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## A fish-based index of estuarine ecological quality incorporating information from both scientific fish survey and experts knowledge

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### ► To cite this version:

A. Tableau, Hilaire Drouineau, C. Delpech, M. Pierre, Jérémy Lobry, et al.. A fish-based index of estuarine ecological quality incorporating information from both scientific fish survey and experts knowledge. *Ecological Indicators*, 2013, 32, p. 147 - p. 156. 10.1016/j.ecolind.2013.03.030 . hal-00824755

**HAL Id: hal-00824755**

**<https://hal.science/hal-00824755v1>**

Submitted on 22 May 2013

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2 survey and experts knowledge

3

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27

28 Abstract

29 In the Water Framework Directive (European Union) context, a multimetric fish based index is required  
30 to assess the ecological status of French estuarine water bodies. A first indicator called ELFI was  
31 developed, however similarly to most indicators, the method to combine the core metrics was rather  
32 subjective and this indicator does not provide uncertainty assessment. Recently, a Bayesian method  
33 to build indicators was developed and appeared relevant to select metrics sensitive to global  
34 anthropogenic pressure, to combine them objectively in an index and to provide a measure of  
35 uncertainty around the diagnostic. Moreover, the Bayesian framework is especially well adapted to  
36 integrate knowledge and information not included in surveys data. In this context, the present study  
37 used this Bayesian method to build a multimetric fish based index of ecological quality accounting for  
38 experts knowledge. The first step consisted in elaborating a questionnaire to collect assessments from  
39 different experts then in building relevant priors to summarize those assessments for each water body.  
40 Then, these priors were combined with surveys data in the index to complement the diagnosis of  
41 quality. Finally, a comparison between diagnoses using only fish data and using both information  
42 sources underlined experts knowledge contribution. Regarding the results, 68% of the diagnosis  
43 matched demonstrating that including experts knowledge thanks to the Bayesian framework confirmed  
44 or slightly modified the diagnosis provided by survey data but influenced uncertainty around the  
45 diagnostic and appeared especially relevant in terms of risk management.

46

47 Keywords

48 anthropogenic pressure; Bayesian method; expert judgment; multimetric fish-based indicator; prior  
49 information; Water Framework Directive

50

51 1. Introduction

52 Coastal and estuarine ecosystems are particularly vulnerable to evolution of human activities  
53 (Henocque and Denis, 2001; Hoegh-Guldberg and Bruno, 2010) and their degradation is widely  
54 observed, e.g. Elliott and Hemingway (2002). In that context, regulation tools such as the European  
55 Water Framework Directive (WFD) aims at stopping this degradation process and at restoring aquatic  
56 ecosystems to a good ecological status (WFD . Directive 2000/60/EC; European Council, 2000). To  
57 fulfil this objective, multimetric indices are widely used to assess the ecological quality of aquatic  
58 ecosystems (Hughes and Oberdorff, 1999). A metric is defined as a measurable variable having an  
59 ecological meaning, which can be associated to any structural or functional aspect of biological  
60 assemblages (Coates et al., 2007). Combining several metrics in a multimetric index assures that the  
61 resulting indices are holistic and sensitive (Deegan et al., 1997; Karr and Chu, 1999). A large variety of  
62 multimetric indices aims at detecting the ecological impact of stressors, e.g. Hering et al. (2006).

63 As fish integrate a large variety of anthropogenic pressures (Elliott et al., 1988; Karr, 1981), fish  
64 assemblages are generally considered as appropriate to develop indicators of ecosystem quality.  
65 Consequently, numerous fish-based multimetric indices have been developed in the context of the  
66 WFD (Pont et al., 2006), especially in transitional waters, e.g. Borja et al. (2004), Breine et al. (2010),  
67 Breine et al. (2007) and Delpech et al. (2010). However, most of those indices suffered from two main  
68 weaknesses. First, qualitative estimates of the respective weight of metrics, correlations among them  
69 and redundancy in information made combinations of metrics in those indices sensitive to the  
70 calculation method. Second, most of those indices did not quantify uncertainty around their  
71 assessment (Perez-Dominguez et al., 2012) though it is especially important for managers (Breine et  
72 al., 2007; McAllister and Kirkwood, 1998). Indeed, the probability for a water body to reach a score  
73 below good status is necessary in terms of risk management (WFD . Directive 2000/60/EC; European  
74 Council, 2000). Bootstrap methods were applied with success by Pont et al. (2006) to estimate these  
75 probabilities but they required a large amount of data, making them inappropriate in data poor  
76 situations, especially in estuarine systems where large standardized sets of surveys data are lacking  
77 (Nicolas et al., 2011).

78 Delpech et al. (2010) proposed an indicator called ELFI to assess the ecological status of French  
79 estuaries. This indicator was based on pressure-impact models, as proposed by Courrat et al. (2009),

80 in order to select relevant metrics that are sensitive to anthropogenic pressures. However, this  
81 indicator suffered from the two weaknesses previously mentioned. Recently, an original method to  
82 build multimetric stressor specific indices was proposed and applied on the French lagoons  
83 (Drouineau et al., 2012). This approach based on the Bayesian theory took up both two challenges.  
84 First, based on the Bayesian theory, it allows an objective combination of the metrics by incorporating  
85 all the information in a probabilistic framework. Secondly, this method provides a measure of  
86 uncertainty in its assessment. Consequently, it is hoped that applying this framework to the indicator  
87 developed by Delpech et al. (2010) would significantly improve the indicator.

88 Drouineau et al. (2012) proposed to further incorporate experts knowledge within the French lagoons  
89 fish-based index in order to combine both experts knowledge and fish data in the ecological  
90 assessment. Integrating experts knowledge in such multimetric index could lead to valuable  
91 improvement (Martin et al., 2005; Murray et al., 2009). Experts knowledge may provide a qualitative  
92 but global image (Knapp et al., 2011) of the ecological status of an ecosystem not only based on a  
93 particular ecological feature (ecological communities or habitats). Furthermore, it does not require  
94 expensive scientific surveys. Indeed, most indices are based on surveys with a limited time and space  
95 scale, sampling a limited fraction of fish assemblages. Consequently, they are based on restricted  
96 image of the ecosystem.

97 In this context, the present approach developed a fish-based multimetric index for French estuaries,  
98 applying the Bayesian method proposed by Drouineau et al. (2012) and incorporating experts  
99 knowledge. This index proposed to fulfil weaknesses of the index developed by Delpech et al. (2010)  
100 while using its pressure-impact approach and the method developed by Courrat et al. (2009) to select  
101 core metrics. The combination of fish data and experts information into the Bayesian framework is  
102 described, the impact of the integration of the experts knowledge in the ecological assessment and its  
103 interest for monitoring estuarine ecological status are analysed.

