

Using integrated multispecies occupancy models to map co-occurrence between bottlenose dolphins and fisheries in the Gulf of Lion, French Mediterranean Sea

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Abstract: In the Mediterranean Sea, interactions between marine species and human activities are prevalent. The coastal distribution of bottlenose dolphins (*Tursiops truncatus*) and the predation pressure they put on fishing stocks lead to regular interactions with fisheries. Multispecies occupancy models are a relevant framework to estimate co-occurrence between two (or more) species while accounting for false negatives and potential interspecific dependance although requiring substantial quantity of data to fit. Here, we extended multispecies occupancy model to integrate multiple datasets to map spatial co-occurrence between trawlers and bottlenose dolphins in the Gulf of Lion, French Mediterranean Sea combining data from aerial surveys and boat surveys at a large spatial scale. The integrated multispecies occupancy model produced more precise estimate than single-dataset multispecies occupancy models. Our results support that both integrated and multispecies frameworks are relevant to map distribution and understand species interactions in our case study. Besides, our application of multispecies occupancy models to bottlenose dolphins and fishing trawlers enabled to map co-occurrence probability, which open promising avenues in the understanding of interactions between human activities and marine mammals that occur at large spatial scales.

29 **Keywords:** cetaceans, human-animal interaction, integrated models, NIMBLE, odontocetes,
30 occupancy models, trawlers

31 **Introduction**

32 The Mediterranean Sea, being on the busiest sea on Earth, is especially affected by anthropogenic
33 pressures (Coll et al. 2012, Giakoumi et al. 2017). In particular, there are significant interactions
34 between marine species and human activities (Avila et al. 2018). Among marine mammals,
35 odontocetes frequently forage in the proximity of fishing vessels (Bonizzoni et al. 2022). Despite
36 facilitating access to prey, foraging behind trawlers leads to depredation or by-catch interactions
37 that pose conservation concerns (Lewison et al. 2004, Snape et al. 2018, Santana-Garcon et al.
38 2018, Bonizzoni et al. 2020, 2022). The coastal ecology of common bottlenose dolphins (*Tursiops*
39 *truncatus*, hereafter bottlenose dolphins) and the depredation pressure they put on fishing stocks
40 lead to regular interactions with human recreational activities and fisheries (Bearzi et al. 2009,
41 Queiros et al. 2018, Leone et al. 2019). Bottlenose dolphins are often reported in close proximity
42 to fishing activities, and are known to forage behind trawlers worldwide, including the
43 Mediterranean Sea (Allen et al. 2017, Bonizzoni et al. 2022). Following documented bottlenose
44 dolphins mortality events (Manlik et al. 2022), interactions have raised conservation concerns and
45 mitigation measures tested to date have not proven effective (Snape et al. 2018, Bonizzoni et al.
46 2020). Interactions between bottlenose dolphins and fisheries have been studied via *in-situ*
47 observations (Santana-Garcon et al. 2018) and passive acoustic monitoring (Bonizzoni et al. 2022)
48 to describe the behavioral drivers of interaction, which constitute a major asset despite such being
49 restricted to a limited spatial scale. At a larger extent, one can use trawlers data as covariate on
50 dolphin distribution models (Pirota et al. 2015). While a useful point, such modelling approach do
51 not take into account biotic interactions that can lead to bias estimation of interaction risks.

52 Mapping human-wildlife interactions is a preliminary step to better understand and manage
53 conservation conflicts and is, therefore, particularly strategic in the case of the mammal by-catch
54 issue. This is usually achieved by calculating and mapping the overlap between the distribution of
55 a species and human pressure(s). This overlapping approach raises two issues. First, when
56 modelling species distributions, failure to account for interspecific interactions between co-
57 occurring species may lead to biased inference, which arises when modelling only abiotic and

58 habitat associations (Rota et al. 2016b). In particular, one needs to account for biotic effects when
59 mapping potential interactions between marine mammals and fisheries as we know that cetaceans
60 can forage in association to trawling vessels (Jourdain & Vongraven 2017, Allen et al. 2017).
61 Second, another challenge when quantifying species interactions is to account for imperfect
62 detection, e.g. when species do co-occur but one or several of the species involved go undetected
63 by sampling (Rota et al. 2016a, Fidino et al. 2019). Ignoring imperfect detection leads to the
64 underestimation of species distribution and imprecise or even inaccurate quantification of species
65 interactions (MacKenzie 2006).

66 To account for these issues, multispecies occupancy models have been developed to estimate
67 occupancy probabilities of two or more interacting species while accounting for imperfect detection
68 (Rota et al. 2016b, Fidino et al. 2019, Devarajan et al. 2020). One caveat of multispecies models is
69 that they require substantial data for robust ecological inference (Clipp et al. 2021). To overcome
70 data scarcity, several authors have suggested combining multiple datasets within an integrated
71 modelling framework (see Kéry & Royle (2020), Chapter 10, for a review). In that spirit, we
72 previously developed a single-species integrated occupancy model to map the distribution of
73 bottlenose dolphins over the Northwestern Mediterranean Sea (Lauret et al. 2021).

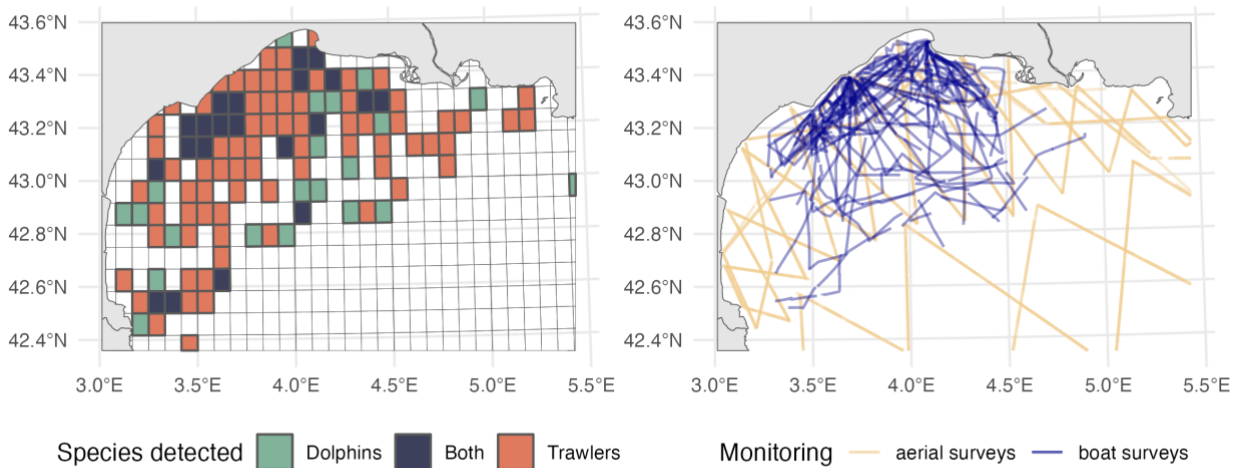
74 Here, our first objective was to showcase the extension of multispecies occupancy models to
75 integrate multiple datasets and to assess its performances. Our second objective was to illustrate a
76 statistical tool that enable to map co-occurrence probabilities of fishing trawlers and bottlenose
77 dolphins while integrating multiple datasets. We built an integrated multispecies occupancy model
78 to quantify interactions between bottlenose dolphins and fisheries using data collected from aerial
79 surveys and boat surveys in the Gulf of Lion (French Mediterranean Sea). We assessed whether
80 the multispecies occupancy model benefit from data integration compared to models using dataset
81 in isolation (hereafter single-dataset models), and whether the multispecies framework helped to
82 estimate dolphins and trawlers occupancy compared to single-species occupancy models. Finally,
83 we discussed the opportunity of multispecies occupancy models to study interactions between
84 marine mammals and fisheries.

85 **Material and Methods**

86 **Data**

87 We combined bottlenose dolphin and fisheries data extracted from two large-scale monitoring
88 programs. First, we used Aerial Surveys of Marine Megafauna (SAMM in French) conducted in
89 2011 and 2012 in the French Mediterranean sea and Italian waters of the Pelagos Sanctuary ([Laran](#)
90 [et al. 2017](#)). These aerial surveys aimed to collect data on marine mammals, seabirds, fish, and
91 human activities ([Baudrier et al. 2018](#), [Lambert et al. 2020](#)). We used detection / no-detection data
92 of bottlenose dolphins and of fishing trawlers collected during 4 sampling occasions, 1 per season
93 (winter, spring, summer, and autumn). The second monitoring program targeted bottlenose dolphin
94 habitats in the French Mediterranean Sea using a boat photo-identification protocol between 2013
95 and 2015 collecting data all year long ([Labach et al. 2021](#)). We focused our attention on the Gulf
96 of Lion and we used data collected by EcoOcean Institut. We extracted data of bottlenose dolphins
97 and trawlers. We considered a trawler every commercial fishing boat that we observed actively
98 dragging. We only used data on trawlers seen fishing as we focused on fishing areas and not
99 traveling routes between harbours and fishing areas.

100 We divided the Gulf of Lion study area into 397 5' × 5' contiguous Marsden grid-cells (WGS 84)
101 for statistical analysis (Figure 1). We calculated the sampling effort as the total length (in km) of
102 transects conducted in each grid-cell by each monitoring program per time unit. We used seabed
103 depth as an environmental covariate affecting spatial variation in occupancy of bottlenose dolphins
104 and trawlers ([Bearzi et al. 2009](#), [Labach et al. 2021](#)). Depth values in meters was scaled before its
105 use in models. At the date of our modelling developments, the resolution of the grid and our ability
106 to explore multiple environmental descriptors of co-occurrence patterns was impaired by the
107 limited size of our datasets. As new monitoring programs are implemented on this case study, we
108 believe that our integrated bottlenose dolphins - fisheries occupancy model would benefit from
109 further ecological investigation when more data would be collected and available to test for
110 competing ecological hypotheses and models ([Broms et al. 2016](#)).



Source: from SAMM and GDEGeM/EcoOcean Institut data collected in the Gulf of Lion

111
 112 *Figure 1: Gulf of Lion detections of bottlenose dolphins and trawlers by aerial surveys (SAMM)*
 113 *and boat surveys (GDEGeM and EcoOcean Institut) along with the sampling effort for each*
 114 *monitoring program. We plotted data on 397 5' × 5' contiguous Marsden grid-cells (WGS 84)*

115 **Integrated multispecies occupancy model**

116 Several assumptions need to be met to safely apply multispecies occupancy models: i) geographic
 117 and demographic closure of grid-cells and of the study area (i.e. individuals do not move in and
 118 out the grid-cell, and no birth or death event occur during the sampling period), ii) independence
 119 of the detection / no-detection data over space and time, iii) accurate identification (i.e. no
 120 misidentification) (Rota et al. 2016b). In our case study, dolphins and trawlers moved in and out
 121 grid-cells during the sampling period making the geographic closure unlikely to be respected. Thus,
 122 we interpreted occupancy as “space-use”, that is the probability that the species uses the grid-cell
 123 given it is present in the study area. In this article, we presented an extension of multispecies
 124 occupancy models to integrate multiple datasets. Then, to ensure clarity of the integrated
 125 multispecies occupancy model we did not perform a deep investigation of ecological predictors.

126 **Latent ecological process**

127 We followed Rota et al. (2016a) to formulate the ecological model describing the occupancy
 128 process. In grid-cell i , the latent occupancy state can take 4 values: $z = [1,0,0,0]$ if neither dolphins
 129 nor trawlers use the grid-cell, $z = [0,1,0,0]$ if dolphins use the grid-cell but trawlers do not, $z =$
 130 $[0,0,1,0]$ if trawlers use the grid-cell but dolphins do not, and $z = [0,0,0,1]$ if both dolphins and

131 trawlers use the grid-cell. Then, ignoring the grid-cell index, our multispecies occupancy model
132 estimated 4 occupancy probabilities.

- 133 • ψ^4 is the probability that both dolphins and trawlers use the grid-cell;
- 134 • ψ^3 is the probability that trawlers use the grid-cell and dolphins do not;
- 135 • ψ^2 is the probability that dolphins use the grid-cell and trawlers do not;
- 136 • ψ^1 is the probability that neither dolphins nor trawlers use the grid-cell, which corresponds
137 to the probability that none of the previous events occurs, with $\psi^1 = 1 - \psi^2 - \psi^3 - \psi^4$.

138 We modeled the occupancy state of each grid-cell z as a multinomial logistic regression, z being
139 draw in vector $\pi = [(1 - \psi^2 - \psi^3 - \psi^4), \psi^2, \psi^3, \psi^4]$:

$$140 \quad z \sim \text{Multinomial}(1, \pi)$$

141 with π adjusted to sum to 1 using a generalized logit link function. We modeled occupancy
142 probabilities ψ^2 , ψ^3 , and ψ^4 as a function of depth and non-parametric functions geographical
143 coordinates of the grid-cell center X and Y with Generalized Additive Models (GAMs) (Wood
144 2006) using a multinomial-logit link. For grid-cell i :

$$145 \quad \psi_i^1 = \frac{1}{1 + \exp(\delta_i^2) + \exp(\delta_i^3) + \exp(\delta_i^2 + \delta_i^3 + \delta_i^4)}$$

$$146 \quad \psi_i^2 = \frac{\exp(\delta_i^2)}{1 + \exp(\delta_i^2) + \exp(\delta_i^3) + \exp(\delta_i^2 + \delta_i^3 + \delta_i^4)}$$

$$147 \quad \psi_i^3 = \frac{\exp(\delta_i^3)}{1 + \exp(\delta_i^2) + \exp(\delta_i^3) + \exp(\delta_i^2 + \delta_i^3 + \delta_i^4)}$$

$$148 \quad \psi_i^4 = \frac{\exp(\delta_i^2 + \delta_i^3 + \delta_i^4)}{1 + \exp(\delta_i^2) + \exp(\delta_i^3) + \exp(\delta_i^2 + \delta_i^3 + \delta_i^4)}$$

149 where, for $k \in \{2,3,4\}$, δ_i^k in grid-cell i is:

$$150 \quad \delta_i^k = \alpha_0^k + \alpha_1^k \text{depth}_i + s^k(X_i, Y_i)$$

151 where $s^k(\cdot)$ is a smooth function (see Supplementary Information). Quantities $s^k(\cdot)$, α_0^k and α_1^k
152 were to be estimated. δ^2 , δ^3 are called first-order parameters estimating log odds of species

153 occurrence, conditional on absence of the other species, while δ^4 is a second-order parameter
154 estimating change in log odds when both species are co-occurring. For additional detail about the
155 modelling formulation, one can refer to Fidino et al. (2019), and Rota et al. (2016a).

156 **Observation process**

157 We considered 4 sampling occasions j with similar sampling effort for each monitoring program
158 (winter, spring, summer, and autumn). We extended the observation process of the multispecies
159 occupancy model of Rota et al. (2016a) to integrate two datasets in the spirit of Lauret et al. (2021).
160 We considered dataset A (i.e. aerial line transects), and dataset B (i.e. boat photo-id surveys). In
161 both monitoring programs, detection and non-detection data on bottlenose dolphins and trawlers
162 were collected. Each “species” had a different detection probability depending on the monitoring
163 program considered, which led to four different detection probabilities:

- 164 • p_d^B that is the probability of detecting dolphins by boat photo-id surveys;
- 165 • p_d^A that is the probability of detecting dolphins by aerial surveys;
- 166 • p_t^B that is the probability of detecting trawlers by boat photo-id surveys;
- 167 • p_t^A that is the probability of detecting trawlers by aerial surveys.

168 For each grid-cell i and each sampling occasion j , we modeled the detection probability $p_{i,j}$ as a
169 logit-linear function of sampling effort. For example, regarding the probability of detecting
170 bottlenose dolphins by boat photo-id surveys, we estimated:

$$171 \quad \text{logit}(p_d^B(i, j)) = \beta_{0d}^B + \beta_{1d}^B \text{sampling effort}_{i,j}^B$$

172 where β_{0d}^B , and β_{1d}^B were to be estimated. One can argue that trawlers trawlers detection is perfect
173 as they are not an elusive animal species. However, due to the large grid-cell size considered (i.e. 55
174 km²), trawlers can remain undetected during sampling, e.g. sparse sampling of the edge of the grid-
175 cell can limit trawlers detection. Then, we accounted for possible imperfect detection of trawlers
176 and we modeled trawlers detection probability as the logit-linear function of sampling effort.

177 The four detection probabilities could then be used to explain the simultaneous detection / no-
178 detection of each species by each survey, resulting in 16 observation “events” (i.e. (2 species)²)

179 detections status)^(2 surveys)) (See Supplementary materials for details about the observation
 180 process).

181 Then, with 4 ecological states (in columns) and 16 observation events (in rows), we described the
 182 observation process with the following (transposed) 4x16 matrix.

$$183 \quad t(\theta) = \begin{bmatrix} 1 & (1 - p_D^B)(1 - p_D^A) & (1 - p_T^B)(1 - p_T^A) & (1 - p_T^B)(1 - p_T^A)(1 - p_D^A)(1 - p_D^B) \\ 0 & p_D^B(1 - p_D^A) & 0 & (1 - p_T^A)(1 - p_D^A)p_D^B(1 - p_T^B) \\ 0 & 0 & p_T^B(1 - p_T^A) & (1 - p_T^A)(1 - p_D^A)p_T^B(1 - p_D^B) \\ 0 & 0 & 0 & (1 - p_T^A)(1 - p_D^A)p_D^Bp_T^B \\ 0 & p_D^A(1 - p_D^B) & 0 & p_D^A(1 - p_T^A)(1 - p_D^B)(1 - p_T^B) \\ 0 & p_D^Bp_D^A & 0 & p_D^A(1 - p_T^A)p_D^B(1 - p_T^B) \\ 0 & 0 & 0 & p_D^A(1 - p_T^A)p_T^B(1 - p_D^B) \\ 0 & 0 & 0 & p_D^A(1 - p_T^A)p_D^Bp_T^B \\ 0 & 0 & 0 & p_T^A(1 - p_D^A)(1 - p_D^B)(1 - p_T^B) \\ 0 & 0 & p_T^Bp_T^A & p_T^A(1 - p_D^A)p_D^B(1 - p_T^B) \\ 0 & 0 & 0 & p_T^A(1 - p_D^A)p_T^B(1 - p_D^B) \\ 0 & 0 & 0 & p_T^A(1 - p_D^A)p_T^Bp_D^B \\ 0 & 0 & 0 & p_D^Ap_T^A(1 - p_T^B)(1 - p_D^B) \\ 0 & 0 & 0 & p_D^Ap_T^Ap_D^B(1 - p_T^B) \\ 0 & 0 & 0 & p_D^Ap_T^Ap_T^B(1 - p_D^B) \\ 0 & 0 & 0 & p_T^Bp_T^Ap_D^Bp_D^A \end{bmatrix}$$

184 Each observation y was linked to the ecological state z via a Categorical distribution. To do so, let
 185 $\theta_z = (Pr(y = 1), Pr(y = 2), \dots, Pr(y = 16))$ represents a column of $t(\theta)$ that lines up with the
 186 latent state of a given grid-cell. In other words, each column of $t(\theta)$ represents all observation
 187 probabilities conditional on the latent state of a given grid-cell and hence sum to 1.

$$188 \quad y|z \sim \text{Categorical}(\theta_z)$$

189 **Assessing the benefit of data integration**

190 To assess the benefit of the integrated model, we ran multispecies occupancy models with aerial
 191 surveys dataset and with boat photo-identification dataset separately. We compared the precision
 192 between each single-dataset multispecies occupancy models and precision of the integrated
 193 multispecies occupancy model (See for more details about this study, we refer to [supplementary](#)
 194 [materials](#)).

195 **Assessing the benefit of the multispecies framework**

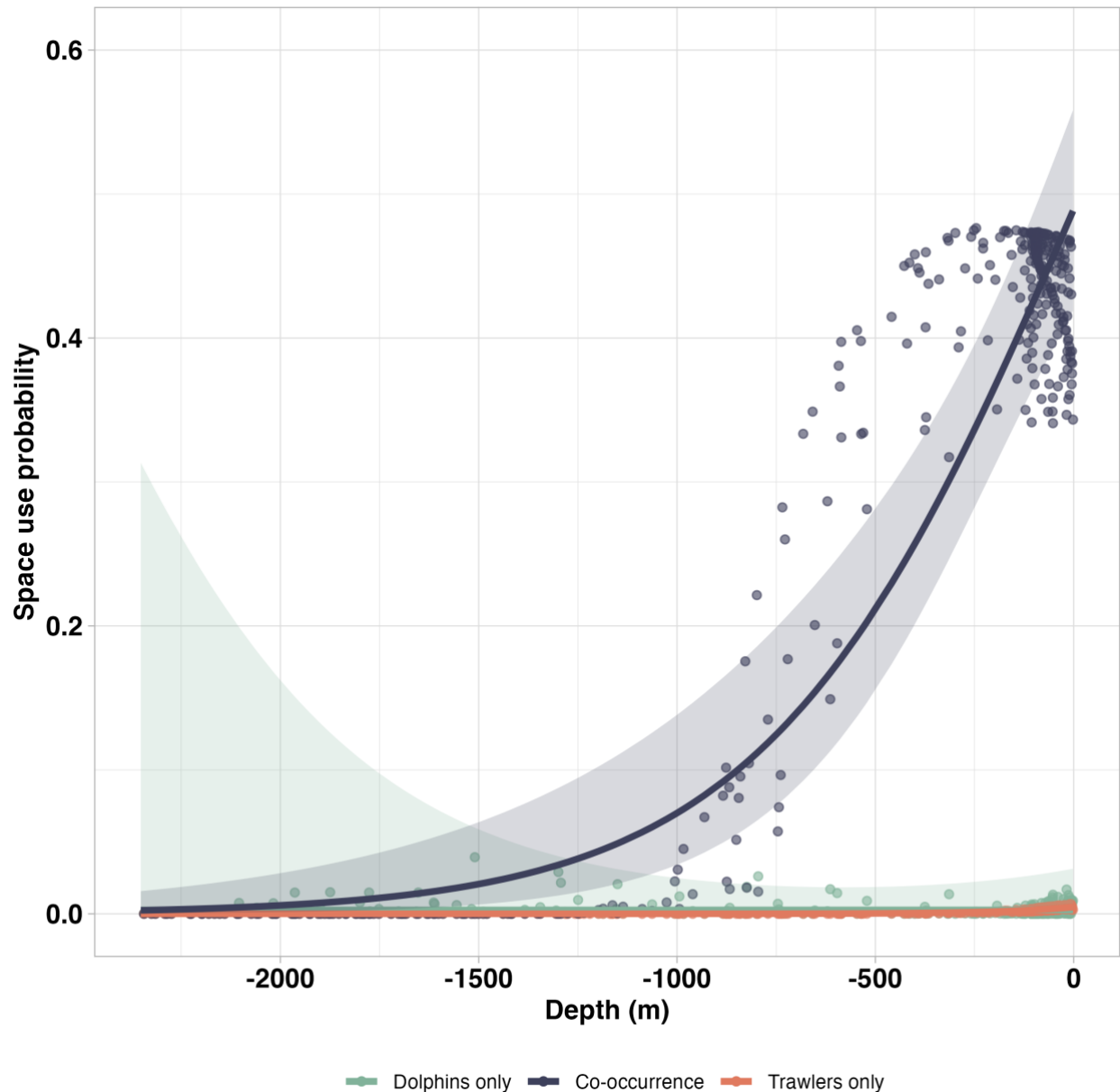
196 To assess the benefit of the multispecies framework, we ran two single-species occupancy models:
197 i) an integrated occupancy model using bottlenose dolphins data, and ii) an integrated occupancy
198 model using trawlers data. We compared the precision of ecological estimation of the two single-
199 species integrated occupancy models to the estimations of the multispecies integrated occupancy
200 model. As we compared models with limited amount of data, note that in this case we modeled the
201 occupancy probabilities with a linear effect of bathymetry (i.e. without the GAM on geographical
202 coordinates as described above). For more details about the model comparison, we refer to
203 [supplementary materials](#).

204 **Implementation in NIMBLE**

205 We used the `jagam()` function in the `mgcv` R package to implement our GAM ([Wood 2019](#)). We
206 ran all models using three Markov Chain Monte Carlo chains with 200,000 iterations and 20,000
207 burnin each in the NIMBLE R package ([Valpine et al. 2017](#)). We reported posterior mean and 80%
208 credible intervals (CI) for each parameter. We considered a significant effect of covariate when its
209 80% CI does not overlap 0. Data and codes are available on a [Zenodo repository](#). For another
210 Bayesian pipeline to fit integrated multispecies occupancy model, one can refer to `{spOccupancy}`
211 R-package ([Doser et al. 2022](#)).

212 **Results**

213 We detected 60 trawlers, and 18 groups of bottlenose dolphins by aerial surveys, while we detected
214 71 trawlers and 30 groups of bottlenose dolphins by boat photo-id surveys.

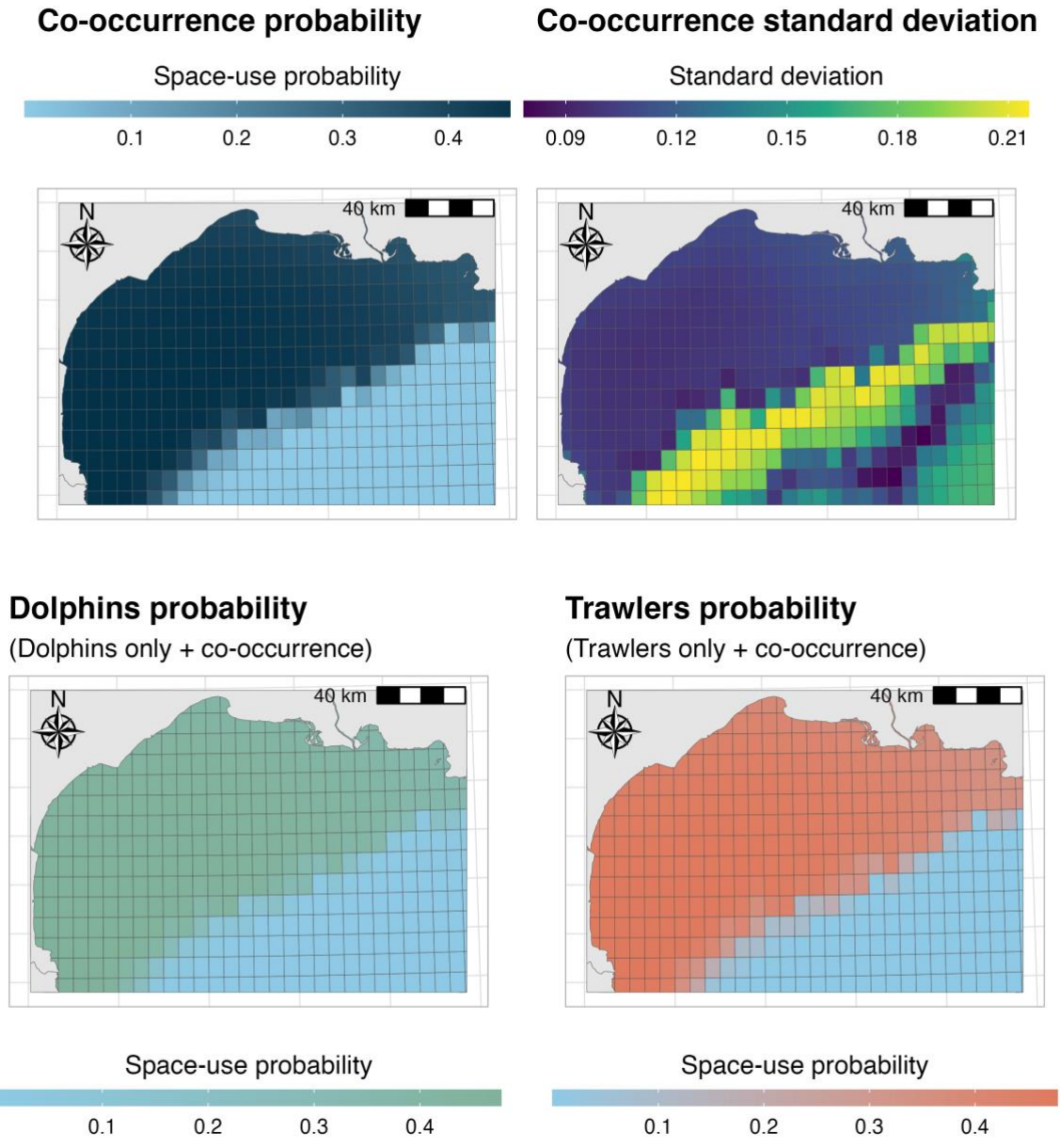


215

216 *Figure 2: Occupancy probabilities estimated from the integrated multispecies model as*
 217 *function of depth (in meters). Green points and lines represent ψ_2 , the probability that only*
 218 *bottlenose dolphins used the space. Orange points and lines represent ψ_3 , the probability*
 219 *that only fishing trawlers used the space. Blue points and lines represent ψ_4 , the probability*
 220 *that both bottlenose dolphins and fishing trawlers used the space, i.e. co-occurrence. We*
 221 *represented 80% credible interval in shaded areas*

