

1 Indian Ocean Kawakawa Assessment : Examining alternative data poor approaches2 Rishi Sharma¹ and Shijie Zhou²3 ¹IOTC, Victoria, Seychelles. Tel: +248 422 5494; Fax: +248 422 4364; Email: rishi.sharma@iotc.org.4 ²CSIRO Marine and Atmospheric Research and Wealth from Oceans Flagship, P.O. Box 2583,
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6 Shijie.zhou@csiro.au.**7 Abstract**

8 CPUE data derived from the Kawakawa CPUE standardization was used in Surplus Production model
9 assessment. Non-informative priors were used on r , and K , assuming the population was at K when
10 the catch time-series begins in 1950. Catch data was used from 1950 and key reference points, namely
11 S_{MSY} & MSY were estimated using the SIR algorithm. Since there is limited information on the CPUE
12 dataset, the range of estimates on reference points is large. The stock status appears to be healthy and
13 not overfished based on the time-series used, though the model has convergence issues, and has a high
14 degree of confounding in r and K estimates. Informative priors help the model converge, though the
15 model is influenced to large extent by these priors. Due to the lack of contrast in the index of
16 abundance data over the period examined, the model has difficulty estimating S_{MSY} , though can still
17 be useful for evaluating stock status and optimal yield targets. The results from the standard
18 approaches are compared to 2 other methods, namely a stock reduction approach with assumed
19 depletion values at different times in the stock trajectory, and a newly developed posterior-focused
20 catch-based assessment method. Both methods are based on a classical biomass dynamics model,
21 requires only catch history but not fishing effort or CPUE. Known population growth rate will
22 improve the assessment result. We use recently updated catch data in the analysis. The preliminary
23 results show that for Kawakawa the median virgin biomass is about 358-408 thousand tonnes
24 depending on the upper depletion level assumed in 2011. The combination of such carrying capacity
25 and growth rate can support a maximum sustainable yield (MSY) of 113-136 thousand tonnes using a
26 new posterior focussed stock reduction analysis technique. This means that catch levels in recent year
27 may have exceeded MSY, and management should be proactive in controlling catches, and protecting
28 the long-term yield of the stock and the overall resource.

29

30 Introduction

31 Most fisheries in the world have limited information for management (Pauly et. al. 2009, Hilborn and
32 Ovando 2014). In the case of the Indian ocean, artisanal fisheries operating on the vast coastlines of
33 Asia and Africa bordering the Indian Ocean is of primary concern as catches keep increasing in these
34 fisheries, and limited information is available for estimating abundance and productivity trends
35 (Parma et. al. 2003) through traditional assessment approaches. The trend in Asia and other lesser
36 developed economies with limited data (Parma et. al. 2003) was to use equilibrium assumptions and
37 simplified approaches like those proposed in the 1980’s (Pauly 1983). This was then made accessible
38 to multiple users through user friendly software (Sparre and Venema 1992), and lead to misleading
39 results that could be overly optimistic/pessimistic on stock status without much information on
40 abundance or dynamic catch trends (Parma et. al. 2003).

41

42 In recent years numerous approaches have been developed to address these data limited approaches
43 that primarily deal with either life history based approaches (Zhou et. al. 2011), or catch based
44 approaches (Martell and Froese 2012). In Australia, the Commonwealth harvest strategy has devoted
45 a lot of effort to address these issues. Methods developed by CSIRO (draft report “Quantitatively
46 defining biological and economic reference points in data poor fisheries” by Zhou et. al. 2013)
47 highlights some methods developed for data poor fisheries using data rich fisheries as a testing
48 platform.

49

50 The species examined in this paper is Indian Ocean kawakawa, which has shown an alarming trend of
51 increasing catches since 2006 (IOTC 2013). Kawakawa (*Euthynnus affinis*) is found in multiple areas
52 of the Indian Ocean along with other neritics (Figure 1). Kawakawa occurs in open waters but always
53 remains close to the shoreline. They tend to form multi-species schools by size with other scombrid
54 species comprising from 100 to over 5,000 individuals (Collette and Nauen 1983). They are a highly
55 opportunistic predator feeding indiscriminately on small fishes, especially on clupeoids and
56 atherinids; also on squids, crustaceans and zooplankton (Collette 2001, Fish Base). Although
57 primarily distributed in the central Pacific, it is an important fishery for numerous countries in the
58 Indian Ocean region, namely Iran, Indonesia, India, Malaysia, and Thailand. Numerous other
59 countries also catch the species (Figure 2a). The species is primarily caught by Purse Seine and
60 gillnets, but other gears are also used to catch the species (Figure 2b). The countries that are the
61 primary users of the resource are India, Indonesia and Iran. An attempt to re-estimate the catches
62 across the region is being undertaken in the Indian Ocean region, and it is likely that some of the
63 numbers reported will be revised (Table 1).

64

65 Numerous methods are developed in this paper to examine the status of this stock. We examine
66 traditional assessment approaches using the surplus production model, and compare it to the data poor
67 approaches developed (Kimura and Tagart 1982, Walters et. al. 2006). One of the new methods
68 developed is a posterior-focused catch-based assessment. The basic idea is similar to the Stock
69 reduction Analysis (Kimura and Tagart 1982; Walters et. al. 2006; Martell and Froese 2012). The
70 technique builds on simple surplus production models (like Shaefer, 1954), that uses removal data and
71 some estimate of carrying capacity and population growth rate. Ideally, these models should have
72 some measure of abundance in one or more recent years. However, with a reasonably assumed upper
73 limit on depletion level and population growth rate, it is possible to derive biological parameters using
74 catch data alone, particularly MSY. In addition to this approaches, a standard stock assessment was
75 also conducted for Indian Ocean kawakawa, (*Euthynnus affinis*) using a surplus production model and
76 an index of abundance developed using the Maldives Pole and Line fisheries in the Indian Ocean
77 region. However, as will be evident the assessment conducted using this series (Sharma and Zhou
78 2013) was non-informative and the paper compares standard Biomass dynamic models with
79 informative and non-informative priors to a standard stock reduction based approach, and a posterior
80 focussed catch reduction based approach.

81 **Material and Methods**

82 **Catch Data**

83 As is evident from the figures, catch trends have increased in recent years primarily due to increases
84 in effort by Iran and Indonesia (Table 1). In recent years due the effect of piracy off the coast of
85 Somalia, effort has been concentrated and redirected from Tropical Tunas to local neritic's by the
86 countries of Iran, Pakistan and other Arabian gulf countries. These catches in recent years (2006-
87 2011) have increased by 50%, and thus an attempt to understand the effect of these increased catches
88 on the species is attempted in this paper.

89 **CPUE Indicators**

90 GLM-based standardization of the Maldivian kawakawa (*Euthynnus affinis*, KAW) pole and line
91 fishery catch rate data were examined for the period 2004-2011 (Figure 3). The raw data consists of
92 around 124000 records of catch (numbers) and effort (fishing days) by month, atoll and vessel; vessel
93 characteristics were added to the CPUE dataset based on information from the registry of vessels. A
94 subset of 25,762 records were extracted from the dataset, identified as records of fishing activity
95 targeting KAW. Fisheries Aggregating Devices (FAD) data was also incorporated into the analysis
96 using the number of active FADS associated with the nearest atoll that the landing data is collected
97 from. Techniques similar to those used in the standardization of skipjack tuna were used (Sharma et.
98 al. 2013). The distribution of FADs was split into three regions incorporating the North Atolls, Middle

99 Atoll and South Atolls. Vessel specific data including hull-type effects, length of the boat (as a vessel
 100 size class) and horse power was also used in the analysis. GLM based models using a log response on
 101 CPUE were examined. The final model presented estimated log(CPUE) from independent variables
 102 Year, Month, Area (N, S, or M), number of FADs used in the area, and Length of vessel, and
 103 interaction effects between the last 3 categories. The data was analysed at a monthly resolution before
 104 being collapsed into quarterly signals for 2004-2011, and finally an annual signal 2004-2011 for
 105 analysis in KAW surplus production assessment fit to the CPUE series derived here (Figure 3).

106 **Methods**

107 **SIR and Surplus Production Model with Non-informative & Non Informative Priors**

108 The model developed is a simple Graham-Schaeffer Surplus Production model (Logistic
 109 Model, Schaeffer 1954), and estimates two parameters r and K (eq. 1, Haddon 2011, Hilborn
 110 and Walters 1992) fit to estimated Biomass.

111 $B_{1950} = K$ (1)

112 $B_{t+1} = B_t + \left(rB_t \left(1 - \frac{B_t}{K} \right) - C_t \right)$ (2)

113 $B_t = \frac{I_{t,f}}{q_{t,f}}$ (3)

114 Closed form solution of q was used (eq. 4)

115

116 $\hat{q}_{t,f} = \exp \left(\frac{\sum_1^n \ln \left(\frac{\hat{B}_t}{I_t} \right)}{n} \right)$ (4)

117 Where q is the catchability in the fleet, r is the intrinsic growth rate, and K is the carrying
 118 capacity assumed when the time series begins in 1950. The state variables are Biomass (B)
 119 and this is a function of r and K. The parameter, r, k and q are estimated by fitting the
 120 estimated Biomass using equation 2 to the observed index of abundance, based on the catch
 121 and series.

122 The Likelihood Equations used a log-normal error structure for the catch and normal error
 123 structure for the Index of abundance (eq. 5):

$$-\ln L(\underline{\theta} | I_{t,f}) = \sum_{f=1}^n \ln(\sigma_f) + \frac{\ln \left(\frac{B_{t,f}}{\hat{B}_{t,f}} \right) - \ln \left(\frac{\hat{B}_{t,f}}{I_{t,f}} \right)}{2\sigma_f^2} \quad (5)$$

127

128 where $\underline{\theta}$ is the set of parameters, namely (r , K , and q , which may be fishery and block
 129 specific) that are estimated to get the best fit by minimizing the negative log-likelihood
 130 function (eq. 6 above) fitting to the Biomass using the index of abundance, and q .

131 Since r and K are highly correlated, we used non-informative Uniform priors on each
 132 parameter and the SIR algorithm (Rubin 1988) to estimate the uncertainty in r , K and derived
 133 parameters of interest B_{2011} , B_{MSY} and MSY . In addition we computed two ratios, B_{2011}/B_{MSY}
 134 and C_{2011}/C_{MSY} to evaluate the current status of the stock relative to these target reference
 135 points.

136 **Priors on r and K**

137 We initially fit the model using the MLE solution, but due to parameter confounding observed a
 138 surface that had a number of solutions that could best fit the data (Figure 4). Based on this r could be
 139 anywhere from 0.4-1.8 and K anywhere from 1.4 M tons to >2.6 M tons. As a result, we ran the SIR
 140 algorithm with uniform priors on r and K ; $r \sim U [0.2, 2.2]$ and $K \sim U [120k, 4.12 M]$. Informative
 141 priors were also run as a comparison with normal priors on r and K ; $r \sim N(1.2, 0.1)$ and $K \sim N(800, 200)$.

142 **Surplus production Model using Catch data Only (Stock Reduction Model).**

143 This simple model (eq. 2) was used in this analysis. It has two unknown parameters, r and K . We set
 144 reasonably wide prior range, for example, K between C_{max} and $500 * C_{max}$. We used the approach
 145 proposed in Martell and Froese (2012) for “resiliency” estimates that tied to the productivity
 146 parameter r (low resiliency levels indicated r between 0.05-0.5, medium resiliency indicated a r
 147 between 0.2-1, and high between 0.5-1.5). These were compared to values obtained in the literature
 148 and alternative methods.

149 We run model (eq. 2) to find all mathematically feasible r values by searching through wide range of
 150 K s for all depletion levels. The model begins at K in 1950 (eq.1). If the feasible choice of r and k
 151 chosen meets the intermediate (0.1 and 1 level of depletion in 1980), and last point depletion levels
 152 (the range specified was 0.3-0.7 level of depletion for Kawakawa) it is kept. The summary of all runs
 153 which meet these criteria are then used, and geometric mean values are reported to be the better
 154 representation of yield targets (Martell and Froese 2012). Biological parameters, including K , r ,
 155 MSY , are derived from the retained pool of $[r, K]$ values. The geometric mean values of these are then
 156 used to assess the stock dynamics over time and reported using a phase plot.

157 **Posterior Focussed Stock Reduction Approach (Adapted SRA as developed by Zhou and** 158 **Sharma 2013).**

159 We again used the Graham-Shaefer surplus production model shown in equation 2 above (Shaefer
 160 1954). This simple model has two unknown parameters, r and K . We set reasonably wide prior range,
 161 for example, K between C_{max} and $500 * C_{max}$. We use six methods to derive possible range for the

162 intrinsic population growth rate r . Note, that the model assumes a carrying capacity when the first data
 163 point is estimated in 1950 (eq. 1), i.e. the model begins at K in 1950 (eq.1).

164 r from literature (fishbase.org).

165 $r = 2 \omega M$, where M is obtained from literature and $\omega = 0.87$ is a scale linking Fmsy to M for teleosts
 166 (Zhou et al. 2012).

167 $r = 2 \omega M$, where $\ln(M) = 1.44 - 0.982 \ln(t_m)$ (eq. 6, Hoenig 1983).

168 $r = 2 \omega M$, where $\log(M) = 0.566 - 0.718 \text{Log}(L_\infty) + 0.02T$ (eq. 7 from www.Fishbase.org)

169 $r = 2 \omega M$, where $M = 1.65/t_{mat}$ (eq. 8, Jensen 1996).

170 $r = 2 \omega M$, where $\ln(M) = 0.55 - 1.61 \ln(L) + 1.44 \ln(L_\infty) + \ln(\kappa)$ (eq. 9, Gislason et al. 2010).

171 $r = 2 \omega M$, where $M = (L/L_\infty)^{-1.5} \kappa$ (eq. 10, Charnov et al. 2012).

172 In these equations, r is the intrinsic population growth rate, κ and L_∞ are von Bertalanffy growth
 173 parameters, T = average annual water temperature, t_m = maximum reproductive age, and t_{mat} = average
 174 age at maturity. The range (min to max) from these methods is used as prior for Model 1. Further, we
 175 set up a series of assumed depletion level $D = B_T/K$, e.g., $D = 0.02$ to 0.80. Here B_T is the assumed
 176 true biomass at the end of the time series. It is unlikely that the any tuna stock has biomass greater
 177 than 80% of unfished virgin population size.

178 We run model (eq. 2) to find all mathematically feasible r values by searching through wide range of
 179 K s for all depletion levels. Optimization routine is used by minimizing objective function $|B_{end} - DK|$,
 180 where B_{end} is the simulated final year biomass (i.e., at the end of time series t).

181 Biological parameters, including K , r , MSY , are derived from the retained pool of $[r, K]$ values. Using
 182 these K , r , and known catch, stochastic simulations are carried out by re-running Model (1) without
 183 any further restrain. From a large number of simulations (e.g., 1000), biomass trajectories, as well as
 184 ending biomass and depletion level are stored. Not all iterations may be viable. Some simulations may
 185 result in $B_t \leq 0$ (extinction) before the end of the time series. These iterations are removed while the
 186 remaining viable quantities are used for parameter references.

187 **Results**

188 **Sample Importance Resample (SIR) using non-informative and informative priors on r and K**

189 The data from the CPUE standardization process (Figure 3b) is flat between 2004-2011, and is such is
 190 not informative as the catch trends increase significantly during the same period (Figure 2b). Using
 191 non-informative priors on r and K and the standard surplus production models, we observe that we

192 have very little information on r and K (Figure 5, Table 2). However, nonetheless based on these non-
193 informative priors still give us some information on the target reference points like maximum yield
194 (Figure 5), and current stock status (Table 2). Since information on r , and K is non-informative,
195 SB_{2011} is also uninformative. Note, that the values for yield seem unrealistically high (between 178-
196 1386 Kt).

197 As a result, we used informative priors on r and K (Figure 6, Table 3), which gave us a fairly
198 optimistic picture on the stock. This is primarily based on the flat CPUE series generated through the
199 standardization (Figure 3b). However, Maldives CPUE series may not be fully representative of the
200 Indian Ocean stock as it accounts for less than 5% of the overall landings and the overall Indian ocean
201 catches have almost doubled in magnitude from 2005 to 2011. In addition, if we change the priors on
202 r , we can get very different outcomes in the results (not shown here). Values of maximum yield are
203 still too high (between 164 Kt- 354 Kt), and thus alternative catch based approaches are used.

204 **Stock Reduction Approach (SRA)**

205 Using deterministic projections on catches (i.e. without uncertainty), and assumptions on Carrying
206 capacity and r , we can build multiple stock trajectories that fit the criteria defined in the methods
207 section (namely that depletion is between 0.1-1 in 1980 and between 0.3 and 0.7 in 2011). Stock
208 trajectories are not shown, but the resulting overall biomass trajectory indicates that the population
209 size could be anywhere from 0.8 to 1.5 of optimal Biomass for maximum yield. Based on this model
210 the optimal yield targets maybe exceeded in recent years as it shows a median estimate of 132 Kt
211 (range of 101 Kt-161 Kt, Figure 7). As shown before there is a high amount of parameter
212 confounding with r and K (Figure 7a), though marginal distributions for r and K (Figure 7b, and
213 Figure 7c) can then be estimated over all possible runs (9054 possible combinations fit these criteria
214 shown above). Since the criteria of what we fit is quite broad and we use the data on catch without
215 error, there is a broad range of results seen over all runs analysed, and thus there is quite a large
216 amount of uncertainty in current biomass levels and fishing mortality (Table 2). Regardless, the
217 approach however provides reasonable rates for target yields and at that level maybe a useful
218 management tool when other information on abundance is missing.

219 **Posterior Focussed Stock reduction Approach (PFSRA)**

220 Six methods were used to estimate r , that ranged from 1.056 to 2.04 for kawakawa (based on eq. 6-
221 10). We first explored how assumed depletion may affect the result. We used eight assumed depletion
222 level in 2011: 0.1, 0.2, ... 0.8 (Figure 8). The results indicate that with the r range used, the population
223 must have been greater than 30% of unfished level in 2011. Typically, the key parameters (i.e., K , r ,
224 MSY) have to be larger to maintain a higher population (i.e., larger depletion, D relative to initial
225 Biomass in 1950).

226 We then used depletion level between 0.02 and 0.80 at a step of 0.02 in Model 1 and combined all
227 feasible results (Figure 9). The possible unfished population may range from about 300 thousand ton
228 to nearly 800 thousand ton (Figure 9). The lowest possible depletion level is 0.38. At this depletion
229 level, 2 data points are retained: $r = 1.11$, $K = 393617$, and $r = 1.06$, $K = 409353$.

230 Since within the assumed depletion levels the upper limit has some effect on the result, we tested the
231 sensitivity by three alternative upper limits: $D = 0.80$, 0.70 , and 0.60 . Again, assuming a higher D
232 results in a higher r , K , MSY , B_{2011} , and D_{2011} (Table 3). However, the magnitude appears to be
233 relatively small. For example, for the three assumed upper depletions, MSY is about 151, 135, and
234 128 thousand tons, respectively (Table 3).

235 While the catch increases over time, biomass continues to decline (Figure 10a). To evaluate
236 management strategy, we investigated two hypothetical harvest levels for the next 10 years. This
237 exercise is based on the conservative upper depletion level **$D = 0.6$** . First, we assumed catch remains
238 at 2011 level from 2012 to 2021 (Figure 10a). The projected biomass trajectories show a quick
239 depletion of the population. Hence, the catch level in 2011 appears to be unsustainable. We then
240 assumed that annual catch is 100 thousand tonnes for the next 10 years (Figure 10b). This results in a
241 very different picture. The population recovers to a higher level and becomes stable after about 7 or 8
242 years.

243 Discussion

244 As noted by Parma et. al. (2003), “*Uncertainty and information quality can be viewed as a continuum*
245 *ranging from very data-rich situations to total lack of information. In theory, harvest targets could be*
246 *adjusted along this gradient according to any given degree of risk-aversion. Consideration of other*
247 *fisheries attributes beyond data availability, however, shows that data-poor cases are not a random*
248 *set of all fisheries. Rather, data poverty tends to be associated with some structural features of the*
249 *system, which compound the management problem and require qualitatively different solutions.*”

250

251 With respect to the above statement and Indian Ocean fisheries, we realize that the information
252 content, other than overall catch is not systematically collected over time. Traditional approaches of
253 assessment like those used in standard integrated assessments rely on a standardized index of
254 abundance that is representative of the stock being analysed. In our case the index is based on a very
255 small proportion of the catch being caught and is probably not a good indicator of abundance.
256 Species, such as kawakawa, account for 10% of the overall catch in the Indian ocean, with other
257 coastal tuna (Neritics) accounting for almost 33% of the catches in the Indian Ocean. Unlike tropical
258 tuna (like yellowfin/bigeeye account for another 30% with skipjack another 30%) normally have
259 systematic sampling programs for the major fleets (longline, purse seine and pole and line for
260 skipjack) that collect size-based data, as well as estimated index of abundance that is used in

261 estimating biomass trajectories over time; neritic tuna only report catch, are caught in small
262 subsistence fleets, and have no systematic sampling on other components of the catch information. As
263 noted, before, the normal approach in these countries and regions with limited data (Parma et. al.
264 2003) was to use equilibrium assumptions and simplified approaches like those proposed in the
265 1980's (Pauly 1983), which often lead to misleading conclusion of the stock status. Given the
266 importance of these fish to coastal communities, management advice needs to be generated for the
267 coastal communities, and thus an attempt to integrate information using alternative approaches is
268 made in this paper.

269

270 Based on the trajectories that is actually estimating fishing mortality (Table 3, PFSRA approach), we
271 can project what may happened to the stock over time given a certain projected catch. Based on
272 PFSRA based approach (Figure 10), it appears that the catches in recent years maybe unsustainable
273 and the stock maybe experiencing some overfishing (Table 2, Figure 10). Catches should be in the
274 vicinity of 110-130 Kt according to this approach. In addition (Figure 11, based on estimated F, and
275 the SRA, Table 2), we can also assess that although the stock appears to be currently healthy (using
276 the SRA approach, 101-160Kt, Table 2), the uncertainty indicates that overfishing is likely to occur
277 and that the stock is on the boundary where larger catches maybe detrimental to the overall
278 persistence of the resource. Based on this limited data, and no other information, we can already see
279 that the stock maybe experiencing overfishing using the SRA, and is experiencing overfishing using
280 the PFSRA. As such some management measures that may restrict overall catch to 120K t at most
281 should be implemented in the Indian Ocean Region. We discount the CPUE based traditional Surplus
282 production analysis as the fits are poor and the CPUE data is largely uninformative (Figure 3), and
283 using a more precautionary based approach, based on alternative methods recommend reducing the
284 target catch levels in the Indian Ocean region to be lesser than the current catch levels for this stock.

285

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292

293

294 **References**

- 295 Charnov, E.R., Gislason, H., & Pope, J.P. 2012. Evolutionary assembly rules for fish life histories.
296 Fish and Fisheries. DOI: 10.1111/j.1467-2979.2012.00467.x
297
- 298 Collette, B.B., 2001. Scombridae. Tunas (also, albacore, bonitos, mackerels, seerfishes, and wahoo).
299 p. 3721-3756. In K.E. Carpenter and V. Niem (eds.) FAO species identification guide for
300 fishery purposes. The living marine resources of the Western Central Pacific. Vol. 6. Bony
301 fishes part 4 (Labridae to Latimeriidae), estuarine crocodiles. FAO, Rome.
302
- 303 Collette, B.B. and C.E. Nauen, 1983. FAO Species Catalogue. Vol. 2. Scombrids of the world. An
304 annotated and illustrated catalogue of tunas, mackerels, bonitos and related species known to
305 date. Rome: FAO. FAO Fish. Synop. 125(2):137 p.
306
- 307 Gislason, H., Daan, N., Rice, J.C. and Pope, J.G. (2010). Size, growth, temperature, and the natural
308 mortality of marine fish. *Fish and Fisheries* 11, 149–158.
309
- 310 Haddon, M. 2011. *Modeling and Quantitative Methods in Fisheries*. 2nd Ed. Chapman & Hall, Inc.,
311 New York.
312
- 313 Hilborn, R. and Ovando, D. 2014. Reflections on the success of traditional fisheries management.
314 *ICES Journal of Marine Science*, doi: 10.1093/icesjms/fsu034.
315
- 316 Hilborn, R., and Walters, C. 1992. *Quantitative fisheries stock assessment: choice, dynamics and*
317 *uncertainty*. Chapman & Hall, Inc., New York.
318
- 319 Hoenig, J.M. 1983. Empirical use of longevity data to estimate mortality rates. *Fishery Bulletin* 82:
320 898–903.
321
- 322 Jensen, A.L. 1996. Beverton and Holt life history invariants result from optimal tradeoff of
323 reproduction and survival. *Can. J. fish. Aquat. Sci.* 53, 820-822.
324
- 325 Kimura, D.K., and Tagart, J.V. 1982. Stock reduction analysis, another solution to the catch
326 equations. *Can. J. Fish. Aquat. Sci.* 39: 1467–1472.
327
- 328 Martell, S. and Froese, R. 2012. A simple method for estimating MSY from catch and resilience. *Fish*
329 *and Fisheries*. doi: 10.1111/j.1467-2979.2012.00485.x
330
- 331 Parma, A. M., Oresanz, J.M, Elias, I. and Jerez, G. 2003. “Diving for shellfish and data: incentives for
332 the participation of fishers in the monitoring and management of artisanal fisheries around
333 southern South America” In Newman, S.J., Gaughan, D.J., Jackson, G., Mackie, M.C.,
334 Molony, B., St John, J. and Kailola, P. (Eds.). 2003. *Towards Sustainability of Data-Limited*
335 *Multi-Sector Fisheries*. Australian Society for Fish Biology Workshop Proceedings,
336 Bunbury, Western Australia 23-24, September 2001. Fisheries Occasional Publications No. 5,
337 June 2003, Department of Fisheries, Perth, Western Australia, 186 pp.
338
- 339 Pauly, D. 1983. Some simple methods for the assessment of tropical fish stocks. Food and Agriculture
340 Organization, Rome, Italy. *FAO Fisheries Technical Paper* No. 234, 52 pp.
341
- 342 Pauly, D. 2009. Aquacalypse now: the end of fish. *The New Republic*, 240: 24–27.
343
- 344 Schaefer, M.B. 1954. Some aspects of the dynamics of populations important to the management of
345 commercial marine fisheries. *Bulletin, Inter-American Tropical Tuna Commission* 1:27-56.
346

- 347 Sharma, R. and Zhou, S. 2013. Indian Ocean Kawakawa Assessment based on the Maldives Pole and
348 Line CPUE Index. IOTC-2013-WPNT-3-24.
- 349 Sharma, R., Geehan, J., Adam, S. and Juahary, R. 2013. Maldivian Kawakawa Pole and Line CPUE
350 Standardization: 2004-2011. IOTC-2013-WPNT-3-23.
- 351 Sparre, P. and Venema, S.C.. 1992. Introduction to tropical fish stock assessment. Part I - Manual.
352 Food and Agriculture Organization, Rome, Italy. *FAO Fisheries Technical Papers* No. 306/1,
353 407 pp.
- 354
- 355 Walters, C. Martell, S., and Korman, J. 2006. A stochastic approach to stock reduction analysis. *Can.*
356 *J. Fish. Aquat. Sci.* 63: 212-223.
- 357
- 358 Zhou, S., Yin, S., Thorson, J.T., Smith, A.D.M., Fuller, M. 2012. Linking fishing mortality reference
359 points to life history traits: an empirical study. *Canadian Journal of Fisheries and Aquatic*
360 *Science*, 69: 1292–1301.
- 361
- 362 Zhou, S., Pascoe, S., Dowling, N., Haddon, M., Klaer, N., Larcombe, J., Smith, A.D.M., Thebaud, O.,
363 and Vieira, S. 2013. Quantitatively defining biological and economic reference points in data
364 poor and data limited fisheries. Final Report on FRDC Project 2010/044. Canberra, Australia.
365

367 **List of Tables**

368 **Table 1: Catch data on IO Kawakawa from 1950-2011 (source IOTC Database)**

369 **Table 2: Comparison of methods and derived reference points**

370 **Table 3: Posterior key biological parameters for Kawaka under three assumed upper depletion level.**

371

372 **Table 1: Catch data on IO Kawakawa from 1950-2011 (source IOTC Database)**

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Year	KAW East IO	KAW West IO	TOT KAW Catch	Year	KAW East IO	KAW West IO	TOT KAW Catch
1950	1,952	3,614	5,567	1981	14,279	15,919	30,198
1951	1,760	1,486	3,246	1982	15,789	19,112	34,901
1952	1,637	1,639	3,276	1983	14,487	16,789	31,276
1953	1,474	1,760	3,234	1984	14,700	20,690	35,391
1954	1,941	2,545	4,486	1985	18,072	23,734	41,806
1955	2,180	3,191	5,372	1986	18,492	24,690	43,181
1956	2,492	3,364	5,855	1987	22,574	23,195	45,769
1957	2,199	3,192	5,390	1988	21,538	28,278	49,816
1958	2,229	2,838	5,067	1989	23,011	23,890	46,901
1959	2,275	2,992	5,267	1990	24,988	27,221	52,209
1960	2,961	4,009	6,970	1991	29,911	26,192	56,103
1961	3,660	5,018	8,678	1992	34,007	32,326	66,333
1962	3,279	2,709	5,988	1993	33,908	25,680	59,588
1963	4,157	4,104	8,261	1994	34,617	32,307	66,924
1964	4,530	5,619	10,149	1995	38,728	32,008	70,735
1965	4,224	4,548	8,772	1996	39,399	35,521	74,920
1966	4,555	4,262	8,818	1997	42,369	41,278	83,648
1967	4,944	4,928	9,872	1998	42,939	44,046	86,985
1968	5,248	5,241	10,489	1999	41,318	47,247	88,565
1969	5,419	5,028	10,447	2000	45,256	48,248	93,504
1970	5,644	5,008	10,651	2001	42,608	45,095	87,703
1971	5,547	6,176	11,724	2002	44,534	49,129	93,663
1972	7,036	6,615	13,651	2003	47,299	47,256	94,554
1973	7,174	6,534	13,708	2004	51,616	50,524	102,140
1974	8,435	10,035	18,470	2005	49,550	52,418	101,968
1975	9,910	9,952	19,861	2006	57,382	57,486	114,868
1976	13,265	15,596	28,861	2007	59,578	60,141	119,719
1977	12,413	12,348	24,761	2008	64,865	71,621	136,486
1978	12,850	10,881	23,731	2009	66,855	70,033	136,888
1979	13,447	18,353	31,800	2010	68,256	63,301	131,557
1980	14,551	17,063	31,614	2011	67,282	76,370	143,652

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SIR Non Informative Priors				SIR Informative Priors			
Parameters	5%	50%	95%	Parameters	5%	50%	95%
B_{MSY}	296	1236	1900	B_{MSY}	284	420	584
MSY	178	622	1386	MSY	164	252	354
r	0.31	1.18	1.88	r	1.04	1.2	1.37
B_{2011}	632	>2000	>2000	B_{2011}	416	712	1030
B_{2011}/B_{MSY}	1.55	1.88	1.95	B_{2011}/B_{MSY}	1.45	1.69	1.79
F_{2011}/F_{MSY}^*	0.09	0.245	0.795	F_{2011}/F_{MSY}^*	0.4	0.57	0.87

SRA				PFCRA**			
Parameters	5%	50%	95%	Parameters	5%	50%	95%
B_{MSY}	149	233	317	B_{MSY}	161	179	198
MSY	101	132	164	MSY	113	128	136
r	0.67	1.18	1.68	r	1.29	1.43	1.58
B_{2011}	182	267	353	B_{2011}	181	193	204
B_{2011}/B_{MSY}	0.78	1.15	1.51	B_{2011}/B_{MSY}	0.96	1.08	1.2
F_{2011}/F_{MSY}	0.12	0.58	1.04	F_{2011}/F_{MSY}^*	1.05	1.12	1.27

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* Indicates that a proxy F is calculated relative to Yield, i.e. C_{2011}/C_{MSY}
 ** Results for the PFCRA are based on the depletion maximum depletion level of 0.6 (Table 3)

379 **Table 3: Posterior key biological parameters for Kawaka under three assumed upper depletion level.**

Upper D	Param	Mean	5%	25%	50%	75%	95%
0.8	<i>K</i>	406.02	350.84	376.13	408.12	434.72	458.6
0.8	<i>r</i>	1.5	1.32	1.39	1.48	1.61	1.72
0.8	MSY	155.32	117.68	132.92	150.96	171.8	205.16
0.8	<i>B</i> ₂₀₁₁	266.14	243.36	255.37	265.15	276.48	290.8
0.8	<i>D</i> ₂₀₁₁	0.66	0.56	0.61	0.65	0.71	0.77
0.7	<i>K</i>	368.01	327.36	346.52	366.84	387.5	407.86
0.7	<i>r</i>	1.48	1.33	1.4	1.48	1.56	1.66
0.7	MSY	136.17	115.63	126.96	135.47	146.83	157.28
0.7	<i>B</i> ₂₀₁₁	214.75	203.08	208.11	213.46	220.14	228.83
0.7	<i>D</i> ₂₀₁₁	0.59	0.51	0.55	0.58	0.62	0.67
0.6	<i>K</i>	358.05	322.45	337.65	358.04	377.72	394.55
0.6	<i>r</i>	1.43	1.29	1.35	1.43	1.51	1.58
0.6	MSY	126.42	113.16	120.92	127.57	132.48	136.37
0.6	<i>B</i> ₂₀₁₁	192.03	181.29	187	191.81	196.55	203.82
0.6	<i>D</i> ₂₀₁₁	0.54	0.48	0.51	0.54	0.57	0.6

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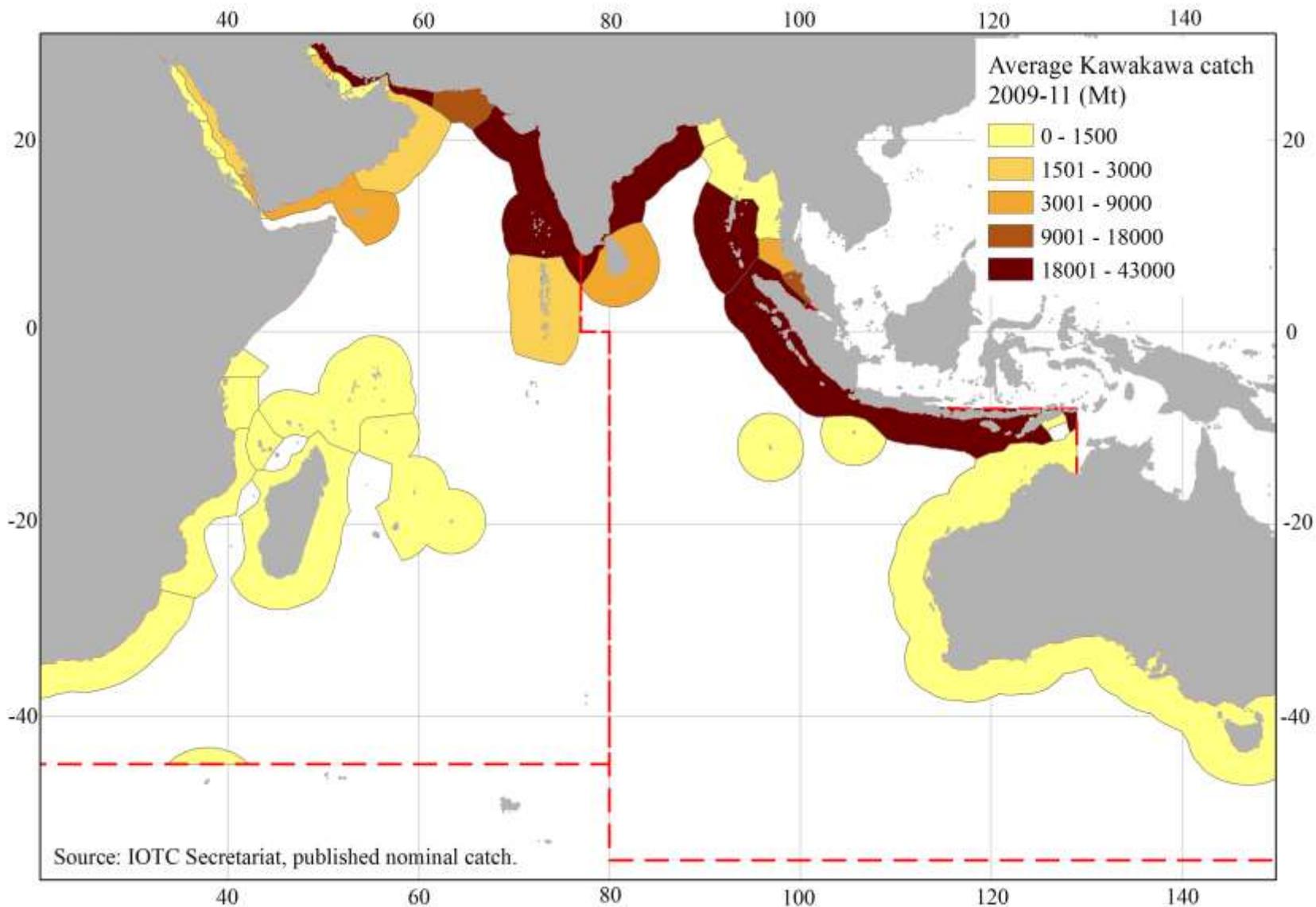


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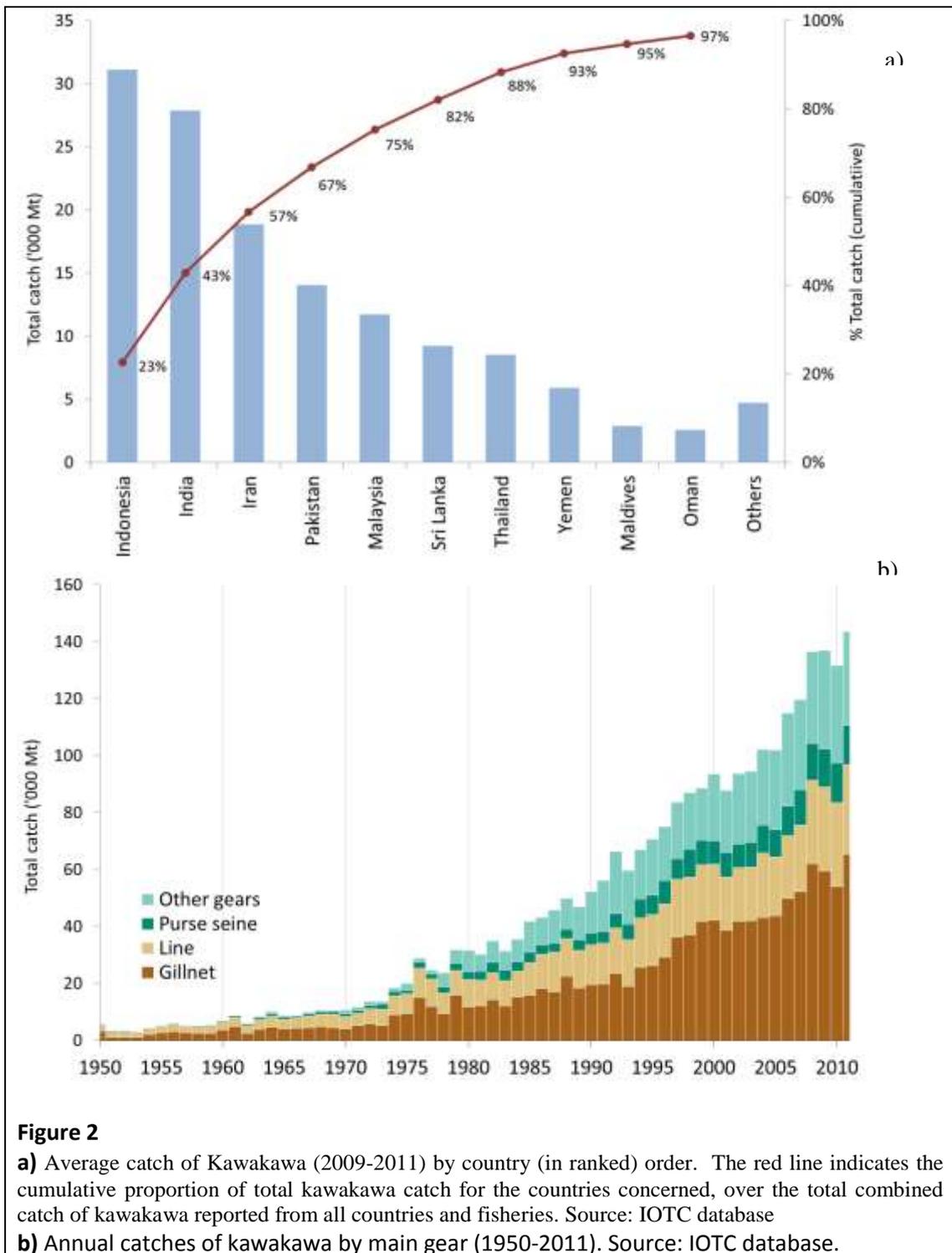


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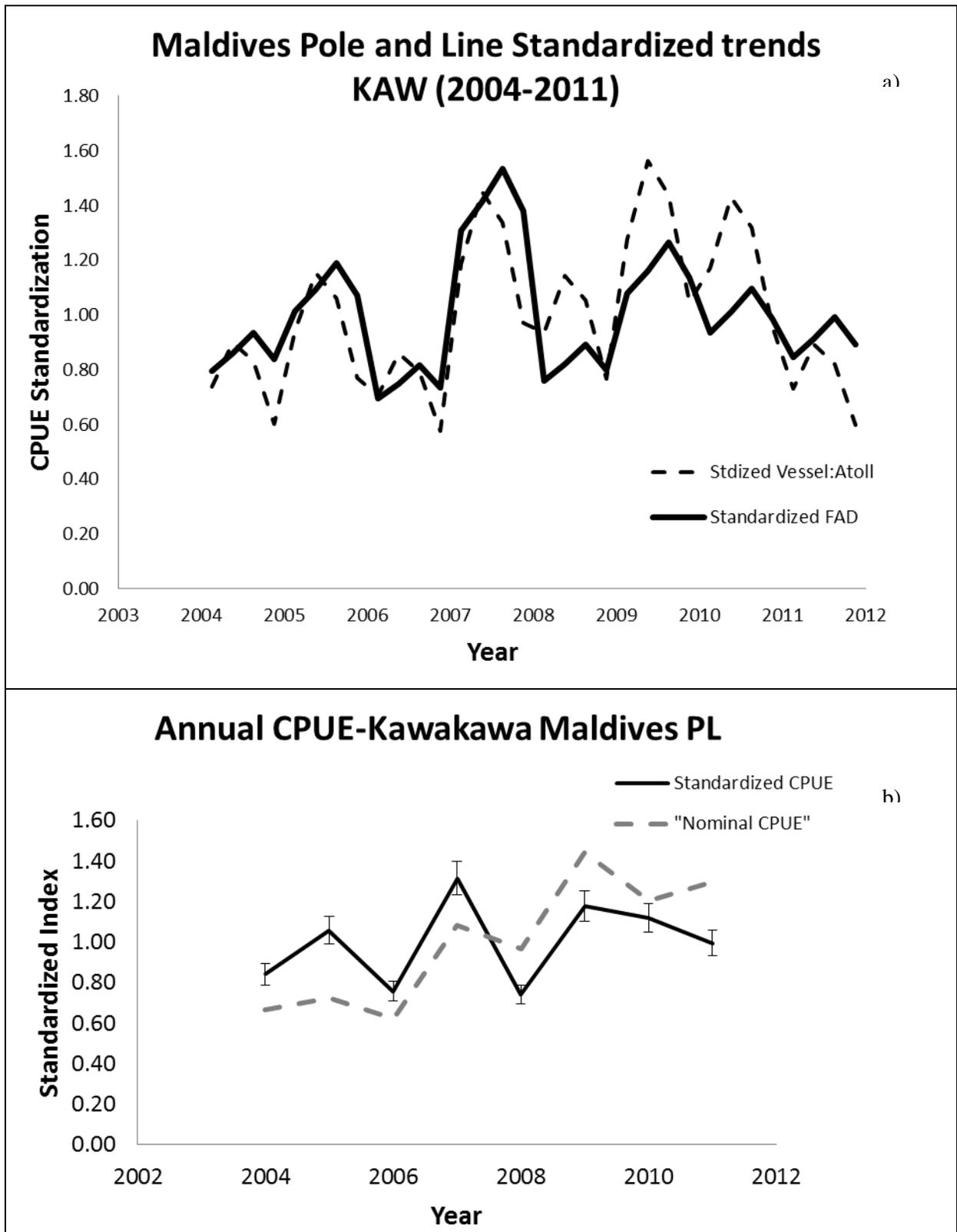


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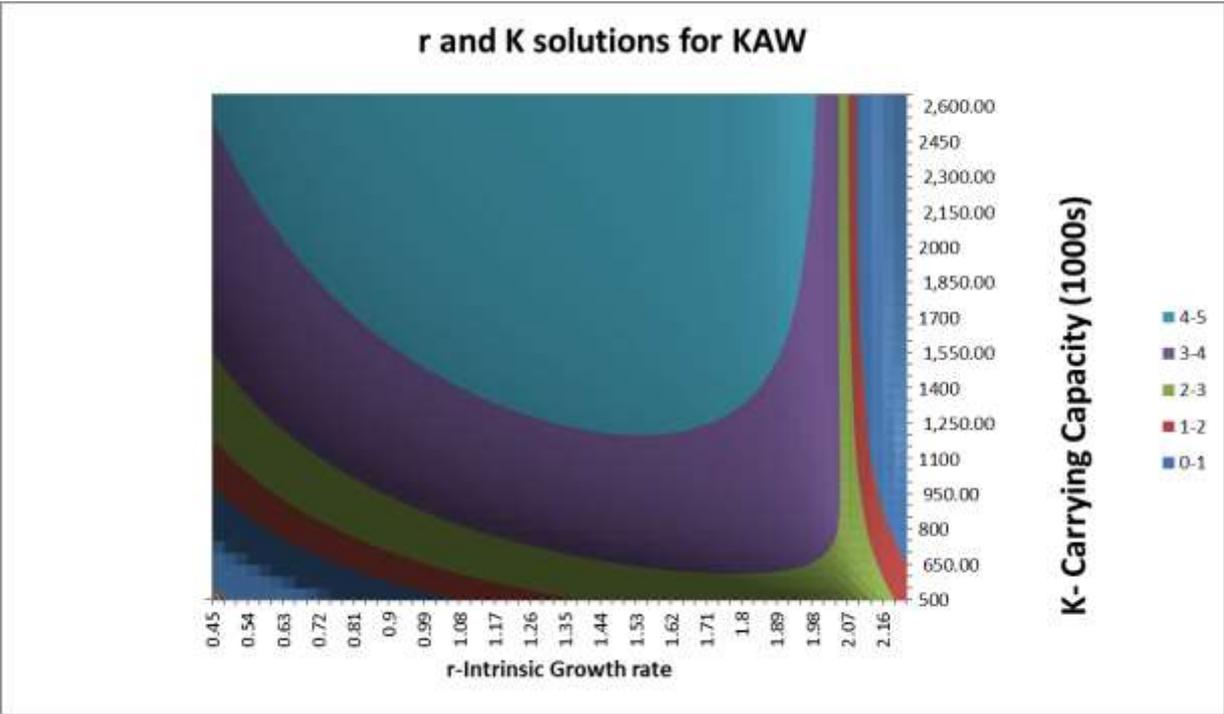


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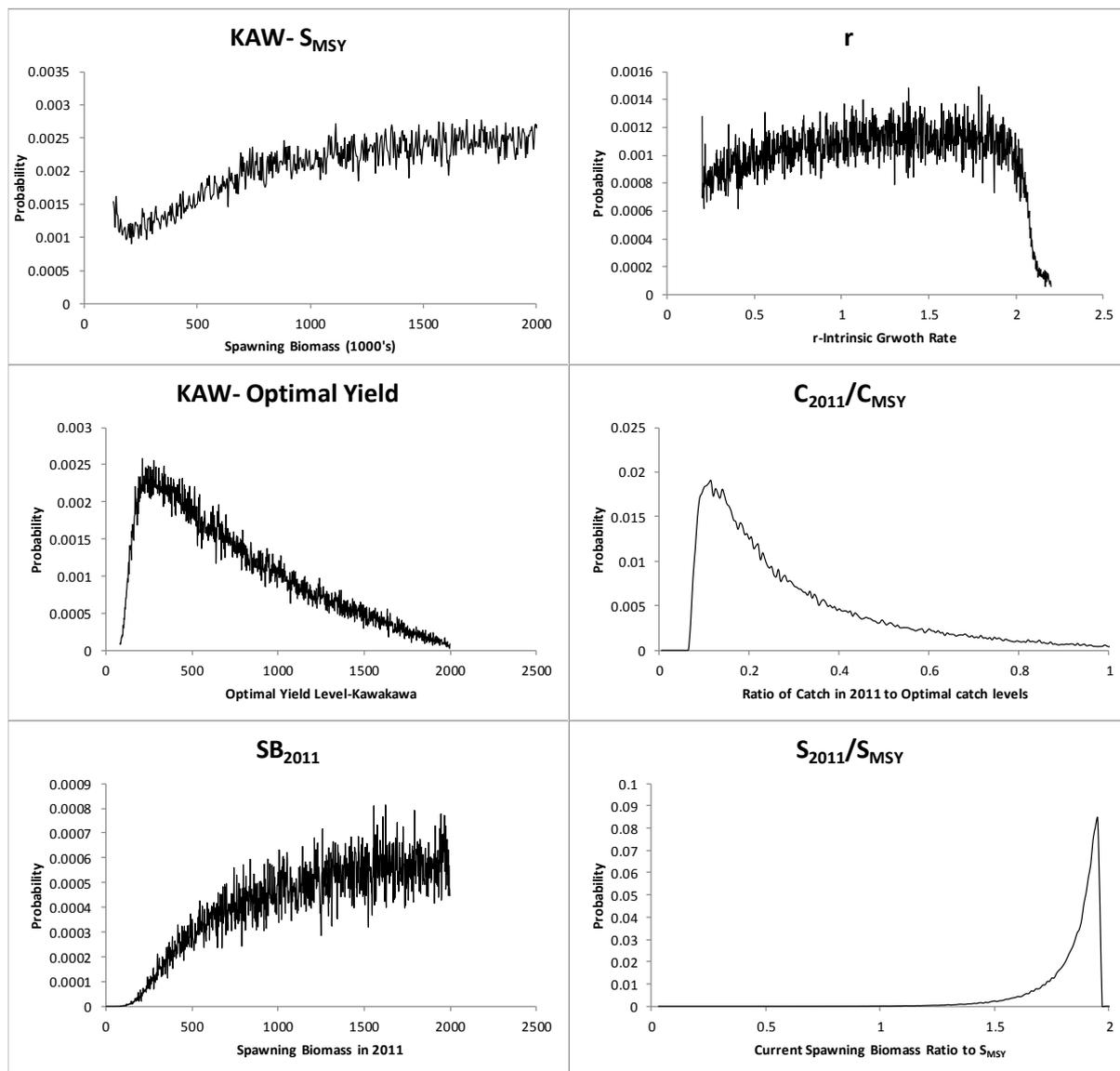


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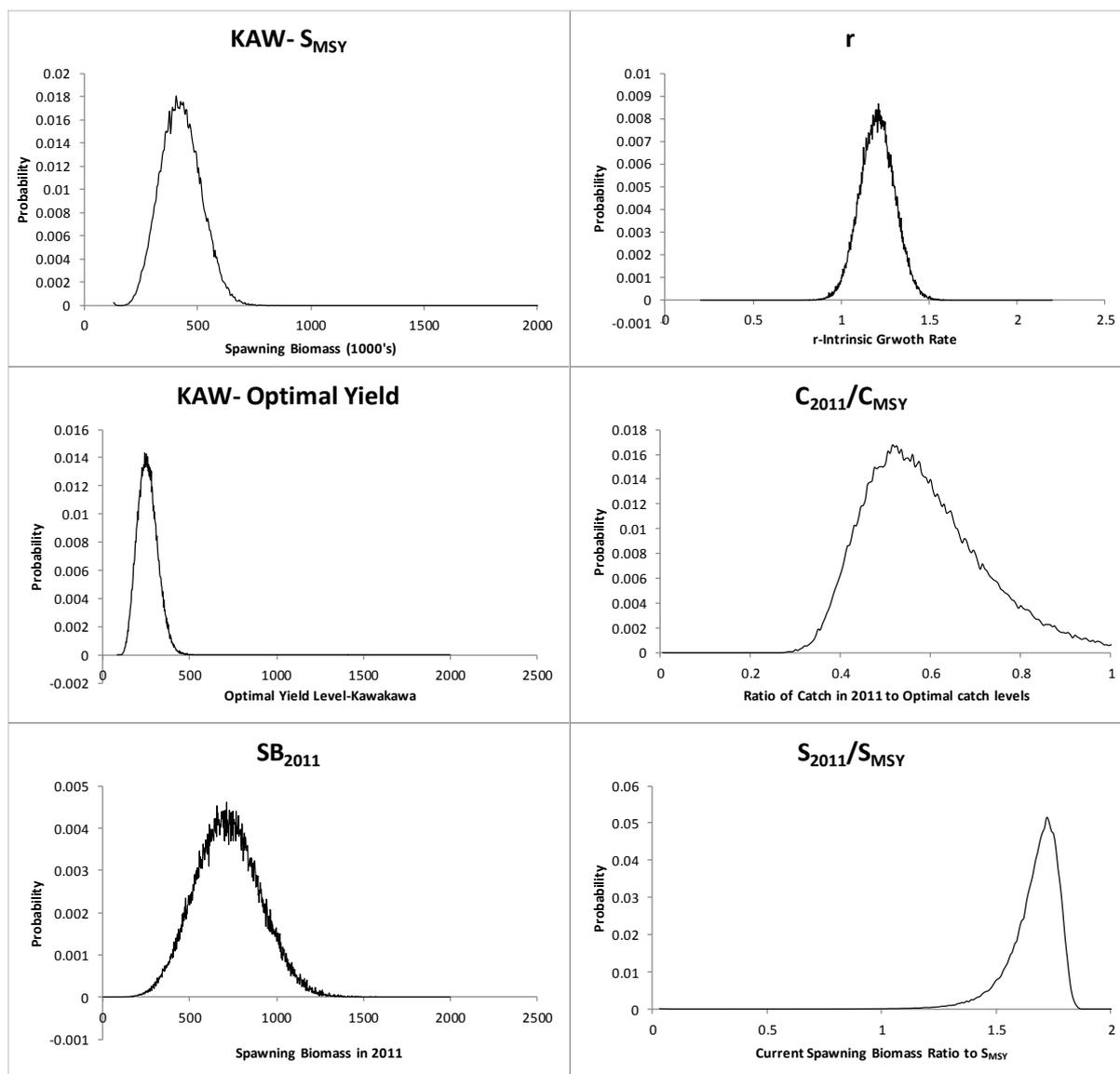


Figure 6: Derived reference points and parameters estimated using the SIR algorithm and informative priors on r and K

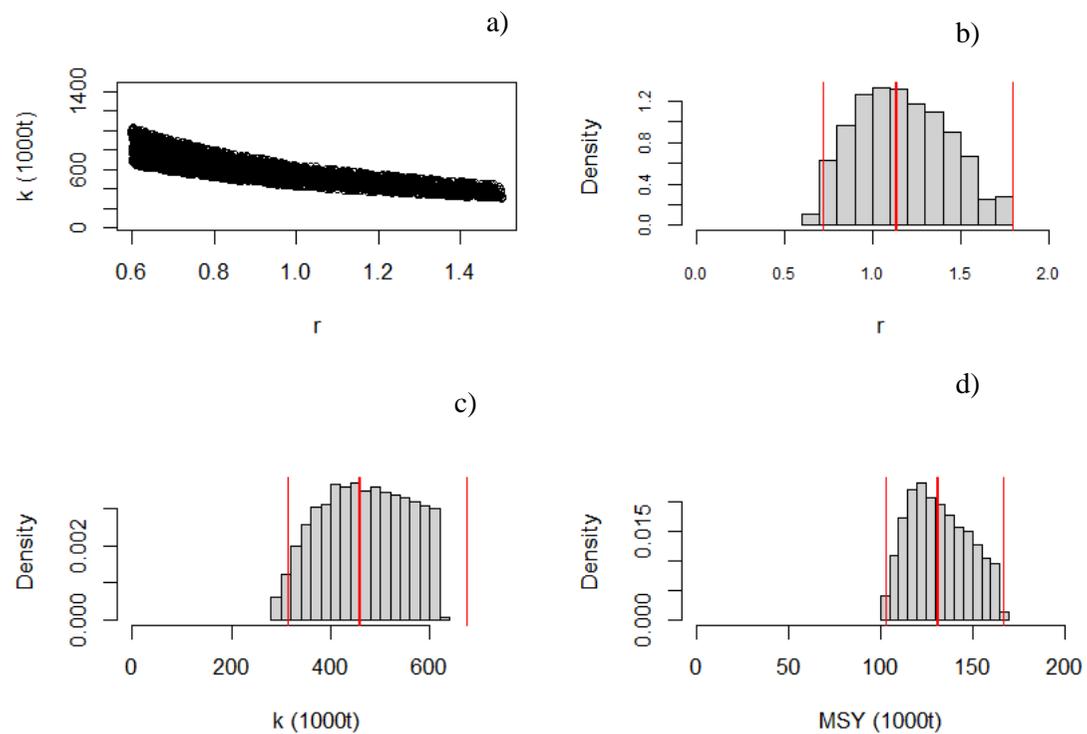


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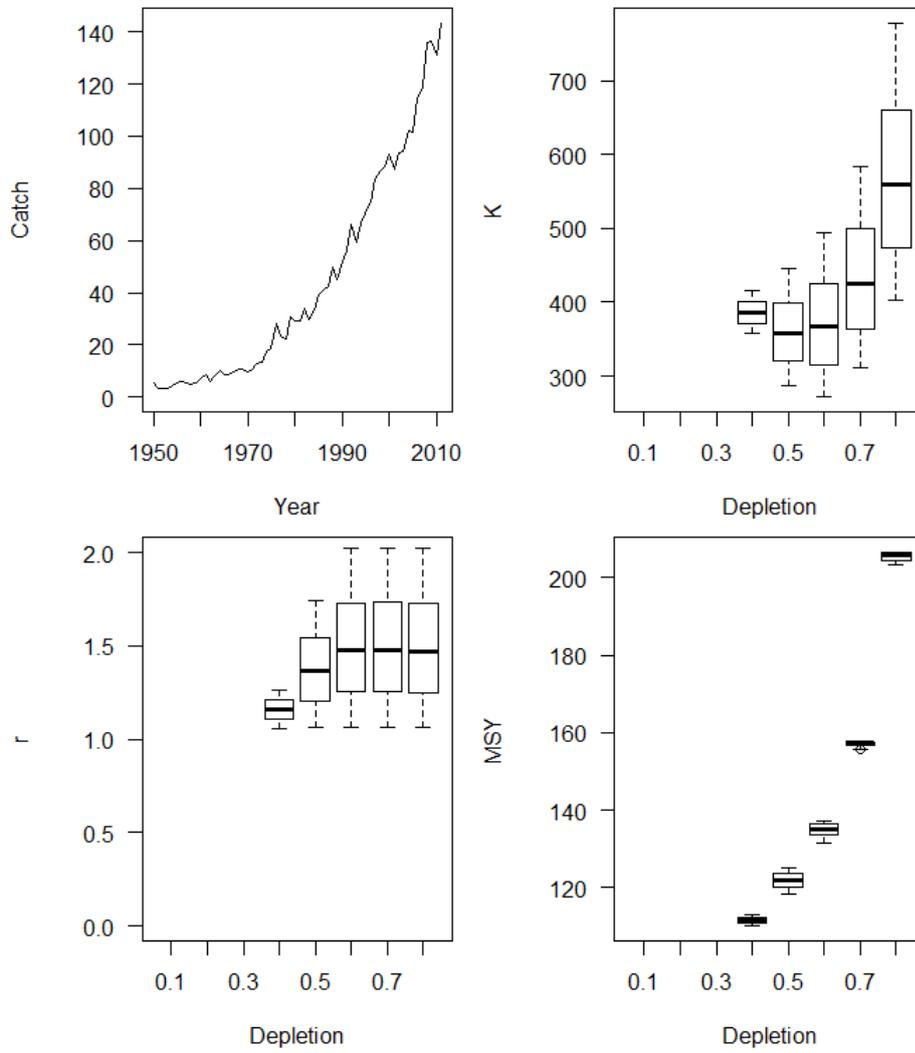


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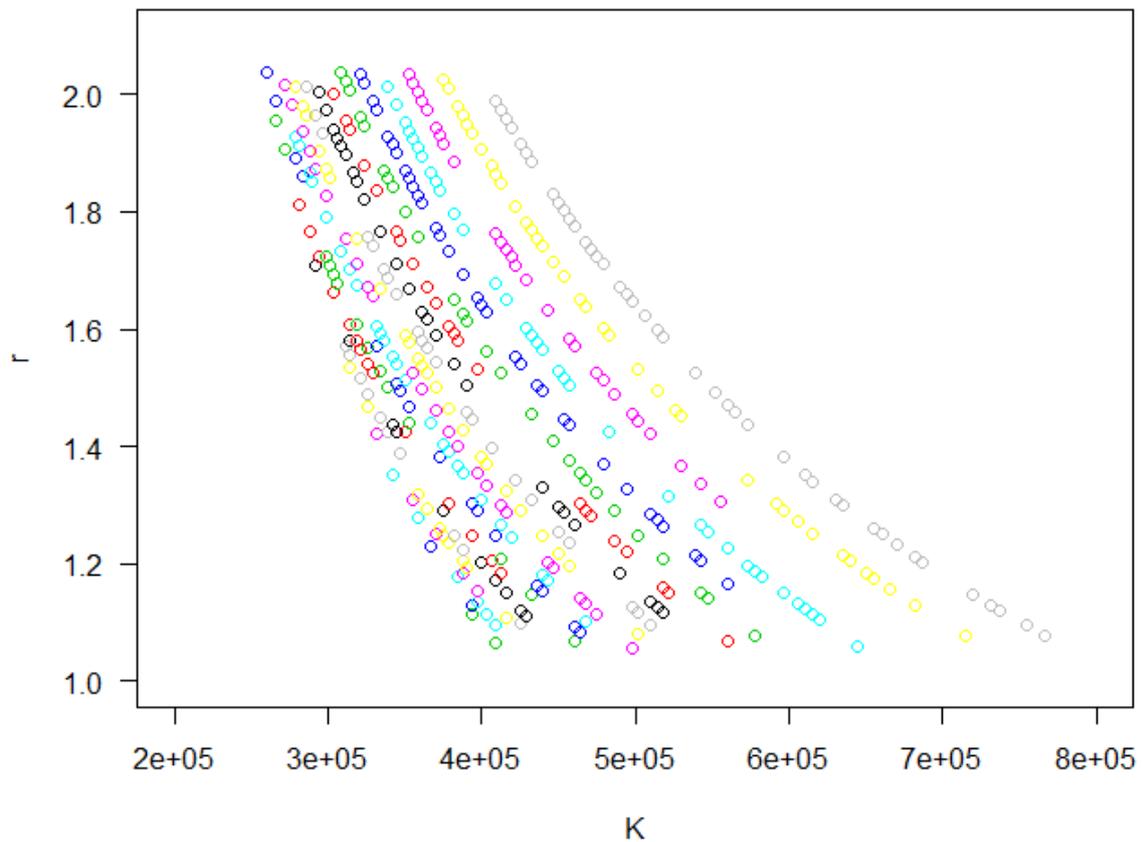


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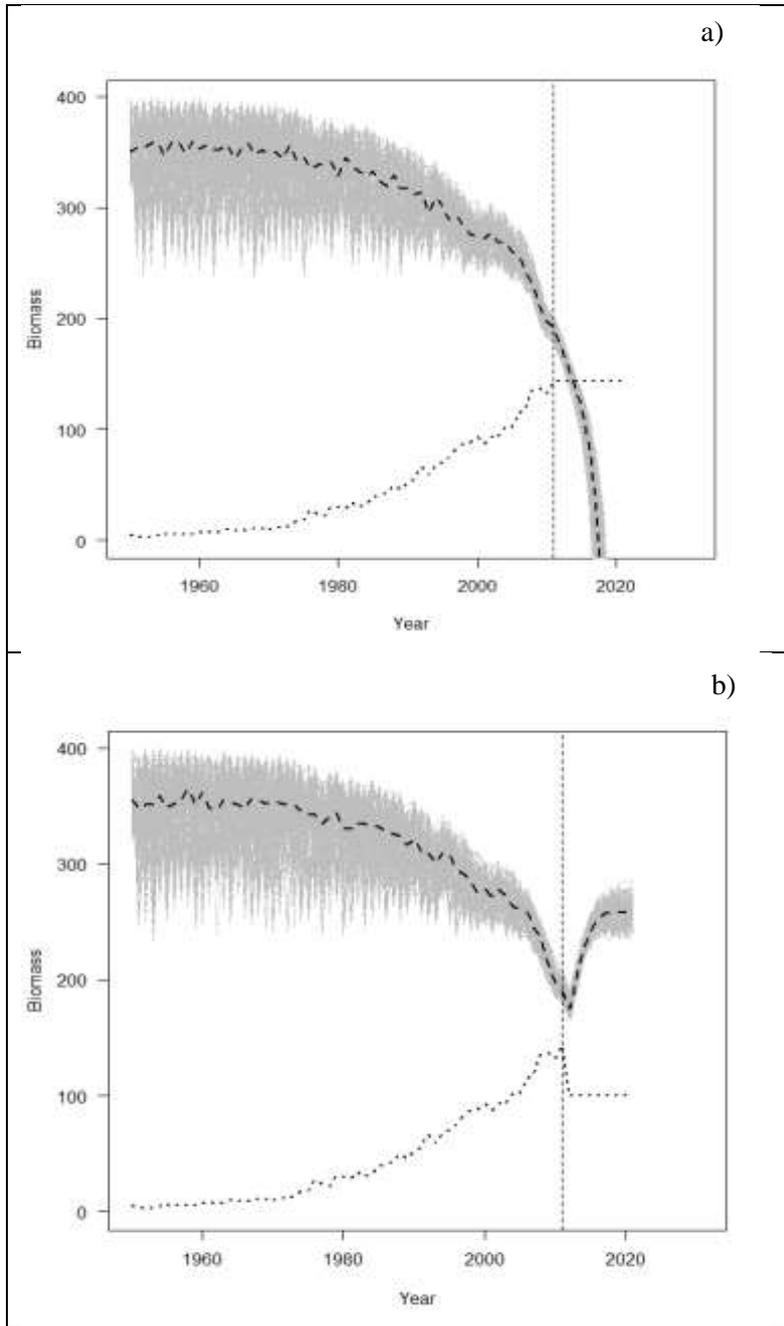


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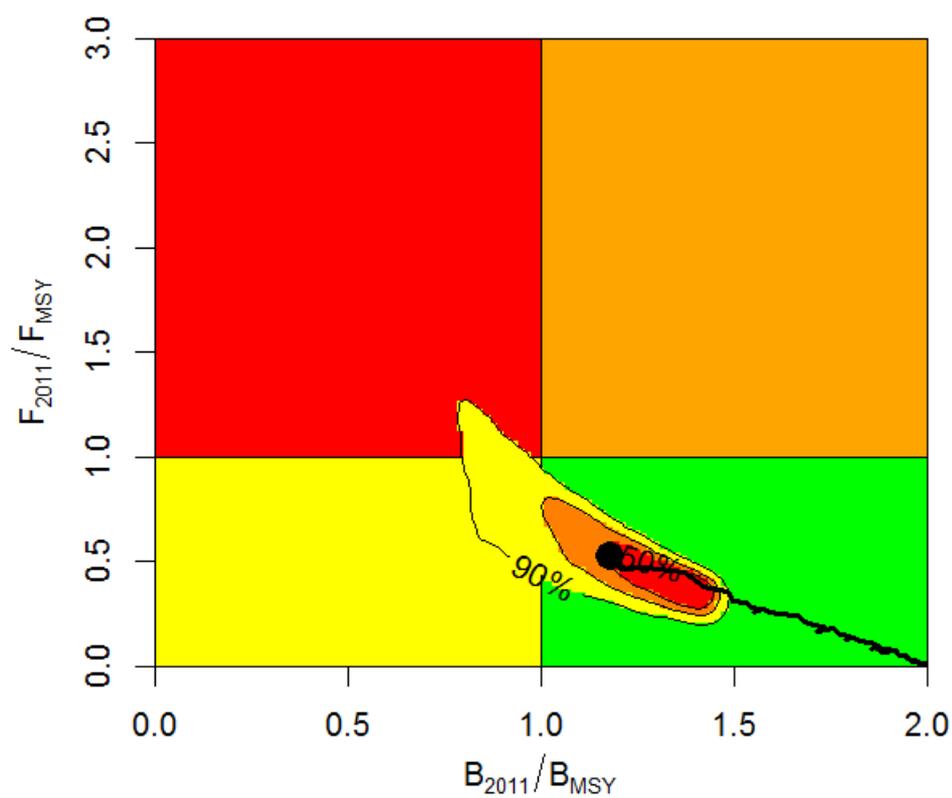


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