

Tracking and monitoring fin whales offshore northwest Spain using passive acoustic methods

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Abstract:

Fin whales produce regular vocalizations with a dominant frequency of c. 20 Hz, similar to that of large airgun sources used in marine seismic surveys. Thus these vocalizations may be recorded on ocean bottom seismometers (OBS) or hydrophones (OBH) deployed during such surveys. We used data recorded by an array of 72 OBS/H with 4-6.5 km spacing, deployed offshore northwest Spain during June-August 2013, to study fin whale movements in this area. Whale vocalizations were identified automatically using signal processing techniques and localized using time delay estimates between several instruments. Airgun shooting took place during the deployment period, but we found no evidence for a correlation between vocalization detection rate and the presence or absence of shooting. Our analysis focused on six fin whale tracks identified during this period. Uncertainties in depth lead to poor confidence intervals, preventing effective analysis of diving behavior for the identified tracks. In the horizontal plane, the localizations had a higher degree of confidence. Use of a Kalman filter resulted in smoother tracks. Mean swim velocities range from 2 to 15 km/hr, and the animals traveled distances of 1.5-15 km in the periods analyzed.

Keywords: ocean acoustics, marine mammals, acoustic tracking

32 **1. Introduction**

33 *Passive acoustic monitoring*

34 Passive acoustic monitoring (PAM) has been used increasingly to study cetaceans because
35 studying marine life from visual observations can be challenging [Moore *et al.*, 2006]. Visual
36 monitoring is limited to daylight hours and periods of good weather, and it is difficult to infer
37 animal behavior from brief and rare sightings. Cetaceans use sound for communication, navigation
38 and locating prey [Nowacek *et al.*, 2016], and it has become clear that detecting their vocalizations
39 is an effective monitoring method that can complement visual observations [Mellinger *et al.*,
40 2007]. PAM can be conducted without interfering with the cetaceans in their natural environment
41 over extended periods of time [Zimmer, 2011]. Recent technological advances mean that acoustic
42 surveys can be conducted at lower expense and over greater periods of time than ever before. Here
43 we use fixed hydrophone PAM to study fin whales (*Balaenoptera physalus*) from their
44 vocalizations (calls). This is a highly efficient technique because at certain times of the year fin
45 whales vocalize frequently and the sound can be detected and recorded at distances of tens of
46 kilometers [McDonald *et al.*, 1995; Stafforda *et al.*, 2007].

47

48 Typically hydrophones are used for passive acoustic surveys and are either towed behind a vessel
49 or fixed in place on the sea floor [Mellinger *et al.*, 2007]. The use of fixed hydrophones can be
50 subdivided into cabled long-term deployments [Au and Lammers, 2016; Clark *et al.*, 2019;
51 McCarthy *et al.*, 2011], where data is returned to shore in real-time (or near real-time) and shorter
52 term deployments of autonomous recorders, that need to be retrieved for data collection [Nguyen
53 Hong Duc *et al.*, 2021; Wiggins and Hildebrand, 2007]. In some instances, as is the case in the
54 work detailed here, the instruments are deployed for an objective unrelated to PAM and the
55 analysis to obtain information regarding marine mammals is secondary [Clark, 1995]. The use of
56 multiple instruments with close spacing allows vocalizations to be detected on several
57 hydrophones and thus to be used to track the source of the sound [Zimmer, 2011]. Ocean bottom
58 seismometers/hydrophones (OBS/H) provide one type of instrument from which make these
59 opportunistic observations of marine mammals [Harris *et al.*, 2013; Harris *et al.*, 2018; Iwase,
60 2015; Matias and Harris, 2015; Rebull *et al.*, 2006]. Such instruments provide a well-suited
61 platform to observe deep-water marine mammals that produce low-frequency sounds. In
62 particular, the distinctive, high intensity calls of fin whales provide an obvious candidate for study.

63

64 By using techniques developed for earthquake seismology, even a single OBS can be used to
65 estimate range to a vocalizing animal [Harris *et al.*, 2013]. A network of devices can be used to
66 improve the localization accuracy, for example, using the time difference of arrivals [Dunn and
67 Hernandez, 2009]. In addition, it has been demonstrated that surface reflections can be used to
68 estimate the depth of a calling whale [Pereira *et al.*, 2020b]. These data can be used for marine
69 management planning and to obtain ecologically significant parameters, such as animal density
70 [Harris *et al.*, 2018].

71

72 *Fin whale vocalizations*

73 Fin whales vocalize within the frequency range 15-142 Hz [Edds, 1988; Širović *et al.*, 2007;
74 Thompson *et al.*, 1992; Watkins *et al.*, 1987]. The low frequency means that their calls can
75 propagate large distances and are likely to be used for communication or navigation [Croll *et al.*,
76 2002; Edds-Walton, 1997; Sirovic *et al.*, 2013]. The most commonly studied fin whale call is the
77 “20 Hz call” [Hatch and Clark, 2004] that here will be considered as the “classic” call and has
78 maximum energy at 21 Hz [Clark *et al.*, 2002]. These calls have a distinctive down sweep in
79 frequency [Locke and White, 2011] which can be obscured at longer ranges where reverberation
80 and attenuation can make this structure difficult to observe. This classic call typically has a signal
81 energy of 40 J, a signal length of approximately 1 s, and a source level measured using OBSs of c.
82 189 dB re 1 μ Pa m [Weirathmueller *et al.*, 2013; Zimmer, 2011].

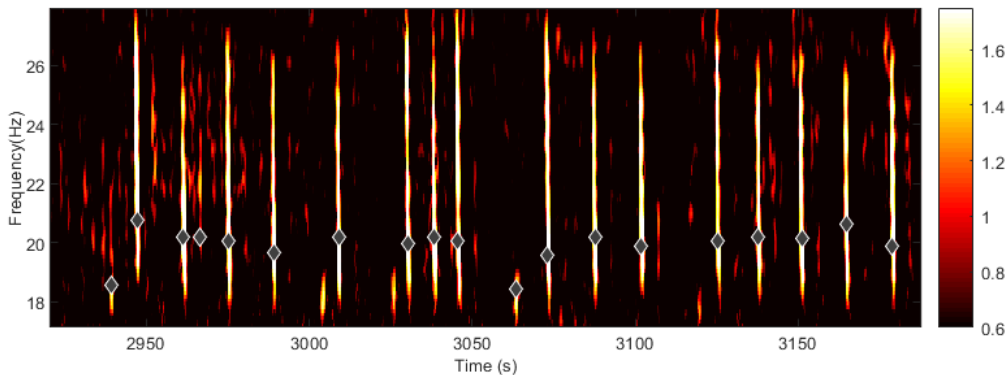
83

84 The calls are typically emitted in trains within which there are interspersed “backbeat” calls which
85 are upweeps that are shorter in duration than the classic calls, have a narrower bandwidth and are
86 approximately 1 Hz lower in frequency (Fig. 1). These sequences of calls may vary in duration
87 and call combinations depending on the activity or social behavior of the fin whale [Edds-Walton,
88 1997; McDonald *et al.*, 1995]. Variations in call trains also have been observed between different
89 fin whale populations and may develop over time. Intervals between consecutive classic calls, the
90 so-called inter-note interval (INI), typically range between 7 and 26 seconds [Watkins *et al.*, 1987].
91 For example, mean intervals are c. 13 s in the eastern North Atlantic but c. 15 s in the western
92 Mediterranean, indicating the presence of two distinct populations [Castellote *et al.*, 2012].
93 Intervals longer than the normal INIs are referred to as rests, and typically last for several minutes

94 [Watkins et al., 1987]. These rests correspond to periods when the whale surfaces to breathe, or
95 dives deep, and the typical rest periods for these activities are 150 s and 600 s, respectively
96 [McDonald et al., 1995]. In cases where calling ceases for over 20 minutes, the silent period is
97 referred to as a “gap” [Watkins et al., 1987].