## 104 2. Materials and method

105 The proposed multimetric index illustrated in Figure 1 was based on two types of data: fish data from  
106 scientific surveys and experts knowledge. Fish data were correlated to an anthropogenic pressure  
107 index using pressure-impact statistical models (Courrat et al., 2009; Delpech et al., 2010) (top box in  
108 Figure 1). Then models were used to convert fish observations in probabilities of experiencing

109 pressures (Drouineau et al., 2012) (left part of the second box). Experts assessments were  
110 aggregated to provide a global assessment per water body (right part of the second box) that was  
111 used as a prior in a Bayesian framework that combined both types of data (Drouineau et al., 2012)  
112 (third box). This allowed to put forward a pressure level applied on the fish communities of the studied  
113 water body. Pressure was decomposed in 5 equal pressure classes. Probability for a water body to be  
114 in each class was calculated (fourth box). Last, this level was associated to a quality level (last box).

## 115 2.1. Data sets

### 116 2.1.1. Fish data and pressure-impact models

117 A panel of 36 water bodies located along the French coasts of the English Channel and the Bay of  
118 Biscay were sampled between 2005 and 2009. A subset of 22 water bodies was sampled in 2010 to  
119 complete the WFD schedule (Fig. 2). Indeed, each water body had to be sampled at least 3 years  
120 during the 6-year WFD program. A detailed description of the sampling protocol was provided by  
121 Delpech et al. (2010) and Lepage and Girardin (2006). Each monitored water body was sampled in  
122 spring and autumn with a beam trawl. Hauls were distributed along the salinity gradient and 3 salinity  
123 classes were defined (Delpech et al., 2010): oligohaline class ( $[0. 5] \text{ g.L}^{-1}$ ), mesohaline class ( $[5. 18]$   
124  $\text{ g.L}^{-1}$ ) and polyhaline class ( $>18 \text{ g.L}^{-1}$ ). In each season, at least 6 hauls were carried out in each  
125 salinity zone of each water body. A minimum of 12 hauls was carried out in the water bodies having  
126 only one salinity zone (e.g. Downstream Seine). In each trawl haul (sample), each fish was identified  
127 to the species level and each species was assigned to functional ecological guilds related to its diet  
128 and its use of the estuarine ecosystems along its life cycle (Elliott and Dewailly, 1995).

129 The lack of pristine estuaries to define reference conditions involved the use of statistical modelling  
130 (Delpech et al., 2010; Pont et al., 2006). A solution was to develop pressure-impact models (Borja et  
131 al., 2006). However, a proxy of anthropogenic pressure is generally required to link fish data to human  
132 disturbances. In this study, an index developed by Courrat et al. (2009) was used. This index was  
133 based on a principal component analysis carried out on heavy metals concentrations measured by the  
134 French national network of quality of the French marine environment since 1979 in suspension feeder  
135 molluscs from various French estuaries. This index was normalized on the range  $[0;1]$ .

136 Based on those data, Courrat et al. (2009) proposed to build pressure-impact models (generalized  
137 linear models) to select metrics that are sensitive to anthropogenic pressure. Delpech et al. (2010)  
138 selected 4 metrics among the 12 metrics tested (density of (i) benthic fish, (ii) diadromous species, (iii)  
139 marine juveniles migrants and (iv) total density of fish respectively denoted DB, DDIA, DMJ and TD)  
140 because they significantly responded to a variation of anthropogenic pressures, and consistently with  
141 expert judgments (Delpech et al., 2010). The pressure-impact models were then used to predict the  
142 expected value of each metric at 3 distinct levels of anthropogenic pressures, providing thresholds for  
143 each metric. A scoring method was then applied to combine the 4 metrics in the indicator.

144 Pressure-impact models as proposed by Courrat et al. (2009) and Delpech et al. (2010) appeared  
145 appropriate to select metrics negatively correlated to pressure, and potentially relevant to be included  
146 in the index. Consequently, the metrics selected by Delpech et al. (2010) were used, except the total  
147 density metric (TD) given its redundancy with the combination of the 3 others (DB, DDIA and DMJ).  
148 Pressure-impact models were fitted and included in the framework proposed by Drouineau et al.  
149 (2012). Models options depended on data distribution of the different metrics. The use of linear  
150 models, consistent for DB metric, was inappropriate for the other metrics composed of 0 inflated.  
151 Thus, a delta type model that consisted in a combination of two models was used: one for  
152 presence/absence modelling, another one for positive values modelling. Those models were similar to  
153 models developed by Delpech et al. (2010), except for the use of generalized linear mixed models  
154 (GLMMs) rather than generalized linear models (GLMs). Indeed, an ~~estuary~~ random effect was  
155 incorporated in the model to avoid correlation between hauls carried out within an estuary. To assess  
156 estuaries quality in 2010, the models were fitted on previous fish data collected between 2005 and  
157 2009, using R software (R Development Core Team, 2011). This dataset (2005-2009) was considered  
158 for calibration of pressure-impact models. Akaike Information Criterion was used to select the most  
159 relevant and parsimonious models (Akaike, 1973).

160 GLMM of a metric  $M_{(i)}$  can be written on a matrix form (Drouineau et al., 2012):

$$161 \quad g_{(i)}(E(M_{(i)})) = \beta_{(i)}X + \beta_{(i)}Pr + Reffect$$

162 with  $g_{(i)}(E(M_{(i)}))$  the link transformed (function  $g_{(i)}$ ) expected value of the i-th metric,  $\beta_{(i)}$  the regression  
163 parameters for covariables,  $X$  the model matrix for the covariables,  $\beta_{(i)}$  the regression parameter for  
164 the pressure,  $Pr$  the vector of pressure values and  $Reffect$  the random effect linked to estuaries. Two

165 kinds of covariables detailed in Delpech et al. (2010) were tested: (i)  $\text{season}$  and  $\text{salinity class}$  were  
166 effects of protocol and (ii)  $\text{size}$  and  $\text{coregion}$  were estuarine features. Fitted GLMMs enabled to  
167 establish the following likelihood function with pressure as a parameter:

$$168 \quad L(\text{fish data}; \text{pressure}) = f(\text{fish data} | \text{pressure})$$

169 With  $f(\text{fish data} | \text{pressure})$ , the density of probability for a fish observation given a level of pressure.

170 This was used to convert 2010 fish data into probability densities; so that metrics were combined on a  
171 common scale (Drouineau et al., 2012).

### 172 2.1.2. Experts knowledge

173 A panel of 23 experts was interviewed to collect knowledge on the different water bodies. Experts  
174 having information on fish data collected in 2010 were not included in the panel to avoid hindsight bias  
175 (redundant information between fish data and experts opinions) (Morgan and Henrion, 1990). Experts  
176 were selected for their abilities to assess a global pressure level for one part of the sampled water  
177 bodies. Finally, the 23 experts provided 100 assessments for the 22 studied water bodies (between 3  
178 and 8 assessments per water body except Risle with only 2 assessments).

179 A user-friendly graphical interface was developed to collect experts assessment per water body. A  
180 cursors system was used to assess both mean level of pressure and to provide a reliability measure of  
181 the assessment (Fig. 3). This reliability box is a self-evaluation of the level of confidence the expert  
182 have on his assessment.

