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1 Highlights

- 2 - Métier of a given fishing trip can be predicted by fishers from its sale record.
- 3 - An algorithm for predicting métier of any fishing trip is provided.
- 4 - Successfully applied to the small scale fishery from Mallorca (162,815 trips).
- 5 - A new métier definition: the unit that fishers can consistently recognize.
- 6 - Definition appropriate for better understanding of the fleet dynamics drivers.

1 **Combining sale records of landings and fishers knowledge for predicting métiers**
2 **in a small-scale, multi-gear, multispecies fishery**

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24 ABSTRACT

25

26 Stock management should be guided by assessment models that, among others,
27 need to be fed by reliable data of catch and effort. However, precise data are difficult to
28 obtain in heterogeneous fisheries. Specifically, small-scale, multi-gear, multispecies
29 fisheries are dynamic systems where fishers may lively change fishing strategy (i.e.,
30 métier) conditioned by multiple drivers. Provided that some stocks can be shared by
31 several métiers, a precise categorization of métiers should be the first step toward
32 métier-specific estimates of catch and effort, which in turn would allow a better
33 understanding of the system dynamics. Here we propose an approach for predicting the
34 métier of any given fishing trip from its landing records. This approach combines the
35 knowledge of expert fishers with the existing sales register of landings in Mallorca
36 (Western Mediterranean). It successfully predicts métiers for all the 162,815 small-scale
37 fishery fishing trips from Mallorca between 2004 and 2015. The largest effort is
38 invested in the métiers Cuttlefish/Fish and Spiny lobster, landings peak for
39 Cuttlefish/Fish and Dolphinfish and revenues for Spiny lobster and Dolphinfish. Métier
40 predictions also allowed us to describe the temporal (seasonal and between-year) trends
41 experienced by each métier and to characterize the species (commercial categories) that
42 are specific to each métier. Seasonal variability is by far more relevant than between-
43 year variability, which confirms that at least some fishers are adopting a rotation cycle
44 of métiers along the year. Effort (fishing trips), landings and gross revenues decreased
45 in the last 12 years (2004 to 2015). The approach proposed is also applicable to any
46 other fishery for which the métier for a fishing trip sample is known (e.g., on-board
47 observers or logbooks), but relying on fishers expertise points more directly to fishers'

48 intention. Thus, métier predictions produced with the proposed approach are closer to
49 the actual uses of fishers, providing better grounds for an improved management.

50

51 Keywords: Classification algorithms, Mallorca (Western Mediterranean), small-scale
52 fishery, data-mining, métier

53

54 **1. Introduction**

55

56 Most fisheries are not homogeneous but consist of a variety of vessels and
57 activities that differ greatly in terms of, among many other factors, vessel size, gears
58 used, technology employed, fishing grounds reached, and degree of expertise of the
59 fishers. All these factors are also highly dependent on the market characteristics the
60 fishery delivers to, and on a range of social aspects such as local culture and the
61 availability of capital investment (Therkildsen, 2007). While all these factors are
62 affected by the targeted fish stocks, they are also affecting the stocks themselves.

63 Conventional fisheries data collection, advice, and management usually target
64 single-stocks. At this basis, assessing fishing mortality throughout the relationship
65 between catch and effort may be affordable for homogeneous, monospecific fleets.
66 Nevertheless, this approach has long been recognized as inadequate when applied to
67 heterogeneous fisheries, which are subjected to interactions between subsets of fishing
68 units (e.g., métiers), and across species (Marchal, 2008). Biased estimation of fishing
69 mortality may result from naïvely pooling catch/effort across heterogeneous units (i.e.,
70 ignoring between-métier differences). This fact is recognized, for example, for multi-
71 fleet, multi-species bio-economic models (e.g., MEFISTO model; Leonart et al., 2003),
72 which are specifically designed for including specific input of effort and catchability for
73 every fishing unit (e.g., métier) considered. Accordingly, not only more accurate
74 predictions of the stock dynamics can be obtained but also better predictions for
75 different métier-specific management decisions can be provided.

76 Several steps have been undertaken in the past to explicitly incorporate the
77 heterogeneity of the fishing activities within the cycle of observing, assessing,
78 forecasting, and managing fisheries. A common sense solution is to identify units as

79 homogeneous as possible. ICES (the International Council for the Exploration of the
80 Sea) considers three types of fishing unit: the fleet, the fishery, and the métier (ICES,
81 2003). A fleet is a group of vessels sharing similar characteristics in terms of technical
82 features and main activity. A fishery is a group of fishing trips targeting the same
83 assemblage of species/stocks, using similar gear, during the same period of the year and
84 within the same area. Nevertheless, fleet and fishery are often too heterogeneous from a
85 managing perspective. Conversely, the concept of métier is specifically aimed to define
86 a homogeneous subdivision of, either a fishery by vessel type or a fleet by type of
87 fishing trip. Specifically, a métier is characterized by the use of a single gear targeting a
88 specific group of species. It usually operates in a given area during a given season,
89 within which each boat deploys a similar exploitation pattern; i.e., the species
90 composition and size distribution of the catches taken by any vessel working in a
91 particular métier will be approximately the same (Alarcón-Urbistondo, 2002; Deporte et
92 al., 2012; Mesnil and Shepherd, 1990). Provided that different métiers can share several
93 target stocks, the total effort and catches upon a stock can only be properly estimated
94 after combining all the involved métiers targeting this stock.

95 In the Mediterranean, the small-scale fleet (SSF) is very relevant socially,
96 economically and has a long history (Stergiou et al., 2006). Around 80% of the
97 registered boats in the European Mediterranean belong to this fleet and these are
98 currently employing about 100,000 people (Maynou et al., 2011). The number of small-
99 scale boats operating at the Spanish Mediterranean has been estimated in 1,462 in 2015
100 (STECF, 2016). The fleet in the Balearic Islands (GSA05; Geographic Sub Area 5 of
101 the General Fisheries Commission for the Mediterranean) follows a similar pattern: it
102 comprises 337 boats, being 85% small-scale (which employ 700 people), 12.5%
103 trawlers and the rest corresponding to different modalities (data for 2012; Grau et al.,

104 2015). It is noticeable that the number of small-scale boats is experiencing a decreasing
105 trend (345 boats in 2009 and 278 in 2015; Grau et al., 2015). This trend may result from
106 both, the implementation of measures aimed to reduce effort and the decrease of fish
107 price (Morales-Nin et al., 2010). Nevertheless, this trend is impaired with landings,
108 which remain around 400 tons/year (Morales-Nin et al., 2010).

109 A peculiarity of most SSF is that some boats may use several fishing systems,
110 which are lively alternated during the year according to the availability of resources,
111 market demand, and other factors, such as management policies (e.g., closing seasons),
112 local environmental characteristics and interaction with other fishing gears (Maynou et
113 al., 2011; Salas and Gaertner, 2004). Therefore, SSF not only constitutes a relevant
114 fraction of the fishing activity in some areas but also is particularly heterogeneous and
115 thus, challenging from a managing perspective.

116 Despite its importance worldwide, SSF practices have been generally subject to
117 little attention by the scientific community and managers when compared to the
118 industrial fishing sector. Therefore, there is an objective need for delineating métiers in
119 such fisheries. However, this is in practice a more challenging goal than expected. The
120 approaches used in the past to identify métiers either (i) make use of existing records on
121 the technical features of fishing trips (e.g., gear and mesh size used, fishing grounds
122 visited, season, boat characteristics), which may be available from fishers' logbooks,
123 (Marchal et al., 2006; Ulrich et al., 2001), or inferred from interviews with fishers
124 (Christensen and Raakjær, 2006; Neis et al., 1999), or (ii) are intended to ascertain the
125 métiers used by retrospectively examining the landings (Deporte et al., 2012; Marchal,
126 2008).

127 In this paper, we propose to combine some of the advantages of all these
128 approaches. Using the small-scale fleet from Mallorca Island (Western Mediterranean)

129 as case study, we demonstrated how fishers' expertise can be combined with the
130 relatively recent implementation of electronic register of landings in order to elucidate
131 the métiers practiced by a particularly heterogeneous fleet. The specific aim of this work
132 is not only to select and test a numerical algorithm for predicting the métier a given boat
133 has practiced from the corresponding sale record, but also to up-scale the predictions of
134 métiers to the entire fleet, which will provide an accurate, quantitative description of
135 catches and effort for each métier. Thereby, more precise assessment of the fishing
136 mortality of all the exploited stocks by the small-scale fishery will be obtained after
137 more precise delineation of the métiers, which in turn should contribute to improve the
138 management of the fishery. Information on the gear/fishing tactic, the main species
139 exploited, the characteristics of the vessels involved plus background on the métier-
140 specific temporal trends in catch, effort, gross revenues, as well as between-métier
141 interactions for the period 2004-2015 are provided.

142

143 **2. Material and methods**

144

145 *2.1. Métiers and data*

146

147 The small-scale fleet in Mallorca is conducted by vessels less than 10 gross tons
148 (Decree 17/2003 of February 21, from the Balearic Islands Government), with 1-3 hand
149 decks, and operating close to the base harbor. This definition is consistent with other
150 EU level definitions such as the Council Regulation (EC) No 1198/2006 of 27 July
151 2006 ('small-scale coastal fishing' means fishing carried out by fishing vessels of an
152 overall length of less than 12 meters and not using towed gear as listed in Annex I of
153 Commission Regulation (EC) No 26/2004 of 30 December 2003 regarding the fishing

154 vessels register of the Community). Specifically, trawlers and large seiners are not
155 considered here as SSF. Less than 1 day outings are compulsory and some combinations
156 of fishing gears in the same fishing trip are not permitted. More details on the fishery
157 management on this fleet are provided elsewhere (Morales-Nin et al., 2010).

158 In Mallorca, the commercialization of all the landings (i.e., SSF, trawlers and
159 seiners) is made through a single central fishing wharf (*OPMallorcaMar*), which is a
160 cooperative composed by all the boat's owners in the island. In addition, fishers are
161 associated in guilds by port (*Confraries*), which in turn are associated in the Balearic
162 Fishers Federation (*Federació Balear de Confraries de Pescadors*). The landings are
163 arranged in standard boxes by the fishers and auctioned daily in decreasing prices. An
164 automatic selling procedure, implemented since 2004, registers for each box, among
165 other data, the commercial category, the weight in kilos, the price and the name of the
166 boat. The personal data of the fisher are encrypted in accordance with the terms of a
167 confidentiality agreement.

