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# 1       **Testing novel methods for short-term forecasting of European glass eel**

## 2   **recruitment**

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19

20 Abstract:

21 Recruitment forecasting constitutes a major issue in population dynamics, especially in stock  
22 assessments. In many cases, high recruitment stochasticity thwarts the determination of a

23 stock-recruitment (SR) relationship. When no SR relationship is available, recruitments can  
24 be projected from past trends using methods such as the geometric means of the past  
25 recruitments. This approach implicitly assumes stability in upcoming years and might not be  
26 appropriate in the case of regime shifts. Recruitment forecasting is particularly critical when  
27 predicting fishing opportunities for recruitment fisheries. The fishery of glass European eels  
28 (*Anguilla anguilla*) is an example of a recruitment fishery. The French glass eel fishery,  
29 which is currently guided by two models to forecast upcoming recruitments and derive fishing  
30 opportunities, has failed to achieve management targets. This study develops new models that  
31 forecast glass eel recruitments without assumptions about the SR relationship, and with  
32 flexible assumptions about future recruitment evolutions. Tests based on multiple criteria  
33 found the best performance in a random slope model, which provides flexibility to track  
34 recruitment dynamics while balancing the interests of fisheries, management and  
35 conservation. This model has wide potential for trend projections in natural resource  
36 management, economics and other fields.

37 Keywords: Recruitment forecasting, Bayesian stock assessment, random walk, multicriteria,  
38 European eel

39

## 40 1 Introduction

### 41 1.1 Recruitment: a key element in population dynamics

42

43 Understanding and quantifying the renewal of populations is important, especially for  
44 exploited species, such as fish, for which renewal is a critical process in the sustainability of  
45 the fishery. Among the many ecological processes, such as mortality (both natural and  
46 anthropogenic) and biomass growth, the fishery population dynamics rely on recruitment,

47 i.e., offspring resulting from reproduction that become harvestable by the fishery (Mangel et  
48 al., 2010). Fish recruitment is typically highly variable since it depends on both biotic (prey,  
49 predators) and abiotic factors (temperature, currents) (Maunder and Thorson, 2019; Miller et  
50 al., 2009; Myers, 1998; Subbey et al., 2014) and is sensitive to regime shifts (Ljunggren et  
51 al., 2010; Mueter et al., 2007; Perretti et al., 2017). In this context, recruitment modeling,  
52 and its temporal variation, plays a critical role in estimating future abundance and in setting  
53 biological reference points that guide sustainable harvesting (Cury et al., 2014; Maunder and  
54 Thorson, 2019; Subbey et al., 2014; Sydeman et al., 2018).

55

## 56 1.2 Forecasting short-term recruitment

57

58 Stock-recruitment (SR) relationships can be used to predict recruitments arising from  
59 a given spawning biomass (Beverton and Holt, 1993; Hilborn and Stokes, 2010; Ricker,  
60 1954). In practice, it is often difficult to discern the nature of an SR relationship and to  
61 estimate its parameters (Myers, 1998; Stocker and Noakes, 1988; Sydeman et al., 2018).  
62 Errors in the choice of such relationships can undermine the reliability of a fishery stock  
63 assessments (Hilborn and Walters, 2013; Maunder and Deriso, 2003; Myers, 2001; Plagányi  
64 et al., 2019).

65 When no clear SR relationship has been established for a stock (ICES, 2003),  
66 forecasting recruitments generally requires making assumptions regarding recent and future  
67 trends. The geometric mean of recent recruitments is often used in such short-term  
68 recruitment forecasts (ICES, 2006; Needle, 2001). Environmental information (e.g., the use  
69 of an upwelling index) or the empirical coupling of environmental and biotic information  
70 can also improve forecasts (Needle, 2001). Since long-term temporal trends have been

71 observed for many stocks (Gascuel et al., 2016; STECF, 2022), the use of methods not  
72 accounting for regime shifts could lead to potential biases in management recommendations.

73

### 74 1.3 Recruitment fishery

75

76 Assumptions about future recruitments are fundamental in the process of estimating  
77 fishing opportunities. They are even more crucial for a fishery exploiting the young of the  
78 year or juveniles, called a recruitment fishery, since fishing opportunity estimations directly  
79 depend on the reliability of these assumptions.

80

### 81 1.4 Case study: the European eel (*Anguilla anguilla*) recruitment fishery

82

83 The glass eel fishery of the European eel (*Anguilla anguilla*) is an example of a  
84 recruitment fishery (Briand et al., 2008; Dekker, 2003, 2002). The European eel is a  
85 facultatively catadromous species that reproduces in a unique spawning ground in the  
86 Sargasso Sea (Wright et al., 2022). European eel larvae are transported across the Atlantic  
87 Ocean through oceanic currents and metamorphose into glass eels as they reach the  
88 continental shelves from Norway to Morocco, including the Mediterranean and Baltic basins  
89 (Tesch, 2003). The arrival of glass eels in the continental waters compels recruitment. The  
90 eels enter the continental waters, turning into yellow eels, and colonize a large range of  
91 habitats from saline to fresh water (Arai and Chino, 2012; Daverat et al., 2006). After a  
92 growth phase, they metamorphose into silver eels and migrate back to the spawning ground  
93 (Righton et al., 2016). Despite its large distribution area, the European eel is panmictic (Als  
94 et al., 2011). The species is targeted by commercial and recreational fisheries throughout its  
95 continental life stages (Dekker, 2019).

96 Glass eel recruitment declined by approximately 15% per year from 1980 to 2010,  
97 remaining at a low level (Dekker, 2019; ICES, 2022; Moriarty, 1990). In 2000, the fishery  
98 was declared outside safe biological limits due to impaired recruitment and threatened stock  
99 renewal (ICES, 2001). The European eel was added to Appendix II of the Convention on  
100 International Trade in Endangered Species of Wild Fauna and Flora in 2007 (CITES, 2007)  
101 and has been listed as critically endangered by the International Union for Conservation of  
102 Nature since 2008 (Freyhof and Kottelat, 2008). In 2007, the European Council adopted  
103 Regulation No. 1100/2007, known as the Eel Regulation, requiring member states to  
104 establish Eel Management Plans (EMPs) in their national waters that aimed at reducing  
105 anthropogenic mortalities at all life stages (EU, 2007). The French EMP goal was to reduce  
106 mortality by 40% (glass eel) or 30% (yellow and silver eels) in the first three years of the  
107 plan, and by 60% by 2015 for each stage mentioned previously (the harvest rate being used  
108 to quantify the mortality). To reduce the fishing mortality of glass eels, France enforced  
109 measures including a national glass eel Total Allowable Catch (TAC) system for commercial  
110 fisheries (Ministère de l'Écologie, de l'Énergie, du Développement durable et de  
111 l'Aménagement du Territoire et al., 2010). In the absence of an established SR relationship,  
112 the Scientific Committee uses two recruitment models based on past abundance indices to  
113 forecast upcoming recruitments to support the determination of a glass eel TAC that will  
114 produce the needed reduction in anthropogenic mortality (Beaulaton et al., 2020). However,  
115 the management target has not been achieved since 2015, questioning the quality of these  
116 short-term forecast models and their underlying assumptions.

117

## 118 1.5 Devising and comparing short-term recruitment forecast models

119

120 Devising recruitment models that are robust to departures from their underlying  
121 assumptions is a key challenge (here, we used “robustness” as defined by Box (1979), i.e.,  
122 the property that makes model outcomes insensitive to departures from ideal assumptions).  
123 In the context of an undefined SR relationship and past recruitment knowledge, this paper  
124 proposes two new recruitment models with flexible recruitment evolution assumptions to  
125 produce robust short-term recruitment forecasts. Furthermore, this work presents a model  
126 comparison strategy based on new criteria for assessing the implications of model outcomes  
127 for conservation, management and exploitation. This work is undertaken through a  
128 recruitment fishery case study: the European eel (*Anguilla anguilla*) recruitment fishery.

129

## 130 2 Material and Methods

131

132 In this work, we considered ourselves to be in the position of the Scientific Committee  
133 of 2020, which met during summer 2020 and was in charge of providing advice for the 2020-  
134 2021 fishing season.

135

### 136 2.1 Glass eel fishery data

137

#### 138 2.1.1 Recruitment time series

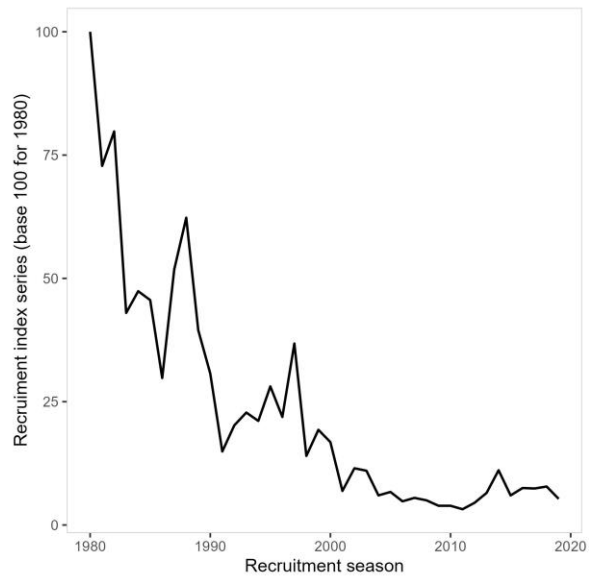
139

140 Using recruitment time series collected from widely distributed monitoring sites and  
141 due to varying regional time series trends in these series, the Working Group on Eels  
142 (WGEEL) uses a General Linear Model (GLM) to derive two glass eel recruitment indices,

143 the “North Sea” and “Elsewhere Europe” (i.e., Europe excluding the North Sea and Baltic  
144 Sea) indices from 1980 to 2019 (ICES, 2022; ICES and EIFAC, 2010). The reconstructed  
145 values are given in reference to the geometric mean of the period 1960-1979. While these  
146 recruitment indices are considered to be good indicators of the population status, the complex  
147 ecology of the species hinders the derivation of abundance indices at later life stages,  
148 including spawning stock biomass (Drouineau et al., 2016; ICES, 2022). As such, while  
149 recruitment trends are well documented, attempts to fit SR relationships have not been  
150 successful (Dekker, 2004; ICES, 2013). Since the “Elsewhere Europe” index covers France  
151 and includes several French time series (ICES, 2022), it is thought to describe past evolution  
152 recruitments in France. Therefore, it was used as a recruitment estimate in this study (Fig. 1).  
153 Since the Scientific Committee focuses on the 1980-2019 recruitment period to make its  
154 forecast consistent with their model assumptions, the dataset is restricted to the post-1980  
155 time range. The 1980 recruitment value is taken as a reference value and set at 100, so  
156 upcoming annual recruitments are calculated as a percentage of this reference value. Since  
157 glass eels reach continental French waters between November and April (ICES, 2020), the  
158 annual recruitment is spread over two calendar years (e.g., glass eel arrivals between  
159 November 2018 and April 2019, also called season 2019). For simplicity, season “ $t$ ” refers to  
160 the season spread over years  $t-1$  and  $t$ .

161





162

163 **Fig. 1.** Recruitment estimates used in this study: the “Elsewhere Europe” recruitment index  
 164 from 1980 to 2019 (ICES WGEEL 2019); it uses base 100 for the 1980 season.

165

166 **2.1.2 Landing data**

167

168 French glass eel landing data reported to the WGEEL from 1980 to 2020 were used  
 169 (catches from 2009 were missing). The harvest rate corresponds to the annual ratio between  
 170 landings data and recruitment. Since recruitment is a relative index (i.e., a dimensionless  
 171 variable rather than an absolute estimate of abundance or biomass), the ratio of the landings  
 172 data and the recruitment index gives a relative harvest rate index, with a mean reference  
 173 harvest rate index calculated over the period 2004-2008 and defined as the 100 baseline  
 174 (Beaulaton et al., 2020).