183 In order to guide his reflection, three sub-pressures (pollution, morphology and hydrology) had to be  
184 considered by the expert before assessing the global pressure (Fig.3). A manual provided  
185 explanations about the definition of each sub-pressure, the scale corresponding to the WFD reference  
186 conditions and the use of probability distributions. Moreover, a table at the end of the questionnaire  
187 presented a summary of all water bodies assessments realized by the expert, so that he could  
188 compare and adjust his assessments.

189 Experts assessments were aggregated in a unique informative prior per water body. To represent the  
190 experts diversity and get a stable prior, a minimum number of opinions is required (Kuhnert et al.,  
191 2005), but a limited number of 3 to 5 experts is suggested to provide a compromise between



192 redundant information and a good representation of experts intervariability (Clemen and Winkler,  
 193 1985; Ferrell, 1985; Makridakis and Winkler, 1983). To get a consistent framework between priors  
 194 given the limited number of available assessments per water body, 3 experts distributions were used  
 195 to build each prior. Given that experts could assess a water body even with a low knowledge level, the  
 196 assessments with the highest precisions were used to assimilate a good quality of information in  
 197 priors.

198 A beta distribution was fitted on the mixture of the 3 assessments to build a consensus prior (O'Hagan,  
 199 1998) for each water body (wb), ranging from [0;1] and denoted  $prior_{wb}$ .

## 200 2.2. Computing the index

201 Experts priors and fish data collected in 2010 were used to assess the quality of the different water  
 202 bodies using the following Bayesian equation (Drouineau et al., 2012):

203 The probability that the pressure level applied on a water body denoted  $wb$  was in a restricted  
 204 pressure class, given  $J$  fish observations, is (1):

$$(1) P(pressure_{wb} \in class_i | fish\ data_{wb}) = \frac{\int_{c_{i\ min}}^{c_{i\ max}} \prod_j f(fish\ data_{wb_j} | pressure_{wb}) * g(pressure_{wb}) . d\ pressure}{\int_{p_{min}}^{p_{max}} \prod_j f(fish\ data_{wb_j} | pressure_{wb}) . d\ pressure}$$

206 With  $[c_{i\ min}, c_{i\ max}]$  and  $[p_{min}, p_{max}]$  the domains of definition respectively of the pressure class  $i$  and the  
 207 whole pressure,  $f(fish\ data_{wb_j} | pressure_{wb})$  the density of probability of fish observation  $j$  ( $j$  in  $[1:J]$ )  
 208 given a pressure level directly calculated from the outputs of GLMMs,  $g(pressure_{wb})$  a density of  
 209 probability coming from a prior distribution of pressure.

210 This equation was summarised as the following relationship in Figure 1 (2):

$$(2) P(pressure_{wb} | fish\ data_{wb}) \propto P(fish\ data_{wb} | pressure_{wb}) * P(pressure_{wb})$$

212 To analyse the influence of experts knowledge, two indices were computed for each water body. The  
 213 first index included the prior based on experts knowledge (the resulting distribution is denoted  
 214  $index_{wb,exp}$ ) corresponding to the final indicator. The second index did not use experts prior but an  
 215 uninformative prior which was a uniform distribution between [0;1] (the resulting distribution is denoted  
 216  $index_{wb,non}$ ). WinBUGS (Lunn et al., 2000) was used to compute the a posteriori distribution, with a

217 Gelman Rubin test (Brooks and Gelman, 1998) to check chains convergence. Probability densities  
218 corresponding to each index were arbitrarily decomposed into 5 equal classes corresponding to 5  
219 quality classes.

220 For each water body, both the posterior probability in percentage in each quality level and the related  
221 mean class were computed for the 3 variables ( $prior_{wb}$ ,  $index_{wb,exp}$  and  $index_{wb,non}$ ). The comparison of  
222 these variables would inform on (i) the agreement level between experts knowledge and information  
223 from field data and on (ii) the effect of the combination of both information sources on quality statuses  
224 assessment. Results were synthesised in a Principal Components Analysis (PCA) where the 22 water  
225 bodies were individuals and the variables the 3 mean quality values.

### 226 3. Results

#### 227 3.1. Generalised linear models

228 The selected models were detailed in Table 1. Regression parameters of pressure were negative  
229 demonstrating that pressure and fish data were negatively correlated as expected. Regarding log  
230 normal models (positive fish data for metrics DDIA and DMJ), the standard deviations for the among-  
231 estuaries random effect, *estuary sd*, of the 3 metrics DB, DDIA and DMJ were respectively 0.70, 0.45  
232 and 0.88, while residuals variations among all fish data, *model sd*, were respectively 1.35, 1.22 and  
233 1.26. The relative high values of standard deviations of the random effect clearly justified the interest  
234 to include it in the models to provide accurate uncertainty assessments.

#### 235 3.2. Quality diagnosis

##### 236 3.2.1. Overview of the diagnosis provided by the 3 indices

237 The results of the 3 indices are summarized in Table 2. Mean classes for  $index_{wb,non}$  (i.e. diagnosis  
238 from fish data) and  $prior_{wb}$  (i.e. diagnosis from experts knowledge) were similar for only 32% of the  
239 water bodies. However, only 18% differed from more than one class, demonstrating a rather good  
240 consistency between fish data and experts knowledge (correlation rate of 0.63), with nonetheless an  
241 important discrepancy in the case of the Vilaine estuary. The final indicator,  $index_{wb,exp}$  (i.e. diagnosis  
242 from fish data and experts knowledge), was distributed between all quality classes, from high quality  
243 for Vilaine and Baie du Mont Saint Michel to bad quality for Bidassoa, Downstream and Central

244 Gironde, Upstream, Central and Downstream Seine. The associated credibility intervals at 95% were  
245 heterogeneous covering from 1 (e.g. Central Seine) to 3 (e.g. Seudre) quality classes. Consequently,  
246 the index precision was variable from one water body to another; it was lower for upstream water  
247 bodies of estuaries and for small estuaries. Comparing  $\text{index}_{\text{wb,exp}}$  to the two other indices showed that  
248 mean class was either between  $\text{index}_{\text{wb,non}}$  and  $\text{prior}_{\text{wb}}$  (14% of water bodies), or that it matched with  
249 both of them (32%), or only with one of them (36% with  $\text{index}_{\text{wb,non}}$  and 18% with  $\text{prior}_{\text{wb}}$ ).

### 250 3.2.2. Quality diagnosis and Water Framework Directive objectives

251 According to the normalized scale of quality retained in the present approach, 5 out of 22 water bodies  
252 fulfilled the objective to be at least in the good quality status and only 2 (Baie du Mont St Michel and  
253 Vilaine) without significant risk, i.e. with insignificant probability to be in the quality statuses lower than  
254 the good status. The Blavet had a high probability to be in a lower quality range and the risk was also  
255 significant respectively at 18% and 14% for Baie des Veys and Laita (Table 2).

