



HAL
open science

Machine learning for characterizing tropical tuna aggregations under Drifting Fish Aggregating Devices (DFADs) from commercial echosounder buoys data

Y. Baidai, Laurent Dagorn, M. J. Amande, D. Gaertner, M. Capello

► To cite this version:

Y. Baidai, Laurent Dagorn, M. J. Amande, D. Gaertner, M. Capello. Machine learning for characterizing tropical tuna aggregations under Drifting Fish Aggregating Devices (DFADs) from commercial echosounder buoys data. *Fisheries Research*, 2020, 229, pp.105613. 10.1016/j.fishres.2020.105613 . hal-03405000

HAL Id: hal-03405000

<https://hal.umontpellier.fr/hal-03405000>

Submitted on 22 Aug 2022

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution - NonCommercial 4.0 International License

1 Machine learning for characterizing tropical tuna aggregations under Drifting Fish
2 Aggregating Devices (DFADs) from commercial echosounder buoys data

3 Y. Baidai^{1,2}, L. Dagorn¹, M.J. Amande², D. Gaertner¹ and M. Capello¹

4

5 ¹ MARBEC, Univ Montpellier, CNRS, Ifremer, IRD, Sète, France yannick.baidai@ird.fr
6 (corresponding author)

7 ² Centre de Recherches Océanologiques (CRO), Abidjan, Côte d'Ivoire

8 **Summary**

9 The use of echosounder buoys deployed in conjunction with Drifting Fish Aggregating Devices
10 (DFADs) has progressively increased in the tropical tuna purse seine fishery since 2010 as a
11 means of improving fishing efficiency. Given the broad distribution of DFADs, the acoustic
12 data provided by echosounder buoys can provide an alternative to the conventional CPUE index
13 for deriving trends on tropical tuna stocks. This study aims to derive reliable indices of presence
14 of tunas (and abundance) using echosounder buoy data. A novel methodology is presented
15 which utilizes random forest classification to translate the acoustic backscatter from the buoys
16 into metrics of tuna presence and abundance. Training datasets were constructed by cross-
17 referencing acoustic data with logbook and observer data which reported activities on DFADs
18 (tuna catches, new deployments and visits of DFADs) in the Atlantic and Indian Oceans from
19 2013 to 2018. The analysis showed accuracies of 75 and 85 % for the recognition of the
20 presence/absence of tuna aggregations under DFADs in the Atlantic and Indian Oceans,
21 respectively. The acoustic data recorded at ocean-specific depths (6 – 45 m in the Atlantic and
22 30 – 150 m in the Indian Ocean) and periods (4 am – 4 pm) were identified by the algorithm as
23 the most important explanatory variables for detecting the presence of tuna. The classification
24 of size categories of tuna aggregations showed a global accuracy of nearly 50% for both oceans.

25 This study constitutes a milestone towards the use of echosounder buoys data for scientific
26 purposes, including the development of promising fisheries-independent indices of abundance
27 for tropical tunas.

28 *Keywords:* Tropical tunas; Direct abundance indicator; Echosounder buoys; Fish Aggregating
29 Devices; Purse seiner

30

31 **1. Introduction**

32 Many marine species are known to naturally aggregate under floating objects. Although still
33 poorly understood, this behaviour is widely exploited by fishermen, who deploy man-made
34 floating objects (hereafter referred to as Fish Aggregating Devices or FADs) worldwide to
35 improve their catches (Kakuma, 2001; Fonteneau et al., 2013; Albert et al., 2014). The use of
36 drifting FADs (DFADs) in tropical tuna fisheries was first introduced in the late 1980s in the
37 Eastern Pacific Ocean by the US purse seine fleet (Lennert-Cody and Hall, 2001) and was later
38 extended to all oceans and fleets from the 1990s. The instrumentation of DFADs with GPS
39 beacons and echosounder buoys, in the mid and late 2000s respectively (Lopez et al., 2014),
40 led to major changes in fishing strategies and behaviour of purse-seine fleets (Torres-Irineo et
41 al., 2014). By providing skippers with almost real-time remote information on the precise
42 location of DFADs, and on the potential presence and size of the tuna aggregation, echosounder
43 buoys reduced the search time between two successful DFAD sets (Lopez et al., 2014). As a
44 result, modern DFADs have significantly increase fishing efficiency (Fonteneau et al., 2013).
45 Consequently, their use has increased considerably in the past few decades. Recent studies
46 indicate that in less than a decade, the number of DFADs deployed in the Atlantic and Indian
47 Oceans have increased at least fourfold (Fonteneau et al., 2015; Maufroy et al., 2017). It is
48 estimated that over half of the annual tropical tuna purse seine catch originate from fishing sets
49 on DFADs (Dagorn et al., 2013; Fonteneau et al., 2013).

50 Aside from being highly efficient fishing tools, the large number and vast spatial distribution
51 of DFADs, coupled with their constantly evolving technology (Lopez et al., 2014), mean that
52 they can also potentially provide unprecedented scientific insights into pelagic communities
53 (Moreno et al., 2016; Brehmer et al., 2018). The echosounder buoys attached to DFADs
54 regularly produce and transmit biomass estimation data. This dataset potentially holds a major
55 opportunity for improving the management of tropical tuna stocks through the development of

56 fishery-independent abundance indices (Capello et al., 2016; Santiago et al., 2016). Currently,
57 the main abundance indicators used in stock assessment for tropical tunas are derived through
58 the standardization of Catch per Unit of Effort (CPUE) from commercial data (Fonteneau et al.,
59 1998; Maunder et al., 2006). However, owing to the constant technological advances occurring
60 in the purse seine fishery, it is extremely difficult to accurately standardize the CPUE time-
61 series (Fonteneau et al., 1999). Traditionally, search time was used to quantify normal fishing
62 effort in this fishery, however, owing to its non-random nature, the DFAD-based fishery has
63 made this metric inconsistent over time, thus introducing major biases and uncertainties in the
64 relationship between tuna catches and abundance (Fonteneau et al., 1999; Gaertner et al., 2015).

65 The need for the consideration of non-traditional data sources to provide alternate abundance
66 indices for stock assessment of tunas is becoming increasingly apparent. In this regard, the large
67 amount of acoustic data autonomously collected by commercial echosounder buoys on DFADs
68 is of undeniable value. However, the direct exploitation of these data remains challenging. The
69 biomass estimate that a buoy produces is limited by the reliability and variability of the
70 information provided, which depends on the hardware and software characteristics of the buoy,
71 and varies between manufacturers (Lopez et al., 2014; Santiago et al., 2016). As a result, the
72 data provided by echosounder buoys are heterogeneous in types and formats, with limited
73 studies having provided an assessment of their accuracy for use in scientific investigations.
74 (Lopez et al., 2016; Baidai et al., 2017; Orue et al., 2019a).

75 In recent years, fisheries scientists have shown a growing interest in machine learning methods
76 for the processing of both passive acoustic data (Roch et al., 2008; Zaugg et al., 2010; Noda et
77 al., 2016; Malfante et al., 2018) and acoustic data collected by scientific echosounders
78 (Fernandes, 2009; Robotham et al., 2010; Bosch et al., 2013). Despite this trend, very few
79 studies have been conducted on the implementation of automated classification methods for
80 analysing the extensive datasets collected by commercial vessels (Uranga et al., 2017).

81 This paper presents a new methodology, based on machine learning, for processing the
82 echosounder data collected from one of the main models of echosounder buoy used to equip
83 DFADs worldwide (Moreno et al., 2019).

84 **2. Material and Methods**

85 *2.1. Database description*

86 2.1.1. Echosounder buoy data

87 We used data from the Marine Instruments M3I buoy (<https://www.marineinstruments.es>),
88 collected on DFADs deployed by the French purse seine vessels operating in the Western Indian
89 and Eastern Atlantic oceans from 2013 to 2018. The dataset consists of more than 60 million
90 data points collected by approximately 35 000 M3I buoys. This model of buoy includes a solar
91 powered echosounder operating at a frequency of 50 kHz, with a power output of 500 W, a
92 beam angle of 36°, and a sampling frequency of 5 minutes (Fig. 1A). The acoustic data are
93 processed by an internal module that automatically converts the acoustic energy into (i) a total
94 biomass index and (ii) 50 integer acoustic scores (ranging from 0 to 7) indicating the acoustic
95 energy recorded within 3 m depth layers, over a total detection range of 150 meters (Fig. 1B).
96 In the default-operating mode, the internal module stores the 50 acoustic scores that correspond
97 to the highest total biomass index recorded every 2 hours. From here on these 50 acoustic scores
98 will be referred to as an “acoustic sample”. The assessment of the accuracy of the total biomass
99 index calculated directly by the buoy’s internal module is presented in the Supplementary
100 Appendix A1. The set of acoustic scores which constitute the acoustic sample is transmitted via
101 satellite to the purse seine vessel every 12 hours under default settings. During the satellite
102 communication, the GPS position of the buoy is also recorded and transmitted.

103 2.1.2 Activity data on DFADs

104 To ground truth the echosounder buoy dataset, catch and fishing activities were obtained from
105 fishing logbooks of purse seine vessels and on-board observer reports from 2013 to 2018 in the
106 western Indian and eastern Atlantic oceans. Observer data were collected under the EU Data
107 Collection Framework (DCF) and the French OCUP program (Observateur Commun Unique
108 et Permanent), which reached a coverage rate of 100% in the Atlantic Ocean in 2015 (Goujon
109 et al., 2018), and over 80% since 2016, in the Indian Ocean (Goujon et al., 2017). From this
110 combined dataset, the date, time, GPS location and buoy identification code associated with (i)
111 fishing sets, (ii) newly deployed DFADs and (iii) visits to DFADs equipped with buoys owned
112 by the vessel and which did not result in a fishing operation, were selected to be cross-
113 referenced with echosounder buoy dataset. For successful fishing sets on DFADs, catch data
114 for the three primary target species; yellowfin (*Thunnus albacares*), bigeye (*Thunnus obesus*)
115 and skipjack tuna (*Katsuwonus pelamis*) were also considered. These catch data were used to
116 ground truth the buoy's ability to detect the presence and size of tuna aggregations, assuming
117 that the entire fish aggregation is encircled and captured by the fishing vessel. Conversely,
118 newly deployed DFADs and visits to DFADs that did not result in any catch were used to
119 ground truth the buoy's ability of detecting the absence of a tuna aggregation. For this
120 assessment, DFAD deployments and visits where fishing sets were reported within the
121 following week were omitted, to ensure that the data truly represented the absence of tuna at
122 the DFADs. Similarly, only the deployments of new DFADs were considered and all other
123 deployment operations were discarded (e.g., reinforcement of an existing DFAD, deployment
124 of a buoy on a natural log).

125 Skunk fishing sets (sets where the tuna school totally or partially escaped) and activities, for
126 which the reported set position was inconsistent with the position reported by the buoy, were
127 removed. Only data for which the buoy identification code corresponded to a buoy code present

128 in the echosounder buoy database were retained in the analysis. The final database used for
129 each activity and ocean is described in Table 1.

130 2.2. Acoustic data pre-processing

131 Daily acoustic data provided by an individual buoy consists of a $50 \times N$ matrix S , where 50
132 represents the number of depth layers and N corresponds to the number of acoustic samples
133 provided for that day according to the operating mode of the buoy (in the default operating
134 mode, the acoustic scores are stored every 2 hours, thus $N=12$). Elements of the matrix S
135 correspond to the daily acoustic scores S_{ij} (i.e., integers ranging between 0 and 7) recorded at
136 different depth layers i ($i=1, 50$) and different times of the day j ($j=1, N$). In a pre-processing
137 step, the temporal and spatial information was aggregated to standardize the data and achieve a
138 reduction in dimensions as follows:

139 (1) the acoustic scores of the two shallowest layers (0 – 6 m depth), representing the transducer
140 near-field, were removed, leading to a $48 \times N$ matrix;

141 (2) for each layer i , the daily acoustic scores S_{ij} were averaged over 4-hours periods, resulting
142 in a reduced matrix S' of 48×6 (Fig. 2);

143 (3) a clustering method was applied on S' along the dimension i , to identify homogeneous
144 groups of depth layers. The clustering method was based on a dissimilarity matrix computed
145 from Euclidean distance and Ward's method (Murtagh and Legendre, 2014). The acoustic
146 scores in each identified group were compared through a Kruskal-Wallis test¹;

147 (4) for each homogeneous group G , the acoustic scores recorded previously for each of the i
148 depth layers constituting the group were summed and rescaled to obtain a unique score (S''_{Gj})
149 per group G and time period j , according to Eq. 1.

¹ Clustering analyses were conducted using the R function “*hclust*” (R Core Team, 2019), and the Kruskal-Wallis test with the R function “*kruskal.test*”

150
$$S''_{Gj} = \frac{\sum_{i=1}^{n_G} S'_{ij}}{\text{maxs} \times n_G} \quad (1)$$

151 where j denotes the 4-hours time period, n_G the number of depth layers belonging to group G
 152 and maxs is a constant denoting the maximum score (7 in the case of M3I buoys). The result of
 153 the pre-processing step leads to a $N_G \times 6$ matrix S'' (i.e., N_G groups of layers \times 6 four-hour
 154 periods recorded during a day), summarizing the acoustic information collected on a daily scale,
 155 and referred to hereafter as a “daily acoustic matrix” (Fig. 2).

156 2.3. Supervised learning classification

157 2.3.1. Training dataset

158 The training datasets were constructed by cross-matching activity data (catch, deployments,
 159 visits without fishing sets) with the daily acoustic matrices, using buoy identification codes,
 160 dates and times for each ocean. A first binary training dataset was constructed for describing
 161 the presence or absence of tuna, in which catch events corresponded to tuna presence and
 162 deployment and visits without catch, to the absence of tuna (see Table 2). A second multiclass
 163 training dataset was created for describing the size of the tuna aggregation. The catch data were
 164 divided into three classes: < 10 tons, 10 – 25 tons, >25 tons, based on the total catch of the set
 165 (i.e., the sum of the catch of the three target tuna species: yellowfin tuna, bigeye tuna and
 166 skipjack tuna). The number and limits of the size classes were selected in order to retain a
 167 sufficient and balanced number of data points in each class for the learning process, while also
 168 maintaining consistency with the catch data. Class limits were based on the first quantile (10
 169 tons) and the average (25 tons) of catches under DFADs in the dataset (see Table 3).

170 The daily acoustic matrices of tuna presence were constructed using the acoustic data recorded
 171 the day before catch events. Similarly, the daily acoustic matrices corresponding to tuna
 172 absence were selected from the daily acoustic matrices obtained the day prior to DFAD visits

173 without fishing sets, and those obtained on the fifth day after new DFAD deployments. The
174 rationale for considering these 5-day periods after deployment was to account for the acoustic
175 signal produced by the non-tuna species. Prior studies (Deudero et al., 1999; Castro et al., 2002;
176 Nelson, 2003; Moreno et al., 2007; Macusi et al., 2017) have indicated that the colonization of
177 DFADs by non-tuna species occurs within a range of a few hours to one week after deployment.
178 Furthermore, preliminary analyses conducted on 528 and 5868 newly deployed DFADs, in the
179 eastern Atlantic and western Indian oceans respectively, indicated a rapid increase in the
180 acoustic signal recorded by the buoys during the first five days following deployment
181 (Supplementary Appendix A3: Fig. A3.1 and A3.2). After considering all of these reasons, we
182 assumed that acoustic data recorded at this post deployment time-scale were more likely to
183 represent the presence of non-tuna species under DFADs.

184 2.3.2. Random forest algorithm

185 The random forest classification algorithm² (Breiman, 2001) was applied on an ocean-specific
186 basis. Predictors were represented by daily acoustic matrix values. Three thousand trees were
187 grown for each classification. This high value does not negatively impact the model's
188 performance (Breiman, 2001), and helps to stabilize the importance of the variables more
189 effectively (Liaw and Wiener, 2002; Probst et al., 2019). For each classification model, the
190 number of variables randomly sampled as candidates at each split was assessed through a grid-
191 search strategy implemented with the R package "caret" (Kuhn, 2008). In order to deal with the
192 imbalanced number of observations in the different size categories a stratified down-sampling
193 procedure, which consisted of resampling the dominant size categories to make their
194 frequencies closer to the least common size category, was also applied (Kuhn and Johnson,
195 2013).

² The random forest classification was performed by using the R package "randomForest" (Liaw and Wiener, 2002)

196 2.3.3. Model evaluation

197 The overall accuracy (i.e., the proportion of correct predictions) and the kappa coefficient
198 (Cohen, 1968) were used to assess the overall performance of both binary and multi-size
199 category classifications. Kappa coefficient is a reliability index estimated according to Eq. 2:

$$200 \quad \text{kappa} = \frac{Pr(a) - Pr(e)}{1 - Pr(e)} \quad (2)$$

201 where $Pr(a)$ is the total proportion of agreement between the observed and predicted classes
202 and $Pr(e)$ is the theoretical proportion of agreement expected by chance. The closer this ratio
203 is to 1, the better the classification performed.

204 In each classification, the conventional statistical measures of the performance of a binary
205 classification test: sensitivity, specificity, and precision were evaluated from confusion
206 matrices, using Eq. 3 - 5:

$$207 \quad \text{Sensitivity} = \frac{TP}{TP+FN} \quad (3)$$

$$208 \quad \text{Specificity} = \frac{TN}{FP+TN} \quad (4)$$

$$209 \quad \text{Precision} = \frac{TP}{TP+FP} \quad (5)$$

210 where for presence/absence classification, TP (true positive) and TN (true negative) are the
211 proportions of presence (or absence) correctly classified; FN (false negative) and FP (false
212 positive) are the proportions of absence (or presence) incorrectly predicted. For multiclass
213 classification, positive cases correspond to the aggregation size category considered during the
214 evaluation, while all other categories correspond to negative cases. Sensitivity (also known as
215 recall or true positive rate) measures the efficiency of the algorithm in correctly classifying
216 positive cases, and specificity (or true negative rate) measures the efficiency of the algorithm

217 in correctly classifying negative cases. Precision (or positive predictive value) is the fraction of
218 correctly predicted presence among all tuna presence prediction.

219 The importance of the predictors in the classification process for each ocean was assessed
220 through the analysis of the mean decrease in accuracy of the random forest model (i.e., the
221 increase of prediction error after permuting each variable while all others remained unchanged
222 during the tree construction; Breiman, 2001). Model training and evaluation were performed
223 through a hold-out validation method which was repeated ten times. In each of the ten replicates,
224 the original dataset was divided into two subsets: the training set and the validation dataset
225 (representing 75% and 25% of the initial data, respectively).

226 **3. Results**

227 *3.1. Pre-processing of sampled depth layers*

228 The clustering analysis carried out on the 3 m depth layers led in both oceans to the formation
229 of six groups with similar layer compositions between the two oceans (Fig. 3). In each ocean,
230 the comparison of the acoustic scores between the identified groups showed highly significant
231 differences (*p-value* at Kruskal-Wallis test < 0.001 for both Indian and Atlantic Oceans). Scores
232 declined strongly with depth (Fig. 4). The deepest group of layers (which also aggregated the
233 greatest number of layers), exhibited the lowest acoustic values, with averages close to zero
234 (Fig. 4).

235 *3.2. Presence/absence classification*

236 The random forest algorithm performed well in discriminating between the presence and
237 absence of tuna, with an overall accuracy of 75 and 85% in the Atlantic and Indian oceans,
238 respectively (Table 4). In the Atlantic Ocean, the classification model was effective in detecting
239 DFAD aggregations with tuna (sensitivity of 0.83), but exhibited a notable level of false

240 positives (specificity of 0.67). In the Indian Ocean the opposite trend was observed with the
241 classification of tuna presence performing well (sensitivity of 0.81) and the detection of their
242 absence also producing reliable results (specificity of 0.90).

243 *3.3. Classification of aggregation sizes*

244 The classification of aggregations into size classes was considerably less efficient than the
245 presence-absence classification, with low overall accuracies (48 and 47 %) observed for the
246 Atlantic and the Indian Oceans, respectively (Table 5). In the Atlantic Ocean, the highest
247 proportion of misclassification was observed in the 10 – 25 tons category (precision of 0.22),
248 whereas tuna schools below 10 tons and above 25 tons both performed similarly (precision of
249 0.32 and 0.28 respectively). In the Indian Ocean, tuna schools over 25 tons and below 10 tons
250 were also the most reliably detected aggregation size classes (precision of 0.44 and 0.42
251 respectively); while intermediate aggregation sizes (10 – 25 tons) were successfully classified
252 less regularly (precision of 0.35).

253 *3.4. Predictor importance*

254 For both binary and multiclass classifications, the importance of the acoustic predictors in the
255 classification process showed strong ocean-specific patterns. In the Atlantic Ocean, the
256 detection of tunas was principally driven by acoustic data recorded from 6 m to 45 m (Fig. 5A
257 and 6A). Conversely, in the Indian Ocean, the main predictors resulted from deeper layers (30
258 m to 150 m, Figure 5B and 6B). In these depth ranges, acoustic data recorded during daytime
259 (4 am - 4 pm) appeared to be the most significant for both oceans and across all types of
260 classifications. It should, however, be noted that in the Atlantic Ocean, the binary classification
261 produced a wider time window (0 to 4 pm) than in the Indian Ocean.

262

263 **4. Discussion**

264 This study describes a new methodology for processing data collected by a commercial
265 echosounder buoy commonly used in the DFAD purse seine fishery. The approach utilizes the
266 acoustic scores (reflective of abundance) recorded at different depths and times of the day and
267 combines data pre-processing procedures and machine learning algorithms to classify tropical
268 tuna aggregations under DFADs. Although several models of echosounder buoys process data
269 internally and generate abundance indices for tuna, previous studies have shown that such
270 information can be unreliable (Lopez et al., 2014, 2016). This could explain why most purse
271 seine skippers pay little attention to this information. Rather than relying solely on these
272 processed outputs, skippers tend to combine the acoustic information recorded at specific
273 depths and times with their empirical knowledge and the oceanographic characteristics of the
274 region to assist their decision making.

275 Working on a different brand of buoy, Lopez et al. (2016) developed the first approach to
276 improve biomass estimations from data collected by echosounder buoys. These authors
277 suggested that the acoustic signal collected during sunrise (i.e., when tuna are generally the
278 most tightly concentrated under DFADs), should be considered for processing and assumed the
279 structure of the aggregated biomass based on knowledge of the vertical behaviour of species
280 under floating objects. Under this assumption, they suggested a vertical segregation between
281 the species that make up the multispecific aggregation under DFADs (non-tuna species [3 – 25
282 m], small tunas [25 – 80 m] and large tunas [80 – 115 m]), and applied an echo-integration
283 procedure to convert the acoustic signal from each depth layer into biomass estimates using
284 specific values of target strength and individual average weight for each group. The application
285 of this approach to a larger dataset in the Indian Ocean (287 fishing sets) by Orue et al (2019)
286 was found to be less effective than expected, and potentially affected by the large spatio-

287 temporal variability between oceanic regions which skewed the main assumptions that underlie
288 the approach.

289 The methodology used by this study did not make any assumptions regarding the vertical and
290 temporal distribution of tuna at DFADs. Using a supervised learning algorithm, this
291 methodology mimics the learning process of the fishers on how they interpret the acoustic
292 scores based on their experience. The training dataset used for this purpose utilizes buoy data,
293 which is considered to be ground-truthed. These ground-truthed data have three underlying
294 assumptions. The first assumption is that the tuna caught by a purse seine vessel around a DFAD
295 represents all the tuna aggregated under that DFAD. This is typically the case, although it is
296 possible that some tuna escape during the fishing procedure, such events are considered to be
297 minor (Muir et al., 2012). In exceptional situations when very large fishing sets are made (>
298 200 t), the skipper may decide to retain only part of the aggregation to avoid damaging the net.
299 The second assumption is that tunas do not immediately associate with newly deployed DFADs.
300 Although Orue et al. (2019b) indicated that tuna may arrive first under DFADs, previous studies
301 (Deudero et al., 1999; Castro et al., 2002; Nelson, 2003; Macusi et al., 2017), including
302 interviews with fishers (Moreno et al., 2007) suggested otherwise. In this study, the daily
303 acoustic matrix recorded five days after the deployment of a new DFAD was used to represent
304 the absence of tuna. It would be useful to develop dedicated studies that would aid in the
305 understanding of the aggregation process of tuna and non-tuna species around DFADs. Finally,
306 the third assumption considered that a purse seine vessel visiting its own DFAD (DFAD
307 equipped with the vessel's buoy) without fishing also represents the absence of a tuna
308 aggregation at the DFAD. It may be countered that a skipper could decide not to set on a DFAD
309 when the vessel is already full, but this is an extremely rare event. External factors (e.g. strong
310 currents) may also impede the fishing operations. However, if a vessel heads towards a DFAD
311 that it owns, it is fair to assume that this would result in a fishing set (if tunas are present).

312 Furthermore, in an effort to avoid any bias associated with the external factors that could
313 influence the skipper's decision, only DFAD visits that were not followed by a fishing set within
314 seven days were taken into consideration. Our decision to include visits without fishing
315 operations in the training database as "absence of tuna" was taken based on numerous
316 discussions with skippers. According to many of them, it is not uncommon that the echosounder
317 buoys report high levels of acoustic energy even if tuna are absent from the aggregation. The
318 objective of including these DFAD visits in the database was to improve the ability of the
319 classification model to detect such false positives.

320 The results from this study highlight the effectiveness of the proposed methodology for
321 discriminating between the presence and absence of tuna aggregations under DFADs equipped
322 with M3I buoys in both the Indian and Atlantic oceans. To date the reliability of this model of
323 buoy in estimating the presence and size of tuna aggregations had only been assessed
324 anecdotally based on opinion and feedback from skippers. The development of reliable methods
325 for processing data provided by commercial echosounder buoys represents a key step in the use
326 of these fishing tools for scientific purposes, particularly the study of the different aspects of
327 the ecology and behaviour of tuna associated with floating objects. The algorithm's lower
328 performance in the Atlantic Ocean, where a higher proportion of false positive predictions of
329 tuna presence were generated, could well be related to the size of the training dataset. In the
330 Atlantic Ocean, this dataset was 5.5 times smaller than that used for the India Ocean. However,
331 this difference may also reflect an ocean-specific vertical distribution of fish aggregations under
332 DFADs. In the Indian Ocean, previous studies have described a vertical segregation between
333 tuna and non-tuna species (Forget et al., 2015; Macusi et al., 2017). Such segregation would
334 result in the determination of an absence of tuna to be straightforward for the classification
335 algorithm. To date no studies have investigated the vertical distribution of tuna and non-tuna
336 species under DFADs in the Atlantic Ocean. The depth of the thermocline in the eastern Atlantic

337 Ocean is known to be shallower than in the western Indian Ocean (Schott et al., 2009; Xie and
338 Carton, 2013). This difference may result in tunas occupying shallower depths and thus mixing
339 more regularly with non-tuna species. Such a phenomenon could provide an explanation for the
340 higher rates of false positives generated in the Atlantic Ocean (i.e., false detection of the
341 presence of tuna). The analysis of the relevance of the predictive factors in the random forest
342 classifications showed that, for both oceans, daytime periods were the most relevant factor for
343 distinguishing the presence of tuna schools from other acoustic targets. This result is likely
344 linked to the behaviour of tuna schools and their spatial and temporal distribution around
345 DFADs. Sonar surveys conducted on DFADs in the Indian Ocean revealed that tuna form a
346 large number of small and dispersed schools during the night, and few and larger schools during
347 daytime (Trygonis et al., 2016). Another possible reason could be related to the influence of the
348 diel vertical migration of the deep scattering layer to the near surface at night (Robinson and
349 Goómez-Gutiérrez, 1998), which may affect the acoustic signal.

350 In both oceans, the performance of the classification algorithm for discriminating between
351 different aggregation sizes was considerably less satisfactory than the presence/absence of
352 tunas. There are several possible explanations for these limitations. One potential source of bias
353 may stem from the differing species composition considered in each size class. Due to skipjack
354 tuna lacking a swim bladder, their acoustic response is very different from that of yellowfin or
355 bigeye tuna (Josse and Bertrand 2000; Boyra et al. 2018), as such an aggregation of a given size
356 would result in different acoustic signatures depending on the percentage of each species that
357 make it up. Another source of bias could be linked to the position of the tuna aggregation in
358 relation to the area that is sampled by the buoy (detection cone). Depending on the size of the
359 aggregation and the behaviour of tuna around the DFAD, it is likely that the buoy's acoustic
360 cone only detects part of the tuna aggregation, especially at shallow depths. Some
361 environmental factors could also affect both the acoustic signal detection and fish behaviour,

362 and could thus have an effect on the classification of the aggregation size. Water temperature,
363 for example, is known to have an effect on both the acoustic signal (Bamber and Hill, 1979;
364 Straube and Arthur, 1994) and the abundance of tuna (Boyce et al., 2008). As such, the
365 interpretation of buoy data, particularly concerning the accurate estimation of the aggregated
366 biomass, may be strongly influenced by area and season-specific factors. In addition, close
367 examination of the scores in the layer groups identified by the cluster analysis also revealed that
368 layers deeper than 50 m were characterized by very low scores (Fig. 4). Previous studies on the
369 vertical distribution of fish species under DFADs found that tuna regularly occurred below this
370 depth (Dagorn et al. 2007a; Dagorn et al. 2007b; Forget et al. 2015; Matsumoto et al. 2016;
371 Lopez et al., 2017). Consequently, it appears fair to assume that the low values obtained for
372 these depths are likely related to the limited detection capability of the device at such depths,
373 which may also explain the poor estimates of the size of the tuna schools.

374 The principle findings of this work showed that machine learning offers promising pathways
375 for processing acoustic data provided by commercial echosounder buoys. Although this work
376 has focused on a single model of buoy, it can easily be expanded to encompass other models
377 and brands. The only essential requirement is access to a large training database.

378 **5. Conclusion**

379 The methodology developed in this study provides an indicator of presence/absence of tuna
380 schools at DFADs in both the Atlantic and Indian Oceans, from simplified acoustic data
381 collected by one of the echosounder buoy models used in the tuna purse seine fishery. This
382 approach has the potential to summarize and analyse a large amount of acoustic data, with an
383 efficiency that obviously depends on the nature and quality of the data provided. Nevertheless,
384 the rapid and continuous evolution in echosounder buoys technology observed since their
385 introduction is likely to provide, over time, better and more detailed data, leading to a

386 substantial improvement in the performance of the proposed methodology, specifically
387 regarding assessment of aggregation sizes under DFADs. Applying this approach to other
388 echosounder buoy models, like new multi-frequency buoy models, widely adopted in recent
389 years, could also allow to assess and compare buoy reliabilities. Finally, although the
390 availability of more extensive databases (with matched acoustic and catch data) and more
391 detailed acoustic data (beyond the discrete 0 – 7 acoustic indices) could improve this
392 methodology, the accurate discrimination between the presence and absence of tuna schools
393 around DFADs obtained in this study constitutes a critical step towards the exploitation of
394 echosounder buoy data for providing novel and robust indicators of abundance for the
395 management of FAD fisheries in years to come.

396 **6. Acknowledgements**

397 This project was co-funded by “Observatoire des Ecosystèmes Pélagiques Tropicaux exploités”
398 (Ob7) from IRD/MARBEC and by the ANR project BLUEMED (ANR-14-ACHN-0002). The
399 authors are grateful to ORTHONGEL and its contracting parties (CFTO, SAPMER,
400 SAUPIQUET) for providing the echosounder buoys data. The authors also thank all the
401 skippers who gave their time to share their experience and knowledge on the echosounder
402 buoys. The authors sincerely thank the contribution of the staff of the Ob7 for their work on the
403 databases of the echosounder buoys and observer data. We are also sincerely grateful to the
404 buoy manufacturers for their useful advice and information on their echosounder buoys.

405

406 **References**

- 407 Albert, J.A., Beare, D., Schwarz, A.M., Albert, S., Warren, R., Teri, J., Siota, F., Andrew,
408 N.L., 2014. The contribution of nearshore fish aggregating devices (FADs) to food
409 security and livelihoods in Solomon Islands. *PLoS One* 9.
410 <https://doi.org/10.1371/journal.pone.0115386>
- 411 Baidai, Y., Capello, M., Billet, N., Floch, L., Simier, M., Sabarros, P., Dagorn, L., 2017.
412 Towards the derivation of fisheries-independent abundance indices for tropical tunas:
413 Progress in the echosounders buoys data analysis. IOTC-2017-WPTT19-22.
- 414 Bamber, J.C., Hill, C.R., 1979. Ultrasonic attenuation and propagation speed in mammalian
415 tissues as a function of temperature. *Ultrasound Med. Biol.* 5, 149–157.
416 [https://doi.org/10.1016/0301-5629\(79\)90083-8](https://doi.org/10.1016/0301-5629(79)90083-8)
- 417 Bosch, P., López, J., Ramírez, H., Robotham, H., 2013. Support vector machine under
418 uncertainty: An application for hydroacoustic classification of fish-schools in Chile.
419 *Expert Syst. Appl.* 40, 4029–4034.
420 <https://doi.org/https://doi.org/10.1016/j.eswa.2013.01.006>
- 421 Boyce, D., Tittensor, D., Worm, B., 2008. Effects of temperature on global patterns of tuna
422 and billfish richness. *Mar. Ecol. Prog. Ser.* 355, 267–276.
423 <https://doi.org/10.3354/meps07237>
- 424 Boyra, G., Moreno, G., Sobradillo, B., Pérez-Arjona, I., Sancristobal, I., Demer, D.A., 2018.
425 Target strength of skipjack tuna (*Katsuwonus pelamis*) associated with fish aggregating
426 devices (FADs). *ICES J. Mar. Sci.* 75, 1790–1802.
427 <https://doi.org/10.1093/icesjms/fsy041>
- 428 Brehmer, P., Sancho, G., Trygonis, V., Itano, D., Dalen, J., Fuchs, A., Faraj, A., Taquet, M.,
429 2018. Towards an Autonomous Pelagic Observatory: Experiences from Monitoring Fish
430 Communities around Drifting FADs. *Thalass. An Int. J. Mar. Sci.* 35, 177–189.
431 <https://doi.org/10.1007/s41208-018-0107-9>
- 432 Breiman, L., 2001. Random forests. *Mach. Learn.* 45, 5–32.
433 <https://doi.org/10.1023/A:1010933404324>
- 434 Capello, M., Deneubourg, J.L., Robert, M., Holland, K.N., Schaefer, K.M., Dagorn, L., 2016.
435 Population assessment of tropical tuna based on their associative behavior around

436 floating objects. *Sci. Rep.* 6, 1–14. <https://doi.org/10.1038/srep36415>

437 Castro, J.J., Santiago, J. a, Santana-Ortega, a T., 2002. A general theory on fish aggregation
438 to floating objects: An alternative to the meeting point hypothesis. *Rev. Fish Biol. Fish.*
439 11, 255–277. <https://doi.org/10.1023/A:1020302414472>

440 Cohen, J., 1968. Weighted kappa: Nominal scale agreement provision for scaled disagreement
441 or partial credit. *Psychol. Bull.* 70, 213–220. <https://doi.org/10.1037/h0026256>

442 Dagorn, L., Holland, K.N., Itano, D.G., 2007a. Behavior of yellowfin (*Thunnus albacares*)
443 and bigeye (*T. obesus*) tuna in a network of fish aggregating devices (FADs). *Mar. Biol.*
444 151, 595–606. <https://doi.org/10.1007/s00227-006-0511-1>

445 Dagorn, L., Pincock, D., Girard, C., Holland, K., Taquet, M., Sancho, G., Itano, D.,
446 Aumeeruddy, R., 2007b. Satellite-linked acoustic receivers to observe behavior of fish in
447 remote areas. *Aquat. Living Resour.* 20, 307–312. <https://doi.org/10.1051/alr:2008001>

448 Dagorn, L., Holland, K.N., Restrepo, V., Moreno, G., 2013. Is it good or bad to fish with
449 FADs? What are the real impacts of the use of drifting FADs on pelagic marine
450 ecosystems? *Fish Fish.* 14, 391–415. <https://doi.org/10.1111/j.1467-2979.2012.00478.x>

451 Davies, T.K., Mees, C.C., Milner-Gulland, E.J., 2014. The past, present and future use of
452 drifting fish aggregating devices (FADs) in the Indian Ocean. *Mar. Policy* 45, 163–170.
453 <https://doi.org/10.1016/j.marpol.2013.12.014>

454 Deudero, S., Merella, P., Massutí, E., Alemany, F., 1999. Fish communities associated with
455 FADs. *Sci. Mar.* 63, 199–207.

456 Fernandes, P.G., 2009. Classification trees for species identification of fish-school echotraces.
457 *ICES J. Mar. Sci.* 66, 1073–1080. <https://doi.org/10.1093/icesjms/fsp060>

458 Filmalter, J.D., Dagorn, L., Cowley, P.D., Taquet, M., 2011. First Descriptions of the
459 Behavior of Silky Sharks, *Carcharhinus Falciformis*, Around Drifting Fish Aggregating
460 Devices in the Indian Ocean. *Bull. Mar. Sci.* 87, 325–337.
461 <https://doi.org/10.5343/bms.2010.1057>

462 Fonteneau, A., Chassot, E., Bodin, N., 2013. Global spatio-temporal patterns in tropical tuna
463 purse seine fisheries on drifting fish aggregating devices (DFADs): Taking a historical
464 perspective to inform current challenges. *Aquat. Living Resour.* 26, 37–48.
465 <https://doi.org/10.1051/alr/2013046>

466 Fonteneau, A., Chassot, E., Gaertner, D., 2015. Managing tropical tuna purse seine fisheries
467 through limiting the number of drifting fish aggregating devices in the Atlantic: food for
468 thought. *Collect. Vol. Sci. Pap. ICCAT*, 71(1), 460-475.

469 Fonteneau, A., Gaertner, D., Nordstrom, V., 1999. An overview of problems in the CPUE-
470 abundance relationship for the tropical purse seine fisheries. *Collect. Vol. Sci. Pap.*
471 *ICCAT* 49, 259–276.

472 Fonteneau, A., Gascuel, D., Pallarés, P., 1998. Vingt-cinq ans d'évaluation des ressources
473 thonières de l'Atlantique : Quelques réflexions methodologiques. *Collect. Vol. Sci. Pap.*
474 *ICCAT* 50, 523–561.

475 Forget, F.G., Capello, M., Filmalter, J.D., Govinden, R., Soria, M., Cowley, P.D., Dagorn, L.,
476 2015. Behaviour and vulnerability of target and non-target species at drifting fish
477 aggregating devices (FADs) in the tropical tuna purse seine fishery determined by
478 acoustic telemetry. *Can. J. Fish. Aquat. Sci.* 72, 1398–1405.
479 <https://doi.org/10.1139/cjfas-2014-0458>

480 Gaertner, D., Ariz, J., Bez, N., Clermidy, S., Moreno, G., Murua, H., Soto, M., 2015. Catch,
481 effort, and ecosystem impacts of fad-fishing (CECOFAD). *Collect. Vol. Sci. Pap. ICCAT*
482 71, 525–539.

483 Goujon, M., Maufroy, A., Relot-Stirnemann, A., Moëc, E., Bach, P., Cauquil, P., and
484 Sabarros, P., 2017. Collecting data on board French tropical tuna purse seiners with
485 common observers: results of ORTHONGEL's voluntary observer program OCUP in the
486 Atlantic Ocean (2013-2017). IOTC-2017-WPDCS-22.

487 Goujon, M., Maufroy, A., Cauquil, P., Sabarros, P., and Bach, P., 2018. Collecting data on
488 board French tropical tuna purse seiners with common observers: results of
489 ORTHONGEL's voluntary observer program ocup in the Atlantic Ocean (2013-2017).
490 *Collect. Vol. Sci. Pap. ICCAT* 74, 3784–3805.

491 Govinden, R., Jauhary, R., Filmalter, J., Forget, F., Soria, M., Adam, S., Dagorn, L., 2013.
492 Movement behaviour of skipjack (*Katsuwonus pelamis*) and yellowfin (*Thunnus*
493 *albacares*) tuna at anchored fish aggregating devices (FADs) in the Maldives,
494 investigated by acoustic telemetry. *Aquat. Living Resour.* 26, 69–77.
495 <https://doi.org/10.1051/alr/2012022>

496 Josse, E., Bertrand, A., 2000. In situ acoustic target strength measurements of tuna associated

497 with a fish aggregating device. *ICES J. Mar. Sci.* 57, 911–918.
498 <https://doi.org/10.1006/jmsc.2000.0578>

499 Kakuma, S., 2001. Synthesis on moored FADs in the North West Pacific region. *Actes*
500 *Colloq. IFREMER* 63–77.

501 Kuhn, M., 2008. Building Predictive Models in R Using the caret Package. *J. Stat. Softw.* 28,
502 1–26. <https://doi.org/10.1053/j.sodo.2009.03.002>

503 Kuhn, M., Johnson, K., 2013. Applied Predictive Modeling, Applied Predictive Modeling.
504 Springer New York, New York, NY. <https://doi.org/10.1007/978-1-4614-6849-3>

505 Lennert-Cody, C.E., Hall, M.A., 2001. The development of the purse seine fishery on drifting
506 Fish Aggregating Devices in the eastern Pacific Ocean: 1992-1998. *Actes Colloq.*
507 *IFREMER* 78–107.

508 Liaw, A., Wiener, M., 2002. Classification and regression by randomForest. *R news* 2, 18–22.
509 <https://doi.org/10.1177/154405910408300516>

510 Lopez, J., Moreno, G., Boyra, G., Dagorn, L., 2016. A model based on data from echosounder
511 buoys to estimate biomass of fish species associated with fish aggregating devices. *Fish.*
512 *Bull.* 114, 166–178. <https://doi.org/10.7755/FB.114.2.4>

513 Lopez, J., Moreno, G., Ibaibarriaga, L., Dagorn, L., 2017. Diel behaviour of tuna and non-
514 tuna species at drifting fish aggregating devices (DFADs) in the Western Indian Ocean,
515 determined by fishers' echo-sounder buoys. *Mar. Biol.* 164, 44.
516 <https://doi.org/10.1007/s00227-017-3075-3>

517 Lopez, J., Moreno, G., Sancristobal, I., Murua, J., 2014. Evolution and current state of the
518 technology of echo-sounder buoys used by Spanish tropical tuna purse seiners in the
519 Atlantic, Indian and Pacific Oceans. *Fish. Res.* 155, 127–137.
520 <https://doi.org/10.1016/j.fishres.2014.02.033>

521 Macusi, E.D., Abreo, N.A.S., Babaran, R.P., 2017. Local Ecological Knowledge (LEK) on
522 Fish Behavior Around Anchored FADs: the Case of Tuna Purse Seine and Ringnet
523 Fishers from Southern Philippines. *Front. Mar. Sci.* 4, 1–13.
524 <https://doi.org/10.3389/fmars.2017.00188>

525 Malfante, M., Mars, J.I., Dalla Mura, M., Gervaise, C., 2018. Automatic fish sounds
526 classification. *J. Acoust. Soc. Am.* 143, 2834–2846. <https://doi.org/10.1121/1.5036628>

527 Matsumoto, T., Satoh, K., Semba, Y., Toyonaga, M., 2016. Comparison of the behavior of
528 skipjack (*Katsuwonus pelamis*), yellowfin (*Thunnus albacares*) and bigeye (*T. obesus*)
529 tuna associated with drifting FADs in the equatorial central Pacific Ocean. *Fish.*
530 *Oceanogr.* 25, 565–581. <https://doi.org/10.1111/fog.12173>

531 Maufroy, A., Kaplan, D.M., Bez, N., De Molina, A.D., Murua, H., Floch, L., Chassot, E.,
532 2017. Massive increase in the use of drifting Fish Aggregating Devices (dFADs) by
533 tropical tuna purse seine fisheries in the Atlantic and Indian Oceans. *ICES J. Mar. Sci.*
534 74, 215–225. <https://doi.org/10.1093/icesjms/fsw175>

535 Maunder, M.N., Sibert, J.R., Fonteneau, A., Hampton, J., Kleiber, P., Harley, S.J., 2006.
536 Interpreting catch per unit effort data to assess the status of individual stocks and
537 communities. *ICES J. Mar. Sci.* 63, 1373–1385.
538 <https://doi.org/10.1016/j.icesjms.2006.05.008>

539 Mitsunaga, Y., Endo, C., Anraku, K., Selorio, C.M., Babaran, R.P., 2012. Association of early
540 juvenile yellowfin tuna *Thunnus albacares* with a network of payaos in the Philippines.
541 *Fish. Sci.* 78, 15–22. <https://doi.org/10.1007/s12562-011-0431-y>

542 Moreno, G., Boyra, G., Sancristobal, I., Itano, D., Restrepo, V., 2019. Towards acoustic
543 discrimination of tropical tuna associated with Fish Aggregating Devices. *PLoS One* 14,
544 e0216353. <https://doi.org/10.1371/journal.pone.0216353>

545 Moreno, G., Dagorn, L., Capello, M., Lopez, J., Filmalter, J., Forget, F., Sancristobal, I.,
546 Holland, K., 2016. Fish aggregating devices (FADs) as scientific platforms. *Fish. Res.*
547 178, 122–129. <https://doi.org/10.1016/j.fishres.2015.09.021>

548 Moreno, G., Dagorn, L., Sancho, G., Itano, D., 2007. Fish behaviour from fishers' knowledge:
549 the case study of tropical tuna around drifting fish aggregating devices (DFADs). *Can. J.*
550 *Fish. Aquat. Sci.* 64, 1517–1528. <https://doi.org/10.1139/f07-113>

551 Muir, J., Itano, D., Hutchinson, M., Leroy, B., Holland, K., 2012. Behavior of target and non-
552 target species on drifting FADs and when encircled by purse seine gear. *West. Cent.*
553 *Pacific Fish. Commission - Sci. Comm.* 8 8 pp.

554 Murtagh, F., Legendre, P., 2014. Ward's Hierarchical Agglomerative Clustering Method:
555 Which Algorithms Implement Ward's Criterion? *J. Classif.* 31, 274–295.
556 <https://doi.org/10.1007/s00357-014-9161-z>

557 Nelson, P.A., 2003. Marine fish assemblages associated with fish aggregating devices
558 (FADs): Effects of fish removal, FAD size, fouling communities, and prior recruits. *Fish.*
559 *Bull.* 101, 835–850.

560 Noda, J.J., Travieso, M.C., Sánchez-Rodríguez, D., Travieso, C.M., Sánchez-Rodríguez, D.,
561 2016. Automatic Taxonomic Classification of Fish Based on Their Acoustic Signals.
562 *Appl. Sci.* 6, 443. <https://doi.org/10.3390/app6120443>

563 Orue, B., Lopez, J., Moreno, G., Santiago, J., Boyra, G., Soto, M., Murua, H., 2019a. Using
564 fishers' echo-sounder buoys to estimate biomass of fish species associated with drifting
565 fish aggregating devices in the Indian Ocean. *Rev. Investig. Mar. AZTI* 26, 1–13.

566 Orue, B., Lopez, J., Moreno, G., Santiago, J., Soto, M., Murua, H., 2019b. Aggregation
567 process of drifting fish aggregating devices (DFADs) in the Western Indian Ocean: Who
568 arrives first, tuna or non-tuna species? *PLoS One* 14, e0210435.
569 <https://doi.org/10.1371/journal.pone.0210435>

570 Probst, P., Wright, M.N., Boulesteix, A.L., 2019. Hyperparameters and tuning strategies for
571 random forest. *Wiley Interdiscip. Rev. Data Min. Knowl. Discov.* 9(3), 1-15.
572 <https://doi.org/10.1002/widm.1301>

573 R Core Team, 2019. R: A language and environment for statistical computing. R Found Stat
574 Comput. <https://www.R-project.org/>

575 Robinson, C.J., Goómez-Gutiérrez, J., 1998. Daily vertical migration of dense deep
576 scattering layers related to the shelf-break area along the northwest coast of Baja
577 California, Mexico. *J. Plankton Res.* 20, 1679–1697.
578 <https://doi.org/10.1093/plankt/20.9.1679>

579 Robotham, H., Bosch, P., Gutiérrez-Estrada, J.C., Castillo, J., Pulido-Calvo, I., 2010.
580 Acoustic identification of small pelagic fish species in Chile using support vector
581 machines and neural networks. *Fish. Res.* 102, 115–122.
582 <https://doi.org/https://doi.org/10.1016/j.fishres.2009.10.015>

583 Roch, M.A., Soldevilla, M.S., Hoenigman, R., Wiggins, S.M., Hildebrand, J.A., 2008.
584 Comparison of machine learning techniques for the classification of echolocation clicks
585 from three species of odontocetes. *Can. Acoust.* 36(1), 41–47.

586 Santiago, J., Lopez, J., Moreno, G., Quincoces, I., Soto, M., Murua, H., 2016. Towards a

587 Tropical Tuna Buoy-derived Abundance Index (TT-BAI). *Collect. Vol. Sci. Pap. ICCAT*
588 72, 714–724.

589 Schott, F.A., Xie, S.P., McCreary, J.P., 2009. Indian Ocean circulation and climate variability.
590 *Rev. Geophys.* 47, 1–46. <https://doi.org/10.1029/2007RG00024>

591 Straube, W.L., Arthur, R.M., 1994. Theoretical estimation of the temperature dependence of
592 backscattered ultrasonic power for noninvasive thermometry. *Ultrasound Med. Biol.* 20,
593 915–922. [https://doi.org/10.1016/0301-5629\(94\)90051-5](https://doi.org/10.1016/0301-5629(94)90051-5)

594 Taquet, M., Dagorn, L., Gaertner, J.-C., Girard, C., Aumerruddy, R., Sancho, G., Itano, D.,
595 2007. Behavior of dolphinfish (*Coryphaena hippurus*) around drifting FADs as observed
596 from automated acoustic receivers. *Aquat. Living Resour.* 20, 323–330.
597 <https://doi.org/10.1051/alr:2008008>

598 Torres-Irineo, E., Gaertner, D., Chassot, E., Dreyfus-León, M., 2014. Changes in fishing
599 power and fishing strategies driven by new technologies: The case of tropical tuna purse
600 seiners in the eastern Atlantic Ocean. *Fish. Res.* 155, 10–19.
601 <https://doi.org/10.1016/j.fishres.2014.02.017>

602 Trygonis, V., Georgakarakos, S., Dagorn, L., Brehmer, P., 2016. Spatiotemporal distribution
603 of fish schools around drifting fish aggregating devices. *Fish. Res.* 177, 39–49.
604 <https://doi.org/10.1016/j.fishres.2016.01.013>

605 Uranga, J., Arrizabalaga, H., Boyra, G., Hernandez, M.C., Goñi, N., Arregui, I., Fernandes,
606 J.A., Yurramendi, Y., Santiago, J., 2017. Detecting the presence-Absence of bluefin tuna
607 by automated analysis of medium-range sonars on fishing vessels. *PLoS One* 12, 1–18.
608 <https://doi.org/10.1371/journal.pone.0171382>

609 Xie, S.-P., Carton, J.A., 2013. Tropical Atlantic Variability: Patterns, Mechanisms, and
610 Impacts, in: *Earth Climate: The Ocean-Atmosphere Interaction*, Geophys. Monogr. pp.
611 121–142. <https://doi.org/10.1029/147GM07>

612 Zaugg, S., van der Schaar, M., Houégnyan, L., Gervaise, C., André, M., 2010. Real-time
613 acoustic classification of sperm whale clicks and shipping impulses from deep-sea
614 observatories. *Appl. Acoust.* 71, 1011–1019.
615 <https://doi.org/https://doi.org/10.1016/j.apacoust.2010.05.005>

616

617 **Tables**

618 Table 1: Number of fishing sets (with catch ≥ 1 ton), visit and deployment data collected from
 619 2013-2018 and used in the presence-absence classification for the Atlantic and Indian Oceans.

	Atlantic Ocean			Indian Ocean		
	Catch	Visit	Deployment	Catch	Visit	Deployment
Logbook	817	255	405	2918	1031	6722
Observers	151	0	228	513	0	2487
Total	968	255	633	3431	1031	9209

620

621 Table 2: Structure of the training dataset used in the presence-absence and multiclass
 622 classification for the Atlantic and Indian Oceans (over the period 2013-2018).

Ocean	No tuna	Tuna		
		< 10 tons	[10, 25 tons]	> 25 tons
Atlantic	888	397	303	268
Indian	10240	904	1288	1239

623

624 Table 3: Summary statistics of major tuna catches (in tons) from DFAD fishing operations
 625 collected from observer and logbook databases from 2013 to 2018, in the Atlantic and Indian
 626 Oceans. (Min. and Max. denote for minimum and maximum catch values, respectively. SD
 627 represents standard deviation and Qu. stands for quantile)

Ocean	Min.	1 st Qu.	Median	Mean	3 rd Qu.	Max.	SD
Atlantic	1	6	15	22.61	30	177.70	25.59
Indian	1	10	20	26.73	34	300	26.77

628

629 Table 4: Summary of tuna presence/absence classification performances for the Atlantic and
630 Indian Oceans: mean and standard deviation values (in brackets) of evaluation metrics.

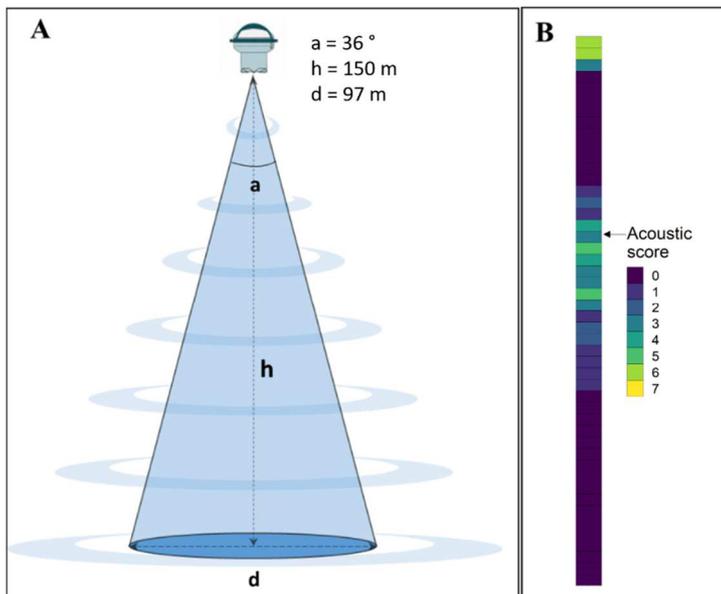
Evaluation Metrics	Atlantic	Indian
Accuracy	0.75 (0.02)	0.85 (0.01)
Kappa	0.51 (0.04)	0.70 (0.02)
Sensitivity	0.83 (0.02)	0.81 (0.01)
Specificity	0.67 (0.03)	0.90 (0.01)
Precision	0.73 (0.03)	0.88 (0.01)

631

632 Table 5: Summary of multiclass classification performances for the Atlantic and Indian Ocean. Mean and standard deviation (in brackets) of
 633 evaluation metrics

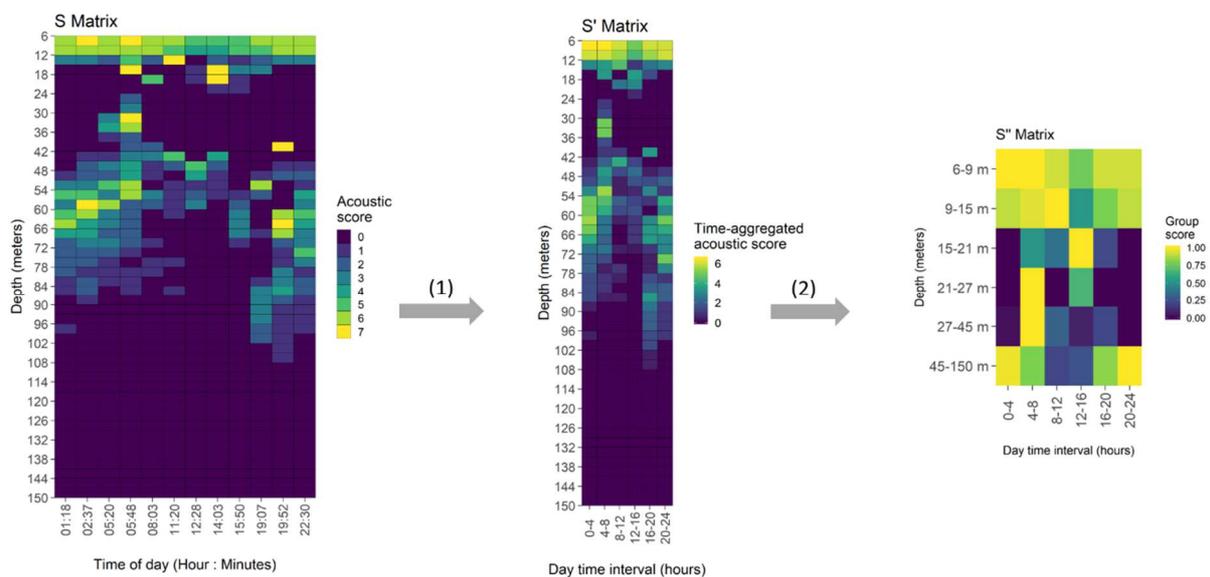
	Atlantic Ocean				Indian Ocean			
	No tuna	<10 tons	[10 , 25 tons]	> 25 tons	No tuna	<10 tons	[10 , 25 tons]	> 25 tons
Sensitivity	0.67 (0.03)	0.36 (0.05)	0.24 (0.08)	0.34 (0.06)	0.87 (0.03)	0.19 (0.01)	0.29 (0.02)	0.54 (0.04)
Specificity	0.82 (0.02)	0.80 (0.03)	0.84 (0.04)	0.85 (0.04)	0.80 (0.01)	0.91 (0.01)	0.82 (0.02)	0.77 (0.01)
Precision	0.77 (0.03)	0.32 (0.04)	0.22 (0.04)	0.28 (0.05)	0.59 (0.02)	0.42 (0.04)	0.35 (0.03)	0.44 (0.02)
Accuracy	0.48 (0.02)				0.47 (0.02)			
Kappa	0.26 (0.03)				0.30 (0.02)			

634



636

637 Fig. 1: Technical specifications of the Marine Instruments M3I echosounder buoy. (A): beam
 638 width or cover angle (a), depth range (h), and diameter (D) at 150 m, (B): example of an acoustic
 639 sample

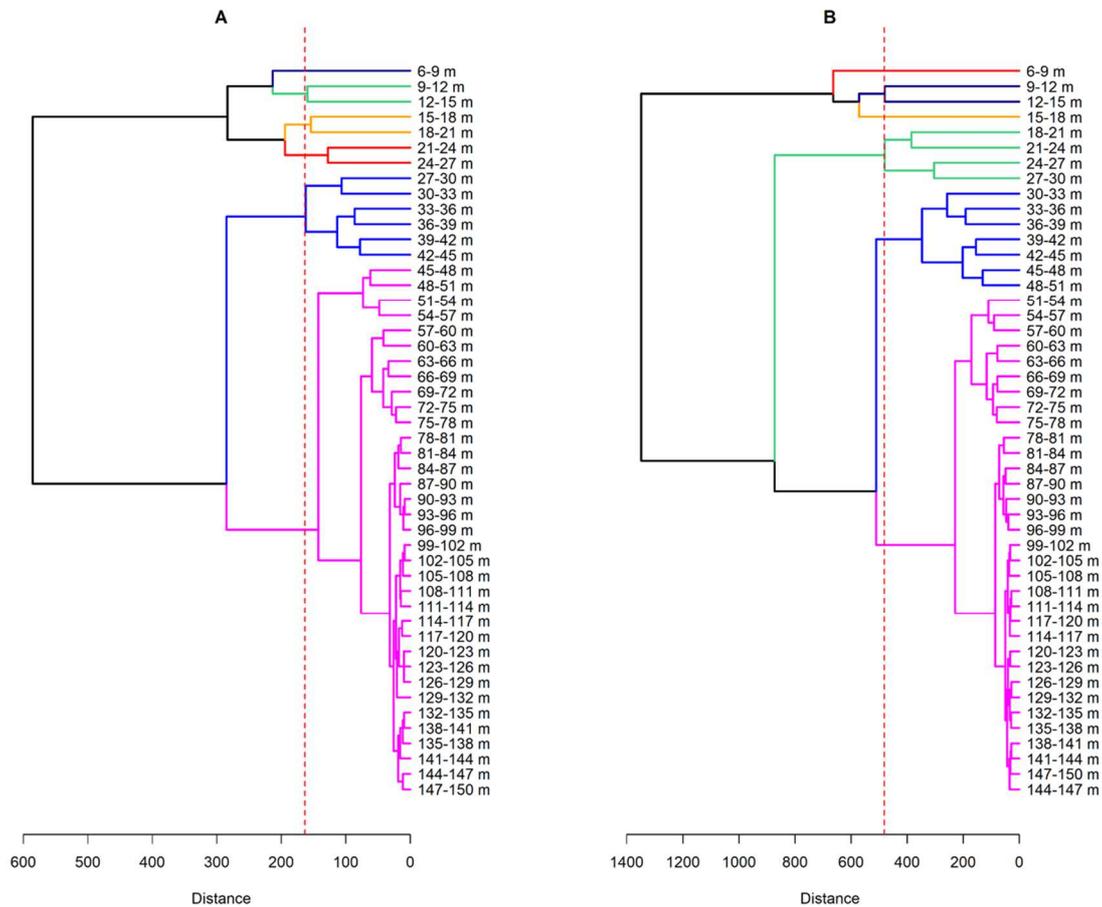


640

641 Fig. 2 : Schematic view of the acoustic data pre-processing. (1) Temporal resolution reduction,
 642 averaging acoustic samples over a 4-hour period. (2) Layer aggregation combining the 48
 643 vertical layers into 6 layers based on cluster analysis. The final output is a 6x6 matrix
 644 summarizing the acoustic signal recorded over 24 hours between 6 and 150 m. Acoustic scores

