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# 1 Performance of catch-based and length-based stock assessment 2 methods in data-limited fisheries

3 Maite Pons <sup>1\*</sup>, Jason M. Cope <sup>1,2</sup>, and Laurence T. Kell <sup>3</sup>

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5 <sup>1</sup> School of Aquatic and Fishery Sciences, University of Washington, Box 355020, Seattle, Washington 98195-  
6 5020, USA. Email: mpons@uw.edu

7 <sup>2</sup> National Oceanic and Atmospheric Administration Fisheries, Northwest Fisheries Science Center, Fishery  
8 Resource Analysis and Monitoring Division, 2725 Montlake Boulevard East, Seattle, Washington 98112-2097,  
9 USA. Email: jason.cope@noaa.gov

10 <sup>3</sup> Centre for Environmental Policy, Imperial College London, London SW7 1NE, UK. Email: [laurie@kell.es](mailto:laurie@kell.es)

11 \* Corresponding author: School of Aquatic and Fishery Sciences, University of Washington, Box 355020,  
12 Seattle, Washington 98195-5020, USA. Email: [mpons@uw.edu](mailto:mpons@uw.edu). Telephone number: +1 206 883 5102.

13

## 14 *Abstract*

15 The quality of data from many small-scale fisheries is insufficient to allow for the  
16 application of conventional assessment methods. Even though in many countries they are  
17 moving to close-loop simulations to assess the performance of different management  
18 procedures in data limited situations, managers in most developing countries are still  
19 demanding information on stock status. In this study we use the common metric of harvest  
20 rate to evaluate and compare the performance of the following catch-only and length-only  
21 assessment models: Catch-Maximum Sustainable Yield (Catch-MSY), State-Space Catch-  
22 Only Model (SSCOM), Depletion Based Stock Reduction Analysis (DBSRA), Simple Stock  
23 Synthesis (SSS), an extension of Catch-MSY (CMSY), Length Based Spawning Potential  
24 Ratio (LBSPR), Length-Based Integrated Mixed Effects (LIME), and Length-Based Bayesian  
25 (LBB). In general, results were more biased for slightly depleted than for highly depleted

26 stocks, and for long-lived than for short-lived species. Length-based models, such as LIME,  
27 performed as well as catch-based methods in many scenarios and, among the catch-base  
28 models the one with the best performance was SSS.

29

30 Keywords: data-limited assessment methods, depletion, life-history, harvest rates

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32 INTRODUCTION

33 Major commercial fish species usually have substantial sets of data that can be  
34 integrated by complex stock assessment models (e.g., Methot and Wetzel 2013); these data  
35 may include time series of total removals, catch-at-length or -age, relative abundance indices,  
36 fishing effort, tag recoveries and information on life-history parameters. These datasets  
37 required for such stock assessments, however, are unavailable for most of the small-scale  
38 fisheries and by-catch species around the world. Fisheries and stocks lacking comprehensive  
39 datasets are commonly known as “data-poor” or “data-limited” fisheries (Costello et al. 2012;  
40 Dowling et al. 2015). Recently, many data-limited approaches have been developed to meet  
41 an increasing demand for science-based fisheries management of unassessed fisheries where  
42 data and resources are limited (Wetzel and Punt 2011; Costello et al. 2012; Dowling et al.  
43 2015, 2016; Chrysafi and Kuparinen 2016; Rosenberg et al. 2017).

44 Assessing stocks using only catch and life-history data started many years ago with  
45 the development of Stock Reduction Analysis (SRA; Kimura and Tagart 1982; Kimura et al.  
46 1984). Since then, SRA has been extended to estimate productivity and reconstruct historical  
47 abundance trends by making assumptions about final biomass relative to unfished or initial  
48 biomass (i.e., stock depletion; Thorson and Cope 2015). SRA has been further extended to  
49 incorporate stochastic variability in population dynamics (Stochastic-SRA; Walters et al.  
50 2006), a flexible shape for the production function (Depletion-Based SRA; Dick and MacCall  
51 2011), prior information regarding resilience and population abundance at the start of the  
52 catch time series (Catch-Maximum Sustainable Yield, Catch-MSY; Martell and Froese  
53 2013), bayesian approaches (CMSY, Froese et al. 2017), and age-structured population  
54 dynamics (Simple Stock Synthesis, SSS; Cope 2013). Despite these differences, this family  
55 of catch-only models share a common dependence on prior assumptions about final stock  
56 depletion. Simulation testing has previously indicated that these methods perform well only

57 when assumptions regarding final relative abundance are met (Wetzel and Punt 2015).  
58 Unsurprisingly, because final stock depletion is a prior assumption, the methods perform  
59 differently under different stock depletion levels (i.e., highly depleted or slightly depleted  
60 stocks, Walters et al. 2006) or under different harvest history or catch trends.

61 For many small-scale fisheries, obtaining reliable time series on historical total catch  
62 is difficult, whereas sampling lengths from the catch is easier. Mean-length mortality  
63 estimators (Beverton and Holt 1957) assume that fishing mortality directly influences the  
64 mean length of the catch under equilibrium conditions. This basic method has been extended  
65 by length-based spawning potential ratio (LBSPR, Hordyk et al. 2015a), length-based  
66 Integrated Mixed Effects (LIME, Rudd and Thorson 2017) and Length-Based Bayesian  
67 approach (LBB, Froese et al. 2018) models, among others. These allow for the estimation of  
68 instantaneous fishing mortality ( $F$ ) and spawning potential ratio (SPR) when basic biological  
69 parameters are known. In contrast to LBSPR and LBB, LIME does not assume equilibrium  
70 conditions. The mixed-effects aspect of LIME extends length-based methods by estimating  
71 changes in recruitment and separating them from fishing mortality over time (Rudd and  
72 Thorson 2018).

73 It is good practice to simulation test the performance of assessment methods before  
74 applying them in practice (Cope 2008). This can be done using a variety of approaches,  
75 though it is most often accomplished using an Operating Model (OM) to generating pseudo-  
76 data with error to fit an assessment model (Punt et al. 2016). Simulation can either be an open  
77 loop or a closed loop with feedback. Carruthers (2016), using closed loop simulations, found  
78 that data-limited methods using observations of stock depletion offer the best overall  
79 performance across life history types, data quality and autocorrelation in recruitment strength.  
80 However, these management procedures are based on setting catch limits and were designed  
81 for use in data-limited fisheries for which annual catch data are available, sometimes together

82 with a relative abundance index (Carruthers et al. 2014). In many data poor fisheries,  
83 measuring total removals is difficult, as is enforcing catch limits. Recently, Hordyk et al.  
84 (2015b) tested some harvest strategies using a simulation approach to assess the utility of  
85 LBSPR as a tool for management in data-limited fisheries using an effort-based harvest  
86 control rule. They found that the LBSPR assessment model with an iterative effort-based  
87 harvest control rule can be used to rebuild an overfished stock to sustainable levels or fish  
88 down a stock to the target SPR. What is needed however, is a comparison of the performance  
89 of both length-based and catch-based methods to estimate stock status. Unfortunately, finding  
90 a common metric between catch-based and length-based stock status metrics is difficult; the  
91 former measures overfishing and the latter stock depletion.

92 Even though in many countries they are moving to close-loop simulations or  
93 Management Strategy Evaluation (MSE) to assess the performance of different management  
94 procedures for data-limited fisheries, managers in most of the developing countries are still  
95 demanding information on stock status in order to manage their fisheries. Furthermore,  
96 Dowling et al. (2019) noted the dangers in the indiscriminate use of generic methods and  
97 frameworks and emphasized the importance of using care in acknowledging and interpreting  
98 uncertainties. Therefore, this study used open-loop simulations to better estimate relative bias  
99 and precision of a range of data-limited methods. A key challenge is to maintain a balance  
100 between the opposing risks of inappropriate management “action” due to assessment  
101 inaccuracy and inappropriate management “inaction” due to assessment uncertainty.

102 We used OMs to represent the main sources of uncertainty and to generate data for  
103 use in data-limited stock assessment methods and to evaluate how well the methods perform  
104 when the data and knowledge requirements are met. A common metric is then used for  
105 comparison across models, namely exploitation or harvest rates, to evaluate the performance  
106 of catch-based and length-based models in a simulation context. We evaluate performance

107 considering three fish stocks with contrasting life-history strategies, under three different  
108 harvest trends, and three different levels of final stock depletion.

109 METHODS

110 Twenty-seven different OMs were created using a factorial design comprising 3  
111 harvest rates, 3 life-history types, and 3 depletion scenarios. The different harvest rates  
112 scenarios, each considered a 20-year time series of fishing, correspond to fishing mortality  
113 histories commonly seen in many fisheries. In harvest rate scenario 1, fishing mortality  
114 increases until it reaches a maximum and starts declining afterwards. This is commonly seen  
115 once management measures are implemented to reduce fishing pressure. Harvest rate  
116 scenario 2 assumes that fishing mortality increases and remains constant after reaching a  
117 maximum. This harvest rate profile could result from the implementation of catch or effort  
118 management limits. Harvest rate scenario 3 has constantly increasing fishing mortality, which  
119 would occur for fisheries that are still developing (Figure 1a).

120 Three life history types of varying longevity and somatic growth rate were simulated,  
121 namely (i) a short-lived fast-growing species, Pacific chub mackerel (*Scomber japonicus*), (ii)  
122 a medium-lived medium-growing fish, albacore tuna (*Thunnus alalunga*, and (iii) a longer-  
123 lived slow-growing species, canary rockfish (*Sebastodes pinniger*) (Table 1). Finally, the  
124 following three depletion levels were considered: (i) heavily fished (depletion = 0.2), (ii)  
125 sustainably fished (depletion = 0.4) and (iii) slightly fished (depletion = 0.6).

126 *Operating model specifications*

127 The OM was developed to simulate resource dynamics under the different fishing  
128 scenarios, life histories and final depletion levels. The OMs consist of an age-structured  
129 population with numbers at age over time modelled as follows:

130

$$131 \quad N_{a,t} = \begin{cases} R_t, & a = 0 \text{ and } t = 0 \\ \frac{N_{a-1,t} e^{(-M - F_t S_{a-1})}}{1 - e^{(-M - F_t S_{a-1})}}, & 0 < a < A \text{ and } t = 1 \\ \frac{N_{a-1,t} e^{(-M - F_t S_{a-1})}}{1 - e^{(-M - F_t S_{a-1})}}, & a = A \text{ and } t = 1 \\ N_{a-1,t-1} e^{(-M - F_t S_{a-1})}, & 0 < a < A \text{ and } t > 1 \\ (N_{a-1,t-1} + N_{a,t-1}) e^{(-M - F_{t-1} S_{a-1})}, & a = A \text{ and } t > 1 \end{cases}$$

132             $R_t$  is the number of age-0 animals at the start of year  $t$ ,  $N_{a,t}$  is the number of fish of  
 133            age  $a$  at the start of the year  $t$ ,  $S_a$  is the selectivity at age,  $F_t$  is the instantaneous fishing  
 134            mortality rate during year  $t$ ,  $M$  is the instantaneous rate of natural mortality, and  $A$  is the age  
 135            of the plus group. Fishing mortality deviations were included as  $F_t \sim \text{lognormal}(F_{t-1}, \sigma_F^2)$ . A  
 136            Beverton–Holt spawner–recruitment function (Beverton and Holt 1957) and annual normally  
 137            distributed recruitment deviations  $N(0, \sigma_R)$  were assumed (Table 1).

138            The biomass in each year  $t$  was calculated as  $B_t = \sum_{a=1}^A N_{a,t} w_a$  where  $w_a = \alpha L_a^\beta$   
 139            (parameters in Table 1). In addition, the predicted total catch by year ( $C_t$ ) was calculated as  $C_t$   
 140             $= \sum_{a=0}^A C_{a,t}$  with:

$$141 \quad C_{a,t} = \frac{F_t S_a}{M + F_t S_a} N_{a,t} (1 - e^{(-M - F_t S_a)})$$

142            For each OM (N=27), 100 time series of fishing mortality were simulated, and the  
 143            harvest rate per year ( $U_t$ ) as  $C_t/B_t$  calculated (Figures S1 to S3). Each simulated population  
 144            began at the unfished biomass level and all fishing trend scenarios terminate at the specified  
 145            depletion level (Appendix Figures A1 to A27).

146            To condition the OM, published life-history parameter values (Table 1) reported in  
 147            formal stock assessments were used (Crone and Hill 2015 for the short-lived Pacific chub  
 148            mackerel; ICCAT 2014 for the medium-lived albacore tuna; and Thorson and Wetzel 2015  
 149            for long-lived canary rockfish). Each population was assumed to be targeted in a single area,  
 150            by one fleet with a selectivity pattern (Table 1) that was logistic and constant through time.

151 Length bins were defined as they were in their respective assessments; every 2 cm  
 152 (Crone and Hill 2015; ICCAT 2014; Thorson and Wetzel 2015). To obtain the catch length  
 153 frequency, the probability ( $p$ ) of being in a length bin ( $j$ ) given age ( $a$ ) was calculated as:

$$154 \quad p_{j,a} = \begin{cases} \emptyset \left( \frac{j - L_a}{L_a CV_L} \right), & j = 1 \\ \emptyset \left( \frac{j - L_a}{L_a CV_L} \right) - \emptyset \left( \frac{j - 1 - L_a}{L_a CV_L} \right), & 1 < j < J \\ 1 - \emptyset \left( \frac{j - 1 - L_a}{L_a CV_L} \right), & j = J \end{cases}$$

155 With the predicted probability of harvest by length bin being:

$$156 \quad \pi_j = p_{j,a} \frac{\sum_{a=0}^A N_{a,t} S_a}{N_t}$$

157 One thousand fish per year were drawn using a multinomial distribution with a  $\pi_j$   
 158 probability (Rudd and Thorson 2018).

### 159 Comparing methods outputs

160 One of the challenges when comparing catch-based and length-based methods is that  
 161 they produce different model outputs. Catch-only models calculate total and/or spawning  
 162 stock biomass and sustainable catches, whereas length-based models estimate exploitation  
 163 and transient SPR, which can be used to infer stock status. Multiple studies have shown that  
 164 catch-based methods might be appropriate to predict sustainable catch at the end of the time  
 165 series, but not to reconstruct a biomass time series (Carruthers et al. 2012; Wetzel and Punt  
 166 2015). These are fundamentally different measures of the population status. As a result, our  
 167 performance metric is defined as the error relative (RE) to the OM, where  $RE = (U_{Method} -$   
 168  $U_{OM}) / U_{OM}$ . This allows for a measure of uncertainty, in both bias and precision, for all  
 169 methods under each scenario, and is used as a standardized metric of model performance.

170 Bias in this study is how far, on average, the performance measure from each estimation  
171 model is from the OM. Imprecision is related to the variability (variance) around the central  
172 tendency.

173 We used  $U$  as a common measure for comparisons between each data limited method  
174 and the OM. For catch-only approaches it is defined as the ratio catch/biomass; while for the  
175 length-based models, the estimated  $F$  was transformed to an exploitation rate via  $U = 1 - \exp(-F)$ . In addition, we present the average RE across the last five years of the time series, not  
176 along the entire time series of data, because we are interested in the estimation of the current  
177 exploitation rates.

179 *Estimation models*

180 All simulations, and data-limited model calculations, were conducted using the open-  
181 source statistical software R (R Core Team 2018). Each catch-based and length-based method  
182 evaluated here are summarized below.

183 *Catch-based data-limited methods*

184 **Catch-MSY** (Martell and Froese 2013) is a SRA approach that assume a Schaefer  
185 biomass dynamic model. Inputs are a time series of removals, priors for the population rate of  
186 increase at low population size ( $r$ ), carrying capacity ( $K$ ), and a range of stock depletion in  
187 the final year (Table 1). Values of  $r$  and  $K$  are randomly sampled using a Monte Carlo  
188 approach to detect ‘viable’  $r$ - $K$  pairs. A parameter pair is considered ‘viable’ if the  
189 corresponding biomass trajectories calculated from a production model are compatible with  
190 the observed catches, so that the population abundance never falls below 0, and is compatible  
191 with the prior assumption of relative biomass (i.e., stock depletion; Martell and Froese 2013).  
192  $r$ - $K$  pairs are drawn from uniform prior distributions and the Bernoulli distribution is used as  
193 the likelihood function for accepting each  $r$ - $K$  pair. CMSY uses catch and productivity to

194 estimate MSY. Here we use the modified version of CMSY (Rosenberg et al. 2017) to extract  
195 biomass trends from all viable  $r$ - $K$  pairs using the R package *datalimited* version 0.1.0  
196 (Anderson et al. 2016). The biomass trajectory is calculated as the median of all viable  
197 biomass trajectories generated under the Monte Carlo process.

198 **CMSY** (Froese et al. 2017) extends Catch-MSY by using a Monte-Carlo filter  
199 (instead of the SIR algorithm) that fixes systematic biases in the Catch-MSY method. It also,  
200 explicitly incorporates process error and estimates target reference points ( $\text{MSY}$ ,  $F_{\text{MSY}}$ ,  $B_{\text{MSY}}$ )  
201 as well as relative stock size ( $B/B_{\text{MSY}}$ ) and exploitation ( $F/F_{\text{MSY}}$ ) from catch data and priors  
202 for  $r$  and depletion at the beginning and the end of the time series. CMSY has an inbuilt  
203 piecewise "hockey-stick" to prevent over-estimating of rebuilding potential at very low  
204 abundance  $B < 0.25B_0$ . The CMSY package implements a Bayesian state-space  
205 implementation of the Schaefer surplus production model (Winker 2019).

206 **SSCOM** is a Bayesian state-space model that integrates across three stochastic  
207 functional forms, variation in effort, population dynamics and fishing efficiency (Thorson et  
208 al. 2013). SSCOM can reconstruct biomass time series from catch data whenever trends in  
209 fishing mortality follow semi-predictable dynamics over time. The different types of  
210 population and effort dynamics can be extracted from the same catch stream using nonlinear  
211 models for population-dynamics as a function of biomass and linear models for effort  
212 dynamics as a function of log-scaled biomass. The package *datalimited* version 0.1.0  
213 (Anderson et al. 2016) was used and the code was extended to extract biomass trajectories  
214 and to use a lognormal distribution for depletion (Table 1). However, the effort dynamic  
215 priors were set as in Anderson et al. (2017). Using this modified version of SSCOM, the  
216 required inputs are priors for  $r$ ,  $K$ , and final stock depletion (Table 1).

217 **DBSRA** (Dick and MacCall 2011) modifies the SRA approach by using Monte Carlo  
218 draws from four parameter distributions ( $M$ ,  $F_{\text{MSY}}/M$ ,  $B_{\text{MSY}}/B_0$ , and *depletion*) and age at

219 maturity ( $A_{mat}$ ) to separate the total biomass into immature and mature biomass (fishery  
220 selectivity is also assumed to have an identical pattern to the age-at-maturity ogive). It uses a  
221 delay-difference production model with a time lag for recruitment and mortality as:

$$B_{t+1} = B_t + P(B_{t-A_{mat}}) - C_t$$

223 where  $B_t$  is the biomass at the start of year  $t$ ,  $P(B_{t-A_{mat}})$  is the latent annual production  
224 based on a function of adult biomass in year  $t-A_{mat}$  and  $C_t$  is the catch in year  $t$ . Biomass in  
225 the first year ( $B_0$ ) is assumed to be equal to  $K$ . The package *fishmethods* version 1.10-3 was  
226 used to perform this analysis (Nelson 2017). For DBSRA we used the  $A_{mat}$  and  $M$  as fixed  
227 inputs and three priors: final stock depletion,  $F_{MSY}/M$ , and  $B_{MSY}/B_0$  (distributions in Table 1).  
228 Each of these is assigned a distribution from which the Monte Carlo draws are taken.

229 **SSS** is based on the Stock Synthesis age-structured stock assessment model (Methot  
230 and Wetzel 2013). SSS fix all parameters in the Stock Synthesis model except for initial  
231 recruitment ( $\ln R_0$ ). It also sets up an artificial index of abundance that represents the relative  
232 stock biomass. The first value of the index is always 1, and the value in the final year  
233 represents the percent of the population left in that year. The values of steepness ( $h$ ) and the  
234 final year of the abundance survey are all randomly drawn from a specified distribution using  
235 a Monte Carlo approach (Cope 2013) and  $\ln R_0$  is then estimated. Benefits of this approach are  
236 that it retains the same modelling framework as the data-rich stock assessments, but still  
237 allows for flexibility in a variety of parameter and model specifications, if desired. The input  
238 priors used for SSS were relative stock status and steepness and selectivity was matched to  
239 the OM (Cope 2019).

