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1 Emergence of negative trophic level-size relationships from a size-based,  
2 individual-based multispecies fish model

3  
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12

13 **Abstract**

14 Modeling the mechanisms underlying trophic interactions between individuals allows the food web  
15 structure to emerge from local interactions, which constitutes a prerequisite for assessing how marine  
16 ecosystems respond to various anthropogenic pressures. Using a multispecies spatially explicit  
17 individual-based model, the emergence of trophic patterns was explored in the eastern English Channel  
18 ecosystem, where pelagic-benthic trophic coupling was recently studied empirically. The OSMOSE model  
19 was applied to this ecosystem by explicitly representing the life cycle of 13 fish species and one squid  
20 group, forced by pelagic and benthic prey fields that are variable over time and space. A matrix defining

21 possible accessibilities between life stages was added to the model to link benthic and pelagic  
22 communities through overlap of vertical distribution. After optimizing some parameters of the model to  
23 represent the average state of the fish community during the 2000-2009 period, the simulated trophic  
24 structure was explored and compared to empirical data. The simulated and stable-isotope-derived  
25 trophic levels of fish were in relatively good agreement. Intraspecific variability of the trophic level is  
26 high in the five stable-isotope datasets but is well encompassed by the model. Despite the hypothesis of  
27 opportunistic size-based predation, the simulation showed a decreasing trend of trophic level with size  
28 for four benthic species, a pattern observed empirically for a different set of species in the ecosystem.  
29 Model exploration showed that this emerging pattern varies spatially and is both explained by the spatial  
30 variability of prey availability and by the independence of trophic and size structures of benthic  
31 invertebrates. The combination of individual-based models of stomach contents and intrinsic tracers,  
32 such as stable isotopes, appears to be a promising tool to better understand the causes of observed  
33 trophic patterns.

34

35 **Highlights** (3 to 5 bullet points with maximum 85 characters, including spaces, per bullet point)

- 36 • An individual-based model successfully simulates the eastern English Channel food web
- 37 • Trophic spectrum of 14 species generally match 2000-2009 stable isotope data
- 38 • Intraspecies trophic variability is high, both in the model and the stable isotope data
- 39 • The emerging relationship of trophic level with size is negative for four species

40

41 **Keywords**

42 Emergent patterns; pelagic-benthic coupling; individual-based model; food web; fish community

43

44 **1. Introduction**

45

46 Trophic ecology has been investigated empirically for decades in marine ecosystems to better  
47 understand key properties of ecosystems, including energy flows in ecosystems, the resilience and  
48 adaptation of ecosystems to large-scale pressures and the relationship between biodiversity and  
49 ecosystem functioning (Belgrano et al., 2005). The current need to establish an integrated management  
50 framework fosters the development of a multitrophic approach, where all interspecific interactions are  
51 addressed (Seibold et al. 2018). Initially addressed through stomach content analysis, trophic ecology is  
52 now based on various tools, including intrinsic tracers, such as stable isotope ratios and fatty acids  
53 (Ramos and González-Solís, 2012). Combining “old” and “modern” techniques is now viewed as the most  
54 powerful approach (Cresson et al., 2014) providing both a detailed vision of prey actually consumed and  
55 a general picture of trophic fluxes and food web topology. In parallel with these field studies based on  
56 biological sampling and chemical analysis, theoretical work has focused either on predator-prey  
57 interactions (e.g., Lotka-Volterra) or on network complexity and stability (Belgrano et al., 2005). The  
58 development of holistic models allowed the coupling of theoretical and empirical approaches by  
59 conceptualizing the food web structure of a particular ecosystem based on data and simulating its  
60 dynamics. Typically, Ecopath models (Christensen and Pauly, 1992) aim at balancing the food web  
61 structure of an ecosystem of interest based on observed diets and produce network indicators such as  
62 the recycling index, average path length and total system throughput (Heymans et al., 2014) but also  
63 information about species trophic positions and functions and their impacts on other functional groups.  
64 Partly to increase their realism and partly to answer a wider range of scientific questions, the complexity  
65 of ecosystem models has been increasing by integrating temporal (e.g., Ecopath with Ecosim) and spatial

66 heterogeneity (e.g., Ecospace (Pauly et al., 2000), Atlantis (Fulton et al., 2011)) and by considering age or  
67 size structure within a trophic node defined to represent a species or functional group. Such models are  
68 currently mostly used to explore ecosystem responses to anthropogenic or environmental pressure, and  
69 their potential for theoretical trophic ecology is most likely underused. Trophic information from field  
70 studies is required to parameterize links between compartments, at least to identify them and  
71 sometimes to set their intensity (i.e., percentage of a prey in the diet of the predator) (Pethybridge et al.,  
72 2018). However, this information is at best used at the species level and is often averaged over several  
73 species to inform functional group trophic habits. Trophic variability exists among individuals and can be  
74 linked to ontogenetic changes, individual variability and composition of the local trophic environment  
75 (spatiotemporal heterogeneity) (e.g., Stehlik and Meise, 2000). Instead of reducing this variability to  
76 parameterize ecosystem models, in this study, we aim to use a complex modeling approach to explore  
77 the individual trophic variability of marine fish. To do so, we used the multispecies individual-based  
78 model OSMOSE (Shin and Cury, 2004, 2001; Travers et al., 2009), where fish individuals constitute the  
79 structural unit of the model. Individual-based models (IBMs) allow for representing individuals that adapt  
80 to their local environment (leading to variability among individuals) and that interact mechanistically  
81 with each other and with their environment (both abiotic and biotic, i.e., composed of other individuals).  
82 Interactions between these adaptive individuals lead to the emergence of population-level properties  
83 (e.g., resilience, spatiotemporal variations of abundance), which are more than the sum of individual  
84 properties (Grimm and Railsback, 2013). Applied to trophic ecology, this means that the trophic structure  
85 of an ecosystem emerges from local predation interactions between fish individuals (being both prey and  
86 predator).

87 We applied the OSMOSE modeling framework to the eastern English Channel (EEC), where several  
88 empirical trophic studies have been recently conducted. The English Channel is an epicontinental sea  
89 located between the United Kingdom and France and is subject to environmental forcing (mega tidal

90 regime and strong influence of rivers) and various human pressures, such as fisheries, aggregate  
91 extraction, maritime traffic, and wind farms (Carpentier et al., 2009). The structure and spatiotemporal  
92 variation of the fish community has been studied (Vaz et al., 2007), and the trophic links structuring this  
93 ecosystem have been recently investigated as well. Cachera (2013) studied the trophic organization of  
94 the fish communities through digestive tract contents and geomorphometric measurements to link it to  
95 morphological and functional trait variation across and within species. Kopp et al. (2015) investigated the  
96 strength of the pelagic-benthic coupling along an inshore-offshore gradient via stable isotope ratios.  
97 Giraldo et al. (2017) coupled both approaches to make conclusions regarding the resource use of fish  
98 along the depth gradient. These studies showed that benthic-pelagic coupling is strong in the EEC, with  
99 benthic sources being important for both benthic and pelagic fish and with a decreasing intensity of the  
100 benthic-pelagic coupling as depth increases. In addition to these empirical studies, a holistic model has  
101 been applied to the EEC to explore the effects of fisheries management options on the flatfish and  
102 demersal fish species (Girardin, 2015). The calibration process of this Atlantis model allowed us to gain  
103 better insight into ecosystem functioning and to identify the main drivers of the system, including the  
104 importance of nutrient input through rivers and the competition interactions between demersal species  
105 (Girardin et al., 2018). While the EEC trophic structure has been investigated through several methods,  
106 some of its variability remains unexplained and is assumed to be related to intraspecific and seasonal  
107 variations. To address the finer dynamics of the predation process and how it can shape observed  
108 patterns at different levels of organization, OSMOSE was applied to the EEC ecosystem to explore the  
109 trophic variability of fish individuals.

110

## 111 **2. Materials and methods**

112

113 The individual-based OSMOSE (Object-oriented Simulator of Marine eCOsystems Exploitation, Shin and  
114 Cury, 2004, 2001; Travers et al., 2009, [www.osmose-model.org](http://www.osmose-model.org)) is a spatial model representing the  
115 whole life cycle of several fish species from eggs and larvae up to juveniles and adults. This multispecies  
116 model is size-structured and based on opportunistic predation that depends only on spatiotemporal  
117 cooccurrence and body size ratios between a predator and its prey. Because of this opportunism, neither  
118 the a priori food web structure nor the diet matrix are set, but they emerge from local trophic  
119 interactions. This model has been applied to a variety of ecosystems, such as upwellings (e.g., Marzloff et  
120 al., 2009; Travers-Trolet et al., 2014; Oliveros-Ramos et al., 2017), estuaries (e.g., Brochier et al., 2013),  
121 semi-enclosed seas (Fu et al., 2012) and shelf seas (e.g., Grüss et al., 2015; Halouani et al., 2016). The  
122 main structure and equations of the model are presented below, before focusing on its application to  
123 the EEC. An extended description of the OSMOSE model following the ODD protocol (Overview, Design  
124 concepts, and Details) proposed by Grimm et al. (2010) and a description of the R packages dedicated to  
125 the model calibration are also available at <https://documentation.osmose-model.org/osmose.html>.

126

## 127 2.1. Model structure and processes represented in OSMOSE

128 The individual element of the OSMOSE model is a super-individual of identical fish (Scheffer et al. 1995),  
129 i.e., of the same size, same trophic level (TL), same location and belonging to the same species. During  
130 each two week time step, the abundance (also called worth) and biomass of each super-individual  
131 changes according to the different modeled processes, described below (Figure 1). Only the main  
132 features and equations are recalled in this paragraph, and more complete details can be found in Shin  
133 and Cury (2004, 2001), Travers et al. (2009), and Travers-Trolet et al. (2014).

134 At the beginning of the time step, super-individuals are distributed over a 2-dimensional grid. The spatial  
135 distribution of fish is driven at the larger scale by presence/absence maps provided as input for each

136 species and possibly for different ages and/or seasons according to available knowledge. When the input  
137 distribution map remains the same between two consecutive time steps, super-individuals can move to  
138 adjacent cells following a random walk pattern (foraging), while always remaining within the limits of  
139 their presence map.