168 The time series (2004-2015) resulting from the daily sale records, provides a
169 valuable information on the fishing activities, and how they change at different time
170 scales (e.g., seasonal and decadal). However, some potentially confounding factors
171 hinder the usefulness of such database for fishing management. For example, some
172 species might be sold as more than one commercial category, e.g., small, medium and
173 large hake (*Merluccius merluccius*); boxes with mixed catches can correspond to
174 different commercial categories depending on the whim of the auctioneer; and boats could
175 have changed their name (and owner) along the time series of data. Nevertheless, one of
176 the major drawbacks is that the métier used for obtaining the catch is not provided.

177 We propose to use fishers' knowledge in order to infer the métier for any fishing
178 trip. The proposed strategy (Fig. 1) started with selecting a representative sample of

179 fishing trips. The list of catches (i.e., the list of the daily sales of a given boat) of those
180 sampled fishing trips were then presented to a number of experts (fishers), who were
181 asked to label them with the métier/s (from a closed list) that they thought had most
182 probably been used to get such a combination of catches. This sample of labeled records
183 was then used for selecting, parametrizing and testing the success of a range of
184 classification algorithms. Finally, the best algorithm was used for up-scaling métier's
185 predictions from the sample to the entire time series (2004-2015) of sales from the daily
186 boat records.

187 The specific details of the full data mining and analysis are summarized in Fig.

188 1. The steps were:

189 1) The information for a given day was received as an ACCES archive that is
190 structured by fish box (each row contents the data from a single box). These files were
191 automatically read using the *RODBC* library (Ripley and Lapsley, 2015) from R
192 (<https://www.r-project.org/>) and stored.

193 2) In general, several of the fish boxes above correspond to the same boat and
194 they must be restructured to summarize the fishing activity of one boat in a day (i.e.,
195 one fishing trip). Therefore, the box data were restructured into a matrix composed by
196 rows consisting in all the fish sold by a boat in a day, and the commercial categories in
197 columns. Two separate matrices were produced for fish weight (kg per fishing trip) and
198 gross revenues (Euros per fishing trip). Provided that fishing trip duration is one-day
199 maximum, and that all the fish landed in a given day is auctioned off after a few hours,
200 any row in the restructured matrix corresponds to all the catches landed by a boat in a
201 single fishing trip (day). The data were cleaned of negative sales, which represent errors
202 in the purchase or devolutions.

203 3) The matrix of daily boat records above included trawlers and large seiners
204 that must be filtered out. Provided that boat category (namely, small-scale, trawler or
205 large seiner) was available for all the active boats in 2012, an auxiliary classification
206 algorithm was implemented using a random forest, as implemented in the *random*
207 *Forest* library (Liaw and Wiener, 2002) of the R package. The performance of such
208 algorithm was tested by cross validation and used to predict the boat category of all the
209 fleet (2004 to 2015).

210 4) The results of the filtering step above were two matrices (either for weight or
211 gross revenues) of rows consisting in the daily boat's sales records for the SSF only
212 (162,815 rows; see Section 3.1), and covering from 2004 to 2015. The columns were
213 the 75 (see Section 3.1) commercial categories considered after removing very
214 uncommon categories.

215 5) A total of 1,550 daily boat records were sampled from the weight matrix in
216 Step 4. The weight matrix was preferred to the gross revenues matrix because seasonal
217 trends of average fish price would confound landing trends. Provided that métier
218 prevalence seems to be largely unbalanced, an *ad-hoc* sampling strategy was adopted to
219 avoid underrepresentation of the less frequent métiers. The weight matrix was submitted
220 to a principal component analysis, the first 10 axes were divided into 10 segments of the
221 same length and, finally, a number of samples proportional to the variance explained by
222 each of those 10 axes were then randomly selected from each of the corresponding
223 segments.

224 6) Independently of the landing data (Steps 1 to 5), a preliminary list of the 12
225 main métiers currently used in Mallorca (Table 1) was drawn up after combining
226 bibliographic (Massuti, 1995), legal normative (Regulation of Artisanal Fisheries in
227 Balearic inland waters, Decree 17/2003, Balearic Official Bulletin 28, 01/03/2003) and

228 face-to-face data, by carrying out unstructured interviews to five very experienced
229 fishers.

230 7) A new panel of 15 expert fishers was then selected. Each one of these 15
231 experts was asked to label a random (see Step 8 below) subsample of 150 daily boat
232 records selected from the total records described in Step 5. Each daily record must be
233 labeled with one or more of the 12 métiers described in Step 6 (i.e., from a closed list).
234 The information available to the fishers was the species list within the catch, the weight
235 per species and the date. The questionnaire was usually completed within around 30-45
236 minutes.

237 8) To test the coherence between each expert when labeling daily boat records
238 with métier/s, 50 of the 150 records in Step 7 were the same for all experts. Provided the
239 nature of the response matrix (0/1 of 12 métiers), a canonical correspondence analysis
240 (CCA), implemented using the *cca* function of the *vegan* library (Oksanen et al., 2014)
241 from R, allowed to test between-fishers differences (Borcard et al., 2011). The initial 15
242 experts were submitted to an expert-by-expert sequential elimination protocol that
243 continued until the remaining experts' set showed non-significant differences between
244 them. Differences were tested using bootstrapping. Specifically, experts were randomly
245 permuted while the order of the daily boat records was kept fixed (i.e., constrained
246 bootstrapping as implemented in the *vegan* library).

247 The remaining data set after removing non-consistent experts were used to select
248 and test a classification algorithm. Full details of the classification strategy are provided
249 in the Section 2.2.

250 Quality control of the prediction success of the classification algorithms was
251 assessed by cross validation. Specifically, some of the initial 12 métiers were found
252 either uncommon or experts were unable to successfully discriminate between some

253 pairs of similar métiers. The outcome was that success classification rate of these
254 métiers were low. Therefore, some of the initial 12 métiers were collapsed or deleted,
255 which results in a final list of métiers. The resulting data set (i.e., coherent experts and
256 finally retained métiers) were used for parameterizing and re-testing the classification
257 algorithm finally selected.

258 9) This final algorithm was used to up-scale métier's predictions to the full time
259 series of daily boat records covering from 2004 to 2015, which allowed us to describe
260 the seasonal trends of effort (fishing trips), landings (kg) and gross revenues (€). The
261 commercial categories of landings that best characterize the métiers finally considered
262 was assessed using SIMPER analysis (Clarke, 1993), as implemented in the *simper*
263 function of the *vegan* library from R.

264

265 2.2. Predicting métier from the sales daily boat record

266

267 Classification problems in which an object can be classified into more than one
268 category are known as multi-label classification problems (Tsoumakas and Katakis,
269 2007). Conventional classification methods, either parametric (e.g., discriminant
270 analysis) or non-parametric (e.g., *random forest*) assume that categories are mutually
271 exclusive (Jones et al., 2017). Two approaches for adapting the conventional methods to
272 multilabel classification have been proposed. *Label powerset* defines a new (mixed)
273 category for the cases a fisher uses two métiers during the same fishing trip. *Binary*
274 *relevance* consists, for a given métier, in splitting the data into two categories: the daily
275 boat records assigned versus non-assigned to the métier considered. Therefore, the
276 problem is transformed in a number (as many as métiers) of binary classification
277 problems.

278 Conventional classification methods can be applied in both cases after adapting
279 the input data. After preliminary inspection of the data structure, *binary relevance* was
280 selected because the success of *label powerset* depends on the assumption that any
281 mixed categories must be well represented, which is not the case in our data (see
282 Results, Section 3). Preliminary inspection and data recoding were completed using the
283 *mldr* library (Charte and Charte, 2015) from the R package.

284 Recoded data were evaluated using all the suitable methods implemented in
285 WEKA (<http://www.cs.waikato.ac.nz/ml/weka/>). WEKA (Witten and Frank, 2005)
286 implements an exhaustive collection of machine learning algorithms within which there
287 are 17 binary classification algorithms. The algorithm selected was which showed the
288 largest cross-validated predictive capability as measured using kappa index (Jones et al.,
289 2017). This process was fully automatized using the *Rweka* library (Hornik et al., 2009)
290 from R.

291

292 2.3. Comparison with the conventional method

293

294 The conventional, alternative approach is aimed to infer the métiers used by
295 retrospectively examining the catch profiles resulting from fishing trips (Deporte et al.,
296 2012; Marchal, 2008). The raw data (or the transformed data after applying some
297 multivariate analysis for reducing dimensionality) is clustered and a cut-off level that
298 minimizes within cluster heterogeneity is selected. Here, *clara* clustering algorithm (as
299 implemented in the cluster library from R; Maechler et al., 2015) was applied to a
300 random sample of 10,000 daily boat records. The optimal number of clusters was
301 selected using the *silhouette* function of the cluster library, after comparing the results
302 obtained with 2 to 15 groups (i.e., métiers). This function computes the average

303 cohesion (how similar an object is to its own cluster in comparison with other clusters),
304 thus it provides the metrics for assessing if there are too many or too few clusters.

305

306 **3. Results**

307

308 *3.1. Cleaning the input data matrix*

309

310 The huge raw dataset, consisting in more than 5 million fish box entries (Step 1;
311 Fig. 1), was successfully reorganized in two matrices (weight and gross revenues) (see
312 Step 2; Fig. 1). The 256,490 rows of these matrices were the daily boat records from
313 2004 to 2015 of all the fleets (i.e., including small-scale, trawlers and big seiners). The
314 columns were all the occurring commercial categories (170).

315 A random forest classification tool for predicting broad categories (namely,
316 small-scale, trawlers and seiners) was successfully implemented with the 2012 subset of
317 data (see Step 3; Fig. 1). As cross-validated success of predictions was excellent (Table
318 2; kappa index = 0.99), this tool was used to predict the broad category for the full time
319 series (2004-2015). The number of small-scale daily boat records for the 2004-2015
320 (Step 4; Fig. 1) was 162,815 (or 63%). After removing trawl- and seine-specific
321 commercial categories, plus a few commercial categories with very low prevalence for
322 SSF, a total of 75 commercial categories were retained.

323 A total of 1,550 daily boat records were selected from SSF (see Step 5; Fig. 1),
324 and these were labeled by fifteen expert fishers into the twelve métiers listed in Table 1
325 (see Step 7; Fig. 1). When experts were found to differ, multivariate (CCA) scores were
326 plotted and the expert showing the most disparate pattern of métier predictions was
327 deleted. As an example, the initial step (15 experts: $F = 2.04$, $df = 14,735$, Prob. <

328 0.001) is shown in Fig. 2. This loop was repeated until no between-expert differences
329 were found, which allowed to successfully detect four outlier experts (i.e., 11 out of 15
330 experts were retained; $F = 0.34$, $df = 10,539$, $Prob. = 0.111$).