### 256 3.2.3. Global comparison between the 3 indices

257 The three variables (mean values of quality for  $\text{index}_{\text{non,wb}}$ ,  $\text{prior}_{\text{wb}}$  and  $\text{index}_{\text{exp,wb}}$ ) were correlated to  
258 the first principal component of the PCA (Fig. 4), representing 86 % of the inertia and separating  
259 deteriorated from low-impacted water bodies.  $\text{index}_{\text{exp,wb}}$  was in intermediate position between  
260  $\text{index}_{\text{non,wb}}$  and  $\text{prior}_{\text{wb}}$ , providing a consensus between fish data and experts knowledge but giving  
261 more weight to fish data. Indeed, the correlation rate of  $\text{index}_{\text{exp,wb}}$  and  $\text{index}_{\text{non,wb}}$  is 0.96 while the  
262  $\text{index}_{\text{exp,wb}}$  and  $\text{prior}_{\text{wb}}$  one is 0.75 and the  $\text{index}_{\text{non,wb}}$  and  $\text{prior}_{\text{wb}}$  one is 0.63.

### 263 3.2.4. Diagnosis general trends

264 The position of the water bodies in the first PCA plane highlighted geographic contrasts (Fig. 4). The  
265 negative correlation between the first principal component and the Adour Garonne district water  
266 bodies revealed their bad quality contrasting with the Loire Bretagne district status. The Seine  
267 Normandie district water bodies were distributed in all quality scale. Moreover, the water bodies of the  
268 largest estuaries, Seine, Loire and Garonne/Gironde, were the most deteriorated of their respective  
269 districts.

270 Three main types of experts knowledge effects on the assessments are illustrated in Figure 5. In the  
271 Charente, the mean classes obtained with  $\text{index}_{\text{wb},\text{non}}$  and  $\text{prior}_{\text{wb}}$  were very different (respectively low  
272 pressure and high pressure) though the precision was similar. As a consequence,  $\text{index}_{\text{wb},\text{exp}}$  provided  
273 a consensus, i.e. medium class with an important uncertainty. A second situation occurred when mean  
274 classes obtained with  $\text{index}_{\text{wb},\text{non}}$  and  $\text{prior}_{\text{wb}}$  were adjacent such as for Baie du Mont Saint Michel. For  
275 this water body,  $\text{index}_{\text{wb},\text{exp}}$  provided an assessment consistent with  $\text{index}_{\text{wb},\text{non}}$  but with a lower  
276 precision. Finally, for some water bodies,  $\text{index}_{\text{wb},\text{non}}$  and  $\text{prior}_{\text{wb}}$  were consistent, such as for the Risle.  
277 In this case,  $\text{index}_{\text{wb},\text{exp}}$  was consistent with both  $\text{index}_{\text{wb},\text{non}}$  and  $\text{prior}_{\text{wb}}$  with a greater precision.

#### 278 4. Discussion

279 Many fish indicators were recently developed in the context of the Water Framework Directive.  
280 However, many of those indicators suffered from two main drawbacks: (i) assessments of  
281 uncertainties around quality diagnostics are missing (Perez-Dominguez et al., 2012) and (ii) the choice  
282 of core metrics combination is rather subjective. Regarding French estuaries, an indicator called ELFI  
283 was developed by Delpech et al. (Delpech et al., 2010), based on pressure-impact models proposed  
284 by Courrat et al. (Courrat et al., 2009). Pressure-impact approach proved to be a relevant method to  
285 choose appropriate metrics, however ELFI still suffered from the two weaknesses. Consequently, this  
286 paper developed an indicator based on ELFI pressure-impact models but applying a Bayesian  
287 framework developed by Drouineau et al. (2012). In addition, a method was proposed to collect and  
288 summarise expert judgments in order to combine them in the Bayesian framework with fish data. This  
289 approach found several interests detailed further.

##### 290 4.1. The pressure-impact Bayesian models

291 The index was based on generalised linear mixed models, and not on previously used generalised  
292 linear models (Delpech et al., 2010). Indeed, fish data were not perfect replicates but pseudo-  
293 replicates: several trawl hauls were collected in each estuary, generating dependency. Given that the  
294 estuary effect could not be taken into account, the independence assumption of data was corrupted. A  
295 rigorous solution was to use random effect in mixed models, with, as a consequence, an increase of  
296 the standard error and uncertainty around the parameters. A random effect of year was also tested but  
297 was not significant. Other random effects such the interaction between salinity class and estuary were  
298 also considered but the present GLMMs were finally considered as suitable. The index was finally

299 assessed on a Bayesian framework (Drouineau et al., 2012) and presented the advantages provided  
300 by this framework: (i) an objective combination of the core metrics and (ii) a quantification of the  
301 uncertainty around the diagnostic.

302 GLMMs were fitted with a pressure index based on water contamination in heavy metals (Courrat et  
303 al., 2009). As mentioned by Courrat et al. (2009), this index is highly correlated to many anthropogenic  
304 activities (industry, urbanisation, agriculture), consequently resulting pressure-impact models should  
305 be more considered as the global effect anthropogenic pressures than a direct effect of heavy metal  
306 contaminations. However, comparing results with models fitted on others global pressure indices could  
307 be relevant to assess the robustness of this hypothesis. It would also be interesting to apply the  
308 method to each different type of pressure separately (for example pollution, hydrology and  
309 morphology) to identify the more likely type of pressure impacting the ecological status. However, the  
310 water bodies are generally affected by various pressures simultaneously, consequently pressures are  
311 highly correlated and it would probably not be possible to conclude on the most likely pressure  
312 impacting a given water body. Moreover, to fulfil the WFD requirements, a method to combine the  
313 results on the different pressures in a unique indicator would be required. Bayesian Network may be  
314 an interesting method in the future to fulfil those challenges.

315 Regarding the indicator calibration and validation, it was chosen to calibrate the indicator on data  
316 collected from 2005 to 2009 and then to apply it on data collected in 2010. Usually, to cross-validate a  
317 model, a random subset of the entire dataset is used to calibrate and the other part of the data-set is  
318 used to validate the model. However, as proposed by Wenger and Olden (2012), it was chosen to  
319 apply a non-random cross-validation strategy which is appropriate to assess time transferability of the  
320 model. This strategy is consistent with the Water Framework Directive context: to assess the  
321 ecological status in a given year, all data from previous years will be used to calibrate the indicator  
322 since time series are often limited.

#### 323 4.2. Taking experts knowledge into account

324 The assessment realized in the Bayesian framework was based on both experts opinions and  
325 scientific surveys. Only another WFD-like index integrated directly experts knowledge in its  
326 architecture (Cabral et al., 2012). Indeed, experts knowledge was rarely considered in ecological  
327 indicators (Carpenter, 2002).

328 4.2.1. A method to collect and standardize knowledge

329 Before assessing the global pressure, it was asked the experts to assess three sub-pressures for  
330 every water body. But assessing sub-pressures before the global one may introduce bias since it may  
331 influence experts judgments. However, it is required to enhance the reproducibility of those experts  
332 assessments. To limit the potential bias, no weighting rates were proposed to establish global  
333 pressure, so each expert provided them on his own.