98
99 Baleen whales commonly migrate between summer feeding grounds at high latitudes and winter
100 breeding and calving grounds at lower latitudes [Kellogg, 1929], but a wide range of migratory
101 behaviors has been observed [Geijer et al., 2016]. Detection of vocalizations in temperate latitudes
102 is strongly seasonal, with peak activity in the winter months and limited activity in the summer
103 [Pereira et al., 2020a; Watkins et al., 1987]. This variation may be linked both to migration
104 patterns and to seasonal variations in behavior associated with the mating season [Oleson et al.,
105 2014]. However, a tagging study near the Azores that focused on the months of March to May in
106 2010-2012 suggested that tagged animals were foraging whilst on a northward migration towards
107 Greenland [Silva et al., 2013].

108

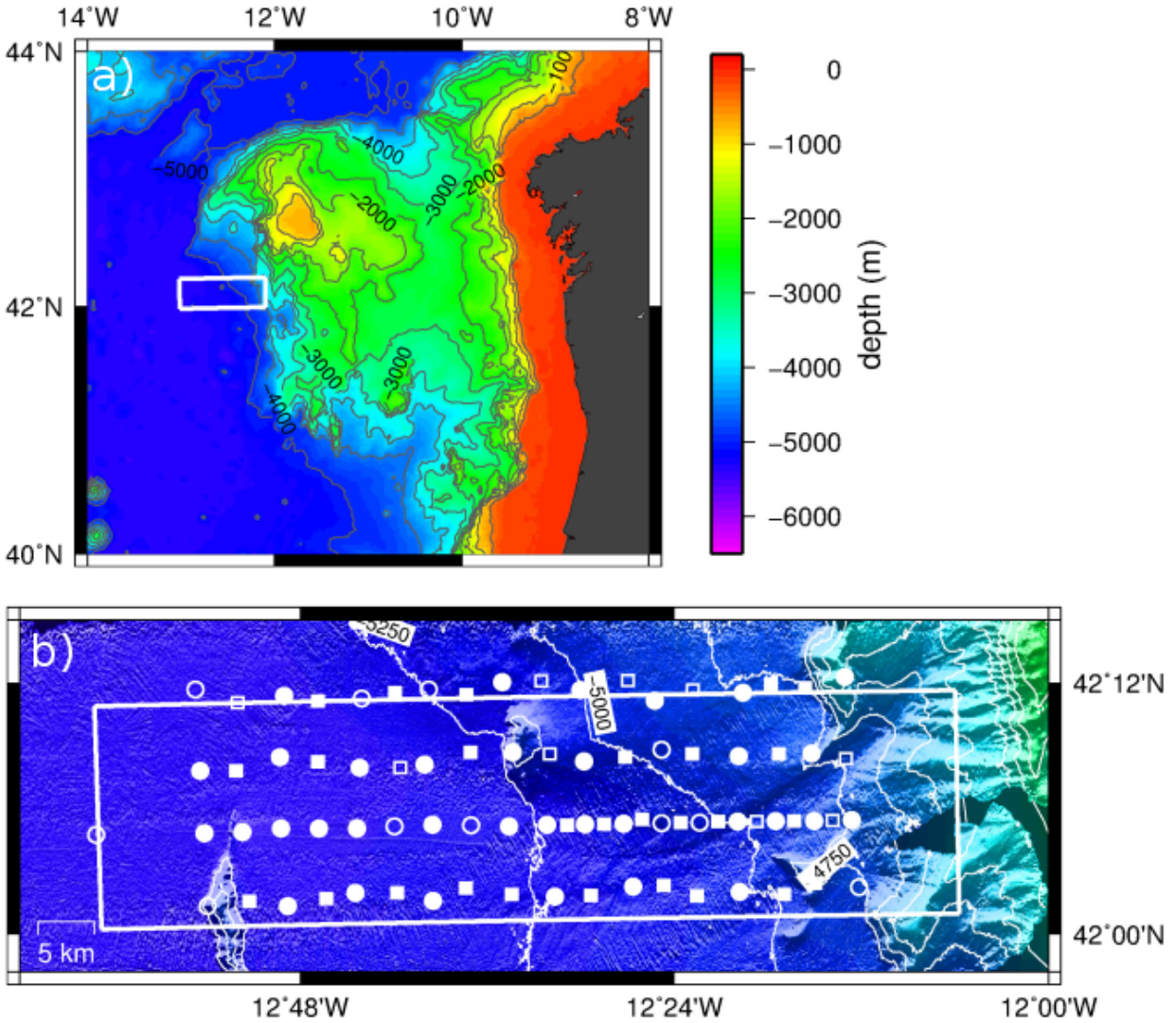


109
110 Figure 1: Normalized spectrogram illustrating a typical fin whale call pattern observed in our
111 dataset. The normalization is described in the text. Broader-band signals are classic calls and
112 narrower-band signals are backbeats. Grey diamond markers indicate call detections by our
113 automated algorithm.

114
115 *Data available for this study*

116 Our dataset comes from 50 four-component ocean bottom seismometers (OBSs) [Minshull et al.,
117 2005] and 28 ocean bottom hydrophones (OBHs) deployed on the seabed in c. 5 km water depth

118 during May-August 2013 as part of the Galicia3D study (Fig. 2), which was focused on the
119 structure of the crust and uppermost mantle in a region where the crust is highly stretched
120 [Bayrakci *et al.*, 2016; Schuba *et al.*, 2018]. The deployment covered the summer period when
121 fewer fin whale vocalizations are expected, and indeed fewer were observed during an OBS
122 deployment offshore Iberia to the south of our study area [Pereira *et al.*, 2020a]. However, the
123 deployment was within an area where fin whales have been previously detected acoustically in the
124 summer months [Rebull *et al.*, 2006]. The instruments were distributed in a 18 x 4 grid with an
125 east-west spacing of c. 6.5 km and a north-south spacing of c. 4 km, to cover an area of 80 km x
126 25 km, with an additional six instruments on a line extending further west that provided limited
127 useful data for our study. Several OBS/H were not retrieved or returned with no usable data,
128 leaving 44 OBSs and 26 OBHs that could be used for our study. OBSs recorded at a sample rate
129 of 250 Hz and OBHs at 200 Hz, with the OBS data being down-sampled to 200 Hz, so that a
130 consistent sample rate was used for all data. Differences in hardware meant that the OBHs and
131 some OBSs recorded for the entire period of their deployment, while other OBSs lost battery power
132 before recovery. The survey involved active airgun shooting during the periods 5th-23rd June
133 (Julian days 156-174) and 16th-31st July (Julian days 197-212), with the survey vessel returning to
134 port in between these periods because of an engine failure. For this study, we used hydrophone
135 data recorded from 5th June to 12th August (Julian days 156-224). Instrument clocks were
136 synchronized with Universal Time on deployment and recovery, and a linear clock drift assumed
137 between these times. Instruments used for detection and location had a mean drift rate of 4 ms/day
138 and the maximum rate was 25 ms/day. If such synchronization was not possible or the clock drift
139 rate was larger, the data were not used. Instrument locations on the seabed were determined using
140 the travel-times of airgun shots [Bayrakci *et al.*, 2016].