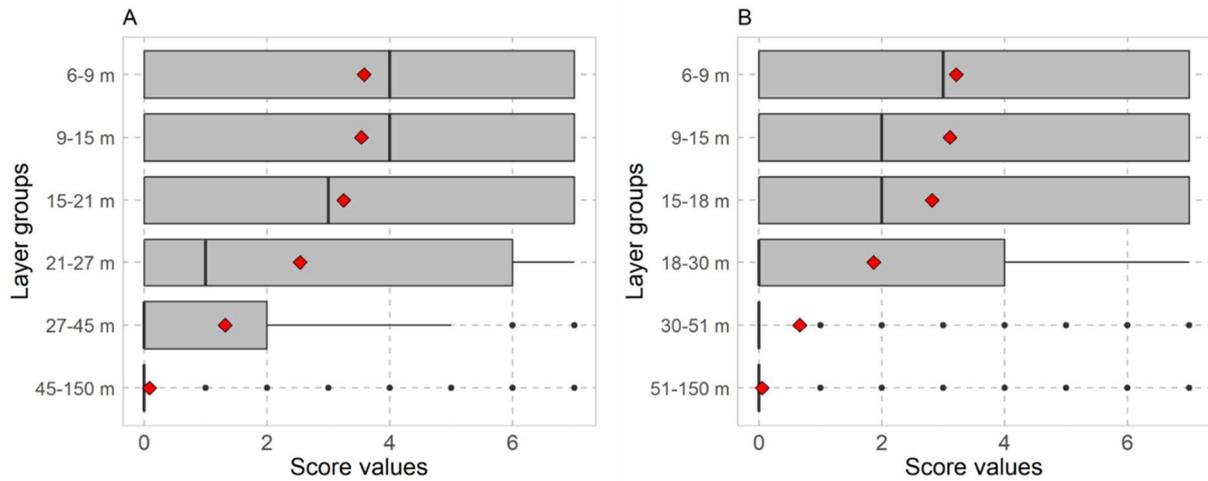
645 are integer values (ranging from 0 to 7), representing the intensity of the acoustic backscattered
 646 signal per 3 m depth layer. Time-aggregated acoustic scores represent the average value of the
 647 acoustic scores over the 4-hour interval. Group scores represent the sum of layer scores (scaled
 648 between 0 and 1) per homogeneous group of layers identified from the clustering analysis.

649



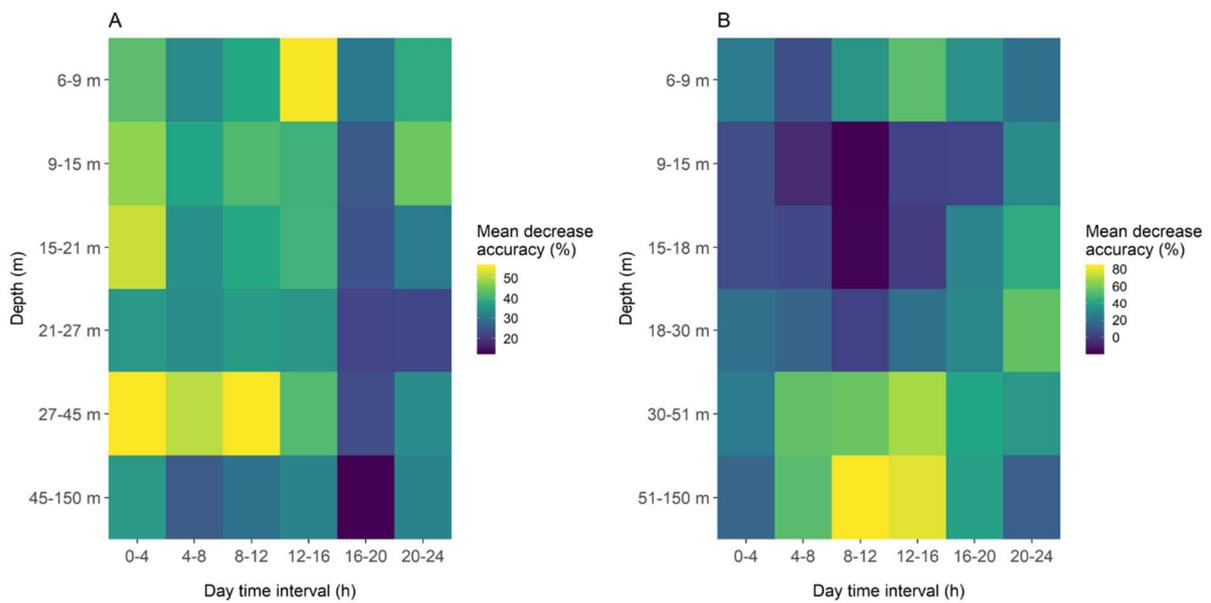
650

651 Fig. 3: Dendrogram from the cluster analysis of raw acoustic data for the Atlantic (A) and Indian
 652 (B) Oceans. The red horizontal line indicates the height at which the dendrogram was sliced to
 653 create the 6 groups of layers. Colors identify the different groups of depth layers used to pre-
 654 process the acoustic data.



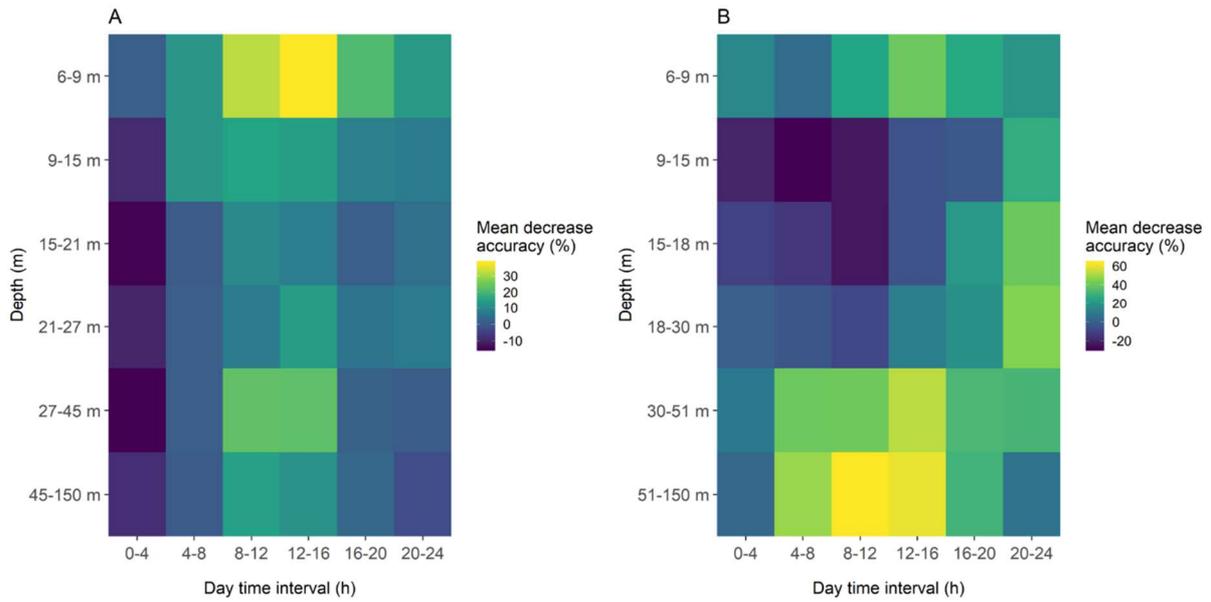
655

656 Fig. 4: Boxplot of acoustic score values in the aggregated-layer groups identified by the cluster
 657 analysis, for the Atlantic (A), and Indian (B) Oceans. Red diamonds represent mean value of
 658 scores in each layer group.



659

660 Fig. 5: Importance of depth layers and day period in presence/absence classification for the
 661 Atlantic (A) and Indian (B) Oceans. Each cell represents a combination of depth and time
 662 period. Colours indicates the importance of the predictor in the classification.



663

664 Fig. 6: Importance of depth layers and day period in multiclass classification for the Atlantic
 665 (A) and Indian (B) Oceans. Each cell represents a combination of depth and time period.
 666 Colours indicates the importance of the predictor in the classification.