140 After movement, all processes involving local interactions occur: explicit predation on other super-  
141 individuals and on plankton and/or benthic invertebrate groups, mortality from this explicit predation,  
142 starvation mortality, fishing mortality and mortality from other sources such as top predators. In the real  
143 world, such processes are concurrent and concomitant. To approximate real continuous time, the  
144 mortality algorithm introduces (i) a subdivision of the time step (here set to 10), (ii) random shuffling of  
145 super-individuals and mortality processes within every time step and (iii) asynchronous updating of the  
146 state variables (i.e., super-individual biomass is updated as the model goes through the processes)  
147 (Caron-Lormier et al., 2008). The predation process first assesses the food requirement for each super-  
148 individual, based on the maximum ingestion rate  $r$  of the predator  $i$ . This value is then compared to the  
149 amount of suitable food available locally, i.e., in the cell of the predator, defined by the suitability of prey  
150 size compared to predator size, the biomass  $B_j$  of each prey available and an accessibility coefficient  $a_{i,j}$   
151 representing vertical overlap and/or morphological constraints between the prey  $j$  and the predator  $i$ .  
152 Depending on the available biomass of prey, a predator can thus eat an amount of food varying between  
153 0 (no prey of suitable size available) and its maximum ingestion rate. The predated biomass  $PB_{i,j}$  of a prey  
154  $j$  by a predator  $i$  is expressed as follows:

$$155 \quad PB_{i,j} = \min \left( r B_i \frac{a_{i,j} B_j}{\sum_k a_{i,k} B_k}, a_{i,j} B_j \right) \quad (\text{Equation 1})$$

156 The predation pressure is applied to all prey, proportional to their relative contribution to the total  
157 amount of edible food (i.e., no preference). Predation mortality is then applied to the preyed super-  
158 individual by reducing its abundance and biomass according to the realized predation pressure, possibly



159 leading the super-individual to disappear if abundance falls below 1. According to the amount of food  
 160 eaten compared to its maximum ingestion, the predation efficiency  $\xi$  is computed for each super-  
 161 individual  $i$ . If  $\xi_i$  falls below the threshold corresponding to maintenance requirement  $\xi_{crit}$ , the starvation  
 162 mortality rate  $M_\xi$  is positive and increases linearly with predation efficiency reduction (Equation 2).

$$163 \quad M_\xi = \frac{-M_{\xi_{max}}}{\xi_{crit}} \xi_i + M_{\xi_{max}} \quad (\text{Equation 2})$$

164 The different mortality rates (starvation  $M_\xi$ , fishing  $F$  and other sources  $M_{oth}$ ) are applied similarly to  
 165 decrease the abundance of a super-individual  $i$  following the survival formula (Equation 3).

$$166 \quad N_{i,t+\Delta t} = N_{i,t} e^{-\Delta t M_x} \quad \text{with } M_x \in \{M_\xi, F, M_{oth}\} \quad (\text{Equation 3})$$

167 The fishing mortality rate is species-specific, but can vary temporally and/or spatially according to  
 168 available knowledge. For the fishing process, knife-edge selectivity was used, affecting only recruited fish  
 169 i.e., fish older than the species age at recruitment. Finally, mortality from other sources is also  
 170 considered by taking into account predation by organisms nonexplicitly represented in the model (e.g.,  
 171 other fish, birds, mammals) as well as diseases and senescence. A particularly high mortality term is  
 172 applied to the first stages (eggs) to represent the bottleneck of survival due to nonfertilization of eggs,  
 173 starvation of first-feeding larvae, advection, sinking and predation by nonexplicitly modeled organisms.  
 174 Because very little quantification exists on these processes, the larval mortality rates are calibrated (see  
 175 section 2.4).

176  
 177 After this loop of interaction processes, growth can occur if the predation was successful enough, i.e., if  
 178 the biomass eaten is higher than maintenance requirements. The length increment depends on the  
 179 predation efficiency and averaged length increment ( $\Delta L$ ) at the super-individual's age derived from the

180 von Bertalanffy growth curve (Equation 4). The weight  $W$  of an individual increases simultaneously with  
 181 its length through an allometric relationship.

$$182 \quad \begin{cases} \Delta L_{i,t} = 0 & \text{if } \xi_i < \xi_{\text{crit}} \\ \Delta L_{i,t} = \frac{2\Delta L}{1-\xi_{\text{crit}}} (\xi_i - \xi_{\text{crit}}) & \text{if } \xi_i > \xi_{\text{crit}} \end{cases} \quad (\text{Equation 4})$$

183 Finally, the time step ends with the reproduction process, where new super-individuals of eggs are  
 184 produced, depending on the spawning stock biomass (computed from a sex ratio of 1:1 and from the  
 185 biomass  $B$  of all fish older than age at maturity  $A_{\text{mat}}$ ), the species relative fecundity  $\varphi$  and the seasonality  
 186 of spawning  $s_t$  (Equation 5).

$$187 \quad N_{0,t} = \varphi s_t \frac{1}{2} \sum_{a > A_{\text{mat}}} B_{a,t} \quad (\text{Equation 5})$$

188

## 189 2.2 Application to the eastern English Channel

190 The EEC ecosystem is modeled with OSMOSE through the explicit consideration of 14 species, which  
 191 constitute 80% of the international landings from this area (ICES area 7d, excluding invertebrates) and  
 192 more than two-thirds of the fish biomass sampled during the scientific bottom trawl Channel Ground  
 193 Fish Survey (CGFS, Coppin and Travers-Trolet 1989). This set of species is composed of mackerel  
 194 (*Scomber scombrus*), horse mackerel (*Trachurus trachurus*), sardine (*Sardina pilchardus*), herring (*Clupea*  
 195 *harengus*), poor cod (*Trisopterus minutus*), cod (*Gadus morhua*), whiting (*Merlangius merlangus*),  
 196 pouting (*Trisopterus luscus*), red mullet (*Mullus surmuletus*), dragonet (mostly *Callionymus lyra*), lesser  
 197 spotted dogfish (*Scyliorhinus canicula*), sole (*Solea solea*), plaice (*Pleuronectes platessa*) and squids  
 198 (*Loligo forbesi* and *Loligo vulgaris*). Species parameters are reported in Table 1 and are mostly derived  
 199 from Carpentier et al. (2009) but also from other literature or online databases (Appendix A). The  
 200 modeled area extends from 49°N - 2°W to 51.2°N - 2.5°E and is composed of 445 cells of 0.6° x 0.6°

201 (Figure 2). Presence/absence maps per species, and per season and/or age class when available, have  
202 been computed from survey data and available literature (Appendix B). Two species migrate out of the  
203 English Channel towards the North Sea: adult horse mackerel from July to September and herring from  
204 April to September. When these species are out of the modeled area, they grow following the von  
205 Bertalanffy curve (Table 1) and undergo an additional mortality of  $1.05 \text{ year}^{-1}$  and  $0.55 \text{ year}^{-1}$ ,  
206 respectively (values derived from an Ecopath model applied to North Sea, Mackinson and Daskalov,  
207 2007). Reproductive seasonality of each species is reported in Appendix C, while the fishing mortality  
208 rate is considered constant over the seasons for all species except for squids (fishing closure from May to  
209 mid-July) and horse mackerel (increased fishing mortality rate from October to December).

210

### 211 2.3 Forcing prey fields: planktonic and benthic groups

212 During the predation process, super-individuals can feed both on other explicitly modeled fish and on  
213 low trophic level (LTL) sources. LTL groups are integrated in OSMOSE through the forcing of biomass prey  
214 fields. Plankton prey fields come from the ECO-MARS3D biogeochemical model applied to the English  
215 Channel (Le Goff et al., 2017; Vanhoutte-Brunier et al., 2008) with a grid of 2 km horizontal resolution  
216 and 10 vertical layers. The nutrients and plankton dynamics simulated with this model have been  
217 validated with data from monitoring stations and correctly reproduce the interannual variability  
218 observed in the English Channel (Le Goff et al., 2017). The biomasses of two phytoplankton groups  
219 (grossly representing dinoflagellates and diatoms) as well as microzooplankton and mesozooplankton  
220 groups have been integrated vertically and over the 2-week time step of OSMOSE to be used as forcing  
221 prey fields. Furthermore, as the current application aims at simulating the EEC ecosystem at a stable  
222 state, plankton climatology was created by averaging data bimonthly from the 2000-2006 period  
223 (Appendix D). Six additional LTL groups were added to complement the LTL food source available to fish:

224 a macrozooplankton group (representing both holoplankton and meroplankton mostly composed of  
225 benthic invertebrate larvae) and five benthic groups of different sizes (Table 2). As available information  
226 on the spatial distribution of these groups was not sufficient, they were considered to be  
227 homogeneously distributed.

228 The grid used in OSMOSE has no vertical dimension; therefore, accessibility coefficients were used to  
229 represent vertical overlap both among super-individuals and between super-individuals and LTL groups  
230 in the computation of prey biomass available for predators. According to their ecology, each stage of  
231 each species and each LTL group was associated with a vertical layer: “pelagic” for plankton, buoyant  
232 eggs, larvae and small pelagic fish, “benthic” for benthic groups and species living on the seabed such as  
233 flatfish, and “demersal” for individuals living near the sea bed and having access to both pelagic and  
234 benthic prey (such as gadoids). The accessibility parameters are presented in Table 3.

235

## 236 2.4 Calibration

237 The model was calibrated using the calibrar R package with the AHR-ES algorithm (Oliveros-Ramos and  
238 Shin, 2016), an automatic evolutionary algorithm developed for calibrating stochastic models such as  
239 OSMOSE. This algorithm explores a range of values for unknown parameters and uses likelihood  
240 objective functions to select the optimal values for the catches and biomass to be comprised within  
241 ranges of observed values when available. Landings per species have been extracted from the ICES  
242 Fisheries Statistics official database (ICES, 2011a) for the ICES area 7d (corresponding to the EEC) over  
243 the period 2000-2009. Total stock biomass estimates are directly available from stock assessment  
244 reports for sole and plaice (ICES, 2011b), while for whiting, cod, mackerel and herring, total stock  
245 biomass estimates were derived from stock assessments covering a wider area (ICES, 2012, 2011b) and  
246 were therefore scaled to the EEC proportional to the relative landings in this area. In OSMOSE, species

247 biomass is computed as the sum over the entire area of the biomass of all super-individuals older than 6  
248 months, averaged annually. Simulated landings come from the fished individuals (equation 3) over the  
249 entire area, integrated at the annual time-scale. The calibration was performed in 3 phases, following  
250 recommendations by Oliveros-Ramos et al. (2017) based on model dependency of the parameters and  
251 availability of initial estimates. First, the 10 LTL accessibility coefficients were adjusted for 200  
252 generations; then, the 14 larval mortality rates were added to the set of parameters to adjust for 200  
253 other generations. Finally, 12 additional mortalities (including fishing mortalities) were added to the  
254 third phase, where 300 generations were run with a total of 36 parameters to estimate. The first two  
255 phases allow optimization of the calibration convergence, while the third phase includes all the  
256 parameters and lasts longer to ensure that an optimal solution is reached.