141
 142 Figure 2: (a) White box marks survey area on the Deep Galicia Margin. Bathymetry is from Smith
 143 and Sandwell (1997). (b) Swath bathymetric grid of survey area. Circles mark OBS locations and
 144 squares mark OBH locations, with filled symbols marking instruments that provided usable data
 145 for this study. White box marks area of airgun shooting.

146
 147 **2. Methods**

148 *Call detection*

149 The recorded data were first converted to day-long WAV files, to allow for audio playback at an
 150 increased speed that renders the vocalizations audible to the human ear. Our analysis is based on
 151 the spectrogram, which is computed using a Hanning window of 512 samples, with an overlap of
 152 87.5% (yielding frequency and time resolutions of 0.4 Hz and 0.32 s, respectively). The

153 spectrogram is normalized based on a robust estimate of the power spectrum, which is computed
154 using the median of the spectrogram values in each frequency bin [Leung and White, 1998]. The
155 normalized spectrogram is obtained by dividing each value in the original spectrogram by the
156 power spectrum at the corresponding frequency.

157

158 In addition to fin whale calls, the instruments recorded the shots of the seismic survey, some
159 earthquakes, and noise from passing vessels, as well as ambient noise due to ocean waves. To
160 reduce errors in the detection of the fin whale vocalizations, filtering can be used to isolate the
161 specific frequency band to promote successful detections. In band and outer band frequency ranges
162 were determined to optimize the filtering of the data. To detect the whale vocalizations the mean
163 energies in three bands are computed based on the normalized spectrogram. The three bands are
164 the *in-band* which are the range of frequencies where a fin whale 20 Hz call is expected to appear,
165 in this case 15-30 Hz is used, and two *out-bands* one covering the frequency range below the in-
166 band, i.e. <15 Hz, and one above the in-band, i.e. >30 Hz. For each one-hour block, the energies
167 in each band are calculated as the mean of the normalized spectrogram in the two bands. A
168 detection is only made if the energy is above the threshold of 5 in the in-band but below the
169 threshold of 5 for both of the out-bands. This threshold value of 5 was determined by testing
170 various values on a small subset of data which had been manually annotated. This dual criterion is
171 used to eliminate false alarms from sounds that occur across a range of frequencies and are not
172 restricted to the 15-30 Hz range.

173

174 *Delay estimation*

175 The localization process for a source is based on estimation of the time differences of arrivals
176 (TDoAs) measured between different instruments. The TDoAs represent the delays of the signals
177 observed on the different sensors. For an array of N sensors, there are two broad strategies that
178 can be adopted regarding which TDoAs to compute. The first is to compute the TDoAs between
179 all possible pairs of sensors [White et al., 2006], which results in $N(N-1)/2$ TDoAs. The second is
180 to select a reference sensor and compute the TDoAs only between the reference sensor and each
181 of the other sensors, which requires only $N-1$ values to be computed. The second approach has the
182 advantage of reducing the computational load because of the smaller number of TDoAs that are
183 computed. Further, in principle, one can compute all the possible TDoAs from the subset computed

184 relative to a reference sensor. However, the first approach is more robust to estimation errors
185 because there is some redundancy in the approach.

186

187 The calculation of the TDoAs is most commonly based on a cross-correlation [*Knapp and Carter,*
188 1976]:

$$\hat{R}_{f_1 f_2}(\tau) = \frac{1}{T - |\tau|} \int_0^T f_1(t - \tau) f_2(t) dt \quad (1)$$

189 where f_1 and f_2 are the time series and T is their duration, and the value of the lag, τ , at which the
190 cross-correlation is maximum was determined and used as the estimate of the TDoA. The
191 correlation can be computed based on the raw acoustic data or using the time series of a metric
192 derived from the acoustic data. If the acoustic data is to be used in the correlation function then
193 the underlying assumption is that the difference between the acoustic signals on two instruments
194 is a simple delay and an amplitude scaling. This may not be true for a variety of reasons, including:
195 complexities in the propagation conditions (e.g. reflections), source directivity and noise. These
196 approximations are more justifiable for sensors that are close to each other.

197

198 For pulsed signals, such as fin whale calls, we can regard the signal as consisting of two
199 components. Borrowing terminology from the fields of communications, radar and sonar, we can
200 refer to the carrier signal as being the frequency of each pulse (c. 20 Hz) and the modulation signal
201 defining the shape of the pulses at frequencies of the order of 0.1 Hz. This decomposition provides
202 two routes for computing the delays. The first is based on correlating the carrier waveforms, which
203 potentially provides greater levels of precision, with the second being based on correlating the
204 modulation waveform, which results in lower precision but greater robustness.

205

206 Here we describe methods based on the modulation function, which use the envelope of the
207 waveform as an estimate of this modulation signal. To reduce the effect of noise, prior to
208 computing the modulation function, two processes are adopted. First, out-of-band noise is removed
209 by bandpass filtering the signals between 15 and 30 Hz. Then noise within the band of fin whale
210 calls is reduced using a technique pioneered for speech enhancement, specifically power
211 subtraction [*McAulay and Malpass, 1980*]. Following filtering and enhancement, the cross-
212 correlation is calculated using the envelope of the signals. The envelope is computed using the

213 analytic signal based on a Hilbert transform. The analytic signal, $f_a(t)$, is a complex representation
214 of a signal $f(t)$ and is given by:

$$f_a(t) = f(t) + i\tilde{f}(t) \quad (2)$$

215 where $\tilde{f}(t)$ is the Hilbert transform of $f(t)$ [Marple, 1999]. The envelope is then the magnitude
216 of the analytic signal.

217

218 A potential problem with the cross-correlation approach is that the call trains have an INI that is
219 nearly constant, so the computed cross-correlation functions have multiple peaks, separated by the
220 INI. Thus the wrong peak may be selected to compute the TDoAs. This possibility is mitigated in
221 two ways. Firstly, the natural variation in the INIs means that averaging across longer time
222 intervals reduces the height of the secondary (false) peaks in the cross-correlation function,
223 favoring the use longer time windows, which capture more of this natural variation. Secondly, the
224 ambiguities generally correspond to unphysical time delays because the interval between calls is
225 around 14 s, which corresponds to path length differences of roughly 20 km. This observation also
226 provides a second motivation for choosing to correlate the modulation function rather than the
227 carrier signal, since the ambiguous peaks observed for the carrier signals occur at much shorter
228 path length distances (~ 0.05 s or 75 m) and are typically physically realistic, so much harder to
229 eliminate.