240 *Length-based data-limited methods*

241 SPR is the proportion of the unfished reproductive potential per recruit under a given  
242 level of fishing pressure (Goodyear 1993). In **LBSPR**, SPR in an exploited population is

calculated as a function of the ratio of fishing mortality to natural mortality ( $F/M$ ), selectivity, and the two life-history ratios  $M/k$  and  $L_m/L_\infty$ ;  $k$  is the von Bertalanffy growth coefficient,  $L_m$  is the size of maturity and  $L_\infty$  is asymptotic size (Hordyk et al. 2015a). The inputs of LBSPR are  $M/k$ ,  $L_\infty$ , the variability of length-at-age ( $CVL_\infty$ ), which is normally assumed to be around 10%, and the length at maturity specified in terms of  $L_{50}$  and  $L_{95}$  (the size at which 50% and 95% of a population matures). Given the assumed values for  $M/k$  and  $L_\infty$  and that length composition data come from an exploited stock, the LBSPR model uses maximum likelihood methods to estimate the selectivity ogive, which is assumed to be of a logistic form defined by the selectivity-at-length parameters  $S_{50}$  and  $S_{95}$  (the size at which 50% and 95% of a population is retained by the fishing gear), and  $F/M$ . The selectivity ogive and relative fishing mortality are then used to calculate SPR (Hordyk et al. 2015a, 2015b). Estimates of SPR are primarily determined by the length of fish relative to  $L_{50}$  and  $L_\infty$ , but it also depends on life history parameters such as fecundity-at-age/length and selectivity. LBSPR is an equilibrium based method with the following assumptions: (i) asymptotic selectivity, (ii) growth is adequately described by the von Bertalanffy equation, (iii) a single growth curve can be used to describe both sexes which have equal catchability, (iv) length at-age is normally distributed, (v) rates of natural mortality are constant across adult age classes, (vi) recruitment is constant over time, and (vii) growth rates remain constant across the cohorts within a stock (Hordyk et al. 2015a). Analyses were conducted using the LBSPR package, version 0.1.3 in R (Hordyk 2018). We used the Rauch-Tung-Striebel smoother function available in the LBSPR package to smooth out the multi-year estimates of  $F$ .

**LIME** uses length composition of the catch and biological information to estimate  $F$  and SPR. LIME has the same data requirements as LBSPR, but does not assume equilibrium conditions. The mixed effects aspect of LIME extends length-based methods by estimating changes in recruitment and fishing mortality separately over time (Rudd and Thorson 2018).

268 LIME uses automatic differentiation and Laplace approximations as implemented in  
269 Template Model Builder (TMB; Kristensen et al. 2016) to calculate the marginal likelihood  
270 for the mixed-effects. All other assumptions are the same as LBSPR but LIME estimates one  
271 selectivity curve for the entire time series of length data while LBSPR estimates one  
272 selectivity curve for each year since each time step estimation in LBSPR is independent  
273 (Hordyk et al. 2015a). The inputs to LIME (Rudd 2019) are:  $M$ ,  $k$ ,  $L_\infty$ ,  $t_0$ ,  $CVL_\infty$ ,  $L_{50}$ ,  $L_{95}$ ,  $h$ ,  
274 and the parameters of the length-weight relationship  $a$  and  $b$  (Table 1).

275 **LBB** is a simple and fast method for estimating relative stock size that uses a  
276 Bayesian Monte Carlo Markov Chain (MCMC) approach (Froese et al. 2018). In contrast to  
277 other length-based methods, LBB uses pre-specified priors on parameters, and thus,  
278 technically does not require further inputs in addition to length frequency data, if the user is  
279 willing to accept the life history defaults. However, it provides the user the option to specify  
280 priors for the inputs  $L_\infty$ , length at first capture ( $L_c$ ), and relative natural mortality ( $M/k$ ). We  
281 specified the true  $M/k$  value and we let the model calculate  $L_c$  (length where 50% of the  
282 individuals are retained by the gear) and  $L_\infty$ , which is approximated by the maximum  
283 observed length  $L_{max}$ . In addition,  $F/M$  is estimated as means over the age range represented  
284 in the length-frequency sample.

285 During our simulation testing, we assumed that length models had the correct values  
286 for the von Bertalanffy length-at-age relationship,  $L_\infty$ ,  $k$  and  $t_0$ , length-weight parameters  $\alpha$   
287 and  $\beta$ ,  $M$ , and the parameters  $L_{50}$  and  $L_{95}$  from a logistic maturity-at-length curve. We did not  
288 evaluate misspecifications in life history parameters inputs. The objective is only to  
289 compare the performance of different data-limited methods under different scenarios, not to  
290 evaluate each of them under different parameters misspecifications, which has already been  
291 done in the original publications of each method.

## 292 RESULTS

293 Large variability is seen in model performance across harvest scenarios, life-history  
294 types, and depletion levels (Figure 1b-d, Figure 2). Figures 1 and 2 can be used to search for  
295 the best model, i.e. to identify the least biased and least imprecise method based on the life  
296 history of the species, harvest trends, and knowledge of final depletion. The imprecision of  
297 each method is shown in the variability around those estimations in Figure 1 and the specific  
298 values in Figure 2. A robust method would show low bias and high precision for all stocks  
299 and harvest scenarios; for example, among all catch-based methods, SSS appears to be the  
300 most and SSCOM the least robust method (Figure 2).

301 In general, catch-based methods tended to be more biased at relatively higher stock  
302 sizes ( $D=0.6$ ) and for long-lived species (Figures 1 and 2). Catch-MSY and SSCOM tended  
303 to perform poorly across a range of scenarios. Among the length-based models, all were less  
304 biased and more precise for the medium-lived species (Figure 2) without a clear different  
305 performance among harvest scenarios. The most biased length-based method was LBSPR  
306 although lesser imprecise than LIME and LBB (Figure 2). Overall, LIME and SSS were the  
307 most robust methods.

308 *Catch-only methods*

309 It was to be expected that the various catch-based models considered in this study  
310 would perform differently among them because they have different model structure and  
311 assumptions. SSS performed best in most cases estimating unbiased exploitation rates across  
312 different scenarios of harvest trends, final stock depletion and life histories. However, it  
313 tended to underestimate harvest rates by 30% for medium and short-lived species at relatively  
314 high stock sizes ( $D=0.6$ ). For long-lived species the estimations were slightly overestimated  
315 for sustainable relative stock sizes ( $D=0.4$ ), but SSS was always the model that was less

316 biased. DBSRA was the most precise but it underestimated harvest rates in general, and in  
317 contrast to the other catch-based methods, it was less biased for stocks at relatively high stock  
318 sizes (Figure 2). Catch-MSY was the most biased of the catch-based models tested,  
319 overestimating harvest rates in particular for stocks at relatively high stock sizes ( $D=0.6$ ). It  
320 was less biased for medium-lived species and produced non-biased estimates of MSY for  
321 highly depleted ( $D=0.2$ ) medium-lived or short-lived species at sustainable relative stock  
322 sizes ( $D=0.4$ ) (Table A1). SSCOM was less biased than Catch-MSY in most scenarios, but  
323 less precise than any other catch-based model, showing the broadest range of RE, particularly  
324 when stocks were at relatively high stock sizes ( $D=0.6$ ) or where catch decreased at the end  
325 of the time series (i.e. harvest scenario 1). SSCOM was also highly and positively biased for  
326 harvest scenario 1 (Figure 1 and 2). SSCOM showed multiple modes across scenarios,  
327 suggesting that the estimates are unstable. CMSY was less biased in the relatively medium to  
328 high stock sizes ( $D=0.4$  and  $D=0.6$ ) and for medium-lived species. In general, catch-based  
329 models were less biased and more precise when stocks were at relatively low stock sizes (i.e.  
330 using a prior centered around 0.2, Figure 1). In general, estimation models in harvest scenario  
331 1 (ramp) produced the most variable estimations in harvest rates (Figure 1). The catch-based  
332 methods performed the best for the medium-lived species.

333

#### 334 *Length-based methods*

335 In many cases, length-based models gave a less biased estimation of  $U$  than catch-  
336 based models (Figure 1). LIME was the least biased length-based method. However, in  
337 general, LIME did not converge around 10% of the time. The three length-based methods  
338 used here (LIME, LBSPR and LBB) produced more variable estimations in harvest scenario  
339 1, where the fishing intensity decreased at the end of the time series (Figure 1) but no clear  
340 pattern was observed in terms of harvest scenarios in bias (Figure 2). LBSPR in general

341 underestimated harvest rates. Compared to itself, LBB performed better in scenarios where  
342 the stocks have relatively low to medium stock sizes ( $D=0.2$  and  $D=0.4$ ) and for medium-  
343 lived species (Figure 2). Both, LBB and LIME were highly variable for long-lived species  
344 and harvest scenario 1 (Figure 1). Multiple modes for harvest scenario 1 may suggest poor  
345 convergence. In general, length-based models were less biased for the medium-lived species.

346 *Short-lived species*

347 For the short-lived life-history strategy, SSS was the least biased and most precise  
348 among the catch-based methods. The second most precise method was CMSY, but this  
349 method was positively biased for relatively high stock sizes ( $D=0.6$ ). Among the three length-  
350 based models, LIME had better overall performance than LBSPR and LBB. However,  
351 LBSPR was less biased in harvest scenario 1. LBB was the one model that presented the most  
352 variability in harvest-rate estimations for the short-lived species.

353 *Medium-lived species*

354 Both catch-based and length-based models gained more precision as the stocks were  
355 more depleted. Among the catch-based methods, CMSY was the less biased followed by  
356 SSS, although SSS was more precise. DBSRA was highly negatively biased particularly for  
357 relatively low stock sizes ( $D=0.2$ ). Catch-MSY was highly positively biased but less so for  
358 highly depleted stocks (Figure 1c). Between the length-based models, LIME showed very  
359 good performance with regards to bias for harvest scenarios 2 and 3 under the three depletion  
360 levels, although it was slightly biased for harvest scenario 1. LBSPR and LBB showed  
361 similar performance but LBSPR was more precise (Figure 1c).

362 *Long-lived species*

363 Both catch-based and length-based methods were less precise (more variability in RE)  
364 as the long-lived stocks had relatively higher stock sizes ( $D=0.6$ ), as they did for the other  
365 life-history strategies. Among the catch-based methods, SSS was the most precise and least  
366 biased method except in harvest scenario 1 and  $D=0.2$  where CMSY was the least biased.  
367 However, SSS underestimated harvest rates in scenarios 2 and 3, where the catch history is  
368 constant or increases at the end of the time series. Among assessment methods, a less biased  
369 and more precise estimation was observed for sustainable depleted stocks ( $D=0.4$ ) than for  
370 other depletion levels. SSCOM was less biased in harvest scenario 3 and  $D=0.4$  (Figure 2)  
371 but highly imprecise (Figure 1). LBSPR and DBSRA was negatively biased in all cases  
372 (Figure 1d). LIME was highly imprecise in harvest scenario 1, but the least biased among the  
373 other length-based methods (Figure 1c, Figure 2).

374

## 375 DISCUSSION

376 Simulation studies commonly make different operating model assumptions from those  
377 of the methods being tested to allow the evaluation of robustness; in some cases, however,  
378 the same population model is used for both simulation and estimation, i.e. self-testing  
379 (Deroba et al., 2015). Using the same model structure for simulation and estimation can result  
380 in more optimistic results that might not be true under many scenarios (Francis, 2012). Since  
381 it is not possible to explore the impact of model assumptions when the model used for  
382 simulation and estimation is the same. If a method performs poorly, however, when the  
383 assumptions in the OM are the same as the assessment model, it is unlikely to perform well in  
384 practice. To evaluate robustness to model structure our approach evaluated multiple data-

385 limited assessment methods with a range of assumptions about population and fishery  
386 dynamics using an operating model decoupled from the tested methods.

387 It is to be expected that the various methods would perform differently. Rosenberg et  
388 al. (2017) used four catch-based data-limited models and found that models frequently  
389 disagreed about population status estimations, with no model showing overall good  
390 performance, i.e. high precision and low bias across all case studies. When scenarios  
391 represent specific resource dynamics or particular stocks or fisheries, it may be difficult to  
392 draw any overall conclusions. Therefore, we chose scenarios that represented different  
393 fishing intensity trends, depletion levels, and life histories. We found that model performance  
394 is highly dependent on all these factors. More imprecision was found, where fishing pressure  
395 decreases at the end of the time series (harvest scenario 1), in comparison with harvest  
396 scenarios where  $F$  was either stable or increasing (harvest scenarios 2 and 3) where both  
397 performed similarly in terms of bias and imprecision. In addition, most bias was found for  
398 scenarios when stock abundance is high and/or for slow-grow long-lived species.

399 In particular, catch-based models performed better (i.e. were less biased and more  
400 precise) for stocks that were medium to highly depleted than for slightly depleted stocks.  
401 Walters et al. (2006) suggested that for SRA, stocks that have experienced extensive  
402 historical depletion gain precision due to a high rate of rejected parameter draws. Moreover,  
403 SSS which is an age structure model, performed better than the models that are based on  
404 surplus production functions such as Catch-MSY, CMSY, DBSRA, and SSCOM, even when  
405 priors for depletion were centered on the true values for all methods. Although SSS seems to  
406 be the least biased catch-based model, unlike other catch-based models, more detailed life-  
407 history information (e.g., age and growth estimates) are required by SSS to define age  
408 structure and remove catch according to age-/size-based selectivity patterns (Cope, 2013).

409           High imprecision was observed in the estimates from SSCOM. To increase precision,  
410 additional and different priors could be specified as well as trying different effort-dynamics.  
411 In this study we used, as a default, the effort dynamics specified in Anderson et al. (2017).  
412 Other effort dynamics could be assumed. Anderson et al. (2017) found that SSCOM was the  
413 most imprecise and that the representation of effort dynamics was more suitable at low  
414 biomasses. In addition, SSCOM might be more appropriate for stocks with longer time series  
415 of catch. Pons (2018) found better performance of SSCOM for the same species using longer  
416 time series (~ 80 years of catch data).

417           Catch-MSY performed poorly in all scenarios, overestimating harvest rates even  
418 when given a prior for depletion close to the true value. A key point of Catch-MSY is the  
419 ability to define a reasonable prior range for the parameters of the Schaefer model, in  
420 particular  $K$ . In our case, we have arbitrarily chosen 100 times the maximum catch as the  
421 upper bound for  $K$  based on Martell and Froese (2013). Other  $K$  values could be explored to  
422 see if this improves the outcome, but it remains a difficult parameter to specify. Rosenberg et  
423 al. (2017) and Free et al. (2017) found that Catch-MSY was the model that performed second  
424 best and better than SSCOM in their scenarios. One of the differences between their study  
425 and with ours is that they considered a uniform prior for depletion in SSCOM and we  
426 considered a lognormal prior centered on the true value.

427           CMSY on the other hand performed particularly well with respect to bias and  
428 precision for medium-lived species, even better than SSS for medium to low depleted stocks  
429 (Figure 2). Also, CMSY was more accurate than the original Catch-MSY method (Martell  
430 and Froese, 2013). The difference is that Catch-MSY was designed to select the most  
431 probable  $r$ - $K$  pair as the geometric mean of this distribution, but CMSY searches not in the  
432 center of the distribution but rather near the right tip of viable pairs. According to Froese et  
433 al. (2017) since  $r$  is defined as the maximum net productivity, the right tip of the distribution

434 of  $r$ - $K$  pairs is where these parameters should be found. So, between Catch-MSY and CMSY,  
435 CMSY is preferred.

436 Hordyk et al. (2015a) explained how LBSPR relies on detecting the signal of fishing  
437 mortality in the right-hand side of the length composition. Consequently, fishing is not likely  
438 to have a visible impact on the length composition until fishing mortality is very high and  
439 stocks are highly depleted. This is why LBSPR was less biased for more depleted populations  
440 and in fishing scenario 1.

441 Our study found that LIME was highly imprecise for long-lived species. Rudd and  
442 Thorson (2017) also showed that LIME is more imprecise for long lived species. The model  
443 is trying to track cohorts through the length data to estimate recruitment deviations and this is  
444 likely difficult for long-lived species when time series of length data are short or much of the  
445 population is found near the asymptotic size (Rudd and Thorson 2017).

446 Hordyk et al. (2019) suggested that LBB has not been sufficiently simulated tested  
447 and it can produce biased estimates of fishing mortality. We found that LBB was the most  
448 biased and imprecise length-based method although for the less depleted stocks it generally  
449 performed better than LBSPR. One of Hordyk et al. (2019) critics to LBB is that it assumes  
450 that  $M/k = 1.5$ , however here, we specified the true  $M/k$  value. So, the main bias was  
451 associated to the estimations of  $L_\infty$  due to the approximation used to the maximum observed  
452 length  $L_{max}$ . In addition to  $L_\infty$ ,  $L_c$  was always overestimated by the LBB assessment model  
453 (see Table A2).

454 In general, all catch-based and length-based methods seem to perform worse for long-  
455 lived life-history types, where there is likely to be less contrast in the dynamics over time,  
456 than for medium and short-lived. The length of the time series for the long-lived canary  
457 rockfish is therefore probably too short in comparison to the age they reach the maximum

458 length (64 years), to capture the true dynamics of the population and the response to different  
459 harvest rates.

460 The present study did not look at parameter misspecification but correctly specified  
461 (unbiased) the life-history parameters and catch histories. As we mentioned before,  
462 parameters misspecification testing was performed in the original publications for each  
463 method. With accurate prior information, length-based models such as LIME showed better  
464 performance in many cases than some catch-based models, as the latter were more sensitive  
465 to the catch history scenarios and depletion levels. LIME was not sensitive to catch trends  
466 because the model integrates the catch scenarios into the length compositions, but in most  
467 cases, LIME was more imprecise than other length-based assessments. In addition, LIME has  
468 lack of convergence in many runs compared to LBSPR and LBB.

469 Bias and precision are both important factors to consider when assessing fish stocks,  
470 bias reflects how close an estimate is to an accepted value and precision reflects  
471 reproducibility of the estimate. For example, if an assessment is to be re-conducted every  
472 year to monitor the impact of a management measure, a precise but biased method would be  
473 able to detect a trend better than an unbiased but imprecise method. As with scientific  
474 instruments this trade-off require calibration, which in the case of fish stock assessment can  
475 be performed using MSE, where the choice of parameters and reference points in a  
476 management procedure are tuned, i.e. calibrated, to meet the desired management objectives  
477 as represented by the OM. Therefore, a biased method (e.g., DBSRA) may be preferable to  
478 one that is less biased, but more imprecise (e.g., LIME). Alternatively, imprecision can be  
479 addressed through the choice of the percentile (e.g., median being the 50% percentile value)  
480 for the derived model output used by management (e.g., catch or SPR); assuming that the true  
481 value is contained within the parameter distribution. For example, instead of taking the  
482 median value, one could instead use the derived model output associated with the 40<sup>th</sup>

483 percentile. Such an approach (Ralston et al. 2011) is used in fisheries management systems to  
484 directly incorporate scientific uncertainty (both bias and imprecision), and can also be tuned  
485 using MSE.

486           *Recommendations*

487           To provide estimates of stock status for unassessed fisheries where data are limited,  
488 but reconstructing time series of catch is possible, SSS is recommended. The performance of  
489 SSS hinges on the correct specification of the input parameters such as stock depletion,  
490 productivity, maturity, and growth parameters. Knowledge about these parameters is likely  
491 to be poor for data-limited stocks, resulting in misspecification of these parameters. Meta-  
492 analyses may offer some starting values for certain parameters (e.g., Myers 2001, Thorson *et*  
493 *al.* 2012, and Zhou *et al.* 2012, 2017), however other inputs remain difficult to specify  
494 (Chrysafi and Cope *in review*).

495           For fisheries where the time series of catch are unavailable, using length-composition  
496 data can provide good approximations of the status of the stock, in particular for medium-  
497 lived species. It has been shown here that in some cases, length-based models such as LIME  
498 can provide the same or less biased estimates of exploitation status than catch-based models.  
499 However, growth parameters are even more important for length-based than for any catch-  
500 based method, so it is important to have good estimates of those parameters before using any  
501 length-based assessment.

502           Making recommendations on which models should be applied to estimate exploitation  
503 intensity in different fisheries is challenging because model choice is dependent on data  
504 availability, trends in fishing intensity, and the biology of the species. If possible, simulation  
505 studies testing different data-limited methods with OMs based on the focus species and the  
506 dynamics of the fishery can greatly inform which method is most appropriate. Likewise,

507 decision support tools such as FishPath (Dowling et al. 2015) can also help one weigh the  
508 input requirements and assumptions to identify the most appropriate methods given data and  
509 life history. Based on the OMs used in this study, we conclude that when only catch data is  
510 available, SSS should be considered. When only length data is available, LIME appeared to  
511 be less biased being able to capture changes in recruitment and fishing mortality better than  
512 LBSPR and LBB. However, Pons et al. (2019) found that neither LBSPR or LIME are good  
513 in all situations, and thus, both should be considered and compared. LIME sometimes  
514 undergoes convergence issues and has difficulties separating changes in recruitment from  
515 changes in fishing mortality (Pons 2018; Pons et al. 2019).

