

Stock assessment on fishery-dependent data: effect of data quality and parametrisation for red snapper fishery

Running title: Stock assessment on fishery-dependent data

Morgana Tagliarolo^a, Jason Cope^b, Fabian Blanchard^a

- a. Ifremer, UMSR LEEISA (CNRS, UG, Ifremer), 275 Route de Montabo, BP477, 97323 Cayenne Cedex, French Guiana, France.
- b. Fisheries Resource Assessment and Monitoring Division, Northwest Fisheries Science Center, National Marine Fisheries Service, NOAA, Seattle, WA, USA

*Corresponding author:

Morgana.tagliarolo@ifremer.fr

Postal address: 275 Route de Montabo, BP477, 97323 Cayenne Cedex, French Guiana, France

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DR MORGANA TAGLIAROLO (Orcid ID : 0000-0002-9659-4565)

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Abstract

Data availability, unreported and unregulated fishing are significant obstacles to evaluating stock status, especially in tropical areas. Limitations in data quantity and quality can lead to model misspecification and erroneous data treatments, potentially causing important changes in model outputs and subsequent management implications. Red snapper *Lutjanus purpureus* (Poey) in French Guiana provides an example of a stock with a long-time series of fishery-dependent data subject to large uncertainty. A flexible catch-at-age model (Stock Synthesis) was applied to the available data and compared to an historically applied assessment approach. Inter-model variability based on different model specifications and data treatments were compared to identify better the status of the resource. Results showed that a major source of uncertainty in the model was the inclusion of a catch-per-unit-effort abundance index with questionable ability to track abundance. The Stock Synthesis model provided a more flexible and viable method than the virtual population analysis approach. Despite large uncertainty, models depicted a similar trend with a notable stock depletion in the late 1990s but with two distinct biomass trends in more recent years depending on the treatment. To reduce uncertainty and preserve this important economic resource, new data collection programmes and management policies are needed.

Keywords

Lutjanus purpureus, French Guiana, data-limited, Stock Synthesis

31 Introduction

32 Quantitative fishery stock assessments look to produce data-driven estimates of population
33 abundance and dynamics to inform management decisions (Hilborn & Walters, 2013).
34 Measurement error associated with a variety of data types and parameters, and natural
35 process variability in population dynamics all lead to uncertainty in analytical outputs (Francis
36 & Shotton, 2011). This uncertainty can hinge greatly on the quality and availability of the data
37 (Chen, Chen, & Stergiou, 2003). Despite the potential for data-derived biases in
38 assessments that could lead to management failures, improvements in quality and data
39 availability are often limited by resources like money, time and available expertise (Chen et
40 al., 2003). Developing harvest strategies based on limited data without waiting for extensive
41 data sets that may never materialize is critical to responsive and responsible natural resource
42 management (Dowling et al., 2015).

43 Data limitation is a global problem, particularly in tropical regions (Amorim, Sousa, Jardim, &
44 Menezes, 2019). In addition to the challenges of monitoring legal activities, unreported and
45 unregulated fishing presents an additional significant challenge to informing stock
46 assessments (Cawthorn & Mariani, 2017). For example, unreported catches and effort can
47 lead to severely biased estimates of biomass and other model outputs (Omori, Hoenig,
48 Luehring, & Baier-Lockhart, 2016). This creates a mixed situation of partial coverage in data
49 streams resulting in uncertainty that deserves respect and acknowledgement, but such
50 uncertainty is an insufficient reason to avoid using science to inform management (Dowling
51 et al., 2016). Unfortunately, numerous valuable fishery resources, especially in tropical
52 areas, remain unevaluated.

53 The red snapper *Lutjanus purpureus* (Poey) fishery in French Guiana constitutes a good
54 example of a data-limited fishery where, despite the availability of long time series of fishery-
55 dependent data, information on the ecology of the species is still poorly understood and data
56 gaps remain. The commercial handline red snapper fishery in French Guiana is
57 predominantly performed by Venezuelan boats under a licensing system introduced in the
58 1980s by the French government and now under EU authority. The licence agreement
59 requires boats to sell 75% of their catch to a processing factory in French Guiana, while the
60 other 25% can be sold abroad. Controls at sea and at landing sites exist, but no information
61 is available on the catch sold beyond French Guiana borders. Moreover, this fishing activity
62 is mostly focused on smaller fish since the international market demands plate-sized fish
63 typically below the size of maturity. This type of size-selective fishery can lead to age
64 truncation if fishing mortality is high (Brunel & Piet, 2013; Reddy et al., 2013). Even if the

65 catch of large fish declines, high fishing intensity on small individuals can threaten population
66 sustainability (Reddy et al., 2013).

67 *Lutjanus purpureus* is particularly vulnerable to fishing pressure due to its behaviour and
68 general life history characteristics (slow-growth, late maturity and seasonal spawning
69 aggregations (Manickchand-Heileman & Phillip, 1996). Red snapper is known to aggregate
70 for spawning, a behaviour that can lead to hyperstable signals of population density and
71 overestimation of the stock size if not accounted for in stock assessments (Erisman, Apel,
72 MacCall, Román, & Fujita, 2014). Additionally, the specific life history of *L. purpureus* is not
73 well understood, creating significant uncertainty in the use of biological parameters (e.g.
74 growth, natural mortality and reproduction) in French Guiana waters (Rivot, Charuau, Rose, &
75 Achoun, 2000).

76 Red snapper in French Guiana provides an example of a stock with multiple data sources
77 (e.g. catch, fishery-dependent index and biological compositions) of limited quality and
78 uncertain life history values. Consequently, it is critical to compare several possible model
79 specifications and data treatments to account for uncertainty in the estimation of
80 management quantities in any stock assessment. This work takes up the challenge of
81 assessing *L. purpureus* by: 1) investigating stock assessment uncertainty based on
82 limitations in the fishery-dependent data and life history inputs using a flexible statistical
83 catch at age approach (i.e. the Stock Synthesis (SS) modelling framework) and 2) comparing
84 results from the SS model to that of a Virtual Population Analysis (VPA) approach that has
85 historically been used to assess the stock. By accounting for the uncertainty in sources of
86 data and inputs, the major sources of model output uncertainty are identified and quantified
87 for management consideration, while using the flexible SS framework may provide a more
88 advantageous modelling environment compared to the more rigid VPA approach.

89 **Material and methods**

90 ***Fishery catch data***

91 In French Guiana, red snapper is mostly fished by Venezuelan hand-liners between 30 and
92 200 m depth. The hand-line fishery is estimated to have started around 1960, with some
93 information on landings beginning in 1976, with the most reliable data recorded from 1985
94 onward when Ifremer (Institut Français de Recherche pour l'Exploitation de la Mer) started a
95 fisheries information database (Tous, 1988). Before 1988, other fishing activities such as
96 trawling were also targeting red snapper, but catches were not monitored (Prevost, 1989;
97 Tous, 1988).

98 In 1984 a licencing system was implemented requiring Venezuelan boats to sell a fixed
99 percentage of their catch in French Guiana (50% for 1984 and 75% from 1985 to present). In
100 addition to the main hand-line fishery, a few boats coming from the French Antilles islands
101 occasionally fished French Guiana waters with fish traps (e.g. in 2019, less than 70 t or 2.6%
102 of total yearly catches). Additionally, bycatch in shrimp trawlers takes small (between 8 and
103 30 cm) red snapper (i.e. in 2007 about 100 t, or 6% of total catches for 23 trawlers), but little
104 information on the historical time series of these catches is available (Caro & Lampert, 2011).
105 Currently, only 10 shrimp trawlers remain, likely reducing the amount of red snapper bycatch.
106 Considering the high uncertainty of the landings data, especially at the beginning of the time-
107 series, and the need to correct for these missing catches, landings data were expanded by
108 25% for all years to estimate total removals from the red snapper population (Fig. 1). No
109 information was available to hypothesise any temporal changes in the expansion value.

110 ***Abundance data***

111 Fishery-dependent catch per unit effort (CPUE) indices were available from 1986 to 2018
112 (Fig. 1). CPUE was calculated by dividing the total annual catches by the total annual
113 number of days at sea estimated from logbooks and/or vessel monitoring systems (VMS)
114 data (t catch / days at sea). CPUE were not standardised since no historical information in
115 changes of the fishing techniques or other factors were available. This lack of standardisation
116 adds uncertainty in the application of this index, but it is the only index available.

117 ***Biological data***

118 Length composition (fork length in cm) data were available from 1986 to 2019. Length is
119 routinely measured by observers at landing sites in Cayenne according to the framework of
120 the fisheries information system (SIH) implemented by Ifremer. The available data set is
121 obtained from a monthly sampling plan that subsamples boats landing red snapper. The
122 sample size has changed over the years following changes in the fishery and improvement in
123 the statistical analysis to try and optimise the sample size. The length frequency of the
124 subsample was therefore expanded to match the 25% expansion in landings (to account for
125 the animals fished in French Guiana waters but landed abroad).