230

231 The window length selected to compute the cross-correlation functions is a compromise. A long
232 window reduces the potential problems of secondary peaks in the cross-correlation function and
233 also increases the signal-to-noise ratio (SNR) of the peaks. A short window allows a greater
234 number of independent localizations to be computed, but the reduced information produces low
235 correlation peaks which are more readily masked by noise. A short window also decreases the
236 influence of motion of the animal during the cross-correlation window, that will blur the main
237 peak, introducing greater uncertainty in the TDoA estimates. This effect suggests a criterion for
238 the maximum window length: that the animal's motion within a window should not result in a
239 TDoA change that is greater than the width of the main correlation peak. The greatest possible
240 change in the TDoA is twice the distance travelled by the whale divided by speed of sound: this
241 would correspond to the whale swimming along the line connecting the two hydrophones, i.e.,
242 swimming and vocalizing at the bottom of the ocean (something that fin whales do not do). For

243 that case, assuming a whale swimming at 10 km/hr and a width of the correlation peak of 1 s (the
 244 typical duration of the call), the corresponding window duration is 280 s. We used a value of 300
 245 s, which based on the extremely conservative nature of the preceding calculation, is a realistic
 246 choice. These windows were overlapped by 50%. The TDoA estimate was assumed to correspond
 247 to a position in the middle of the time window. The effects of absolute propagation time were
 248 neglected, leading to a systematic position error of up to a few 10s of metres (depending on swim
 249 speed) that does not affect swim speed estimates.

250

251 The TDoA estimates were post-processed to remove outliers by examining the errors relative to a
 252 linear trend. Time delays were also displayed graphically and only used to determine tracks if they
 253 showed a smooth progression in time. We used the closest instrument to the whale as a reference
 254 and only computed the TDoAs between this instrument and all of the other instruments. An
 255 alternative approach would be to compute TDoAs across all pairs of instruments which detect the
 256 whale.

257

258 *Localization and tracking*

259 Various methods have been used to localize the source of whale vocalizations from time delay
 260 estimates [Baggenstoss, 2011; Rebull *et al.*, 2006; Wilcock, 2012]. We used the method of *White*
 261 *et al.* [2006] to localize and track the whales. An inversion model from the time delays needs to
 262 be applied, and this is achieved with a maximum likelihood estimator by minimizing the weighted
 263 least squares cost function:

$$\Psi(\mathbf{s}(n)) = \sum_{k=2}^N \frac{(\Delta_{1k}(n) - M_{1k}(\mathbf{s}(n)))^2}{\sigma^2} \quad (3)$$

264 where \mathbf{s} is the estimated source location of a discrete time n , Δ_{1k} is the estimated time delay
 265 between sensor 1 and sensor k , M_{1k} is the modelled delay between sensor 1 and sensor k and σ^2
 266 the weighted variance of the time delays [White *et al.*, 2006]. For efficiency a linear sound speed
 267 model was adopted, where the speed of sound at the ocean surface is 1505 m/s and the vertical
 268 gradient is 0.017 /s. The gradient represents the change in hydrostatic pressure with increased
 269 depth for a constant temperature and salinity in the water column, corresponding to the deep
 270 isothermal layer [Etter, 1995]. This simplification allows rapid localization and reproduces

271 correctly the flattening of propagation paths in the deep ocean, but overestimates the mean sound
272 speed of c. 1520 m/s [e.g., Davy *et al.*, 2018] by c. 2%. When attempting the localization it is
273 assumed that there is only one whale present, that the delay times are valid with no false detections
274 and that there are no surface reflections or echoes present in the data. If for a given OBS and
275 detection a direct path could not be computed, the delay time for that OBS and detection was not
276 used. Manual checks were made on the INI to check that tracks used involved only one animal.
277 The extension of this method to tracking multiple animals is a significant step, leading to the field
278 of multi-target tracking [Mahler, 2004].

279

280 A minimum of four instruments are needed to successfully locate the source. For computational
281 convenience the hydrophone locations were projected into Cartesian coordinates; the areas of
282 interest were small enough to neglect the curvature of the Earth. The localization was achieved by
283 minimizing the cost function (3) using a Nelder-Meade simplex method, implemented with
284 random multiple initializations. A Monte Carlo method was employed to quantify the errors
285 associated with noise processes. The depth at which fin whales vocalize is poorly characterized,
286 with acoustic tag data suggesting that depths of up to 30 m [Stimpert *et al.*, 2015], so the algorithm
287 was run both constrained such that the whale was assumed to be at the sea surface, and
288 unconstrained such that its depth could correspond to anywhere in the water column. Prior
289 knowledge of the depth distribution of vocalizing animals could usefully be incorporated into the
290 method via a Bayesian framework.

291

292 *Kalman filter*

293 By constructing a sequence of localizations from a whale, one can form tracks of the whale motion
294 during the time it is calling. Once localizations had been conducted for each sequential
295 vocalization, the next procedure was to apply a Kalman filter to create a final animal track. The
296 use of a Kalman filter estimates the movement parameter of the whales and presents the “most
297 probable” whale track from the data. If the stochastic processes are Gaussian and the system is
298 linear, then the Kalman filter represents an optimal estimator, both in the minimum mean squared
299 sense and more generally as the Bayesian maximum *a posteriori* estimate of the state vector [Bibby
300 and Tautenburg, 1977]. The Kalman filter predicts the motion of the fin whale whilst reducing
301 noise with the associated measured points and relies upon a state-space model of the whale motion

302 and measurement processes. A state-space model builds a representation of a system through
 303 defining a state vector; in this case the state vector is taken as containing the whale’s position and
 304 velocity. The model here describes the whale’s motion in either two or three dimensions. In the
 305 case of two dimensions the model is simplified by assuming that the animal only moves in a
 306 horizontal plane, i.e. the vertical motions can be neglected, which is valid if the diving depth of
 307 the whale is small compared to the water depth. In the following, we provide details of the two-
 308 dimensional model; the extension to three dimensions follows straightforwardly. The state vector,
 309 $\mathbf{x}_s(n)$, describing the whale’s motion in two dimensions is given by:

$$\mathbf{x}_s(n) = [x(n), \dot{x}(n), y(n), \dot{y}(n)]^t \quad (4)$$

310
 311 where $(x(n), y(n))$ is the whale’s position in the plane at time n and the dot notation is used to denote
 312 differentiation with respect to time.

313
 314 This state-space model has two update equations, one describing the motion of the animal, i.e. how
 315 $\mathbf{x}_s(n)$ evolves with time, and the second the measurement process. The motion model is:

$$\mathbf{x}_s(n+1) = \mathbf{A}\mathbf{x}_s(n) + \mathbf{w}(n+1) \quad (5)$$

317 Here the linear transition matrix \mathbf{A} describes the movement from time t_n to t_{n+1} , and $\mathbf{w}(n)$ represents
 318 stochastic processes driving the animal’s motion. We used a “near constant velocity” model [Li
 319 and Jilkov, 2003] to define \mathbf{A} , which is widely used in tracking problems, for example to track
 320 aircraft in radar applications, and a Gaussian white noise process for the vector $\mathbf{w}(n)$. According
 321 to this model the matrix \mathbf{A} has the form:

$$\mathbf{A} = \begin{bmatrix} 1 & \Delta & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & \Delta \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (6)$$