175

176 **2.2 Recruitment forecasting models**

177

### 178 2.2.1 General principle

179

180 In France, the Scientific Committee in charge of recommending TACs for the forthcoming  
181  $t+1$  fishing season generally meets in early summer  $t$ . At this point, recruitment data are  
182 available up to season  $t-1$  (since fishing season  $t$  is not yet finished). Therefore, the Scientific  
183 Committee needs to forecast recruitments for seasons  $t$  and  $t+1$  to support fishing  
184 opportunities for season  $t+1$ . To provide first insights on the recruitment level of the ongoing  
185 season  $t$ , the Scientific Committee collects qualitative feedback from professional fishermen,  
186 associations in charge of on-field scientific monitoring of diadromous fish, environmental  
187 inspectors, and foreign scientists. This qualitative information allows building minimum and  
188 maximum recruitment values for fishing season  $t$  as compared to the previous season, which  
189 are then used as a censor interval in Bayesian forecasting models. In accordance with the  
190 general pattern observed by the Scientific Committee, and since the 2020 season is  
191 uncompleted, recruitment in 2020 is equivalent to recruitment in 2019 (e.g., 5.3) but with a  
192 substantial uncertainty interval (e.g.,  $5.3 \pm 3$ ) (Beaulaton et al., 2020). Based on the WGEEL  
193 “Elsewhere Europe” recruitment index from 1980 to 2019, and on the qualitative expert  
194 feedback for 2020, the recruitment models are able to forecast the upcoming recruitment.

195

### 196 2.2.2 Existing glass eel recruitment models: single-trend and two-trend models

197

- 198 • Modeling framework

199

200 To forecast glass eel recruitment, two models fitted in a Bayesian framework have been  
201 developed by the Scientific Committee and have been in use since 2014. Both models have a

202 yearly time step (Beaulaton et al., 2020). They are fitted to the WGEEL “Elsewhere Europe”  
203 recruitment index from 1980 to 2019, considering the censor season for 2020.

204

- 205 • Introduction of the two existing recruitment models

206

207 This first recruitment model, called the single-trend (ST) model, postulates that  
208 recruitment changes exponentially at a constant rate. Thus, recruitment is assumed to vary  
209 linearly with a unique slope coefficient  $a$  in the log scale. Perturbations are autocorrelated in  
210 time to reflect the fact that recruitment above the decreasing central trend is generally  
211 followed by recruitment above the central trend (Beaulaton et al., 2020):

212

$$213 \quad \mathbf{1} \quad \text{For } t \text{ in } [1980; 2022], IR_t \sim Ln(\mu_{IR_t}, \sigma_{IR}^2)$$

214

$$\mu_{IR_t} = \mu_{IR_0} + a \cdot t + \rho \cdot \varepsilon_t$$

$$\varepsilon_t = \log(IR_{t-1}) - [\mu_{IR_0} + a \cdot (t - 1)]$$

215

216 where  $IR_t$  is the recruitment index for year  $t$  that follows a lognormal distribution of mean  $\mu_{IR_t}$   
217 and variance  $\sigma_{IR}^2$  (log scale).  $\mu_{IR_0}$  is an initialization parameter,  $a$  is the recruitment slope,  $\varepsilon_t$  is  
218 the annual autocorrelated random disturbance and  $\rho$  is its autocorrelation coefficient.

219

220 Due to a possible change in trends in recent years (ICES, 2019), the Scientific Committee  
221 proposed an alternative recruitment model in 2014. This model postulates a change in the  
222 recruitment trend in 2012, as it is the first year in which the implementation of EMPs could  
223 have had an effect on recruitment (Beaulaton et al., 2020). Two recruitment slopes  $a_1$  (before  
224 2012) and  $a_2$  (since 2012) are considered. The two-trend (TT) model is defined as follows:

225

226 **2** For  $t$  in  $[1980; 2022]$ ,  $IR_t \sim Ln(\mu_{IR_t}, \sigma_{IR}^2)$

227 **For  $t < 2012$  (time period 1)**,  $\mu_{IR_t} = \mu_{IR_0} + a_1 \cdot t + \rho \cdot \varepsilon_{t_1}$

228  $\varepsilon_{t_1} = \log(IR_{t-1}) - [\mu_{IR_0} + a_1 \cdot (t - 1)]$

229

230 **For  $t \geq 2012$  (time period 2)**,  $\mu_{IR_t} = \mu_{IR_{2011}} + a_2 \cdot (t - 2011) + \rho \cdot \varepsilon_{t_2}$

$\varepsilon_{t_2} = \log(IR_{t-1}) - [\mu_{IR_{2011}} + a_2 \cdot (t - 2011)]$

231

232

233 The variables are similar to the ones in the ST model (Equation 1). Then,  $\varepsilon_{t_1}$  and  $\varepsilon_{t_2}$   
234 represent annual autocorrelated random disturbances depending on time periods (before or  
235 after 2012), and  $\rho$  is the common autocorrelation coefficient. Models currently used to support  
236 glass eel TAC recommendations are innovative because of their integration of a long-term  
237 trend and a possible regime shift with the TT model. However, because of their rigid  
238 underlying assumptions on recruitment future evolution, both model outcomes critically  
239 depend on whether a regime shift occurred and whether it took place in 2012. Moreover, the  
240 TT model is open only to a regime shift in a specific year and not to any other regime shift.

241

242 **2.2.3** Development of alternative glass eel recruitment models: the spike and slab model

243 and the random slope model

244

245 Two new models were developed to address the limitations of the existing models.

246

247 **2.2.3.1** *Spike and slab model*

248

249 In contrast to the TT model, the spike and slab (SS) model aims to objectively test for the  
250 existence of a change in slope in 2012.

251

- 252 • The spike and slab method

253 The spike and slab method is a Bayesian selection technique to identify the most  
254 relevant predictors of interest (George and McCulloch, 1993; Ishwaran and Rao, 2005; Titsias  
255 and Lázaro-Gredilla, 2011). It relies on a specific mixture of priors based on a binary  
256 indicator called  $\gamma$ , which quantifies, *a posteriori*, whether the variable of interest should be  
257 included in the model (George and McCulloch, 1993).

258

- 259 • Spike and slab model formulation

260 The spike and slab prior appears suitable for objectively assessing the existence of a  
261 change in the recruitment slope: it provides insights into whether a slope change actually took  
262 place in 2012. Similarly to the TT model (Beaulaton et al., 2020), a potential slope change is  
263 assumed to occur in 2012 in the SS model. A new variable  $diff_a$  was introduced as the  
264 difference between the two slopes  $a_2$  and  $a_1$ :

265

$$266 \quad \mathbf{3} \quad diff_a = a_2 - a_1$$

267

268 Instead of setting the priors to  $a_1$  and  $a_2$  (as in the TT model), we set the priors to  $a_1$  and  
269  $diff_a$ :

270

$$271 \quad \mathbf{4} \quad diff_a \sim N(0, \sigma_{diff_a}^2)$$

$$272 \quad \sigma_{diff_a}^2 = c \cdot (1 - \gamma) + d \cdot \gamma \text{ with } c = 1 \cdot 10^{-4} \text{ and } d = 3 \cdot 10^{-2}$$

273

$$\gamma \sim Ber(0.5)$$

274

275  $\gamma$  is a binary value; when set to 0, the  $diff_a$  prior is narrow at approximately 0, so  $a_2$  is  
276 constrained to be similar to  $a_1$ ; when set to 1, the resulting prior promotes  $diff_a$  distinct from 0,  
277 so  $a_2$  is distinct from  $a_1$ . Parameters  $c$  and  $d$  tune the mixture of the two normal distributions  
278 of the different priors. Following Ishwaran and Rao (2005), they were chosen to provide  
279 sufficiently distinct probability distributions to distinguish slope changes from slope  
280 conservation. A sensitivity analysis is provided in the Supplementary Material. Posterior  
281 distributions of  $\gamma$  and  $diff_a$  indicate whether the slope change should be included (mean of the  
282  $\gamma$  posterior distribution  $\approx 1$  and  $diff_a \neq 0$ ) or not (majority of  $\gamma = 0$  and  $diff_a$  close to 0). With  
283 such priors, the SS model is the combination of the *a posteriori* distribution relative weights  
284 of situations where  $\gamma = 0$  (equivalent to the ST model) or  $\gamma = 1$  (equivalent to the TT model),  
285 and the ST and TT models are two subcases of the SS model.

286

### 287 2.2.3.2 The random slope recruitment model

288

289 The TT and SS models allow a change in the recruitment trend in a single specific year  
290 or no changes at all. An alternative option is to consider the recruitment slope as a time-  
291 varying random variable. Local linear trend models are widely used to model and predict  
292 macroeconomic time series (Delle Monache and Harvey, 2012). In such models, the slope is  
293 itself a time-varying random variable following a random walk. Therefore, the random slope  
294 (RS) model is defined as follows:

295

296 5 For  $t$  in  $[1980;2022]$ ,  $IR_t \sim Ln(\mu_{IR_t}, \sigma_{IR}^2)$

297  $\mu_{IR_t} = \mu_{IR_{t-1}} + a_t + \eta_t$  with  $\eta_t \sim N(0, \sigma_\eta^2)$

298  $a_t = a_{t-1} + \delta_t$  with  $\delta_t \sim N(0, \sigma_\delta^2)$

299

300 where  $IR_t$  is still the recruitment index for year  $t$  that follows a log normal distribution of  
301 parameters  $\mu_{IR_t}$  (mean in the log scale) and  $\sigma_{IR_t}^2$  (variance in the log scale). Then,  $\mu_{IR_t}$  is  
302 assumed to be centered around its previous value, plus a slope  $a_t$  and a random noise  $\eta_t$ . The  
303 slope  $a_t$  itself follows a random walk, with random noise  $\delta_t$ . It can be demonstrated that  $\sigma_\delta$   
304 (variance of the noise of the mean changes) and  $\sigma_\eta$  (variance of the noise of the slope random  
305 walk) are redundant, and as such, estimating both parameters can lead to identifiability issues  
306 (Cole, 2020; Schnute, 1994). Here, we assumed that  $q_\delta = (q_\eta / 2)^2$ . By doing so, the model  
307 is then equivalent to a commonly used double exponential smoothing (Harvey, 1986) and  
308 yields robust predictions (Delle Monache and Harvey, 2012). The ST, TT and SS models are  
309 special cases of this more generic RS model.

310

### 311 2.3 Bayesian inference and priors

312

313 The Bayesian models were fitted using JAGS (Plummer, 2003). We used the runjags  
314 package as an interface between R and JAGS (Denwood, 2016). Uninformative priors were  
315 used for most parameters (Table 1). Three chains were run in parallel for 200,000 iterations  
316 with a thinning period of ten after a burn-in period of 200,000 iterations. Model convergence  
317 was checked using Gelman tests (Gelman and Rubin, 1992) and with graphical verifications  
318 by traceplots.

319

320 **Table 1.** Priors on the models (“ST”: Single-trend; “TT”: Two-trend; “SS”: Spike and slab;  
321 “RS”: Random slope) parameters and the number of associated equations (“Eq.”).

	<b>Variables</b>	<b>ST</b> (Eq. 1)	<b>TT</b> (Eq. 2)	<b>SS</b> (Eq. 4)	<b>RS</b> (Eq. 5)
1	$\mu_{IR_0}$			N(0,0.01)	
2	$\sigma_{IR}$			Gamma(0.01,0.01)	
3	$\rho$		U(-1,1)		
4	$\eta$		N(0,1)		For t in [1980 ;2022], $\eta_t \sim N(0, \sigma_\eta^2)$
2	$\sigma_\eta$				Gamma(0.01,0.01)
6	$a$	N(0,0.01)			N(0,0.01)
7	$a_1$		N(0,0.01)		
8	$a_2$		N(0,0.01)		
9	$diff_a$			N(0, $\sigma_{diff_a}^2$ )	
10	$\gamma$			Ber(0.5)	
11	$\delta_t$				For t in [1980 ;2022], $\delta_t \sim N(0, \sigma_\delta^2)$
12	$\sigma_\delta$				$\sigma_\delta = (\sigma_\eta^2 / \sigma_{IR}) * 0.5$

322

## 323 2.4 Model comparison strategy

324

### 325 2.4.1 Deviance Information Criterion to assess model fitting quality

326

327 The Deviance Information Criterion (DIC), a Bayesian version or generalization of the  
328 Akaike Information Criterion, quantifies the trade-off between goodness of fit and model  
329 complexity (Spiegelhalter et al., 2002). The DIC is one of the most widely used criteria to  
330 assess the performance of Bayesian models (Gelman et al., 2014). The DIC was calculated  
331 through 200,000 iterations with a thinning period of ten for each model. Like the AIC, the



332 DIC assesses the capacity of the model to predict observed data and, as such, quantifies the  
333 hindcasting capacity of the model. However, it does not assess the forecasting ability of a  
334 model, which is necessary to underpin robust stock management advice (Kell et al., 2021).

335

#### 336 2.4.2 Assessing model forecasting performance through a simulation exercise

337

338 Assessing the predictive capacity of the models requires a dataset in which the “true”  
339 recruitment is known and can be compared to model forecasts. In this context, we carried out  
340 a simulation exercise to generate artificial “surrogate” datasets.

341

- 342 • Generating surrogate recruitment time series

343

344 Three scenarios were used to simulate surrogate recruitment time series from 2020 to  
345 2030. To simulate the declining recruitment in Scenario 1, we used the ST model to construct  
346 a forward recruitment index series from 2020 to 2030. The TT model enabled the generation  
347 of a forward recruitment time series for Scenario 3 to replicate an increasing recruitment trend  
348 since 2012. Finally, Scenario 2 was an intermediate situation between Scenarios 1 and 3. The  
349 future recruitment of Scenario 2 was simulated by the TT model with  $diff_a$  set as the  
350 difference between the  $median(a_2)$  and  $median(a_1)$  (both estimated by the TT model), which  
351 equates to  $diff_a$  close to 0. Thus, Scenario 2 roughly assumes stable recruitment. For each  
352 scenario, 2,000 “observed” recruitment time series were generated (Fig. 2, Part 1).

353

- 354 • Fitting the model to the simulated recruitment time series

355 Each model was fitted to the simulated recruitment time series up to season  $t$  according to  
356 the following iterative algorithm, mimicking the process of the Scientific Committee (Fig. 2,  
357 Parts 2 and 3):

- 358 • For each Scenario  $s$  from 1 to 3
- 359 • For each time series  $i$  from 1 to 2,000
- 360 • For each model  $m$  from 1 to 4
- 361 • For each year  $t$  from 2020 to 2029
  - 362 ○ The combination of the WGEEL time series (from 1980 to 2019) and the  
363 simulated recruitment from 2020 to  $t-1$  is used as input data (for  $t =$   
364 2020, only the WGEEL time series is used).
  - 365 ○ The censor interval for recruitment  $t$  is set as the value at time  $t-1 \pm 3$  (to  
366 reproduce the management task).
  - 367 ○ The model  $m$  forecasts recruitment in  $t+1$ , and this forecasted value is  
368 compared with the corresponding “observed” value (i.e., from the  
369 simulated recruitment time series).

370

371 This process generates recruitment forecasts from 2021 to 2030. All the recruitment  
372 models were fitted to the three recruitment scenarios. For this prospective analysis, one chain  
373 was run with 5,000 iterations with a thinning period of ten, resulting in 500 samples (after a  
374 burn-in period of 10,000 iterations for the ST, TT and SS models, and 200,000 iterations for  
375 the RS model to ensure convergence, since it has many more parameters). These parameters  
376 were applied to the three scenarios.

- 377
- 378 • Quantifying model forecasting performances

379

380 The forecasting performance of each model was evaluated by calculating Percent BIAS  
381 (PBIAS) (Gupta et al., 1999). The PBIAS indicates whether the model tends to overestimate  
382 (negative PBIAS) or underestimate (positive PBIAS) compared to “observed” recruitment  
383 indices, where 0 is the optimal PBIAS value.

384 For a Scenario  $s$  (1:3), a simulated recruitment index series  $i$  (1: 2,000), a model  $m$  (1:4),  
385 and a year  $t$  (2021:2030), an annual PBIAS is calculated by comparing the yearly “observed”  
386 recruitment  $IR_{obs}$  with the median of the posterior distribution estimated by the forecasting  
387 model  $q50(IR_{sampled})$ . We therefore obtain 20,000 PBIAS values (2,000 simulated recruitment  
388 trajectories\*10 years) per model for each scenario (i.e., 20,000\*4\*3 PBIAS values *in fine*)  
389 (Fig. 2). Therefore, PBIAS is calculated as follows:

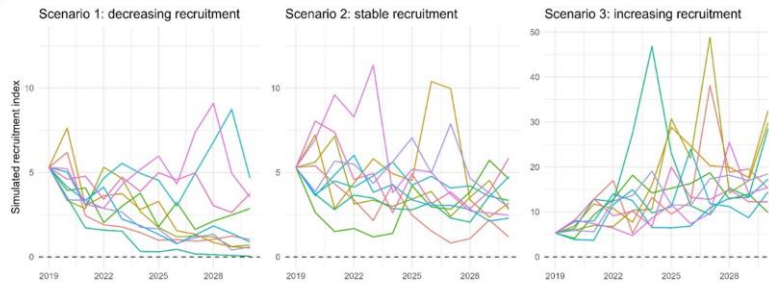
390

$$PBIAS_{s,m,i,t} = \frac{IR_{obs\ s,i,t} - q50(IR_{sampled\ s,i,m,t})}{IR_{obs\ s,i,t}} \times 100$$

391

392

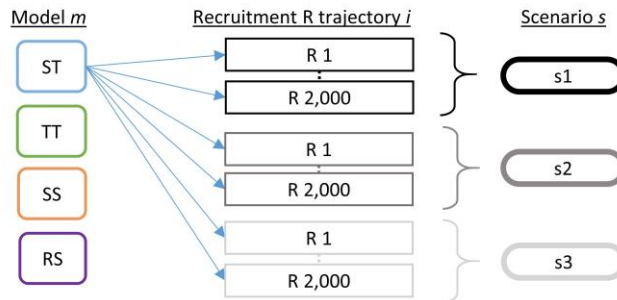
**1 Simulating recruitment trajectories through 3 scenarios**



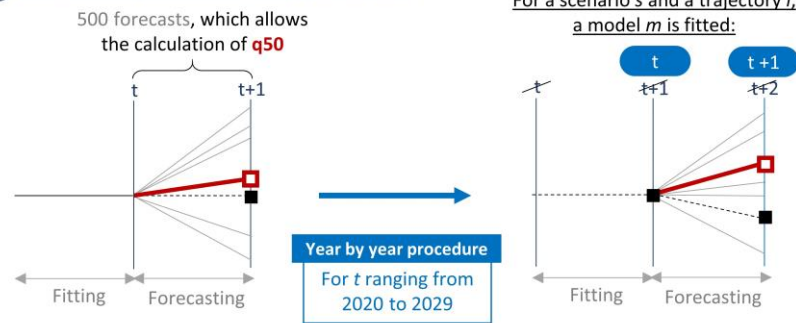
Evolution of recruitment according to the three scenarios considered. Each colored line represents a recruitment trajectory (10 trajectories plotted among the 2,000 trajectories simulated).

**2 Material for the simulation exercise**

Each model is fitted to each trajectory of each scenario.



**3 Model fitting and forecasting year by year**



**4 Indicators calculation: PBIAS**

For  $s$  ranging from 1 to 3,  
 For  $i$  ranging from 1 to 2,000,  
 For  $m$  varying between ST, TT, SS, RS,  
 For  $t$  ranging from 2021 to 2030:

$$PBIAS_{s,i,m,t} = \frac{\blacksquare_{s,i,t} - \blacksquare_{s,i,m,t}}{\blacksquare_{s,i,t}} \times 100$$

Legend  
 ■  $I_{Obs}$ : "Observed" value at  $t$  from a trajectory  $i$  of a scenario  $s$   
 □  $q50(I_{Rsampled})$ : Estimated value (q50) at  $t$  by model  $m$  fitted on trajectory  $i$  of scenario  $s$

393

394 **Fig. 2.** Diagram showing the quantification of the forecasting performance through the  
 395 calculation of PBIAS and its different steps (from 1 to 4).

396

- 397 • Quantification of the risk for exploitation, resource and management: three  
 398 comparison criteria

399

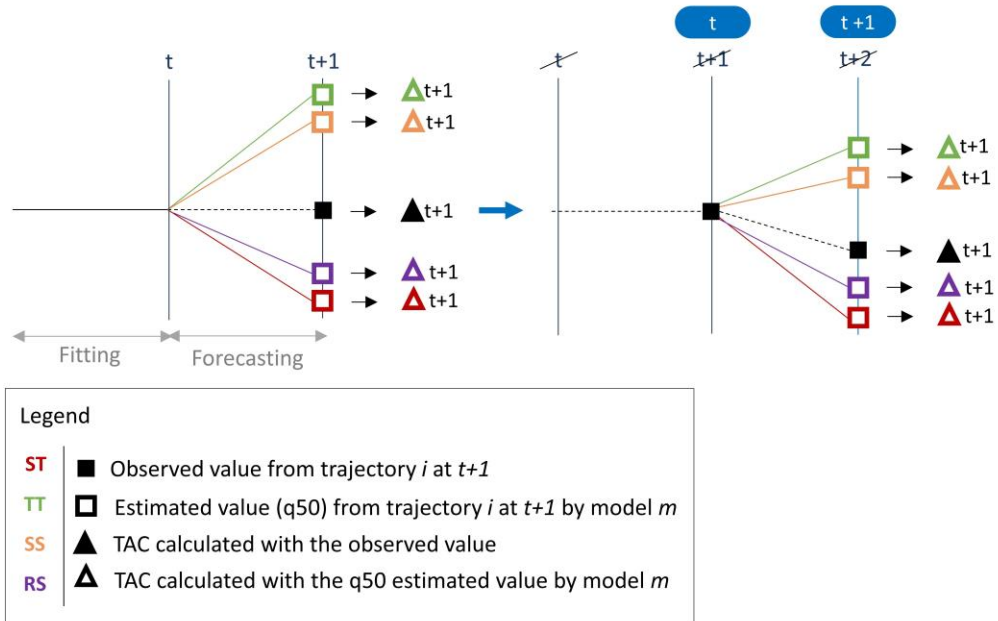
400 For each model fit (i.e., a combination of a simulated time series and a recruitment  
401 model), we set the annual TAC by multiplying the target harvest rate by the median of the  
402 posterior distribution of the forecasted recruitment  $q50(IR_{sampled})$ . Tests were also carried out  
403 with quantiles of 25% and 75% and are presented in the Supplementary Material. We also  
404 calculated the corresponding catch at the management target (i.e., the target harvest rate  
405 multiplied by the “observed” recruitment  $IR_{obs}$ ) (Fig. 3, Step 4a).

406 The application of recruitment forecasting models affects species conservation, the glass  
407 eel fishery, and compliance with management objectives. We developed quantitative criteria  
408 to compare model performance with respect to these effects (Fig. 3, Step 4b). For each  
409 scenario, each model and each simulated recruitment time series, we computed the annual  
410 average predicted catch TAC over the period 2021-2030, representing the Fishery criterion.  
411 Then, the proportion of years in which the management target was met from 2021 to 2030  
412 (years with predicted catch TAC < catch at the management target) was used as the  
413 Management criterion. The quantity of glass eels saved if a given model is chosen,  
414 representing the Conservation criterion, is computed as the annual mean of the difference  
415 between the highest predicted TAC among the models and the predicted TAC of the  
416 considered model over the period 2021-2030.