257

## 258 2.5 Scenarios and exploration of simulated trophic patterns

259 Once the model is calibrated, it is run for 120 years, with the first 100 years corresponding to the spin-up  
260 time during which the system stabilizes and is no longer driven by the model initialization. The results  
261 presented thereafter, corresponding to the average state of the EEC ecosystem in the period 2000-2009,  
262 are computed from averaging the last 20 simulated years to smooth any interannual variability.  
263 Furthermore, OSMOSE is a stochastic model, and 50 replicates were run using the same input  
264 parameters.

265 Following the pattern-oriented modeling approach (POM, Grimm et al., 2005), the model's ability to  
266 reproduce independent patterns is explored by comparing simulated output with data neither used  
267 during the parameterization nor during the calibration. As the OSMOSE model is based on opportunistic  
268 predation, validation patterns could include emerging features linked to the predation process, such as  
269 realized diets and associated TLs or food web structures. Here, we used independent data of TLs

270 calculated from nitrogen stable isotope ratios (SI) measured on the same species in the same ecosystem  
271 (Cresson et al., 2017, 2018; Jennings and van der Molen, 2015; Kopp et al., 2015, Mialet et al., 2017). TL  
272 calculations are based on the premise that the nitrogen isotopic ratio ( $\delta^{15}\text{N}$  hereafter) is gradually  
273 enriched at each TL, a phenomenon called trophic enrichment. TL is thus considered as the isotopic  
274 difference between the species of interest and a trophic baseline, i.e., a proxy of the ultimate organic  
275 matter source at the base of the food web, divided by the trophic enrichment factor (TEF). The queen  
276 scallop *Aequipecten opercularis* was used as a trophic baseline due to the trophic importance of benthic  
277 production and because the use of a primary consumer (i.e., at TL = 2) allows smoothing of the small  
278 scale isotopic fluctuations of primary production that are not integrated in fish isotopic ratios. Two  
279 methods are used, where TEF is either considered the same at all levels of the food web (e.g., in Kopp et  
280 al., 2015; Cresson 2017; 2018; Mialet et al., 2017) or decreases with increasing  $\delta^{15}\text{N}$  of the diet (Jennings  
281 and van der Molen, 2015). Details about the method can be found in dedicated literature (Hussey et al.,  
282 2014), but sensitivity analyses demonstrated that for intermediate-TL species such as the ones  
283 considered in the present study, calculated TLs are rather similar regardless of the method (Jennings and  
284 van der Molen, 2015; P. Cresson unpubl. results).

285 In OSMOSE, each super-individual has a proper TL, which depends on its feeding history. The TL  
286 computation of a super-individual  $i$  is based on the classical formula in which the TL of a predator equals  
287 1 plus the average TL of the prey weighted by their relative ingested biomass (Equation 6):

$$288 \quad TL_{i,t} = 1 + \sum_j TL_{j,t} DC_{j,i,t} \quad (\text{Equation 6})$$

289 where  $TL_{i,t}$  is the trophic level of  $i$  at time  $t$  and  $DC_{j,i,t}$  is the proportion of prey  $j$  in the diet of predator  $i$  at  
290 time  $t$ . While the TL of explicitly modeled individuals is dynamic, the TL of the LTL groups is fixed and has  
291 been set to 1 for phytoplankton and derived from TL estimates based on stable isotope studies in the  
292 same area (Kopp et al., 2015) for the other groups (Table 2). The TL of very small benthos is set to 3 to

293 represent the omnivory of this group (partly composed of meiofauna). The TL of newly spawned eggs  
294 within OSMOSE is arbitrarily set to 3 to be close to the TL of the first-feeding larvae. Finally, we assume  
295 that an individual that has not fed keeps its previous TL.

296 After comparison of simulated TLs with data, model exploration is performed by analyzing the variation  
297 of diet composition and TL with size for all species. Diet composition is computed using the following  
298 predefined size classes for predators: [0;5[, [5;10[, [10;15[, [15;20[, [20;25[, [25;30[, [30;40[, [40;50[,  
299 [50;60[, [60;70[, [70;90[, [90;110[ and [110;130[. From all super-individuals pertaining to a size-class, the  
300 biomasses of the different prey eaten (including other super-individuals and LTL groups) are grouped by  
301 species over the entire area. To explore the relationship between TL and size, super-individuals are  
302 grouped by centimeters and the TL distribution within each size group is computed (min, first quartile,  
303 median, third quartile, max). The TL-size relationship is then explored spatially by fitting a linear model in  
304 each cell with more than 10 super-individuals. The resulting slope values are then mapped for each  
305 species, with indication of the quality of the fit using  $R^2$  values.

306

### 307 **3. Results**

308 The evolutionary algorithm used for calibrating the model converged to an acceptable configuration  
309 where all median values of simulated biomass distribution are within the range of observed values  
310 (Figure 3). Median values of simulated catches are within the range of observations for half of the  
311 species (lesser spotted dogfish, whiting, cod, mackerel, sardine and squids), while for red mullet, horse  
312 mackerel and herring, catches are underestimated as only 42%, 42% and 18% of the 50 simulated  
313 replicates are within the range of the observations, respectively. Simulated catches of pouting, sole and  
314 plaice are smaller than the observations (median values corresponding to 73%, 57% and 80% of the  
315 minimal observed values, respectively), even if the biomass of the flatfish species corresponds to the

316 total stock biomass estimates through the stock assessment (ICES 2011). For the other assessed species  
317 (whiting, cod, mackerel and herring), simulated biomass also displays a good fit to biomass estimated  
318 over the period of 2000-2009. The optimized values of accessibility parameters show high variability  
319 across the LTL groups, from approximately  $10^{-4}$  for dinoflagellates to approximately 0.4 for meso-  
320 zooplankton and very large benthos (Table 2), two important prey groups for the fish community.

321 A comparison of simulation outputs with published TLs from empirical SI analysis is performed as a  
322 validation process. Figure 4 displays the trophic spectra of the modelled species, i.e., for each species,  
323 the distribution of the individual TL weighted by the individual biomass. In the simulations, the width of  
324 the trophic spectrum (i.e., the difference between the maximal and minimal individual TLs) varies  
325 according to species from 1.6 levels for red mullet up to 3.9 levels for herring. More importantly, the way  
326 biomass is distributed along TLs also varies: for some species, biomass distribution is concentrated  
327 around a particular TL (e.g., approximately 3.9 for red mullet, pouting, poor cod, dragonet, sole), while  
328 for other species, biomass is spread over a wide range of TLs (e.g., whiting, cod, sardine, squids). The  
329 biomass concentration of approximately 3.9 for benthic fish species is linked to the dominant proportion  
330 of very small benthos and small benthos (TL=3 and TL=2.9, respectively, Table 2) in the diet of these  
331 species (Figure 5). Plaice individuals of intermediate length (15-50 cm) also largely rely on these prey  
332 groups, explaining the concentration of biomass around TL=3.8 in the trophic spectrum (Figure 4). The  
333 biomass around TL=4.5 is explained by the presence of very large benthos (TL=3.6) in the diet of larger  
334 plaice individuals. The wide trophic spectra of lesser spotted dogfish, whiting and cod are explained by  
335 the diversity of prey composing their diets (Figure 5).

336 Simulated trophic spectra were in good agreement with the range of TLs estimated from stable isotope  
337 measurements for most species. For red mullet, poor cod, and plaice, simulated TLs were similar to SI-  
338 derived TLs, which were, moreover, coherent between empirical studies. For lesser spotted dogfish,



339 pouting, whiting, sole, horse mackerel and mackerel, empirical data display high variability across  
340 studies, but this variability is generally well encompassed by the model. However, empirical TL estimates  
341 show that the maximal TL observed for sole can be higher than that simulated, while mackerel can have  
342 a minimal SI-derived TL smaller than that simulated. It is worth noting that for mackerel, the model  
343 simulates two TL modes, approximately 3.6 and 4.3, corresponding respectively to young individuals  
344 feeding only on mesozooplankton (TL=2.6, Table 2) and larger individuals feeding on small squids and  
345 small fish, mostly young sardine and horse mackerel (Figure 5). Similarly, empirical estimates of mackerel  
346 TL show low values of approximately 3.5 in Cresson et al. (2017) and Jennings and van der Molen (2015),  
347 with fish being between 16.9 and 41 cm long (Table 4), while TL values are higher than 4 in the three  
348 other studies but for similar fish lengths (18 to 34 cm, Table 4). If we assume that TL estimated from  
349 stable isotopes are representative of the trophic position of the bulk of a species, then the EEC-OSMOSE  
350 model tends to slightly overestimate the TL of cod, dragonet and squids and to underestimate the TL for  
351 herring. The SI-derived TL of sardine corresponds to the bulk of the simulated biomass, but the model  
352 also simulates sardine individuals at a TL between 2 and 3 (feeding on diatoms and mesozooplankton,  
353 Figure 5).

354 To further explore the drivers of individual variability among species TL distribution, the evolution of the  
355 mean TL with size is presented in Figure 6. While mean TL generally increases with size for most species,  
356 this is not the case for red mullet, poor cod, dragonet, and sole and for pouting and plaice to a lesser  
357 extent (respectively, from 10 to 35 cm and from 20 to 50 cm), for which the mean TL decreases with size.  
358 These species are characterized by a benthic diet, with the proportion of very small benthos (TL=3)  
359 decreasing with size and the proportion of medium benthos (TL=2.2) increasing as fish grow larger,  
360 which explains the decreasing TL with size for these species. The evolution of mean TL with size is not  
361 linear, and most species display a strong change of TL at smaller size, while mean TL varies less with size  
362 for larger individuals. Tipping points can be identified and linked to ontogenetic changes in the diets of

363 species. For instance, sardine and herring fish longer than 20 cm no longer feed on diatoms (Figure 5),  
364 explaining the abrupt TL increase at this size. Other ecological features can be observed, such as the  
365 marked shift from a plankton-feeding larval stage (roughly for fish smaller than 5 to 10 cm on Figure 6) to  
366 a benthic feeding juvenile stage for all benthic and demersal species. Finally, other TL breakpoints linked  
367 to diet shifts exist for larger fish: the occurrence of very large benthos for lesser spotted dogfish larger  
368 than 30 cm, pouting larger than 35 cm, whiting larger than 15 cm, cod larger than 20 cm and plaice larger  
369 than 50 cm, and the disappearance of mesozooplankton for horse mackerel and mackerel larger than 20  
370 cm. To supplement the patterns observed over the entire area between TL and size, the spatial  
371 distribution of the TL-size relationship is mapped (Figure 7). The negative relationship between TL and  
372 size is confirmed in every grid cell for red mullet, dragonet and sole. This pattern appears robust ( $R^2 >$   
373  $0.3$ ) in the Dover Strait (Northeast), in the north of the Central English Channel (Northwest) and in the  
374 Bay of Seine (South). For poor cod, another species showing a decreasing TL-size relationship at the  
375 global scale, the spatial distribution of the slope is less informative ( $R^2 < 0.3$ ) but shows both positive and  
376 negative relationships (the latter occurring also in the Dover Strait and north of the Central English  
377 Channel). For plaice and pouting, the relationship is positive in most cell grids and is probably driven by  
378 the strong difference of TL between fish of intermediate size and larger fish. Robust positive  
379 relationships between TL and size also occur for pouting, herring, sardine and squids.