323 where Δ is the interval between two samples. The model for measurements in this application is
 324 straightforward: specifically, the measurements are assumed to be observations of the locations
 325 corrupted by additive noise:

$$\mathbf{y}_m(n+1) = \mathbf{C}\mathbf{x}_s(n+1) + \mathbf{v}(n+1) \quad (7)$$

327 where \mathbf{C} is the measurement matrix and $\mathbf{v}(n)$ is the noise associated with the measurement process
 328 [Zimmer, 2011]. The measurement matrix, for the two-dimensional case has the form:

$$\mathbf{C} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \quad (8)$$

330 The Kalman filter uses the state space model defined by (4)-(7) to produce recursive estimates of
 331 the true positions contained in $\mathbf{x}_s(n)$ based on the observed measurements, $\mathbf{y}_m(n)$. In this case the
 332 measurement vector contains the estimated locations of the whale. In situations where the state
 333 evolution and measurement are linear and the stochastic processes are Gaussian then the Kalman
 334 filter yields the maximum *a posteriori* estimate of the states based on all of the measurements up
 335 to time n [Arulampalam *et al.*, 2002]. This is achieved by a two-step process, first a prediction
 336 step, wherein the estimates are updated based on the state model (4) and an update step in which
 337 the estimate is refined based on the new measurement. The updates for the Kalman filter can be
 338 written as [Arulampalam *et al.*, 2002]:

339 *Prediction step:*

$$340 \quad \hat{\mathbf{x}}_s(n+1|n) = \mathbf{A}\hat{\mathbf{x}}_s(n)$$

$$341 \quad \mathbf{P}(n+1|n) = \mathbf{A}\mathbf{P}(n|n)\mathbf{A}^t + \mathbf{Q}$$

342 *Update step:*

$$343 \quad \boldsymbol{\varepsilon}(n+1) = \mathbf{y}_m(n+1) - \mathbf{C}\hat{\mathbf{x}}(n+1|n)$$

$$344 \quad \mathbf{K}(n) = \mathbf{P}(n+1|n)\mathbf{C}^t(\mathbf{C}\mathbf{P}(n+1|n)\mathbf{C}^t + \mathbf{R})^{-1}$$

$$345 \quad \hat{\mathbf{x}}_s(n+1) = \hat{\mathbf{x}}_s(n+1|n) + \mathbf{K}(n)\boldsymbol{\varepsilon}(n+1)$$

$$346 \quad \mathbf{P}(n+1|n+1) = (\mathbf{I} - \mathbf{K}(n)\mathbf{C})\mathbf{P}(n+1|n) \quad (9)$$

347

348 where, in two dimensions \mathbf{Q} (4×4) and \mathbf{R} (2×2) are the correlation matrices of the Gaussian noise
 349 processes $\mathbf{w}(n)$ and $\mathbf{v}(n)$ respectively, which are provided to the algorithm. The quantities of the
 350 form $\hat{\mathbf{x}}_s$ are estimates of the state vector $\mathbf{x}_s(n)$. The notation “ $(n+1|n)$ ” is used to represent estimates
 351 of a quantity at time $n+1$ based only on measurements up to time n , sometimes referred to as *a*
 352 *priori* estimates, accordingly notation of the form “ $(n|n)$ ” denotes estimates of a quantity at time n
 353 based on all of the available measurements up to that time. The vector $\mathbf{K}(n)$ is called the Kalman
 354 gain and \mathbf{P} (4×4) is an estimate of the correlation matrix for the errors in the state estimates, so
 355 provides information regarding the accuracy of the method. The state estimate is initialized using
 356 the first localisations and assuming a velocity of zero, whereas $\mathbf{P}(0)$ is initialised as the identity
 357 matrix \mathbf{I} .

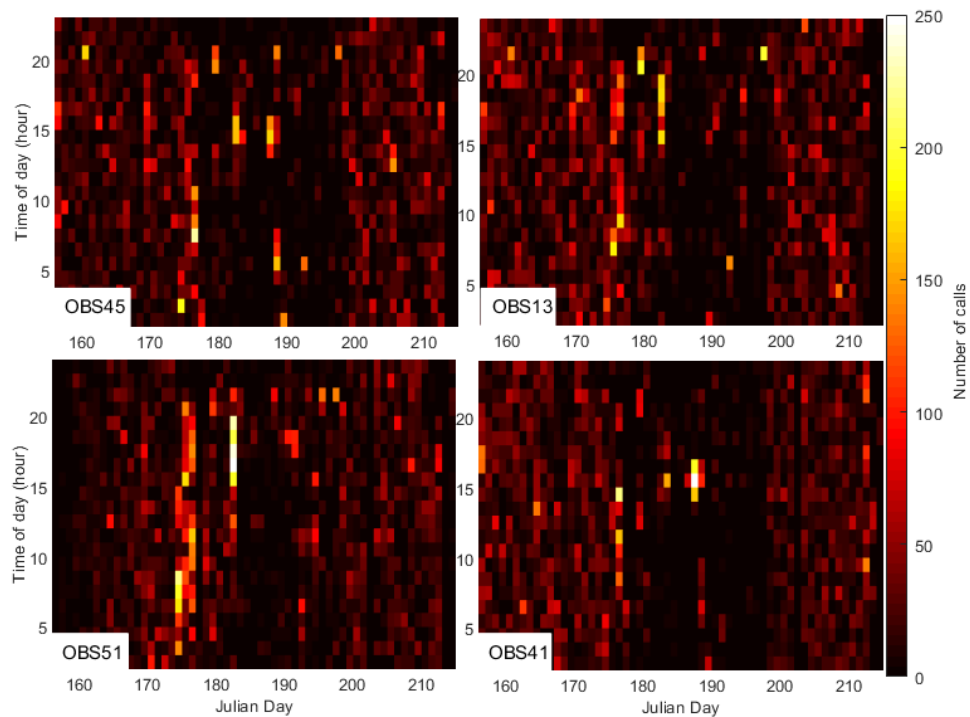
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359 **3. Results**

360 *Detections*

361 The dataset was very large (c. 300 Gb), so it was not feasible to run the location and tracking
362 algorithms on the entire dataset. The detection algorithm was applied for periods of 1 hour on each
363 day for four representative instruments (OBSs 13, 41, 45 and 51) in different parts of the study
364 area (Fig. 3) to determine peak hours for whale vocalizations. There was a large variation in the
365 hourly detection rate (Fig. 3). There were periods with low call rates on all four instruments, e.g.,
366 Julian days 156-170 and 213-215. Our analysis of the full dataset also showed that there were
367 hours on particular days with very high call rates on multiple instruments, including days 175, 182
368 and 222. In addition, there was a high density of calls during the 16th hour of day 187 on OBS 41
369 and the 18th hour of day 182 on OBS 51. In summary, high call rates were found on multiple OBSs
370 in the network over 1-2 hour periods on days 175, 179, 182, 187, 197 and 222. These peak hours
371 are indications of fin whale presence in the area of the OBS array, and therefore likely to be
372 identified on surrounding OBSs. These periods when large numbers of calls are detected presented
373 the best opportunity of finding a sequence of vocalizations long enough to define a track. During
374 days 156-174 and 197-212, when there was regular airgun shooting in the survey area, call
375 detection rates were moderate, while outside these periods, rates were lower for some periods and
376 higher for others (Fig. 3).