126 ***Life history relationships and values***

127 Natural mortality was assumed constant across ages and time. Individual growth was
128 modelled as a von Bertalanffy function, fecundity was modelled as proportional to weight,
129 and a Beverton-Holt stock-recruit relationship was assumed. Life history values were fixed in
130 the reference model and were obtained from literature sources (Table 1). Exploration of
131 uncertainty in natural mortality (M) and the Beverton-Holt steepness parameters (h ;

132 recruitment compensation, or average recruitment of a population reduced to 20% of
133 unfished levels relative to average recruitment of the unfished population) are described in
134 the next section on sensitivity analysis.

135 ***Model description and specification***

136 The assessment was conducted using the Stock Synthesis (SS version 3.30.13.02)
137 framework that uses maximum likelihood estimation (MLE) to obtain values and calculate
138 asymptotic uncertainty for estimated parameters and model outputs (Methot Jr & Wetzel,
139 2013). The model is configured as one sex as females and males were assumed to have the
140 same life history parameters. Fishery-dependent data (catch, CPUE and length
141 compositions) were specified as one fleet with dome-shape selectivity as the largest
142 individuals are not taken in the fishery, a parameterization choice confirmed by fishermen. A
143 selectivity time block was applied with a break implemented after 1996 and 2018 to account
144 for a possible change in fishing practice (targeting smaller individuals to adapt to market
145 demand) as suggested by local fishermen that changed the size composition of the fish
146 landed. The model with a time block in selectivity improved model fit to the length
147 compositions (see Appendix B and C). Catch in metric tonnes was assumed known while the
148 CPUE index assumed a lognormal error with a standard deviation of 0.3 for all years. Length
149 composition data were modelled with 2-cm length bins between 15 and 85 cm, and relative
150 sample sizes among years were determined by the samples by trip weighted by catch. The
151 list of the parameters used in the reference model is provided in Appendix A. The data and
152 model outputs were summarised using the r4SS package (<https://github.com/r4ss/r4ss>).
153 Additional data weighting for lengths and CPUE were unnecessary given the model fit (see
154 Appendix C).

155 ***Sensitivity analysis and likelihood profiles***

156 Model sensitivity to parameter uncertainty was explored via likelihood profiles—the fixing of
157 the model to various values of a specific parameter to see how model fit and derived outputs
158 change. Likelihood profiles demonstrate the amount of information (measured by the
159 changing likelihood metric) contained in the data for the featured parameter. Using the
160 negative log likelihood metric, any value outside of 1.96 units from the maximum likelihood
161 estimate (MLE) is considered significantly less supported by the data. The spread of model
162 outputs within the interval of significant data support therefore provides a measure of
163 uncertainty in model output based on parameter input. To demonstrate how model output
164 changes across profiled parameter values, three model outputs were considered: 1) initial
165 spawning output (SO_0); 2) terminal year spawning output (SO_{2018}); 3) the stock status in the
166 terminal year (SO_{2018}/SO_0). Comparing the information content of a particular parameter

167 value to the associated model output allows a mapping of model information (i.e. data) to
168 sensitivity in the model output (i.e. results). Likelihood profiles were conducted for the
169 following two parameters:

170 Natural mortality

171 Natural mortality is one of the most influential and difficult parameters to estimate in fisheries
172 stock assessment (Lee, Maunder, Piner, & Methot, 2011). Stock assessments often use an
173 external estimate of M as a fixed value, but may also estimate M within the model. Estimating
174 M depends on other model specifications (e.g. having at least one fishery with asymptotic
175 selectivity) and necessitates an exploration of model performance (Brodziak, Ianelli,
176 Lorenzen, & Methot Jr, 2011; Lee et al., 2011).

177 The range of M values used in the likelihood profile were defined by first estimating M
178 indirectly using meta-analytical and empirical methods based on life history parameters. “The
179 Natural Mortality Tool” (http://barefootecologist.com.au/shiny_m) application was used to
180 access to many different empirical M estimators. The methods based on maximum age
181 (Hamel et al., 2015; Then, Hoenig, Hall, & Hewitt, 2015) and on the von Bertalanffy K
182 parameter (Alverson & Carney, 1975; Jensen, 1996, 1997; Zhang & Megrey, 2006) and
183 FishLife (Thorson, Munch, Cope, & Gao, 2017) estimates were selected. M estimates varied
184 between 0.09 and 0.46 per year with a median value of 0.39 per year. These values were
185 also compared to that of Rivot et al. (2000) who compared three different estimation methods
186 for French Guiana red snappers suggesting that M ranged from 0.18 to 0.61 per year (Pauly
187 & Moreau, 1997; Ralston & Polovina, 1987; Rikhter & Efanov, 1976), with 0.29 per year
188 considered the most plausible. A likelihood profile range of M from 0.10 to 0.60 per year at
189 an interval of 0.05 was defined using both of the above sources (The Natural Mortality Tool
190 and Rivot et al. 2000).

191 Steepness

192 It is common in stock assessments to define the functional relationship between spawners
193 and recruits using the reparameterized Beverton-Holt function (Mace & Doonan, 1988) where
194 steepness (h) is a key parameter. Steepness technically ranges from 0.2 to 1 in the
195 Beverton-Holt model, though values below 0.3 are often deemed unsustainable (He, Mangel,
196 & MacCall, 2006). A higher h value loosens the relationship between stock and recruits,
197 producing higher productivity at smaller stock sizes. A value of $h=1$ essentially decouples the
198 stock-recruit relationship (Mangel et al., 2013; Shertzer & Conn, 2012). Steepness defines
199 some management quantities (e.g. MSY and F_{MSY}), but direct estimation requires contrast in
200 the data at low and high population sizes.

201 Externally-derived steepness values are much more commonly used, and come from life
202 history parameters and meta-analyses on ecologically similar species (Shertzer & Conn,
203 2012). The R package “FishLife” (<https://github.com/James-Thorson-NOAA/FishLife>;
204 Thorson (2020)) was used to specify h (0.7) for *L. purpureus*, and the subsequent likelihood
205 profile range of h was 0.40 to 1 with an interval of 0.05.

206 ***Uncertainty in length data***

207 The impact of bias in unsampled lengths was explored from the unreported international
208 fishery. Unfortunately, no data were available on the proportion of fish sold abroad, but local
209 fisherman indicate bigger fish are typically landed for markets outside French Guiana. To test
210 this hypothesis, length compositions of the non-monitored landings (assumed to represent
211 25% of the total catch) from 1991 to present were modified to include individuals larger than
212 40 cm following the average length distribution composition for years 1986-1991 (period
213 when larger individuals were fished). This model was then compared to the reference model
214 using only sampled lengths.

215 ***Uncertainty in CPUE***

216 The available raw CPUE data used in this study were exclusively derived from fishery-
217 dependent time series and were non standardised since little information are available on
218 sampling conditions, fish biology and movement patterns, or on changes in fishing behaviour.
219 To understand the influence of the CPUE index on model outputs better, the reference SS
220 model was compared to a model with no CPUE index, thus relying only on catches and
221 lengths as inputs. The assumption of linearity between CPUE and abundance was
222 investigated by estimating the exponent of a power function relationship between the CPUE
223 index and the catchability (Hilborn & Walters, 2013; Methot, 2009).

224 ***Comparison to VPA***

225 The *L. purpureus* stock was first assessed in 2012 by applying a VPA on commercial length
226 frequency data from 1986 following a von Bertalanffy growth relationship and assuming a
227 maximum age of 13 years (Lampert, 2012). VPA uses a backward projection to estimate
228 recruits with no stock recruit relationship, while SS assumes the Beverton-Holt stock-
229 recruitment relationship. The SS model also assumes length variability at age, whereas the
230 length-age relationship in the VPA was taken straight from the von Bertalanffy curve. The
231 VPA model was constructed following the equations in example 18 of Sparre and Venema
232 (1998). A plus-group was employed for the last age group. F (and Z) are age-specific with
233 the plus group applying a constant average F value. The VPA model does not explicitly
234 specify selectivity. The VPA model did not consider the CPUE data and applied a constant

235 fishing mortality by cohorts (averaged over the most recent 5 years) to estimate stock
236 biomass. Natural mortality in the VPA model was fixed at 0.29. The VPA model was run
237 again with the most recent data and main outputs (total biomass, recruitment, spawning
238 biomass and relative spawning biomass relative to the first year of the model) were
239 compared to the SS model.