417

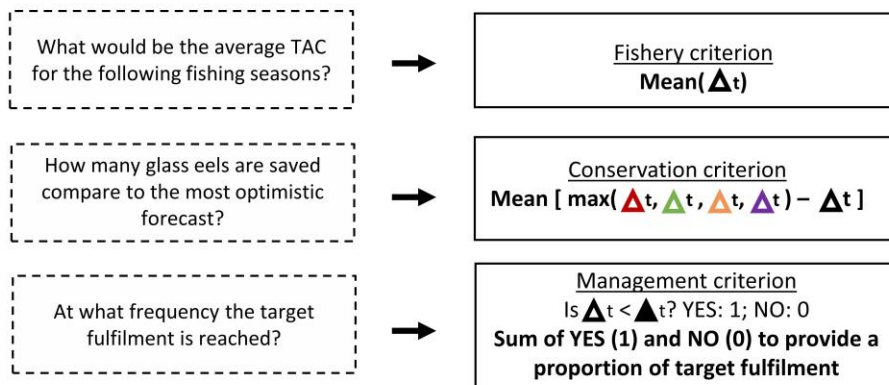
4a **Indicators calculation: Total Allowable Catch (TAC) year by year calculation**

For a scenario  $s$  and for a trajectory  $i$ :  
 For  $t$  ranging from 2020 to 2029:



4b **Indicators calculation: comparison criteria**

For a scenario  $s$ , for a model  $m$  and for  $t$  ranging from 2021 to 2030:



418

419 **Fig. 3.** Diagram showing the quantification of the forecasting performance through the  
 420 simulation exercise: Total Allowable Catch calculation (Step 4a) and comparison criteria  
 421 calculation (Step 4b) (see Fig. 2 for previous steps).

422

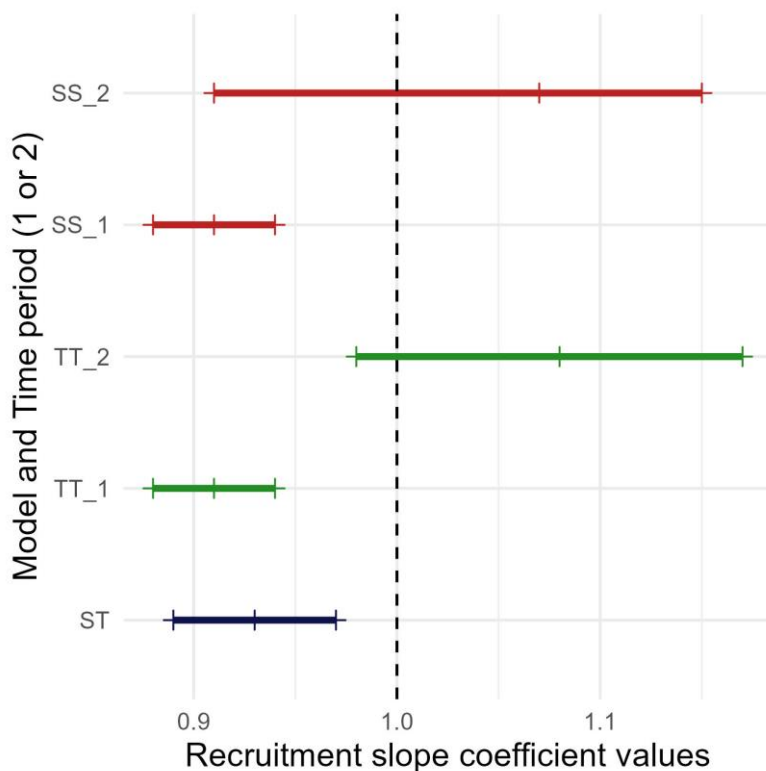
423 **3 Results**

424

425 3.1 Evolution of the recruitment slope over time depending on models

426

427 When comparing strictly declining recruitment slopes (i.e., coefficient distributions <  
428 1), the ST model tends to estimate the lightest declining trend compared to the TT and SS  
429 declining trends (the ST median recruitment slope is superior to other medians; Fig. 4). For  
430 both the TT and SS models, recruitment declines during the first period ( $a_1$  strictly inferior to  
431 1), while the recruitment trend evolution during the second period is unclear (since 1 is within  
432 the 95% credibility interval of  $a_2$  and corresponds to stable recruitment). Recruitment slopes  
433  $a_1$  and  $a_2$  are distinct for the TT model, while the 95% confidence intervals of the two time  
434 periods overlap for the SS model. The TT and SS models also differ by a larger amplitude of  
435 the 95% credibility interval for the SS model compared to the TT model during time period 2.  
436 These results arise from the fact that the SS model is constructed as a mixture of cases  
437 rejecting or considering a change in slope between the two time periods, with 7.6% of cases  
438 not considering a change in the recruitment slope (according to  $\delta$  posterior distribution).

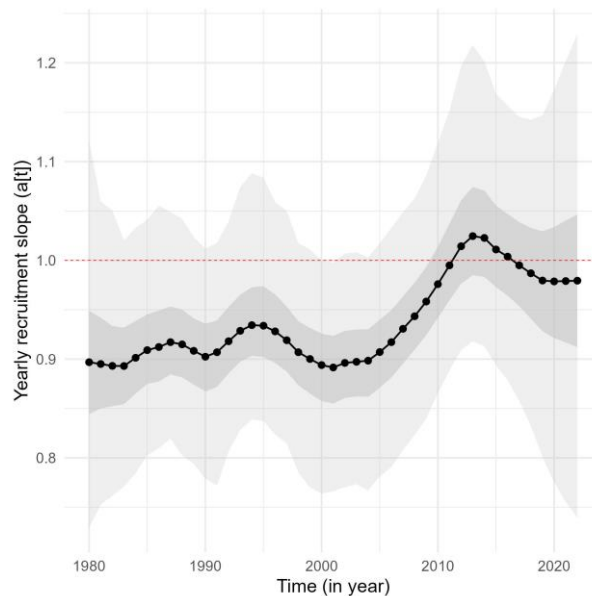


439

440 **Fig. 4.** Annual recruitment slope coefficients  $a$  (in linear scale). The letters and colors account  
441 for the recruitment models. The numbers “1” and “2” account for time periods (1: 1980-2011;  
442 2: 2012-2022; when no time period is assigned, the value is estimated through the entire time  
443 period, i.e., 1980 to 2022). Dashes represent q2.5, q50 and q97.5.

444

445 For the RS model, the yearly varying random slope posterior distributions are mainly  
446 (q50 and q75) below 1 (and strictly below 1 in 2001) until the mid-2000s, suggesting a  
447 declining trend (Fig. 5). After a q50 increase between 2005 and 2013 in favor of an increase  
448 in recruitment, there is no clear trend in the most recent years, with later posterior  
449 distributions approximately 1. The mean and median recruitment slopes over the time series  
450 are 0.9, representing a decrease of 8% in recruitment each year (on a linear scale).  
451 Unsurprisingly, the forecasted slopes (for the 2020, 2021 and 2022 seasons) have larger  
452 credibility intervals than the other models.



453

454 **Fig. 5.** Evolution of the annual recruitment slope over time according to the RS model. Black  
455 line and dots: q50; the darker ribbon: the 50% credibility interval; the lighter ribbon: the 95%  
456 credibility interval.



457

## 458 3.2 Model performance

459

### 460 3.2.1 Deviance Information Criterion

461

462 According to the DIC, the TT and SS models outperform the ST model (Table 2).

463 However, the RS model outperforms them despite its greater complexity.

464

465 **Table 2.** The Deviance Indicator Criterion value according to the recruitment model (“ST”:

466 Single-trend; “TT”: Two-trend; “SS”: Spike and slab; “RS”: Random slope)

Recruitment model	ST	TT	SS	RS
DIC	249.9	251.0	255.1	238.9

467

468

### 469 3.2.2 Error in recruitment estimations depending on model and scenario

470

471 The models mainly overestimate recruitment in Scenario 1 (The PBIAS values are

472 mostly negative) and underestimate recruitment in Scenario 3 (The PBIAS values are mostly

473 positive) (Fig. 6). The results are less obvious for Scenario 2; the ST and RS models

474 underestimate recruitment, while the TT and SS models overestimate recruitment.

475 Unsurprisingly, the ST and TT models perform particularly well in scenarios in which they

476 were used to simulate the data.

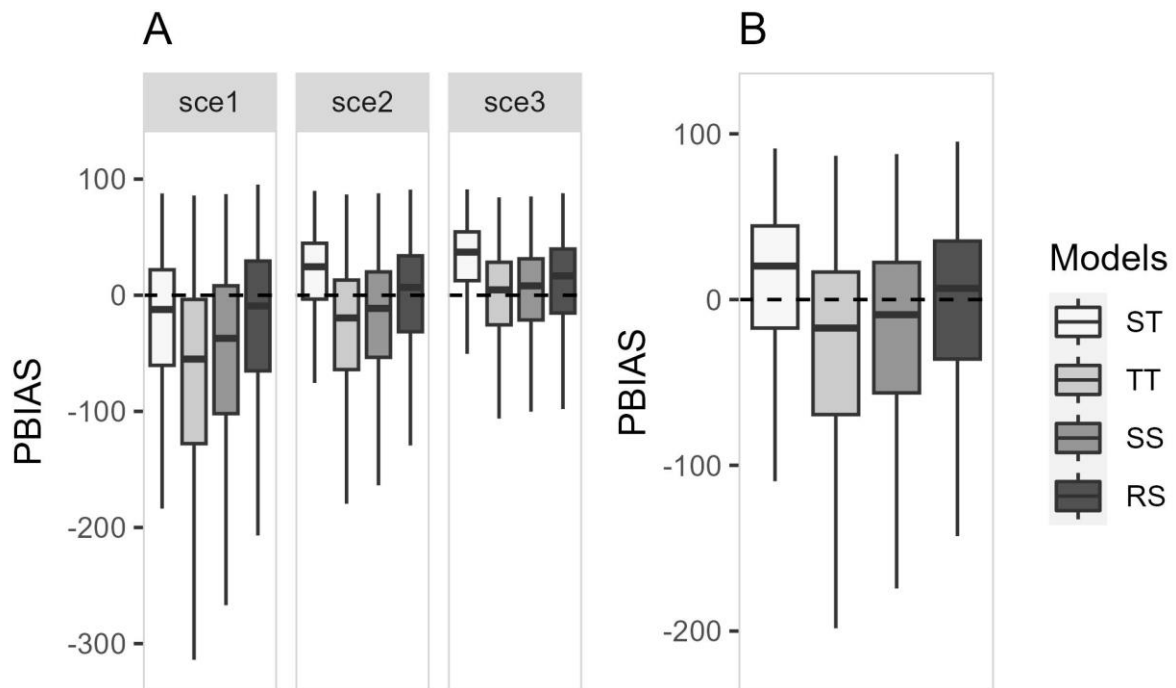
477 Interestingly, while the PBIAS distributions vary among models, and for each model

478 among the scenarios, the boxplot distribution pattern remains similar across the scenarios,

479 namely the ST model, the RS model, the SS model and the TT model in order of decreasing

480 PBIAS values. Across scenarios, the RS model appears to be the least biased model (The  
 481 PBIAS oscillating by approximately 0) (Fig. 6A) and underestimates recruitment by 6.7%  
 482 (median(PBIAS) over all the scenarios; closest value to 0 among models) (Fig. 6B).

483



484

485 **Fig. 6.** Boxplots presenting the PBIAS for the four models through the three scenarios (A) or  
 486 combining all scenarios (B) (“ST”: Single-trend; “TT”: Two-trend; “SS”: Spike and slab;  
 487 “RS”: Random slope). The outliers are not displayed for better readability but are considered  
 488 in the calculation of values (such as median) (strategy q50).

489

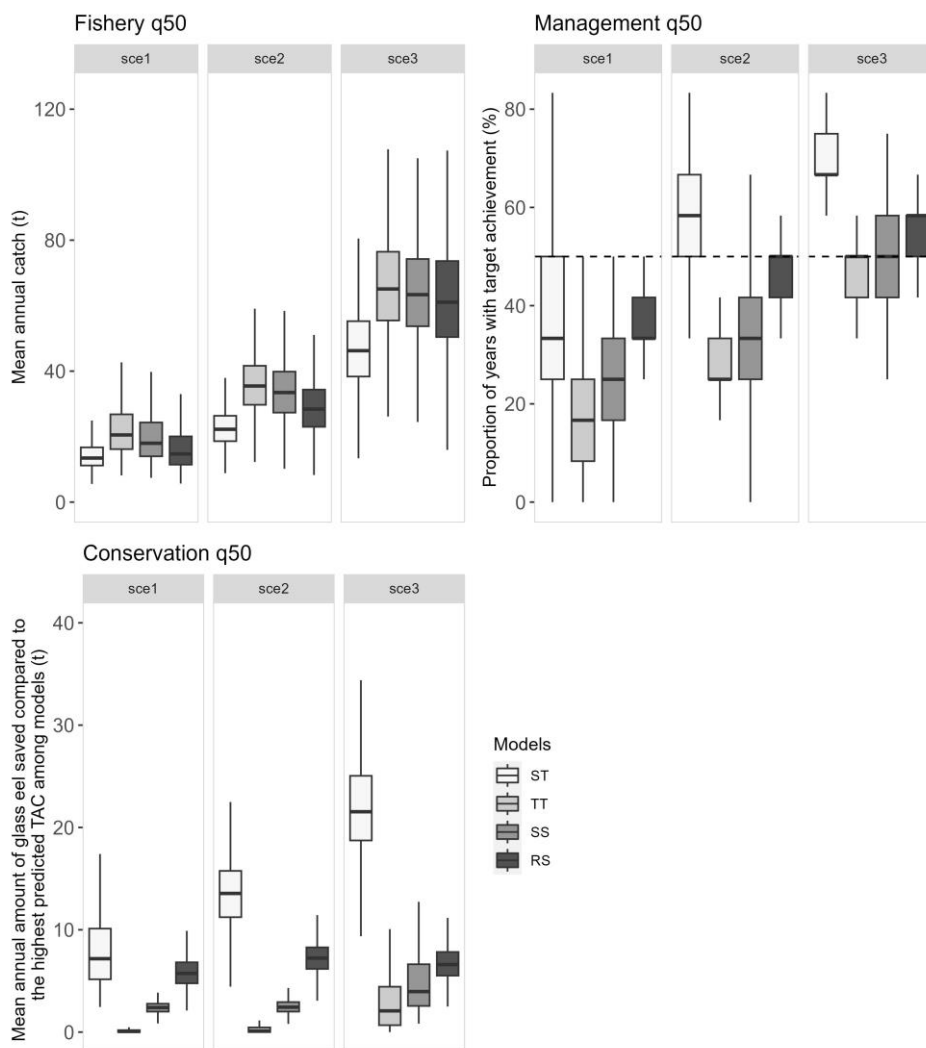
490 The RS model behaves in a similar way regardless of the scenarios during this 10-year  
 491 period, suggesting that the model is robust to varying recruitment patterns.

492

### 493 3.2.3 Quantification of the risk for fisheries, management and conservation

494

495 Fig. 7 displays the distributions of the Fishery, Conservation and Management criteria  
 496 depending on the scenario and the model.



497  
 498 **Fig. 7.** Boxplots presenting the three criteria “Fishery”, “Management” and “Conservation”  
 499 across scenarios (“sce”) and among models (“ST”: Single-trend; “TT”: Two-trend; “SS”:  
 500 Spike and slab; “RS”: Random slope) over the 10 years of simulation. The outliers are not  
 501 displayed for better readability but are considered for building the graph and the calculated  
 502 values (such as the median) (strategy q50).

503  
 504 Unsurprisingly, since the ST model was used to simulate the recruitment series of  
 505 Scenario 1, it performs well (i.e., limited potential catch loss when comparing mean annual

506 TAC to others, very good compliance to the management rule and many eels saved) in this  
507 scenario. For Scenarios 2 and 3, the ST model reaches the management target with a high  
508 frequency and provides a high quantity of glass eels saved at the cost of large reductions in  
509 catches, resulting in the lowest mean annual catch.

510 Across scenarios and criteria, the TT and SS models have similar results when estimating  
511 recruitment, and regarding the criteria comparison strategy. These models frequently miss the  
512 management target and result in the lowest glass eel escapement, except for Scenario 3 (the  
513 one in which the TT model was used to simulate the time series). On the other hand, these  
514 models lead to the highest TAC (slightly higher for the TT model than for the SS model).

515 Considering a time period of 10 years, the RS model behaves in a similar way regardless  
516 of the scenarios (i.e., intermediate mean TAC, proportion of years with target achievement  
517 oscillating approximately 50%, and stable amount of glass eels saved), confirming its  
518 robustness to different recruitment trends.

519

## 520 4 Discussion

521

522 Recruitment is a key question in population dynamics, especially for short-term  
523 forecasting (Maunder and Thorson, 2019). This article provides insights into building and  
524 comparing forecasting models. The RS model stands apart as the more robust method to  
525 forecast short-term recruitment indices based on its bias quantification results and its  
526 implications for management, exploitation and conservation.

527

### 528 4.1 Innovative recruitment forecasting models

529

530 • Model rationales

531

532 Spike and slab priors are widely used in Bayesian variable selection (Ishwaran and Rao,  
533 2005; Titsias and Lázaro-Gredilla, 2011). The inclusion, or not, of a predictor is estimated  
534 internally in the model, and the resulting predictions are a weighted average of the model with  
535 and without the predictor (Titsias and Lázaro-Gredilla, 2011). As such, this approach appears  
536 appropriate for testing the existence of a regime shift, objectively balancing the predictions of  
537 the ST and TT models. However, the parametrization of a spike and slab prior remains  
538 partially subjective (tuning the coefficients  $c$  and  $d$  in the expression of the variance) and  
539 based on expertise to separate plausible values from impossible ones (George and McCulloch,  
540 1993). A sensitivity analysis (see the Supplementary Material) demonstrated that our results  
541 are not overly sensitive to the parameter values (this is not surprising, as situations with a  
542 slope change largely dominate). However, this could change in the future, especially if  
543 recruitment starts decreasing again and the weight of the ST model (i.e., the frequency of  $\gamma =$   
544 0) increases. Therefore, it would seem necessary to repeat the sensitivity analysis regularly  
545 and update the parametrization of the prior in any future use of the SS model. Various slight  
546 modifications have been proposed to help in the parametrization of the spike and slab priors  
547 and to reduce the resultant uncertainty (George and McCulloch, 1993; Ishwaran and Rao,  
548 2005). However, these modifications would not entirely remove the subjectivity of the  
549 resulting model and the need to check its sensitivity.

550

551 The SS model imposes a change in the recruitment trend at a fixed and unique year.  
552 This could be challenged by future data. One could imagine adding other years of trend  
553 change, or at least modeling the year of the change as a random variable. However,  
554 preliminary tests have shown that the resulting models fail to converge. In this framework, the

555 RS model is much more flexible. A random slope model appears suitable for resolving the  
556 debate between a model with either a single or two slopes, and determining the year in which  
557 a potential regime shift occurs. Indeed, random slope models have proven to provide robust  
558 predictions, even in the presence of cyclic patterns or trend changes (Delle Monache and  
559 Harvey, 2012).

560

- 561 • Model and data uncertainty handling

562 Following the Scientific Committee, we used the EIFAAC-ICES-GFCM WGEEL  
563 “Elsewhere Europe” index as an indicator of French recruitment in our analysis. The use of  
564 this indicator was needed given the limited number of ongoing French recruitment time series  
565 (ICES, 2014). Since the index is partly derived from time series collected in regions other  
566 than France, this might lead to bias (ICES, 2022). More importantly, the WGEEL data were  
567 taken to be accurate and were known to be without error in the ST, TT and SS models. We  
568 considered an estimation error in the RS model (Equation 5), which is an improvement.  
569 However, the variance is assumed to be constant over time. The use of year-specific  
570 estimation errors generated by the GLM would probably be more realistic.

571

## 572 4.2 Model comparison strategy

573

574 Inspired by the Management Strategy Evaluation approach (Smith, 1999), we developed  
575 a multicriteria strategy to compare the performance of models.

576

- 577 • Bias in model estimation

578 First, we explored biases in recruitment forecasts, since systematic biases would result  
579 in systematic overestimations or underestimations of fishing opportunities. In our simulations,

580 the ST model tends to underestimate recruitment, while the TT and SS models tend to  
581 overestimate recruitment. Due to its enhanced flexibility, the RS model provides the least  
582 biased recruitment estimates across the three recruitment scenarios. As the RS model behaves  
583 the same way across scenarios, it appears to be the least sensitive to possible changes in future  
584 recruitment trends and the most robust, as defined by Box (1979).

585

- 586 • Model implications for European eel fishery, management and conservation

587 Inspired by the work of Lebot (2021) and Bevacqua (2007), we developed three criteria  
588 to assess and illustrate the trade-off between mean annual catch, management target  
589 achievement and quantity of glass eel saved. The ST model favors conservation by frequently  
590 achieving the management target but at the cost of lower TACs. On the other hand, both the  
591 TT and SS models promote the highest TACs but with a high risk of overshooting the  
592 management target and compromising conservation. The RS model provides the best trade-off  
593 since it shows intermediate responses for all considered sectors compared to other models.  
594 Moreover, the outcomes of the RS model are minimally sensitive to the scenarios, unlike  
595 other models.

596

### 597 4.3 Application to glass eel fishing opportunity evaluation

598

599 The current French evaluation of glass eel fishing opportunities relies on two  
600 recruitment models (ST and TT) with contrasting recruitment forecasts (Beaulaton et al.,  
601 2020). The Scientific Committee lacks a method for choosing between the two models, which  
602 leads to some misunderstanding from stakeholders. The RS model appears to be a good  
603 candidate for estimating glass eel fishing opportunities in France. Its use could overcome the  
604 difficulty of having two recruitment models by providing a single recruitment forecast. By

605 doing so, it could improve the reliability of the assessment and make the decision-making  
606 process more understandable to stakeholders. Moreover, the simulation strategy can be used  
607 to carry out a long-term risk analysis that would support science-based management.

608

#### 609 4.4 A generic approach

610

- 611 • Comparing abundance forecast outcomes

612

613 As scientific results can be difficult to convey (Lehuta et al., 2016; Pita et al., 2016), we  
614 have proposed three explicit quantitative criteria with the aim of providing accessible  
615 information to those who make management decisions. The model selection method presented  
616 herein is not based on traditional statistical criteria, but on socioeconomic and environmental  
617 criteria. Since managers generally have to deal with trade-offs among competing interests, the  
618 multicriteria assessment appears to be an attractive decision-aiding tool that provides trade-off  
619 overviews across multiple sectors of interest (exploitation, management and conservation in  
620 this study) (Antunes et al., 2006; Röckmann et al., 2012). We do not pretend that the criteria  
621 we propose here are the only ones possible; however, we aim to demonstrate our trade-off  
622 exploration strategy. Indeed, implementing more relevant criteria, as well as adding a relative  
623 weight to each criterion to obtain a final score per model could arise from a co-construction  
624 involving all stakeholders (e.g., managers, fishers, scientists, NGOs) involved in the  
625 management of the European eel (Drouineau et al., 2021). This collaboration, as part of  
626 participatory modeling, could help to enhance the involvement of each stakeholder in fishery  
627 management, strengthening mutual trust and understanding (Drouineau et al., 2021;  
628 Röckmann et al., 2012). The same applies to the scenarios (here, we used three contrasting  
629 scenarios to simulate future recruitment time series, but these scenarios could be co-



630 constructed with stakeholders) and to quantiles of the posterior distribution of the forecasted  
631 recruitment used to calculate TACs (here, we used strategies q25, q50 and q75).

632

- 633 • Index-based abundance short-term forecasts

634

635 Analytical stock assessments of European (*Anguilla anguilla*) and American (*Anguilla*  
636 *rostrata*) eel have not been achieved despite much effort (ASMFC, 2023; ICES, 2019). As an  
637 alternative to analytic stock assessment, abundance index methods are being looked at as a  
638 means to generate harvest rules (e.g., the ITarget method, trend indicators) (ICES, 2023;  
639 Legault et al., 2023). With eel abundance indices playing a central role in supporting  
640 management advice and no viable alternative in sight, eel assessment scientists ought to be  
641 looking carefully at the best options to use abundance time series to guide harvest  
642 management. Of the modeling approaches tested here, the RS model best accounts for the  
643 recruitment variability. We therefore recommend its use for recruitment modeling and  
644 forecasting to guide European glass eel management advice.

645 The index-based methods presented in this paper could be applied to other eel life  
646 stages, and to other species. More generally, these methods could be easily implemented to  
647 support management advice when an analytical stock assessment cannot be conducted (e.g.,  
648 rejected assessments, data-limited stock) (NEFSC, 2020; Punt et al., 2020) and could also be  
649 used in artisanal and traditional coastal recruitment fisheries (e.g., the sardine fry fishery in  
650 Italy) (STECF, 2023a, 2023b). Although this work is conducted at the recruitment fishery  
651 scale, these index-based forecasting methods could conceivably be applied to a wide range of  
652 scientific and economic fields.

653

654 [CRediT authorship contribution statement](#)

655 **Mathilde Benezech:** Conceptualization, Methodology, Software, Formal analysis, Writing –  
656 original draft, Writing –review and editing; **Hilaire Drouineau:** Conceptualization,  
657 Methodology, Software, Formal analysis, Writing –review and editing, Project administration,  
658 Supervision; **Anthony Acou:** Conceptualization, Writing –review and editing; **Agnès**  
659 **Bardonnet:** Conceptualization, Writing –review and editing; **Clarisse Boulenger:**  
660 Conceptualization, Writing –review and editing; **Patrick Lambert:** Conceptualization,  
661 Writing –review and editing; **Etienne Prévost:** Conceptualization, Software, Formal analysis,  
662 Writing –review and editing; **Laurent Beaulaton:** Conceptualization, Methodology, Writing  
663 –review and editing, Project administration, Supervision.

664

665 [Declaration of Competing Interest](#)

666 The authors declare that they have no known competing financial interests or personal  
667 relationships that could have appeared to influence the work reported in this paper.

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674

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## Supplementary Material

### **Testing novel methods for short-term forecasting of European glass eel recruitment**

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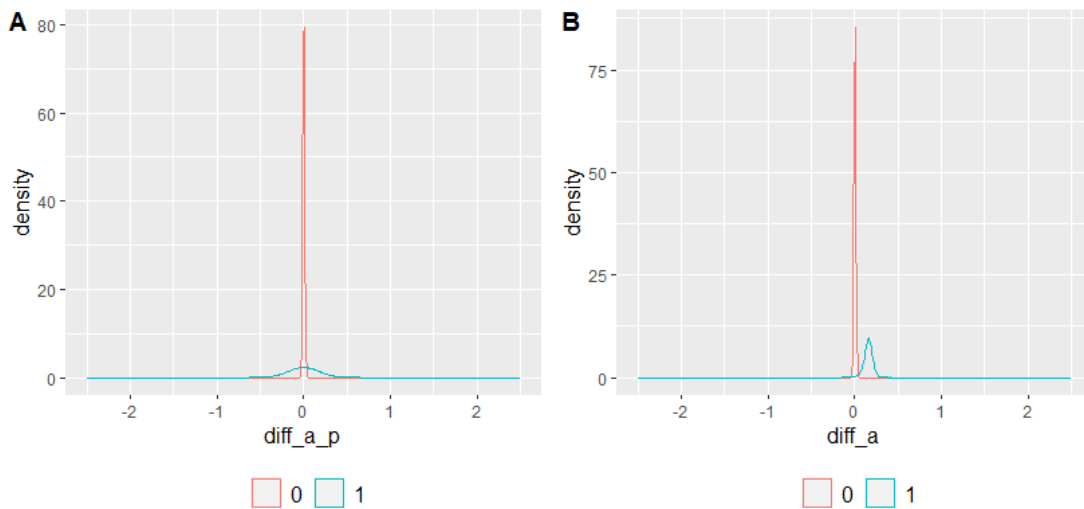
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# 1 The spike and slab model

## 1.1 Density of probability for $diff_a$

As recommended by Georges and McCulloch (1993), we check that the intersection of the median value of  $diff_a$  with the a priori distributions of  $diff_a$  for  $\gamma = 0$  and  $\gamma = 1$  ensures an important difference (Fig. 1). Fig 1 confirms that the posterior distribution is different from the prior distribution and that the conditional posterior distribution of  $diff_a$  with  $\gamma = 1$  and  $\gamma = 0$  are distinct.



**Fig. 1.** - Density of probability of the the two normal distributions that define the prior of  $diff_a$   
**(A)** - marginal posterior distributions of  $diff_a$  depending on the value of  $\gamma$  **B**

## 1.2 Sensitivity analysis to variance parameters $c$ and $d$

### 1.2.1 Setting $c$ and $d$ parameters

Tuning the coefficients  $c$  and  $d$  in the expression of the variance  $\sigma_{diff_a}^2$  (Eq. 4) can be considered subjective (George and McCulloch, 1993). As mentioned earlier, the prior for  $diff_a$  is bivariate with a narrow normal prior around 0 if the change of slope is rejected, and a wide normal prior (large variance) if the change of slope is accepted. Parameters  $c$  and  $d$  tune these two normal distributions. As such  $c$  (variance of the narrow normal) should be chosen so that the prior is restricted to values that are small enough to be considered as an insignificant change. Conversely,  $d$  (variance of the wide normal) should be large enough to allow significant change of slope (i.e. large  $diff_a$ ) but small enough to eliminate impossible values (otherwise, the prior would be too flat leading to too small differences of density of probabilities between the two normal distributions). These priors will allow the model to select the relevant explanatory variables in a model in an autonomous way.



Remind that  $\exp(\text{diff}_a)$  can be interpreted as a rate of change between time periods 1 and 2. If there is no change in the recruitment trend, the multiplicative coefficient between  $\exp(a_1)$  and  $\exp(a_2)$  should be close to 1. As a first guess, we assumed that a variation of less than 2% around 1 is considered as a non-significant change in the recruitment trend. Just as an illustration, Dekker (2019) estimated that the recruitment dropped consistently by approximately 15% per year. This would correspond to  $\exp(a_1) = 0.85$  and to reject a shift for  $0.85 \cdot 0.98 = 0.83 \leq \exp(a_2) \leq 0.85 \cdot 1.02 = 0.87$ . Restricting a change of less than 2% between time periods 1 and 2 implies that  $\text{diff}_a$  is restricted between  $\log(0.98) = -0.02$  and  $\log(1.02) = 0.02$ . A normal distribution with standard deviation  $0.02/1.96 = 0.01$  would mean that 95% of  $\text{diff}_a$  values are between  $-0.02$  and  $0.02$ . We therefore chose  $c = (\mathbf{0.01})^2 = \mathbf{1.10^{-4}}$ .

In recent years, the rate of decrease may have changed and the recruitment tends to be stable or slightly increasing according to the WGEEL. If the recruitment decreased by about 15% in the first period (Dekker, 2019), stabilising the trend would correspond to a change of  $1/0.85 = 1.17$ . It is very unlikely that recruitment is now increasing as a rate similar to the former rate of decrease, so  $1.15/0.85 = 1.35$  appears to be a reasonable upper bound for a situation of significant change in the recruitment trend. This corresponds to a  $\text{diff}_a$  of  $\log(1.35) = 0.30$ . A normal distribution with standard deviation  $0.30/1.96 = 0.15$  means that 95% of  $\text{diff}_a$  values are ranging from  $-0.30$  to  $0.30$ . As a result, we chose  $d = (\mathbf{0.15})^2 = \mathbf{3.10^{-2}}$ .

The values of parameters  $c$  and  $d$  have been chosen to provide sufficiently distinct probability distributions in order to distinguish situations of change in slope from situations of previous slope conservation. Indeed, situations where  $\gamma = 0$  should not be accepted as a change of slope, and reciprocally. In order to evaluate model sensitivity to  $\text{diff}_a$  prior, several pairs of values of  $c$  and  $d$  have been tested looking at the proportion of  $\gamma = 1$  depending on these values.

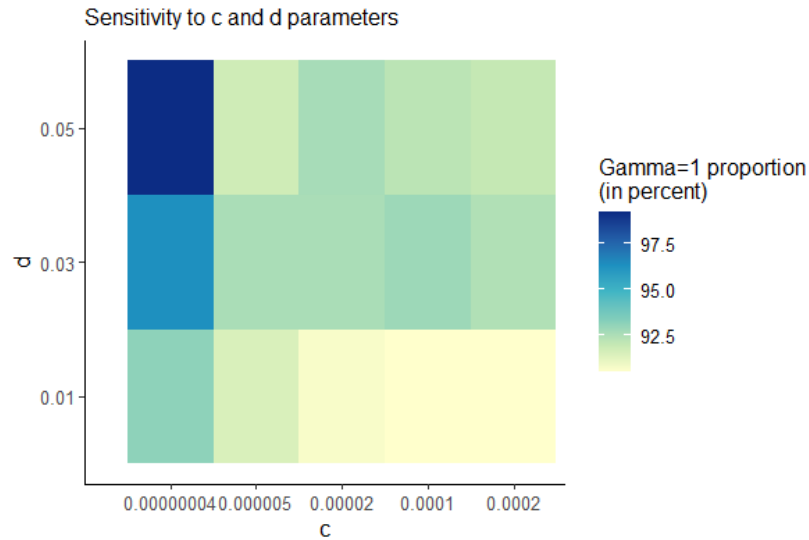
### 1.2.2 Sensitivity assessment

Since the tuning of parameters  $c$  and  $d$  of the bimodal variance are partly subjective, we check the sensitivity of the model to these parameters by fitting the spike and slab model with different pairs of  $c$  and  $d$  values (Table 1).

**Table 1.** Values chosen and their meaning in terms of recruitment evolution to evaluate model sensibility to  $c$  and  $d$  choices.

Tested values for $c$	Percent of maximum decrease and maximum increase tolerated between two consecutive years
$4 \cdot 10^{-8}$	0.1%
$5 \cdot 10^{-6}$	0.5%
$2 \cdot 10^{-5}$	1%
$1 \cdot 10^{-4}$	2%
$2 \cdot 10^{-4}$	3%
Tested values for $d$	Percent of maximum decrease and maximum increase tolerated between two consecutive years
$1 \cdot 10^{-2}$	20%
$3 \cdot 10^{-2}$	35%
$5 \cdot 10^{-2}$	55%

We compared the proportion of  $\gamma = 1$  in the  $\gamma$  posterior distribution (Fig. 2). For the tested  $c$  and  $d$  values, the frequency of  $\gamma = 1$  is greater than 90%. As such, the sensitivity of the model to  $c$  and  $d$  appears limited.



**Fig. 2.** Sensitivity matrix to values of  $c$  and  $d$  represented by the proportion of cases where  $\gamma$  is 1 (in percent).

## 2 Multi-criteria comparison approach

### 2.1 Retrospective exercise

*The metrics to quantify models forecasting performances and the risk for exploitation, resource presented hereby are the initial versions of the ones presented in the article.*

In this exercise, we fitted all models (ST, TT, SS and RS) on the WGEEL recruitment index up to season  $t$ , assuming that recruitment in season  $t+1$  falls in an interval ranging from  $-3$  to  $+3$  around recruitment of season  $t$  (interval censorship). This mimicked the strategy used by the Scientific Council (Beaulaton et al., 2020). Then, we compared the model predictions for season  $t+2$  with the time-corresponding « true » WGEEL value. We carried out this exercise for  $t$  ranging from 2013 to 2017, since the regime shift is supposed to take place in 2012 and the last WGEEL index is in 2019. Three chains were run in parallel with 60,000 iterations with a thinning period of ten after a burn-in period of 200,000 iterations.

#### 2.1.1 Material and methods

### 2.1.1.1 Recruitment prediction error formulation

We compared models forecasting performance by quantifying the discrepancy between recruitment forecasts and “true” values (the WGEEL time series) through a variable called the “Recruitment prediction error”. The difference between each predicted recruitment value and the WGEEL of the corresponding year value was calculated and named as the “prediction error”. If the prediction error was negative, the recruitment was underestimated (respectively, positive prediction error translated recruitment overestimation).

### 2.1.1.2 Evaluation of risks for both exploitation and resource: development of two criteria

We developed two quantitative criteria to lead a quantitative risk assessment (Aven and Renn, 2009). We formulated these criteria thanks to the two following answers.

- **If recruitment is overestimated in year  $t+2$ , how often is it overestimated if a certain model (among the four) is used to predict recruitment index?**

For each year and model, we computed the frequency of samples from the posterior distribution of recruitment that were greater than the corresponding WGEEL index value. This frequency of recruitment overestimation represents how often recruitment is overestimated when using a certain model to predict it. It quantifies the risk of not achieving the management target. Therefore, we called this frequency of recruitment overestimation the “Conservation Risk Indicator” (CRI).

Let  $S_i(t,m)$  be a logical indicator with  $i$  ranging from 1 to the number of iterations (60,000 in this study) for the year  $t$  for one model  $m$ . If the difference between a recruitment prediction and the value of the WGEEL was positive, then the indicator  $S_i(t,m)$  took the value 1, indicating a situation of overestimation of recruitment. Respectively, when the difference was negative,  $S_i(t,m)$  took the value 0 and represented a situation of recruitment underestimation. We thus obtained a series of 1 and 0 of length 60,000. The following formula was then applied to obtain the frequency of overestimation of recruitment for one year  $t$  for one model  $m$ :

$$(1) \text{ Overestimation frequency}(t, m) = \frac{\sum_1^{\text{number of iterations}} S_i(t,m)}{\text{number of iterations}}$$

where number of iterations = 60,000.

Therefore, we obtained five frequencies of recruitment overestimation for each model for the retrospective analysis.

- **What is the potential loss of catches if a certain model (among the four) is used to predict recruitment in year  $t+2$ ?**

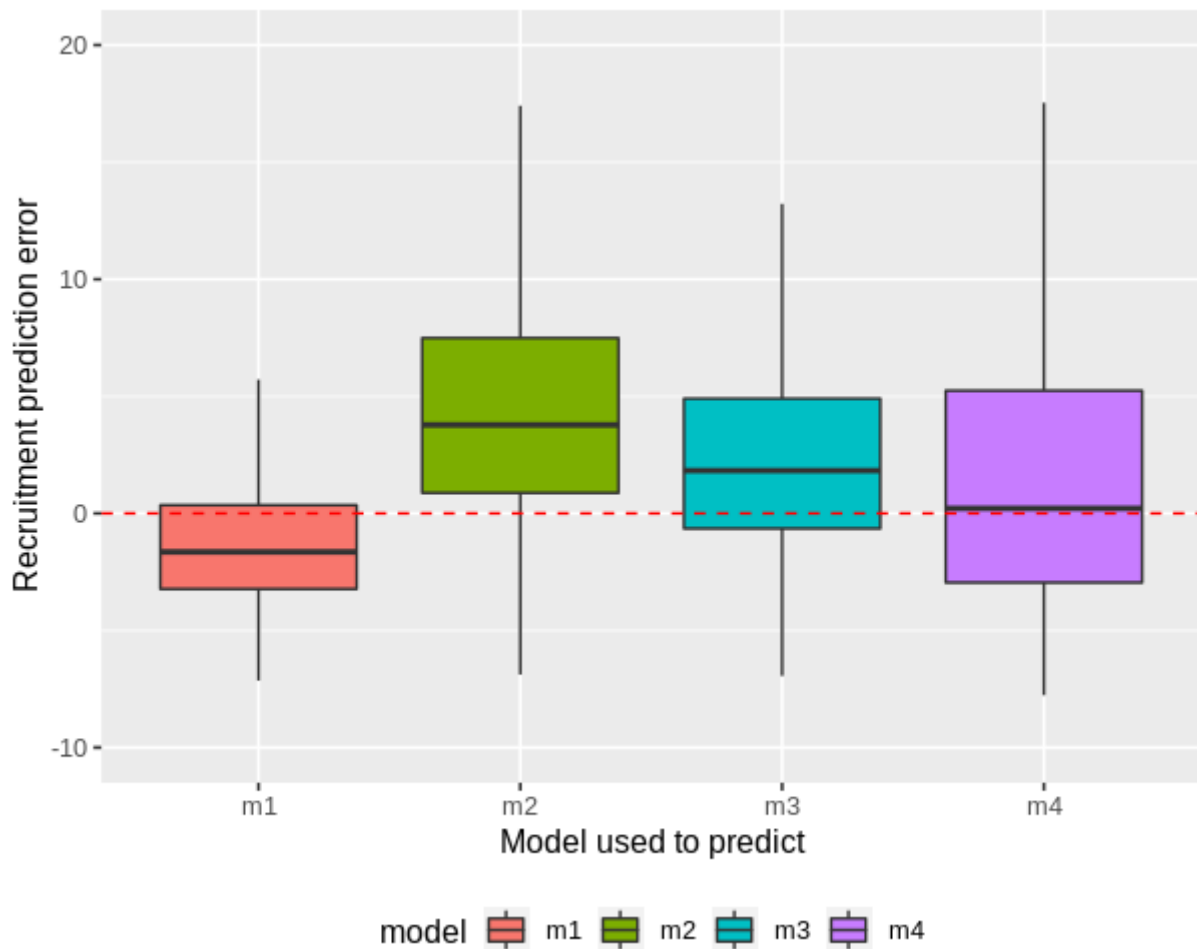
Underestimating recruitment would lead to implement too restrictive quotas and therefore generate potential catches losses for the fishery. Using the same approach as for the calculation of the recruitment prediction error, we computed the difference between predicted recruitment and the “true” value, except that if this difference was positive, we set the value at 0. Indeed, with a positive difference (i.e. an overestimated recruitment), there was no risk for

the fishery to loose potential catches. This new indicator is called the “Fish Risk Indicator” (FRI).

We assessed the Conservation Risk Indicator (CRI) and the Fishery Risk Indicator (FRI) for each model to analyse the trade-offs between conservation and exploitation.

## 2.1.2 Results

### 2.1.2.1 Recruitment prediction error



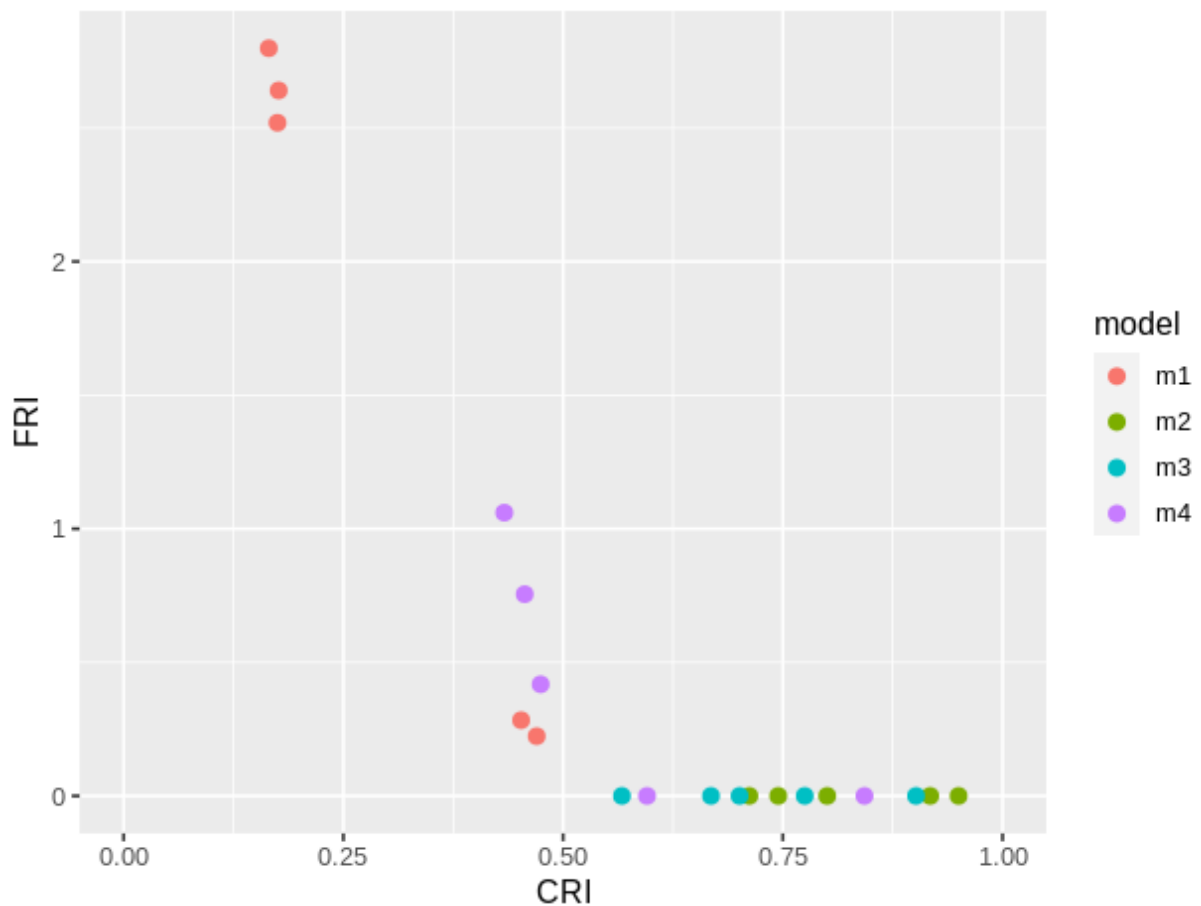
**Fig. 3.** Boxplots presenting recruitment prediction error for the four recruitment models through the retrospective analysis from 2015 to 2019 (m1: “ST” single-trend model; m2: “TT” two-trend model; m3: “SS” spike and slab model; m4: “RS” random slope model).

According to Figure 3, the ST model mainly underestimates recruitment compared to the ICES WGEEL recruitment index (median prediction error =  $-1.64 < 0$ ). This is consistent with previous observations of the decreasing exponential trend in the model slope. On the other hand, the TT model tends to be over-optimistic compared to WGEEL recruitment index (median =  $3.92 > 0$ ). With a median prediction error of 1.85, the SS model is the intermediate

between the ST model and the TT model. This result is consistent with the structure of the model, which is a mixture of the two models. Nevertheless, Figure 3 shows that the SS model mainly overestimates recruitment. The RS model appears to be the least biased model (median prediction error = 0.96).

#### 2.1.2.2 CRI and FRI

Since the Conservation Risk Indicator (CRI) represents compliance or non-compliance with the conservation rule and the Fishery Risk Indicator (FRI) traduces the potential loss of catches for the commercial fishery, Figure 4 illustrates the trade-off between conservation and fishery objectives.



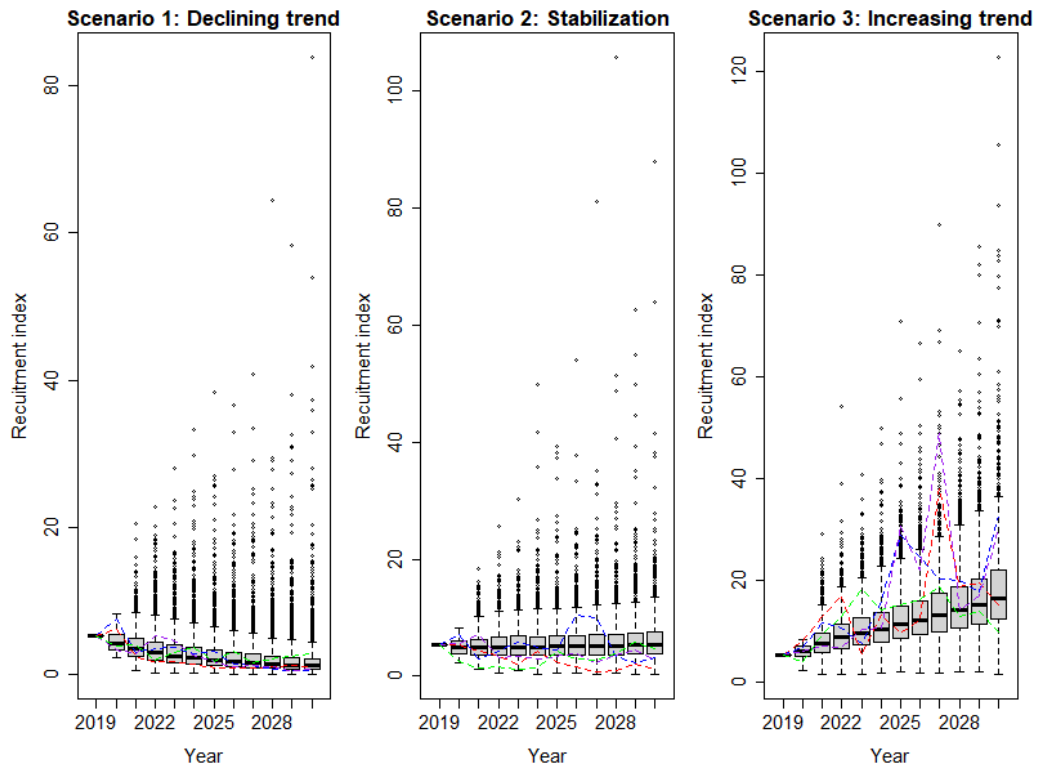
**Fig. 4.** Position of the four recruitment models when considering simultaneously the Fishery Risk Indicator (FRI) and the Conservation Risk Indicator (CRI) during the retrospective analysis from 2015 to 2019 (m1: “ST” single-trend model; m2: “TT” two-trend model; m3: “SS” spike and slab model; m4: “RS” random slope model).

A model with a CRI of about 0.5 would randomly alternates between over- and under-estimation situations (since CRI is the recruitment overestimation frequency), as expected for

a non-biased model. Ideally, a model should also have a FRI as small as possible (i.e. limiting too strong underestimation of recruitment and therefore restricting potential loss of catch). As such, the model that comes closest to this  $CRI = 0.5$  and  $FRI = 0$  point is the RS model (Figure 4). Indeed, points relative to the RS model are always close to the 50% overestimation frequency threshold and minimize catches loss compared to the ST model. Indeed, the ST model favours compliance with the conservation rule, but at the expense of catches loss for the fishery. On the other hand, the TT and SS models ensure limited catch losses but at the cost of a systematic recruitment overestimation.

## 2.2 Simulation exercise

### 2.2.1 Evolution of simulated recruitment series



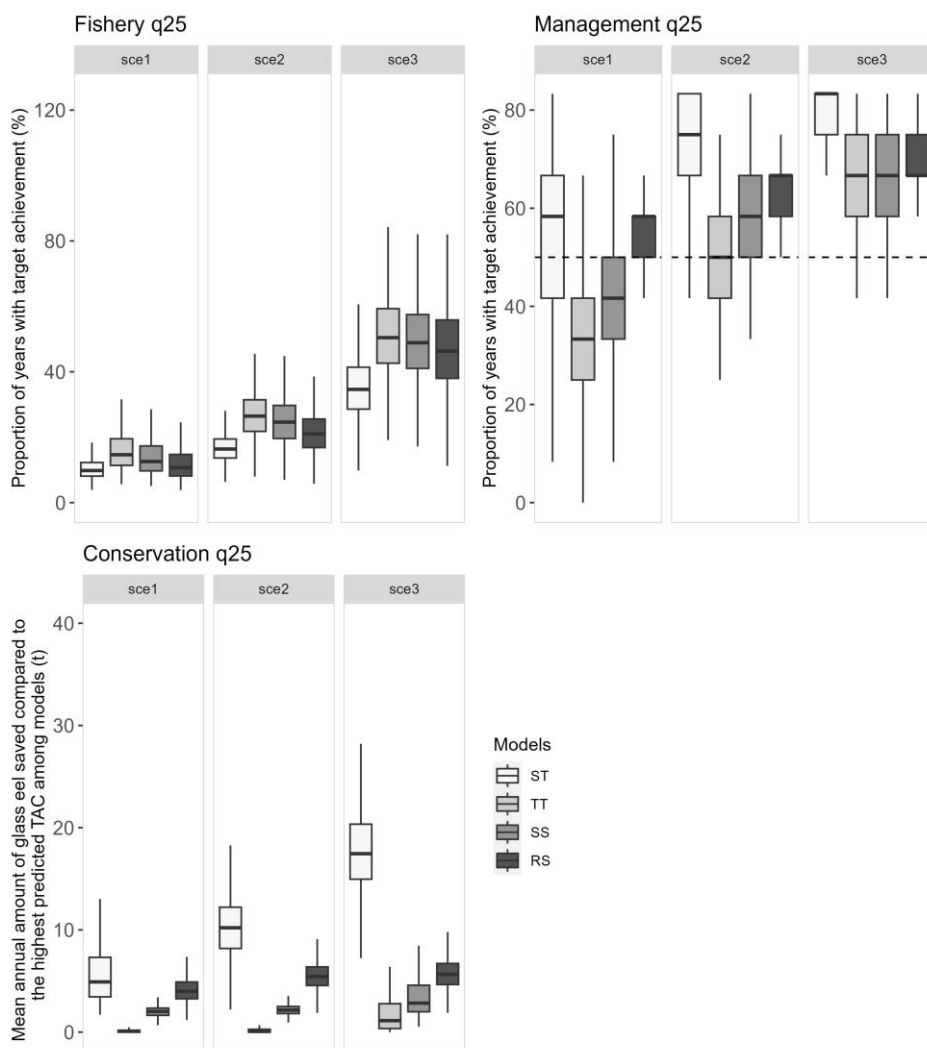
**Fig. 5.** Evolution of the simulated recruitment index over time according to the three scenarios (Scenario 1: decrease in recruitment; Scenario 2: stabilization of recruitment; Scenario 3: increase in recruitment). The coloured lines represent four time series of recruitment (of the total 2,000 simulated recruitment series) in order to highlight the heterogeneity among individual trajectories.

As expected, the 3 scenarios provide different trends in recruitment over time: a decreasing trend (i.e., scenario 1), a stable trend (i.e., scenario 2), and an increasing trend (i.e., scenario 3) (Figure above). However, it should be noted that the boxplots hide a great deal of heterogeneity between individual simulated time series. By testing the model on such

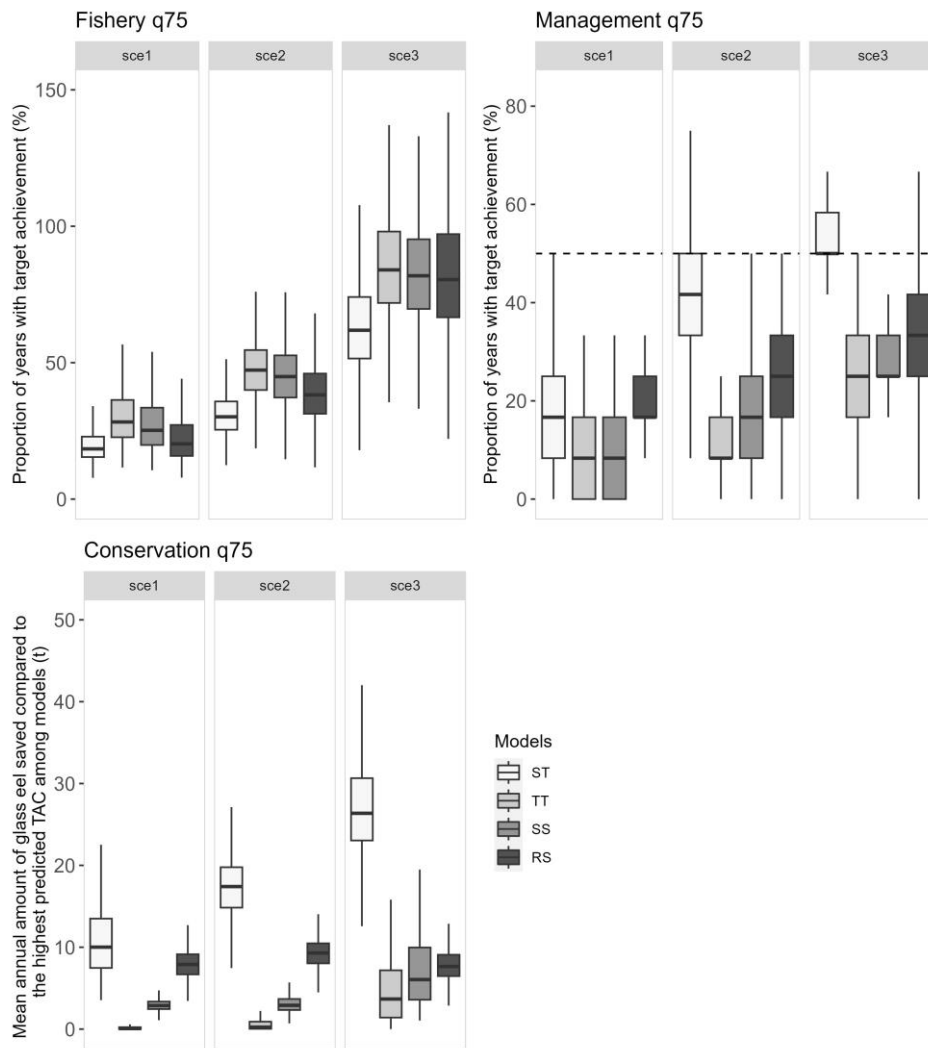
contrasted trajectories relying on different assumptions, it is possible to assess the robustness of forecasting models as defined by Box (1979).

## 2.2.2 Other strategies when calculating quotas

In the main document, we assumed that the quota was set based on the median of the posterior prediction of predicted recruitment (strategy q50). Here, we show how the fishery, management and conservation criteria would be effected if we use the quantiles 25% (strategy q25) or 75% (strategy q75). Main results are not affected though there is a high probability of not achieving the management target with the strategy q75.



**Fig. 6.** - Boxplots presenting the three criteria “Fishery”, “Management” and “Conservation across scenario (“sce”) and among models (“ST”: single-trend; “TT”: two-trend; “SS”: spike and slab; “RS”: random slope) over the 10 years of simulation. Outliers not displayed for a better readability but considered for the graph and the calculated values (such as median) (strategy q25).



**Fig. 7.** - Boxplots presenting the three criteria “Fishery”, “Management” and “Conservation across scenario (“sce”) and among models (“ST”: single-trend; “TT”: two-trend; “SS”: spike and slab; “RS”: random slope) over the 10 years of simulation. Outliers not displayed for a better readability but considered for the graph and the calculated values (such as median) (strategy q75).

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