377



378

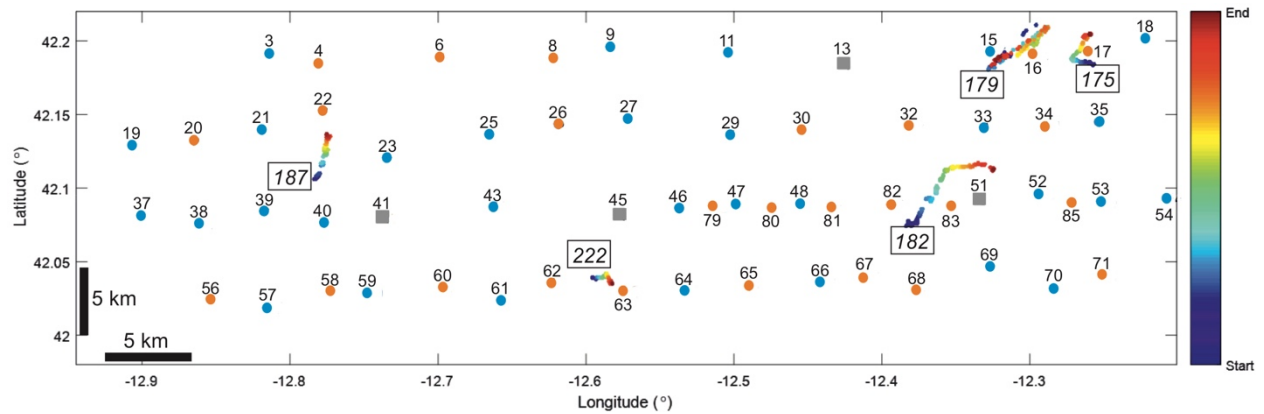
379 Figure 3: Hourly rates of call detection for four representative instruments during the time period
380 covered by all four (see Fig. 4 for locations). The period of recording available varies between
381 instruments.

382

383 *Localization*

384

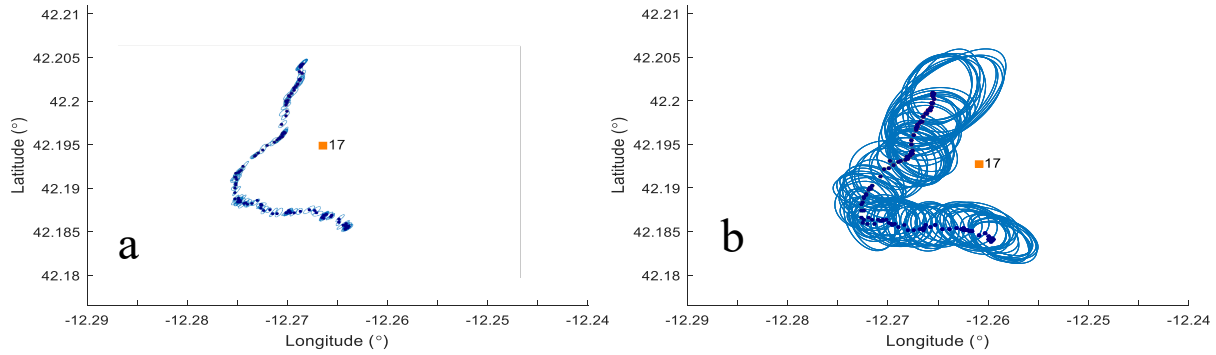
385 Five tracks were constructed from stable sequences of 81-240 localisations during these periods
386 (Fig. 4). On day 175, during the 80-minute period analysed, the whale initially travelled at an
387 azimuth of c. 280° for c. 1 km and then turned approximately 100° clockwise to continue travelling
388 at an azimuth of c. 020° for 1.7 km past OBS17. The mean velocity of the animal was around
389 2 km/hr. A track determined on day 179 covers a two-hour period, during which the whale travels
390 backwards and forwards near OBS16 at an azimuth of c. 50° over a length of 4.5 km (Fig. 4).
391 Many successive localisations are separated by distances that would represent impossible swim
392 velocities and/or accelerations, but a linear fit of velocity against time results in velocities between
393 22 and 27 km/hr. A track on day 182 also covers a two-hour period, during which the whale travels
394 5 km at an azimuth of c. 20° , before turning to an azimuth of c. 80° for a further 3 km close to
395 OBS51. The mean swim speed is 4 km/hr, but successive localisations indicate swim speeds of up
396 to 24 km/hr for short periods. A track on day 187, close to OBS21, continues for a little less than
397 one hour, during which the whale travelled c. 15 km. This track is more discontinuous than the
398 others, suggesting that there were some rest periods. Swim speeds were generally between 10 and
399 20 km/hr. Localisations on day 197 were close to OBS29 and were too scattered to construct a
400 coherent track. These calls occurred when airgun shooting was nearby, and we infer that the shots
401 led either to false detections or to spurious cross-correlation maxima. Finally, a one-hour track was
402 detected on day 222 near OBS64. The whale travelled to the northeast and then to the south, with
403 a total track length of only 1.5 km and swim speed generally below 10 km/hr.



404
 405 Figure 4: Fin whale tracks successfully followed. Colours on tracks mark an arbitrary time scale.
 406 Symbols mark OBS/OBH positions. Instrument locations marked with grey squares are those used
 407 for detection, blue circles are OBSs and orange circles are OBHs. Numbers in boxes mark the
 408 Julian day of each track.

409
 410 To assess the uncertainties in these tracks, we analysed in further detail the track determined on
 411 day 175 (Fig. 5). A Monte-Carlo analysis [*White et al., 2006*] applied to localisations using OBS13
 412 as the reference instrument yielded 95% confidence ellipsoids with mean x and y dimensions of
 413 39 m and 43 m, respectively (Fig. 5a). We also tested the sensitivity of inferred positions to the
 414 choice of reference instrument by re-computing the tracks using OBS/H 18, 35, 51, 52 and 54 as
 415 the reference instruments. Although the resulting tracks were all visually similar, Monte Carlo
 416 analysis of the combined results yielded 95% confidence ellipsoids with mean x and y dimensions
 417 of 325 m and 355 m respectively (Fig. 5b). Ellipsoid dimensions in the vertical plane were >100
 418 m for both approaches, with some calls appearing to be above the ocean surface (perhaps due to
 419 our choice of sound speed profile), so it is clear that network geometries were not suitable for
 420 determining call depth.

421



422 Figure 5: (a) Monte Carlo 95% confidence ellipses for localisations on day 175 when OBS13 is
 423 used as the reference instrument. (b) Corresponding confidence ellipses when localisations using
 424 six different OBH/S as reference instruments are combined.

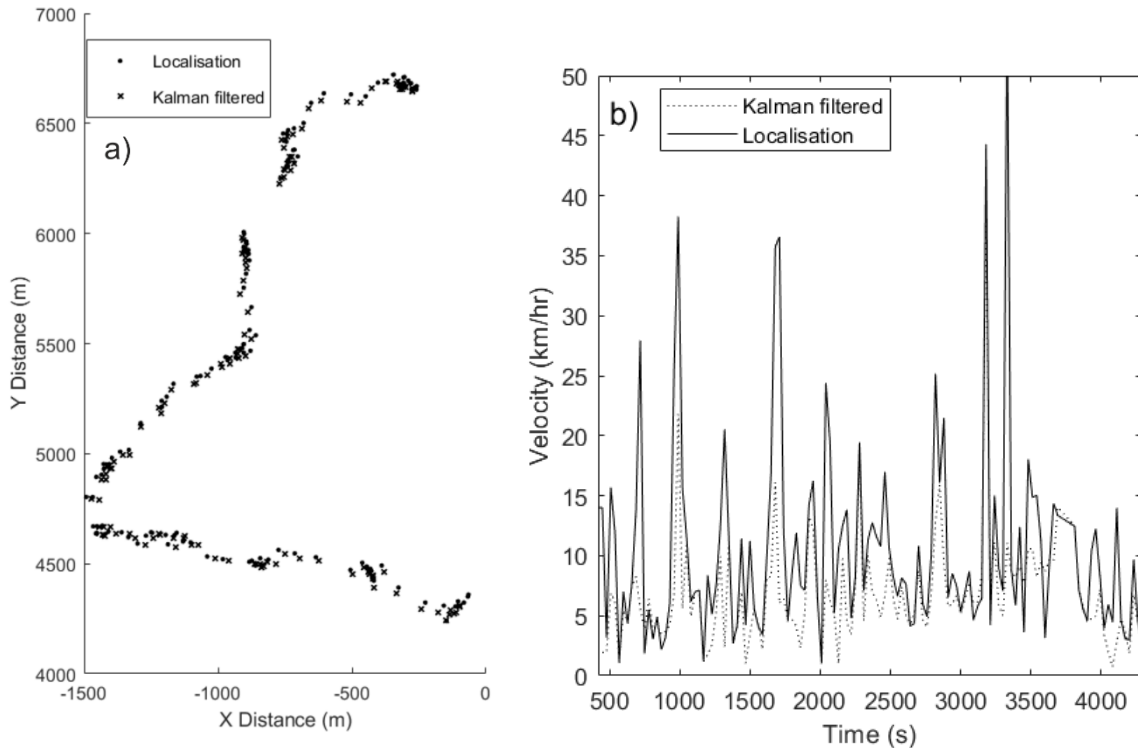
425

426 One should note that when using multiple reference sensors the accuracy of the estimates degrades
 427 significantly. This may appear counter-intuitive, since using multiple reference sensors employs
 428 more sensor pairs, so one might anticipate a subsequent performance enhancement. Part of this
 429 location uncertainty comes from our simplification of the sound speed profile, which can result in
 430 range errors of up to a few hundred metres at the longest ranges, that are mitigated by the broad
 431 azimuthal distribution of OBSs used in localization. In addition, it should be noted that because
 432 the reference sensor used in the single reference sensor case is the sensor closest to the whale, all
 433 of the TDoA estimates are formed using at least one measurement with a high SNR. When using
 434 multiple reference sensors, there are some TDoA estimates which are formed when both sensors
 435 collect data with a relatively poor SNR. In those cases the TDoA estimates are unreliable and add
 436 considerable uncertainty to the location estimates, as seen in Fig. 5b.

437

438 *Tracking*

439 Because of the poor depth control, the Kalman filter was just applied in the horizontal plane, with
 440 the whale assumed to be at the ocean surface, consistent with previous suggestions that these
 441 animals dive no deeper than 50-100 m [Croll *et al.*, 2001; Watkins *et al.*, 1987]. The filter yielded
 442 very similar tracks to the localization method for all tracks. A representative example is shown in
 443 Fig. 6. However, it resulted in significant smoothing of calculated speeds, which are unrealistic if
 444 successive locations are used without filtering (Fig. 6b).



445
 446 Figure 6: a) Comparison between tracks from localisation algorithm (filled circles) with those
 447 generated by the Kalman filter (crosses) for the track on day 175. b) Comparison of speed estimates
 448 based on localisation tracks with those from the Kalman filter for the track shown in a).
 449

450 **4. Discussion**

451 We found no clear correlation between detection rate and the presence or absence of shooting.
 452 Other whale species have been found to increase the source level and frequency of their calling
 453 patterns to compensate for the presence of loud ambient noise [Clark *et al.*, 2002], but we cannot
 454 infer such a pattern from our data. No reliable whale tracks were recovered during the period of
 455 shooting, probably because of the low signal-to-noise ratio during these periods and the
 456 corresponding likelihood of spurious cross-correlation peaks.

457
 458 Localizations were possible on six days with a range of success, over periods of 1-2 hours.
 459 Horizontal coordinates were recovered well, but we were not able to recover whale depths. The
 460 most continuous tracks were found on Julian days 175, 182, 187 and 222. The maximum error
 461 associated with these localizations was on the order of hundreds of metres, so significantly larger
 462 than the spacing between adjacent calls. Based on visual observations, swim speeds as high as 20

463 km/hr have been reported for a period of 20 mins [Watkins, 1981]. Using acoustic methods, *Dunn*
464 *and Hernandez* [2009] estimated speeds of 3-7 km/hr. Using tags tracked by satellite, *Silva et al.*
465 [2013] calculated mean swim speeds of 5.7 km/hr during foraging and 7.7 km/hr during migration,
466 with large variations around these means. Recent work has showed that the swim speed of males
467 is related to whether or not they are singing [Clark et al., 2019] suggesting that singing animals
468 mainly swim at slower speeds. In that study the mean swimming speed of all tracked whales was
469 found to be 6.7 km/hr with a standard deviation of 3.7 km/hr. The mean swim speeds observed in
470 this study correspond well with these data, although there are some point to point estimates that
471 produce significantly higher values as a consequence of some remaining outliers in the
472 localizations that the Kalman filter is unable to smooth sufficiently.

473
474 The tracks here cover periods up to 2 hours. The slow speeds estimated on days 175, 182 and 222,
475 produce more meandering paths that are consistent with a singing male, whereas the changes in
476 direction could be indicative of foraging behaviour [Croll et al., 2001]. The track on day 187 is
477 considerably faster and unidirectional, suggesting that the whale is showing a transiting behaviour.
478 These two tracks types: transiting and meandering, are reported elsewhere [McDonald et al., 1995;
479 *Rebull et al., 2006; Wilcock, 2012*] albeit in most of these instances the tracks are of longer
480 duration.

481

482 **5. Conclusions**

483 We have used serendipitous recording of fin whale vocalisations during a deployment of 72 ocean
484 bottom hydrophones/seismometers on the seabed with typical spacings of 4-6.5 km in c. 5 km
485 water depth west of Iberia to locate their sources and ultimately to track several animals. From our
486 analysis, we conclude the following:

- 487 1. Our call detection algorithm based on the ratios of signal strengths in different frequency
488 bands appears to be highly successful in detecting the broad-band classic calls, but failed to
489 detect a larger proportion of the narrower-band back-beats.
- 490 2. Analysis of a c. two-month time series for several representative instruments revealed up to c.
491 200 calls per hour,. There was no evidence that call detection rates were affected by the
492 presence of airgun shooting.