334 In addition, experts assessments may contain biases linked to the lack of neutrality (Choy et al., 2009;  
335 Dennis, 1996). Moreover, experts are usually overconfident (Hora et al., 1992; Kadane and Wolfson,  
336 1998; Winkler, 1967a, b). Consequently, too precise priors may drive parameters assessment rather  
337 than only provide a direction (Dennis, 1996). To get around both issues, knowledge of several experts  
338 was used to build priors to counterbalance both the bias linked to each expert background (Martin et  
339 al., 2005) and overconfidence. Indeed, the inter-variability between experts is generally higher than  
340 the variability of any expert opinion (Kuhnert et al., 2005; Uusitalo et al., 2005). Consequently, prior  
341 precision was mainly influenced by the agreement level between experts rather than the confidence  
342 level of each assessment.

343 Alternative methods exist to collect experts opinions. For instance, a simple choice in a range of  
344 different values is efficient if the number of experts is sufficient (Kuhnert et al., 2005; Martin et al.,  
345 2005). In other cases, and especially in the present approach, the limited number of experts involved  
346 the use of probability distributions. Assessing successive percentiles (Garthwaite and Dickey, 1996;  
347 Kadane and Wolfson, 1998) is a precise method but time consuming. A faster but less precise method  
348 (O'Hagan, 1998) aims at assessing a mean and a credibility interval of 50%. Both these methods can  
349 suffer of underestimation of distribution tails (Hora et al., 1992; Winkler, 1967a, b). Accordingly,  
350 assessing a graphical distribution directly was here preferred for its simplicity and user-friendliness, in  
351 order to use the instinct qualities of experts. A pressure scale with a colour gradient was developed  
352 instead of any common numerical scale to prevent the halo effect (Nisbett and Wilson, 1977), i.e. bias  
353 linked to the distorted perception of numerical scales of a repeated question.

354 Different solutions may be investigated to improve the precision of priors. The DELPHI method  
355 (Jacobs, 1995; Linstone et al., 1975) allows a prior to be elicited from several experts. A consensus is  
356 constructed indirectly after several assessment rounds. Between each round, each expert consults the

357 assessments and associated rationales provided by the others before updating his opinion. This kind  
358 of method generally provides a more precise prior though a direct consensus between experts could  
359 also be supported (O'Hagan, 1998). However, such method is time and costs consuming for the  
360 experts. In addition, they may suffer from a potential strong influence of few dominating experts,  
361 leading to a precision overestimation (Kuhnert et al., 2005). Another method (Coolen and Newby,  
362 1994) consists in defining a range of possible values, i.e. possible pressure levels here, selected by  
363 experts. A uniform prior is defined on the range. Such a prior is very informative because some  
364 pressure levels are unconsidered in the final index, leading to an unsuitable minor influence of fish  
365 data, and often to some problems in the convergence of Monte-Carlo Markov Chains.

#### 366 4.2.2. Insights provided by experts knowledge

367 The questionnaire used in the present approach proved to be efficient, with an answer rate greater  
368 than 75%. As a positive side-effect, it also proved to be an interesting communication tool: experts  
369 were interested by sharing their opinions and felt involved in the index development. On the whole,  
370 experts knowledge was rather consistent with fish data, demonstrating that the indicator provides an  
371 objective consensus between both data sources. Nevertheless, some discrepancies allowed to point  
372 out that experts knowledge may provide information not included in the data. Especially, the Vilaine  
373 estuary appeared rather specific, with a large disagreement between fish data and experts knowledge.  
374 In this estuary, a dam was built in 1970 and greatly impacted the water body (i.e. meso-haline and  
375 oligo-haline have entirely disappeared and this water body is considered as heavily modified in the  
376 WFD (Borja and Elliott, 2007)) explaining the negative assessment provided by the experts. However,  
377 the impact was not detected from surveys in the remaining poly-haline zone and the assessment  
378 based on fish data only was positive. Indeed, the impacts of removing parts of estuarine system were  
379 difficult to quantify from fish data given samplings were performed in remaining surfaces (Courrat et  
380 al., 2009). Though the small prior precision did not allow the assessment to be influenced significantly,  
381 this example legitimises the interest of experts knowledge in the indicator.

382 On one hand, when experts disagreed with the conclusion provided by fish data (e.g Vilaine but also  
383 Charente and Baie du Mont Saint-Michel), the impact of the prior on the indicator depended on two  
384 factors. The more precise and in contradiction with fish data was the experts consensus, the more the  
385 final main quality class was modified. So, the weighting between fish data and experts knowledge in

386 the final index is directly linked to their relative precisions. On the other hand, when experts knowledge  
387 and fish data matched, experts knowledge increased the final index precision (e.g. Risle). This last  
388 point illustrates another yet main advantage when using experts knowledge as the final assessment  
389 gains precision in a legitimate way. Applying experts knowledge appeared particularly essential in  
390 those situations where the most reliable assessment as possible should be obtained.

#### 391 4.3. Ecological status assessment of estuarine water bodies from fish data and experts knowledge

392 Using the present approach, the probability of the fish based index to be in any range of stressor  
393 values can be easily calculated. This allocation was here based on an arbitrary decomposition into 5  
394 equal classes of quality. A calibrating phase of the thresholds with the other European indices would  
395 be necessary to provide a relevant index with the WFD. Indeed, this approach focused on the interest  
396 of incorporating experts knowledge in fish index to improve quality assessment. It appeared especially  
397 appropriate to visualize sensitivity in allocation on a range of classes with well distributed data. In a  
398 WFD context, these classes do not necessary fit with five classes of environmental status. A  
399 calibrating phase of the thresholds with the other European indices will be necessary to provide a  
400 relevant index with the WFD. Nevertheless, this approach allowed to analyse patterns in quality  
401 assessment and associated variability among both estimation methods and water bodies.

402 The current index appeared particularly appropriate in the context of risk management, a notion  
403 developed by McAllister and Kirkwood (1998), and precautionary approach. In the WFD context, the  
404 risk may be defined by the probability of not being in a good ecological status which is provided by the  
405 Bayesian method (Drouineau et al., 2012). This might lead to different management measures for two  
406 water bodies such as Baie des Veys and Blavet. Both were qualified as having a good ecological  
407 status, but with different levels of risks (respectively 18% and 45%). In that context, though it had a  
408 moderate effect on the final mean class, including experts knowledge was a significant improvement  
409 because it often had a significant effect on the assessment precision.