380

## 381 **4. Discussion**

382

### 383 4.1 Ability of the model to capture EEC ecosystem dynamics

384

385 In this study, we were able to adapt the 2D OSMOSE model using a vertical overlap matrix and apply it to  
386 the EEC shallow ecosystem characterized by strong benthic-pelagic coupling. After parameterizing the  
387 model, the semiautomatic calibration method produced an overall good fit of the model to the 2000-  
388 2009 average state of the EEC ecosystem, with biomass of all species and catch values of half of the  
389 species being within the range of the observed values. The discrepancies observed for some species  
390 between modeled and observed catches and biomasses can be explained by several factors. First, a  
391 constant fishing mortality is applied in OSMOSE to individuals older than the age at recruitment (i.e.,  
392 similar to broken-stick selectivity with age), while in reality due to the different fleet selectivity and  
393 variable catchability-at-age, the fishing pressure endured by fish varies with age/length (Quinn and  
394 Deriso, 1999). Nonetheless, it is worth noting that the total mortality varies with age within OSMOSE,  
395 notably due to explicit predation mortality, which tends to decrease with size. Second, the biomass  
396 target values come from single-stock assessments, i.e., correspond to model outputs with specific  
397 hypotheses and thus should be taken as estimates with associated uncertainty rather than exact values  
398 (Brooks and Deroba, 2015). Similarly, target catch values come from declared landings completed by  
399 estimates of discards when available. Even if the EEC is considered a data-rich ecosystem, some  
400 uncertainties persist when estimating discards and total catches (Enever et al., 2007; Pauly and Zeller,  
401 2016). Furthermore, the hypothesis made to allocate the biomass of widely distributed stock to the ICES  
402 7.d area based on the landings ratio does not take into account the spatial variability of fishing effort and  
403 assumes a homogeneous distribution of fish, again contributing to the uncertainty around biomass  
404 target values. Third, the calibration process was limited to the optimization of 36 unknown parameters,  
405 therefore constraining the space of simulated output reachable during the calibration.

406 Despite these limits, the model was able to reproduce species biomasses and most species catches, but  
407 also other features independent of the data used for parameterization and calibration. For most species,  
408 the simulated TLs are in good accordance with TL estimates derived from SI data, both in terms of

409 average values and variability within species. However, EEC-OSMOSE underestimates sardine and herring  
410 mean TLs compared to SI estimates. The exploration of simulated TL and diet composition versus size  
411 shows that the smaller size classes have a diet mostly composed of diatoms and mesozooplankton  
412 (resulting in small TL values), while the larger individuals rely on mesozooplankton, explaining their  
413 higher TL. One hypothesis for the difference observed between the data and the model is that empirical  
414 data underestimate the importance of phytoplankton food source. This could be explained by the  
415 absence of very small individuals (smaller than 5 cm for herring, smaller than 7.7 cm for sardine, Table 4)  
416 in the sample, and/or by the sampling season (autumn) corresponding to higher zooplankton food  
417 available compared to phytoplankton. Another hypothesis is the biased simulation of diet shift from  
418 phytoplankton to zooplankton prey at larger size than observed for herring and sardine. Both species are  
419 known to consume these two types of prey, with seasonally variable intensity (Costalago et al., 2012),  
420 but the ontogenetic shift in their diet has been reported at an earlier larval stage (e.g., Denis et al.,  
421 2016). These results suggest that the minimum and maximum predation size ratios set for herring and  
422 sardine may be revised, possibly by setting different ratios according to individual ontogenetic  
423 development (e.g., Travers-Trolet et al., 2014). Moreover, due to the model structure and lack of suitable  
424 stable isotope data, the mesozooplankton group has a fixed TL that prevents simulation of the  
425 spatiotemporal variability of the TL of the zooplankton community available to fish. It should  
426 nevertheless be remembered that fish stable isotope ratios (and the derived TL values) can be seen as  
427 emergent properties, resulting from their diet but also from a large set of environmental or physiological  
428 parameters (e.g., Boecklen et al., 2011). Among these, large spatial and temporal variations of  
429 phytoplankton isotopic ratios (Magozzi et al., 2017) at the basis of the food web and/or fish migrations  
430 between zones where primary production exhibits different isotopic ratios may drive changes in fish  
431 isotopic ratios that are hard to capture and that may blur TL calculation.

432 The overestimation of the trophic position of cod in the model comes with an overestimation of the  
433 proportion of fish in the diet. The model simulates the proportion of fish biomass in cod diets as  
434 between 50% and 80% according to size classes, while fish represent nearly one quarter or less of the  
435 prey found in stomach content analysis (crustaceans being the main prey for juveniles and adults,  
436 Cachera, 2013; Pinnegar 2014; Mialet et al., 2017). This bias is due to the relatively simple accessibility  
437 matrix set for representing the proportion of prey biomass available to a predator according to their  
438 vertical distributions. For this matrix, cod is considered to be demersal, i.e., to have full access to other  
439 demersal individuals and to have access to half of the pelagic biomass and half of the benthos biomass.  
440 To better represent the feeding behavior of cod, accessibility coefficients should be revised, for instance  
441 by increasing accessibility to benthic prey and reducing accessibility to pelagic and demersal individuals.  
442 For this study, the accessibility matrix was introduced to mimic vertical overlap between predators and  
443 prey as required to model both benthic and pelagic communities with an opportunistic size-based  
444 predation, but its parameterization was kept as simple as possible. For their coupled size-spectrum  
445 model, Blanchard et al. (2009) considered that all predators spent half of their time feeding on benthic  
446 invertebrates and the other half feeding on pelagic organisms. Future developments on how to better  
447 set these accessibility parameters could involve consideration of the spatial variability of trophic  
448 interactions (e.g., depth-driven variability in benthic-pelagic coupling; Giraldo et al., 2017) or use  
449 morphological attributes (trait-based approach) of the different species (e.g., orientation of the mouth).

450

#### 451 4.2 Relationship between size and TL

452

453 When considering TL with regard to size for the different species modeled, two main patterns emerge  
454 from the simulations. The most frequent pattern is an increase of TL as size increases, which is often

455 more pronounced for the smaller size classes. This positive relationship can display some breakpoints  
456 linked to diet composition shifts, as illustrated by planktivorous fish species at 20 cm. The second pattern  
457 is observed for only four benthic species (red mullet, poor cod, dragonet and sole) and corresponds to a  
458 decrease of TL with increasing size. For the small individuals of these four benthic species (smaller than  
459 5-10 cm), the initial increase in TL is explained by the pelagic and planktivorous mode of the larvae  
460 before settlement on the sea bottom, modeled through change of the accessibility predation coefficient  
461 (Table 3).

462 In aquatic ecology, the assumption that larger individuals have a higher TL is often admitted, as  
463 predation is constrained by body size through gape limitation. Such a relationship has been explored and  
464 confirmed across species in various ecosystems by confronting the mean or maximum size of species  
465 with their mean  $\delta^{15}\text{N}$  (e.g., France et al., 1998; Romanuk et al., 2011). However, other studies have  
466 reported an absence of correlation between species mean length and their trophic position (e.g., Layman  
467 et al., 2005). Jennings et al. (2001) also documented a weak cross-species relationship between the  
468 maximum size of fish species and their mean  $\delta^{15}\text{N}$  value but a strong relationship at the community level,  
469 i.e., using the individual length of fish and pooling the data together within size classes. The ontogenetic  
470 increase of TL with increasing size has also been confirmed for benthic fish species by Badalamenti et al.  
471 (2002). Investigating the North Sea trophic structure, Jennings et al. (2002a) found a significant positive  
472 relationship between fish length and  $\delta^{15}\text{N}$  for 16 species over 31. More interestingly, this relationship  
473 was found to be negative for herring and plaice whose TL decreases as their length increases. In addition,  
474 the pattern observed may be positive in one environment but negative in another (Jennings and van der  
475 Molen 2015). The results obtained in the present study thus demonstrate that the variability may appear  
476 at even a lower spatial scale, confirming the call for a better understanding of the effect of  
477 environmental gradients on trophic functioning (Ings et al., 2009). Based on stable isotope data in the  
478 EEC, Kopp et al. (2011) confirmed this decreasing trend of TL with size for plaice but also for skates and

479 even for whiting in some particular habitats (located in the central Bay of Seine and part of the Dover  
480 Strait). In half of the region  $\times$  species combinations they studied, Jennings and van der Molen (2015)  
481 observed no relationship between mass and TL, and the positive relationships mostly occurred for  
482 piscivore species. As they have to capture mobile prey, gape size is a key factor driving feeding abilities in  
483 these species. In benthic systems, feeding mechanisms could be more based on opportunistic predation  
484 of carrion and living organisms. In this context, prey size may not be as important in driving the feeding  
485 mechanism as for pelagic systems.

486 While based on opportunistic size-based predation, OSMOSE was unexpectedly able to reproduce  
487 decreasing trends of TL with size for some benthic species. In EEC-OSMOSE, the benthic species  
488 demonstrating a clear declining TL trend with size are not the same as the benthic species found to  
489 display this pattern empirically. However, it is worth noting that the empirical negative relationship  
490 found for plaice between 9 and 48 cm (Jennings et al. 2002a) is partly present in the model if we focus on  
491 intermediate-sized individuals, i.e., before the introduction of very large benthos in the diet (at about 50  
492 cm).