516 For long-lived species it is necessary to have longer time series of data to draw more  
517 conclusions. However, Pons (2018) recommended SSS and LBSPR when long time series  
518 (i.e. 80 years) of data are available for a species that lives more than 60 years to evaluate  
519 changes in fishing intensity.

520 If both catch and length data are available, models that integrate both data types  
521 should be considered. LIME, although primarily length based, allows for the inclusion of  
522 catch data as well as an index of abundance if one is available. Moreover, integrated  
523 assessment models (that use catch as well as length information) like Stock Synthesis could  
524 also be considered (Methot and Wetzel 2013). Length information can therefore be added to  
525 the SSS data file, with the possibility of freeing up the stock status assumption input, and  
526 running the model more like a traditional statistical-catch-at-age model (Cope 2013).

527 For the scenarios analyzed here, including the specific life-histories considered, we do  
528 not recommend Catch-MSY for estimating exploitation rates, even with a good estimate of  
529 stock depletion. This method will however, as it was originally created to do, produce  
530 unbiased estimates of MSY, in particular for short and medium-lived and highly depleted  
531 species (Table A1).

532            *Future directions*

533            Dowling et al. (2019) in a review of data limited methods, noted the dangers in the  
534 indiscriminate use of generic methods and recommended obtaining better data, using care in  
535 acknowledging and interpreting uncertainties, developing harvest strategies that are robust to  
536 these higher levels of uncertainty and tailoring them to the species and fisheries specific data  
537 and context. Therefore, methods should be tested using a management strategy evaluation  
538 (MSE) to specify Management Procedures (MP) that can help ensure robust and sustainable  
539 fisheries management. Where a MP is the combination of pre-defined data, together with an  
540 algorithm to which such data are input to provide a value for a management control measure.  
541 This must include evaluation of the robustness of the methods to misspecification of input  
542 parameters and the benefits of improving knowledge on them.

543            This study provides a way of conditioning OMs and generating pseudo data for use by  
544 the MP. The importance of considering assessment methods as part of a MP is that a method  
545 that provides biased estimates with high precision may be better for setting management  
546 regulations than an unbiased but imprecise estimator. Additionally, if a method only provides  
547 estimates of exploitation level or MSY, then management controls may be different i.e. have  
548 to be based on a total allowable catch or effort. Traditional stock assessment and advice based  
549 upon it mainly considers measurement and process error only. MSE allows for the  
550 consideration of additional uncertainty, such as uncertainty in the actual dynamics, which has  
551 a larger impact on achieving management objectives (Punt 2008).

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562

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- 736
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Draft

- 1    **Table 1.** Life-history information and priors for the three species used in the study. Notation is as follows: *Lognormal* ( $\mu$ ,  $\sigma^2$ ); Uniform  $U(a, b)$ .
- 2    Priors for  $K$  were Uniform between the maximum catch in the time series and 100 times the maximum catch. For the Catch-MSY method, the
- 3    depletion priors were Uniform centered on the true value with a minimum of *true* - 0.1 and a maximum of *true* + 0.1.

<b>Operating model inputs</b>	<b>Symbol</b>	<b>Short-lived</b>	<b>Medium-lived</b>	<b>Long-lived</b>
Maximum age	$Age_{max}$	10	15	64
Age at 50% maturity (years)	$A_{mat}$	3	5	16
Length where 50% of the fish are mature (FL cm)	$L_{50}$	29	90	55
Length where 95% of the fish are mature (FL cm)	$L_{95}$	34	100	57
Length-weight scaling parameter	$\alpha$	$2.73 \times 10^{-6}$	$1.34 \times 10^{-5}$	$1.80 \times 10^{-5}$
Length-weight allometric parameter	$\beta$	3.444	3.107	3.094
Von Bertalanffy Brody growth coefficient (1/years)	$k$	0.40	0.21	0.14
Von Bertalanffy asymptotic length (cm)	$L_\infty$	38.2	122.2	60.0
Theoretical age at length=0	$t_0$	-0.6	-1.3	-1.9
Coefficient of variation of length at age for all ages	$CVL$	0.1	0.1	0.1
Natural mortality (1/years)	$M$	0.60	0.30	0.05
Steepness	$h$	0.5	0.9	0.8
Selectivity at 50% (cm)	$S_{50}$	25	60	45
Selectivity at 95% (cm)	$S_{95}$	30	75	50
Recruitment deviations	$\sigma_R$	0.3	0.4	0.5
Fishing mortality deviations	$\sigma_F$	0.2	0.2	0.2
<b>Estimation models prior distributions</b>				
Depletion (used for all catch-based models)	$XB_0$	<i>Lognormal</i> ( <i>true</i> , 0.1) $U(\max(\text{catch}), \max(\text{catch}) \times 100)$	<i>Lognormal</i> ( <i>true</i> , 0.1) $U(\max(\text{catch}), \max(\text{catch}) \times 100)$	<i>Lognormal</i> ( <i>true</i> , 0.1) $U(\max(\text{catch}), \max(\text{catch}) \times 100)$
Carrying capacity (used for Catch-MSY, CMSY and SSCOM)	$K$			
Population rate of increase (used for Catch-MSY, CMSY and SSCOM)	$r$	$U(0.8, 1.2)$	$U(0.2, 0.6)$	$U(0.05, 0.4)$
Steepness (used for SSS)	$h$	<i>Normal</i> (0.5, 0.1)	<i>Normal</i> (0.9, 0.1)	<i>Normal</i> (0.8, 0.1)
Vulnerability (used for DBSRA)	$F_{MSY}/M$	$U(0, 2)$	$U(0, 2)$	$U(0, 2)$
Compensation (used for DBSRA)	$B_{MSY}/B_0$	$U(0, 1)$	$U(0, 1)$	$U(0, 1)$

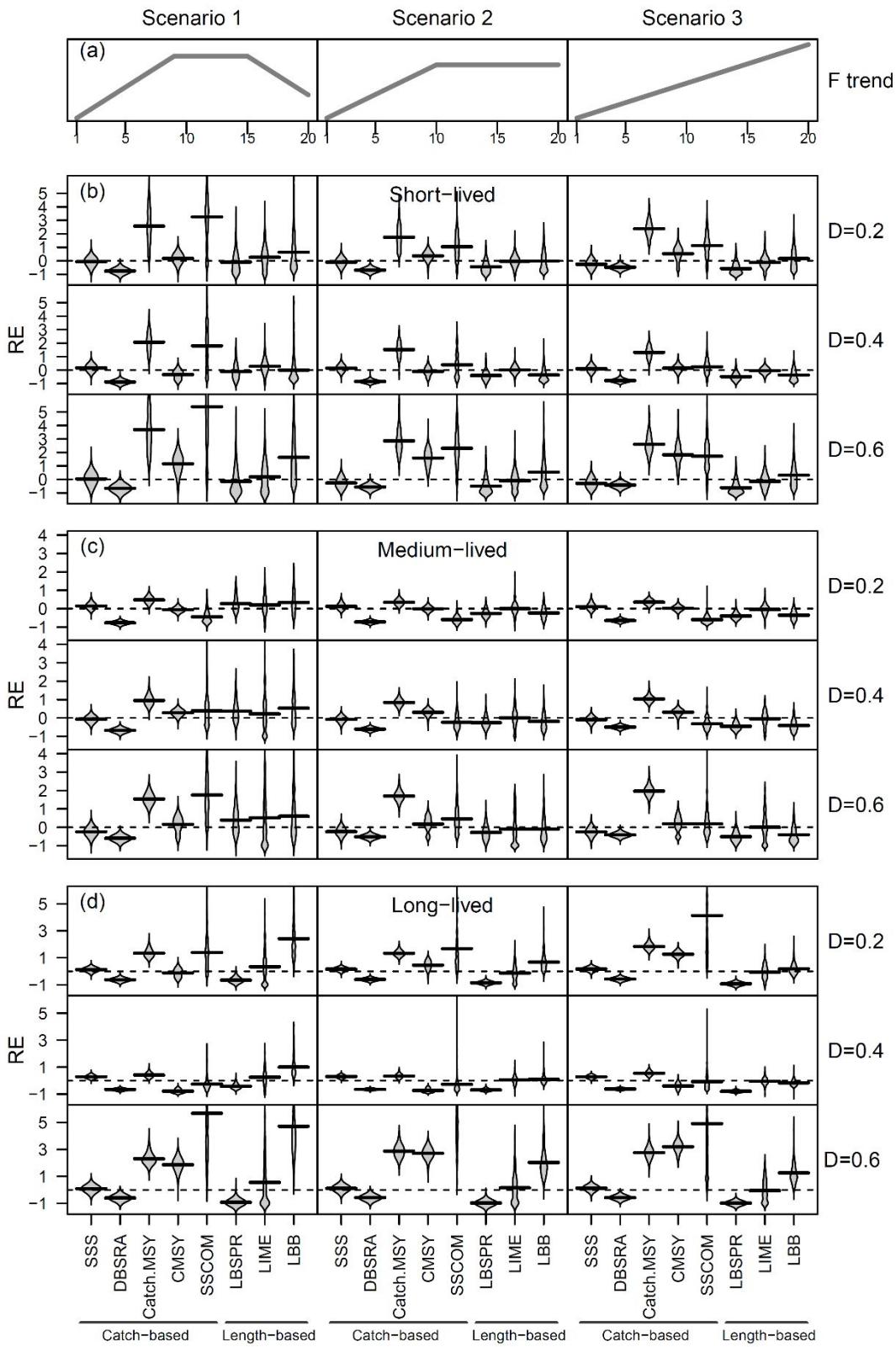
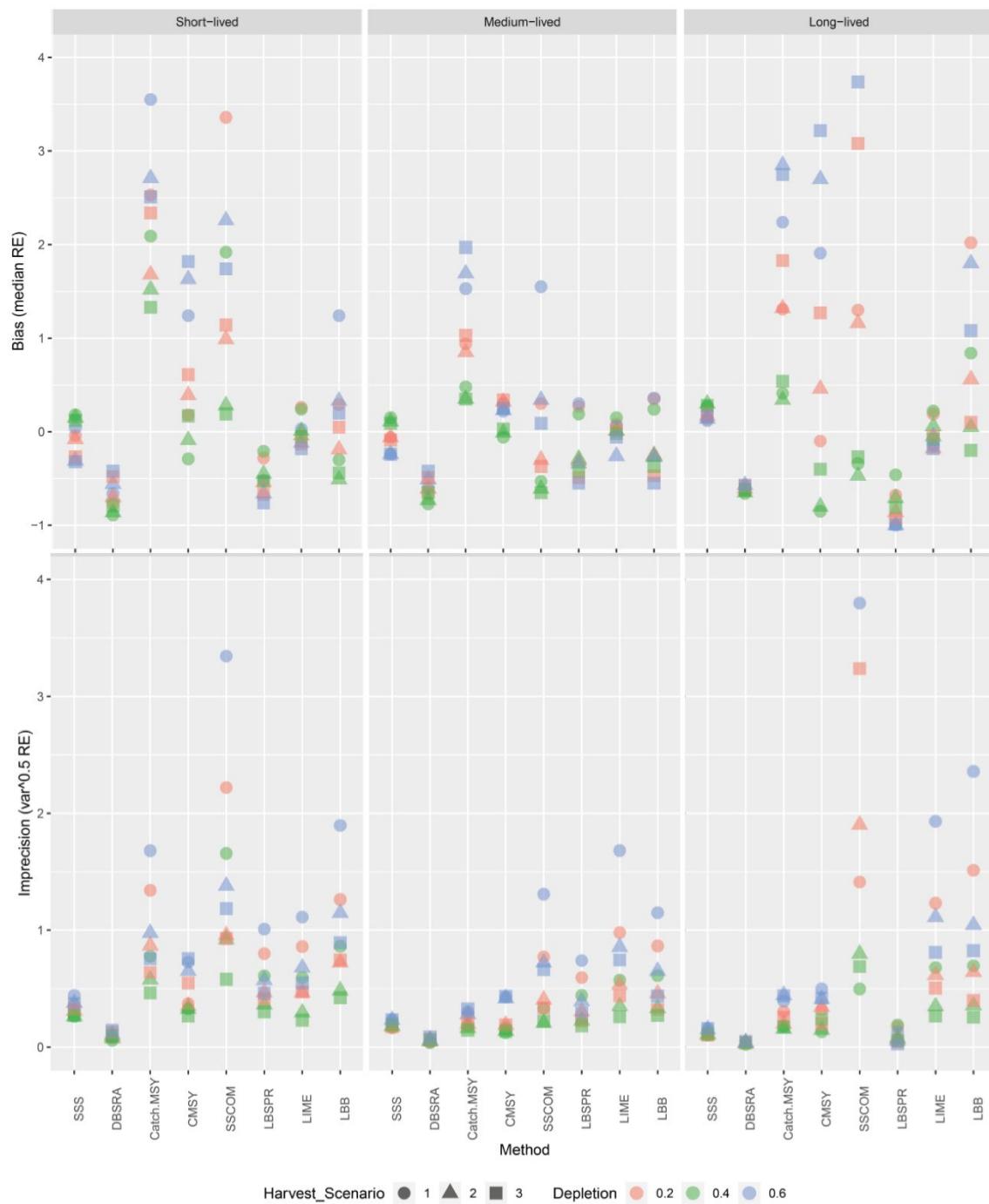


Figure 1. Relative error (RE) in exploitation rate for all the catch-based and length-based models considered under the different harvest scenarios (a) and depletion scenarios for differing life histories, (b) short-lived, (c) medium-lived, and (d) long-lived.



**Figure 2.** Bias (top panels) and imprecision (bottom panels) for all the catch-based and length-based models considered under the different harvest scenarios and life histories. The y-axes were truncated at 4, so 3 and 2 scenarios are not visualized in the upper and lower panels, respectively.

## Appendix

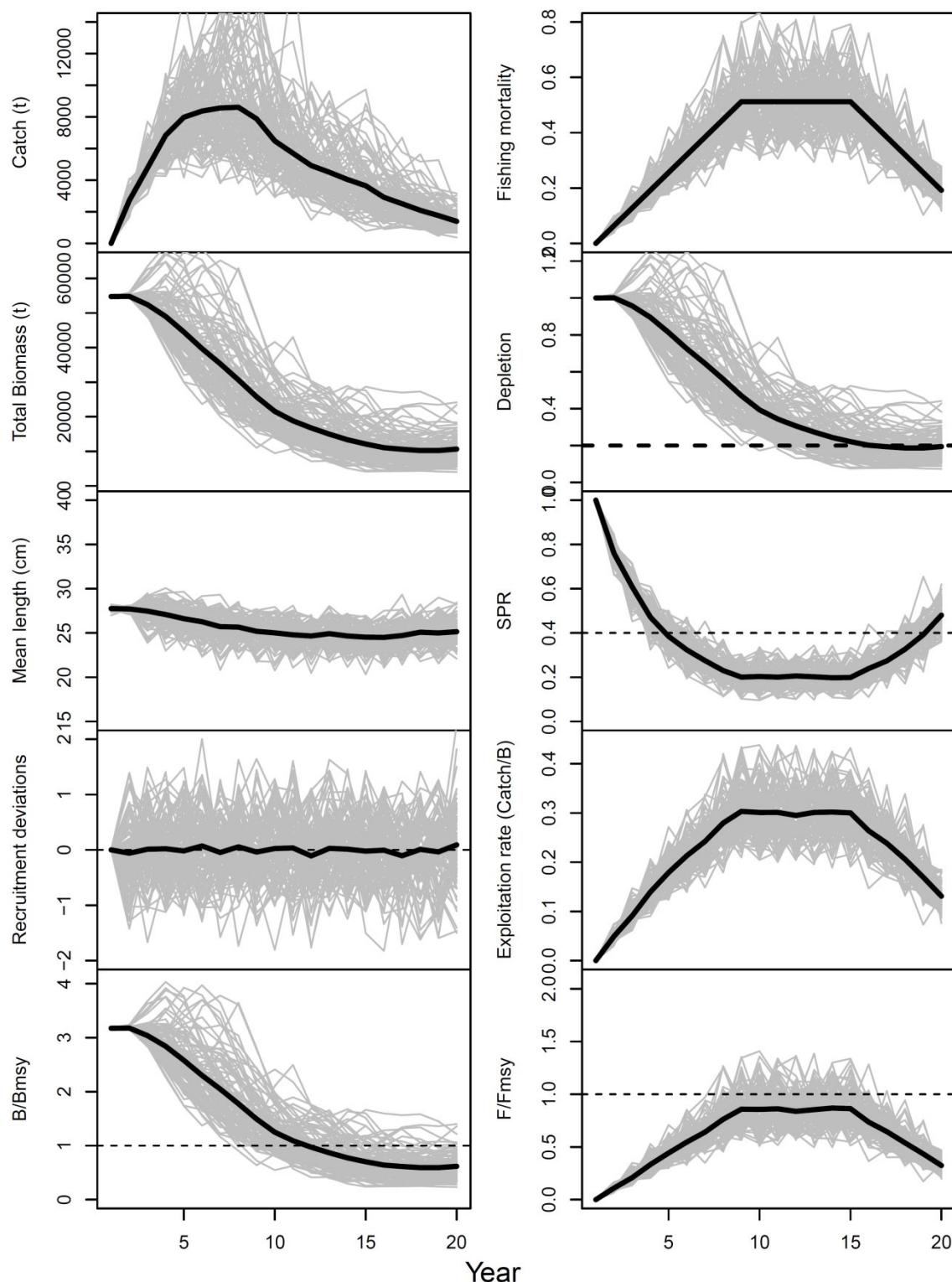


Figure A1. Time series for each simulated fast-grow chub mackerel population for harvest scenario 1 and depletion = 0.2. The black solid lines represent the mean value for all runs.

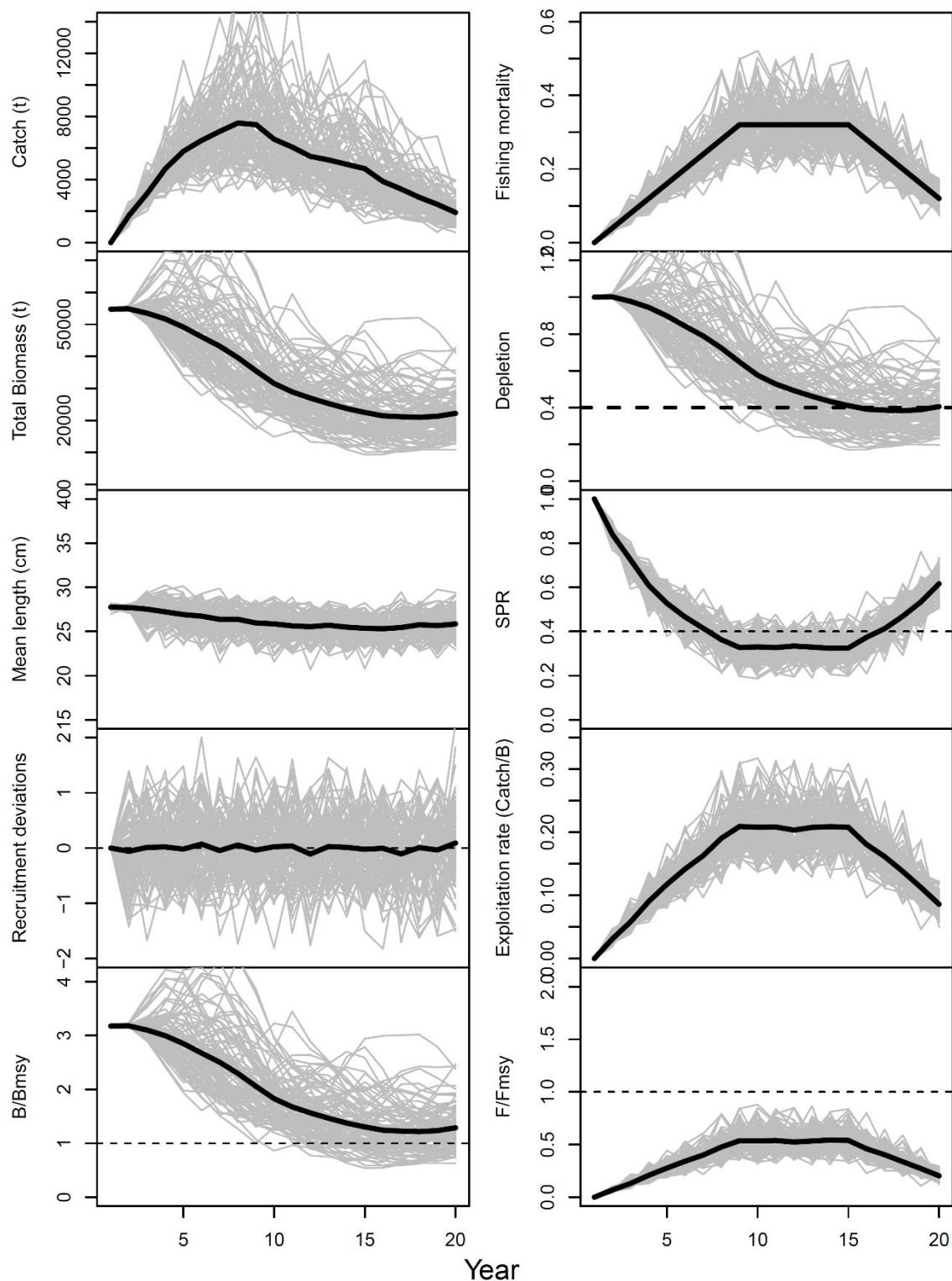


Figure A2. Time series for each simulated fast-grow chub mackerel population for harvest scenario 1 and depletion = 0.4. The black solid lines represent the mean value for all runs.