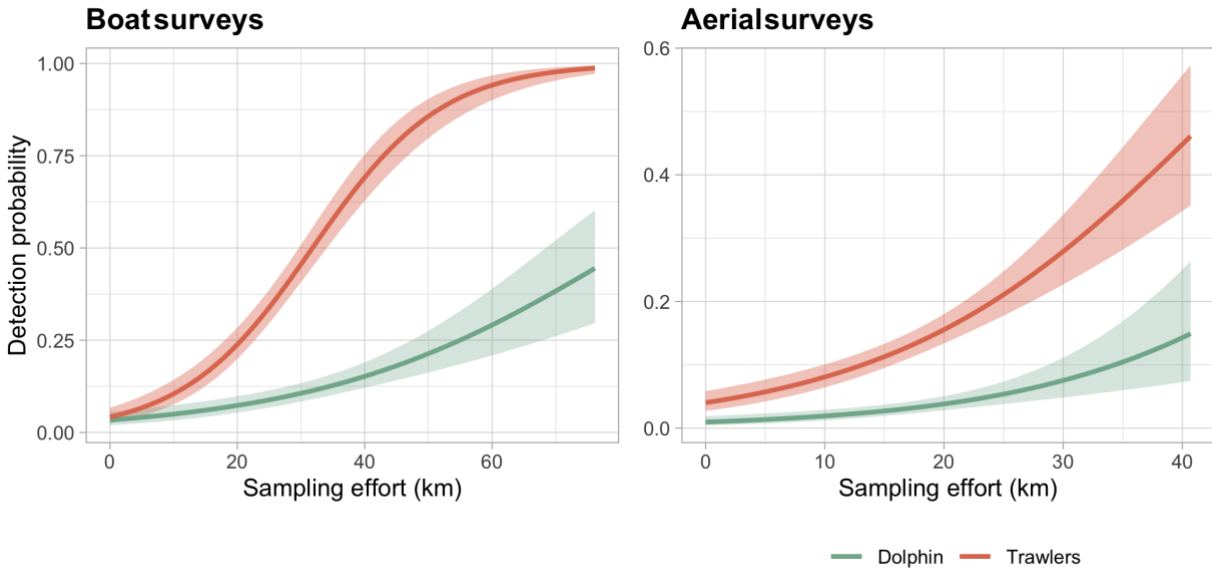
222 Overall, the probability that dolphins only ψ_2 or that trawlers only ψ_3 use a grid-cell was lower
 223 than the co-occurrence probability ψ_4 (Figure 2). Comparing average co-occurrence probability
 224 ($\psi_4 = 0.29$) to marginal dolphins space-use ($\psi_2 + \psi_4 = 0.30$) or trawlers space-use ($\psi_3 + \psi_4 =$

225 0.30), we conclude that most of the study area displays either a high probability that both species
226 use the grid-cell, or a low probability for any species to use the grid-cell, *i.e.* space-use of both
227 species overlap. Co-occurrence probability increased with decreasing depth (Figure 2 & 3). Both
228 trawlers space-use ($\psi_3 + \psi_4$) and dolphins space-use($\psi_2 + \psi_4$) were higher in the coastal waters
229 than the pelagic seas (Figure 3, and Supplementary Information). Although, dolphins space-use
230 probability in pelagic seas appeared to be higher than trawlers space-use probability in Figure 2,
231 the difference is not significant.



232
 233 *Figure 3: Co-occurrence probability of dolphins and trawlers in the Gulf of Lion (Northwestern*
 234 *Mediterranean Sea) and associated standard deviation (upper panel). Lower panel shows*
 235 *dolphins and trawlers space-use probabilities.*

236 Both dolphins and trawlers detection probabilities increased with increasing sampling effort. Boat
 237 photo-id monitoring had higher detection probabilities than aerial surveys (Figure 4). Trawlers
 238 were more easily detected than bottlenose dolphins for both monitoring programs.

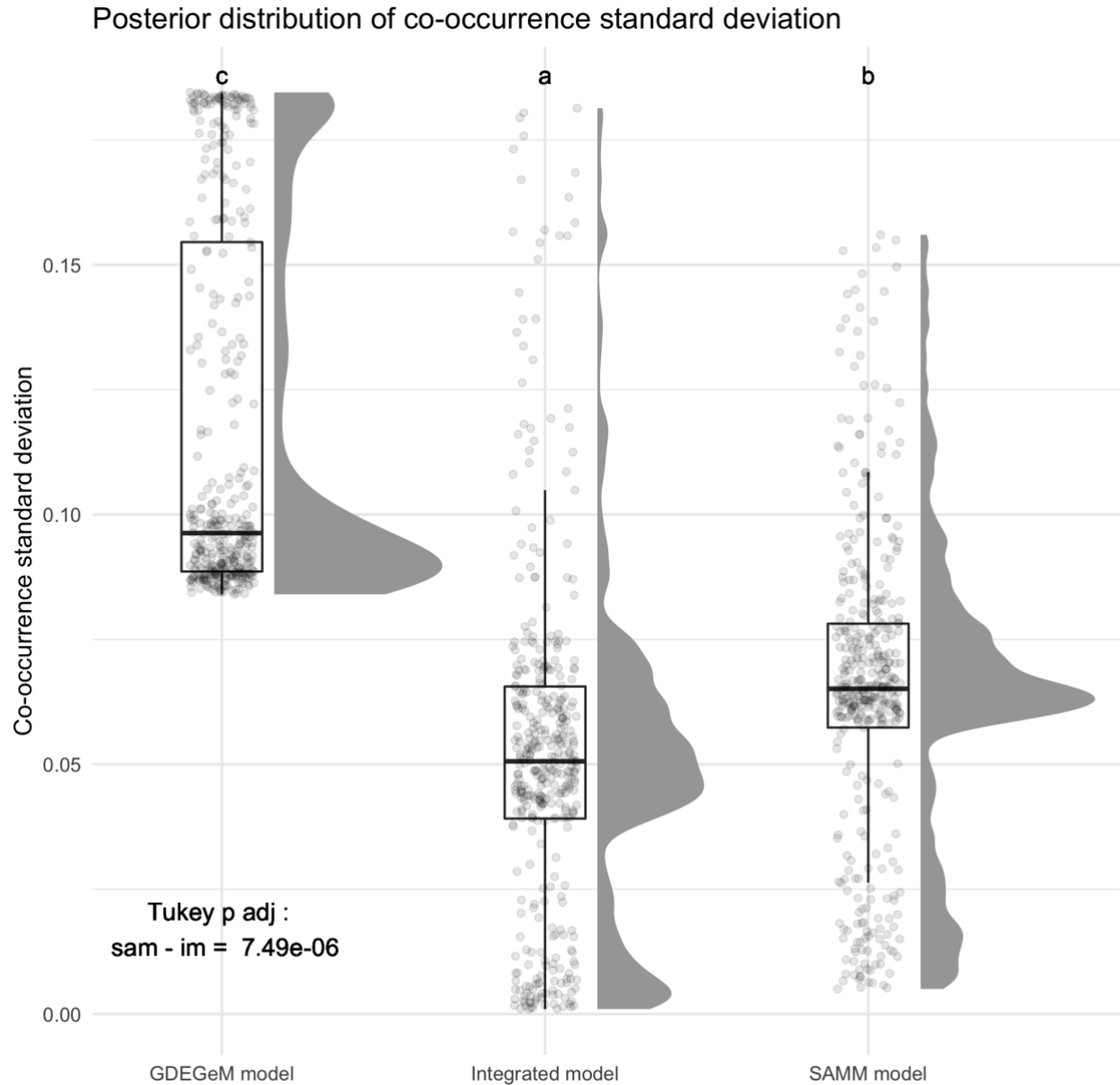


239

240 *Figure 4: Estimated detection probability of dolphins and trawlers as a function of sampling*
 241 *effort for each monitoring program. We provide posterior medians (solid line) and 80%*
 242 *credible intervals (shaded area).*

