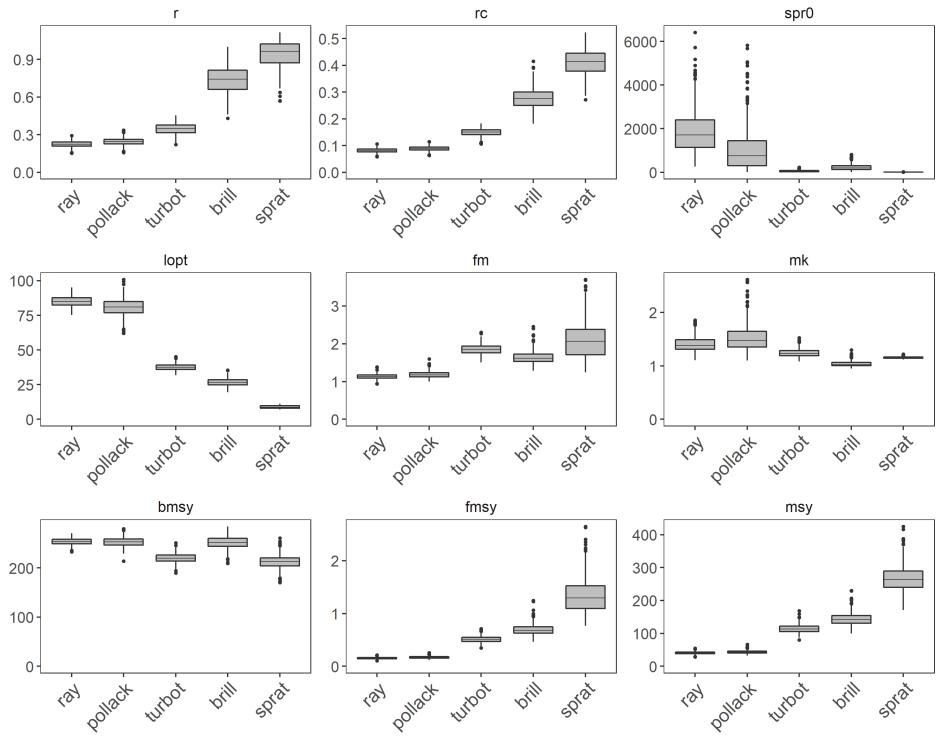


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