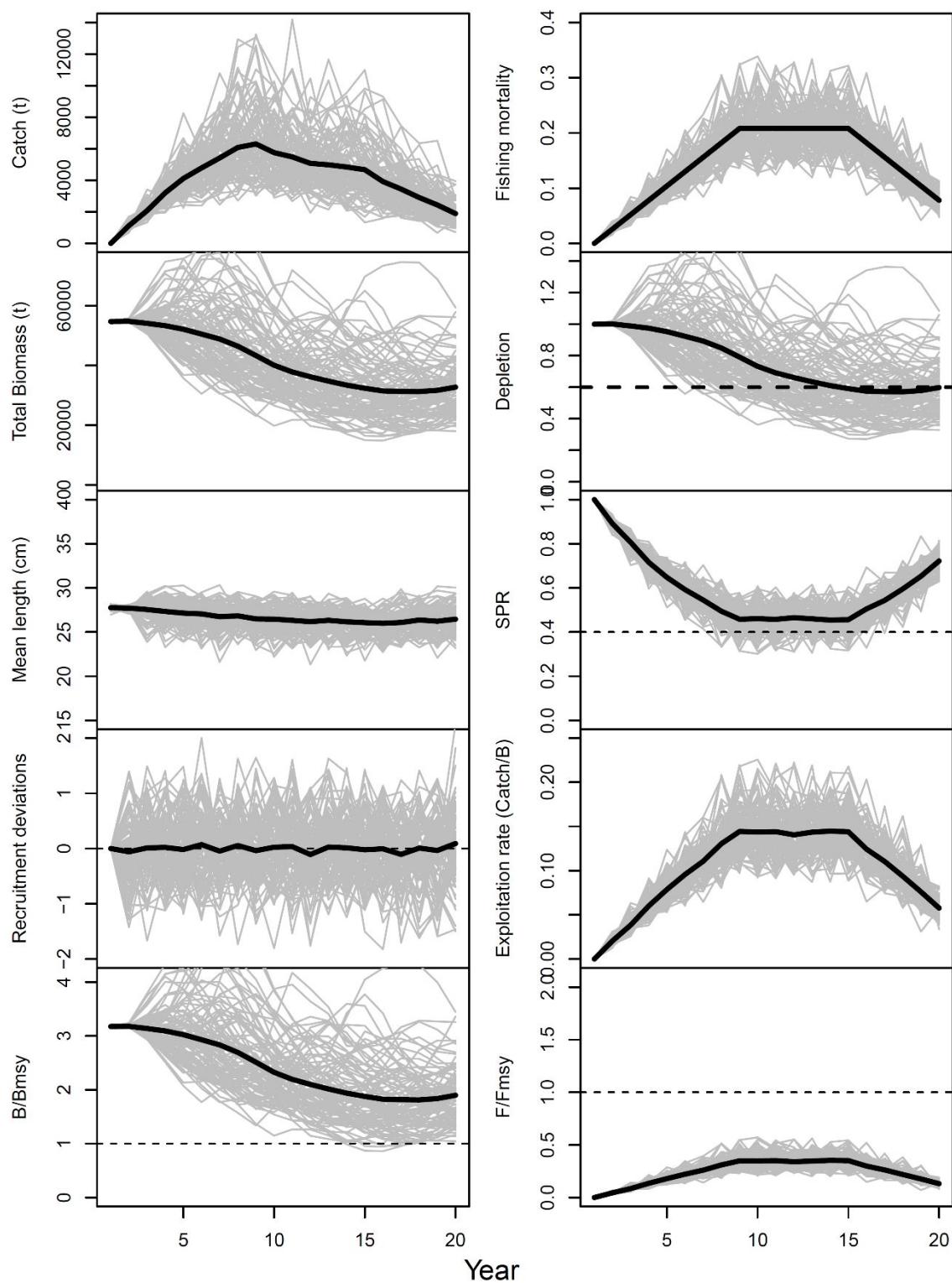


Figure A3. Time series for each simulated fast-grow chub mackerel population for harvest scenario 1 and depletion = 0.6. The black solid lines represent the mean value for all runs.

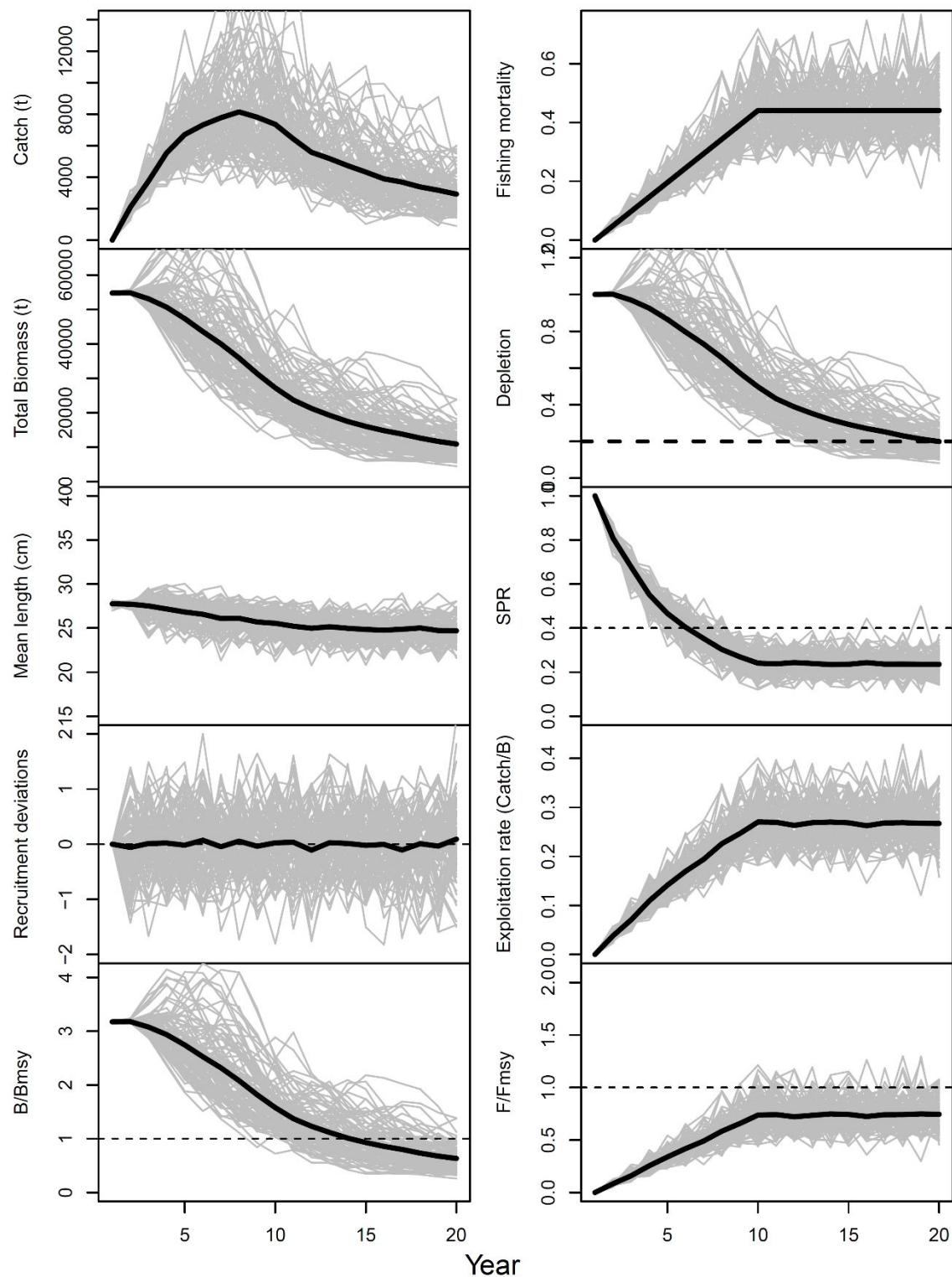


Figure A4. Time series for each simulated fast-grow chub mackerel population for harvest scenario 2 and depletion = 0.2. The black solid lines represent the mean value for all runs.

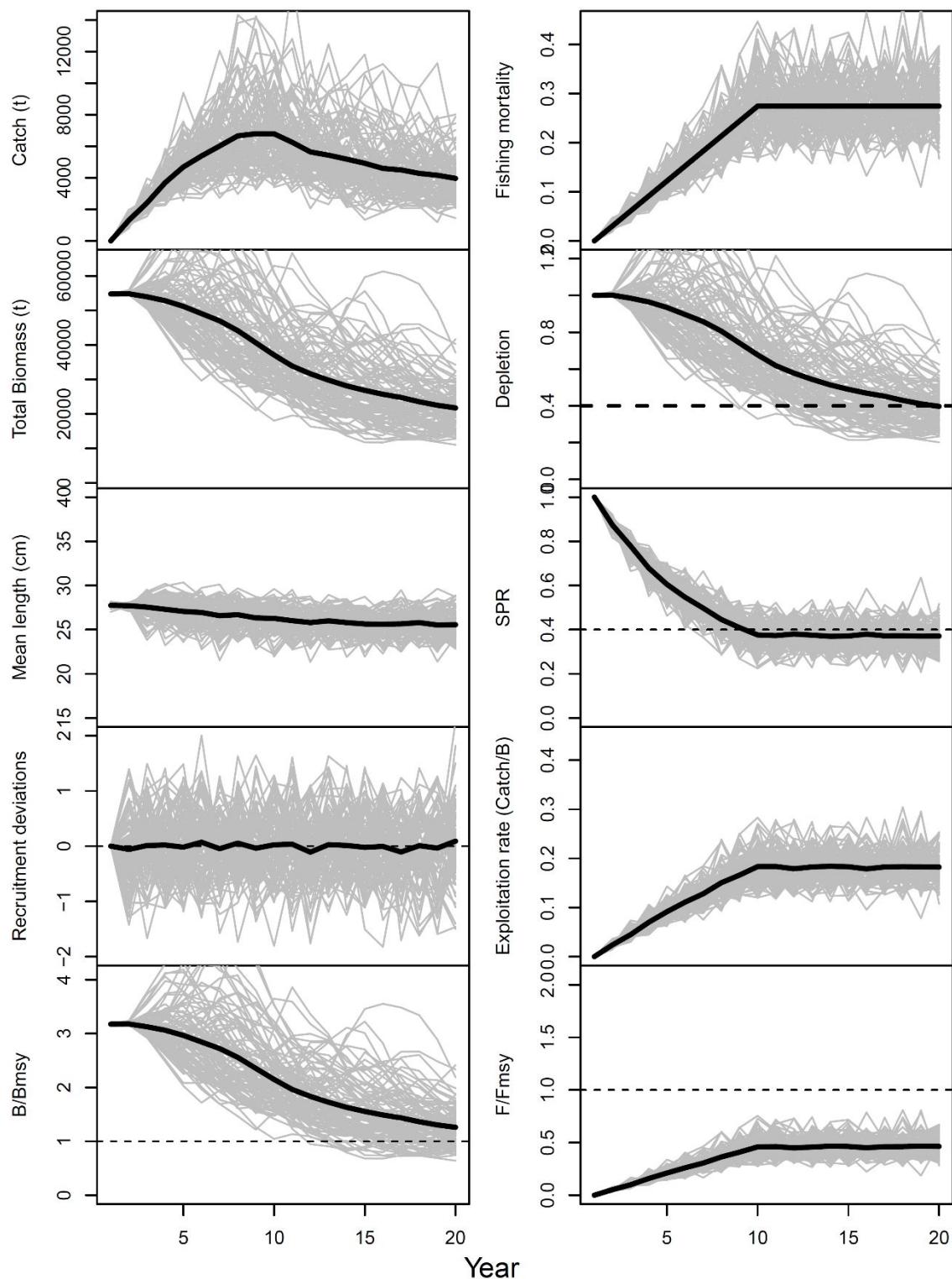


Figure A5. Time series for each simulated fast-grow chub mackerel population for harvest scenario 2 and depletion = 0.4. The black solid lines represent the mean value for all runs.

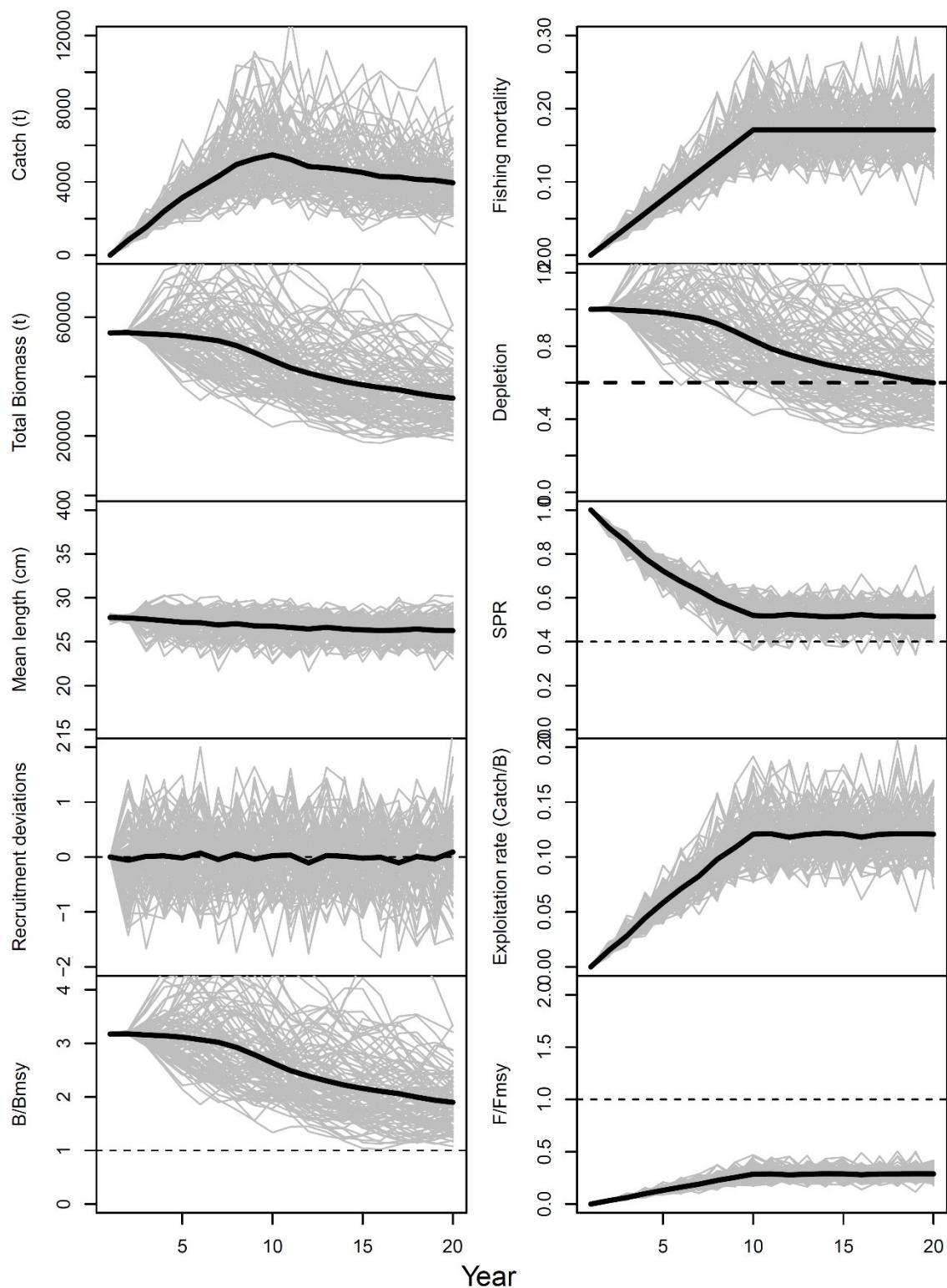


Figure A6. Time series for each simulated fast-grow chub mackerel population for harvest scenario 2 and depletion = 0.6. The black solid lines represent the mean value for all runs.

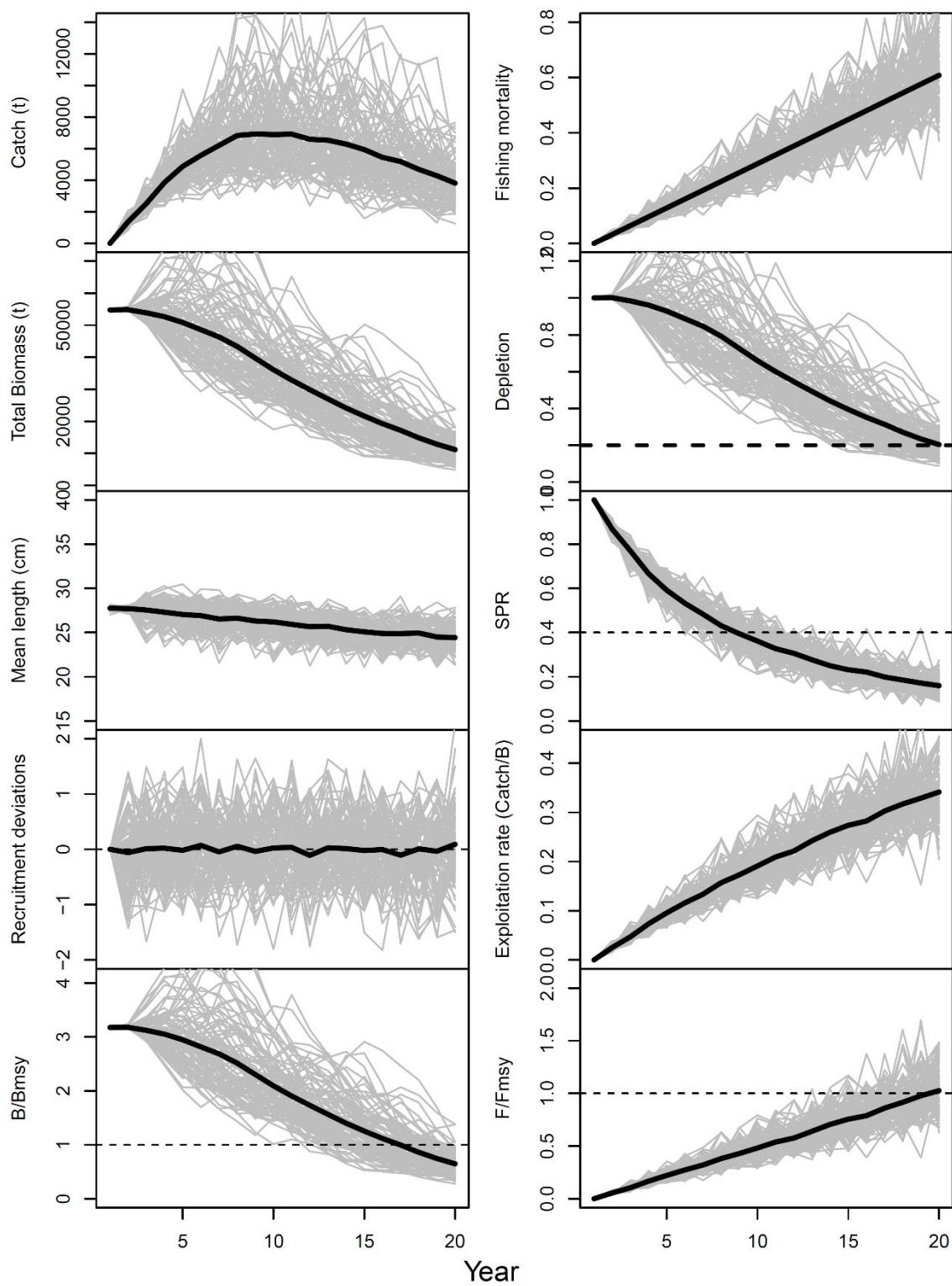


Figure A7. Time series for each simulated fast-grow chub mackerel population for harvest scenario 3 and depletion = 0.2. The black solid lines represent the mean value for all runs.