243 **Increased precision of integrated and multispecies frameworks**

244 Integrated multispecies occupancy model estimated more precise co-occurrence probability
 245 (i.e. lower standard deviation) than multispecies occupancy models using datasets in isolation
 246 (Figure 5).



247

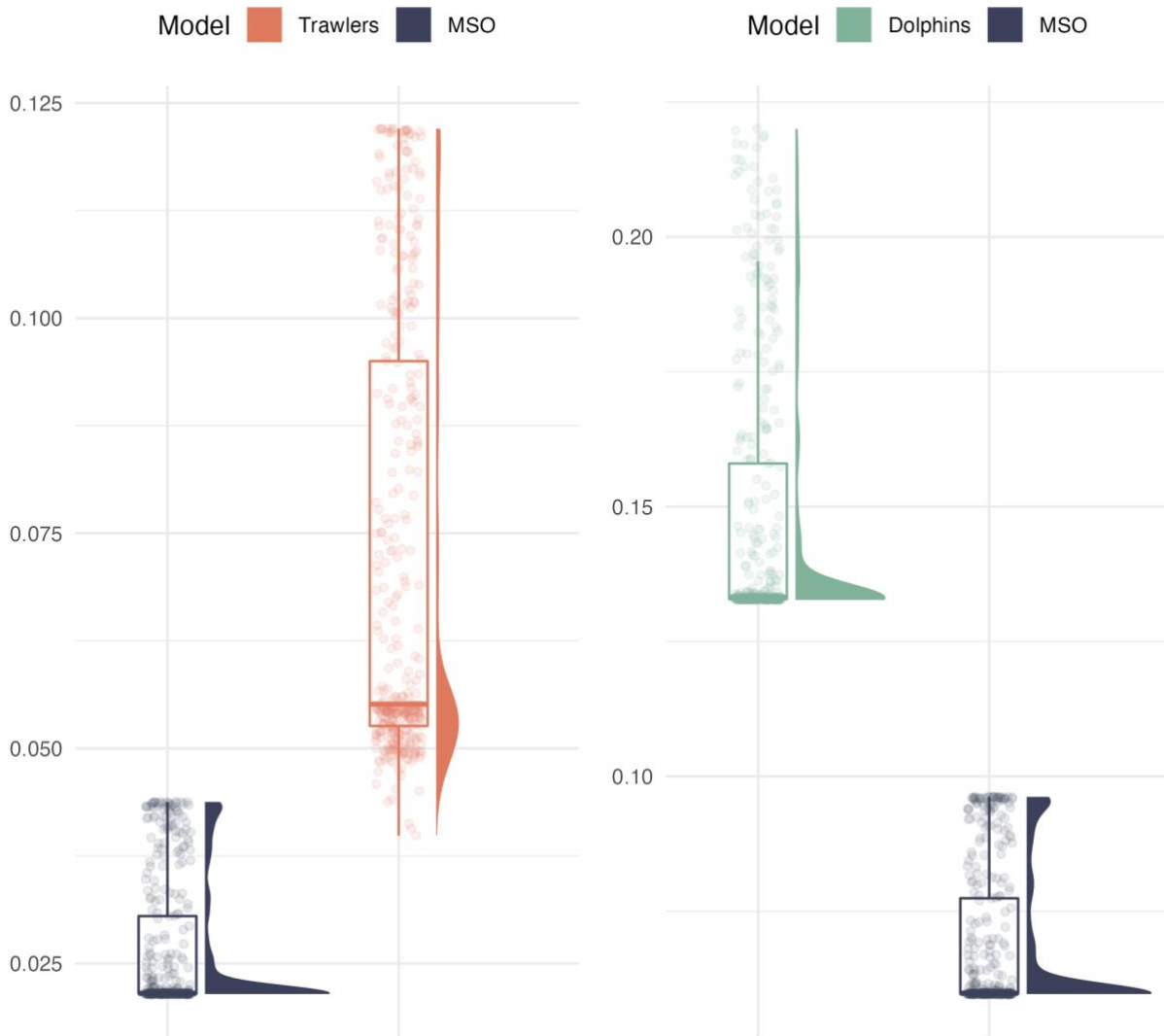
248 *Figure 5: Standard deviation associated with co-occurrence probability. SAMM model uses*
 249 *only aerial surveys data, GDEGeM model uses only boat surveys data. We tested for statistical*
 250 *differences between posterior distribution. 'sam' and 'im' respectively refer to SAMM and*
 251 *integrated model*

252 Similarly, multispecies integrated occupancy model exhibits a higher precision of marginal space-
 253 use probabilities of dolphins and trawlers (i.e. lower standard deviation) than single-species
 254 occupancy models that estimate dolphins or trawlers occupancy in isolation (Figure 6). Trawlers
 255 data being more abundant than bottlenose dolphins data, standard deviation of space-use
 256 probability are lower for trawlers than for dolphins (Figure 6).

Posterior distribution of space-use standard deviation

Trawlers

Dolphins



257

258 *Figure 6: Standard deviation associated with space-use probability for single-species vs*
259 *multispecies integrated occupancy models.*

260 Discussion

261 Using integrated multispecies occupancy models, we mapped the probability of co-occurrence
262 between French fisheries and bottlenose dolphins in the Gulf of Lion waters (Figure 3). Our
263 integrated multispecies occupancy models estimated a 0.40 probability of co-occurrence between
264 trawlers and bottlenose dolphins in the coastal seas of the Gulf of Lion.

265 While multispecies occupancy models require substantial amount of data to precisely estimate co-
266 occurrence ([Clipp et al. 2021](#)), integrated approaches can provide stronger inferences compared to
267 an analysis of each dataset in isolation ([Zipkin et al. 2019](#), [Lauret et al. 2021](#)). Our integrated
268 multispecies occupancy model helped to overcome data scarcity and produced more precise
269 estimations of co-occurrence probabilities than multispecies models using separated datasets
270 (Figure Figure 5 & Supplementary materials). Our integrated approach emphasized that data
271 integration can be particularly promising for multispecies occupancy models that are impaired by
272 data quantity. Besides, fitting multispecies occupancy models helped to precise ecological
273 estimations of space-use probabilities that are fitted with single-species occupancy models (Figure
274 6 & Supplementary materials). Thus, both the multispecies and the integrated frameworks benefit
275 to our occupancy models to study the co-occurrence of bottlenose dolphins and fishing trawlers.