331 After removing those experts, a reliable métier prediction is assumed for the
332 remaining 1,100 daily boat records. Nevertheless, the cross-validated classification
333 success of up to 17 algorithms leaved room for improvement in five out of the twelve
334 métiers initially considered (Step 6; Fig. 1). In most of the cases, these métiers are old-
335 fashioned and underrepresented, thus machine learning algorithms seem unable to build
336 a reliable model. Therefore, they were merged or deleted. The case of the métiers
337 Cuttlefish (targeting *Sepia officinalis*) and Fish (mixed fish) deserves particular
338 attention because there are two trammel nets that differ by legal normative in mesh size
339 and in seasonality (Regulation of Artisanal Fisheries in Balearic inland waters, Decree
340 17/2003, Balearic Official Bulletin 28, 01/03/2003). Yet, expert fishers were not able to
341 efficiently discriminate between them, suggesting that catches may be quite similar, at
342 least during a certain period of the year. Therefore, these two métiers have been merged
343 in a single category (Cuttlefish/Fish).

344

345 3.2. Classification algorithm

346

347 The cleaned data set consisted in 1,100 daily boat records, for which a reliable
348 métier prediction is available among a closed list of seven possible métiers
349 (Cuttlefish/Fish, Transparent goby, Dolphinfish, Squid jigging, Spiny lobster, Red
350 mullet and Longline; Table 1), were re-tested using the same seventeen WEKA
351 classification algorithms. The algorithm showing the best performance (after cross-
352 validation) was *IBk*. This algorithm implements a k-nearest neighbor classifier (Fix and

353 Hodges, 1951). Membership prediction of a new object depends on the membership of
354 the majority of their k-nearest neighbors. The confusion matrices for each one of the 7
355 métiers considered are shown in Table 3. In four cases (Transparent goby, Dolphinfish,
356 Squid jigging and Longline), the percentage of correct predictions was perfect (100%)
357 and for the remaining three métiers the number of failures was negligible.

358 Provided that the cross-validated predictions of the classification algorithm were
359 excellent, this method was used for predicting the métier that most plausibly had been
360 used in each one of the 162,815 fishing trips carried out for the Majorcan SSF between
361 2004 and 2015 (Step 9; Fig. 1). The relative importance of the 7 main métiers both in
362 effort, landings and gross revenues are summarized in Table 4. Note that the total effort
363 may be higher than the number of daily boat records due to the simultaneous use of
364 more than one métier per day by some boats. The largest effort was invested in
365 Cuttlefish/Fish (mean \pm sd; $4,964.3 \pm 600.1$ fishing trips/year; $n = 12$ years). The main
366 contributors to the landings were Cuttlefish/Fish (122.9 ± 19.1 tons/year; $n = 12$ years)
367 and Dolphinfish (109.4 ± 33.7 tons/year; $n = 12$ years), albeit the main income
368 corresponds to Spiny lobster with a mean value of 0.99 ± 0.1 million euros/year (from
369 now on MEuros; $n = 12$ years) due to its higher price, followed by Cuttlefish/Fish (0.96
370 ± 0.1 MEuros/year; $n = 12$ years) and Longline (0.7 ± 0.1 MEuros/year; $n = 12$ years).
371 Note also the disproportionately lesser effort invested in Dolphinfish (8.2%) in front of
372 Cuttlefish/Fish (33.9%), which is related with the seasonal pattern of resource
373 exploitation (Section 3.3).

374

375 *3.3. Temporal and seasonal trends*

376

377 The temporal patterns displayed for the SSF along with all the considered period
378 (2004-2015) are displayed in Fig. 3. Based on the values estimated after fitting the
379 annual data (12 years; 2004 to 2015) to a linear trend, we can conclude that landings of
380 the entire SSF have decreased in 23%, from 526 tons in 2004 (95% confidence interval,
381 CI: 407 to 645) to 401 tons in 2015 (282 to 520). The monthly trend for landings is
382 displayed in Fig. 3a. The decreasing trend for effort (number of fishing trips of the
383 entire SSF) was 20%, going from 16,280 fishing trips in 2004 (95% CI: 14,708 to
384 17,850) to 13,044 fishing trips in 2015 (11,473 to 14,616). The monthly trend for effort
385 is displayed in Fig. 3b. Finally, the decreasing of gross revenues in nominal terms (i.e.,
386 without adjusting for inflation) was 18%, from 4.5 MEuros in 2004 (95% CI: 4.2 to 4.9)
387 to 3.7 MEuros in 2015 (3.3 to 4.1). Note however, that the actual decrease in real terms
388 (i.e., after adjusting for inflation) was 33%. The monthly trend for gross revenues is
389 displayed in Fig. 3c. Contrasting with those decreasing trends, CPUE (landings per
390 fishing trip; Fig. 3d) seems to be stationary (the slope of a linear trend of annual
391 averaged CPUE was not significantly different from zero; Prob. = 0.57; mean \pm sd; 31.5
392 \pm 2.3 kg per fishing trip; n = 12 years). Gross revenues per fishing trip in nominal terms
393 (Fig. 3e) seem stationary too (slope of a linear trend of annual averaged data was not
394 significantly different from zero; Prob. = 0.59; mean \pm sd; 283 \pm 12 euros per fishing
395 trip; n = 12 years).

396 Métier-specific patterns for the period 2004-2015 are depicted in Fig. 4. Overall,
397 the fishers strategies (i.e., relative importance of the different métiers at the year scale)
398 have not experienced large changes over time. Between-year variations (e.g., high of the
399 seasonal maximums) are small, excepting in the case of the landings of Dolphinfish.
400 Contrasting with such a relatively small variability at the decadal scale, seasonal
401 variability is very important (Fig. 4). The periodicity at the métier level was precisely

402 regular across years, for effort, landings and gross revenues. Concerning effort, when
403 the predictions were pooled by month across the 12 years considered (Fig. 5), the
404 resulting pattern supports the hypothesis that some métiers are seasonally rotated. The
405 canonical cycle was already described (Iglesias et al., 1994) but here a more precise
406 delineation of the métier-specific periodicity is provided. The cycle starts with
407 Transparent goby in winter, followed by Cuttlefish/Fish (but see below) in spring, Spiny
408 lobster in summer and Dolphinfish in autumn. The other métiers did not show a so clear
409 seasonal pattern or were carried out with similar intensity along the year (e.g.,
410 Longline). The extended exploitation pattern predicted for Cuttlefish/Fish from August
411 to December was due to the inability of the experts to discriminate between Cuttlefish
412 and Fish (Fig. 5).

413 Finally, the results of the SIMPER analysis completed for identifying the
414 commercial categories that better characterize (in terms of landed weight by category)
415 each one of the 7 métiers is detailed in Table 5. In three cases (Transparent goby,
416 Dolphinfish and Squid jigging), landings are composed by the target species (*Aphia*
417 *minuta*, *Coryphaena hippurus* and *Loligo vulgaris* respectively), plus a very few
418 secondary categories of commercialized by-catch. The case of Squid jigging is
419 noticeable because this métier may be a secondary activity: fishers would target squid
420 (*Loligo vulgaris*) while using another static métier that forces them to wait for the catch.
421 In this case, the squid gear used (hand line) is very selective and renders few but high
422 quality and high valued product. The same squid species reaches a lower price when
423 captured with other gears (i.e., trawling).

424 Conversely, Cuttlefish/Fish, Spiny lobster and Red mullet are set nets (trammel
425 nets and gillnets) characterized by a long list of by-catch in addition to the main target
426 species, which are *Sepia officinalis*, *Palinurus elephas* and *Mullus surmuletus*,

427 respectively. However, such a by-catch is not only a relevant fraction of the landings but
428 also of the gross revenues, especially in the case of Spiny lobster. Finally, the landings
429 of Longline (also called *Palangr6*) are largely unspecific, being large sparids and
430 serranids (e.g., *Epinephelus marginatus*) the most valued of the target species.

431

432 *3.4. Comparison with the conventional method*

433

434 The conventional method showed that the optimal number of groups (i.e.,
435 m6tiers) in which a random sample of 10,000 daily boat records can be optimally split
436 after clustering the landings profiles is only two. The silhouette index peaked at two
437 groups and showed an irregular but decreasing trend while increasing the number of
438 potential m6tiers (see Fig. 6). After analyzing the species composition of these two
439 clusters, the first one seems to fit well with the Dolphinfish m6tier, but the second is a
440 mix of the other six m6tiers considered here. Therefore, in our case it seems that m6tiers
441 cannot be unequivocally assessed by clustering the landings profiles, irrespective of the
442 technicalities applied (e.g., with or without applying a preliminary multivariate analysis
443 for reducing dimensionality, the distance/dissimilarity metrics or the clustering
444 algorithm).

445

446 **4. Discussion**

447

448 *4.1. Toward a pragmatic m6tier concept*

449

450 The results reported here support that fishers are able to successfully classify
451 fishing trips into discrete units using landings only. We propose that it is possible

452 because landings reflect fisher's intention (e.g., métier choice or even specific fishing
453 tactics), which can be accurately inferred from fisher perception (i.e., the fisher believe
454 on another fisher intention given only the landings of a trip). We propose that such
455 ability is the result of fisher's experience.

456 The decreasing trend on the number of boats and gross revenues in the last
457 decades, and the small average gross revenues per trip reported here supports that most
458 small-scale fleets may be close to economic sustainability. Accordingly, fishers have to
459 be continuously adapting fishing strategies and tactics. Thus, impelled by market
460 demands, experienced fishers (i.e., those that remain in the activity because they
461 successfully compete) have learned how to modify fishing strategy (e.g., métier choice)
462 and tactics (any specific detail of the fishing strategy) for maximizing the likelihood of
463 obtaining the desired landings (i.e., those that achieve better price). In the same way but
464 opposite direction, experienced fishers are able to consistently cluster fishing trips into
465 métiers based on landings only, even when the signal provided by landings is very
466 noisy.

467 Provided that fisher intention (e.g., métier choice) can be accurately inferred
468 from fisher perception based on landings only, all fishing trips that are classified in a
469 given group are sharing very close fishing strategies and tactics. Therefore, the natural
470 units for structuring management decisions (i.e., the métiers) should be the units that
471 fishers can consistently recognize. Stock assessment based in units that accurately and
472 precisely reflect the actual uses (i.e., fisher intention) of the fleet would better predict
473 any threat for sustainability, thus allowing the implementation of precise (i.e., métier-
474 specific) management rules.

475 Therefore, the framework proposed here allows defining métiers in a more
476 pragmatic way, and describing them comprehensibly for management purposes. We

477 suggest a new method to predict the métier for any fishing trip from historical time
478 series of landings data. Briefly, métier prediction for the entire SSF is made possible
479 after training a classifier with a sample of landing records that has been classified into
480 métiers by a panel of expert fishers (Fig. 7). This strategy points more directly to fishers
481 intention and, to our knowledge, this is the first time that experts' knowledge is
482 combined with a sale record of landings in such a way. An obvious limitation of the
483 method is that a landing record for each fishing trip should exist already. Nevertheless,
484 its implementation is promoted by the EU (Marchal, 2008), hence the proposed
485 framework might expand within other countries.

486 The conventional approach for inferring métiers from landing records has been
487 to cluster fishing trips according to their similarity in landing composition. The rationale
488 behind is that the clusters obtained include the fishing trips in which the same métier
489 was used (Alemany and Álvarez, 2003; García-Rodríguez, 2003; Tzanatos et al., 2006).
490 This approach has two practical drawbacks (Palmer et al., 2009): (i) to objectively
491 determine the optimal number of clusters and (ii) to unequivocally define a métier for a
492 given cluster, which is carried out *a posteriori*. That is, the most common species in the
493 landings profiles from a cluster are assumed to characterize the (single) métier used for
494 all the fishing trips in that cluster. In addition, the unit of the landing records should be
495 the fishing trip because when pooling units together (Alemany and Álvarez, 2003;
496 García-Rodríguez, 2003; Poulard and Leaute, 2002), any subjacent variability will be
497 confounded.

498 In the case of SSF from Mallorca, the conventional clustering approach seems
499 unsuccessful because only two métiers can be objectively identified (Fig. 6). The large
500 variability of catches (e.g., up to 75 commercial categories and a striking seasonal
501 pattern) is the possible cause behind such a failure. Even though that the clustering

502 approach has represented a relevant improvement and it is being successfully used in
503 some fisheries (Deporte et al., 2012; Marchal, 2008), it may be suboptimal for
504 heterogeneous fisheries, as most SSF are.

505 Palmer et al. (2009) proposed the use of a sample of on-board observations for
506 training conventional and machine-learning classifiers with landings profiles. The
507 framework suggested here (Fig. 7) goes a step further, in that on-board observations
508 (i.e., the observer selects a métier from an *a priori* defined and closed list of métiers)
509 has been changed by the perception of expert fishers on what métier has probably been
510 used for obtaining a given landings profile.

511 In summary, accordingly with the key role of fishers intention, we propose a
512 more pragmatic métier delineation as the unit that fishers can consistently recognize.
513 Similarly, the optimal number of métiers in which a fleet could be divided and should
514 be managed will be those that fishers can consistently recognize. The outcomes of this
515 paradigm change are discussed in the two next sections.

516

517 *4.2. Practical advantages, limitations and technicalities*

518

519 The method proposed here (Fig. 1) is able to accurately predict the métier that
520 most plausibly has been used in a given fishing trip. The excellent cross validated
521 prediction success (close to 100%) for a sample of 1,100 boat daily records reinforces
522 the reliability of up-scaling predictions from such a sample to the entire SSF and for the
523 period from 2004 to 2015.

524 Concerning the technicalities of the classification protocol, it is noteworthy that
525 some of the expert fishers which labeled boat daily records may behave in a different
526 way, thus the need of a strict quality control is fully justified. The sequential removal of

527 outlier experts used here is a straightforward option as it ensures between-expert
528 coherence while minimizing the number of excluded experts. Another relevant
529 technicality is the use of an adequate data-mining platform. In this regard, the R
530 libraries have provided an invaluable support because any step of the data-mining
531 process can be easily structured in a single ad-hoc script. Finally, the use of
532 classification methods that allow for multiple labeling of the same object (Tsoumakas
533 and Katakis, 2007) has been decisive as in most SSF more than one métier can be used
534 during a single fishing trip. Nevertheless, in the case of the Balearic Islands, only some
535 combinations are allowed. Therefore, multiple assignments can reflect either uncertainty
536 of the expert fishers when assigning métier or the fact that more than one métier have
537 been actually used. Specific improvements on discriminating those cases should be
538 desirable.

539 Replacing on-board observers by a panel of expert fishers represents an
540 additional advantage: extensive programs of on-board observations are relatively
541 common in trawlers and other large vessels but sporadic in SSF. Moreover, EU vessels
542 under 10 m are not required to report any logbook. Interview surveys have been used to
543 collect quantitative information (Marchal, 2008) but provided the large number of
544 participants in SSF, to engage a representative panel of expert fishers may be a better
545 and economically more affordable option.

546 The use of landing profiles for defining métiers has been criticized because it
547 does not consider discarding (Marchal, 2008). Certainly, sale records comprise, in
548 addition to the main targets, the by-catch fraction that is commercialized only.
549 However, no information is available on the relevance of the discards or on their
550 composition by métier. On-board observations are thus unavoidable to quantify
551 discards. In the case of the SSF from Mallorca, a specific on-board sampling program is

552 in progress (Program EU Horizon 2020 Research and Innovation Action SFS-634495).
553 Therefore, the results of these on-board samples of discards will allow us to up-scale the
554 discards per métier to the entire fleet after taking into account the effort per métier
555 provided here.

556 In the specific case of the Mallorcan SSF, expert fishers were not able to
557 efficiently discriminate from the reported catches which of two specific trammel nets
558 (Cuttlefish and Fish) had been used. These nets actually differ by legal normative in
559 mesh size and in seasonality (Section 3.1) but the fishing grounds are similar. Cuttlefish
560 nets are usually set at the lower boundary of the seagrass *Posidonia oceanica* and Fish
561 is not as habitat-specific. Catch composition may smoothly change in a way that fishers
562 are not able to discriminate between them. In those cases, additional information of the
563 size distribution of the catches will be decisive for properly splitting a currently merged
564 métier (Cuttlefish/Fish). To solve this situation, the managing authorities (*Direcció*
565 *General de Pesca del Govern de les Illes Balears*) and the IMEDEA are launching a
566 specific monitoring program.

567

568 4.3. Management outcomes

569

570 Small-scale fisheries represent more than half of the world's annual marine fish
571 catch of 98 million tonnes (Berkes et al., 2001), contributing with 0.3 million tonnes in
572 EU (STECF, 2016). However, they are usually left behind industrial fisheries, mostly
573 due to the lack of data regarding stock trends or the fishery's socio-economic impacts
574 (Stergiou et al., 2006). This partly explains some of the constraints faced by SSF (FAO,
575 2005-2015). In the Mediterranean, SSF performs a relevant fraction of the effort. The
576 data here reported suggests that 63% of the fishing trips are operated by SSF. Therefore,

577 albeit trawlers and seiners provided most of the landed fish in Mallorca (Quetglas et al.,
578 2016), the direct and indirect economic impact of SSF are noticeable (Carreras et al.,
579 2015). According to Quetglas et al. (2016), SSF represents 20% of landings and 27% of
580 gross revenues. Moreover, the quality of the product provided (and consequently the
581 gross revenues obtained) by SSF in Mallorca is excellent (Morales-Nin et al., 2013).
582 Hence, this activity has an important socio-economical relevance (Maynou et al., 2013;
583 Morales-Nin et al., 2010).

584 Nonetheless, the number of small-scale boats in Mallorca has been experiencing
585 a relevant decrease in the last decades (Section 1). The data reported here suggests that
586 effort, landings and gross revenues for the entire small-scale fleet are decreasing too
587 (Section 3), which proves the weakness of the system and suggests that it may collapse
588 in the near future if not properly managed. The mean age of the fishers engaged and the
589 low replacement rate points at this direction (Maynou et al., 2013). Thus, in this case, an
590 eventual fisheries collapse may not be directly related with resource status. The trends at
591 a boat level cannot be properly analyzed due to a confidentiality agreement, yet it will
592 be very interesting to disentangle if the less efficient boats are those that are quitting the
593 activity (fishers sorting). In this case, apparent stability of CPUE (landings per fishing
594 trip) may mask a decrease in stock abundance (van Poorten et al., 2016). Alternatively,
595 warning signs should not be deducted from stationary CPUE.

596 In contrast with such difficult perspectives, further efficient management
597 measures as co-management are already being implemented. This approach may be
598 particularly advantageous for small-scale fisheries. In the Mediterranean, this strategy
599 has been suggested as promising since fishers seem prone to adopt it (Lleonart et al.,
600 2014). For example, in the case of the spiny lobster fishery from Mallorca, fishers
601 would agree in maximizing profits instead of catches (Amengual-Ramis et al., 2016).

602 The case of the Mediterranean sand eel (*Gymnammodytes cicerellus*) fishery is a
603 positive example of a new way of managing a resource because it allows the fishers to
604 control their own fishery, with the help of scientists (marine biologists and
605 socioeconomists), policy makers and NGOs (Lleonart et al., 2014). A similar approach
606 has been implemented in Balearic Islands for the transparent goby fishery (Morales-Nin
607 et al., 2017).

608 In this scenario, the concept of *métier* and the analytical approach provided here
609 became even more relevant. The fact that *métiers* are defined and delimited by the local
610 fishers suggests an, only apparent, drawback: the set of defined *métiers* and their limits
611 (i.e., their characteristics in terms of landing composition) will be useful only at the
612 local scale. Nevertheless, spatially well delimited stocks as those exploited by SSF in
613 Mallorca (the Balearic Islands waters being encompassed within a single GFCM area,
614 GSA05) will be better managed at a local scale (Quetglas et al., 2012). Obviously, this
615 is not the same case of transnational stocks, exploited by several, well differentiated
616 fleets, for which a transnational *métier* concept as the one suggested by Deporte et al.
617 (2012) would be a better option.

618 In summary, we suggest a local management of the SSF from Mallorca. The new
619 *métier* definition proposed and the analytical tools provided here are more appropriate
620 for this management scale. The precise categorization of *métiers* given here should be
621 the first step towards *métier*-specific estimates of catches, effort and gross revenues,
622 which in turn, should allow a better understanding of the drivers of system's dynamic
623 (i.e., the drivers of fisher decisions on the specific *métier* to be adopted at any moment).
624 In this scenario, co-management would receive better scientific advice and would have
625 more chance for success.