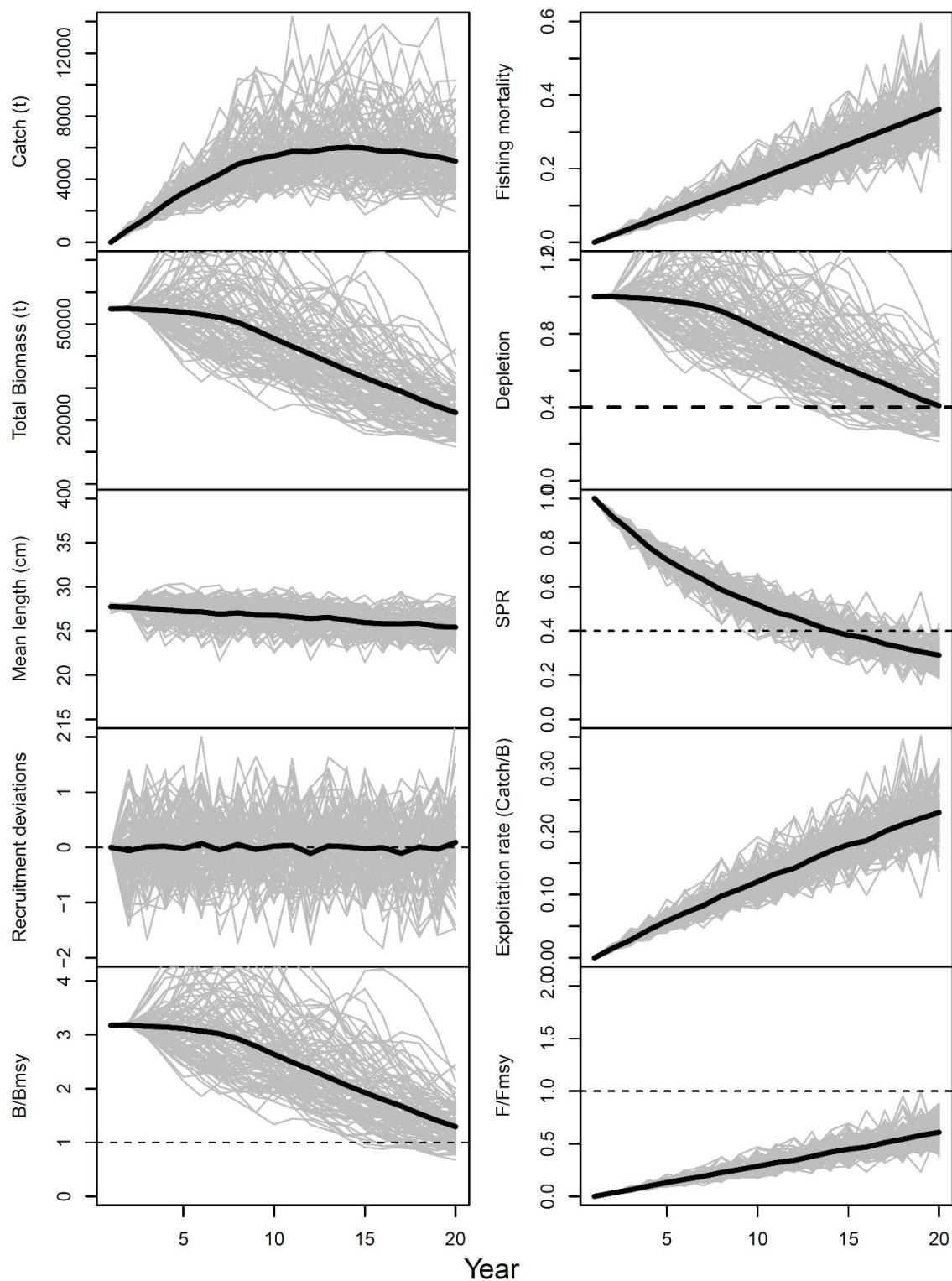


Figure A8. Time series for each simulated fast-grow chub mackerel population for harvest scenario 3 and depletion = 0.4. The black solid lines represent the mean value for all runs.

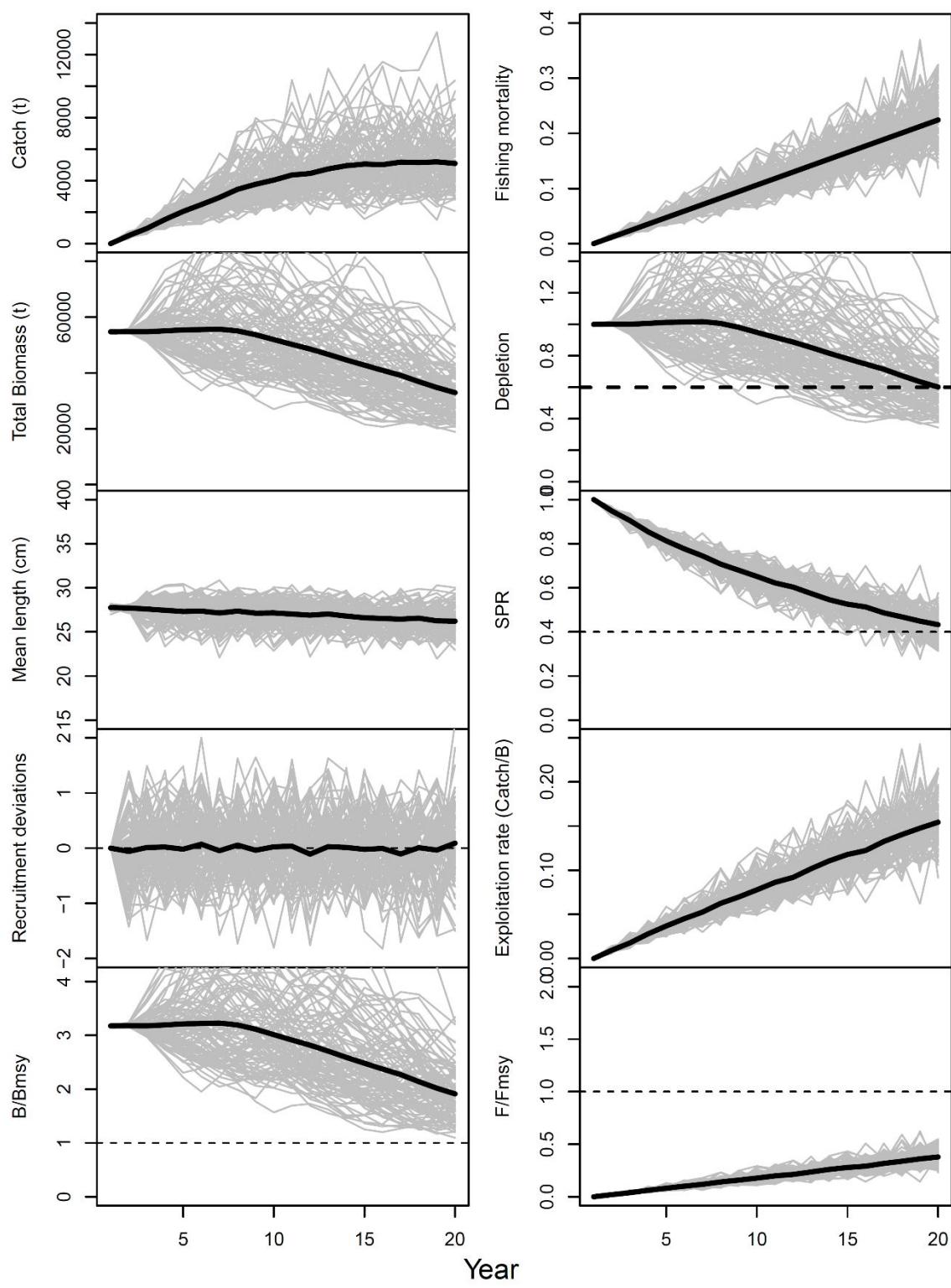


Figure A9. Time series for each simulated fast-grow chub mackerel population for harvest scenario 3 and depletion = 0.6. The black solid lines represent the mean value for all runs.

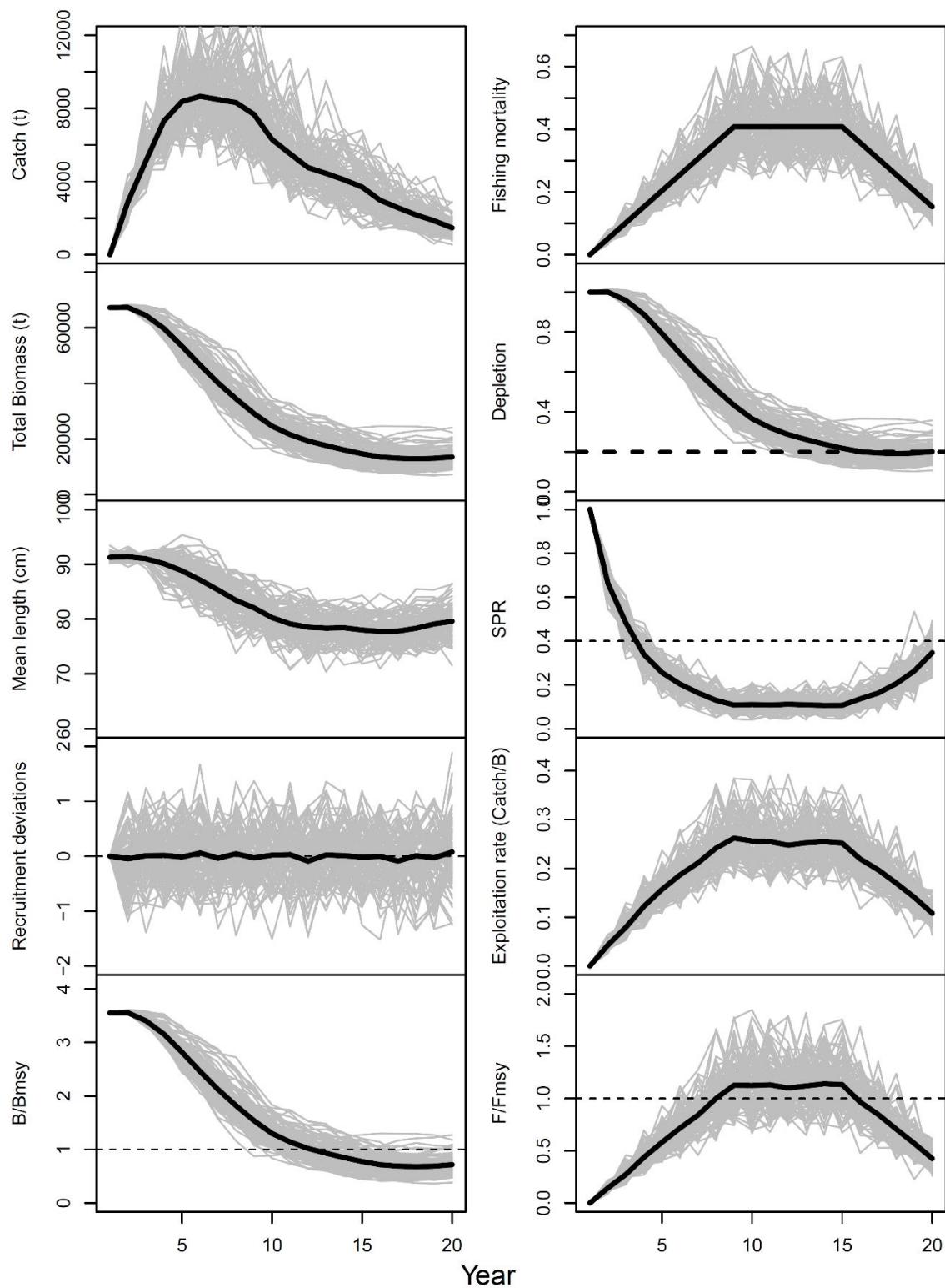


Figure A10. Time series for each simulated medium-grow albacore tuna population for harvest scenario 1 and depletion = 0.2. The black solid lines represent the mean value for all runs.

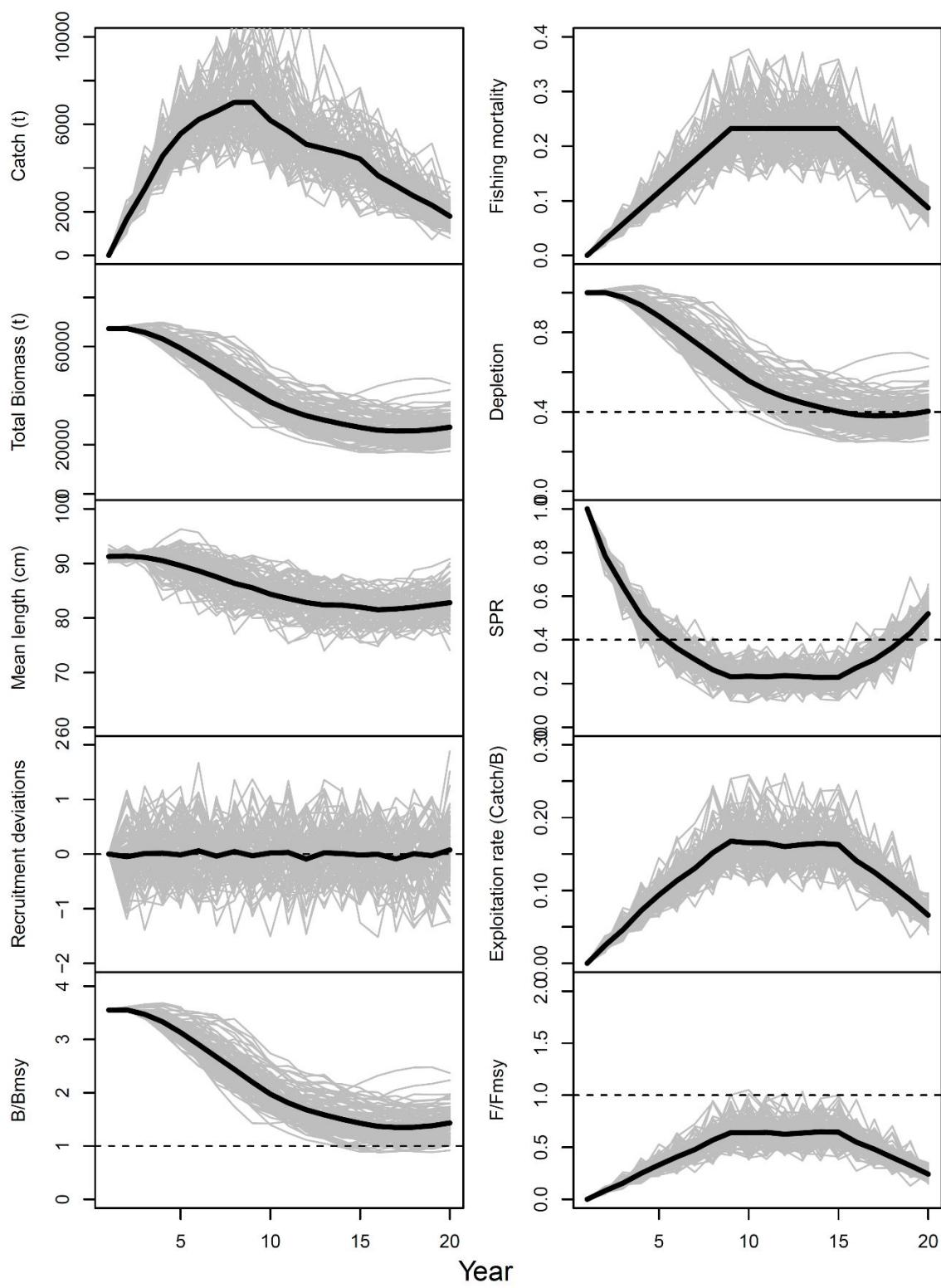


Figure A11. Time series for each simulated medium-grow albacore tuna population for harvest scenario 1 and depletion = 0.4. The black solid lines represent the mean value for all runs.

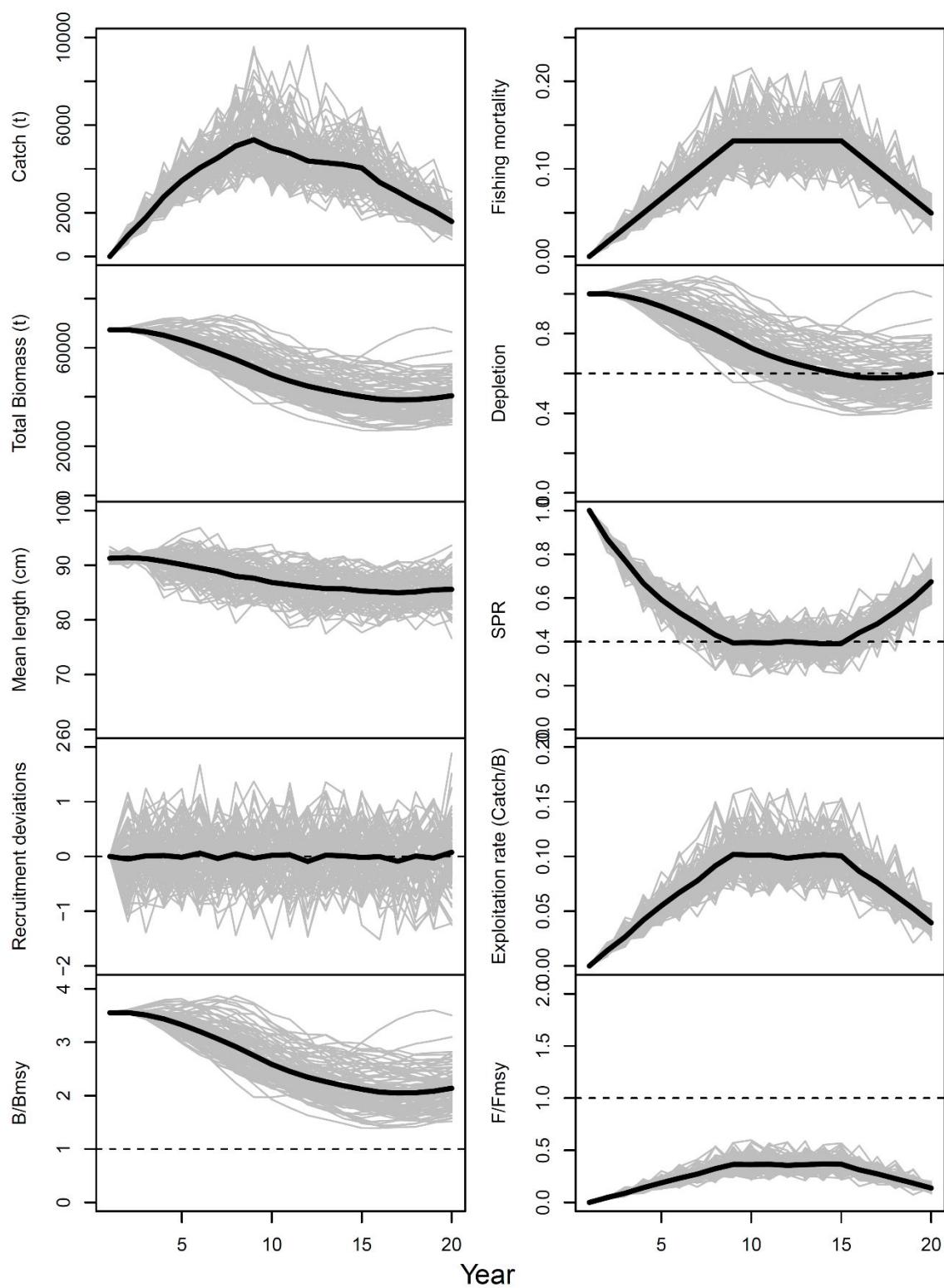


Figure A12. Time series for each simulated medium-grow albacore tuna population for harvest scenario 1 and depletion = 0.6. The black solid lines represent the mean value for all runs.