276 However, we underlined that we inferred co-occurrence probability and not interactions between
277 dolphins and trawlers. This means that, despite the fact that interactions can occur, dolphins and
278 trawlers also use the same space without interacting. Mapping co-occurrence, we include potential
279 interactions such as depredations or bycatch, and co-occurrence without interactions. However, to
280 understand species interactions, mapping co-occurrence is definitely a first step. Beyond mapping,
281 multispecies occupancy enables to estimate potential human-wildlife interaction as a function of
282 covariates (*i.e.* how co-occurrence is affected by depth in our case study), which is crucial to
283 understand mechanisms driving interaction risks and ultimately to implement management
284 ([Devarajan et al. 2020](#)).

285 Our approach echoes recent work integrating human activities into multispecies occupancy models
286 to identify and quantify threats of anthropic pressures on the environment ([Marescot et al. 2020](#)).
287 Outside the Gulf of Lion case study, integrated multispecies occupancy models can be leveraged
288 to provide robust maps of co-occurrence between marine megafauna and anthropogenic activities
289 while integrating several data sources. Additional presence-absence data, e.g. from scientific
290 fishing surveys, aerial surveys for tuna stock assessment ([Bauer et al. 2015](#)), or Automatic
291 Identification System for fishing vessels would further allow to better delineate fishing areas and
292 hence areas of potential interactions. Building co-occurrence maps is the first step when studying
293 species interactions. From there, practitioners can design dedicated surveys to determine what
294 features favor the shift from co-occurrence to interaction. The flexibility of occupancy models and

295 the extension to integrated occupancy models enable to accommodate a large panel of sampling
296 protocols and to include data from several monitoring programs in the same analysis, which permit
297 to foster the complementarity of different sampling designs and protocols (Lauret et al. 2021).

298 The ability to predict areas of human-wildlife potential interactions is of critical importance to
299 implement conservation measures as required under conservation legislation (e.g. the European
300 Union Marine Strategy Framework Directive). To mitigate marine mammal depredation and/or
301 bycatch, acoustic deterrents are implemented worldwide despite raising ethical and conservation
302 concerns (Santana-Garcon et al. 2018, Bonizzoni et al. 2022). Using multispecies occupancy
303 models to map potential hotspots of depredation may help to reduce the deployment of acoustic
304 deterrents and minimize the associated negative impacts (Estabrook et al. 2016, Snape et al. 2018).
305 Similarly, fin whales (*Balaenoptera physalus*) and sperm whales (*Physeter macrocephalus*) are at
306 high risk of collision with ferries in the Northwestern Mediterranean Sea and in particular in the
307 Pelagos Sanctuary Marine Protected Area (Ham et al. 2021, David et al. 2022). Mapping collision
308 risk with multispecies occupancy models can ultimately direct the measures of speed limitation.
309 Overall, we support that integrated multispecies occupancy models represent promising tools to
310 understand and map human-cetacean interactions hotspots.

311 **Data script and codes**

312 Data and codes are available on a [Zenodo repository](#).

313 **Supplementary materials**

314 Supplementary materials are available on a [Zenodo repository](#).

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318 **Conflict of interest disclosure**

319 The authors declare they have no conflict of interest relating to the content of this article.

320 **References**

- 321 Allen SJ, Pollock KH, Bouchet PJ, Kobryn HT, McElligott DB, Nicholson KE, Smith JN,
322 Loneragan NR (2017) [Preliminary Estimates of the Abundance and Fidelity of Dolphins](#)
323 [Associating with a Demersal Trawl Fishery](#). *Scientific Reports* 7:4995.
- 324 Avila IC, Kaschner K, Dormann CF (2018) [Current Global Risks to Marine Mammals: Taking](#)
325 [Stock of the Threats](#). *Biological Conservation* 221:44–58.
- 326 Baudrier J, Lefebvre A, Galgani F, Saraux C, Doray M (2018) [Optimising French Fisheries](#)
327 [Surveys for Marine Strategy Framework Directive Integrated Ecosystem Monitoring](#).
328 *Marine Policy* 94:10–19.
- 329 Bauer RK, Fromentin J-M, Demarcq H, Brisset B, Bonhommeau S (2015) [Co-Occurrence and](#)
330 [Habitat Use of Fin Whales, Striped Dolphins and Atlantic Bluefin Tuna in the Northwestern](#)
331 [Mediterranean Sea](#). *PLOS ONE* 10:e0139218.
- 332 Bearzi G, Fortuna CM, Reeves RR (2009) [Ecology and Conservation of Common Bottlenose](#)
333 [Dolphins *Tursiops Truncatus* in the Mediterranean Sea](#). *Mammal Review* 39:92–123.
- 334 Bonizzoni S, Furey NB, Bearzi G (2020) [Bottlenose Dolphins \(*Tursiops Truncatus*\) in the](#)
335 [North-western Adriatic Sea: Spatial Distribution and Effects of Trawling](#). *Aquatic*
336 *Conservation: Marine and Freshwater Ecosystems*:aqc.3433.
- 337 Bonizzoni S, Hamilton S, Reeves RR, Genov T, Bearzi G (2022) [Odontocete Cetaceans](#)
338 [Foraging Behind Trawlers, Worldwide](#). *Reviews in Fish Biology and Fisheries*.
- 339 Broms KM, Hooten MB, Fitzpatrick RM (2016) [Model Selection and Assessment for Multi-](#)
340 [Species Occupancy Models](#). *Ecology* 97:1759–1770.
- 341 Clipp H L, Evans AL, Kessinger BE, Kellner K, Rota CT (2021) [A Penalized Likelihood for](#)
342 [Multi-Species Occupancy Models Improves Predictions of Species Interaction](#). *Ecology In*
343 *press*.
- 344 Coll M, Piroddi C, Albouy C, Lasram FBR, Cheung WWL, Christensen V, Karpouzi VS,
345 Guilhaumon F, Mouillot D, Paleczny M, Palomares ML, Steenbeek J, Trujillo P, Watson R,
346 Pauly D (2012) [The Mediterranean Sea Under Siege: Spatial Overlap Between Marine](#)
347 [Biodiversity, Cumulative Threats and Marine Reserves](#). *Global Ecology and Biogeography*
348 21:465–480.
- 349 David L, Arcangeli A, Tepsich P, Di-Meglio N, Roul M, Campana I, Gregoriotti M, Moulins A,
350 Rosso M, Crosti R (2022) [Computing Ship Strikes and Near Miss Events of Fin Whales Along](#)
351 [the Main Ferry Routes in the Pelagos Sanctuary and Adjacent West Area, in Summer](#).
- 352 Devarajan K, Morelli TL, Tenan S (2020) [Multi-Species Occupancy Models: Review,](#)
353 [Roadmap, and Recommendations](#). *Ecography* 43:1612–1624.
- 354 Doser JW, Finley AO, Kéry M, Zipkin EF (2022) [spOccupancy: An R Package for Single-](#)
355 [Species, Multi-Species, and Integrated Spatial Occupancy Models](#). *Methods in Ecology and*
356 *Evolution* 13:1670–1678.