493 Being able to reproduce the negative TL-size relationship using such a model allows for drawing two  
494 nonexclusive hypotheses of its origin. First, the spatial distribution of fish individuals changes with age  
495 (Appendix B), which may result in different prey compositions being available locally, including the case  
496 where only prey with lower TLs are available in the area inhabited by larger fish individuals. The spatial  
497 distribution of the TL-size relationship confirms this spatial heterogeneity for some species. Thus, the  
498 absence of squid eggs in the Dover Strait and the North Central Channel is linked to the strong TL-size  
499 negative relationship observed in these areas, where the benthic fish diet is only composed of benthic  
500 invertebrates. For mackerel, the absence of juveniles in the Bay of Seine explains the spatial  
501 heterogeneity of the signal and suggests that a negative TL-size relationship could be observed

502 empirically if focus was placed on the adults of this region. In the current model, spatially homogeneous  
503 benthic prey fields were used because insufficient knowledge of benthos dynamics was available at this  
504 scale. The simulated trophic spatial variability would probably be higher if a more realistic benthic  
505 community was included in the model.

506 The second hypothesis underlying the simulated pattern is that, conversely to what is largely admitted  
507 for the pelagic prey, the trophic structure of the benthic prey is not linked to the size structure of the  
508 benthic invertebrate community. In the diet of the simulated benthic fish, the increasing proportion of  
509 medium benthos with a small TL compared to the proportion of small benthos with a higher TL leads  
510 mathematically to a TL decreasing with size at the predator level. This pattern is linked to the predation  
511 hypothesis underlying the model and reflects the actual opportunistic pattern of the benthic fish species  
512 that consume the most available resources (van Denderen et al., 2018). The selection of species used to  
513 set the TL of the benthic groups could have an impact on the overall TL-size relationships of fish.  
514 However, they were selected because of their abundance in the area, therefore they were considered  
515 suitable to represent the main prey available for fish. Only a few studies have investigated the  
516 relationship between size and trophic position for marine benthic invertebrates. Jennings et al. (2002b)  
517 demonstrated that for benthic invertebrates, the relationship between size and TL reflected intraspecific  
518 patterns (i.e., individual growth) and not interspecific patterns (i.e., no evidence for a relationship  
519 between maximum body size and TL across species). Similarly, Dinmore and Jennings (2004) observed a  
520 negative relationship between TL and body mass, demonstrating that body dimension may not be a  
521 major driver of predation in benthic systems. In their coupled size-based model, Blanchard et al. (2009)  
522 confirmed that benthic invertebrates share a common size-unstructured resource and therefore are not  
523 strongly trophically size-structured. In other words, two benthic invertebrates of different sizes can  
524 exhibit the same TL as their diet would be the same. An ontogenetic diet change in the predator could  
525 thus result in an inconclusive or decreasing length-TL pattern.



526

527 4.3 Variability of TL across sources

528 The current study benefited from the existence of several stable-isotope analyses performed in the EEC.  
529 Here, we used the available TL estimates at the individual level and explored the intraspecies variability  
530 of SI-derived TLs, which increased both with the number of fish individuals sampled and with the width  
531 of body sizes sampled (Table 4). The high variability of TLs within a species was confirmed by the model,  
532 where individuals can have different TLs depending on their size (involving different size ranges of  
533 available prey), their spatial location (local encounters with different prey) and the feeding history of  
534 their prey (leading to different TLs of the prey). While the intraspecific TL variability from stable isotopes  
535 was required to validate the emergent patterns of the model, the comparison of TL values between  
536 different SI studies was also informative. Indeed, the agreement observed between the five studies (e.g.,  
537 plaice) increases the reliability of these estimates, both in terms of value and width of distribution. For  
538 sardine, the very similar TL distribution observed between two studies counterbalances the low number  
539 of individuals sampled (10 in each study) and therefore improves the reliability of these data. While the  
540 five empirical studies provided similar estimates of species mean TLs and variability for some species,  
541 they can lead to different estimates of the TL for other species (e.g., the lesser spotted dogfish mean TL  
542 goes from 3.5 to 4.8; the whiting mean TL ranges from 4 to 5.1). Discrepancies between the empirical  
543 studies (and with the model) can be due to differences in sampling dates and therefore temporal  
544 variation of diet and integration dynamics (seasonal and/or interannual, e.g., Schafer et al., 2002), the  
545 spatial location of sampling and its effect on diet (Kopp et al., 2015; Giraldo et al., 2017), the variability of  
546 the trophic baseline used (Magozzi et al., 2017) or hypothesis regarding TEF (Hussey et al., 2014). These  
547 intraspecific variations are nonetheless classically observed (e.g., Jennings and van der Molen, 2015).

548

549 Isotopic data allowed validation of the model, but other trophic data sources could have been used to  
550 provide a complementary vision. Comparison with stomach content data allowed for a better  
551 understanding of the discrepancies regarding the cod TL; the TL overestimation is linked to the  
552 overestimation of fish in the cod diet composition. Both isotopic and stomach content data sources are  
553 now considered complementary (e.g., Cresson et al., 2014; Giraldo et al., 2017), the latter one informing  
554 a snapshot diet with identified prey, while the former integrates trophic fluxes over months and allows  
555 us to quantify the fluxes between predators and a pool of prey of similar isotopic signatures. The  
556 ecosystem model can now be added to the list of available tools to explore trophic function and  
557 individual variability of TLs and could be used in a similar way to explore individual variability across  
558 seasons and/or space (i.e., at different depths).

559

## 560 **5. Conclusion**

561 Using a multispecies IBM constrained by size-based opportunistic predation, we were able to reproduce  
562 the average trophic structure of the EEC over 2000-2009, including benthic and pelagic communities.  
563 Due to the individual variability in terms of size, spatial location and feeding history, the model  
564 simulations displayed patterns that were observed in empirical studies but were unexpected from a size-  
565 based predation approach. Here, the IBM framework has been shown to be effective in investigating  
566 among-individual trophic variability and for understanding the plausible drivers of the negative TL-size  
567 relationship observed empirically for some species. The uncoupling of the trophic structure and size  
568 structure of benthic invertebrates appeared to be the key to this pattern, but future studies should  
569 further explore this potential link and identify morphological aspects to better represent the predation  
570 of fish on benthic invertebrates. The availability of TL estimates from stable isotopes has been a key to  
571 validating the model and encouraging strong collaborations between modelers and field/laboratory

572 scientists. Indeed, while trophic data are often used to parameterize or validate ecosystem models  
573 (Pethybridge et al., 2018), complex models - and particularly IBMs - appear useful to inform on the  
574 trophic functioning of an ecosystem and to explore different hypotheses regarding the causes of  
575 observed patterns. As the trophic patterns simulated with OSMOSE have been validated for the EEC, the  
576 model will now be available to explore the ecosystem impacts of different scenarios, including  
577 management measures and climate change. The flexibility of the food web structure emerging from local  
578 interactions in OSMOSE appears promising when aimed at exploring the cumulative impacts of different  
579 pressures.

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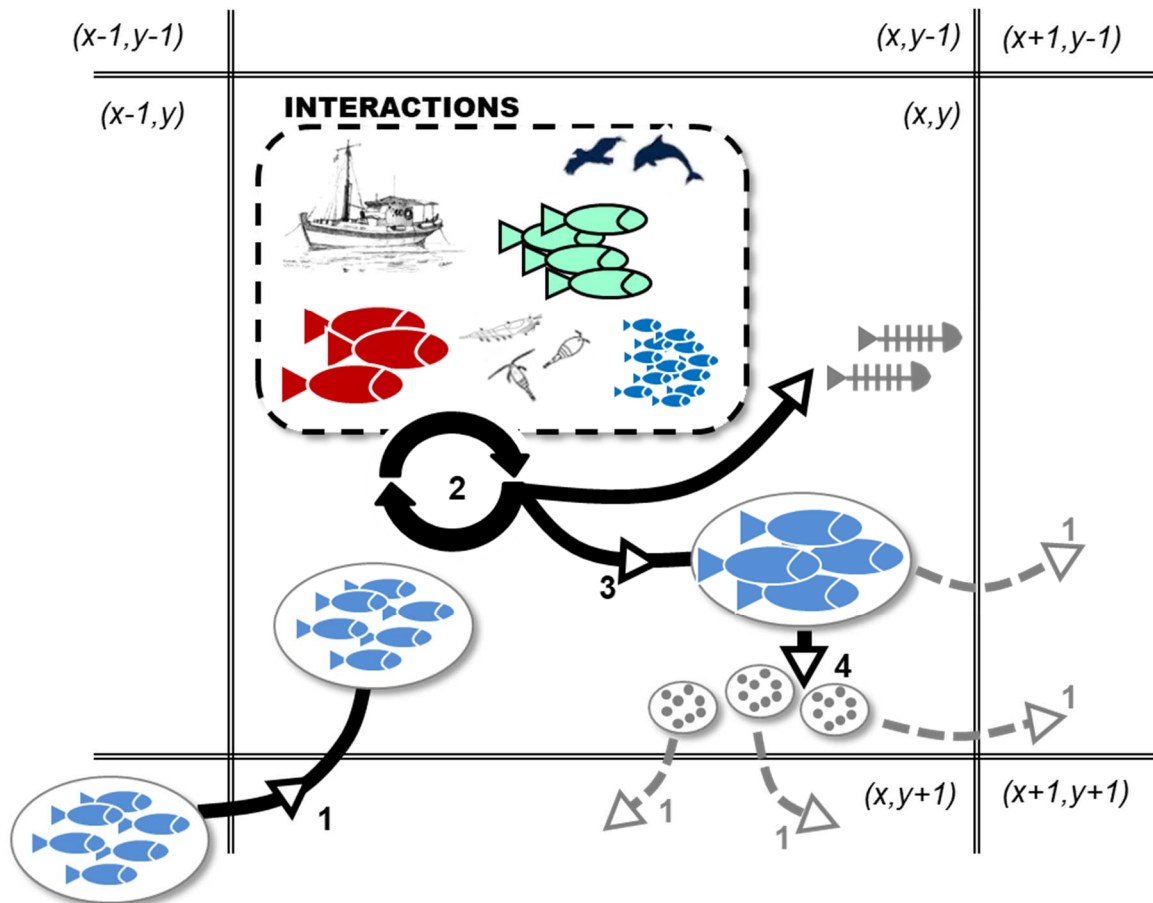
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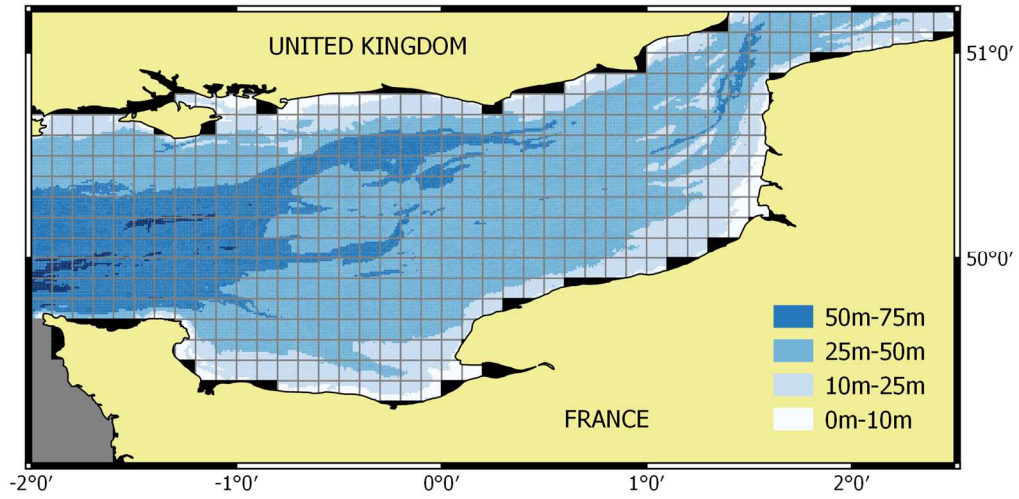
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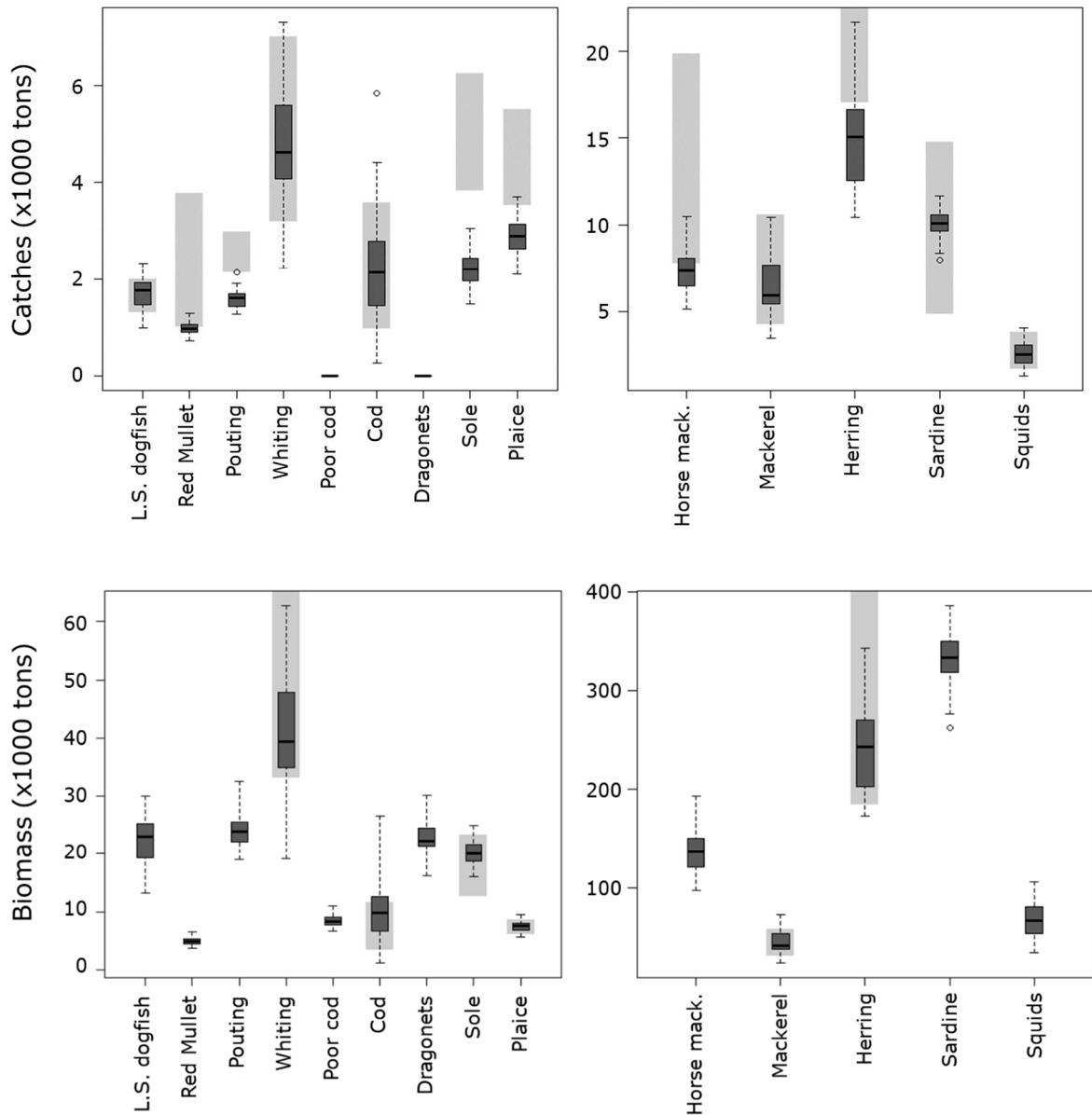
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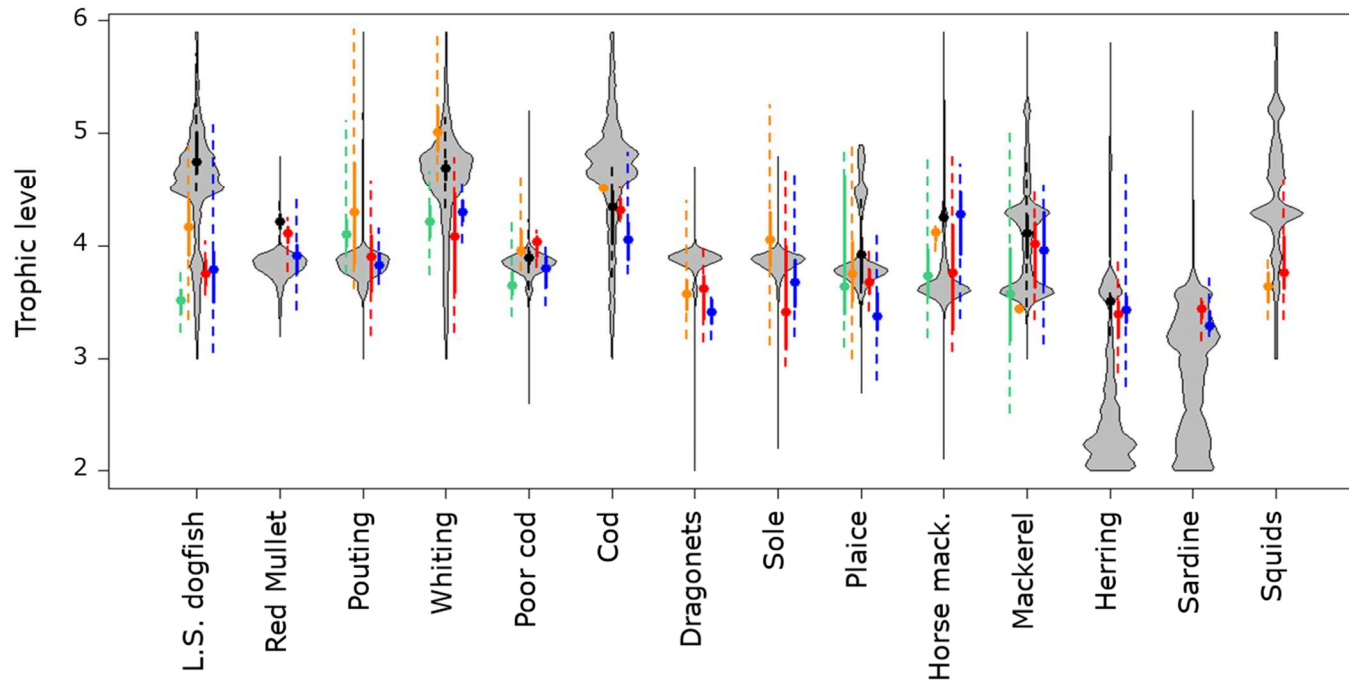
**Figure 1:** Processes undertaken by a superindividual during a 2-week time step : 1) Movement of individual in a 2D grid either driven by input maps or due to random walk; 2) local interactions and resulting mortalities (explicit predation mortality upon other superindividuals and upon plankton and benthos groups present in the same cell, starvation mortality, fishing mortality and mortality from other sources) looping over 10 subdivisions of the time step in order to approximate real continuous time; 3) growth proportionally to predation efficiency and 4) reproduction which creates new superindividuals of eggs for the next time step.



**Figure 2:** Grid corresponding to the modeled EEC ( $0.6^\circ \times 0.6^\circ$  cells) with indication of depth (from GEBCO website)

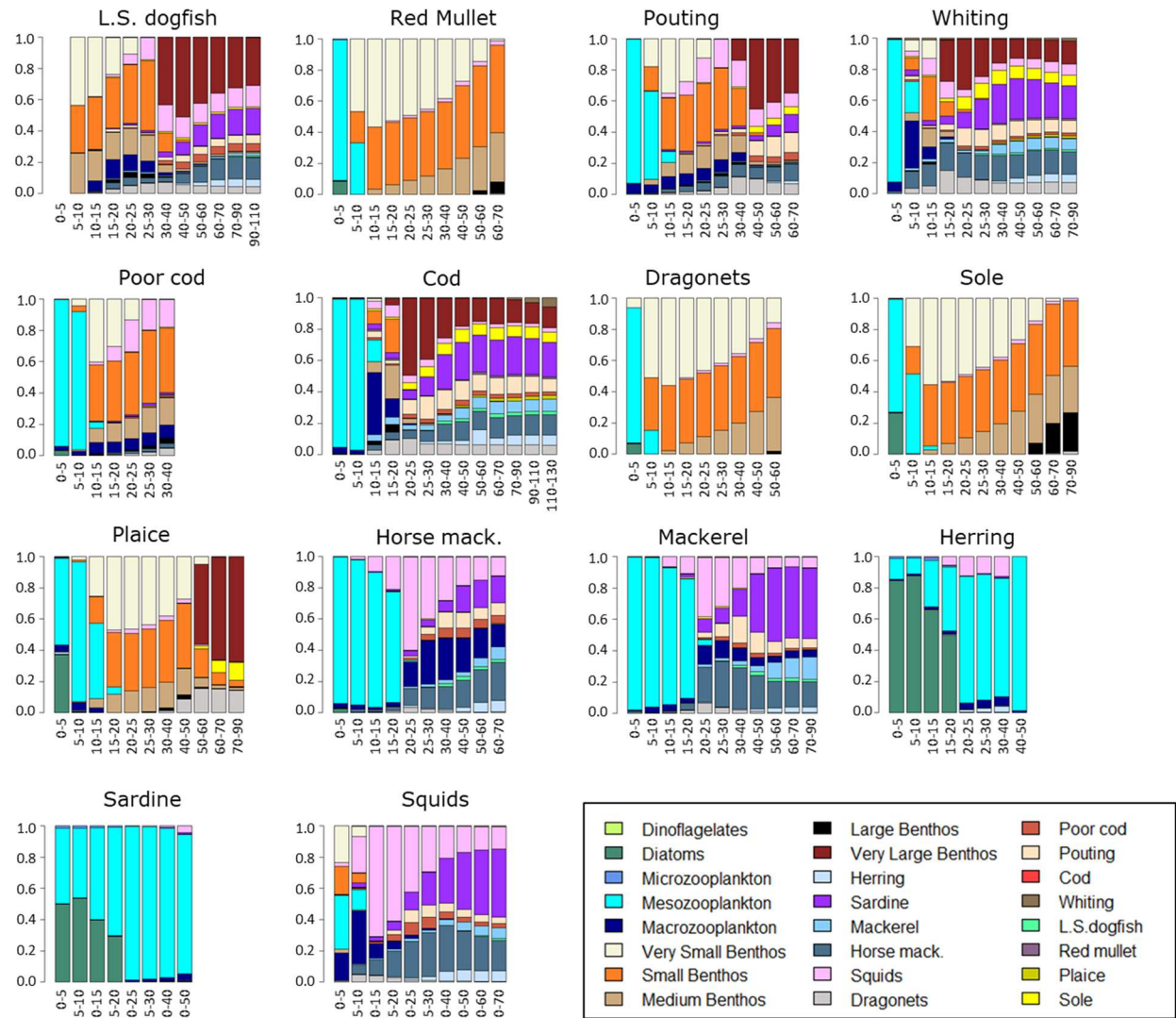


**Figure 3:** Distribution of the simulated catches (top) and biomass (bottom) over the 50 replicates (dark boxplots representing median and quartiles), and comparison with observations: minimal and maximum values of catches over 2000-2009 are indicated in the top panels by the grey bars. Minimum and maximum estimated biomass values are only presented for assessed species in the bottom panels.

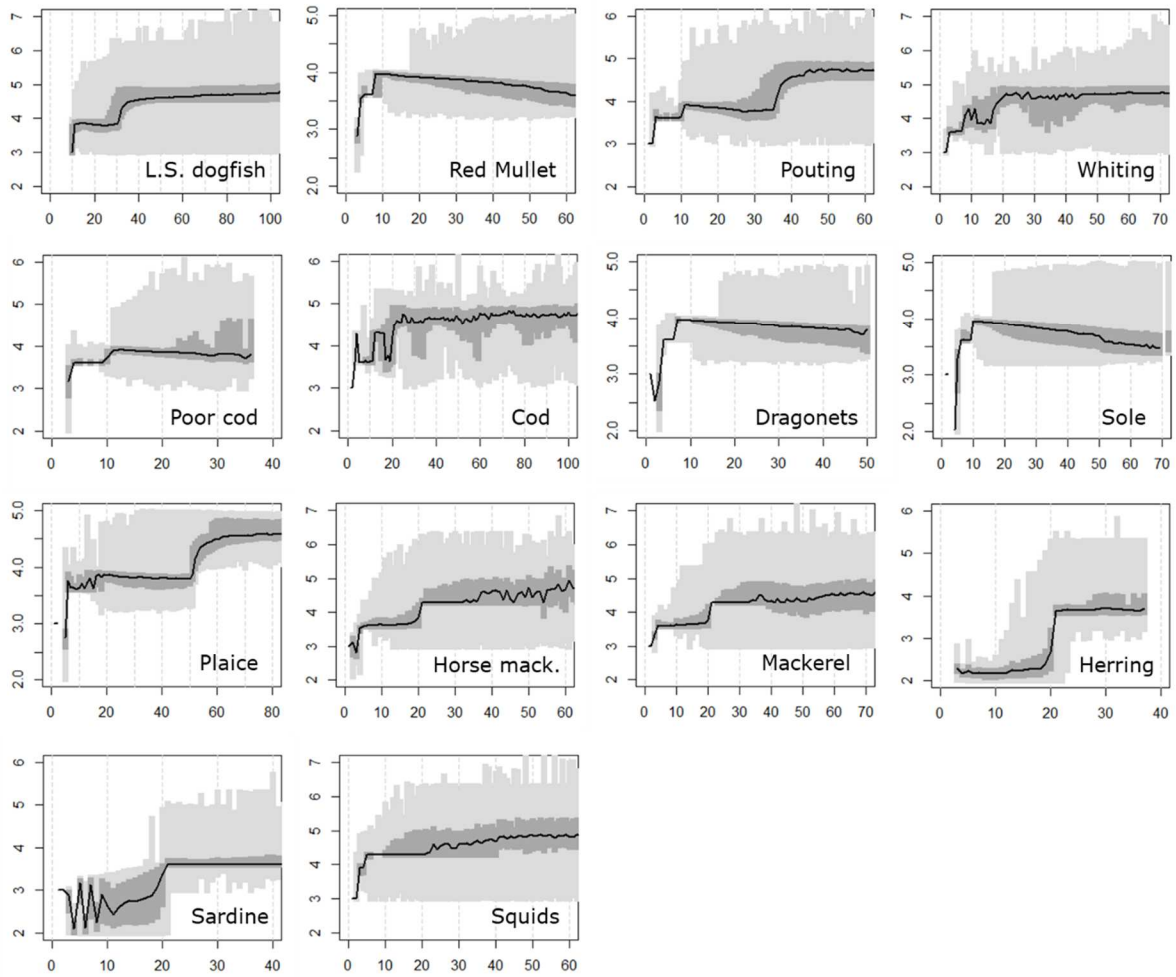


**Figure 4:** Modelled distribution of species biomass across TLs (trophic spectra, in grey), and comparison with published TLs for these species in the same area based on stable isotopes analysis (in green: Cresson et al. (2017), in orange: Jennings and van der Molen (2015), in black: Mialet et al. (2017), in red: Cresson et al. (2018), in blue: Kopp et al., (2015)). For SI-derived TL, the dotted line represents the range of TL measured (from minimal value to maximal value), the bold line represent values between the 1st and the 3rd quartiles and the filled dot represent the median values. Number of samples used in each study is reported in Table 4.

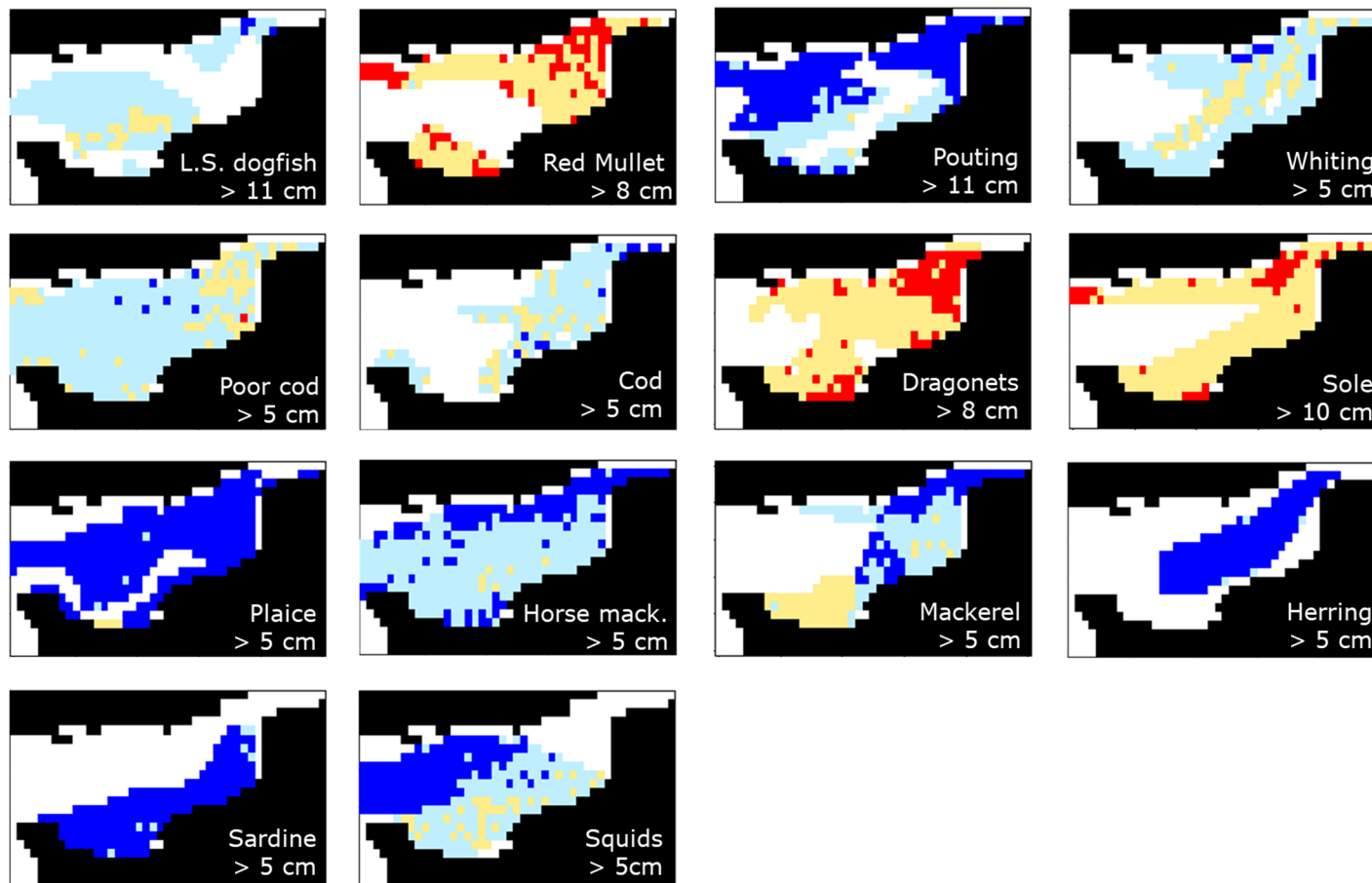




**Figure 5:** Emerging diet composition across size classes for the 14 modelled species over the entire area. Size classes are not regular in order to emphasize the rapid diet change of smaller individuals. Prey are grouped by species but include individuals of various length within a species group.