626

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635

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Table

MÉTIER (Local name)	Gear group	Target assemblage	Mesh size/gear characteristics	Target species	Activity period
Cuttlefish/Fish (<i>Sipia/Peix</i>)	Bottom trammel net	Benthic assemblages	67 mm/ max. 4.500 m per vessel	Cuttlefish (<i>Sepia officinalis</i>), mixed fishes	Winter
Spiny lobster (<i>Llagosta</i>)	Bottom trammel net	Benthic assemblages	130 mm/ max. 4.500 m per vessel	Spiny lobster (<i>Palinurus elephas</i>)	Spring-Summer
Red mullet (<i>Moll</i>)	Bottom trammel net	Benthic assemblages	50 mm/ max. 4.500 m per vessel	Red mullet (<i>Mullus surmuletus</i>)	Summer - Autumn
Longline (<i>Palangró</i>)	Bottom long-lines	Benthic assemblages	Hooks min. 9 mm wide /max. 1.000 hooks per vessel	Red porgy (<i>Pagrus pagrus</i>), red scorpionfish (<i>Scorpaena scrofa</i>)	All year
Transparent goby (<i>Jonquillera</i>)	Special pelagic surrounding net	Pelagic fishes	- / max. 100 m	Transparent goby (<i>Aphia minuta</i>)	Winter
Dolphinfish (<i>Llampuguera</i>)	FADS and special surrounding net	Epipelagic fishes	- / max. 200 m	Dolphinfish (<i>Coryphaena hippurus</i>)	Autumn
Squid jigging (<i>Potera</i>)	Hand line	Squid	Hooks min. 9 mm wide	Squid (<i>Loligo vulgaris</i>)	All year
Trolling (<i>Fluixa</i>)	Hand line	Pelagic fishes	Hooks min. 9 mm wide	Mediterranean bonito (<i>Sarda sarda</i>), great amberjack (<i>Seriola dumerili</i>)	All year
Bottom hand line (<i>Volantí</i>)	Hand line	Demersal fishes	Hooks min. 9 mm wide	Red porgy (<i>Pagrus pagrus</i>), red scorpionfish (<i>Scorpaena scrofa</i>), comber (<i>Serranus cabrilla</i>), razorfish (<i>Xyrichtys</i>)	All year

<i>Solta</i> trap net (<i>Solta</i>)	Fishing trap	Coastal fishes	80 mm/ max. 300 m	<i>novacula</i> Mediterranean bonito (<i>Sarda sarda</i>), great amberjack (<i>Seriola dumerili</i>)	All year
<i>Moruna</i> trap net (<i>Moruna</i>)	Fishing trap	Coastal fishes	50 mm/ max. 500 m	Great amberjack (<i>Seriola dumerili</i>)	Spring-summer
<i>Almadraba</i> trap net (<i>Almadraba</i>)	Fishing trap	Coastal fishes	200 mm/ max. 500 m	Great amberjack (<i>Seriola dumerili</i>)	Winter
Trawl (<i>Arrossegament</i>)	Bottom trawl	Benthic assemblages	40 mm square mesh/ -	Red shrimp (<i>Aristeus antennatus</i>), Norway lobster (<i>Nephrops norvegicus</i>), hake (<i>Merluccius merluccius</i>), red mullet (<i>Mullus surmuletus</i>)	All year

1

2 **Table 1**

3 Main characteristics of the 12 métiers initially identified. Expert fishers were asked to
 4 label a sample of daily boat records with one or more of these 12 métiers. The 7 métiers
 5 finally selected were denoted in bold. Note that an additional 13th category was
 6 considered for trawling because a few daily boat records from trawlers were erroneously
 7 included within the SSF data base.

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	Trawlers	Small-scale	Seiners
Trawlers	218	0	0
Small-scale	0	176	0
Seiners	0	3	195

13

14 **Table 2**

15 Cross-validated confusion matrix for the classification algorithm intended to filter out

16 trawlers and seiners. Successful predictions are at the main diagonal (in bold).

17

Cuttlefish/Fish	Transparent goby		Dolphinfish		Squid jigging		Spiny lobster		Red mullet		Longline			
	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES		
NO	683	0	1045	0	1000	0	1044	0	867	0	1017	0	857	0
YES	5	412	0	55	0	100	0	56	2	231	1	82	0	412

19

20 **Table 3**

21 Cross-validated confusion matrix for the classification algorithm intended to predict

22 métier from the daily boat record of landings. Note that in that case a binary

23 classification was completed for each one of the métiers considered. Successful

24 predictions are at the main diagonal (in bold).

25

	TOTAL	Cuttlefish/Fish	Transparent goby	Dolphinfish	Squid jigging	Spiny lobster	Red mullet	Longline
Effort (fishing trips)	14,652	4,964 (33.9%)	657 (4.5%)	1,208 (8.2%)	915 (6.2%)	3,204 (21.9%)	1,352 (9.2%)	2,350 (16.0%)
Landings (kg)	422,839	122,991 (29.1%)	15,874 (3.8%)	109,445 (25.9%)	12,088 (2.9%)	58,360 (13.8%)	32,861 (7.8%)	71,217 (16.8%)
Gross revenues (€)	3,893,379	959,577 (24.6%)	274,498 (7.1%)	504,539 (13.0%)	202,950 (5.2%)	999,674 (25.7%)	233,170 (6.0%)	718,968 (18.5%)

27

28 **Table 4**

29 Métier-specific average annual estimates of effort (fishing trips), landings (kg) and
30 gross revenues (euros) of the small scale fleet from Mallorca between 2004 and 2015.

31

32

33

MÉTIERES						
Cuttlefish/Fish	Transparent goby	Dolphin fish	Squid jigging	Spiny lobster	Red mullet	Longline
SIPIA PT <i>Sepia officinalis</i>	JONQUIL LO <i>Aphia minuta</i>	LLAMP UGA <i>Coryphena hippurus</i>	CALA MAR POT. PT <i>Loligo vulgaris</i>	LLAGO STA ROJA <i>Palinurus elephas</i>	MOLL VERMELL GR <i>Mullus surmuletus</i>	RATJAD A <i>Raja clavata</i>
VARIAT* Mixed fish	JONQ./C ABOTI Mixed <i>A. minuta</i> and <i>Pseudaphya ferreri</i>	PAMPO L <i>Naucrates ductor</i>	CALA MAR POT. GR <i>Loligo vulgaris</i>	RATJA DA <i>Raja clavata</i>	MOLL VERMELL PT <i>Mullus surmuletus</i>	DENTO L GR <i>Dentex dentex</i>
SIPIA GR <i>Sepia officinalis</i>		VERDE ROL <i>Seriola dumerili</i> juvenile		CAP ROIG MITJA <i>Scorpaena scrofa</i>	VARIAT* Mixed fish	PAGUE RA PT <i>Pagrus pagrus</i>
MORRALLA GR* Mixed fish				RAP MITJA <i>Lophius budegas</i> sa	MORRALL A GR.* Mixed fish	DENTO L PT <i>Dentex dentex</i>
POP GR <i>Octopus vulgaris</i>				CAP ROIG GR <i>Scorpaena scrofa</i>	MORRALL A PT.* Mixed fish	MORRA LLA GR* Mixed fish
ESCORPORA GR <i>Scorpaena porcus</i>				CAP ROIG PT <i>Scorpaena scrofa</i>	ESPARRA LL <i>Diplodus annularis</i>	CONGR E <i>Conger conger</i>
CAP ROIG PT <i>Scorpaena scrofa</i>				RATA <i>Uranoscopus scaber</i>	POP MITJA <i>Octopus vulgaris</i>	GATO <i>Scyliorhinus canicula</i>
ESCORPORA PT <i>Scorpaena porcus</i>				RAP PT <i>Lophius budegas</i> sa	RATA <i>Uranoscopus scaber</i>	SIRVIOL A GR <i>Seriola dumerili</i>

POP MITJA <i>Octopus vulgaris</i>	RAP GR <i>Lophius budegas sa</i>	PAGELL PT <i>Pagellus spp</i>	CANTE RA GR <i>Spondylis osoma cantharus</i>
RATA <i>Uranoscopus scaber</i>	SIRVIO LA PT <i>Seriola dumerili</i>	VAQUES/ VACAS <i>Serranus scriba</i>	MUSSO LA <i>Mustelus mustelus</i>
TORD <i>Symphodus spp.</i>	GALL S.PEDR O MITJA <i>Zeus faber</i>		ORADA <i>Sparus aurata</i>
PALOMIDA <i>Lichia amia</i>	MOLLE RA PT <i>Phycis spp.</i>		PAGUE RA GR <i>Pagrus pagrus</i>
LLISSA <i>Mugil spp</i>	PAGEL L PT <i>Pagellus spp</i>		ANFOS PT <i>Epinephelus spp.</i>
ESCORBALL <i>Sciaena umbra</i>	FERRA SSA <i>Dasyatis pastinaca</i>		MOREN A <i>Muraena helena</i>
SALPA <i>Salpa salpa</i>	LLAGO STA ROJA GR <i>Palinurus elephas</i>		ARANY A CAP NEGRE <i>Trachinus radiatus</i>
CARACOLA/ CORNET <i>Trunculariopsis trunculus</i>	GALL S.PEDR O GR <i>Zeus faber</i>		SARD MITJA <i>Diplodus sargus</i>
GALL S.PEDRO PT <i>Zeus faber</i>	LLAGO STA ROJA MITJA <i>Palinurus elephas</i>		SARD GR <i>Diplodus sargus</i>

VARIADA <i>Diplodus</i> <i>vulgaris</i>	CIGAL A <i>Scyllari</i> <i>des</i> <i>latus</i>	ANFOS GR <i>Epinephe</i> <i>lus</i> spp.
BURRO/ASE <i>Dactylopterus</i> <i>volitans</i>	PELAI A PT <i>Solea</i> <i>spp.</i>	SERRA <i>Serranus</i> <i>cabrilla</i>
POP PT <i>Octopus</i> <i>vulgaris</i>		ESPET GR <i>Sphyraen</i> <i>a viridis</i>
SURE <i>Balistes</i> <i>carolinensis</i>		MOLLE RA GR <i>Trisopter</i> <i>us</i> <i>minutus</i> CANTE RA PT <i>Spondilos</i> <i>oma</i> <i>cantarus</i>

35

36 **Table 5**

37 List of the commercial categories that significantly contributed to define the seven
38 métiers (i.e., results of the SIMPER analysis). First sale commercial categories (rows)
39 for each métier (columns) for the small-scale fisheries from Mallorca (see Table 1 for
40 the definition of métiers). The actual label (i.e., the label selected by the auctioneer from
41 a closed list) is provided followed by the size when that determines the category. The
42 species corresponding to each category is detailed. *GR*: big size; *MITJA*: medium size;
43 *PT*: small size; * denotes the three commercial categories that contain several species.

1 Figure captions

2 **Fig. 1.** Analytical approach proposed for predicting the métier of each fishing trip from
3 Mallorca Island's small scale fleet. The high numbers are those detailed in Section 2.1.

4 **Fig. 2.** Results of the multivariate analysis (CCA) aiming to check between-expert
5 coherence. According to the expert-by-expert sequential elimination protocol (Step 8 in
6 Section 2.1), the labeling of expert 6 did not match with the one of the other experts,
7 hence it was deleted in the first loop. The four experts finally deleted are denoted in
8 bold.

9 **Fig. 3.** Temporal trends for the effort (a), landings (b), gross revenues (c), landings per
10 fishing trip (CPUE) (d) and gross revenues per fishing trip (e) for Mallorca's small scale
11 fleet. Fishing trips have been polled by month.

12 **Fig. 4.** Fishing trips temporal trend distributed by métier. Separate panels denote effort
13 (a), landings (b), and gross revenues (c). Fishing trips have been polled by month.

14 **Fig. 5.** Seasonal temporal trends (fishing trips of the same month are polled across the
15 timeline considered in this study).

16 **Fig. 6.** Plot showing the optimal number of groups (i.e. métiers) in which the fishing
17 trips are clustered. The vertical axis represents the average ratio between the similarities
18 of a fishing trip with the centroid of its cluster, in relation to the similarity to other
19 clusters. The horizontal axis represents the number of cluster considered. It is expected
20 that the curve would peak at the optimal number of groups (2 métiers).

21 **Fig. 7.** General workflow proposed for predicting all the fishing trips métiers for other
22 fisheries. According with Section 4.1, expert fishers' classification is preferred over the
23 alternative pathways (denoted by dashed lines).

Figure 1
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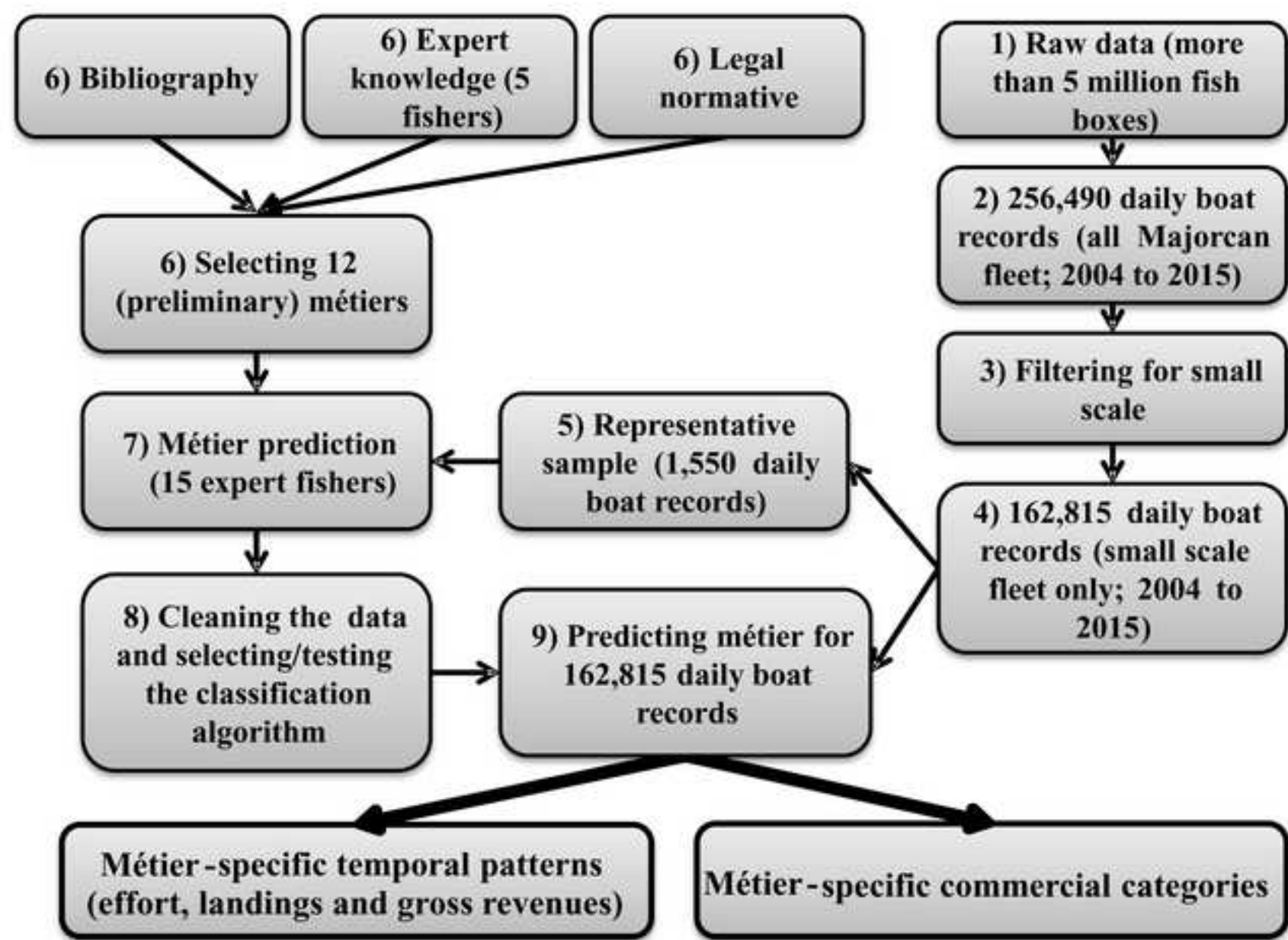


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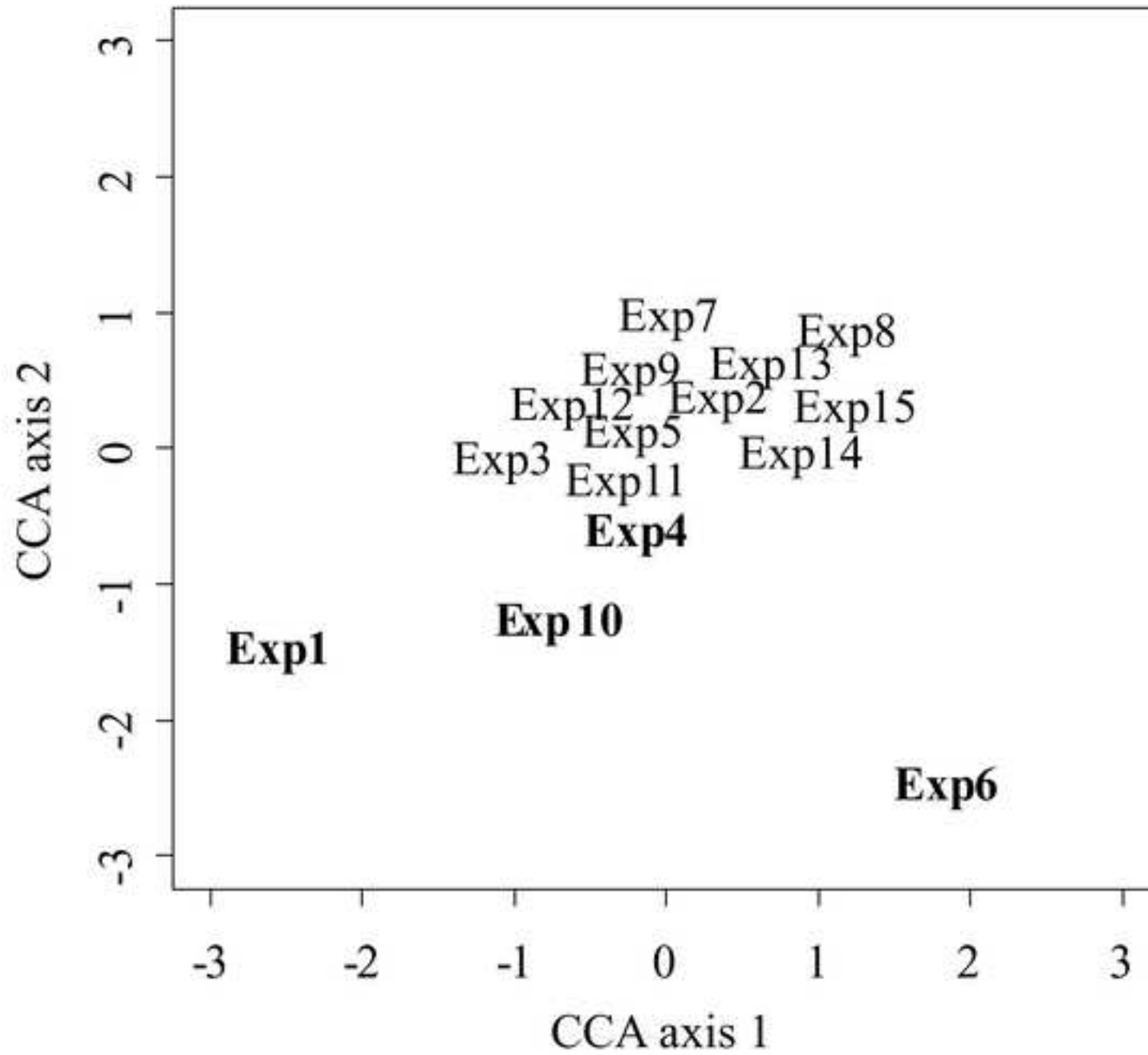