240 **RESULTS**

241 ***Reference model***

242 The reference SS model of the red snapper shows a stock in initial decline, but in recent
243 years increases in biomass despite increasing catches (Fig. 2). Recruitment is at its highest
244 post-2000, when the CPUE time series shows a steady increase. Current relative stock
245 status is very high and well above what would be considered maximum sustainable biomass
246 (Fig. 2).

247 **Likelihood profiles**

248 Natural mortality

249 The model tends to support higher values of natural mortality (Fig. 3, likelihood panel), but
250 the amount of information in the model on natural mortality is very limited. Most of the
251 information comes from the assumed prior on M when looking at the likelihood components
252 in the profile (Appendix C). Initial and final spawning output are very sensitive to the
253 assumption of lower M values (Fig. 3). Despite the sensitivity in the absolute biomass
254 measures, the relative biomass was similar across the full profile (Fig. 3). This illustrates a
255 situation where the model is poorly informed on the absolute biomass of the stock, but the
256 current stock status is robust to changes in perception of M and indicative of a high stock
257 status.

258 The SS-estimated M value was particularly high (0.46 per year) and probably unrealistic for
259 *L. purpureus* given the life history and lack of information on M contained in the data (Fig. 3).
260 For this reason, the median value of 0.39 per year from the nine empirical estimation
261 methods was fixed and assumed for both sexes in the reference assessment model.

262 Steepness

263 The steepness likelihood profile showed the available data had no information on the
264 steepness value (Fig. 4). Biomass changed non-linearly to steepness, with higher biomass at
265 lower steepness values, a typical result when looking across steepness values. Relative
266 stock status, while somewhat sensitive to the value of h , was consistently high across all
267 steepness values given the other data and parameter specifications in the reference model.

268 ***Uncertainty in length data***

269 The inclusion of larger individuals on the length compositions resulted in slightly different
270 estimated selectivity parameters in the two-time periods (Appendix E) that result in large
271 overlap in biomass estimates between the length composition treatments (Fig. 6). The small
272 differences between models are highlighted by slightly larger biomass estimates, higher
273 relative stock sizes and lower fishing pressure in the model including larger individuals,
274 although well within the bounds of uncertainty of the reference model.

275 ***Uncertainty in CPUE***

276 Removing the CPUE index strongly affected model output, resulting in a more pessimistic
277 situation for both ending biomass and subsequent stock status (Fig. 7 and Appendix D). The
278 scale of the initial population biomass was not sensitive to inclusion of the CPUE index, but
279 the final biomass was sensitive, pointing to the importance of the CPUE index as a source of
280 current stock status information. Whether this data sets contains an unbiased signal relative
281 to noise regarding the trend in the population is a critical assumption when interpreting these
282 results.

283 The SS model using a power relationship between the CPUE index and the catchability
284 suggests hyperdepletion in the raw CPUE (estimated catchability power value of 2.62). The
285 model outputs also incorporated more uncertainty relative to the reference model but the
286 trends were similar (Appendix F). Any interpretation using the raw CPUE index should be
287 considered with enormous caution.

288 ***Comparison to VPA***

289 SS outputs for the reference model and the model without CPUE were compared to the
290 results from the VPA model (Fig. 2). As previously demonstrated, these two specifications of
291 the SS models differ mostly in years after 2001. Before 2001, the VPA model showed
292 relatively lower biomass levels compared to the SS outputs, though both models suggest the
293 lowest biomass was in the early 2000s (Fig. 2). From about 2010, the outputs of SS model
294 without CPUE (recruitments, SSB and total biomass) resulted closer to the VPA estimation.
295 On the other hand, the relative stock status as defined by the first year of the time series
296 ($SSB_{current}/SSB_{1986}$) indicates a larger decline for SS model without CPUE compared with the
297 VPA. Note, the VPA uses only the length data, not the CPUE, yet still shows recovery,
298 whereas the SS with no CPUE scenario shows a persistent decline.

299 Given the historical VPA assumes a lower M value than the SS models, an additional VPA
300 model with the same M value used in the SS model was performed. This sensitivity did not

301 result in enough change in the VPA model to account for the different biomass scales
302 between the VPA and SS models.

303 **Discussion**

304 When applying complex stock assessment models in data-limited situations, it is important to
305 have the flexibility to explore major axes of uncertainty and alternative model specifications,
306 and not rely on the output of just one model. SS is a powerful and flexible modelling
307 framework accommodating many ways of exploring uncertainty, including data inputs and
308 major life history parameter exploration. Sensitivity analysis can be performed on several
309 assumptions (e.g. growth parameters or selectivity shape), but results can be difficult to
310 interpret if the probabilistic statements for the different values are unknown (Maunder &
311 Piner, 2015). Natural mortality and particularly steepness can be difficult to estimate in stock
312 assessments, as both benefit from contrast in the data. Although empirical estimators for M
313 are available, their imprecision (Kenchington, 2014) requires further characterisation of
314 uncertainty outside one model specification (i.e. using only one value of M). Sensitivity
315 analyses are recommended to test for the robustness of model outputs to parameter and
316 data choices and offer a fuller representation of uncertainty and effects of model
317 misspecifications (Brooks & Deroba, 2015). Erroneous estimation of M can lead to over- or
318 underestimates of stock biomass and status, poorly informing management of the resource
319 (Kenchington, 2014). Mortality rates for *Lutjanus* species reported in literature from Florida to
320 Brazil range widely from 0.11 to 0.49 per year (Arreguín-Sánchez, Munro, Balgos, & Pauly,
321 1996; Burton, 2002; Rivot et al., 2000; Topping & Szedlmayer, 2013). Our likelihood profile
322 and sensitivity analysis showed the largest changes in model output with low M values.
323 Given the prior constructed here (based on life history values via empirical M estimators)
324 drove the estimation of M and profiling showed no information to delineated M values >0.4 ,
325 fixing M to 0.39 per year seemed a very reasonable decision when determining a reference
326 model.

327 This model also showed sensitivity to steepness for several model derived quantities, a
328 common result as changes in the steepness value usually causes major uncertainty in the
329 estimation of management quantities (Zhou, 2007). But the model also was unable to
330 estimate steepness given the lack of strong contrast in population biomass and recruitment,
331 despite the u-shaped population dynamics in the model using CPUE (Lee, Maunder, Piner, &
332 Methot, 2012; Magnusson & Hilborn, 2007).

333 Length composition data are one of the easier data sources to collect for many species,
334 although non-representative sampling can potentially cause bias in interpreting sampled
335 lengths. Length data are a central component for age-structured models, especially when

336 aging data are typically not available (Heery & Berkson, 2009), providing information on gear
337 selectivity, recruitment pulses, and stock status (as well as life history parameter information
338 in some situations). Length data can suffer from systematic errors during the sampling of
339 catch that make it unrepresentative of the true catch. While the causes of bias in sampling
340 fishery-dependent length composition data are recognised (e.g. non-random sample
341 collection, limited access to fishery catch or poor sampling design), the effect of it on stock
342 assessment is always not straightforward (Gerritsen & McGrath, 2007; Heery & Berkson,
343 2009). Here it was demonstrated that correcting for the main source of sampling error (no
344 sampling of the exported portion of catch) for *L. purpureus* had little effect on model outputs.
345 While this lack of model sensitivity points to model robustness to this particular data
346 scenario, representativeness in the length data should always either be ensured through
347 proper sampling design or evaluated in the model with the exploration of data scenarios.

348 One of the biggest sources of uncertainty in the red snapper model was the inclusion of the
349 CPUE-based abundance index. CPUE misspecification can cause a significant weakness in
350 the model performance when linking the population trend to the abundance index (Methot Jr
351 & Wetzel, 2013; Wiedenmann & Jensen, 2017). In the case of this model, the final trend in
352 the population dynamics demonstrated a major dichotomy in results depending on the
353 treatment of the CPUE index. Removing it caused the population to continue to decline (as
354 the catch continued to increase) instead of rebound. This also demonstrates how the signal
355 in the index was different to that of the length composition data. Competing signals in data
356 sources are very common in integrated stock assessments, and must be resolved using data
357 weighting or, ideally, alternative model specification (Maunder and Piner, 2017). Such data
358 weighting choices are a major consideration when model building and defining appropriate
359 sensitivity analyses.

360 Fishery-dependent CPUE is known to vary over time violating the assumption of being
361 proportional to abundance. Several methods have been employed to incorporate time-
362 varying catchability into stock assessments (e. g. random walk) but fishery-dependent CPUE
363 generally need standardisation (Wilberg, Thorson, Linton, & Berkson, 2009). CPUE data
364 series can be standardised to account for a variety of factors, however standardisation can
365 only correct for measured factors and require available data for each factor (Wilberg et al.,
366 2009). Information on stock spatial and temporal variability and technological changes in the
367 French Guiana red snapper fishery is fragmentary and incomplete, thus, CPUE
368 standardisation for this red snapper model is currently not possible. The incorporation of a
369 non-linear power function between the CPUE index and the catchability suggests possible
370 hyperdepletion that added more uncertainty to the model outputs. One possible mechanism
371 explaining this result is that the grouping behaviour of snappers can lead to localised

372 depletions as already showed for *Lutjanus* spp. In the Gulf of Mexico (Saul, Brooks, & Die,
373 2020). Nevertheless, those results should be interpreted with caution since the CPUE
374 integrated in the model were not standardised. Future use of CPUE as an index in this
375 assessment should consider the possibility of incorporating time-varying or non-proportional
376 catchability if additional data could be collected to improve CPUE standardisation and
377 application.

378 The VPA approach has a long history of application to major fished stocks in French Guiana
379 and several European regions, but this methods requires a relatively complete data set and
380 can often accommodate only the most recent period of the fishery since age composition
381 data are rarely available for the beginning of the fishery (Stewart & Martell, 2015). The VPA
382 approach requires a complete catch-at-age time series that is often estimated from cohort
383 slicing of length data (Ailloud et al., 2015). This type of procedures can introduce a large and
384 unpredictable uncertainty that can influence VPA assessments (Carruthers, Kell, & Palma,
385 2017). The SS model does not need catches-at age and can directly integrate length
386 datasets using growth parameters and uncertainty in length at age, thus integrating this
387 uncertainty in the assessment (Methot Jr & Wetzel, 2013). SS and VPA follow a similar
388 process but in opposite directions (VPA is a backward projection model while SS is a forward
389 projection model) and adopt a different selectivity approach (Punt, Hurtado-Ferro, & Whitten,
390 2014) and treatment of recruitment. In the recent years, French Guiana stock assessments
391 has been performed with both methods to compare the results. The possibility to use SS
392 exclusively for future assessments is now a consideration. The differences result in a notable
393 difference in absolute biomass estimation among the approaches. Stewart and Martell (2015)
394 also found a biomass difference comparing VPA and SS models. The catch and length
395 version of the SS model, which is the most similar SS model to the data used in the VPA
396 model, was also different in both population trend and biomass size. These models all give
397 very different measures of absolute and/or relative stocks size, and thus management should
398 consider the most appropriate way to weight these different model specifications to inform
399 management (Stewart & Martell, 2015). The SS model allows for flexibility and uncertainty
400 specification and should be preferred over VPA for further management scenarios.

401 **Conclusion**

402 Dealing with data-limited fisheries and unreported times series can be particularly
403 challenging, and model misspecification and data treatments can cause important changes in
404 the model outputs and management suggestions. Prioritising some of the data and down-
405 weighting others can be a solution to reduce conflicts but it can be difficult to choosing these
406 weightings (Ichinokawa, Okamura, & Takeuchi, 2014). These conflicts instead should be

407 confronted with model exploration to avoid model mis-specification (Wang & Maunder, 2017)
408 or re-evaluation of the representativeness of the data in question. Thorough sensitivity
409 analysis and even simulation analysis may be needed to identify potential bias and
410 misspecifications.

411 The present results showed that for French Guiana *L. purpureus* the SS model provided a
412 flexible and viable method to assess the exploitation status of the stock and the uncertainty
413 to model specification and data set choices given the limitations in available data and life
414 history inputs. The available data were insufficient for the estimation of natural mortality and
415 steepness, necessitating a sensitivity exploration through a likelihood profile to understand
416 how model outputs were affected by the values of these parameters. This model also
417 showed sensitivity to data inputs, as the CPUE index seems to contrast with the length
418 composition data-set. Whether this is due to truly different signals in the data, lack of proper
419 standardization in the CPUE, or unrepresentativeness of the data is not known at this time,
420 but it does pinpoint a critical research topic to improve future stock assessments of red
421 snapper. Despite the above uncertainties, all models were depicting a similar trend with
422 notable stock depletion in the late 1990s. Biomass is recovering in recent years when using
423 the CPUE abundance index (~60% of the unfished spawning biomass) despite stable fishing
424 mortality. To preserve this important economic resource, new data collections (e.g.
425 measuring lengths of all catches; improving the quality of the CPUE time series with
426 electronic monitoring; development of a fishery-independent survey; collecting ageing
427 structures) can be added directly to the SS model configured here, while enforceable
428 management measures (e.g. hook size regulations; developing spatial and temporal
429 restrictions; limit illegal activities; catch limits) should be explored.

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436

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592
593

594 **Tables**

595 **Table 1: Life history parameters employed in this study**

von Bertalanffy growth coefficient (k)	0.12 year ⁻¹	(Rivot et al., 2000)
von Bertalanffy asymptotic length (L _{inf})	105 cm	(Rivot et al., 2000)
length-weight allometric parameter (b)	2.95455	(Lampert, Achoun, & Levrel, 2013)
length-weight scaling parameter (a)	1.97E-05	(Lampert et al., 2013)
maximum age	13 year	(Rivot et al., 2000)
maximum length	88 cm	(Rivot et al., 2000)
Length at 50% maturity	32 cm	

596

597 **Figure legends**

598 Fig. 1: Catches and catch per unit effort (CPUE) data employed in red snapper SS model.

599 Fig. 2: Comparison of the main model outputs for the reference SS model, the SS model
600 without catch per unit effort (CPUE) and the virtual population analysis (VPA).

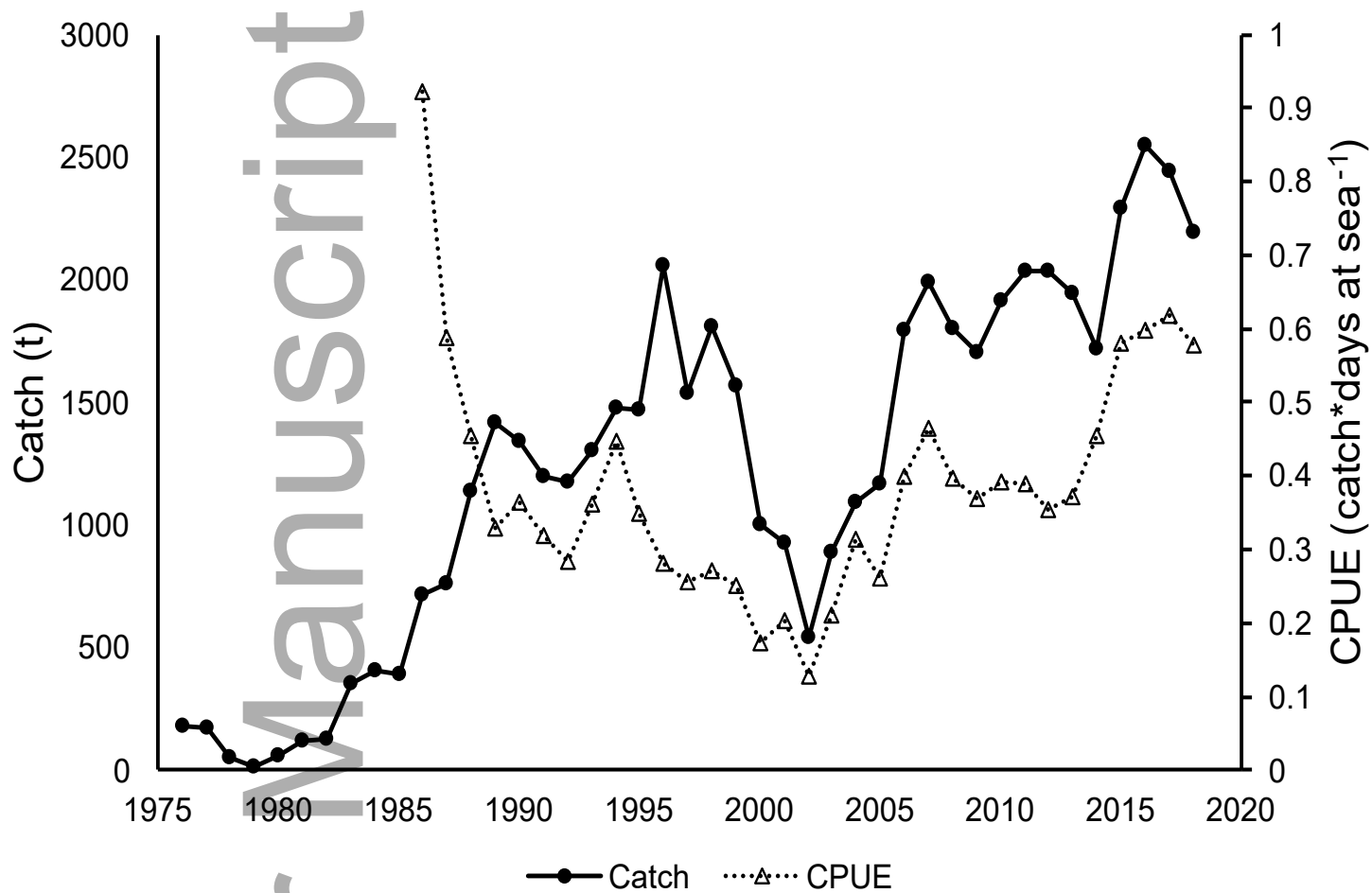
601 Fig. 3: Likelihood profile for natural mortality and derived quantities (initial spawning output
602 (SO_0); spawning output in 2018 (SO_{2018}), stock status (SO_{2018}/SO_0) in the French Guiana red
603 snapper SS model. The natural mortality of 0.39 estimated by “The Natural Mortality tool” is
604 showed by a grey dot.

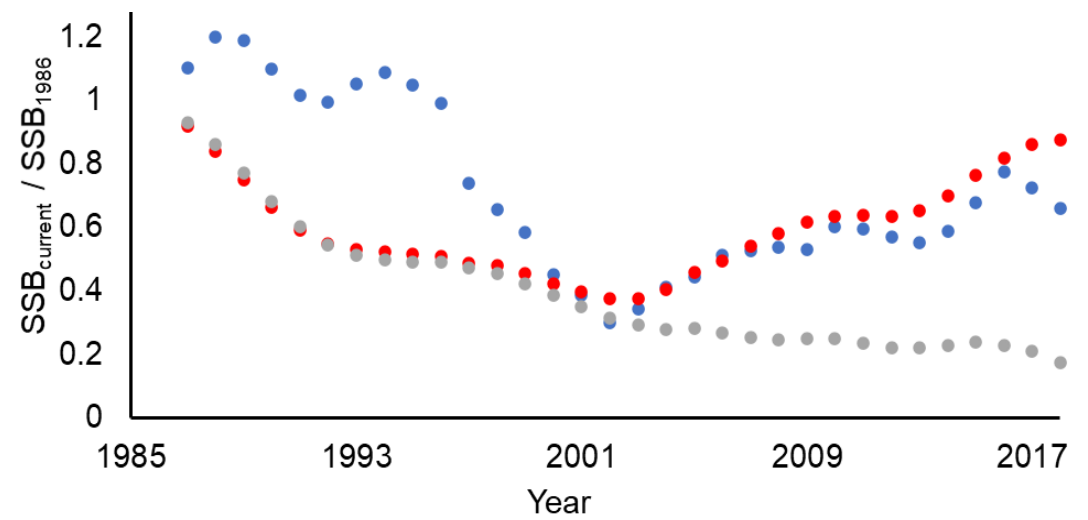
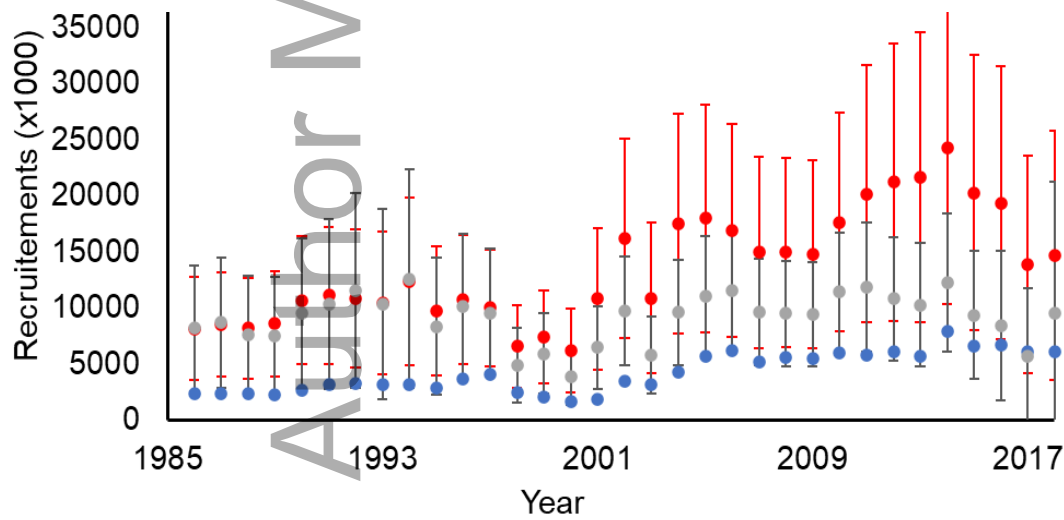
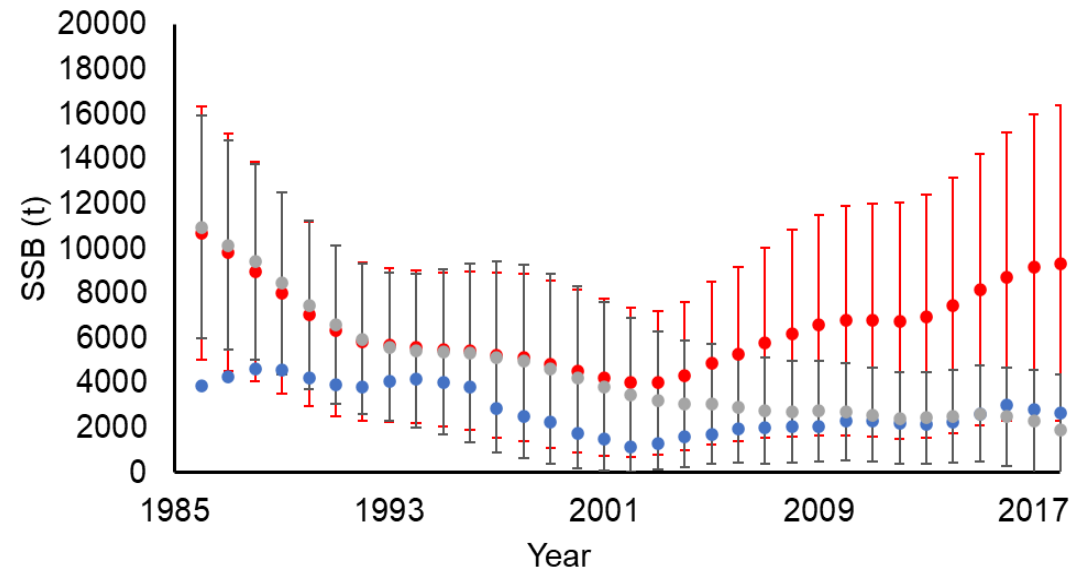
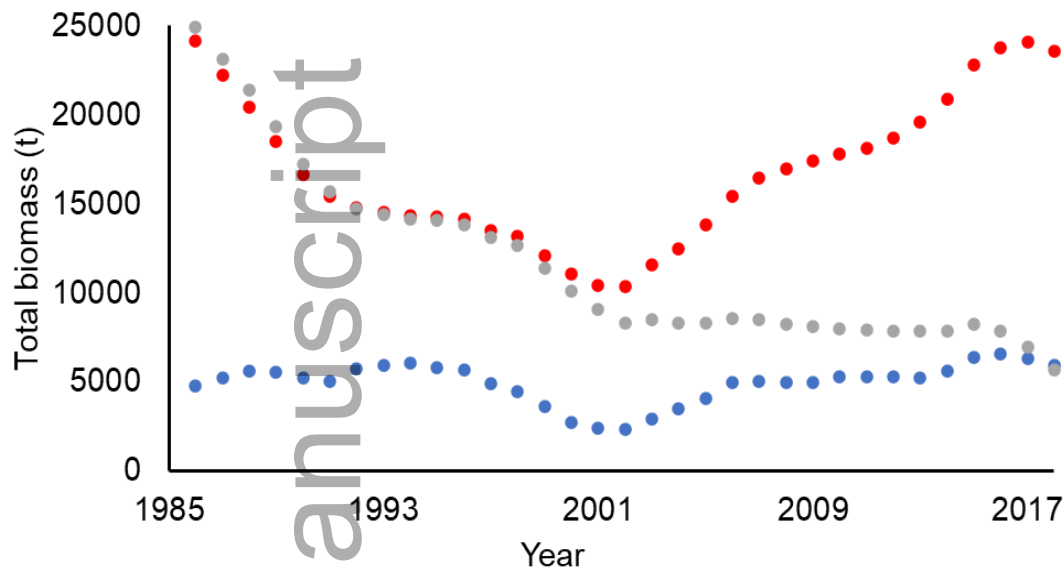
605 Fig. 4: Likelihood profile for steepness (h) and derived quantities (initial spawning output
606 (SO_0); spawning output in 2018 (SO_{2018}), stock status (SO_{2018}/SO_0) in the French Guiana red
607 snapper SS model. The steepness value of 0.7 estimated by Fishlife is showed by a grey
608 dot.

609 Fig. 5: Comparison of the main model outputs and index fit for the reference model and the
610 model using the modified length composition dataset.

611 Fig. 6: Comparison of the main model outputs and index fit for the reference model and the
612 model without catch per unit effort (CPUE).

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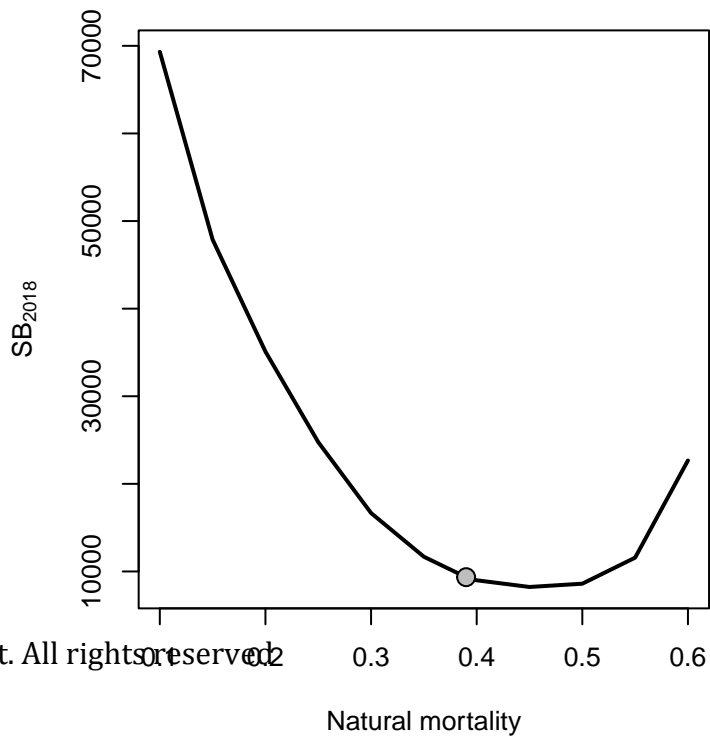
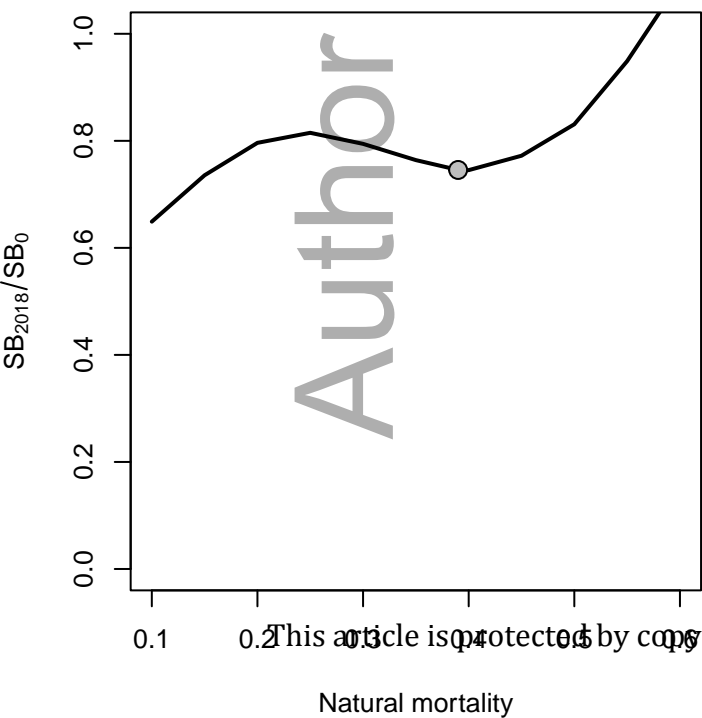
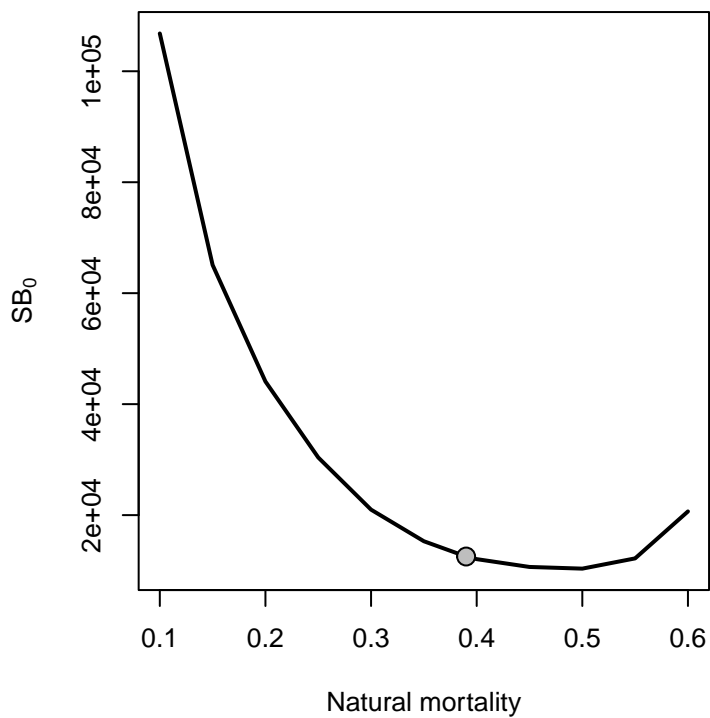
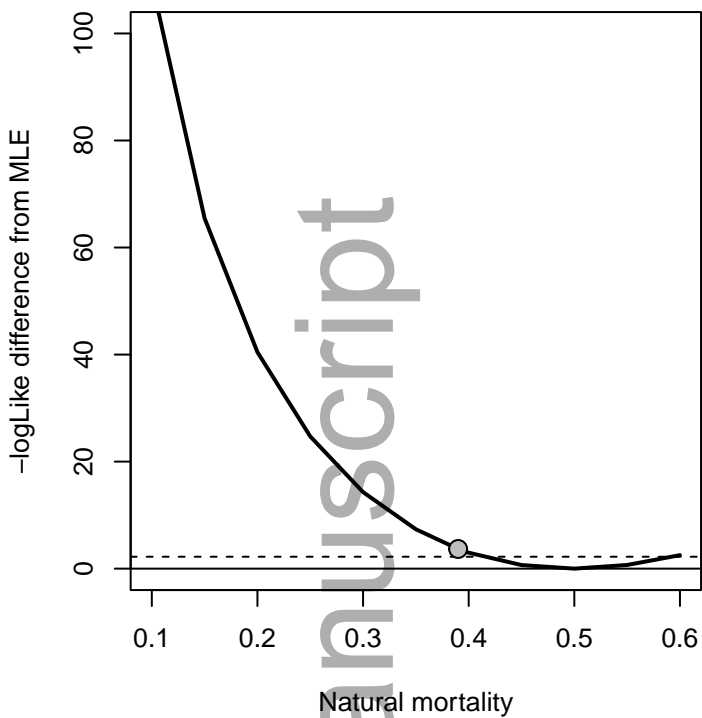




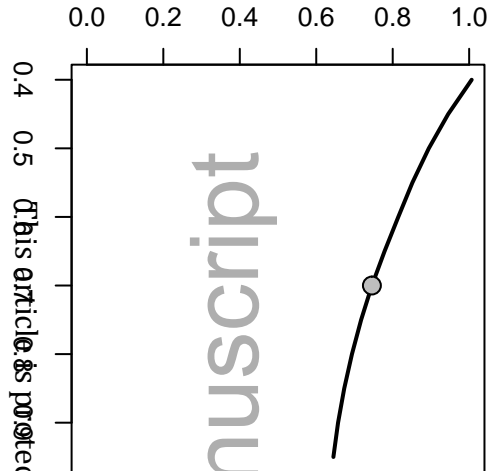
● VPA

● Reference SS model

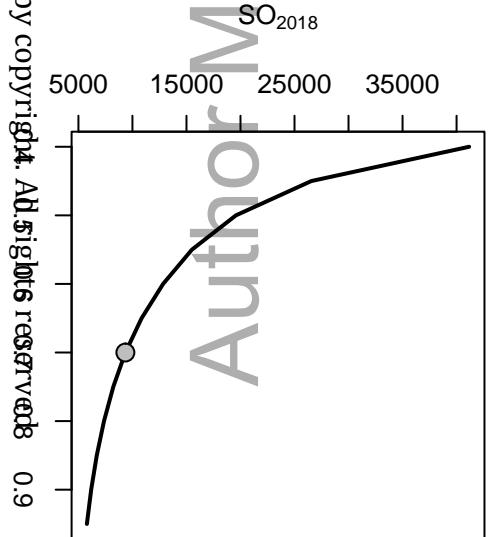
● Without CPUE SS model



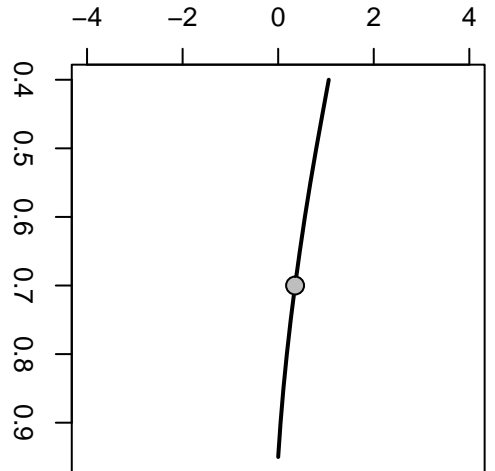
Steepness



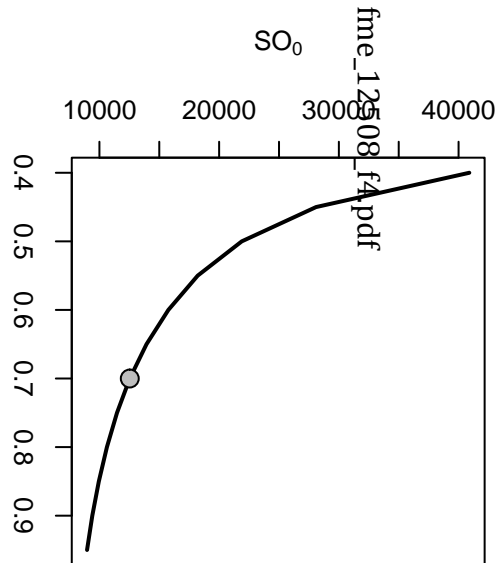
Steepness

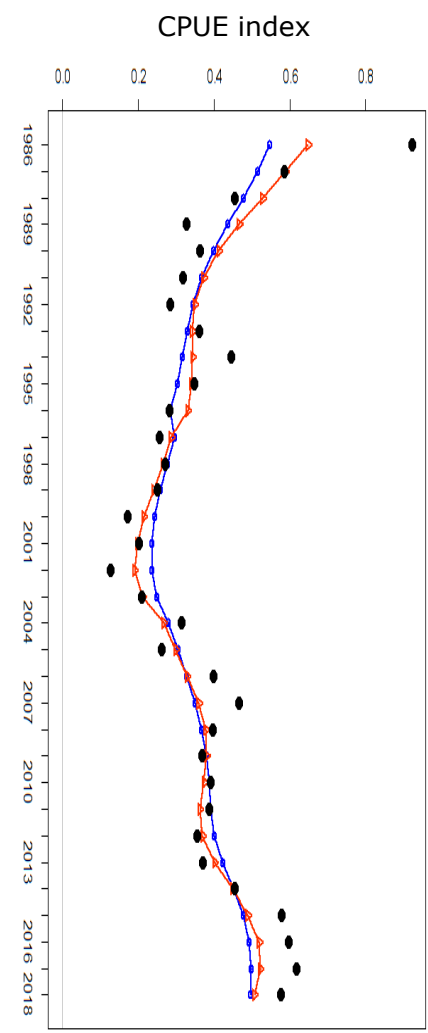
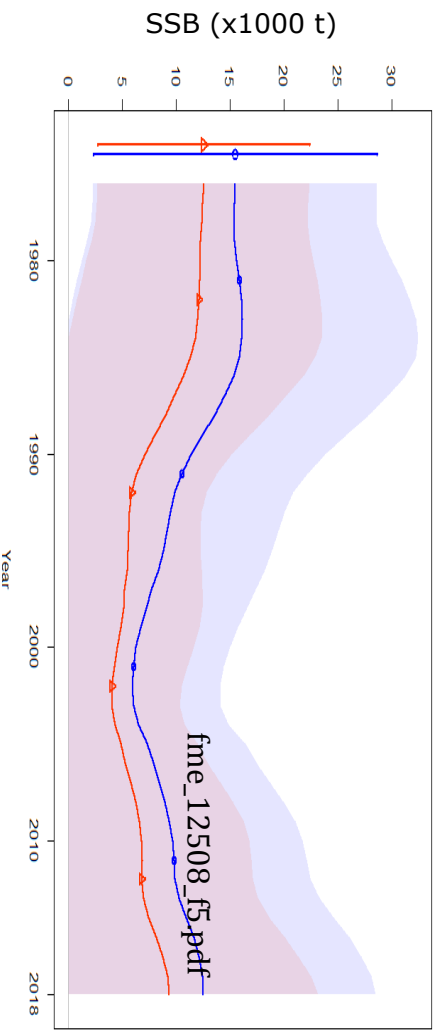
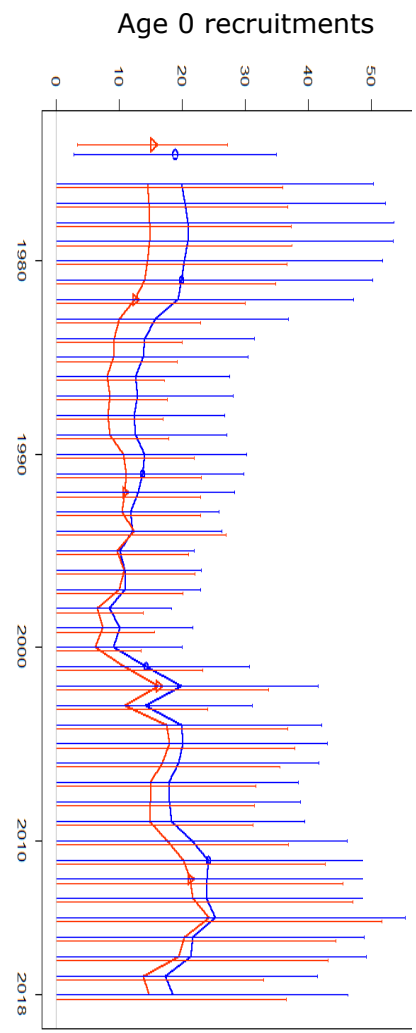
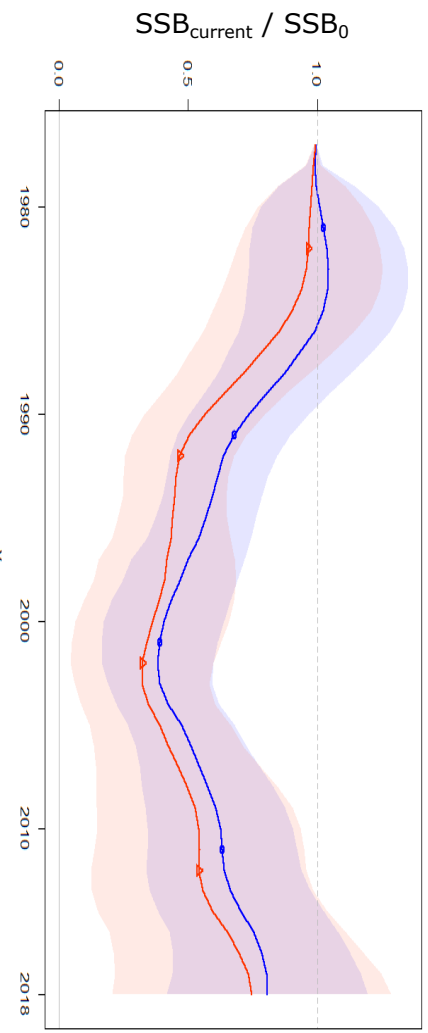
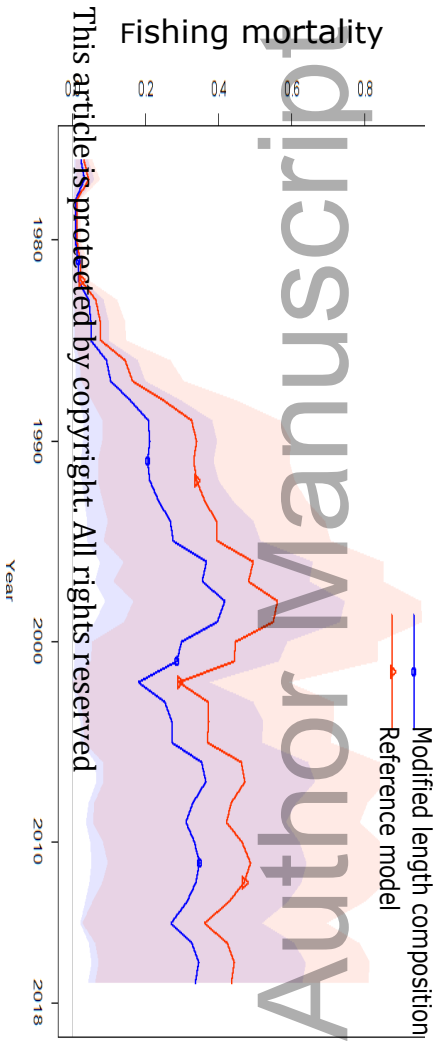


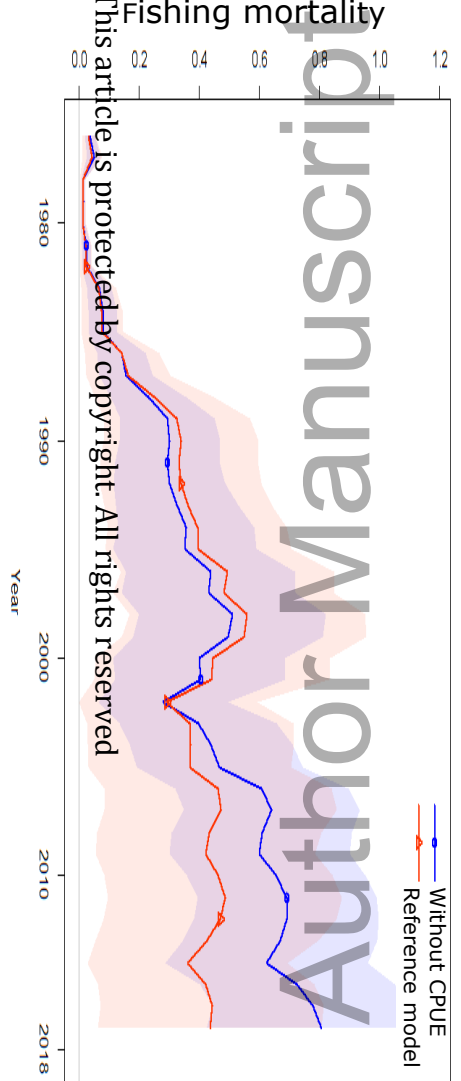
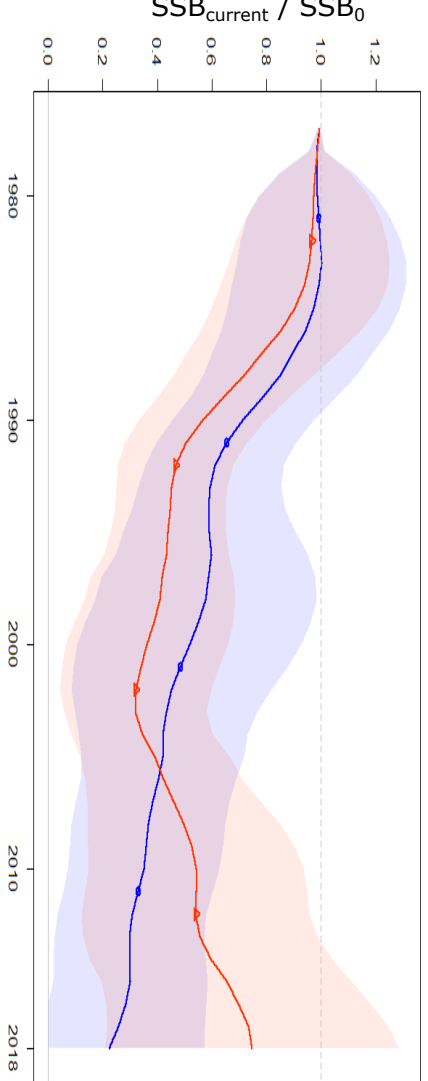
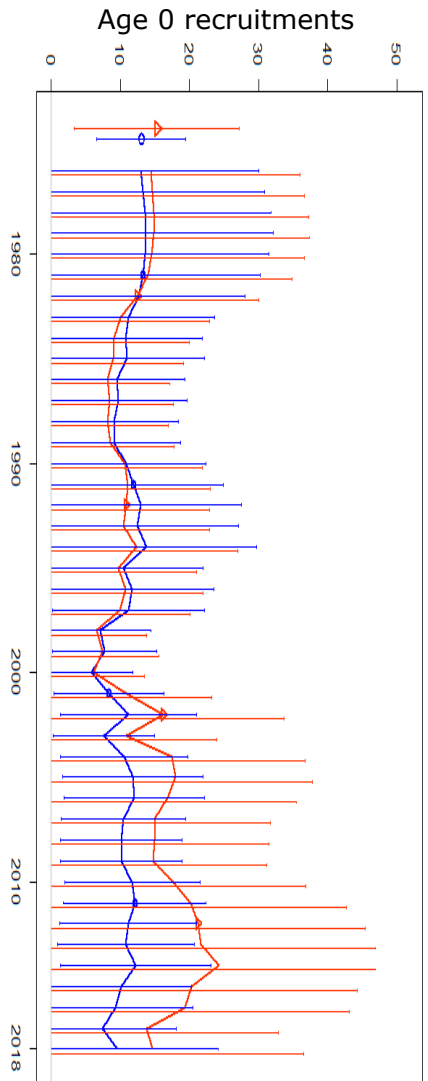
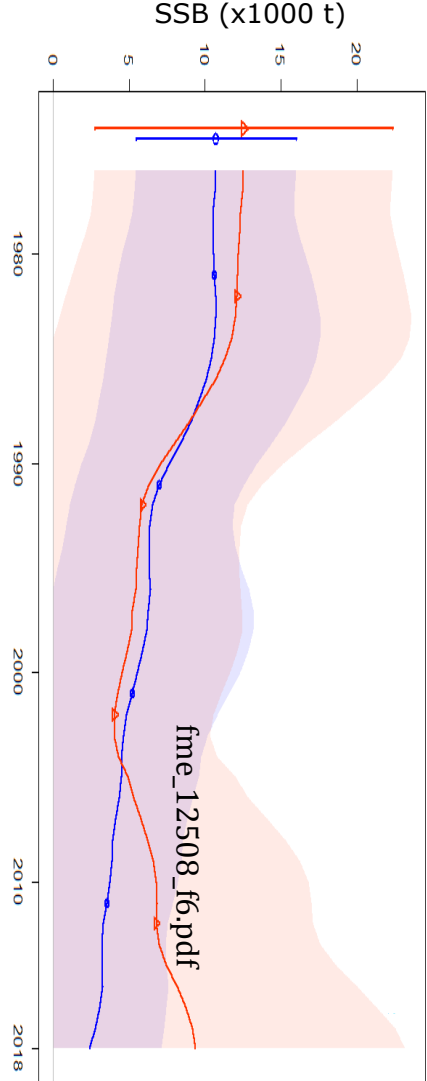
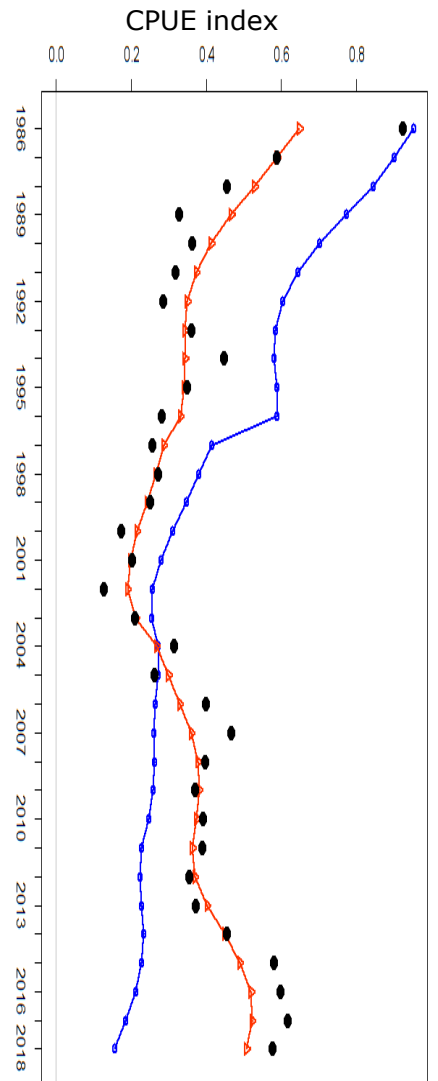
Steepness



Steepness







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—○— Without CPUE
—△— Reference model

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