**Figure 6:** Modelled distribution of superindividuals' TL across 1-cm size classes for the simulated species. The light grey areas indicate minimal and maximal individual TL per centimeter, the dark grey areas indicate the 1<sup>st</sup> and 3<sup>rd</sup> quantiles of the TL distribution per centimeter and the black lines indicate the median TL per centimeter.



**Figure 7:** Spatial distribution of the direction of the TL-size relationship. In each cell with more than 10 superindividuals, a linear model has been applied between TL and size. Dark blue: positive slope with  $R^2 > 0.3$ ; light blue: positive slope with  $R^2 < 0.3$ ; orange: negative slope with  $R^2 < 0.3$ ; red: negative slope with  $R^2 > 0.3$ .

**Table 1:** Input parameters of OSMOSE for the 14 fish species modelled explicitly.  $L_{\infty}$ ,  $K$ , and  $t_0$  are the parameters of the von Bertalanffy growth model, with a linear growth before the threshold age  $a_{th}$  and a growth following the von Bertalanffy model after  $a_{th}$ ;  $c$  is Fulton's condition factor and  $b$  the exponent of the L-W allometric relationship;  $L_{mat}$  is length at maturity and  $\phi$  is relative fecundity;  $a_{max}$  is longevity;  $F$  is the annual fishing mortality rate and  $a_{rec}$  is age of recruitment;  $M_{oth}$  is an additional mortality rate (resulting from predation by other species of the ecosystem that are not explicitly modelled);  $M_{\xi max}$  is the maximum starvation mortality rate,  $M_L$  is the larval mortality rate applied to the first life stage; min and max size ratios define suitable prey size for a predator,  $\xi_{crit}$  is the critical predation efficiency corresponding to maintenance requirements, max ingestion rate corresponds to the maximum amount of food edible per year relatively to the predator mass. Values reported in the table come from literature (references in Appendix 1) except from  $M_{oth}$ ,  $F$  and  $M_L$  which come from calibration.

Species	GROWTH AND CONDITION						REPRODUCTION		SURVIVAL						PREDATION			
	$L_{\infty}$	$K$	$t_0$	$a_{th}$	$c$	$b$	$L_{mat}$	$\phi$	$a_{max}$	$F$	$a_{rec}$	$M_{oth}$	$M_{\xi max}$	$M_L$	Min size ratio	Max size ratio	$\xi_{crit}$	max ingestion rate
	cm	$y^{-1}$	y	y	$g.cm^{-3}$		cm	eggs.g <sup>-1</sup>	y	$y^{-1}$	y	$y^{-1}$	$y^{-1}$	month <sup>-1</sup>				$g.g^{-1}$
Lesser spotted dogfish	87.4	0.118	-1.09	0.5	0.00308	3.029	57	0.14	10	0.09	4	0.087	0.3	4.29	50	3	0.57	3.5
Red mullet	53.3	0.18	-1.23	1	0.00716	3.178	16.7	500	11	0.194	0.4	0	0.3	13.01	125	10	0.57	3.5
Pouting	37.6	0.46	-0.77	0.5	0.00657	3.202	23	620	4	0.106	1	0.12	0.3	6.69	50	3.5	0.57	3.5
Whiting	40.2	0.63	-0.37	1	0.00621	3.103	20	797	20	0.122	1	0.405	0.3	17.03	30	1.5	0.57	3.5
Poor cod	22.2	0.462	-0.679	0.5	0.0092	3.026	13	100	3	0	1	0.085	0.3	4.73	50	3.5	0.57	3.5
Cod	103.9	0.19	-0.1	0.5	0.00835	3.053	56	800	25	0.219	1	0	0.3	21.95	50 / 20*	2.3 / 1.8*	0.57	3.5
Dragonet	28.3	0.471	-0.443	0.5	0.0262	2.442	17.4	255	6	0	1	0.148	0.3	2.58	125	10	0.57	3.5
Sole	37.3	0.35	-1.61	0.5	0.00391	3.264	29	482	20	0.187	1.5	0	0.3	7.4	125	10	0.57	3.5
Plaice	71.7	0.23	-0.83	0.5	0.0103	3.017	27	255	15	0.44	1	0	0.3	13.52	125	5	0.57	3.5
Horse mackerel	39.2	0.18	-1.515	1	0.0054	3.114	22	1655	15	0.052	0.5	0	0.3	3.52	100	2.5	0.57	3.5
Mackerel	42	0.24	-2.07	1	0.00338	3.241	29	1070	17	0.142	0.5	0	0.3	7.94	100	2.5	0.57	3.5
Herring	29.2	0.37	-0.67	0.5	0.00503	3.1	25	458	11	0.156	1.5	0.008	0.3	1.24	1000	5	0.57	2
Sardine	24.6	0.79	-0.22	0.5	0.00594	3.077	15	2228	15	0.03	0.5	0.216	0.3	14.07	1000	5	0.57	3.5
Squids	50	2	0.5	0.7	0.25	2.27	30	50	2	0.036	0.5	0.298	0.3	7.97	20	1.5	0.57	3.5

\*below and above 12cm respectively

**Table 2:** Parameters of the low trophic level (LTL) groups used in OSMOSE as forcing prey field. Size range of plankton groups correspond to size class used in biogeochemical models, and size class of benthic invertebrates are arbitrarily set to represent a discretized size spectrum. Trophic levels are either set arbitrarily (identified by \*) or derived from SI-derived estimates from (Kopp et al., 2015) with the corresponding species indicated. Accessibility coefficients are calibrated.

	LTL groups	Size range (cm)	Trophic level	Accessibility coefficient
PELAGIC PREY	Dinoflagellates	0.0002 – 0.002	1*	$10^{-3.98}$
	Diatoms	0.002 – 0.02	1*	$10^{-2.79}$
	Micro-zooplankton	0.002 – 0.02	2*	$10^{-0.97}$
	Meso-zooplankton	0.02 – 0.2	2.6 (copepods)	$10^{-0.37}$
	Macro-zooplankton	0.2 – 2	3.8 ( <i>Crangon crangon</i> )	$10^{-1.56}$
BENTHIC PREY	Very small benthos	0.02 – 0.5	3*	$10^{-1.20}$
	Small benthos	0.5 – 1	2.9 ( <i>Nereis sp.</i> )	$10^{-1.30}$
	Medium benthos	1 – 5	2.2 (bivalves)	$10^{-1.87}$
	Large benthos	5 – 10	2.3 ( <i>Psammechinus miliaris</i> )	$10^{-2.96}$
	Very large benthos	10 – 15	3.6 ( <i>Maja brachydactyla</i> )	$10^{-0.38}$

**Table 3:** Accessibility coefficients between individuals depending on their vertical position, representing the proportion of prey biomass available to a predator. The vertical position of individuals depends on their stage and is indicated in the last column.

		Predator			
		Pelagic	Demersal	Benthic	
Prey	Pelagic	1	0.5	0	Red mullet, Pouting, Whiting, Dragonet, Plaice younger than 3 months Cod younger than 0.4 year Sole younger than 0.15 year Horse mackerel, Mackerel, Herring, Sardine Dinoflagellates, Diatoms, Microzooplankton, Mesozooplankton, Macrozooplankton
	Demersal	0.5	1	0	Lesser spotted dogfish older than 0.45 year, Pouting, Whiting older than 3 months Cod older than 0.4 year Squids older than 1.5 month
	Benthic	0	0.5	1	Lesser spotted dogfish younger than 0.45 year, Red mullet, Dragonet, Plaice older than 3 months Sole older than 0.15 year Squids younger than 1.5 month Very small benthos, Small benthos, Medium-size benthos, Large benthos, Very large benthos

**Table 4:** Size range and number of fish individuals (N) used to estimate species TL based on SI measurement in four empirical studies realized in the EEC. For Jennings and Cogan (2015), body size are estimated from body mass using allometric relationship (Robinson et al. 2010; Mahé et al. 2018). Squid length was estimated based on an unpublished relationship ( $\ln(\text{Length}) = 2.86 + 0.44 \ln(\text{mass})$ ) calculated on individual length-mass measurement performed during CAMANOC survey in the English Channel (K. Mahé, Ifremer Halieutic Information System, pers. comm.)

	Kopp et al., 2015	Jennings and Cogan, 2015	Mialet et al. 2017	Cresson et al., 2017	Cresson et al., 2018
Lesser spotted dogfish	11-64 cm N=36	17-63.7 cm N=53	40-63 cm N = 18	42-67.9 cm N=25	50.5-65 cm N=10
Red mullet	7-32 cm N=63	N=0	20-25 cm n=5	N=0	15-19.6 cm N=10
Pouting	9-27.5 cm N=24	7.9-33.9 cm N=37	n=0	12.9-32.9 cm N=50	11.9-22.7 cm N=19
Whiting	7-41 cm N=39	12.5-32.7 cm N=28	21-38 cm N=30	14.6-35 cm N=80	6.8-36.4 cm N=16
Poor cod	10.6-21.5 cm N=12	7.2-19.3 cm N=27	9-12 cm n=9	8.4-17.5 cm N=77	9.3-15.6 cm N=10
Cod	35-73 cm N=33	36cm N=1	29-93 cm N=18	N=0	33.2-68.7 cm N=8
Dragonet	9-23 cm N=18	5.8-24.5 cm N=83	N=0	N=0	12-18.7 cm N=15
Sole	9-38 cm N=51	12.7-36.7 cm N=78	N=0	N=0	7.5-29.5 cm N=1
Plaice	9-43 cm N=37	8.5-55.3 cm N=134	20-38 cm n=40	22.5-42.6 cm N=28	13.4-25 cm N=15
Horse mackerel	8-39 cm N=54	19.6-21.4 cm N=7	10-13 cm N=7	11.4-31.5 cm N=148	4.3-20.4 cm N=23
Mackerel	18-37 cm N=39	32cm N=1	30-34 cm N=6	16.9-41 cm N=158	24.3-28.9 cm N=10
Herring	6.2-29 cm N=10	N=0	5-27 cm N=6	N=0	7-25.1 cm N=15
Sardine	7.7-29 cm N=10	N=0	N=0	N=0	9.8-20.2 cm N=10
Squids	N=0	11.5-16.8 cm N=4	N=0	N=0	9-31 cm N=17