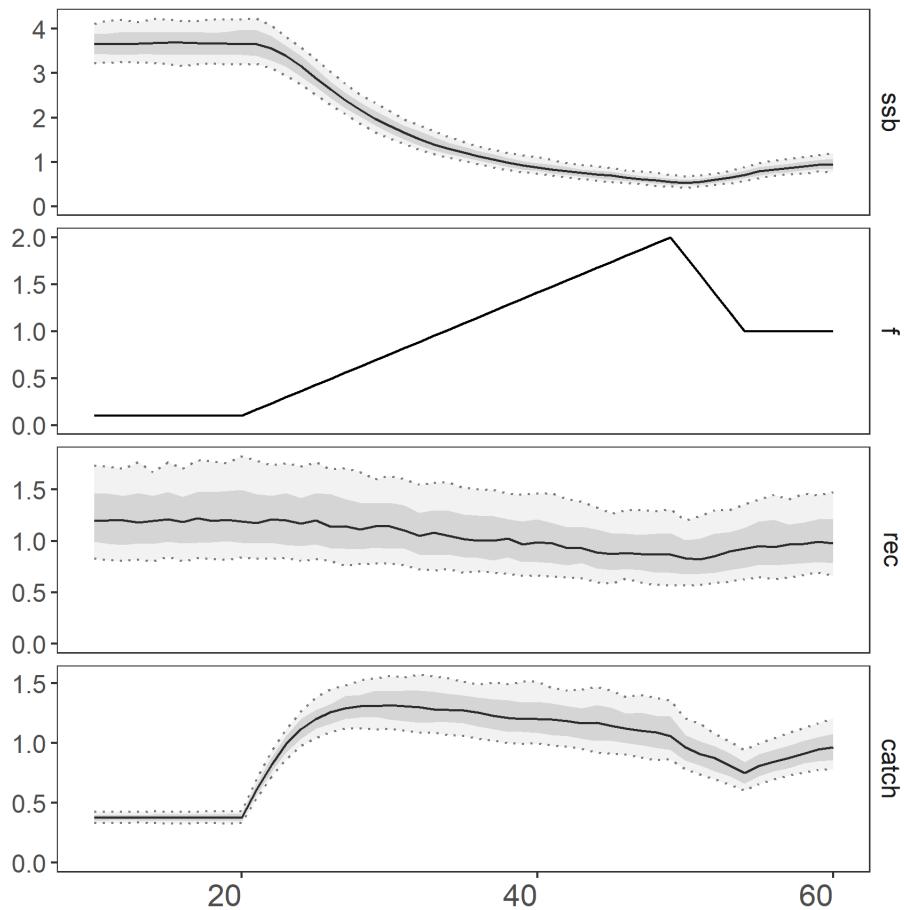


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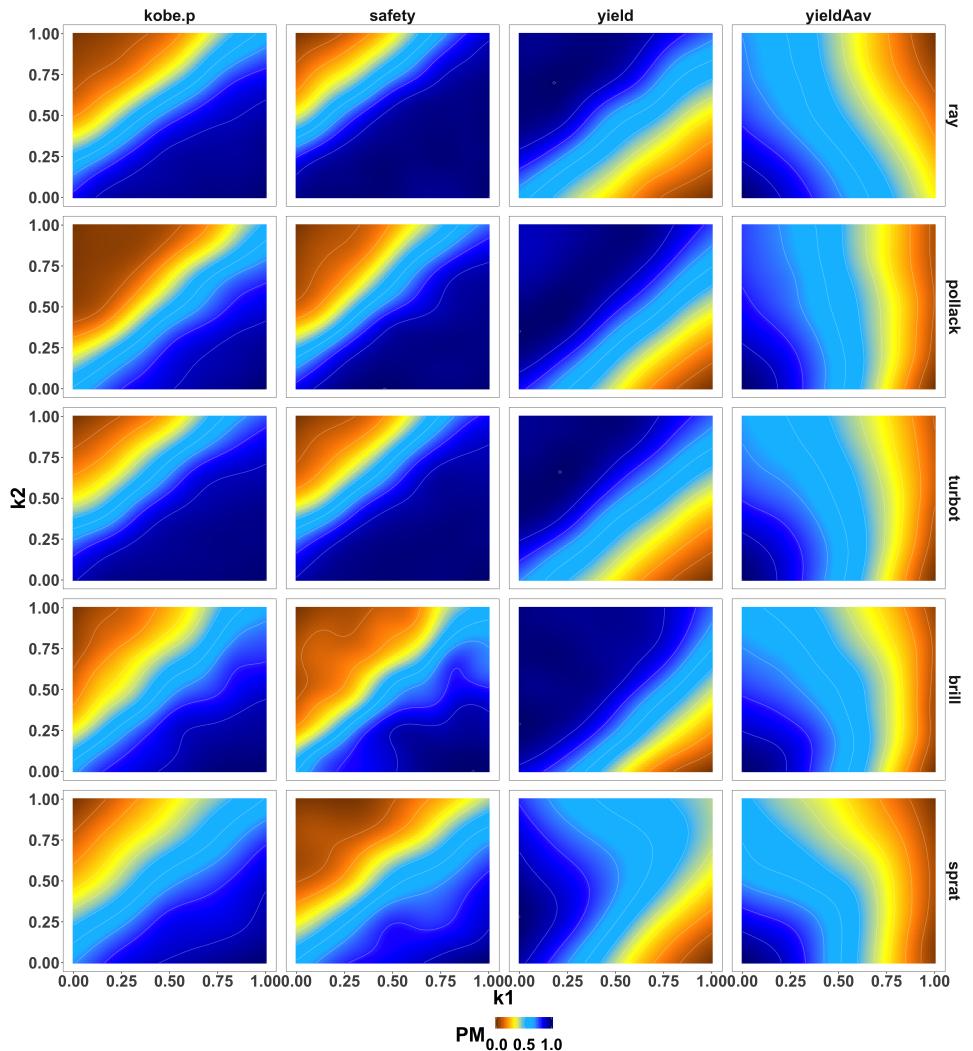


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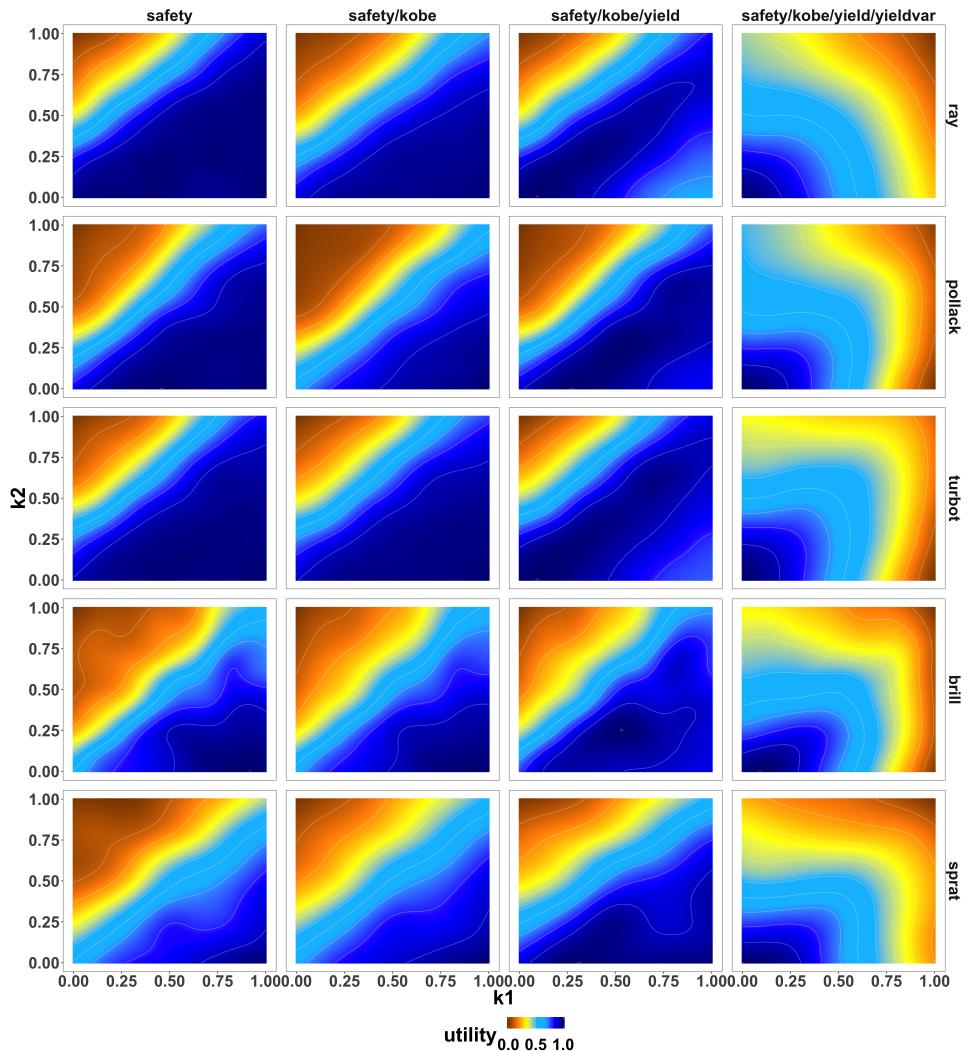


Figure 6: