

Unnecessarily Complicated Research Title

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Abstract

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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 ($B/B_{MSY} > 1$), yield ($yield/MSY$), kobe proportion (proportion of years that stay in the green zone of kobe plot ($B/B_{MSY} > 1$), and Yield Annual Variation (yield changes by 10% year on year).

2. Material and Methods

2.1. Materials

Life history parameters 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 [10] 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 [11]. 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 @vonbert1957quantitative

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

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.

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 2.2.1. Operating Model

137 Age based.

138 2.2.2. Management Procedure

139 The management procedure was based on an empirical MP, where an
140 increase in an index of abundance resulted in an increase in the TAC, while
141 a decrease in the index results in a decrease in the TAC.

142 2.2.3. Random Search

143 When running an MSE commonly a set of MP scenarios are run to tune
144 the MP, this requires running the MSE for each OM scenario for a range of
145 fixed values in the HCR and then choosing the rule that best meets manage-
146 ment objectives. If there are a lot of parameters to tune then a grid search
147 may become unfeasible. An alternative is random search [12] as randomly
148 chosen trials are more efficient for parameter optimisation than trials based
149 on a grid.

150 3. Results

151 Estimates of the simulated life history parameters obtained from Fishbase
152 (<http://www.fishbase.org>) are presented in Fig.1. These show that for fast
153 growing species which are small in size l_{∞} (asymptotic length parameter)
154 species such as sprat, the growth parameter k is high. The sprats age-at-
155 50%-maturity a_{50} are low, in contrast to a slower growing larger longer lived
156 species l_{∞} such as rays or pollack.

157 Observations in Fig.2 shows that the assumed maturity in the OM is
 158 related to selectivity and that the faster growing species are more susceptible
 159 to fishing, although the slower growing larger (by mass and length) species
 160 (e.g. pollack has a higher natural mortality rate at lower ages) with the
 161 most significant rate increases associated with turbot. A levelling off in the
 162 mortality rate is evident for ray just prior to age 4.5. In contrast, there have
 163 been less steep declines in natural mortality estimates for brill, but most
 164 notably for sprat.

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

175 **[EXAMPLES TO BE UPDATED]**

- 176 • Figure 3 shows the life history parameters
- 177 • Figure 2 shows the vectors
- 178 • Figure 4 shows the time series relative to reference points
- 179 1.
- 180 2.
- 181 3.
- 182 4.
- 183 5. Figure 5 shows the utility functions for the seven study stocks
- 184 points area
- 185 1.
- 186 2.
- 187 3.
- 188 4.

189 4. Discussion

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

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

- 207 • Bullet point one
- 208 • Bullet point two

209 5. Conclusions

- 210 • Bullet point one
- 211 • Bullet point two

212 6. References

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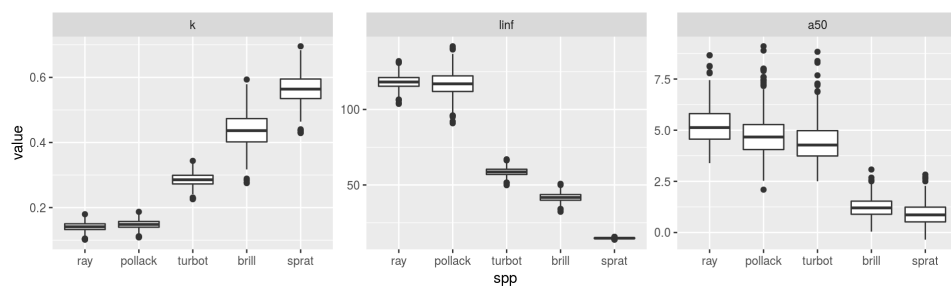


Figure 1:

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252 7. Figures

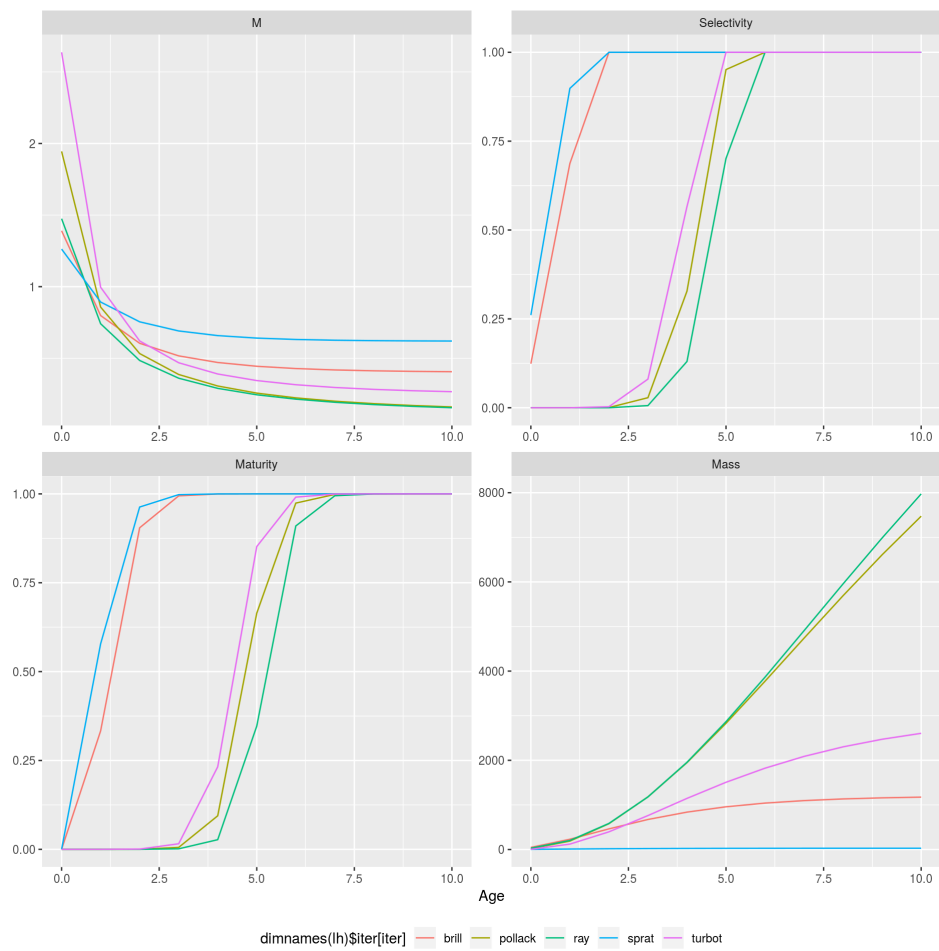
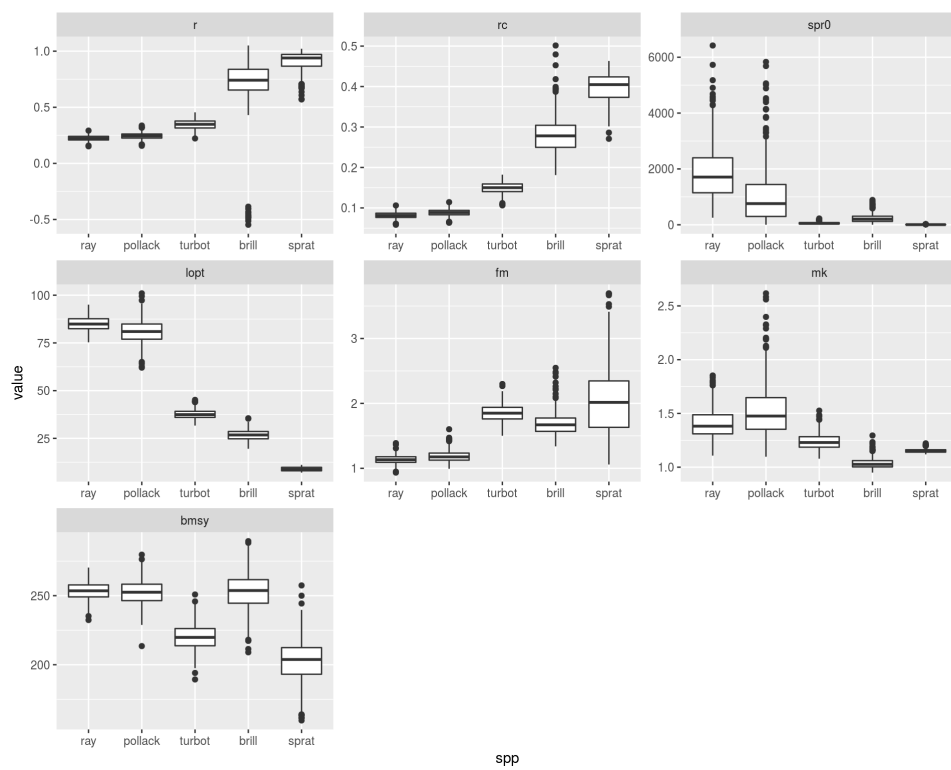


Figure 2:



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Figure 3:

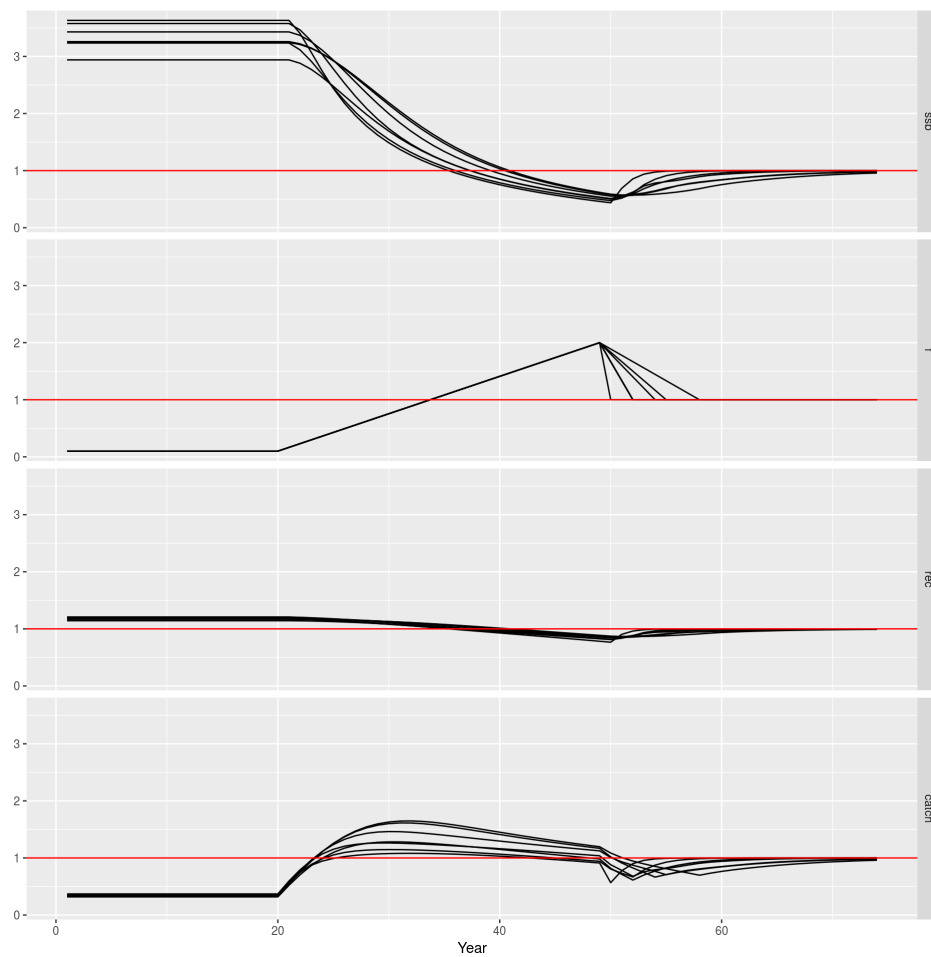


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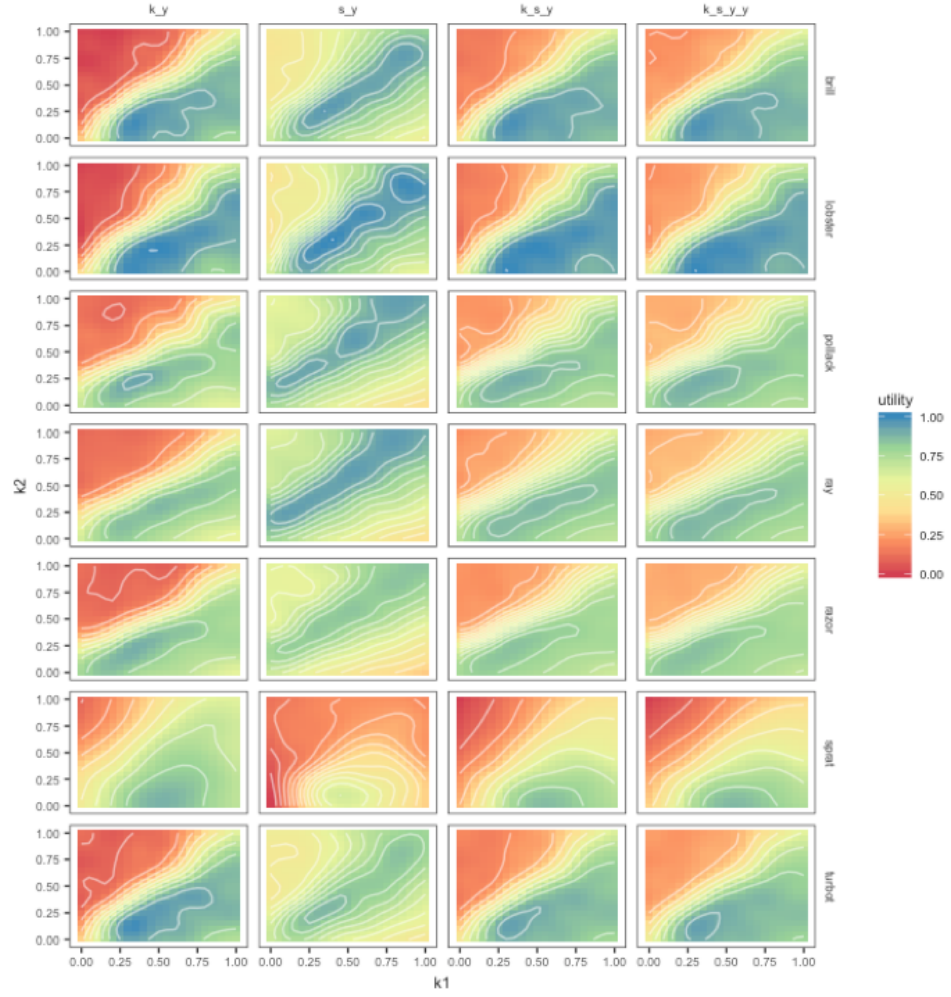


Figure 5: