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

Prof. Laurie Kell

Henstead, UK

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 chanllenge 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 hollistic 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

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

These conservation objectives are currently being achieved by introducing biological target (e.g. can fluctuate around targets) and limit (i.e must not be exceeded) reference points e.g. population size (stock biomass) and/or yields (e.g. management of fish stocks under the CFP based on a target exploitation rate achieved by Total Allowable Catch (TAC) management) 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 target, growth and recruitment overfishing. Therefore to achieve MSY requires limit as well as target reference points.

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 quantitive assessment based on conventional mehods that require large amounts of data that include a long historical time series of catches and sound biological information [7]; or *data-limted* [8](categories 3 and 4) (often called data poor) those without assessment, forecasts and have limited funding for research. For data-rich stocks ICES uses two types of reference points for providing fisheries advice;

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

stock status and exploitation relative to precautionary objectives) and

2. MSY reference points (those relating to achieving MSY)

In contrast for data limited stocks MSY *proxy* reference points are used to estimate stock status and exploitation. Often many of the methods used to estimate MSY proxy reference points require length based inputs as they are cheap, easy to collect [10] and are related to life history paramters such as fish size, mortality and fecundity as well as fishery selectivity. For example many methods are being developed to estimate MSY, but currently only 4 are approved by ICES, these include, Surplus Production model in Continuous Time (catch based) (SPiCT; [11], Mean Length Z (MLZ; [12]), Length Based Spawner Per Recruit (LBSPR; [13]) and Length Based Indicators (LBI; e.g. [14]). The aforementoned data limited procedures have differing data requirements, intended uses and obviously have their own strengths and weaknesses.

To test the performance of candidate management procedures often requires evaluation of alternative hypothesis about the dynamics of the system e.g. population dynamics (life history dynamics such as growth parameters which are an indication of fishery exploitation levels and management) and the behaviour of the fishery (e.g range contraction and density dependence) etc.. Due to the nature of conflicting objectives, stakeholder interests and the uncertainty in the dynamics of the resource and/or the plausibility of alternative 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 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 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 [20].

This paper describes a generic method to simulate differing life history parameters for 5 commercially important european fish species (sprat; *Sprattus pprattus*, ray; *Rajidae*, pollack; *Pollachius pollachius*, turbot; *Psetta maxima* and brill; *Scophthalmus rhombus* and to simulation test the performance of each empirical HCRs. Asessment is made via a set of utility functions that indicate where the stock is in relation to ICES limit reference points (probability of avoiding limits), target reference points (probability of achieving targets, recovery and long-term) and economics (MSY and variability in yield). Our approach is to show the benefits and advance management procedures by using an emprical approach for data limited stocks in comparison to a constant catch HCR strategy i.e one where 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 TAC.

2. Material and Methods

2.1. Materials

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

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

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

A variety of functional forms can be assumed for all of the various process, i.e. growth, mortality, maturity, the selection pattern of the fisheries and the stock recruitment relationship. Commonly processes such as growth an maturity-at-age are well known while those for natural mortality and the stock recruitment relationship are poorly known [22]. In the later case assumptions have to be made and to evaluate the sensitivity of any analysis to those assumptions a variety of scenarios are considered.

2.2. Methods

Individual Growth

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

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

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

Length is converted to mass using the length-weight relationship

$$W = aL_t^b \tag{2}$$

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

Maturity-at-age

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

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

Natural Mortality

Natural mortality of exploited fish populations is often assumed to be a species-specific constant independent of body size. This assumption has important implications for size-based fish population models and for predicting the outcome of size-dependent fisheries management measures such as mesh-size regulations [24]. Direct estimates of the instantaneous natural mortality made in controlled studies, however, are shown to vary by age [25]. Although M can sometimes be estimated within an assessment model for example where data from tagging provide information independent of fishing mortality rates [26]; [27] in most cases M is derived from a variety of life history relationships, e.g. based on size [28]; [29]; [30]; [31]; [32]; [33]. The large and ever increasing literature on this subject is a reflection of the uncertainty. [24] in an emprirical study showed that M is significantly related to body length, asymptotic length and k. Temperature is non-significant when k is included, since k itself is correlated with temperature, i.e.

$$M = 0.55L^{1.61}L_{\infty}^{1.44}k \tag{4}$$

Selection Pattern

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

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

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

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

$$R = Sa/(b + S) \tag{6}$$

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

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

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

$$S = \sum_{i=0}^{p} N_i Q_i W_i \tag{8}$$

where fecundity-at-age is assumed proportional to biomass and the sex ratio to be 1:1. Proportion mature is 50% at the age that attains a length of $l50$, 0% below this age and 100% above.

2.2.1. Operating Model

Age based Equilibrium Analysis

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

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

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

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

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

Forward Projection

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

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

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

2.2.2. Management Procedure

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

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

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

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

$$TAC_{y+1} = 0.5 \times \left(TAC_y + C^{\text{targ}}_y\right) \tag{13}$$

2.2.3. Random Search

When running an MSE commonly a set of MP scenarios are run to tune the MP, this requires running the MSE for each OM scenario for a range of fixed values in the HCR and then choosing the rule that best meets management objectives. If there are a lot of parameters to tune then a grid search may become unfeasible. An alternative is random search [20] as randomly chosen trials are more efficient for parameter optimisation than trials based on a grid. The random parameter search is performed where random combinations of hyperparameters k1 and k2 are used to find the optimal solutions for the MSE model in terms of performance measures: a) safety, (recruitment in relation to virgin recruitment), b) yield (catch/MSY), c) proportion of years in the kobe green zone i.e $B/B_{MSY} > 1$ and $F/F_{MSY} < 1$ and d) Average annual variation in a TAC from one year to the next (expressed as a proportion of the average annual catch). For instance as the process is random at each iteration its likely that the whole of the grid space would be covered in the simulation providing that there are enough iterations, there is a greater chance of finding the optimal parameter pairs.

2.2.4. Utility function

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

3. Results

Results from our simulated life histories illustrate the diversity in relation to growth, size and maturity and are presented in Fig.1. These plots show that for fast growing species which are small in size l_∞ (asymtopic length parameter - maximum attainable length) species such as sprat, the growth parameter k is high. There are also inherent relationships between length at maturity and the maximum attainable length. For instance sprats length-at-50%-maturity *l50* are low, in contrast to a slower growing larger species l_∞ such as ray or pollack.

Observations in Fig.2 shows the resulting trends of the vectors from the OM for natural mortality, selectivity, maturity and length in relation to age. Selectivity is derived from maturity and results show that the faster growing species (Fig.1 i.e. sprat) are more selective to fishing, have a high natural mortality at lower ages and thus length. However for the slower growing larger (here represented by length) species (e.g. pollack or ray) have a higher natural mortality rate at lower ages, are more selective/mature with age increases. Interestingly the most significant natural mortality rate increases are associated with turbot at lower ages, however in contrast for the similar flatfish brill, the rate isnt as steep.

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

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

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

The outputs from the MSE and hyperparameters relative to performance measures were rescaled by species, measure and 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 value of the hyperparameter k1 must be increased conversely k2 must be of a lower value for all species. Observations for safety (recruitment relative to virgin recruitment) expectedly show the same patterns as for kobe.p. In contrast, for yield the trend is opposite for all species, i.e by decreasing k1 and ensuring k2 is of a high value the yield would increase. While for sprat, the relationship is particularly different in that the isopleths depict that the best yields are obtained when k2 are at 25% when k1 is at zero. The variable representing variation in year on year yield, YieldAav, shows that if k1 and k2 are reduced to 0 the variability in catch is at it lowest.

Fig.6 shows that when combining performance measures a utility function can be derived to indicate how the different components could potentially meet the objectives, i.e. ICES limit reference points, target reference points and in terms of economics. Given that the performance measures are on the same scale it is thus possible to interpret the combined utilities. It can be clearly seen that to achieve managements goals in terms of limit reference points scenario safety, the hyper-parameter k1 value should be increased and k2 decreased. Meeting both target and limit reference points i.e safety and kobe.p requires similar values of k1 and k2 as mentioned previously when solely observing safety. When combining safety and kobe.p with the economic component yield the high recruitment and high yield meet to form a central diagonal darker band i.e where the utility is highest, potentially reflecting that when you have a higher recruitment you have a highr yield in relation to MSY.

4. Discussion

Fisheries management is often faced with multiple conflicting objectives e.g social, biological and economic, and it is widely recognised that their is a need to incorporate these objectives into management plans [37]. 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 situtations where knowledge and data are limited, but also in data rich situtaions as simulation testing an assessment procedure using a model conditioned on the same assumptions is not necessarily a true test of robustness [38].

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 spcific combinations.

5. Conclusions

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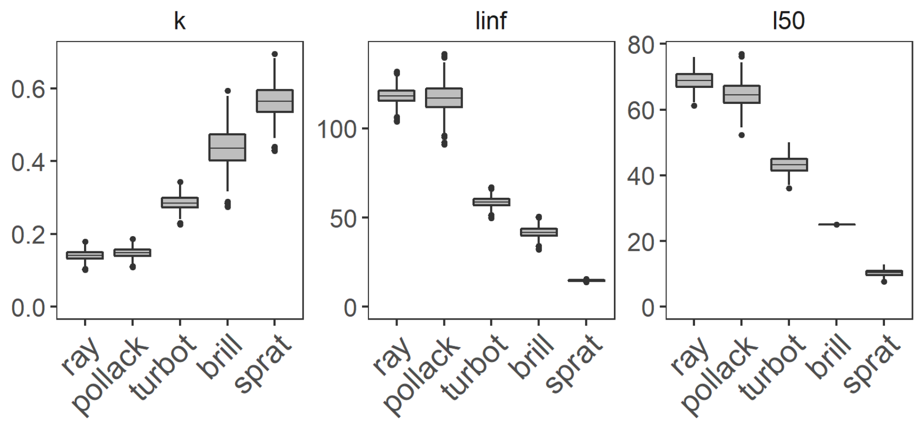

Figure 1:

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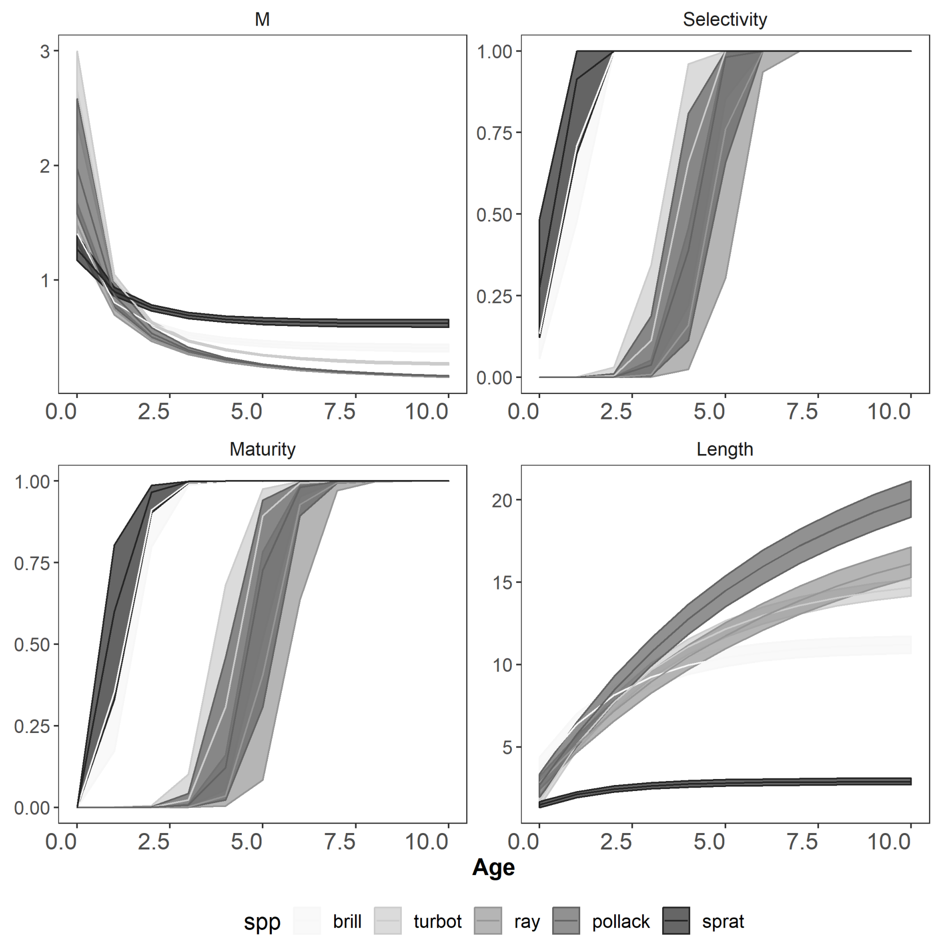

M
Selectivity
Maturity
Length
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ray
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Figure 2:

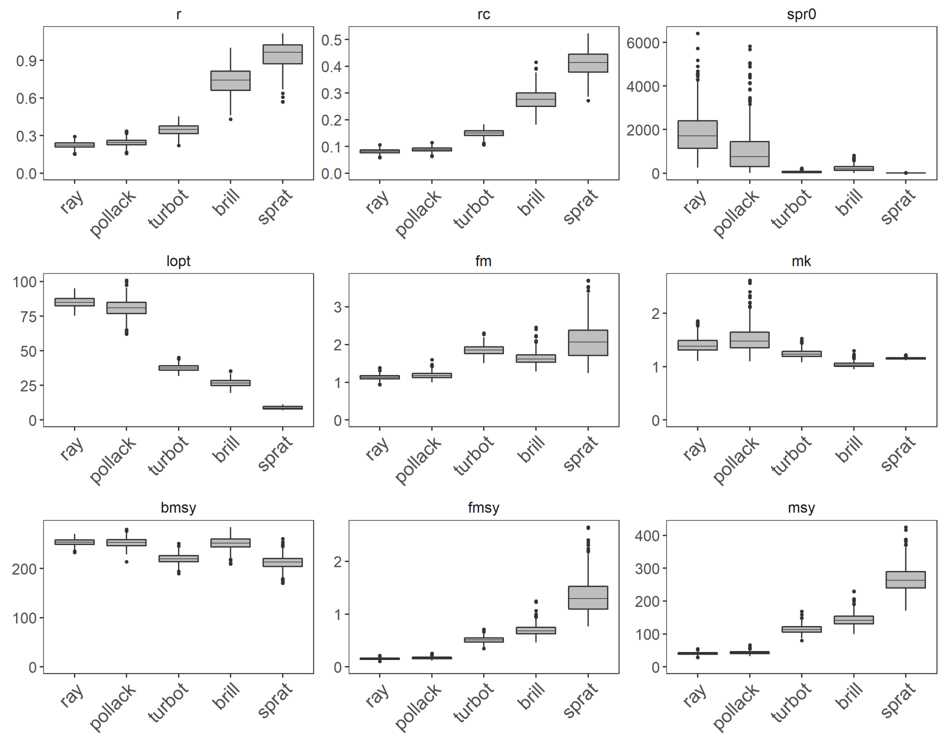
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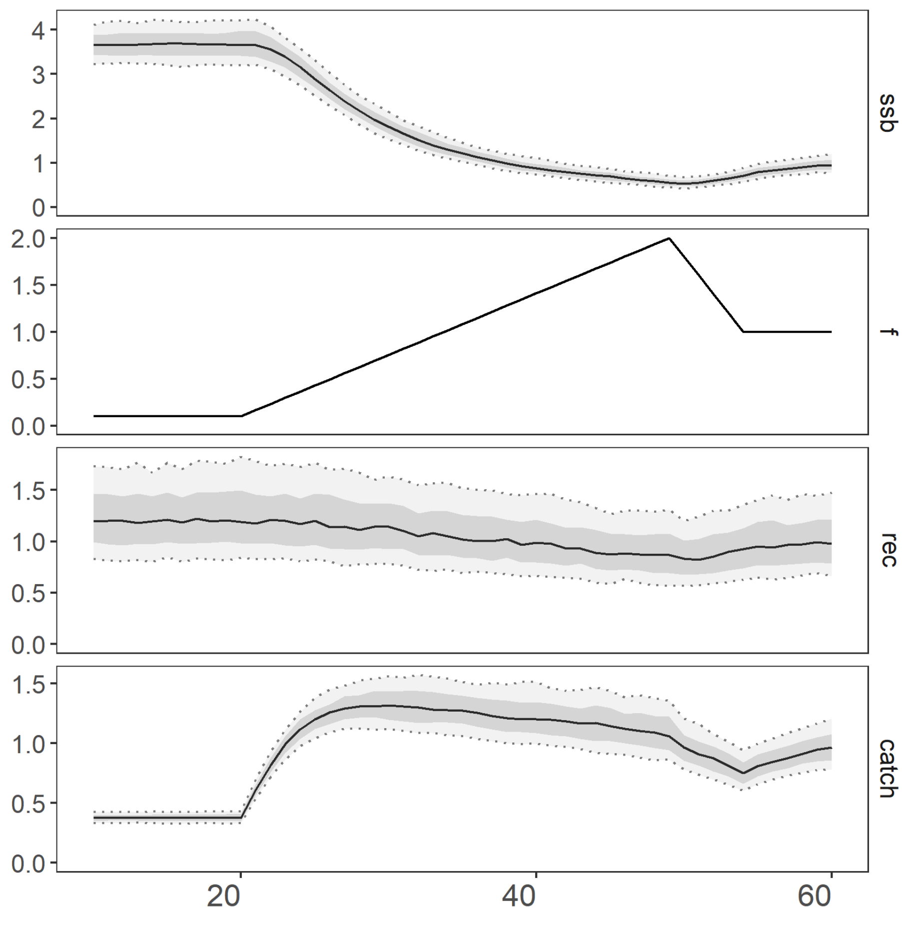
Figure 3:



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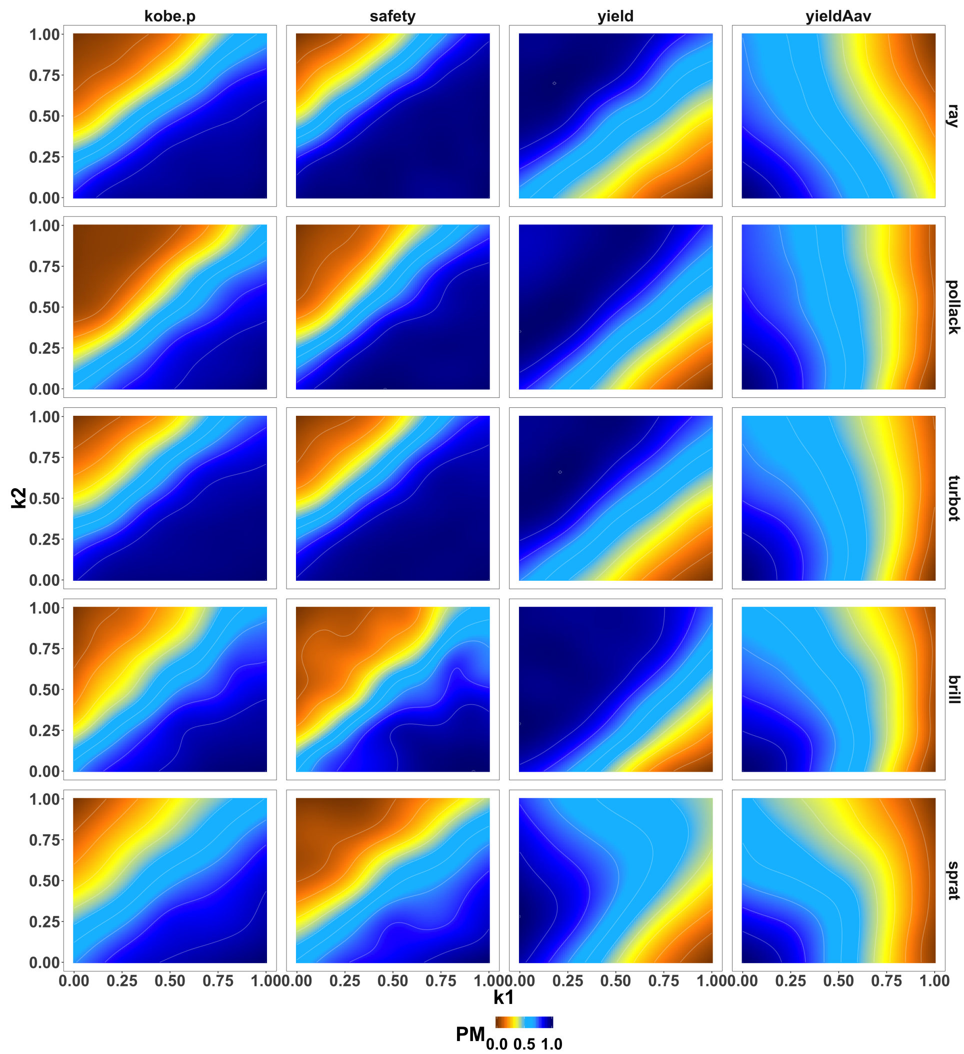
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yield
yieldAav
ray
pollack
turbot
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sprat
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0.75
0.50
0.25
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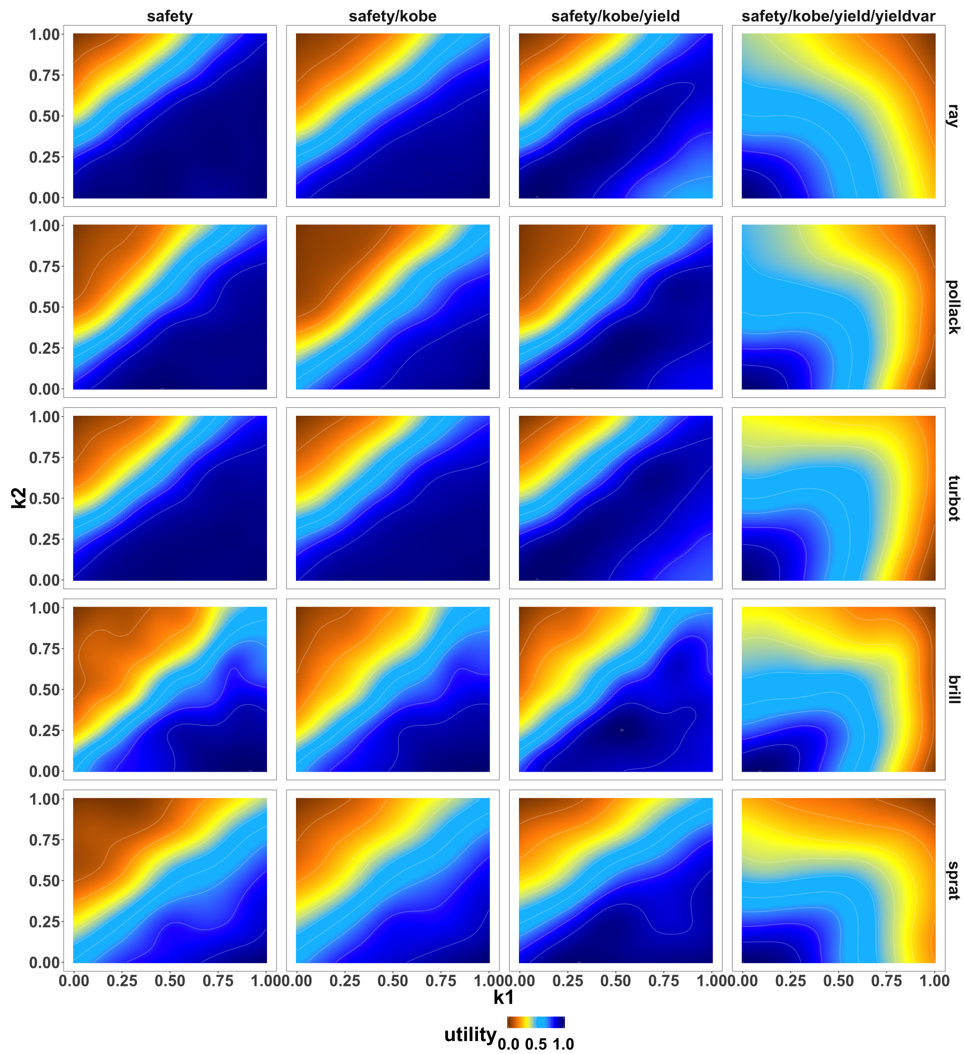
Figure 5: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safety/kobe
safety/kobe/yield
safety/kobe/yield/yieldvar
ray
pollack
turbot
brill
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0.75
0.50
0.25
0.00
utility
0.0 0.5 1.0

Figure 6: