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Keywords: Bay of Biscay Anchovy; Calibration; ISIS-Fish; Model skill assessment; Process modelling; Uncertainty.

Corresponding Author: Dr. Sigrid Lehuta, Ph.D

Corresponding Author's Institution: IFREMER

First Author: Sigrid Lehuta, Ph.D

Order of Authors: Sigrid Lehuta, Ph.D; Pierre Petitgas, Ph.D; Stéphanie Mahévas, Ph.D; Martin Huret, Ph.D; Youen Vermard, Ph.D; Andrés Uriarte

Abstract: Complex fishery models are recommended to investigate the functioning of fisheries and assess the impact of management strategies, particularly spatial measures. However their use is limited due to the difficulty of parameterizing and gaining confidence in such parameter inflated models. Here we propose an approach that combines integration of information, fitting procedures and hypotheses testing to parameterize, validate and achieve the most plausible formulation of a model. The approach is applied to the anchovy fishery in the Bay of Biscay. Literature was first reviewed for parameter values determination. When contradictory or vague information was found, as was the case for reproduction duration, migration timing and egg mortality, two alternative modelling assumptions were proposed. Combining these assumptions led to eight alternative models. Each one was calibrated to assess missing parameter values for accessibility and adult mortality. Hindcast simulations were finally run to corroborate the alternative models with several time series of observations of different kind and at various aggregation levels. Summary statistics were calculated to quantitatively assess model skills and rank alternative parameterizations. The impacts of the intrinsic variability in selected parameters on the fishery dynamics were evaluated. The results suggested higher egg and adult mortality than formerly estimated and identified the most likely pattern of migration. The scoring system evidenced the strengths and weaknesses of each model. We conclude on the structural realism of the model making it relevant for management evaluation, but it is necessary to take into account the intrinsic variability in larval mortality as an important source of uncertainty in predictions.

Suggested Reviewers: Steve Cadrin  
Fisheries Oceanography, School of Marine Science and Technology, UMass Dartmouth  
SCadrin@umassd.edu

Miguel Bernal  
Pelagic fish, Instituto Espanol de Oceanografia, Vigo  
miguel.bernal@cd.ieo.es

Volker Grimm  
Ecological Modelling, Helmholtz Center for Environmental Research, Leipzig

volker.grimm@ufz.de

Jonathan Hare

Narragansett Laboratory, NOAA NMFS Northeast Fisheries Science Center, Narragansett  
jon.hare@noaa.gov

Opposed Reviewers:

Brian D. Fath  
Editor in Chief  
Ecological modelling

Dear Sir,

Please find enclosed the manuscript of an article we would like to submit for publication in Ecological Modelling. This paper deals with a methodology to parameterise a complex fishery model in a context of uncertainty to ultimately evaluate recovery and management plans. The proposed method uses simulations design to select the most relevant hypotheses of fishery functioning. The adequacy of several assumptions reviewed in the literature and sometimes contradictory is assessed. Model skill is characterized using summary statistics of model fit against multiple time series of observations. This approach is applied to the Bay of Biscay anchovy fishery.

We hope you find this paper suitable for publication in Ecological Modelling. My co-authors, Pierre Petitgas, Stéphanie Mahévas, Martin Huret, Youen Vermard and Andrés Uriarte fully participated in and accept responsibility for the work.

Yours sincerely,  
S. Lehuta

Sigrid LEHUTA  
Département Ecologie et Modèles pour l'Halieutique  
IFREMER BP 21105  
44311 Nantes Cedex 3  
France  
Email : Sigrid.Lehuta@ifremer.fr

## **Highlights**

ISIS-Fish model parameters of the anchovy fishery in the Bay of Biscay are revised.

Alternative fishery parameterizations are considered under contrasted assumptions.

For each parameterisation unknown parameters are assessed by calibration procedures.

Summary statistics quantify the fit of hindcasted time series to multiple observations.

The most plausible parameterization is validated for management evaluation.

1 **Dealing with incomplete and contradictory information when**  
2 **parameterizing a complex fishery model? An example of the**  
3 **anchovy fishery of the Bay of Biscay.**

4  
5 Sigrid Lehuta <sup>a,\*</sup>, Pierre Petitgas <sup>a</sup>, Stéphanie Mahévas <sup>a</sup>, Martin Huret <sup>a</sup>, Youen Vermard <sup>b</sup>  
6 and Andrés Uriarte <sup>c</sup>

7  
8 <sup>a</sup>IFREMER, rue de l'île d'Yeu BP 21105, 44311 Nantes Cedex 03, France.

9 <sup>b</sup>IFREMER, 150 quai Gambetta, B.P. 699, 62321 Boulogne/Mer Cedex, France.

10 <sup>c</sup>AZTI tecnalia, Herrera Kaia-Portualdea z/g E20110, Guipuzcoa, Spain.

11 \* Corresponding author E-mail address: sigrid.lehuta@ifremer.fr.

12

13

14 Abstract

15 Complex fishery models are recommended to investigate the functioning of fisheries  
16 and assess the impact of management strategies, particularly spatial measures. However their  
17 use is limited due to the difficulty of parameterizing and gaining confidence in such parameter  
18 inflated models. Here we propose an approach that combines integration of information,  
19 fitting procedures and hypotheses testing to parameterize, validate and achieve the most  
20 plausible formulation of a model. The approach is applied to the anchovy fishery in the Bay  
21 of Biscay. Literature was first reviewed for parameter values determination. When  
22 contradictory or vague information was found, as was the case for reproduction duration,  
23 migration timing and egg mortality, two alternative modelling assumptions were proposed.  
24 Combining these assumptions led to eight alternative models. Each one was calibrated to

25 assess missing parameter values for accessibility and adult mortality. Hindcast simulations  
26 were finally run to corroborate the alternative models with several time series of observations  
27 of different kind and at various aggregation levels. Summary statistics were calculated to  
28 quantitatively assess model skills and rank alternative parameterizations. The impacts of the  
29 intrinsic variability in selected parameters on the fishery dynamics were evaluated. The  
30 results suggested higher egg and adult mortality than formerly estimated and identified the  
31 most likely pattern of migration. The scoring system evidenced the strengths and weaknesses  
32 of each model. We conclude on the structural realism of the model making it relevant for  
33 management evaluation, but it is necessary to take into account the intrinsic variability in  
34 larval mortality as an important source of uncertainty in predictions.

35

## 36 **Keywords**

37 Bay of Biscay Anchovy, Calibration, ISIS-Fish, Model skill assessment, Process modelling,  
38 Uncertainty

39

## 40 **1. Introduction**

41 Complex fishery models are needed to properly assess the impact of management  
42 rules, now involving spatial regulations and/or combinations of measures (Pelletier and  
43 Mahévas, 2005). We are defining complex models as dynamic, parameter rich models that  
44 explicitly account for processes related to resources and exploitation dynamics, in a spatial  
45 context. Because of their complexity, these models cannot be analytically solved and they rely  
46 on simulations (Mahévas and Pelletier, 2004). Although their use is recommended to account  
47 for spatial and seasonal processes and fleet behavior (Pelletier and Mahévas, 2005), the  
48 challenge of their implementation often discourages users. First, difficulties arise in the  
49 parameterization as numerous parameters must be estimated. In many existing fishery models,

50 optimisation procedures are used to assess all parameter values simultaneously (Drouineau et  
51 al., 2010; Pech et al., 2001). This is not feasible with complex models given the high number  
52 of parameters, confounding effects and computation costs. Another approach consists of  
53 assessing parameters independently, using available knowledge and integrating this  
54 information in the model (Fulton et al., 2004; Kraus et al., 2009; Lehuta et al., 2010; Travers  
55 et al., 2006). Sensitivity analysis is recommended to identify the most influential parameters  
56 in the model and focus estimation efforts on these important ones (Saltelli et al., 2000). The  
57 review of available knowledge could lead to alternative and potentially contradictory views of  
58 how the fishery functions. In those cases, experts could help sort hypotheses or weight  
59 knowledge sources according to their reliability (Stefansson, 1998). If a valid likelihood  
60 function can be constructed, the Bayesian approach is well adapted to assign weights to  
61 alternative assumptions (see for instance Patterson, 1999). Otherwise alternative hypotheses  
62 should normally be stored for inclusion in uncertainty analyses (Hill et al., 2007). In any case,  
63 a rigorous validation of the final model must be carried out to support or conversely question  
64 the validity of the modelling choices. Validation often consists of visual comparisons between  
65 past time series and simulation outputs, with the constraint that these time series should not  
66 have been used for parameter estimation (Sterman, 1984). To provide more quantitative  
67 elements for model skill evaluation, several authors promote the use of specific metrics that  
68 reflect all aspects of model skill (Jolliff et al., 2009).

69

70         The parameterization of the simulation model ISIS-Fish (Pelletier et al., 2009) for the  
71 anchovy fishery in the Bay of Biscay illustrated all the steps of this modelling process. The  
72 anchovy (*Engraulis encrasicolus*) fishery in the Bay of Biscay has been closed from 2005-  
73 2010 after its biomass was assessed below biological limits (i.e. Blim: 21000t, ICES, 2009).  
74 Several restoration plans were considered to allow the reopening of the fishery. ISIS-Fish was

75 used to model the fishery and to assess the impact of spatial management measures (Lehuta et  
76 al., 2010). The values of the fishing activity parameters were based on statistical analyses of  
77 logbook data whereas most of the biological parameters were obtained from a literature  
78 review (Lehuta et al., 2010). A sensitivity analysis was performed that pointed out that the  
79 most sensitive parameters were biological parameters related to mortality, reproduction and  
80 migrations (Lehuta et al., 2010). Accessibility was also revealed as sensitive in interaction  
81 with total fishing time, but the other parameters related to fishing activity were less  
82 influential.

83

84 In this paper we develop a comprehensive approach to model parameterization and use  
85 a case study of the Bay of Biscay anchovy fishery to explain how the best parameterization  
86 possible can be achieved given the knowledge at hand and the model structure. In light of the  
87 sensitivity analysis results, the choices made concerning the parameterization of sensitive  
88 processes were questioned. To refine parameterization of these sensitive processes, we used  
89 the model as an experimentation platform to investigate model fit to historical series by  
90 hindcast simulations. Parameters were classified into four categories. Three of the categories  
91 related to the level of uncertainty in parameter values: i) well-documented parameters or  
92 parameters for which a unique source of information was available, ii) parameters with  
93 contradictory values found in the literature and iii) parameters with poorly established values.  
94 Last set of parameters (iv) gather parameters that fluctuate from year to year (e.g., larval  
95 survival).

96 To deal with the two categories of uncertain parameters, we developed the following  
97 strategy. First, vague and contradictory information (ii) was summarised in two alternative  
98 possible parameter values. The combination of these alternative parameter values resulted in  
99 alternative model parameterizations. Secondly, hindcast simulations were run to calibrate

100 inaccurately known parameter values (iii) and to assess the realism of the alternative  
101 parameterizations by quantitative comparison of simulation outputs and observations using  
102 various summary statistics.

103         Since the mechanisms responsible for the variability in category iv parameters were  
104 unknown, these parameters were considered as forcing variables. The impact of using the  
105 average value of fluctuating parameters rather than forcing them annually to observed values  
106 was assessed. Finally, we discuss the approach used and its relevance for model prediction.

## 107 **2. Materials and Methods**

### 108 2.1. Contradictory information

109

110         A distinction was made between accurately known biological processes or at least  
111 known through a unique source (category i) (Table 1) and processes that are either uncertain  
112 or contradictorily described in the literature (categories ii and iii) (Table 2). In the latter case,  
113 for the timing of migration to spawning grounds, the duration of spawning for small-sized  
114 anchovy and the value of egg mortality, the possible values were summarised in two  
115 alternative parameterizations. Uriarte et al. (1996) assumed that the migration of adults to  
116 spawning grounds occurs in winter but the exact timing is uncertain. The two contrasting  
117 hypotheses considered were a migration at the beginning of the winter season (January,  
118 hypothesis **MigJ**) or at the end (April, hypothesis **MigA**). Spawning is known to take place  
119 from April to August and fecundity, although sensitive, is relatively accurately known  
120 (Motos, 1996). However, individual spawning duration has not been characterized precisely.  
121 Pertierra et al. (1997) estimated spawning to last for three months, based on the number of  
122 batches and spawning frequency, while Motos (1996) gave a duration of 2.5 months and  
123 differentiated between fish of length smaller and larger than 14 cm. Five age-1 classes that  
124 potentially have different spawning durations are described in the model (Lehuta et al., 2010)

125 according to their month of birth. Thus we defined a first hypothesis **R1** in which the two  
126 smallest age-1 classes (born in July and August of the previous year) spawn during two  
127 months only while the other age-1 classes (born earlier in the year) spawn during the full  
128 period of three months as adults do. In the alternative hypothesis **R2**, the three smallest age-1  
129 classes (born from June to August) spawn for two months only, while the larger fish spawn  
130 during three months. Finally, a survey-based estimate of egg mortality in the Bay of Biscay  
131 (2000-2005) was  $0.266 \text{ day}^{-1}$  (ICES, 2007) (**Megg1**) while Pertierra *et al.* (1997) assessed an  
132 egg mortality value of  $0.56 \text{ day}^{-1}$  (**Megg2**) in the Catalan Sea. These two egg mortality rates  
133 were considered as possible starting points for mortality curves adjusted from birth to the end  
134 of the first reproduction (455 days) following a Pareto decay (Lo et al., 1995; Table 1).  
135 Combining the two alternative hypotheses for each of these three processes (egg mortality:  
136 **Megg1 or Megg2**, spawning duration: **R1 or R2** and migration date to spawning grounds:  
137 **MigA or MigJ**) resulted in eight (2x2x2) alternative parameterizations of the model.

138

## 139 2.2. Poorly known parameters

140

141 Adult mortality and accessibility were also sensitive parameters that were uncertain or  
142 poorly documented (category iii). Natural mortality can be considered almost constant after  
143 the first reproduction (Chen and Watanabe, 1989), which applies to age 1 anchovies. This  
144 mortality for adults is estimated at  $1.2 \text{ year}^{-1}$  by ICES (ICES, 2008). However, using a  
145 mortality decay Pareto model from the egg mortality **Megg1** (or **Megg2**) value to the adult  
146 mortality of 1.2 resulted in a very high survival rate from egg to recruitment (age 1),  
147 inconsistent with the estimated value of  $10^{-5}$  (Petitgas and Massé, 2003). The value of adult  
148 mortality was thus considered questionable and the optimisation procedure described below  
149 (see 2.4) was applied to estimate the adult mortality at age 1.

150

151 No value was available in the literature for the accessibility parameter (sensu Seber,  
152 1982), so we relied on expert judgement. According to experts, the accessibility of anchovy is  
153 mainly age-dependent. Three values of accessibility ( $q_0$ ,  $q_1$  and  $q_2$ ) were thus determined  
154 corresponding respectively to age-0 fish (until the first reproduction), age-1 and age-2+. The  
155 same fitting procedure based on the simplex algorithm was used as in Lehuta et al. (2010). It  
156 causes the estimated values to be dependent on the rest of the parameterization and they were  
157 re-estimated when any other parameter was changed.

158

### 159 2.3. Forcing variables

160

161 We distinguished between uncertain parameter values and parameters that may  
162 fluctuate from year to year due to unresolved causes (category iv). There was intrinsic  
163 variability in the anchovy spawning spatial distribution, time spent fishing and fishing  
164 strategies for the period 2000-2008. Larval survival also showed intrinsic variability,  
165 depending on environmental conditions. The individual-based larval drift and survival model  
166 (Huret et al., 2010) was used to estimate the potential survival of larvae depending on  
167 spawning area and date of birth. The effect of annual environmental conditions on larval  
168 survival was estimated by fitting an additive linear model to survival rates by year, month and  
169 area for the period 2000-2007 (Table 1). In hindcast simulations over the period 2000-2008,  
170 annual values of larval survival, observed stock distribution across spawning areas, and  
171 observed fishing effort and strategies of each fleet were used as forcing variables.

172

### 173 2.4. Hindcast simulations to fill knowledge gaps

174

175 For each of the eight parameterizations of the model, an optimisation procedure was  
176 used to assess the values of natural mortality of adults and the accessibility. As natural  
177 mortality and accessibility may have confounding effects, we used a sequential calibration on  
178 two contrasting periods. We first assessed natural mortality using a time series covering the  
179 period when no fishing occurred and then assessed accessibility during an open fishery  
180 period.

181 We first calibrated mortality curves over the period 2005-2008. Because of the  
182 anchovy fishing ban from 2005-2010, the population suffered only natural mortality in recent  
183 years, thus accessibility values were not required to simulate the period. A Pareto regression  
184 modelled the decline in mortality during larval and juvenile stages (Table 1). The Pareto  
185 model was fitted using a range of values for adult mortality. The best fitted outcome of the  
186 observed population growth rate, as estimated by the slope of the SSB time series over the  
187 period 2005-2008 (ICES, 2009), was retained for each of the eight alternative  
188 parameterizations.

189 Parameter values for accessibility coefficients  $q_0$ ,  $q_1$ ,  $q_2$  were optimised using the  
190 variable step simplex algorithm (Walters et al., 1991) by comparing the catches at age by  
191 quarter reported by ICES (2000-2004) to the simulated ones. The sum of squared differences  
192 (MSE) (least square minimisation) was used to measure how well the model fitted the data.

193 Other simulated outputs were then compared to observations that were not used for  
194 parameterization and calibration for the purpose of evaluating model skills and deciding on  
195 the most realistic alternative parameterization of the model among the eight considered.  
196 Available observations were: spawning stock biomass and recruitment biomass assessed by  
197 ICES (ICES, 2000-2008), average distribution of egg production per month over the  
198 spawning season (Allain et al., 2007a), monthly catches by fleet reported in logbooks for the

199 period 2000-2004 and annual catches over the period 2000-2004 (ICES, 2008). Different  
 200 summary statistics were used, which reflected particular aspects of the model fit:

201 • correlation of time series:  $r = \left( \sum_{i=1}^n (O_i - \bar{O})(P_i - \bar{P}) \right) / \left( \sqrt{\sum_{i=1}^n (O_i - \bar{O})^2 \sum_{i=1}^n (P_i - \bar{P})^2} \right)$

202 • model prediction accuracy:  $MSE = \frac{1}{n} \times \sum_{i=1}^n (P_i - O_i)^2$

203 • modelling efficiency (Stow et al., 2009):

204  $MEF = \left( \sum_{i=1}^n (O_i - \bar{O})^2 - \sum_{i=1}^n (P_i - O_i)^2 \right) / \left( \sum_{i=1}^n (O_i - \bar{O})^2 \right)$

205 where  $P_i$  is the  $i_{th}$  of  $n$  model predictions,  $O_i$  the  $i_{th}$  of  $n$  observations and  $\bar{O}$  and  $\bar{P}$  are  
 206 the observation and prediction averages respectively. MEF measured how well the model  
 207 predicts relative to the average of the observations.

208 Finally exploratory runs were performed to assess the impact of inter-annual  
 209 variability in the parameters. The most plausible parameterization among the eight was run  
 210 for the period 2000-2008 and inter-annual forcing factors (i.e. larval mortality, distribution  
 211 across spawning areas, fishing time and strategies) were relaxed one by one as suggested by  
 212 Mackinson et al. (2009). The model forced with constant average values was also run. This  
 213 helped us evaluate whether an average value in prediction was appropriate or whether  
 214 scenarios needed to be considered. Results were explored using the same summary statistics.  
 215

216 For simulations, initial numbers of fish in each stage in January of the starting year  
 217 were required. The ICES BBM model only provided the total biomass of recruits in January  
 218 2000 and the SSB in May 2000. The ICES ICA model (ICES, 2000) provided population  
 219 numbers at age in May 2000. Recruit numbers at each stage were thus derived from recruit  
 220 biomass converted into numbers at each stage using the survey-derived length-weight  
 221 relationship and a theoretical length distribution. For adults, we used estimated biomass in

222 May and the demographic structure resulting from ICES ICA model and back calculated the  
223 number at age from May to January by correcting for mortality.

224

### 225 **3. Results**

#### 226 3.1. Calibration

227

228 Adult mortality rates calibrated on population growth rate over the period 2005-2008  
229 were much higher than the value of 1.2 used by ICES (from 1.63 to 3.03 depending on the  
230 parameterization) (Table 3). Accessibility values of juvenile fish (before the first  
231 reproduction) were 100 times lower than those of adults regardless of the model  
232 parameterization (Table 3). The largest differences between accessibility values (particularly  
233 for  $q_1$ ) occurred for parameterizations in which egg mortality differed (Table 3). According to  
234 the least squares minimisation between simulated and observed catches, the best fit was  
235 obtained between simulated and observed catches for the parameterization with hypotheses  
236 **Megg2**, **R2** and **MigJ** (Table 3) and more generally for parameterizations assuming **Megg2**.  
237 Therefore egg mortality could be higher than previously thought or a high value could be  
238 necessary to compensate for other parameters.

239

#### 240 3.2. Corroboration with observations

241

242 We used radar plots displaying summary statistic values on every output variables  
243 simultaneously to compare model performance according to the three fitting characteristics:  
244 correlation ( $r$ ), accuracy (MSE) and efficiency (MEF) (Figure 1).

245 Temporal correlations ranged from 0.18 for the catches at age 2 to 0.99 for spawning  
246 distributions. Although the models were calibrated on catches at age, the temporal

247 correlations seldom exceeded 0.8 for these output variables. Correlation values did not differ  
248 much between models, except for catches at age 2, for which hypotheses **Megg2** and **MigA**  
249 appeared more suitable (Figure 2).

250 MSE values differed considerably between output variables because of the variety of  
251 metrics and temporal scales. To be able to compare alternative parameterizations across  
252 output variables, the value displayed on the radar plot is the rank of each parameterization  
253 according to its MSE value (8 corresponding to the lowest MSE value: best, 1 to the highest:  
254 worst). The rank of the parameterization highly depended on the output variable considered.  
255 Annual catches, catches at age, biomass and spawning distribution appeared more accurately  
256 reproduced using models with hypotheses **Megg2** and **MigA**, while **Megg1** fitted better to  
257 catches of trawler fleets. The representation used enabled parameterizations to be ranked  
258 according to spawning distribution, which is probably the most direct consequence of the  
259 hypotheses on reproduction patterns. Although inter-annual variations were important  
260 particularly in July, the spatial and temporal distribution of egg production was close to the  
261 average pattern reported by Allain et al. (2007a) (Figure 3). Differences mostly concerned the  
262 month in which egg production peaks. The observed peak egg abundance in June could be  
263 achieved assuming **Megg2** and **R1** only. Therefore spawning duration for most of the age-1  
264 fish could be as long as that of age-2 and spawning timing is probably influenced by age  
265 structure. Finally, model efficiency was relatively low with frequent negative values  
266 indicating that the observation average would be a better predictor than the model results. In  
267 particular, modelled catches of purse seiners profile 1 (CBo11), and trawlers profile 2 (CPe1 2)  
268 were far from observations. Once again, the better model depended on the output variable  
269 considered. Parameterizations with **Megg2** gave poor results when considering catches of  
270 trawler fleets (particularly CPe12), mostly because catches in the first year are overestimated  
271 (Figure 4), but these parameterizations were appropriate for the majority of the other outputs.

272

273 Based on this ability to fit biomass and total annual catches, which represent a high level of  
274 process integration, the parameterization assuming **Megg2**, **R1** and **MigA** was selected.

275

276 3.3. Impact of inter-annual variations

277

278 Exploratory simulations were run with the selected parameterization (egg mortality  
279 hypothesis **Megg2**, first reproduction function (**R1**) and migration of adults in April (**MigA**)).  
280 We focused on the impacts of taking intrinsic variability into account on temporal correlations  
281 between simulated and observed variables. Each output variable reacted differently and  
282 revealed the process that most impacted its dynamics (Figure 5). Biomass, catches at age 0,  
283 recruitment and catches of purse seiners fleets, were highly influenced by the forcing by  
284 larvae survival. Relaxing the forcing generally improved the correlation except for catches at  
285 age 0, showing that the processes occurring between egg and recruit stages are not fully  
286 resolved. However visual validation (Figure 6) showed that forcing by the larval survival time  
287 series captured part of the biomass trend, although it anticipated the biomass drop that really  
288 occurred in 2002. Average migration had a low impact and generally decreased correlation  
289 while average effort significantly decreased the correlation for purse seiners profile 1.  
290 Consequently, scenarios are needed for larval survival and migration, as they largely  
291 influenced the dynamics. On the other hand, the average effort and strategies should be  
292 appropriate for most of the fleets except for purse seiner profile1 (CBol1).

293

## 294 **4. Discussion**

295 Our methodology enabled us to develop the most plausible parameterization of the  
296 Bay of Biscay anchovy fishery using a combination of 3 approaches: 1) literature review for

297 well established parameter values, 2) hindcast simulations with alternative hypotheses when  
298 parameter values were conflicting, and 3) optimisation to estimate poorly known parameters.  
299 The selected parameterization provides a slightly different picture of the anchovy life cycle  
300 than previously envisaged: 1) egg and adult mortality may be higher than reported; 2) the  
301 spawning period may be as long for new recruits (one year old) as it is for adults, and 3)  
302 adults may return to the spawning grounds in April just before spawning. The egg mortality  
303 selected agreed with the values observed in the Mediterranean rather than in the Atlantic  
304 (ICES, 2007; Pertierra et al., 1997). Migration date however, was coherent with the catches of  
305 anchovy in winter in the north of the Bay of Biscay as reported in log-books. Simulation  
306 results gave insight into a likely functioning of the fishery that could be further tested by  
307 winter surveys for migration patterns or studies on physiology in relation to environmental  
308 conditions to improve knowledge of spawning duration mechanisms.

309         This approach proved that complex models can help investigate the coherence of our  
310 knowledge as well as provide plausible values for parameters that are difficult to measure  
311 such as natural mortality. They also reveal emergent properties of the system as a result of the  
312 interactions between explicit processes that are described independently.

313

314         Given model characteristics (high number of parameters, large simulation time), the  
315 use of literature values and the independent estimation of parameters (integration of  
316 information) was preferred to simultaneous optimisation of all model parameters. Also an  
317 integrated estimation (e.g. using likelihood) would require many data sources and their  
318 compliance with model assumptions, a situation seldom encountered (Pech et al., 2001).  
319 Integrating information in the model first required the inventory of knowledge and  
320 uncertainties. This step is also essential in operational management procedures applied toward  
321 the achievement of robust management (Hill *et al.*, 2007). It tends to be more largely carried

322 out, at least qualitatively, through the use of pedigree matrix that aims to reflect the quality of  
323 data sources, knowledge and assumptions used in policy decisions (see for instance Ulrich et  
324 al., 2010). Sensitivity analysis (Lehuta et al., 2010) supported the identification of the most  
325 important processes to investigate. Here we went further in the approach by listing alternating  
326 hypotheses and ranking them based on quantitative criteria.

327

328 The method consisted of using available time series for calibration and validation of  
329 the model. It simultaneously enabled us to improve knowledge and falsify unlikely  
330 hypotheses (or combinations of hypotheses).

331 Fitting procedures were limited to few parameters. However the estimated values  
332 should be interpreted cautiously. The parameters are estimated conditional to assumptions  
333 made elsewhere in the model, and the estimated parameter values may thus compensate for  
334 the value of other parameters to achieve a good fit. The estimate of adult mortality can be  
335 discussed as an example. Firstly, the short duration of the calibration period (only four years)  
336 gives low robustness to the mortality estimate. Secondly, because the values appeared very  
337 sensitive to other assumptions of the model and the value of 3.03 was out of range according  
338 to experts, it should be interpreted in the context of our model. The biomass time series used  
339 for calibration resulted from an assessment model (ICES WGANSA, 2009) for which  
340 assumptions regarding recruitment (random) and adult mortality (1.2) differed from ours.  
341 Validation based on trends in scientific survey indices is perhaps an option to consider in  
342 future studies. For the same reasons, the calibrated values of the stock accessibility should  
343 also be interpreted carefully because compensating effects are likely to occur due to errors in  
344 the other parameters relating fishing effort with fishing mortality.

345 Our approach of corroboration against multiple time series could be seen as a concrete  
346 application of pattern oriented modelling (Wiegand et al., 2003). The use of several time

347 series of observations guaranteed the model 'structural realism'. In effect, the model cannot  
348 reproduce simultaneously multiple patterns observed at different scales and hierarchical levels  
349 if key processes are not captured realistically (Cury et al., 2008). Secondly, because of the  
350 multiple, confounding factors that can have synergistic or antagonistic effects on fishery  
351 dynamics, one needs more than a single series of observations to distinguish between several  
352 hypotheses of description for a phenomenon (Mackinson et al., 2009). It enables model  
353 developers to filter implausible combinations of hypotheses even if their effects are generally  
354 confounded. For instance, model fit on biomass was equivalent across parameterizations, as  
355 biomass is mainly driven by variation in recruitment. However, the underestimation of egg  
356 mortality in parameterizations with **Megg1** induced incompatible low proportions of age-2+  
357 in the population and very low catches for these classes. Reducing spawning duration for one  
358 cohort and changing the date of migration had almost no effect on SSB, but it respectively  
359 modified the distribution of egg production in time and influenced the seasonality of catches.  
360

361         Here we tried to make the validation step more objective by quantifying model skill  
362 through statistical criteria. This approach is largely applied for validation of coupled physical-  
363 biological models (Allen and Somerfield, 2009; Jolliff et al., 2009; Stow et al., 2009) that  
364 often make use of geo-referenced validation data. Indeed parameterization of fishery models  
365 using fitting procedures generally requires all available data and, as a consequence,  
366 independent information is lacking for validation. It should be recognized that absolute  
367 validation of a model is merely impossible, and this notion could be replaced by a measure of  
368 model skill based on model predictions (Serman, 1984). Though reference points could also  
369 be defined for correlation and model efficiency (Maréchal, 2004), defining a reference MSE  
370 value is rarely done. This could potentially be achieved by comparison of model MSE to  
371 observation error of the data as the model could not be expected to give more accurate

372 predictions than the observations. However those observation errors are themselves rarely  
373 determined. Further developments of summary statistics for time series would also be  
374 necessary to complete the description. Moreover the best model is not always the one with the  
375 best fit (Mackinson et al., 2009), as illustrated here by the fit of biomass that appeared worst  
376 with the larval survival forcing, although the visual comparison proved that part of the pattern  
377 was captured.

378 Jolliff et al. (2009), proposed summary diagrams such as Taylor diagrams together  
379 with reference points to help summarise model skills, while Allen and Somerfield (2009)  
380 relied on multivariate analyses. We ranked alternative parameterizations using radar plots for  
381 each criterion. This approach also allowed comparing visually the different parameterizations  
382 on different output variables. The selected parameterization was not unanimously supported  
383 neither across summary statistics, nor across output variables. Stefansson (1998) proposed to  
384 give preference to the most reliable knowledge sources, but again, reliability is hard to  
385 determine. When the sources are so conflicting that the model cannot explain all the data  
386 sources simultaneously, Pech et al. (2001) proposed an iterative procedure of partial fit and  
387 Stefansson (1998) suggested questioning model structure. Here we based our appreciation of  
388 reliability mostly on biomass and catches, as these output variables are relevant for  
389 predictions.

390 An advantage of the method was that it transparently evidenced the strengths and  
391 weaknesses of each parameterization and pointed out the errors we avoided by using the  
392 selected hypotheses. Even if reproducing time series gave confidence in the model, failures in  
393 fitting the model were also informative and offered the opportunity to reveal gaps in the  
394 current understanding of the system and provide indications of where further knowledge  
395 could be usefully gained. For example, Spanish purse seiner catches were underestimated in  
396 2001 and French trawlers catches were overestimated over the first years (not shown). A

397 possible explanation could be that Spanish purse seiners target bigger fish than the French  
398 trawlers, a hypothesis that could be verified by analysing fishery data further. The model is  
399 designed to enable the integration of knowledge when it becomes available. Finally some of  
400 these discrepancies between observed and modelled data can also be explained by the  
401 propagation of errors from the population sub-model to the exploitation sub-model. For  
402 instance, some of the output variables (catches at age 2-3) were better simulated without  
403 constrained larvae survival.

404

405         The ultimate aim of the model development is to evaluate the impact of a mixture of  
406 spatial and catch regulations that have never been enforced on this fishery. The present study  
407 has shown that the main processes were understood and successfully modelled and that past  
408 trends were reproduced when annual variability in some processes was forced. Consequently,  
409 we consider the model relevant and suggest that the rejected alternative hypotheses should not  
410 necessarily be included in a future uncertainty analysis. Yet, large natural variability in some  
411 parameters, mainly larval survival, limits prediction reliability and scenarios should be  
412 considered. Finally, the sensitivity analysis run on the preliminary version of the model  
413 (Lehuta et al., 2010) showed that even if uncertainties in some processes seemed to have low  
414 impact on population dynamics, interactions with management might result in changes in the  
415 relative importance of the sources of uncertainty. We thus recommend accounting for both the  
416 intrinsic variability and estimation uncertainty in prediction by running the model within an  
417 uncertainty analysis framework.

418

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428  
429

430

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546

Figure 1: Radarplots of the scores of each alternative parameterisation (coloured lines) against each output variable (radial lines) and summary statistics with best parameterisation at the outer ends (top left: correlation value, top right: rank (from 1 to 8) of the parameterisation according to its mean squared error value, bottom left: model efficiency). Biomass: time series of annual spawning stock biomass 2000-2008, Catch/y: time series of annual catches 2000-2004, Cage0 (resp. Cage1, Cage2, Cage3): time series of the catches at age 0 per quarter (resp. age 1, age 2, age 3+), CPe11 (resp. CPe12, CBol1, CBol2, CBolSp): time series of monthly catches by French pair trawler profile 1 2000-2004 (resp. French pair trawlers profile 2, French purse seiners profile 1, French purse seiners profile 2, Spanish purse seiners), R: time series of annual recruitment biomass, Sp. distr.: average distribution of egg production per month over the spawning season. See text for details on statistics.

Figure 2: Catches (numbers) of anchovy of age 2 per quarter over the period 2000-2004 as reported in ICES (2005) (black line) and as predicted by the alternative parameterisations (coloured lines). A: Megg1R1MigA; B: Megg1R1MigJ; C: Megg1R2MigA; D: Megg2R2MigJ; E: Megg2R1MigA; F: Megg1R2MigJ; G: Megg2R2MigA; H: Megg2R1MigJ.

Figure 3. Comparison of the average fraction of eggs produced each month (Allain et al., 2007a) (drawn lines) with box-whisker plots of the inter-annual variability in the estimates based on models assuming MigApr, Megg2 and R1 (A), MigApr, Megg2 and R2 (B).

Figure 4: Monthly catches (kg) of anchovy by the pair trawler fleet profil2 over the period 2000-2004 as reported in log-books (black line) and as predicted by the parameterisations with R1, MigApr and Megg1 (grey, continuous lines) R1, MigApr and Megg2 (grey, dashed lines).

Figure 5: Impact on model fit of the forcing variables. Simulations are run with all forcing variables (forced model), or with one forcing relaxed (average effort, average mortality, average migration) or with all forcing variables averaged (average model). Radarplot displays the correlation between observations and predictions (best at the outer end) for each simulation (coloured lines) and each output variable (radial lines).

Figure 6: Time series of population biomass in May (2000-2008) from ICES assessment of anchovy (Estimated SSB), and hind-casted with different scenarios: forced with larval mortality, spatial distribution and fishing effort (grey dots), leaving out the forcing factors one at a time (replaced by average values), and using no forcing at all (average).

Figure1

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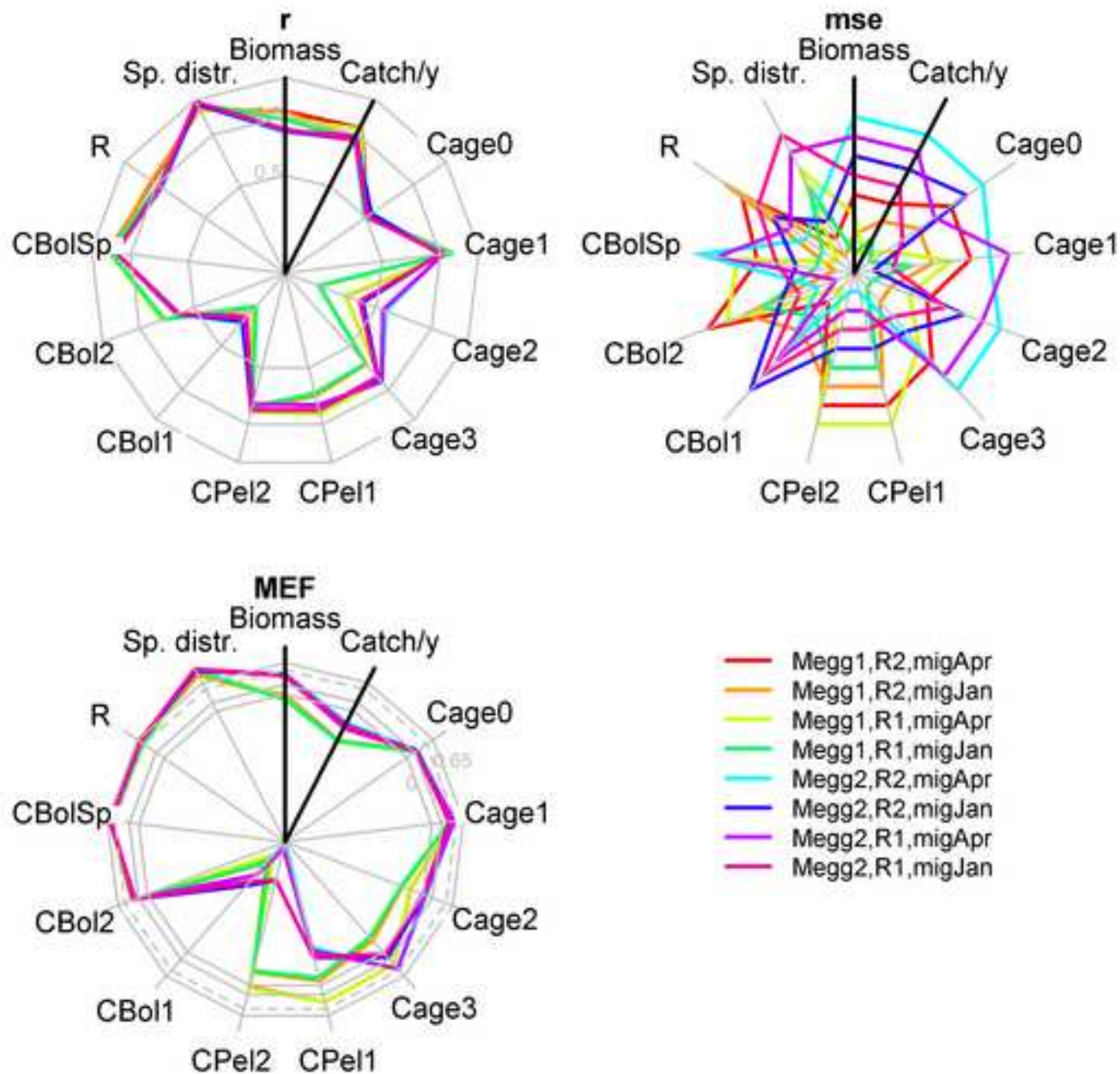


Figure2

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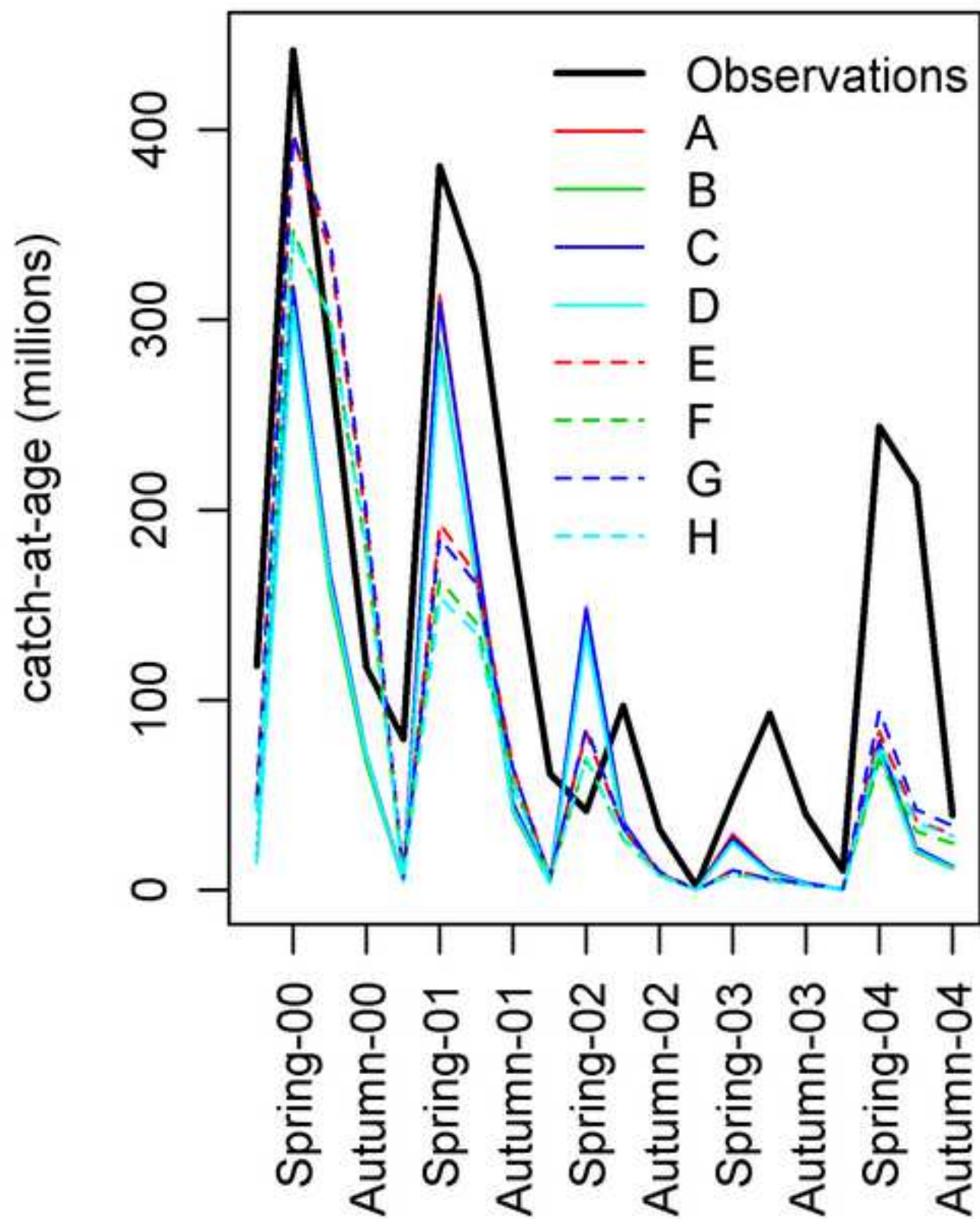


Figure3  
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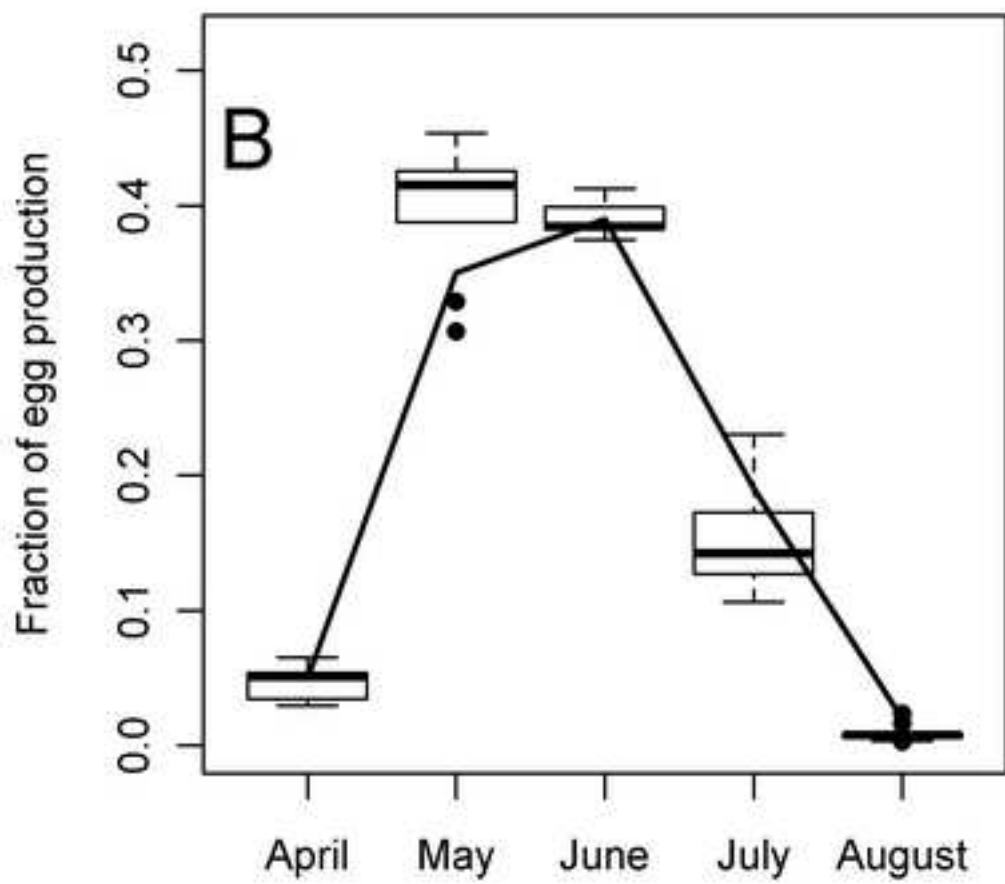
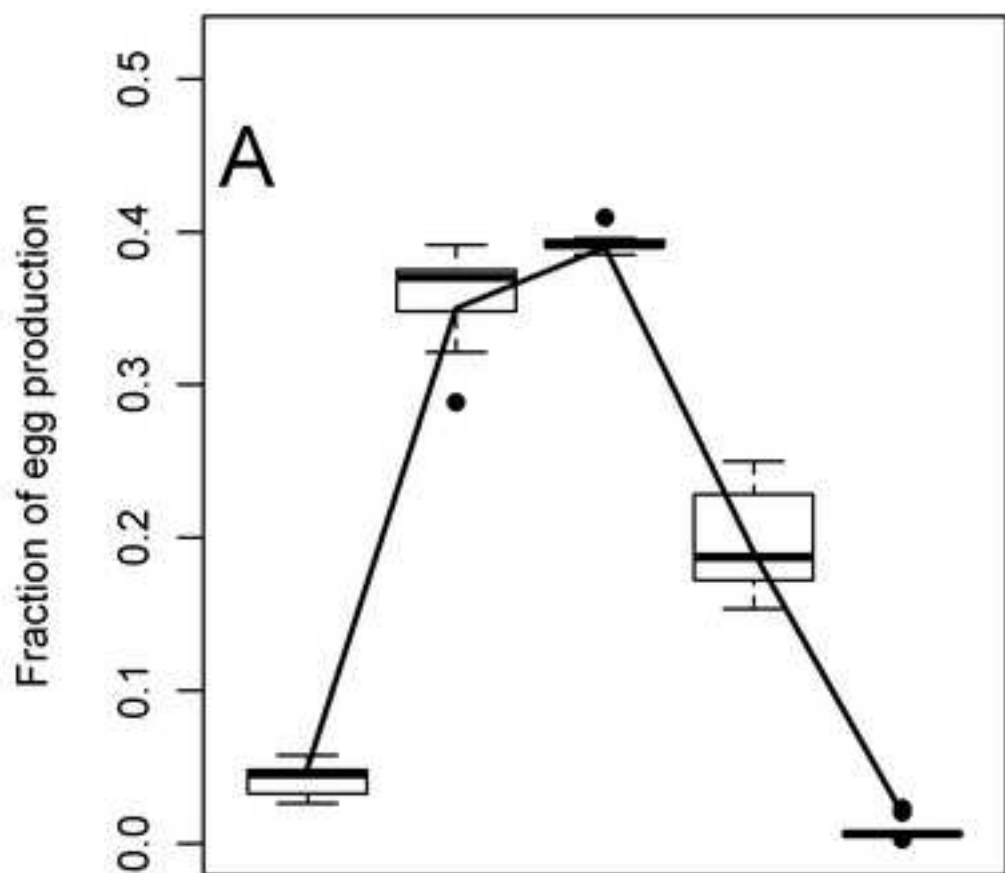


Figure4

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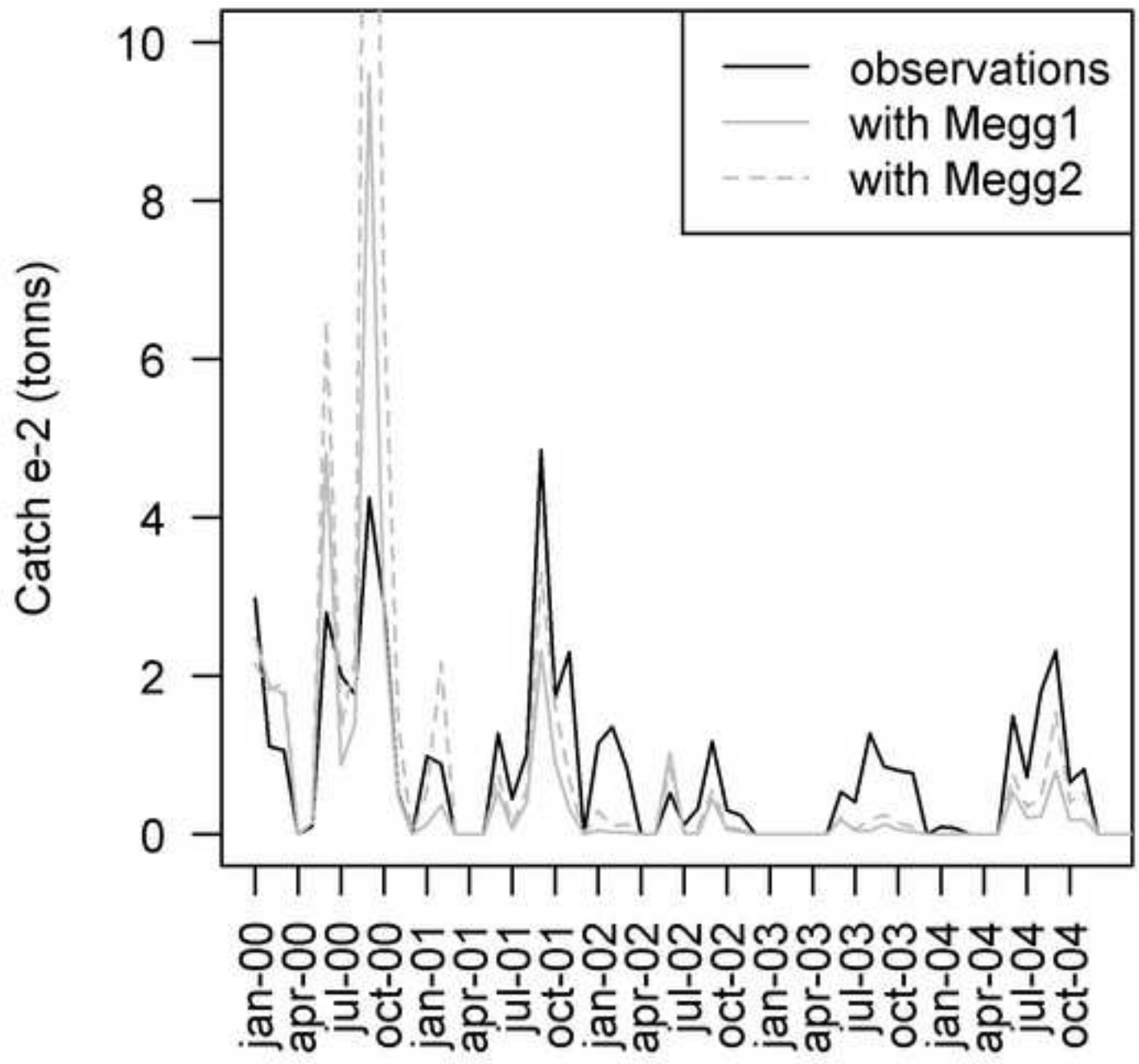




Figure6  
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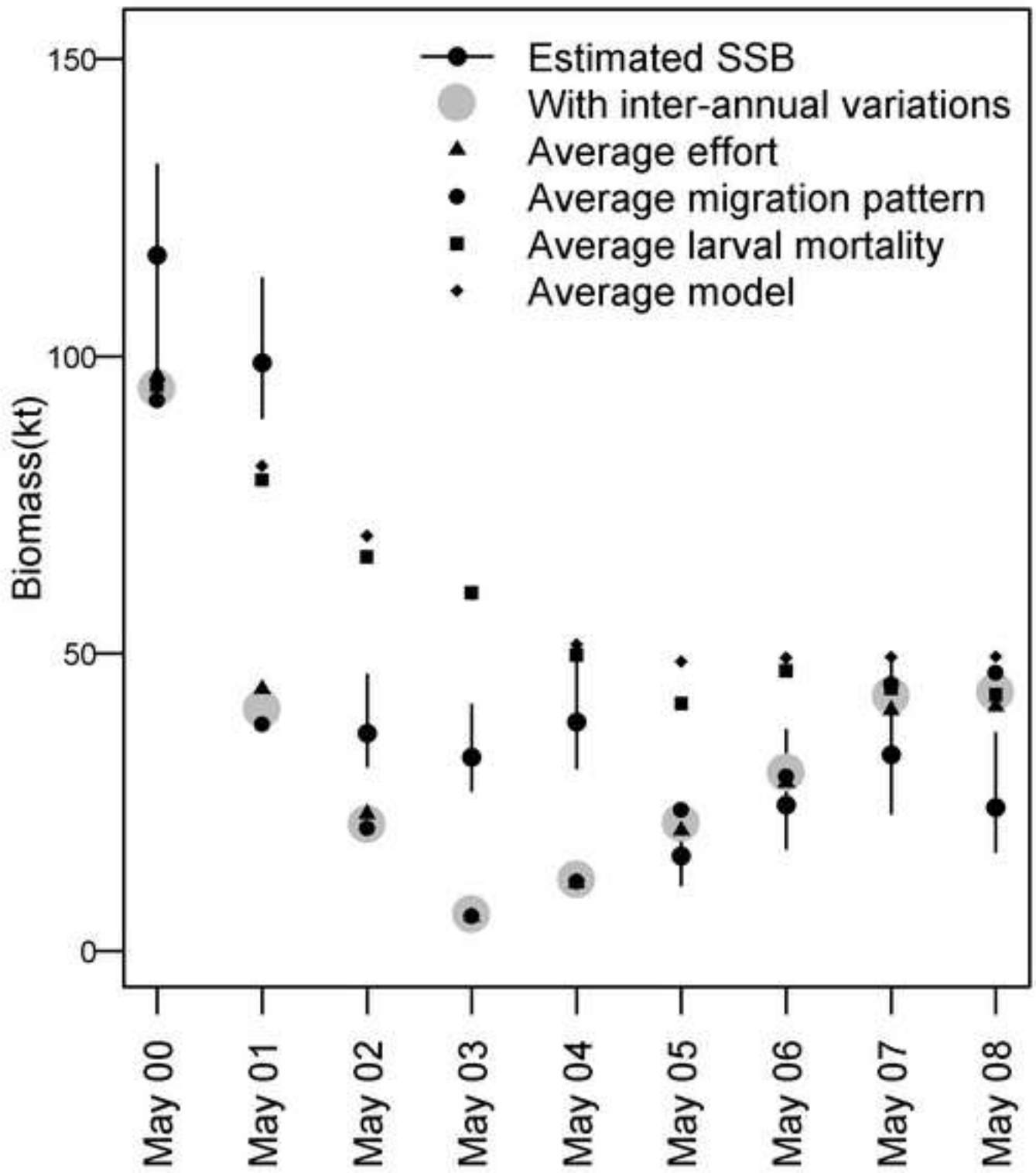


Table1

Process	Modelling assumptions	Parameter values	Reference																		
<b><i>Spatial organization</i></b>																					
Population areas	Five population areas that correspond to habitats occupied seasonally by the different age groups		Vaz et al., 2002; Uriarte et al., 1996; Motos et al., 1996																		
Spatial distribution in spawning areas	Determined by migration coefficients	Percent of observed number-at-age in May per area each year. Average values (%) are reported below :	Motos et al., 1996 ; Pelgas surveys (2000-2008) Vaz et al., 2002; Motos et al., 1996																		
		<table border="1"> <thead> <tr> <th>Area</th> <th>Age-1</th> <th>Age-2+</th> </tr> </thead> <tbody> <tr> <td>Gironde</td> <td>47</td> <td>29</td> </tr> <tr> <td>Landes coastal</td> <td>11</td> <td>15</td> </tr> <tr> <td>Landes Large</td> <td>8</td> <td>18</td> </tr> <tr> <td>Rochebonne</td> <td>27</td> <td>33</td> </tr> <tr> <td>North</td> <td>7</td> <td>5</td> </tr> </tbody> </table>	Area	Age-1	Age-2+	Gironde	47	29	Landes coastal	11	15	Landes Large	8	18	Rochebonne	27	33	North	7	5	
Area	Age-1	Age-2+																			
Gironde	47	29																			
Landes coastal	11	15																			
Landes Large	8	18																			
Rochebonne	27	33																			
North	7	5																			
Migration along Cantabrian coast	Supposed to occur only in years of great Anchovy abundance	Ignored	Uriarte et al., 1996																		
Feeding area	Area “North” defined based on fishing spatial distribution assuming that fishermen follow fish migration and cover the entire anchovy distribution area																				
Migration to feeding area in autumn	Adults migrate in August, recruits (1 year old) in September.		Uriarte et al., 1996; Catch analysis.																		
Population spatial distribution in autumn and winter	Determined by migration coefficients	65% of age-1+ biomass is in area “North” (Figure 1)	Evohe surveys																		
Larval drift and juvenile concentration	Definition of a coastal “Recruit” area where they migrate at the age of 3 months.		Allain et al., 2007b																		

in coastal  
waters

### ***Vital rates***

Growth (cm)	Function of age (monthly scale) with update each month for juveniles, each year for adults.	Von Bertalanffy growth function Linf = 18.77 K = 1.25 t0 = -0.17	Pelgas, 2000-2005
Weight (kg)	Function of length for adult in spring and summer and juveniles all year. Function of age in autumn and winter.	$4.18 \times \text{length}^{3.2} 10^{-6}$ age-1=0.018; age-2=0.031; age-3=0.04	Pelgas, 2000-2005 Market sampling (ICES, WGMHSA, 2000-2004)

### ***Mortality***

Juvenile mortality (month <sup>-1</sup> )	Function of age, monthly updated for juveniles (until the end of the first reproduction)	Exponential decay (Pareto regression) between egg mortality and adult mortality.	Lo et al., 1995
Weighting factor per area of the mortality of larvae	The value is derived from IBM results through linear modeling.	Gironde=0.9; Landes coastal=1.33; Landes offshore=0.96; Rochebonne=0.97; North=0.95	Allain et al., 2007a; Hinrichsen et al., 2011
Weighting factor per year of the mortality of larvae	The value is derived from IBM results through linear modeling.		Hinrichsen et al., 2011

### ***Reproduction***

Fecundity	Function of month and dry weight (90% of fresh weight)	Apr.=200, May=500, Jun-Aug = 650	Motos, 1996
Spawning fraction		Apr=0.18, May-Aug=0.25	Motos, 1996
Maturity	All individuals mature after their first winter		Motos, 1996
Sex ratio		0.5	Motos, 1996
Reproduction function	Linear. Biomass in the last years considered low and consequently	Number of eggs (t,area) = fecundity x spawning biomass(t, area)	

far from saturation threshold.			
Spawning timing and location	Depend on area and date.	Start mid-April in Gironde, Landes coast and Landes offshore; in May in Rochebonne; in June in North.	Uriarte et al., 1996 ; Allain et al., 2007a

Table 1: Well-known population processes integrated in the model, with modelling assumptions, parameter values and references.

Table2

Process	Modelling assumptions	Parameter values	Reference
Migration to spawning area	Juveniles (age-1): January Adults (age-2+): either January ( <b>MigJ</b> ) or April ( <b>MigA</b> )		Uriarte et al., 1996, spatial distribution of fishing effort.
Egg mortality rate (day <sup>-1</sup> )		0.266 ( <b>Megg1</b> )  0.565 ( <b>Megg2</b> )	Eggs survey, Somarakis et al., 2004; ICES 2006, 2007, 2008, 2009; Pertierra, 1997
Adults mortality (year <sup>-1</sup> )	U-shaped curve: age-2 mortality lower than age-1 and age-3	1.2 [0.5 ;3]  calibrated on 2005-2008 period	ICES WGMHSA, Chen and Watanabee, 1989
Spawning duration	Depends on individual length at the beginning of the spawning season	3 months for adults. Oldest juveniles spawn for three months like adults, youngest for two months. Hypothesis <b>R1</b> states that youngest fishes are those born in July and August, while hypothesis <b>R2</b> states that youngest fishes are those born in June, July and August.	Pertierra et al., 1997; Motos, 1996
Accessibility	Probability for a fish in a given area at a given season to be fished by a standard fishing unit with non-selective gear	calibrated on 2000-2004 period	

Table 2: Poorly-known or contradictorily described population processes integrated in the model, with alternative modelling assumption or estimation method and references.

Table3

	Parameterizations			Calibrated parameters			RSS	
	Egg mortality	Reproduction duration	Migration date	Adult mortality	q0	q1		q2
Hindcast models forced by past time series	<b>Megg1</b> = 0.266	<b>R1</b>	April	3.03	3.56e-5	4.68e-3	2.20e-3	2.66e18
			January		3.23e-5	4.46e-3	2.41e-3	2.70e18
		<b>R2</b>	April	2.97	3.59e-5	4.48e-3	2.18e-3	2.62e18
			January		3.30e-5	4.29e-3	2.36e-3	2.66e18
	<b>Megg2</b> = 0.565	<b>R1</b>	April	1.67	8.98e-5	2.66e-3	2.70e-3	2.36e18
			January		8.35e-5	2.27e-3	3.31e-3	2.35e18
		<b>R2</b>	April	1.63	8.44e-5	2.59e-3	2.70e-3	2.29e18
			January		7.67e-5	2.18e-3	3.23e-3	2.28e18

Table 3: Calibration results of the adult natural mortality and accessibility coefficients (q0, q1 and q2) and corresponding residuals sum of squares value (RSS) between simulated and observed catches at age per quarter, for different scenarios of egg mortality, reproduction duration and migration date.