- 357 Estabrook B, Ponirakis D, Clark C, Rice A (2016) [Widespread Spatial and Temporal Extent of](#)
358 [Anthropogenic Noise Across the Northeastern Gulf of Mexico Shelf Ecosystem](#). *Endangered*
359 *Species Research* 30:267–282.
- 360 Fidino M, Simonis JL, Magle SB (2019) [A Multistate Dynamic Occupancy Model to Estimate](#)
361 [Local Colonization–Extinction Rates and Patterns of Co-occurrence Between Two or More](#)
362 [Interacting Species](#). *Methods in Ecology and Evolution* 10:233–244.
- 363 Giakoumi S, Scianna C, Plass-Johnson J, Micheli F, Grorud-Colvert K, Thiriet P, Claudet J, Di
364 Carlo G, Di Franco A, Gaines SD, García-Charton JA, Lubchenco J, Reimer J, Sala E, Guidetti P
365 (2017) [Ecological Effects of Full and Partial Protection in the Crowded Mediterranean Sea:](#)
366 [A Regional Meta-Analysis](#). *Scientific Reports* 7.
- 367 Ham GS, Lahaye E, Rosso M, Moulins A, Hines E, Tepsich P (2021) [Predicting Summer Fin](#)
368 [Whale Distribution in the Pelagos Sanctuary \(North-Western Mediterranean Sea\) to](#)
369 [Identify Dynamic Whale–Vessel Collision Risk Areas](#). *Aquatic Conservation: Marine and*
370 *Freshwater Ecosystems* 31:2257–2277.
- 371 Jourdain E, Vongraven D (2017) [Humpback Whale \(Megaptera Novaeangliae\) and Killer](#)
372 [Whale \(Orcinus Orca\) Feeding Aggregations for Foraging on Herring \(Clupea Harengus\) in](#)
373 [Northern Norway](#). *Mammalian Biology* 86:27–32.
- 374 Kéry M, Royle J (2020) [Applied hierarchical modeling in ecology: Analysis of distribution,](#)
375 [abundance and species richness in r and bugs: Volume 2: Dynamic and advanced models,](#)
376 1st ed. Elsevier, Cambridge.
- 377 Labach H, Azzinari C, Barbier M, Cesarini C, Daniel B, David L, Dhermain F, Di-Méglio N,
378 Guichard B, Jourdan J, Lauret V, Robert N, Roul M, Tomasi N, Gimenez O (2021) [Distribution](#)
379 [and Abundance of Common Bottlenose Dolphin \(Tursiops Truncatus\) over the French](#)
380 [Mediterranean Continental Shelf](#). *Marine Mammal Science* n/a.
- 381 Lambert C, Authier M, Dorémus G, Laran S, Panigada S, Spitz J, Van Canneyt O, Ridoux V
382 (2020) [Setting the Scene for Mediterranean Litterscape Management: The First Basin-Scale](#)
383 [Quantification and Mapping of Floating Marine Debris](#). *Environmental Pollution*
384 263:114430.
- 385 Laran S, Pettex E, Authier M, Blanck A, David L, Dorémus G, Falchetto H, Monestiez P, Van
386 Canneyt O, Ridoux V (2017) [Seasonal Distribution and Abundance of Cetaceans Within](#)
387 [French Waters- Part I: The North-Western Mediterranean, Including the Pelagos Sanctuary](#).
388 *Deep Sea Research Part II: Topical Studies in Oceanography* 141:20–30.
- 389 Lauret V, Labach H, Authier M, Gimenez O (2021) [Using Single Visits into Integrated](#)
390 [Occupancy Models to Make the Most of Existing Monitoring Programs](#). *Ecology*:848663.
- 391 Leone AB, Bonanno Ferraro G, Boitani L, Blasi MF (2019) [Skin Marks in Bottlenose Dolphins](#)
392 [\(Tursiops Truncatus\) Interacting with Artisanal Fishery in the Central Mediterranean Sea](#).
393 *PLOS ONE* 14:e0211767.

- 394 Lewison RL, Crowder LB, Read AJ, Freeman SA (2004) [Understanding Impacts of Fisheries](#)
395 [Bycatch on Marine Megafauna](#). *Trends in Ecology & Evolution* 19:598–604.
- 396 MacKenzie DI (ed) (2006) *Occupancy estimation and modeling: Inferring patterns and*
397 *dynamics of species*. Elsevier, Amsterdam ; Boston.
- 398 Manlik O, Lacy RC, Sherwin WB, Finn H, Loneragan NR, Allen SJ (2022) [A Stochastic Model](#)
399 [for Estimating Sustainable Limits to Wildlife Mortality in a Changing World](#). *Conservation*
400 *Biology* 36:e13897.
- 401 Marescot L, Lyet A, Singh R, Carter N, Gimenez O (2020) [Inferring Wildlife Poaching in](#)
402 [Southeast Asia with Multispecies Dynamic Occupancy Models](#). *Ecography* 43:239–250.
- 403 Pirotta E, Thompson PM, Cheney B, Donovan CR, Lusseau D (2015) [Estimating Spatial,](#)
404 [Temporal and Individual Variability in Dolphin Cumulative Exposure to Boat Traffic Using](#)
405 [Spatially Explicit Capture-Recapture Methods: Variability in Wildlife Exposure to](#)
406 [Disturbance](#). *Animal Conservation* 18:20–31.
- 407 Queiros Q, Fromentin J, Astruc G, Bauer R, Saraux C (2018) [Dolphin Predation Pressure on](#)
408 [Pelagic and Demersal Fish in the Northwestern Mediterranean Sea](#). *Marine Ecology*
409 *Progress Series* 603:13–27.
- 410 Rota CT, Ferreira MAR, Kays RW, Forrester TD, Kalies EL, McShea WJ, Parsons AW,
411 Millspaugh JJ (2016a) [A Multispecies Occupancy Model for Two or More Interacting Species](#).
412 *Methods in Ecology and Evolution* 7:1164–1173.
- 413 Rota CT, Wikle CK, Kays RW, Forrester TD, McShea WJ, Parsons AW, Millspaugh JJ (2016b) [A](#)
414 [Two-Species Occupancy Model Accommodating Simultaneous Spatial and Interspecific](#)
415 [Dependence](#). *Ecology* 97:48–53.
- 416 Santana-Garcon J, Wakefield CB, Dorman SR, Denham A, Blight S, Molony BW, Newman SJ
417 (2018) [Risk Versus Reward: Interactions, Depredation Rates, and Bycatch Mitigation of](#)
418 [Dolphins in Demersal Fish Trawls](#). *Canadian Journal of Fisheries & Aquatic Sciences*
419 75:2233–2240.
- 420 Snape RTE, Broderick AC, Çiçek BA, Fuller WJ, Tregenza N, Witt MJ, Godley BJ (2018)
421 [Conflict Between Dolphins and a Data-Scarce Fishery of the European Union](#). *Human*
422 *Ecology* 46:423–433.
- 423 Valpine P de, Turek D, Paciorek CJ, Anderson-Bergman C, Lang DT, Bodik R (2017)
424 *Programming with Models: Writing Statistical Algorithms for General Model Structures*
425 *with NIMBLE*. *Journal of Computational and Graphical Statistics* 26:403–413.
- 426 Wood S (2019) *Mgcv: Mixed GAM Computation Vehicle with Automatic Smoothness*
427 *Estimation*. R-Package Version 1.8–31.
- 428 Wood SN (2006) [Generalized Additive Models: An Introduction with R](#). Chapman; Hall/CRC,
429 New York.

430 Zipkin EF, Inouye BD, Beissinger SR (2019) [Innovations in Data Integration for Modeling](#)
431 [Populations](#). Ecology:e02713.