410 According to the indicator, large estuaries (Seine, Gironde and Loire) were shown to be the most  
411 deteriorated estuaries of their district. As precision was high for these estuaries, this statement could  
412 be considered as reliable. As a consequence, specific restoration effort should be dedicated to large  
413 estuaries. Assessments from fish data tended to be less precise for upstream water bodies than for  
414 corresponding downstream water bodies. This indicated more restricted knowledge, perhaps linked to



415 the choice of metrics or the fishing gear (beam trawl) used during the surveys, less appropriate for  
416 upstream water body. Similar remarks could be made when comparing small estuaries, which quality  
417 estimates were uncertain, to large ones. Two converging facts explained that point. First, the size of  
418 small estuaries limited sometimes the number of trawl hauls and consequently the assessment  
419 precision. Secondly, given small estuaries were not as studied as the large ones in the past, prior  
420 precision was globally smaller and did not match with fish data as much as for the large water bodies.  
421 In that context, new data acquisition should be obtained from upstream and small water bodies in  
422 priority, either from other surveys or by consulting specific experts.

423 The index proposed here appears especially relevant in data poor situation. For example in France,  
424 only 22 water bodies have presently been monitored (for 14 more, a previous estimate was realized  
425 between 2005 and 2009) though 54 estuarine transitional water bodies are listed in the WFD context.  
426 For the remaining estuaries, given the cost of scientific surveys, the index may first provide an  
427 assessment only based on experts knowledge. However, in this situation, these very preliminary  
428 assessments would be based on experts opinion including all the implied subjectivity. Moreover, the  
429 lack of quantitative assessment will prevent from measuring effects of restoration if water bodies are  
430 not considered in good ecological status.

431 In conclusion, the Bayesian approach is a generic method fulfilling WFD index objectives. It can be  
432 used for any index based on a pressure-impact approach. Its main advantages are (i) its flexibility in  
433 the modelling phase, (ii) its estimates of uncertainty and (iii) its possibility to integrate easily and  
434 rigorously experts knowledge. The presented method to collect and combine experts opinions in a  
435 prior should not be ignored given its cost-efficiency and its adequacy with the common availability of  
436 experts.

437

#### 438 Acknowledgements

439 Authors would like to thank the French Water Agencies and the Onema for their collaboration and all  
440 the partners involved in the collect of survey data. They also would like to thank the experts who have  
441 participated to the study. This work is part of the WISER European project (Water bodies in Europe:  
442 Integrative Systems to assess Ecological status and Recovery) funded by the European Union under

443 the 7th Framework Programme, Theme 6 (Environment including Climate Change) (contract No.  
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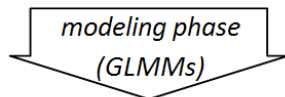
573

574 Figure captions:

FOR ALL WATER BODIES

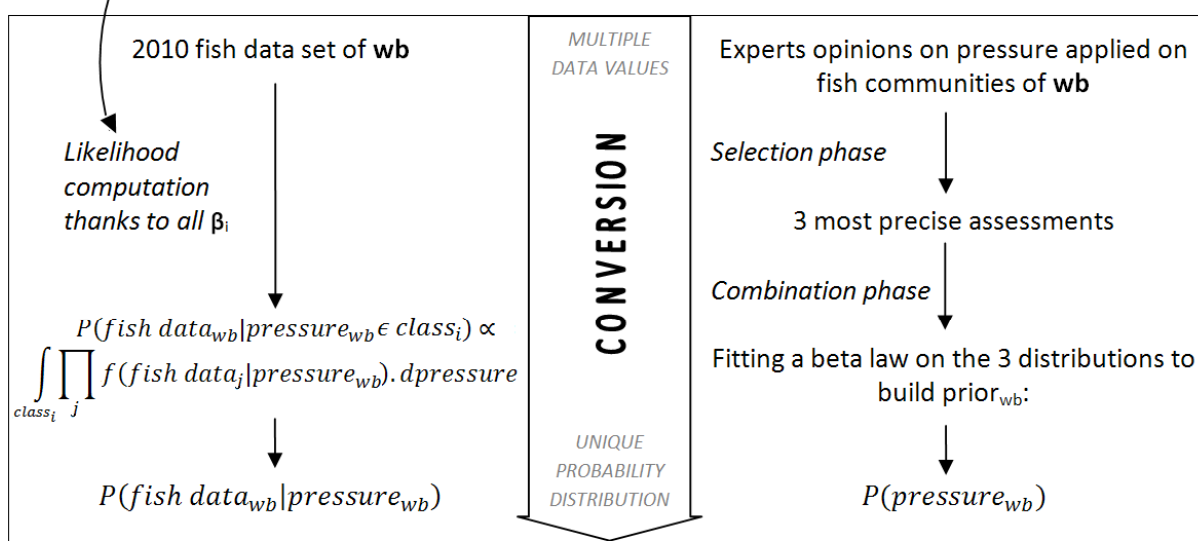
PRELIMINARY PHASE

2 data sets on all available water bodies:  
 i) the calibration fish data set (2005-2009)  
 ii) the associated pressure index



$\beta_i$ : the fitted links between fish data of metric<sub>i</sub> and pressure index

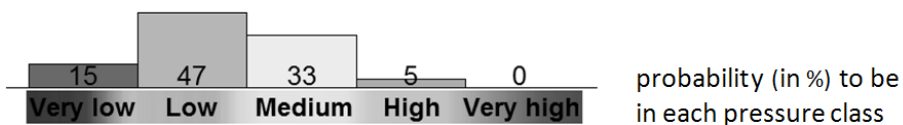
FOR A UNIQUE WATER BODY DENOTED WB



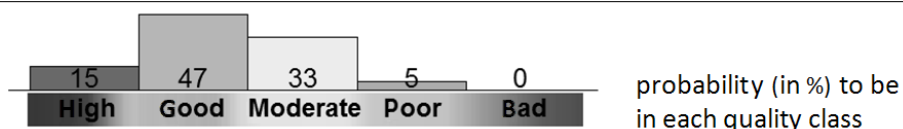
BAYESIAN FRAMEWORK

$$P(\text{pressure}_{wb} | \text{fish data}_{wb}) \propto P(\text{fish data}_{wb} | \text{pressure}_{wb}) * P(\text{pressure}_{wb})$$

PRESSURE<sub>wb</sub> PROFILE



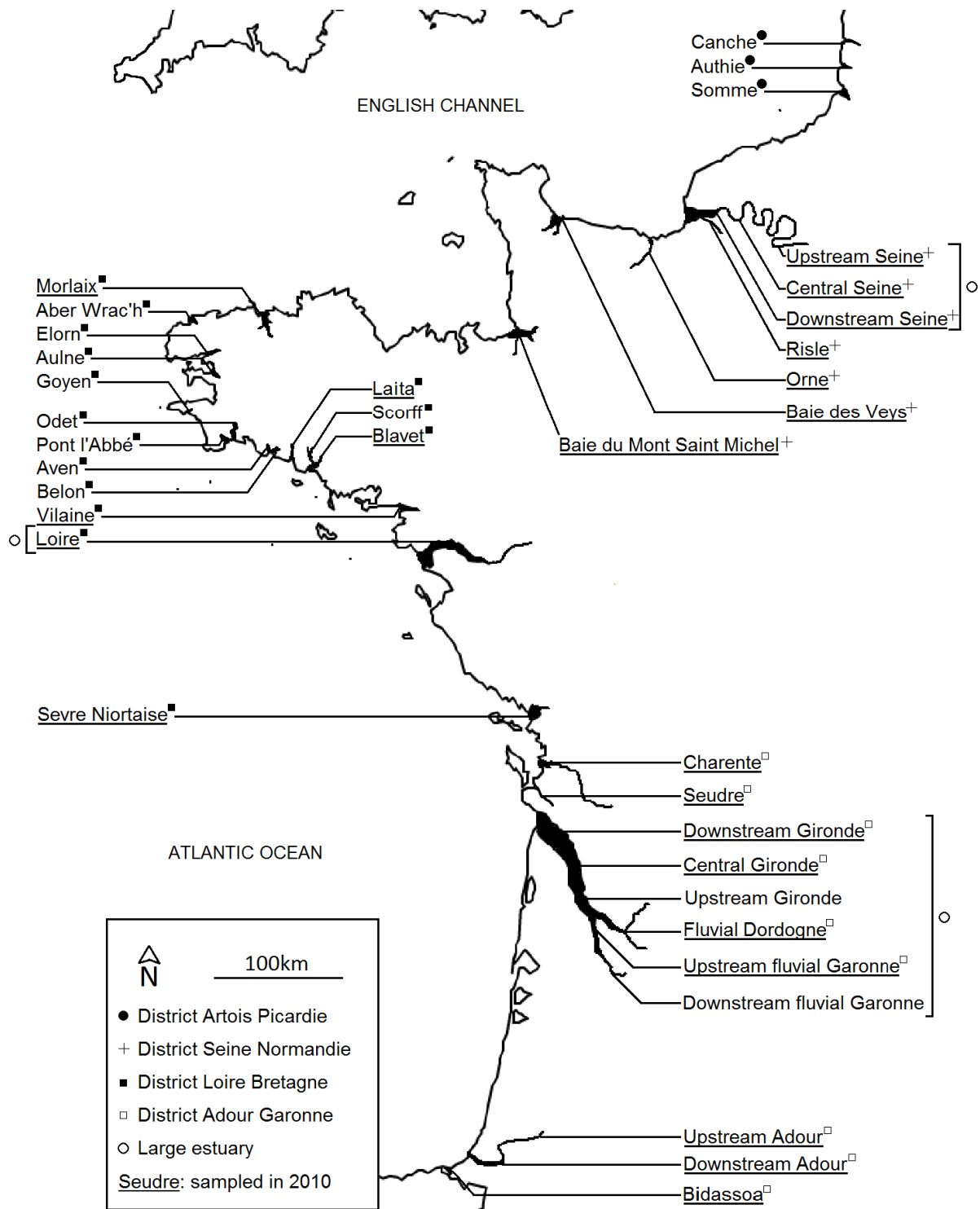
QUALITY<sub>wb</sub> PROFILE



575

576 Fig. 1: General methodology to develop the index

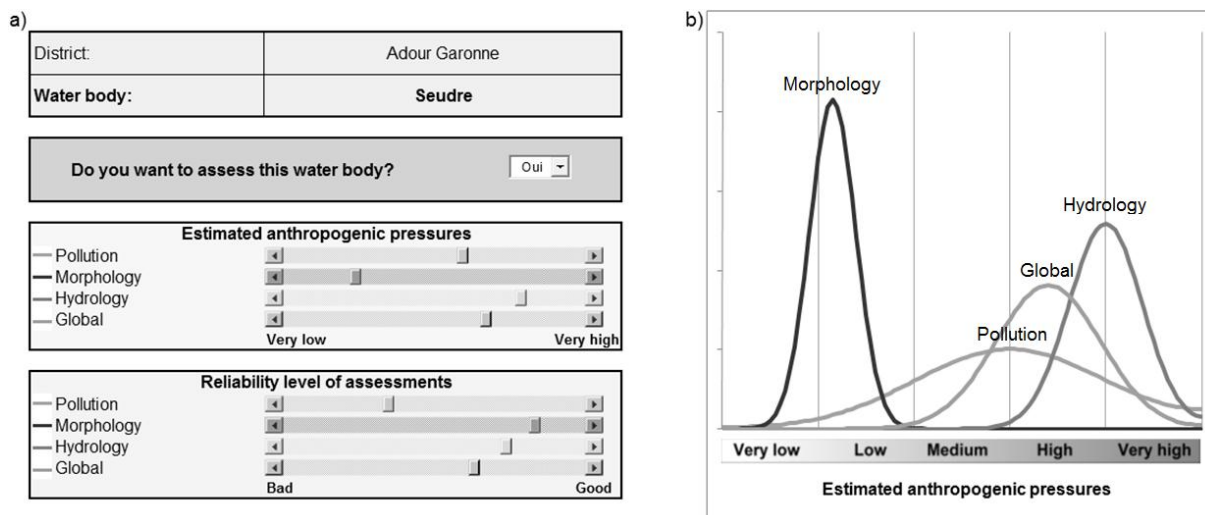




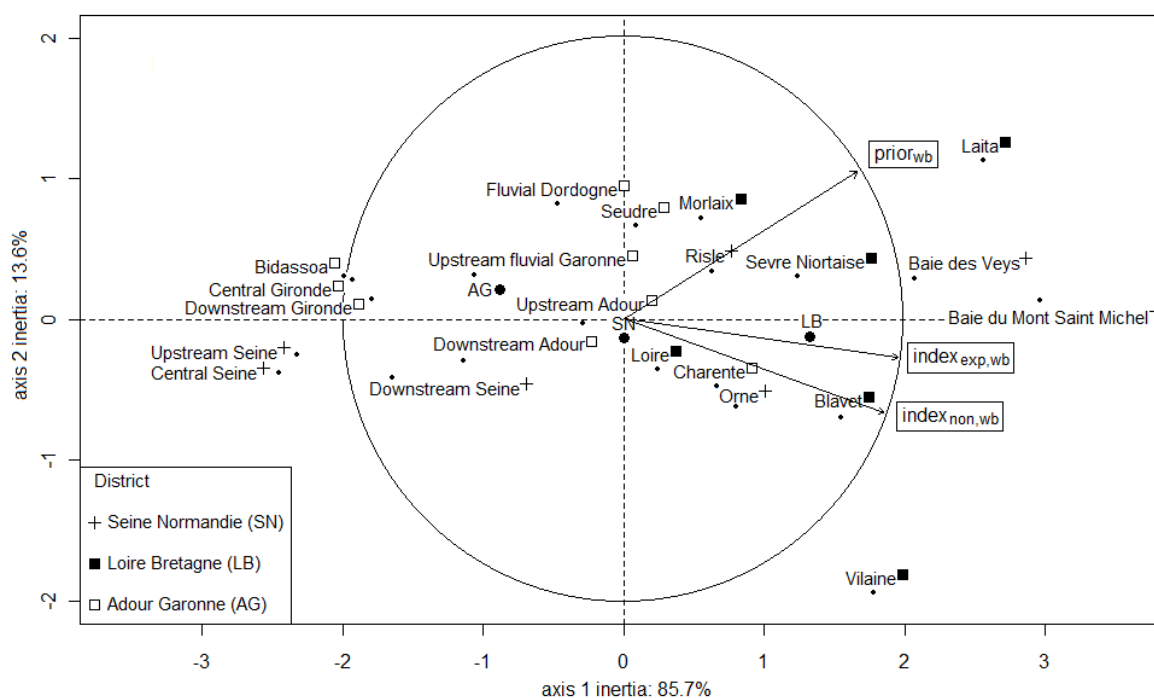
577

578 Fig. 2: Study area and investigated water bodies in 2010 gathered in 3 geographical groups

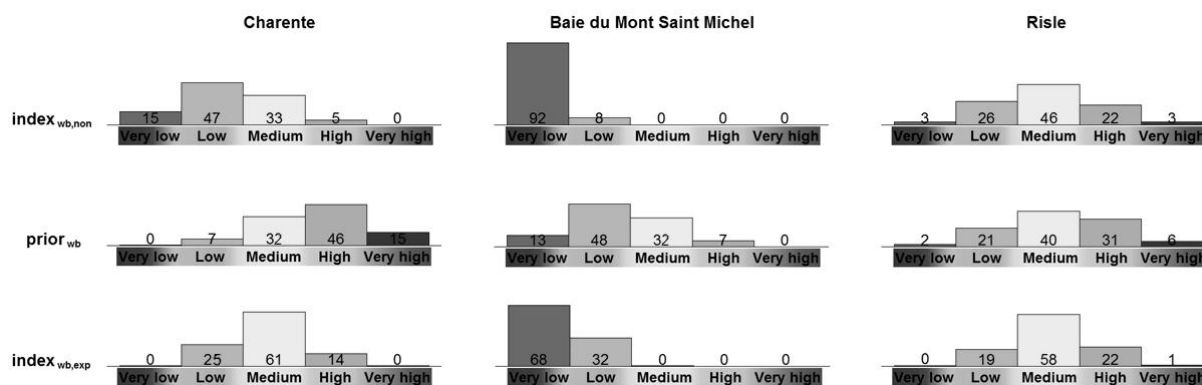
579 corresponding to 3 districts; an estuary can be made up of several water bodies



580  
 581 Fig. 3: Interface provided for experts to assess the pressure level of each water body: a) Table to fill by  
 582 each expert; b) related representation



583  
 584 Fig. 4: Correlation circle of the PCA on the 3 indices ( $index_{wb,non}$ ,  $prior_{wb}$  and  $index_{wb,exp}$ ), the scale is  
 585 twice the original one; individuals (water bodies) are gathered according to their respective district in  
 586 the first factorial plan of the PCA



587  
 588 Fig. 5: Distributions of each index ( $index_{wb,non}$ ,  $prior_{wb}$  and  $index_{wb,exp}$ ) for 3 water bodies (Charente,  
 589 Baie du Mont Saint Michel, Risle), the number in each stick represents the rounded probability in  
 590 percentage to be in the associated pressure class

Metric (density of fish)	Model type	Model
Benthic (DB)	Log normal	$\text{Log}(DB+1) \sim \text{season} + \text{salinity} + \text{size} + \text{pressure} + \text{estuary random effect}$ pressure $rp$ : -1.62, estuary $sd$ : 0.70, model $sd$ : 1.35
Diadromous (DDIA)	Bernoulli	$\text{Logit}(DDIA_{0/1}) \sim \text{season} + \text{salinity} + \text{size} + \text{ecoregion} + \text{pressure} + \text{estuary random effect}$ pressure $rp$ : -1.36, estuary $sd$ : 1.19
	Log normal	$\text{Log}(DDIA_{+}) \sim \text{season} + \text{salinity} + \text{size} + \text{ecoregion} + \text{pressure} + \text{estuary random effect}$ pressure $rp$ : -2.57, estuary $sd$ : 0.45, model $sd$ : 1.22
Marine juveniles (DMJ)	Bernoulli	$\text{Logit}(DMJ_{0/1}) \sim \text{season} + \text{size} + \text{ecoregion} + \text{pressure} + \text{estuary random effect}$ pressure $rp$ : -4.78, estuary $sd$ : 1.16
	Log normal	$\text{Log}(DMJ_{+}) \sim \text{season} + \text{salinity} + \text{size} + \text{pressure} + \text{estuary random effect}$ pressure $rp$ : -2.75, estuary $sd$ : 0.88, model $sd$ : 1.26

591  
 592 Table 1: Models structure of the 3 metrics used; an arbitrary value of 1 is added to each value of DB  
 593 metric; delta type models composed of one sub model for presence/absence ( $_{0/1}$ ) and another one for  
 594 positive values (+); pressure regression parameter is denoted  $pressure\ rp$ ; standard deviation of the  
 595 estuary random effect is denoted  $estuary\ sd$ ; model residuals standard deviation is denoted  $model\ sd$

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Water body	High	Good	Moderate	Poor	Bad
<b>DISTRICT: SEINE NORMANDIE</b>					
Upstream Seine*	0	0	0	7	<b>93</b>
Central Seine*	0	0	0	4	<b>96</b>
Downstream Seine*	0	0	0	40	<b>60</b>
Risle	0	19	<b>58</b>	22	1
Baie des Veys	13	<b>69</b>	17	1	0
Orne	1	37	<b>53</b>	9	0
Baie du Mont Saint Michel	<b>68</b>	32	0	0	0
<b>DISTRICT: LOIRE BRETAGNE</b>					
Morlaix	0	12	<b>62</b>	25	1
Laita	31	<b>55</b>	14	0	0
Blavet	0	<b>55</b>	44	1	0
Vilaine	<b>71</b>	29	0	0	0
Loire*	0	4	<b>57</b>	38	1
Sevre Niortaise	0	31	<b>66</b>	3	0
<b>DISTRICT: ADOUR GARONNE</b>					
Charente	0	25	<b>61</b>	14	0
Seudre	0	5	<b>50</b>	43	2
Upstream fluvial Garonne*	0	0	11	<b>63</b>	26
Fluvial Dordogne*	0	5	20	<b>44</b>	31
Central Gironde*	0	0	0	23	<b>77</b>
Downstream Gironde*	0	0	0	35	<b>65</b>
Upstream Adour	0	2	34	<b>57</b>	7
Downstream Adour	0	0	4	<b>72</b>	24
Bidassoa	0	0	0	15	<b>85</b>

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606 Table 2: For each water body ranked by district, posterior probabilities (in %) from the index with  
 607 experts prior,  $index_{wb,exp}$ , to be in each quality class; the mean classes are indicated for  $index_{wb,exp}$   
 608 (bold character),  $index_{wb,non}$  (box) and  $prior_{wb}$  (shaded); the water bodies of large estuaries are  
 609 indicated with the symbol: \*

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