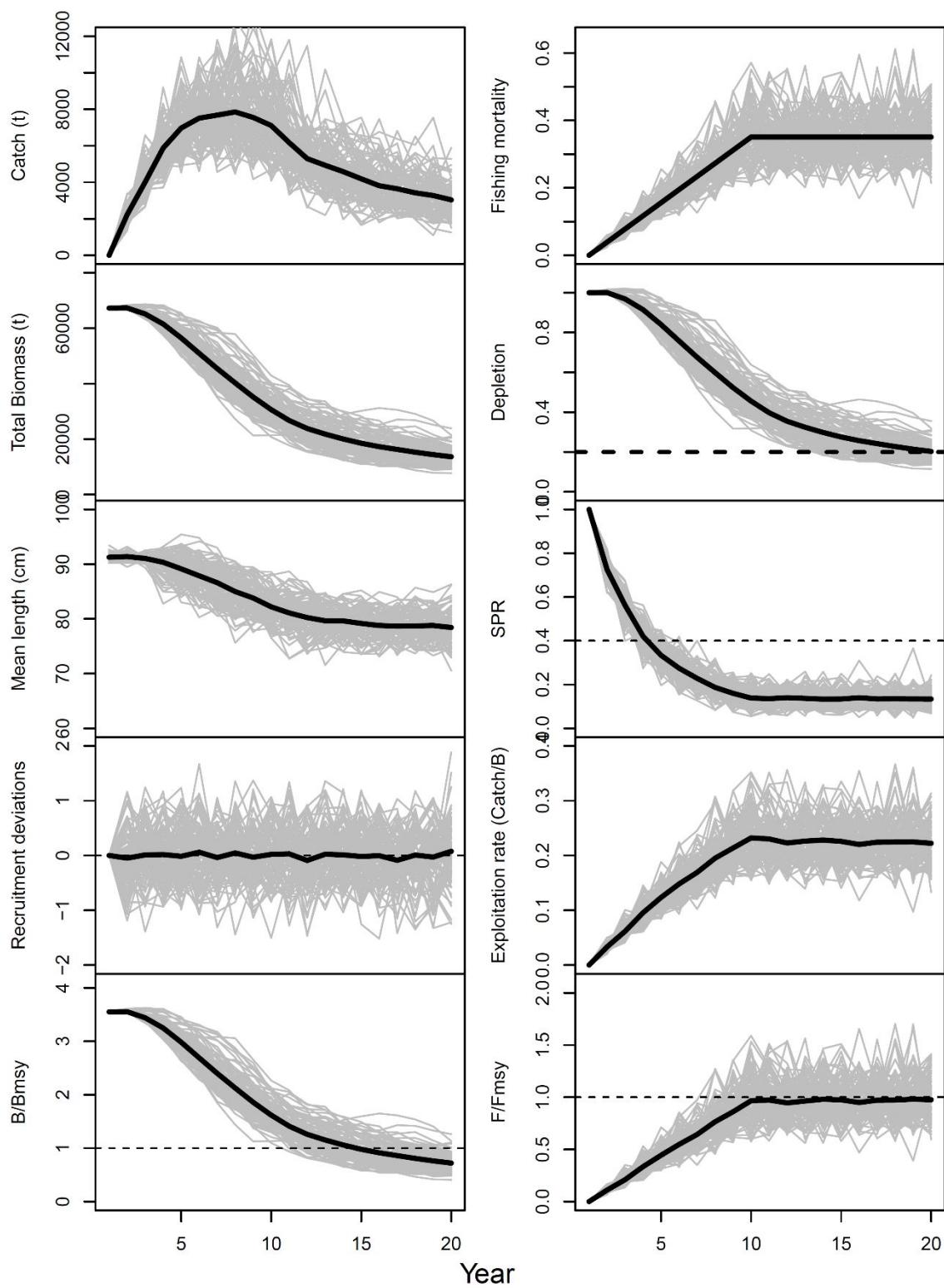


Figure A13. Time series for each simulated medium-grow albacore tuna population for harvest scenario 2 and depletion = 0.2. The black solid lines represent the mean value for all runs.

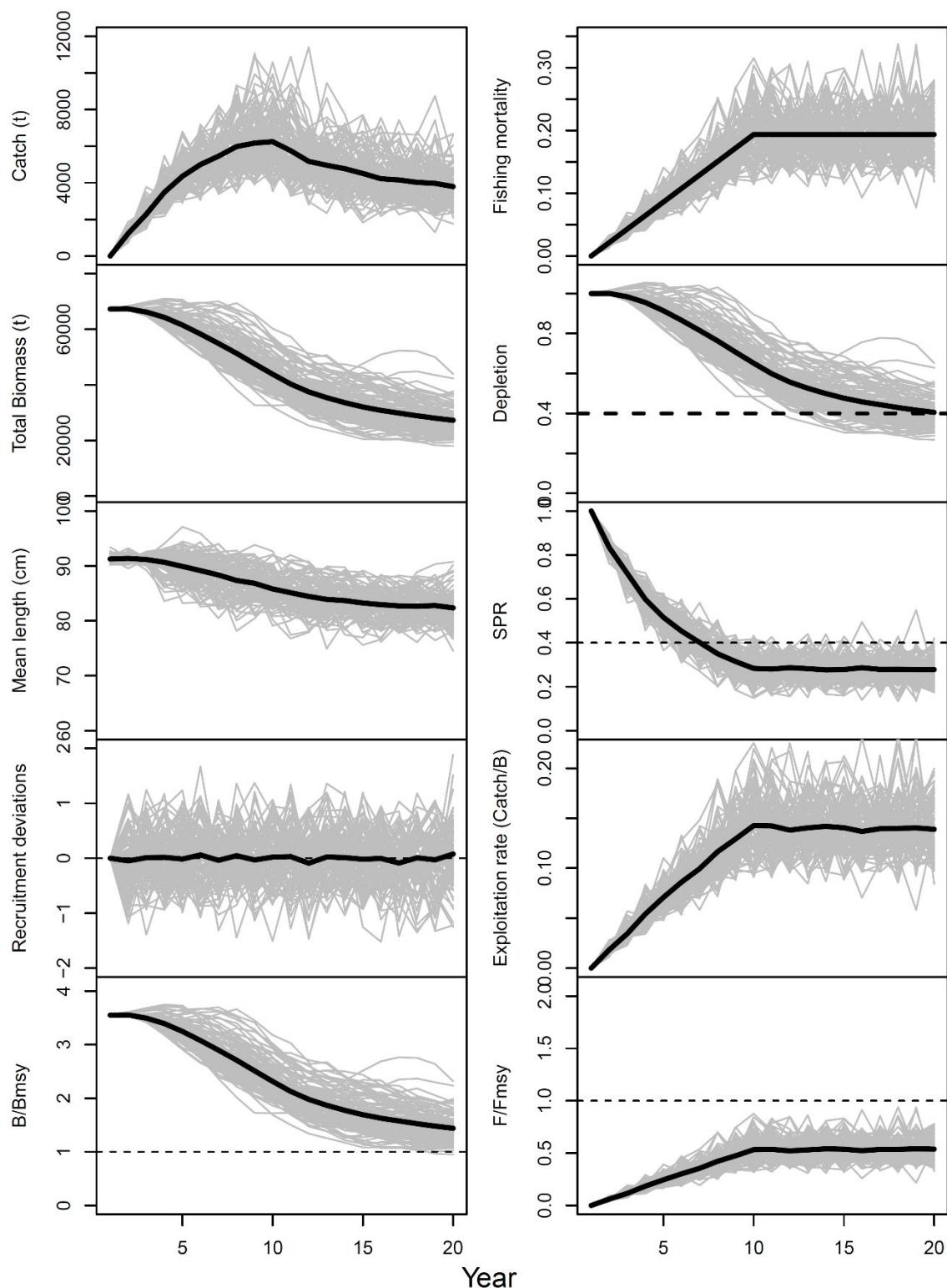


Figure A14. Time series for each simulated medium-grow albacore tuna population for harvest scenario 2 and depletion = 0.4. The black solid lines represent the mean value for all runs.

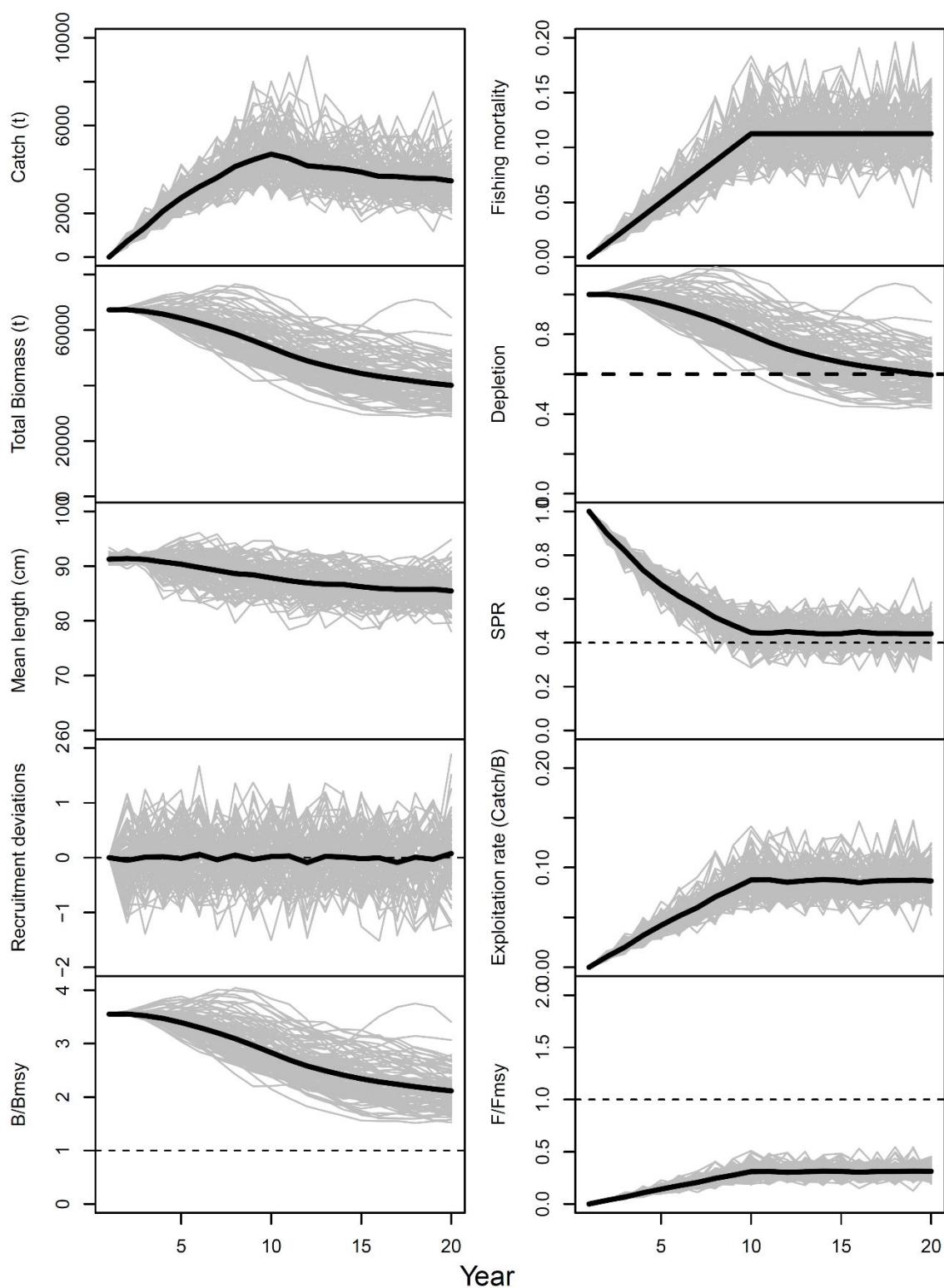


Figure A15. Time series for each simulated medium-grow albacore tuna population for harvest scenario 2 and depletion = 0.6. The black solid lines represent the mean value for all runs.

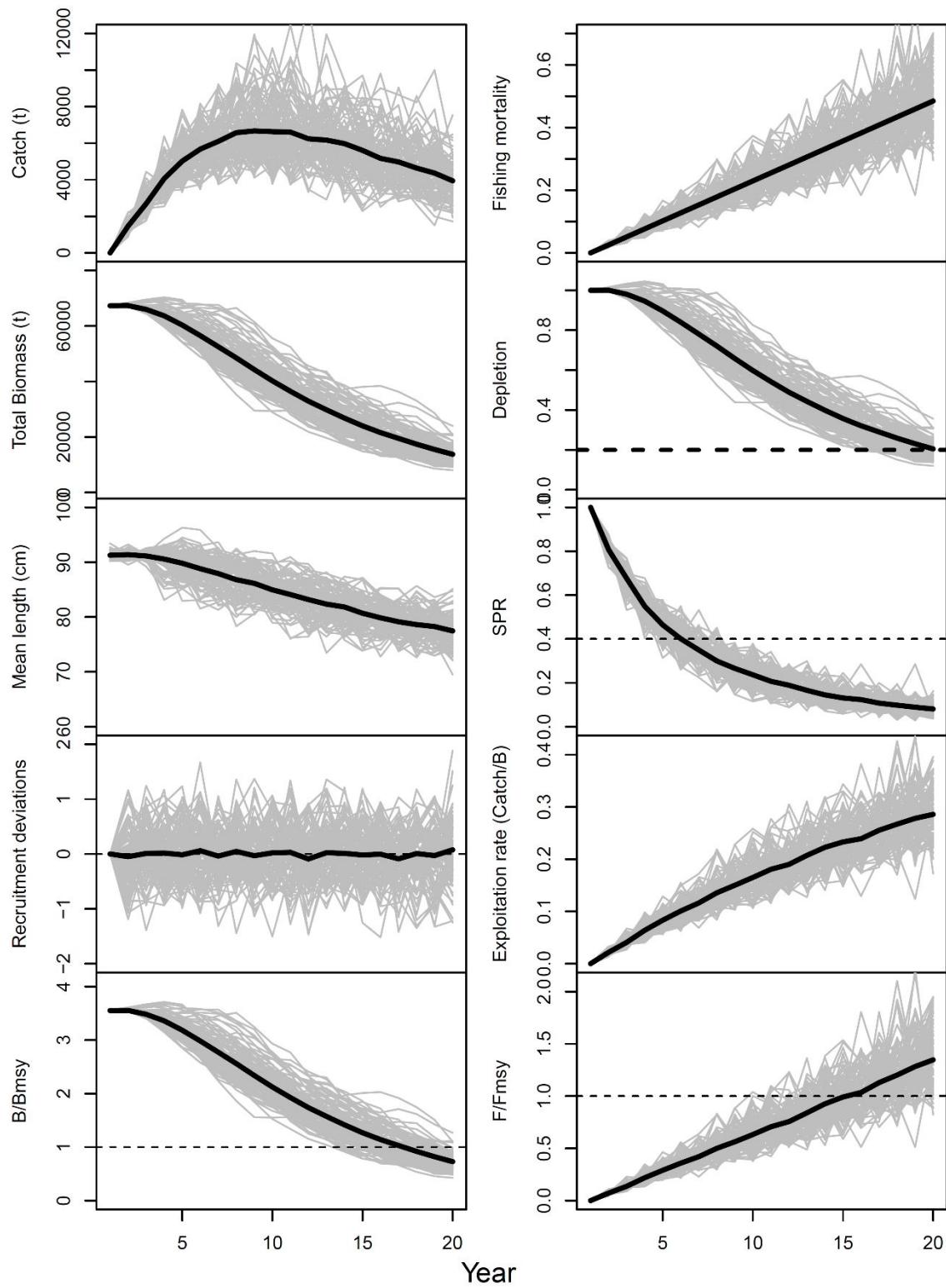


Figure A16. Time series for each simulated medium-grow albacore tuna population for harvest scenario 3 and depletion = 0.2. The black solid lines represent the mean value for all runs.

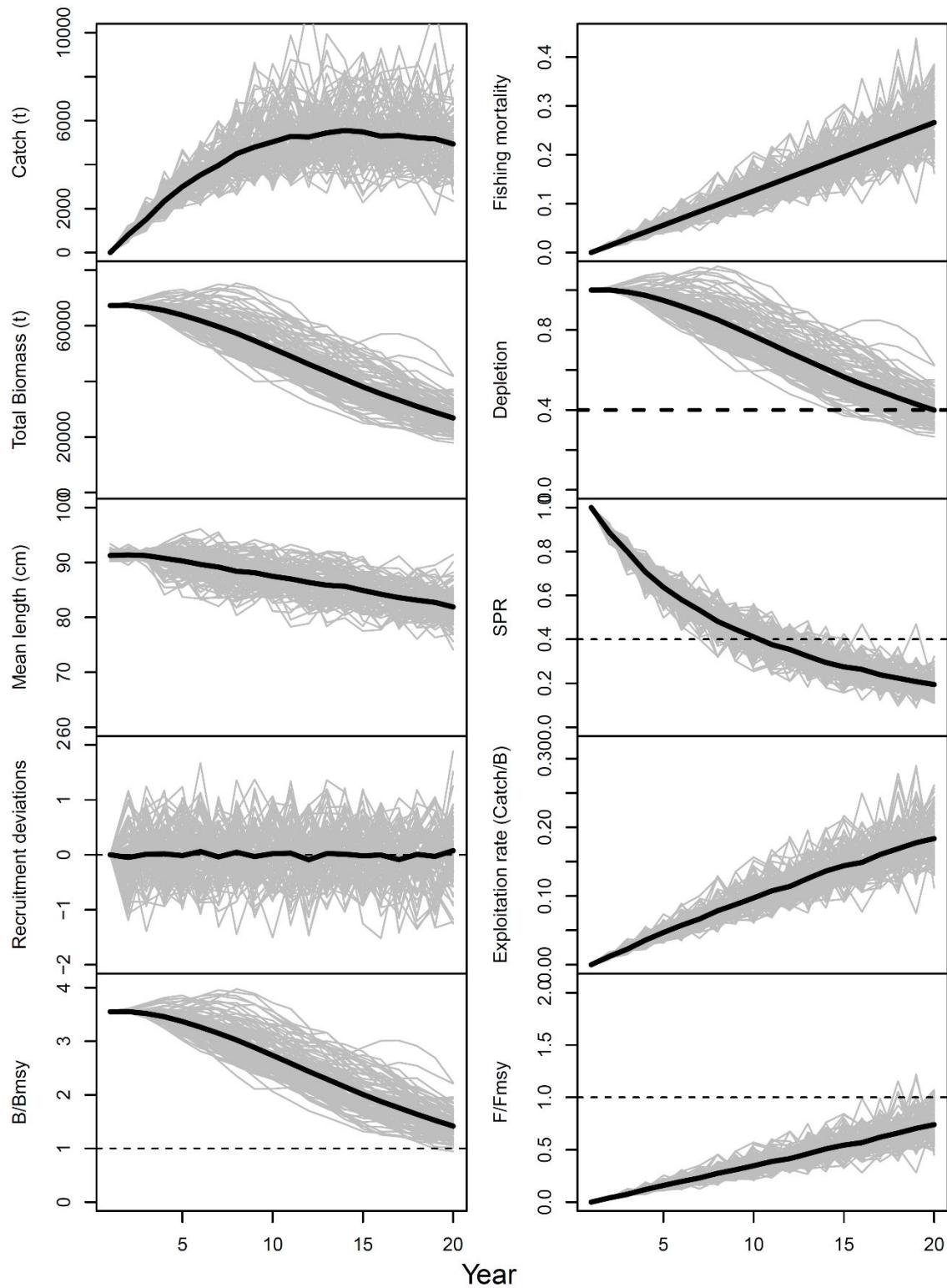


Figure A17. Time series for each simulated medium-grow albacore tuna population for harvest scenario 3 and depletion = 0.4. The black solid lines represent the mean value for all runs.

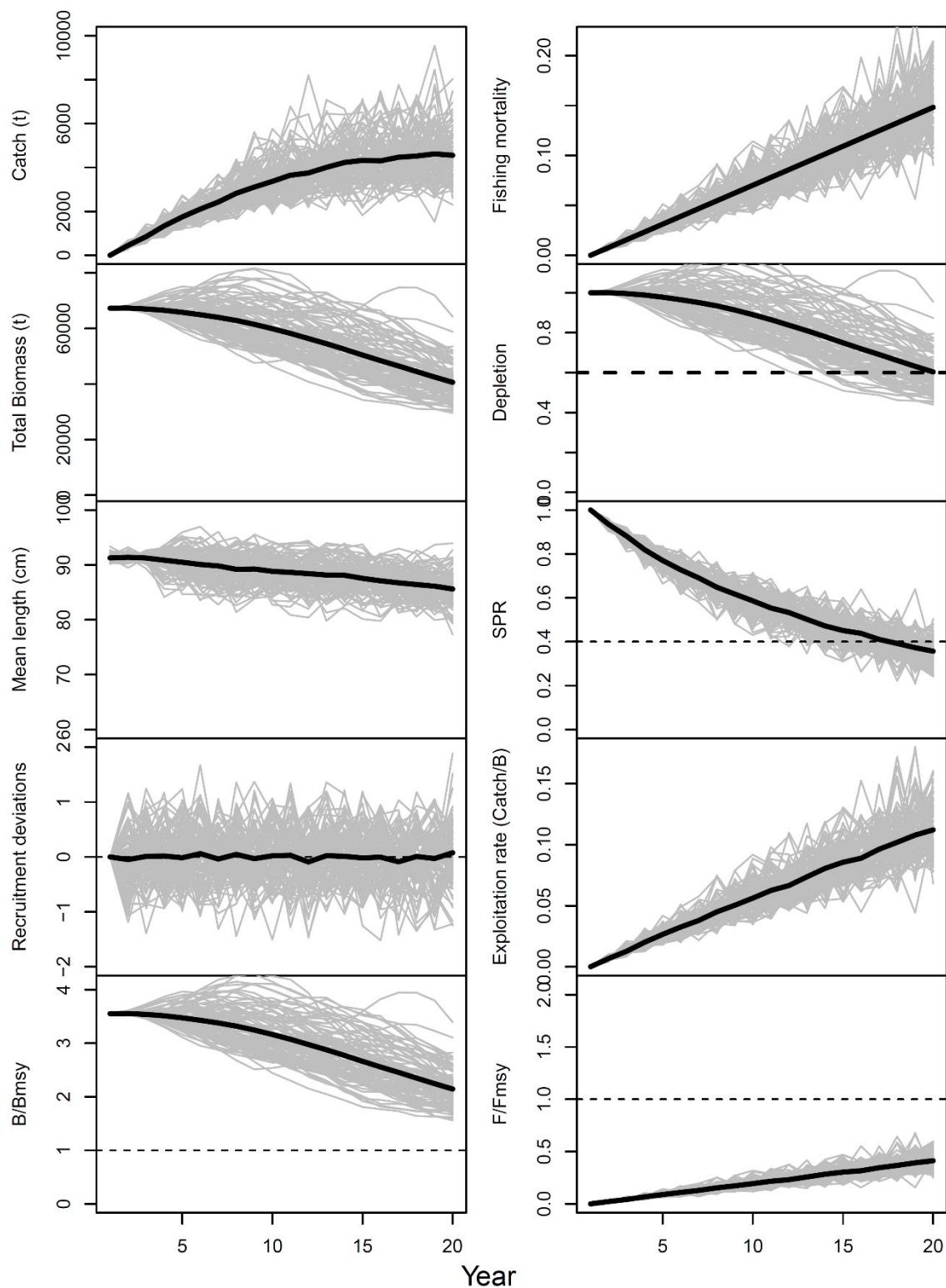


Figure A18. Time series for each simulated medium-grow albacore tuna population for harvest scenario 3 and depletion = 0.6. The black solid lines represent the mean value for all runs.

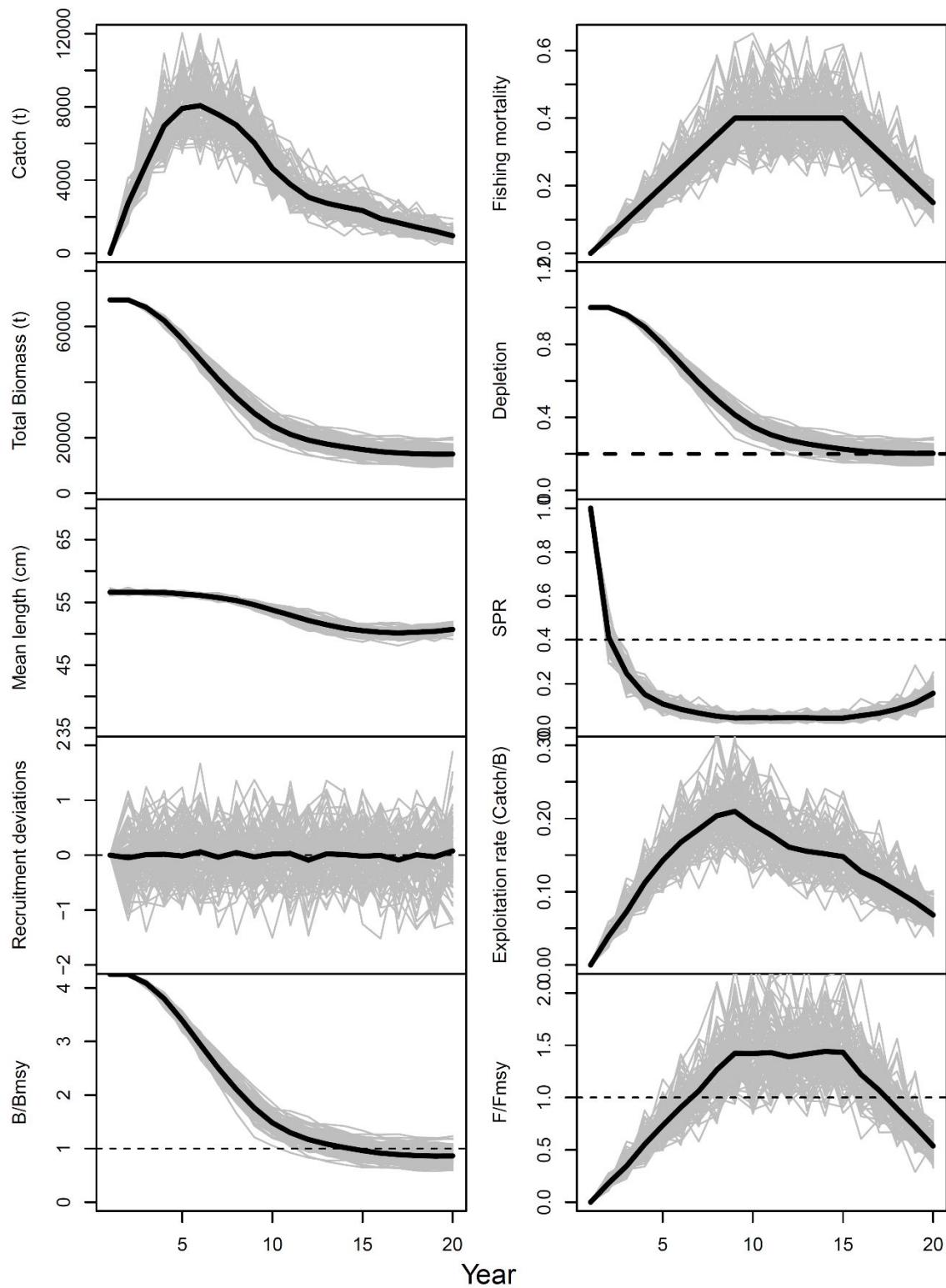


Figure A19. Time series for each simulated slow-grow canary rockfish population for harvest scenario 1 and depletion = 0.2. The black solid lines represent the mean value for all runs.

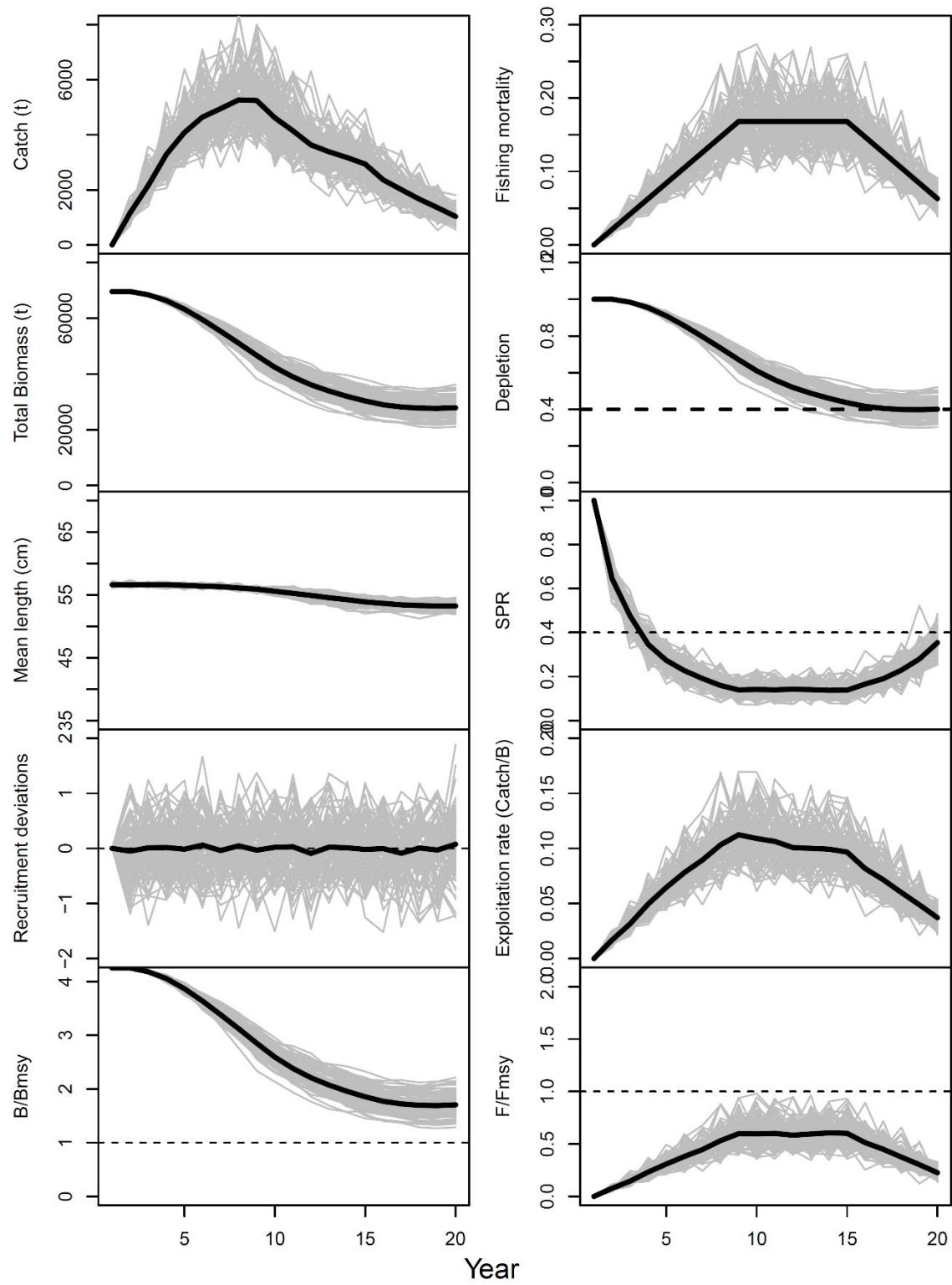


Figure A20. Time series for each simulated slow-grow canary rockfish population for harvest scenario 1 and depletion = 0.4. The black solid lines represent the mean value for all runs.

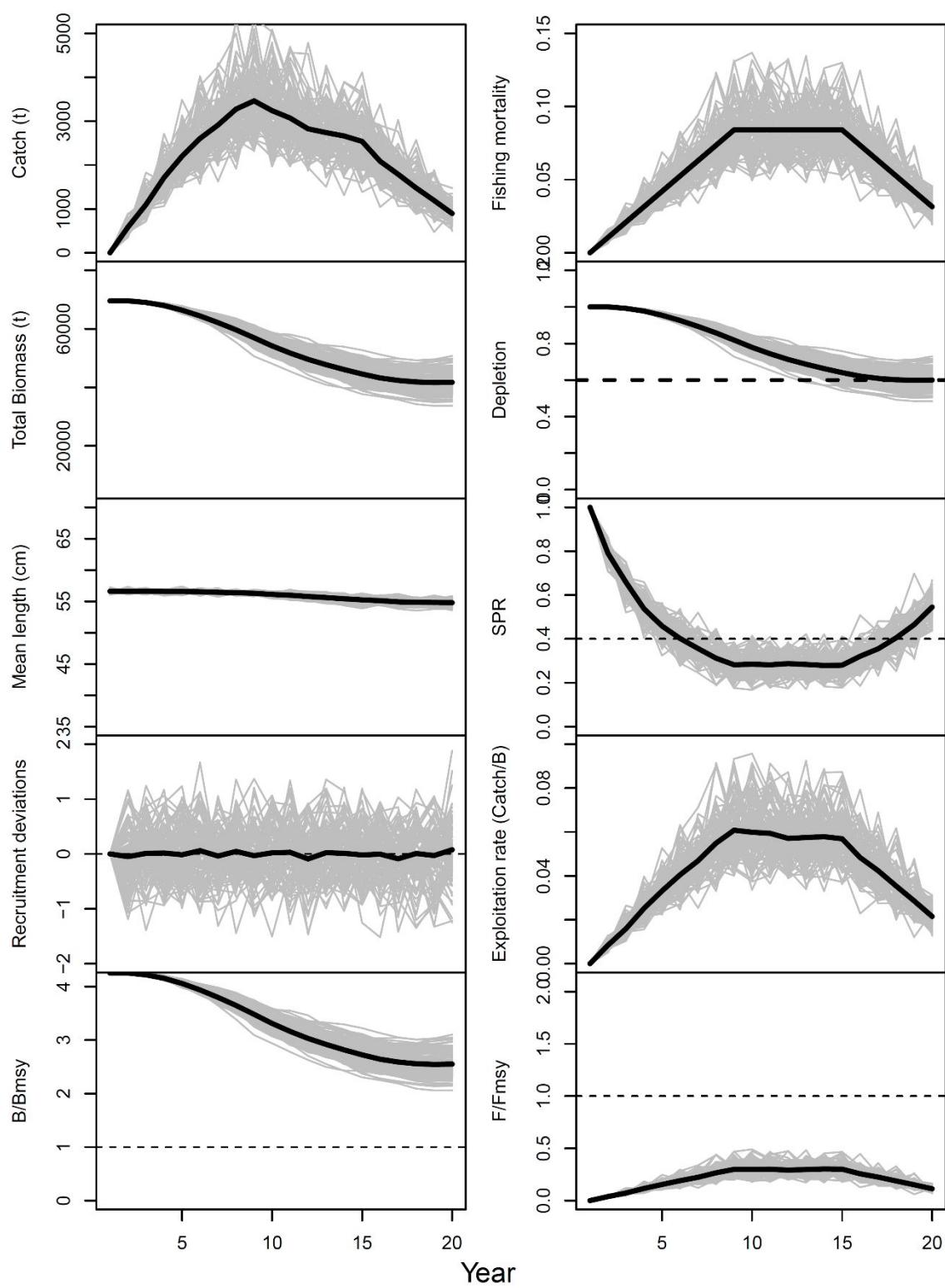


Figure A21. Time series for each simulated slow-grow canary rockfish population for harvest scenario 1 and depletion = 0.6. The black solid lines represent the mean value for all runs.

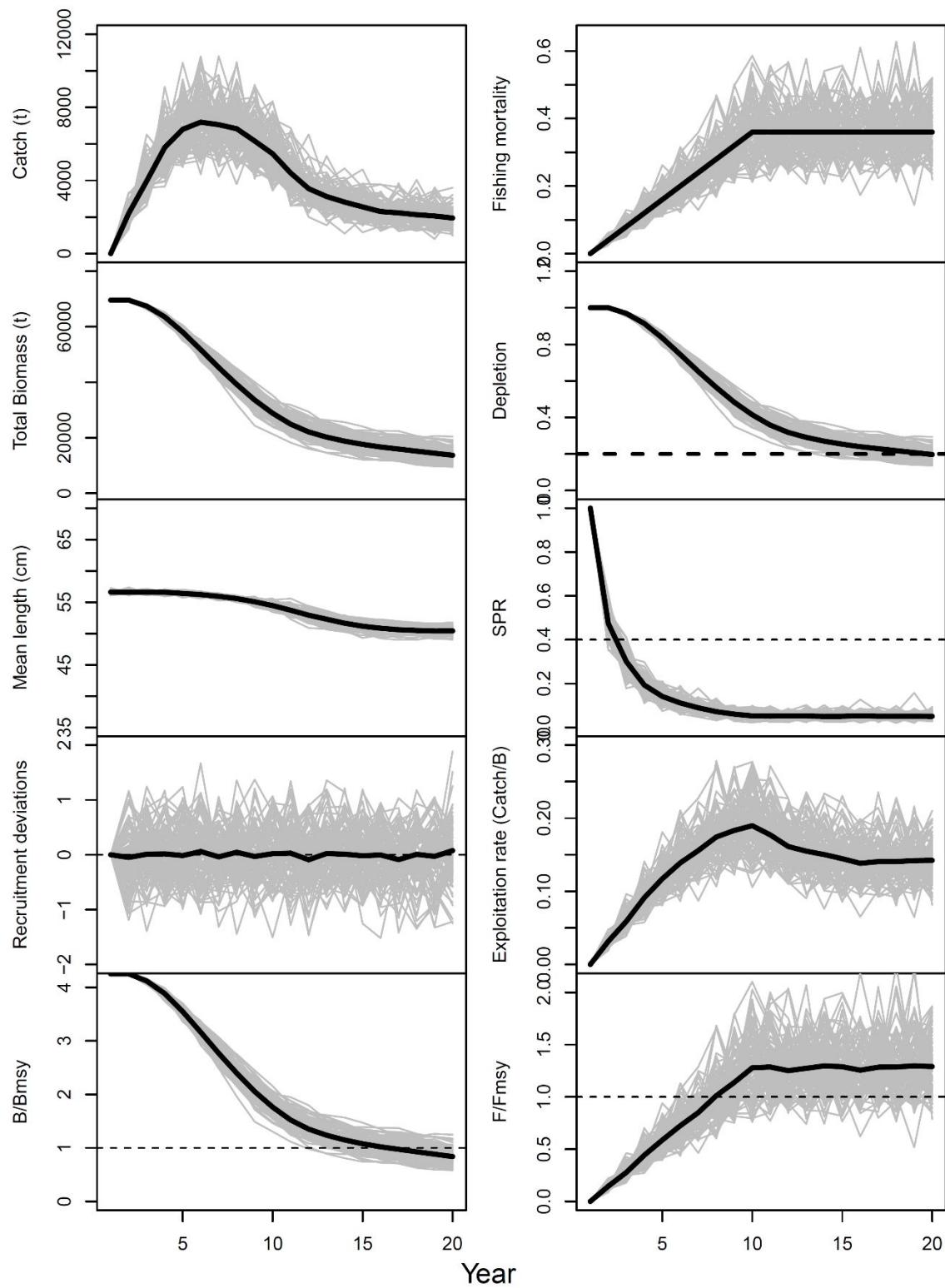


Figure A22. Time series for each simulated slow-grow canary rockfish population for harvest scenario 2 and depletion = 0.2. The black solid lines represent the mean value for all runs.

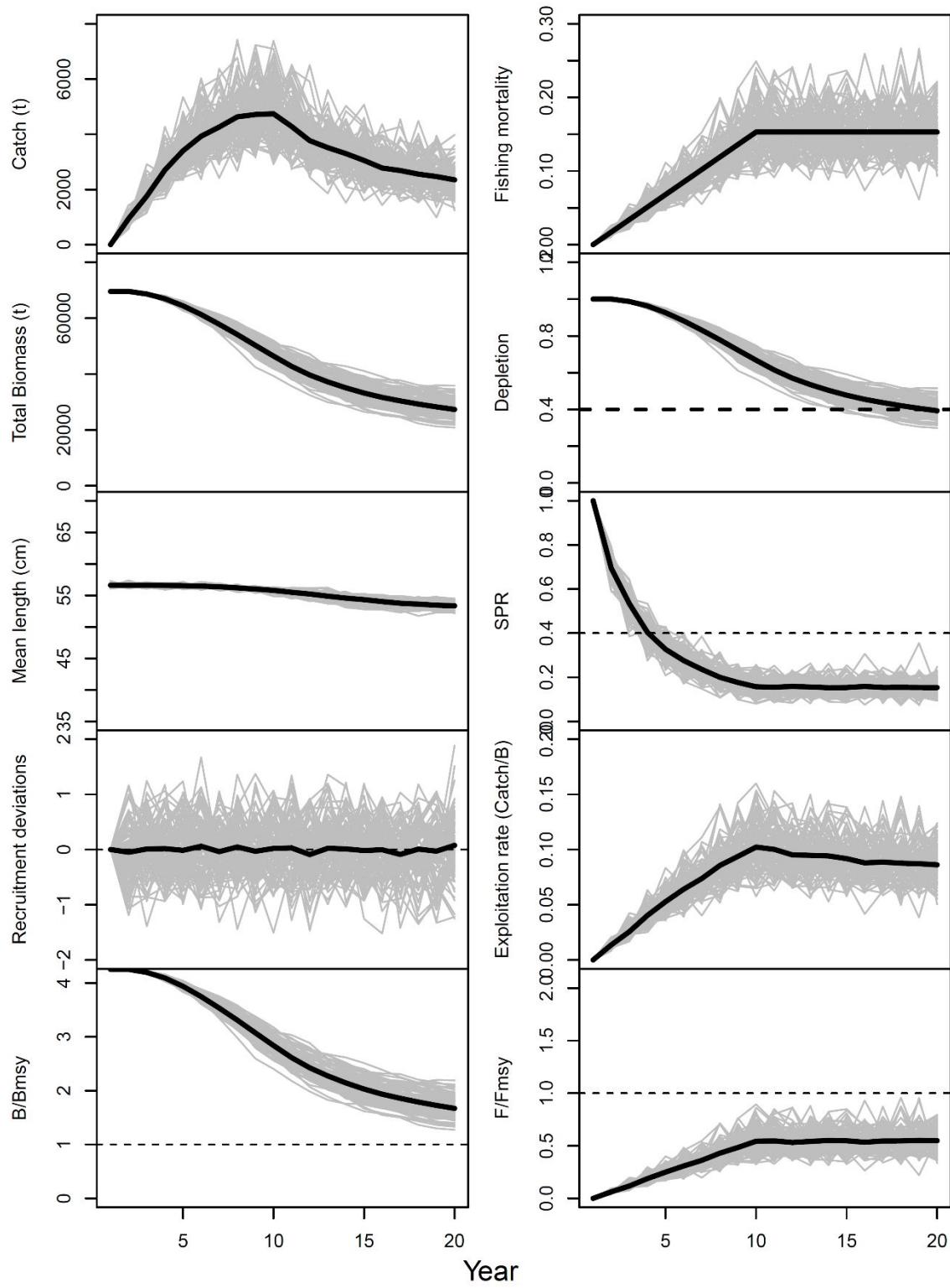


Figure A23. Time series for each simulated slow-grow canary rockfish population for harvest scenario 2 and depletion = 0.4. The black solid lines represent the mean value for all runs.

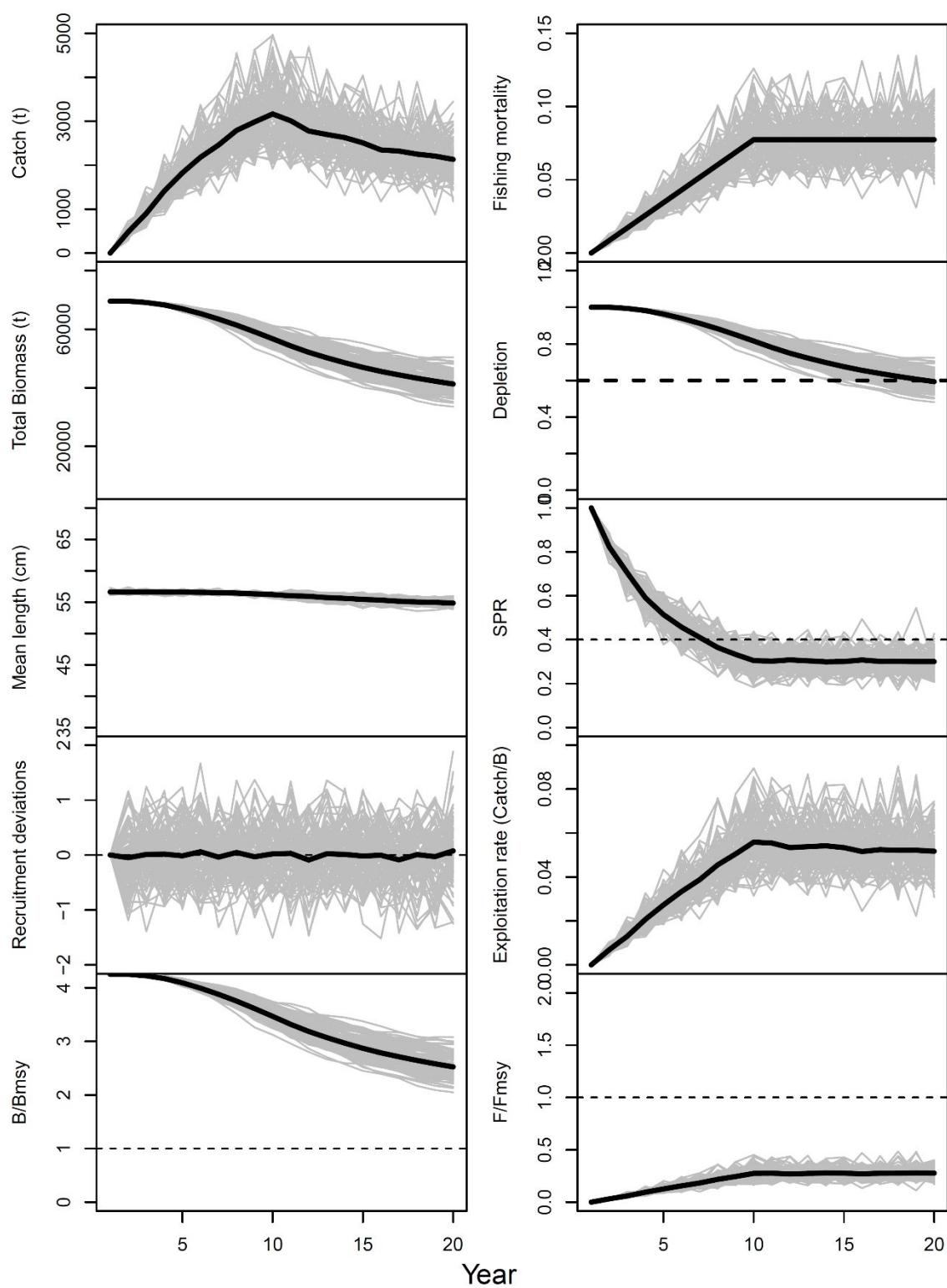


Figure A24. Time series for each simulated slow-grow canary rockfish population for harvest scenario 2 and depletion = 0.6. The black solid lines represent the mean value for all runs.

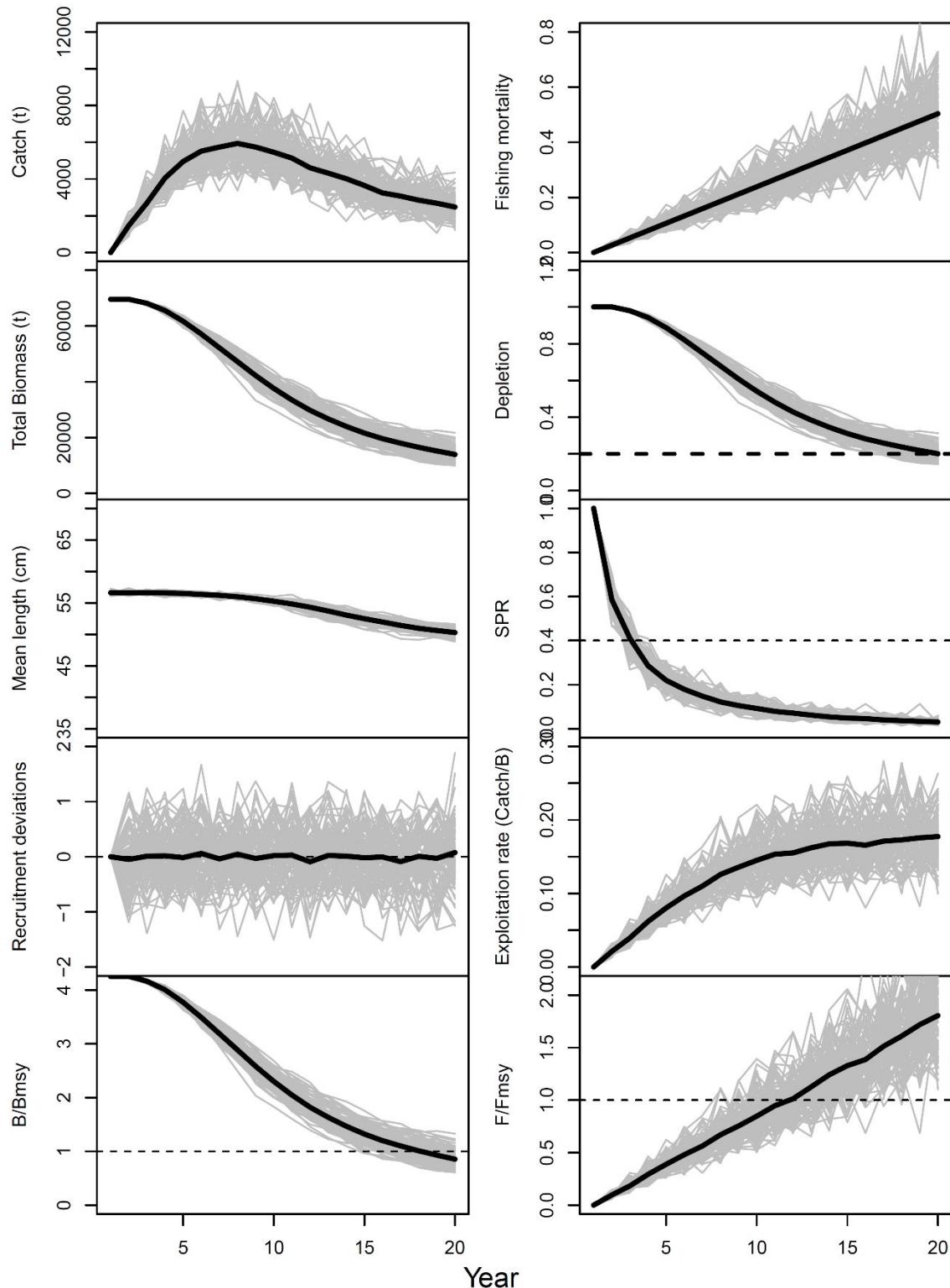


Figure A25. Time series for each simulated slow-grow canary rockfish population for harvest scenario 1 and depletion = 0.2. The black solid lines represent the mean value for all runs.

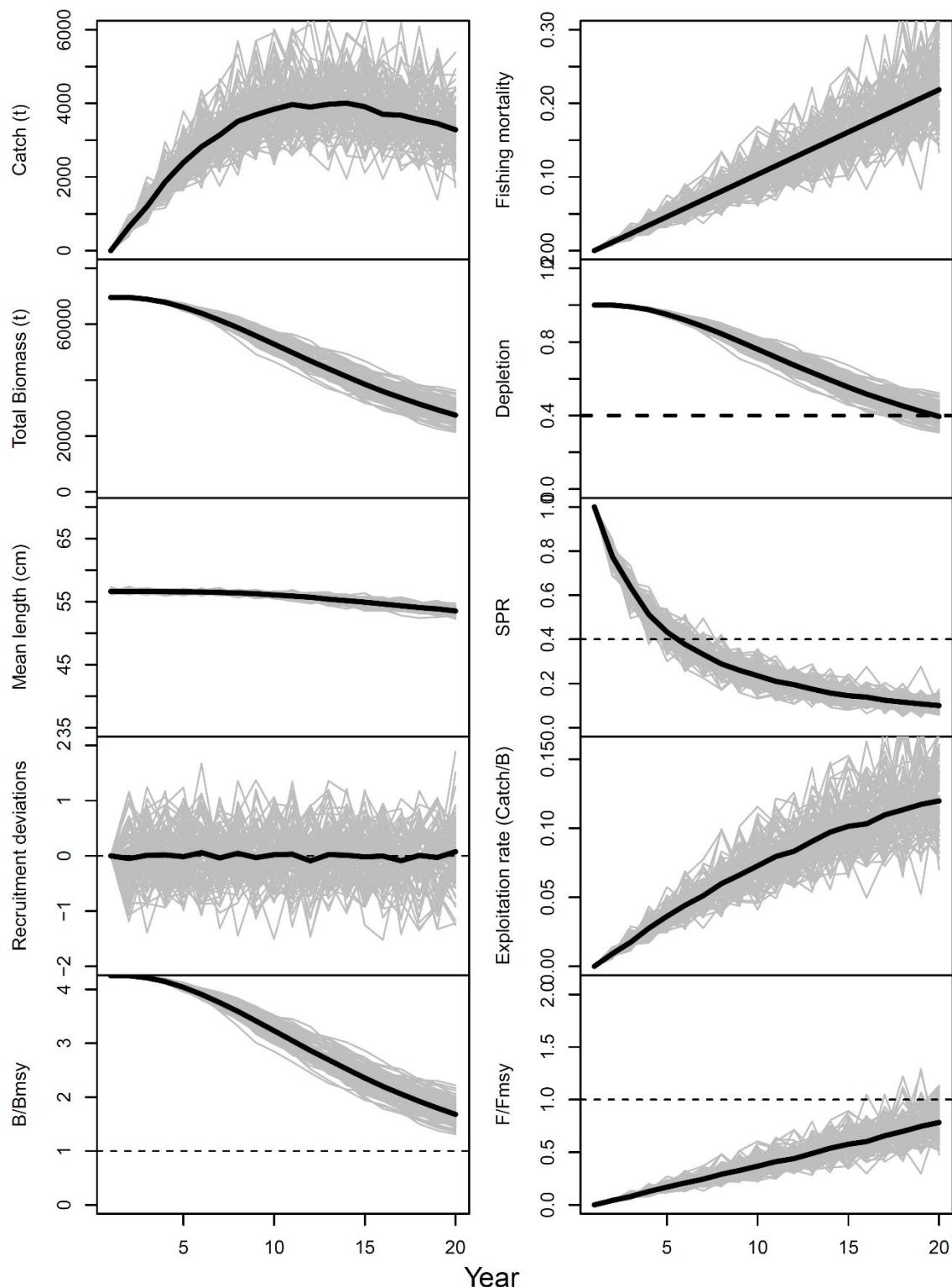


Figure A26. Time series for each simulated slow-grow canary rockfish population for harvest scenario 3 and depletion = 0.4. The black solid lines represent the mean value for all runs.

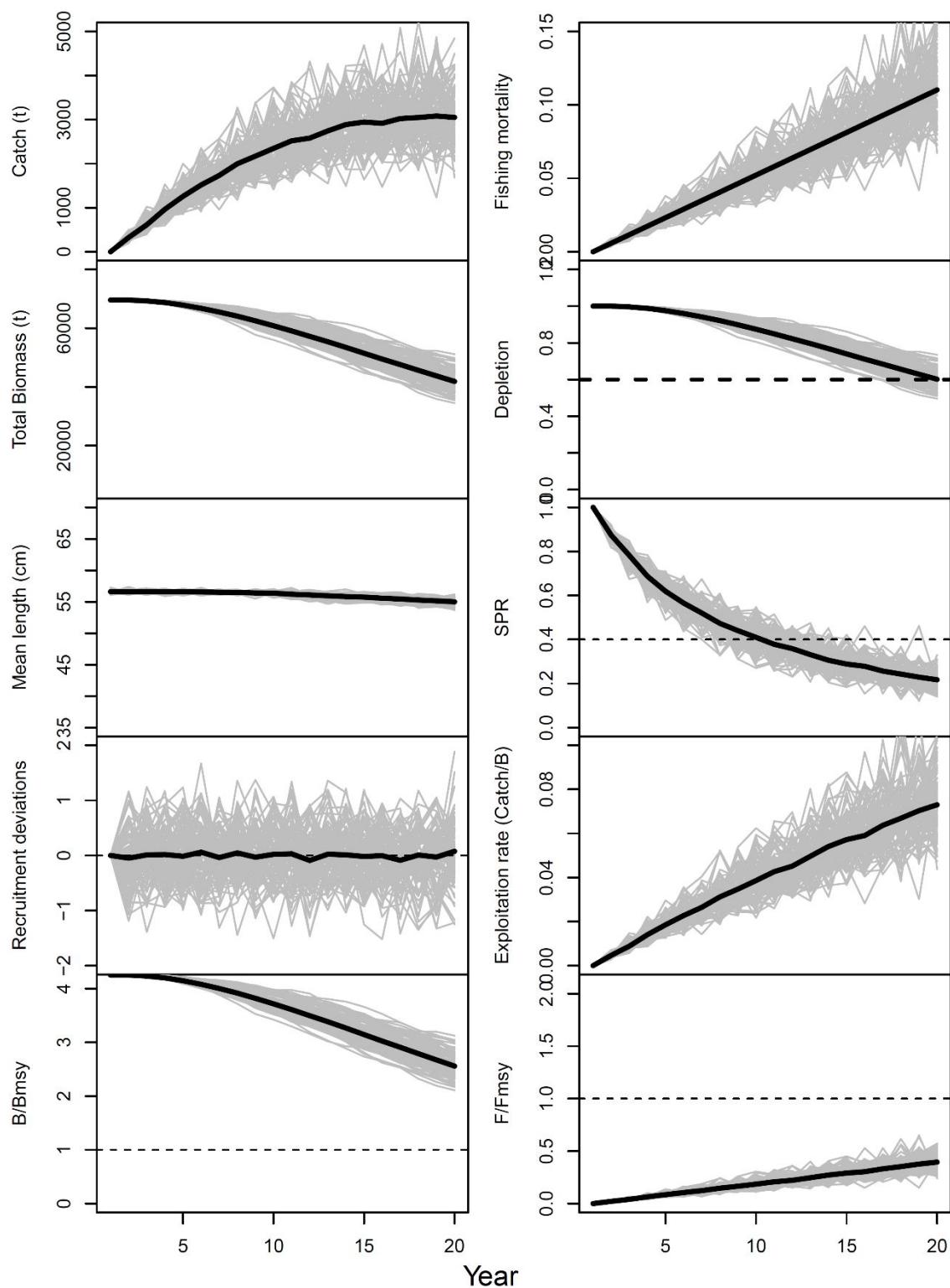


Figure A27. Time series for each simulated slow-grow canary rockfish population for harvest scenario 3 and depletion = 0.6. The black solid lines represent the mean value for all runs.

Table A1. Mean and standard deviation of relative error (RE) between the maximum sustainable yield (MSY) estimated by the operating model (OM) and the MSY estimated by the CMSY method. Values are proportions. Positive values mean that the MSY was overestimated and negative values that it was underestimated.

Species	Harvest Scenario	Mean ± Standard deviation		
		Depletion level		
		0.2	0.4	0.6
Mackerel	Scenario 1	0.37 ± 0.08	0.18 ± 0.09	-0.13 ± 0.15
	Scenario 2	0.28 ± 0.08	0.03 ± 0.09	-0.22 ± 0.13
	Scenario 3	0.33 ± 0.11	0.05 ± 0.11	-0.26 ± 0.14
Albacore	Scenario 1	-0.07 ± 0.02	-0.18 ± 0.03	-0.46 ± 0.02
	Scenario 2	-0.25 ± 0.02	-0.42 ± 0.02	-0.42 ± 0.02
	Scenario 3	-0.12 ± 0.02	-0.24 ± 0.02	-0.43 ± 0.02
Rockfish	Scenario 1	1.61 ± 0.27	1.13 ± 0.31	0.80 ± 0.32
	Scenario 2	1.67 ± 0.26	1.27 ± 0.33	0.86 ± 0.34
	Scenario 3	1.77 ± 0.33	1.29 ± 0.45	0.94 ± 0.45

Table A2. True OM and LBB estimated values for  $L_{\infty}$  and  $S_{50}$  ( $\sim L_c$ ). LCL is the lower confidence limit and UCL the upper confidence limit for the estimated values.

Scenarios	Life-history	Harvest trend	Final depletion	True $L_{\infty}$	True $S_{50}$	Estimated $L_{\infty}$	Estimated LCL $L_{\infty}$	Estimated UCL $L_{\infty}$	Estimated $L_c$	Estimated LCL $L_c$	Estimated UCL $L_c$
1	Short-lived	Scenario 1	0.2	38.2	25	44.5	44.0	45.1	16.9	16.5	17.4
2			0.4	38.2	29	43.6	43.3	44.0	15.6	15.5	15.8
3			0.6	38.2	29	45.1	44.6	45.6	20.1	19.5	20.7
4		Scenario 2	0.2	38.2	29	44.7	44.2	45.2	18.0	17.4	18.6
5			0.4	38.2	29	43.7	43.4	44.1	15.7	15.5	15.8
6			0.6	38.2	29	45.3	45.0	45.8	20.3	19.7	20.9
7		Scenario 3	0.2	38.2	29	45.5	45.2	46.0	20.3	19.8	21.0
8			0.4	38.2	29	44.5	44.0	45.1	15.9	15.7	16.1
9			0.6	38.2	29	45.7	45.4	46.2	20.7	20.1	21.3
10	Medium-lived	Scenario 1	0.2	122.2	60	142.5	141.4	143.6	62.4	61.7	63.2
11			0.4	122.2	60	141.4	140.1	142.5	60.4	59.7	61.0
12			0.6	122.2	60	143.2	142.7	143.9	64.1	63.2	64.9
13		Scenario 2	0.2	122.2	60	143.0	141.8	143.9	62.8	62.0	63.6
14			0.4	122.2	60	141.9	141.1	143.3	60.7	60.0	61.4
15			0.6	122.2	60	143.3	143.0	144.0	64.6	63.8	65.4
16		Scenario 3	0.2	122.2	60	143.3	143.0	144.0	63.3	62.5	64.1
17			0.4	122.2	60	142.5	141.4	143.7	61.1	60.4	61.8
18			0.6	122.2	60	143.5	143.1	144.3	65.4	64.5	66.3
19	Long-lived	Scenario 1	0.2	60.0	60	76.7	76.0	77.6	50.4	49.9	51.0
20			0.4	60.0	45	75.3	74.5	76.3	47.0	46.5	47.4
21			0.6	60.0	45	76.9	76.2	77.8	51.2	50.7	51.8
22		Scenario 2	0.2	60.0	45	76.5	75.8	77.4	50.5	50.0	51.1
23			0.4	60.0	45	75.4	74.6	76.4	47.8	47.2	48.3
24			0.6	60.0	45	77.0	76.3	78.0	51.4	50.8	52.0
25		Scenario 3	0.2	60.0	45	76.8	76.1	77.7	51.0	50.4	51.6
26			0.4	60.0	45	76.0	75.3	76.9	49.5	49.0	50.1
27			0.6	60.0	45	77.1	76.3	78.0	51.7	51.1	52.2