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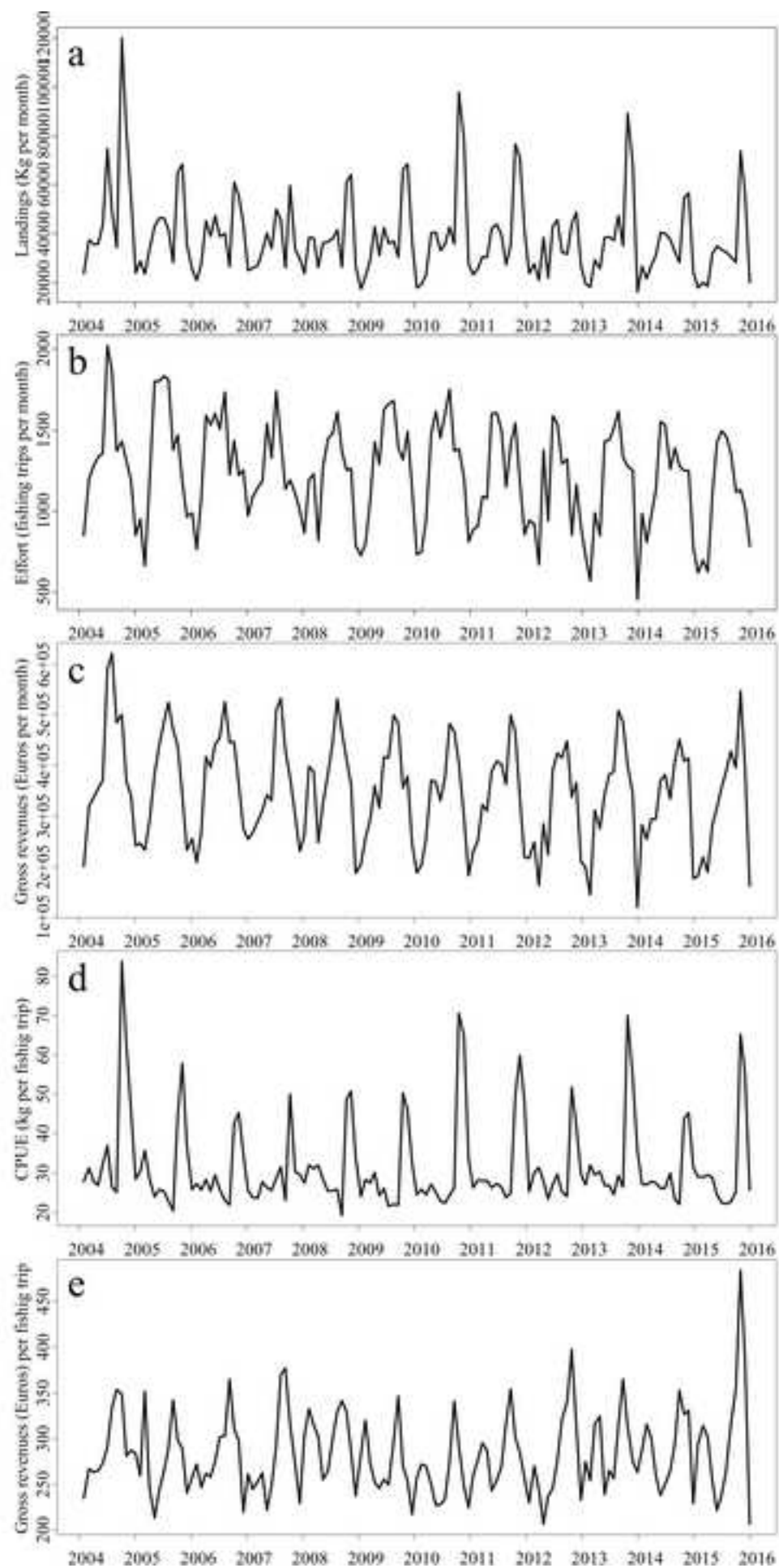


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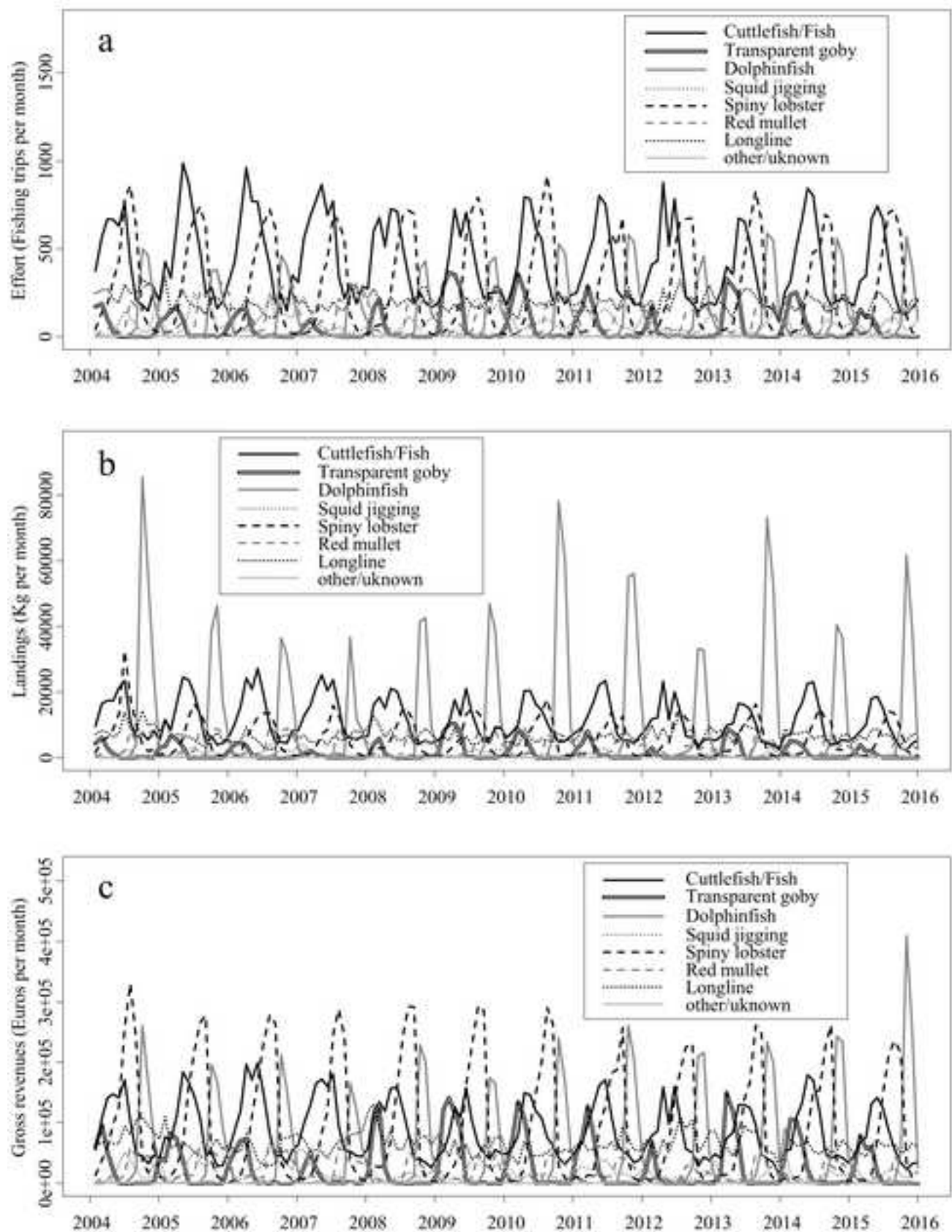


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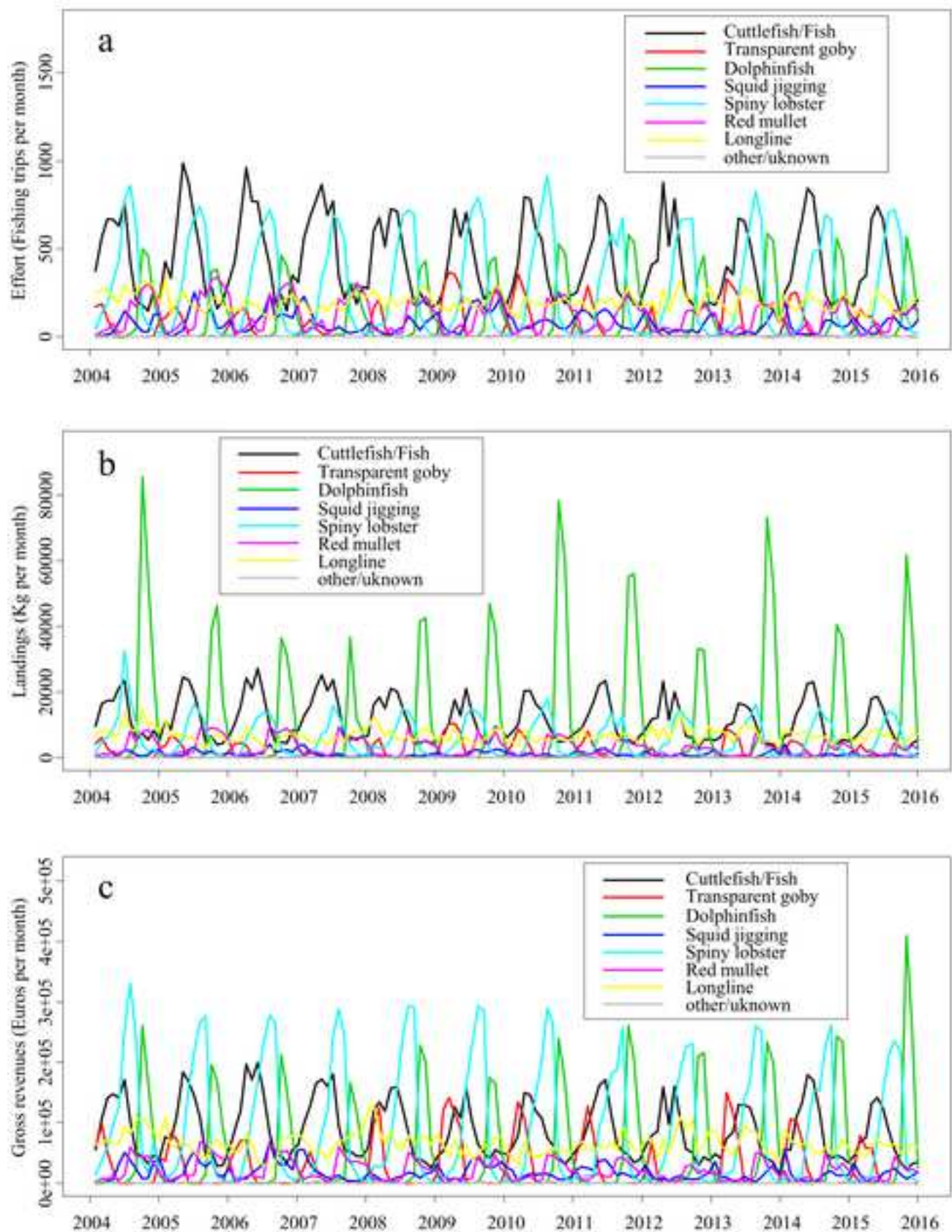


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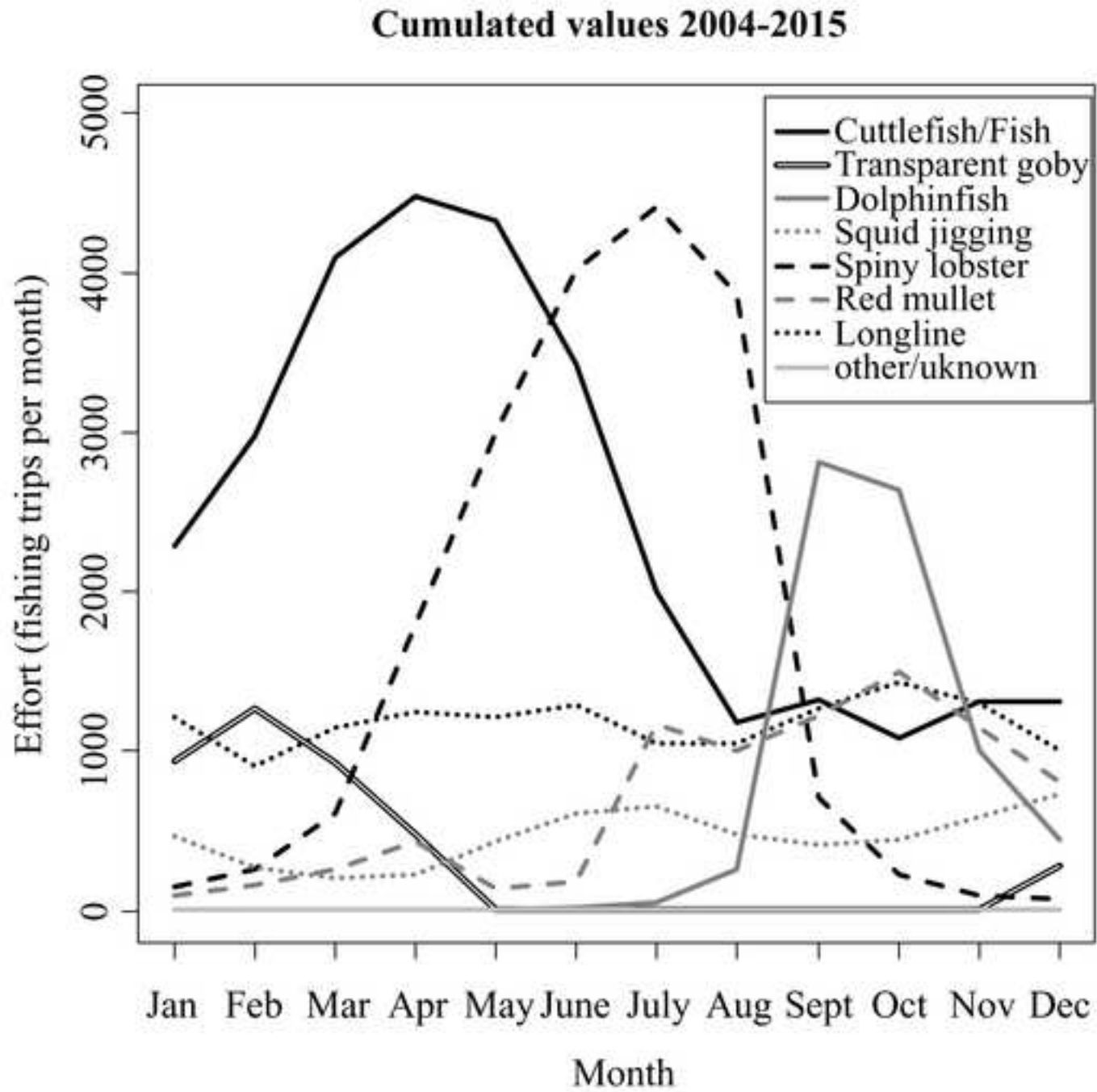


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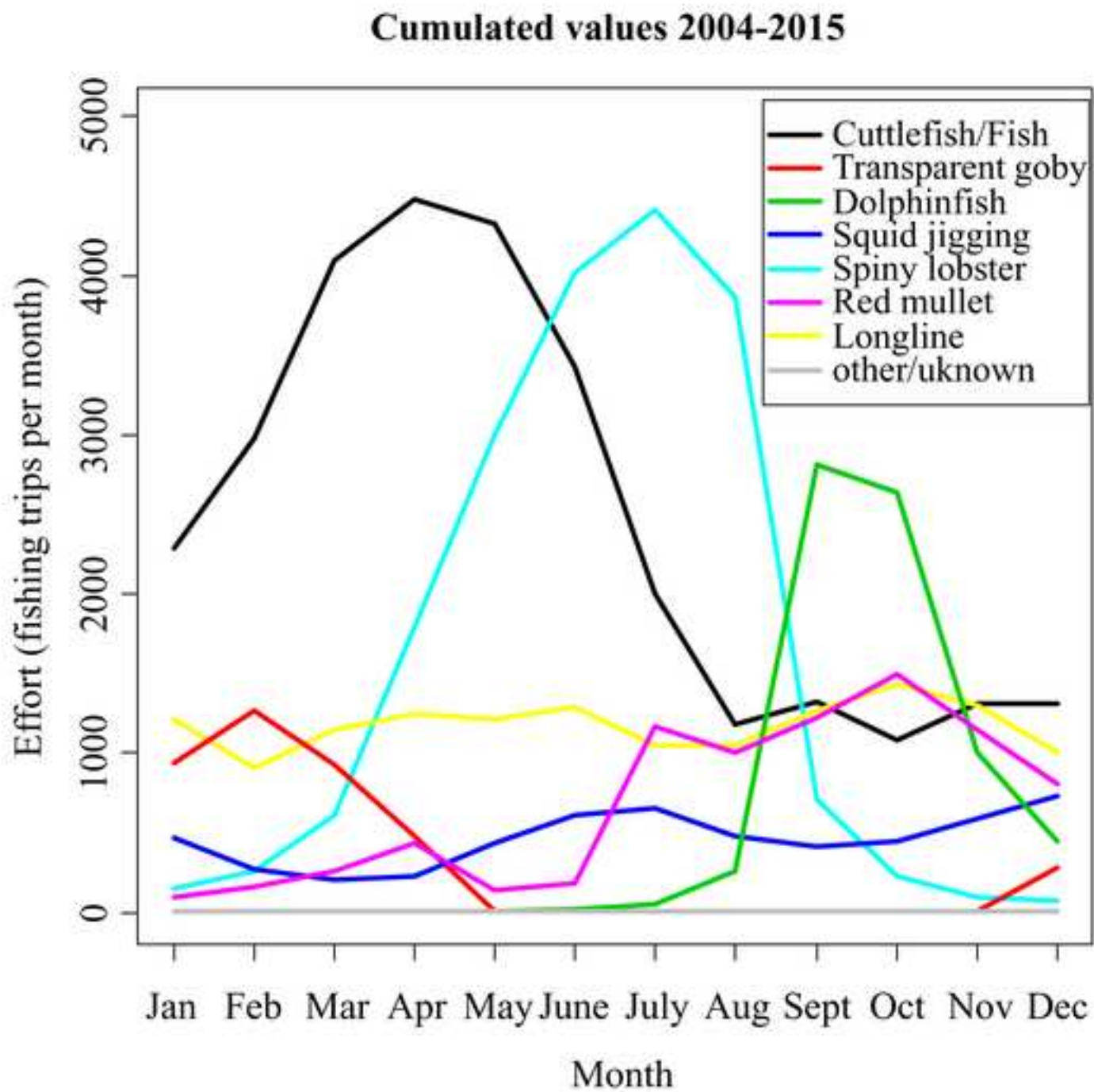


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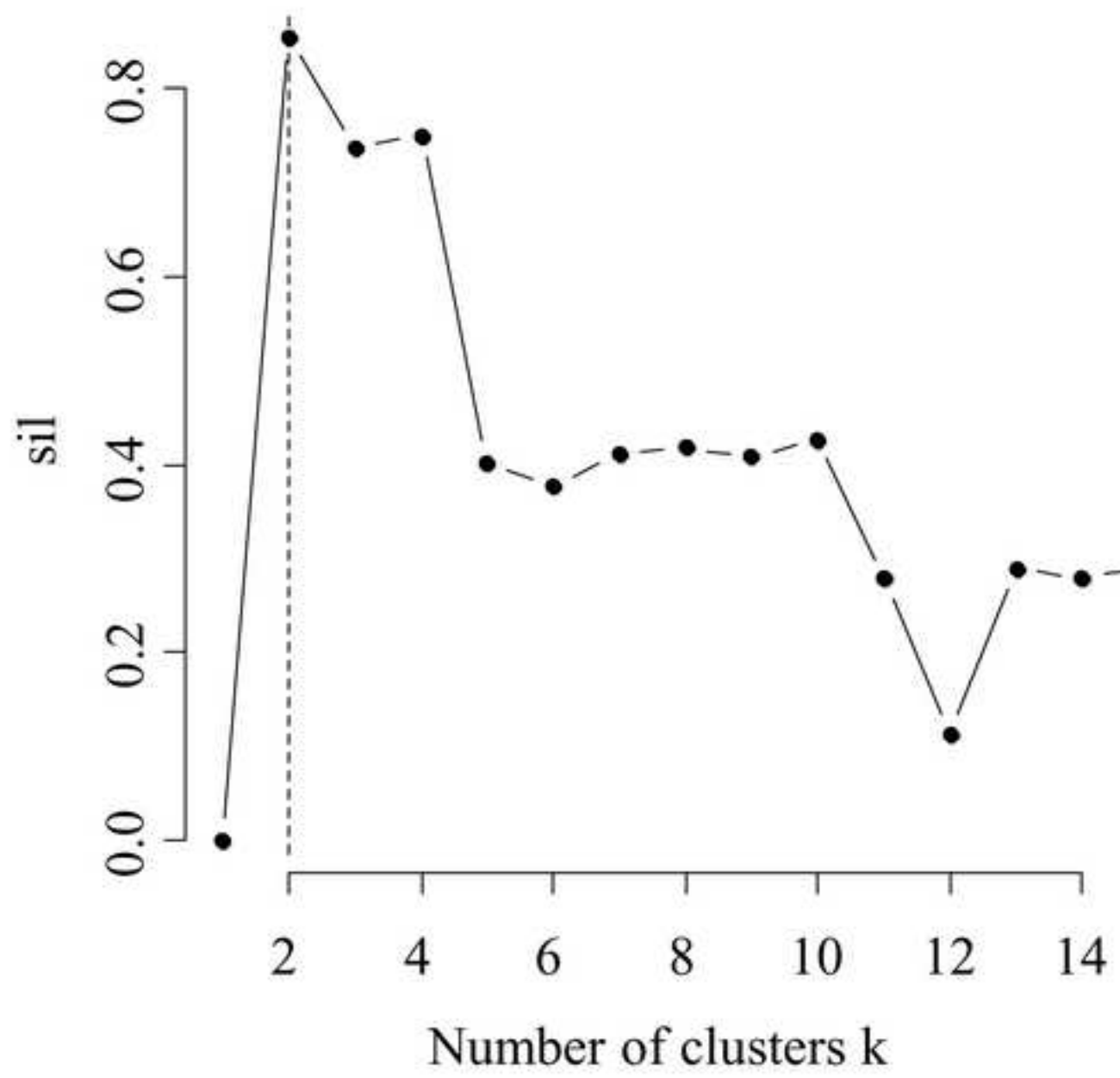


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