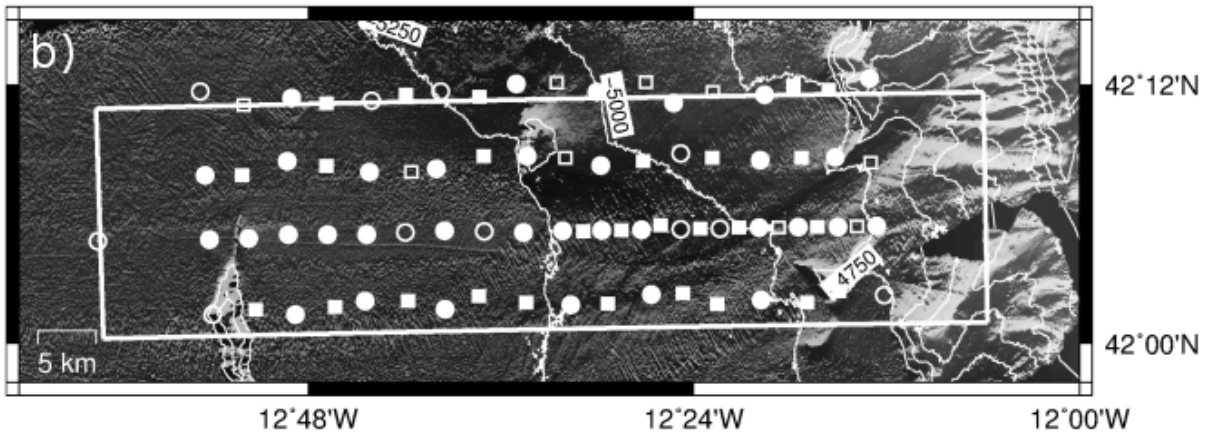
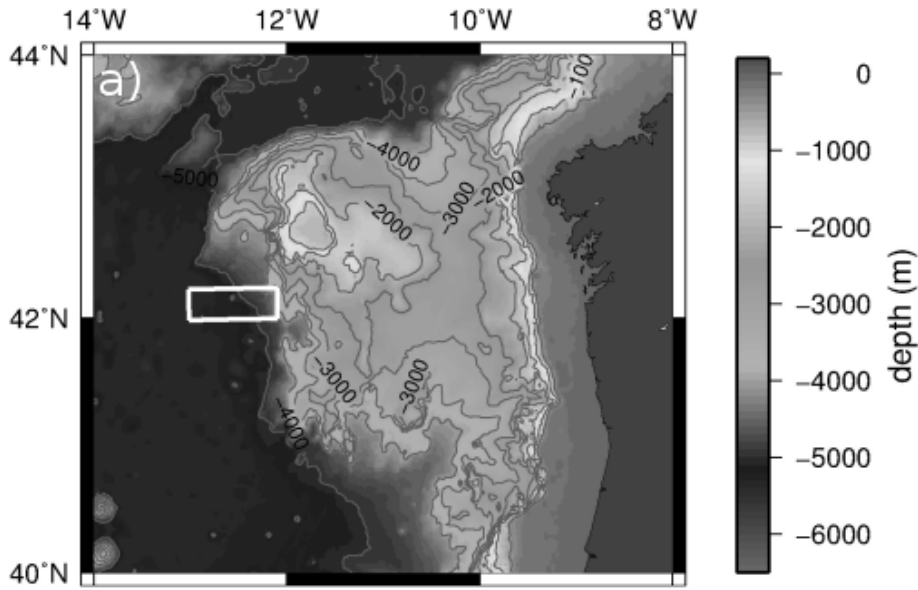
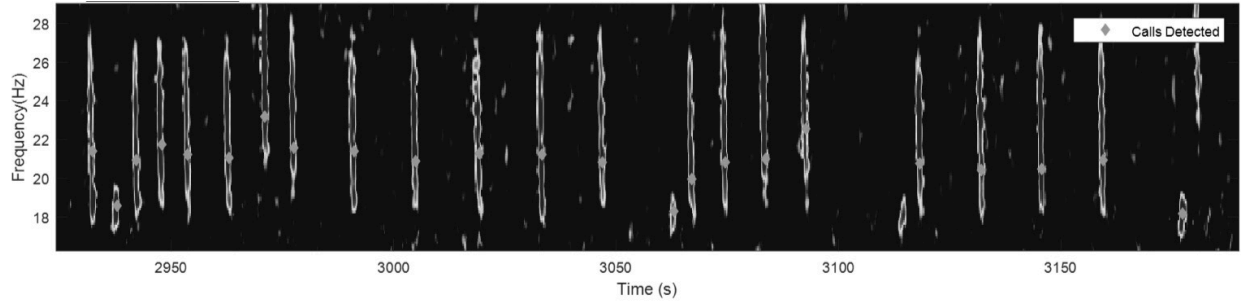
- 493 3. In a few cases a series of calls lasting up to two hours was detected on enough seabed
494 instruments to allow reliable estimation of time delays between instruments, and thus
495 localisation and tracking. The use of a Kalman filter resulted in smoother tracks. Swim speeds
496 along these tracks were highly variable, with means in the range 2-15 km/hr, and these
497 variations may be linked to a variety of whale behaviours.
- 498 4. Long deployments of networks of fixed sound detectors on the seabed can provide rich
499 datasets for the study of fin whale behaviour, but the detector spacing of 4-6 km used in our
500 study limited our ability to locate and track the animals.

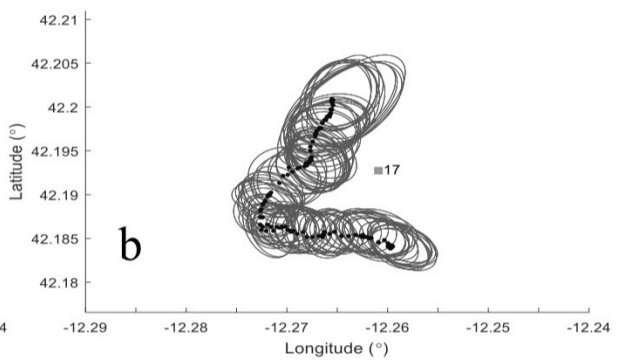
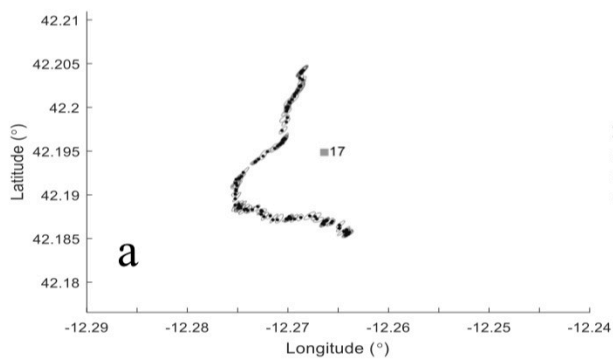
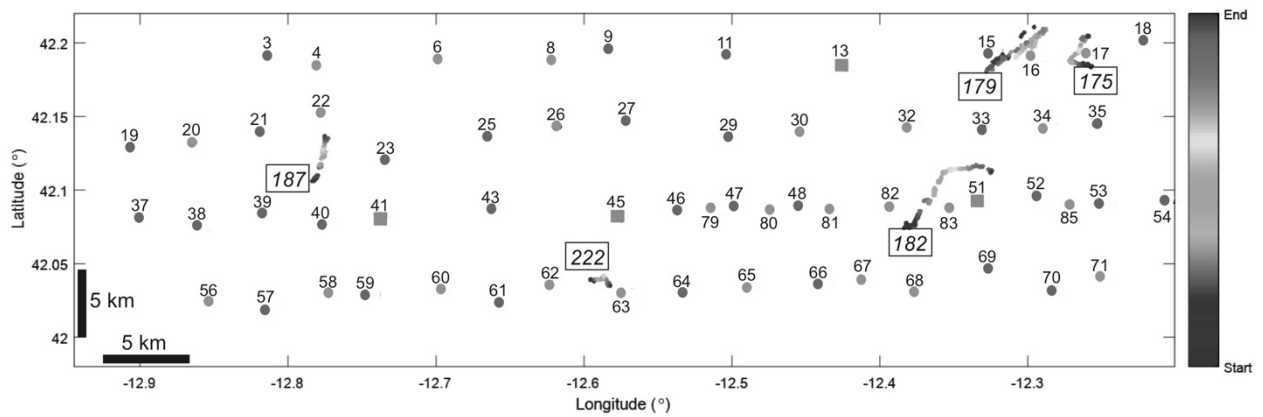
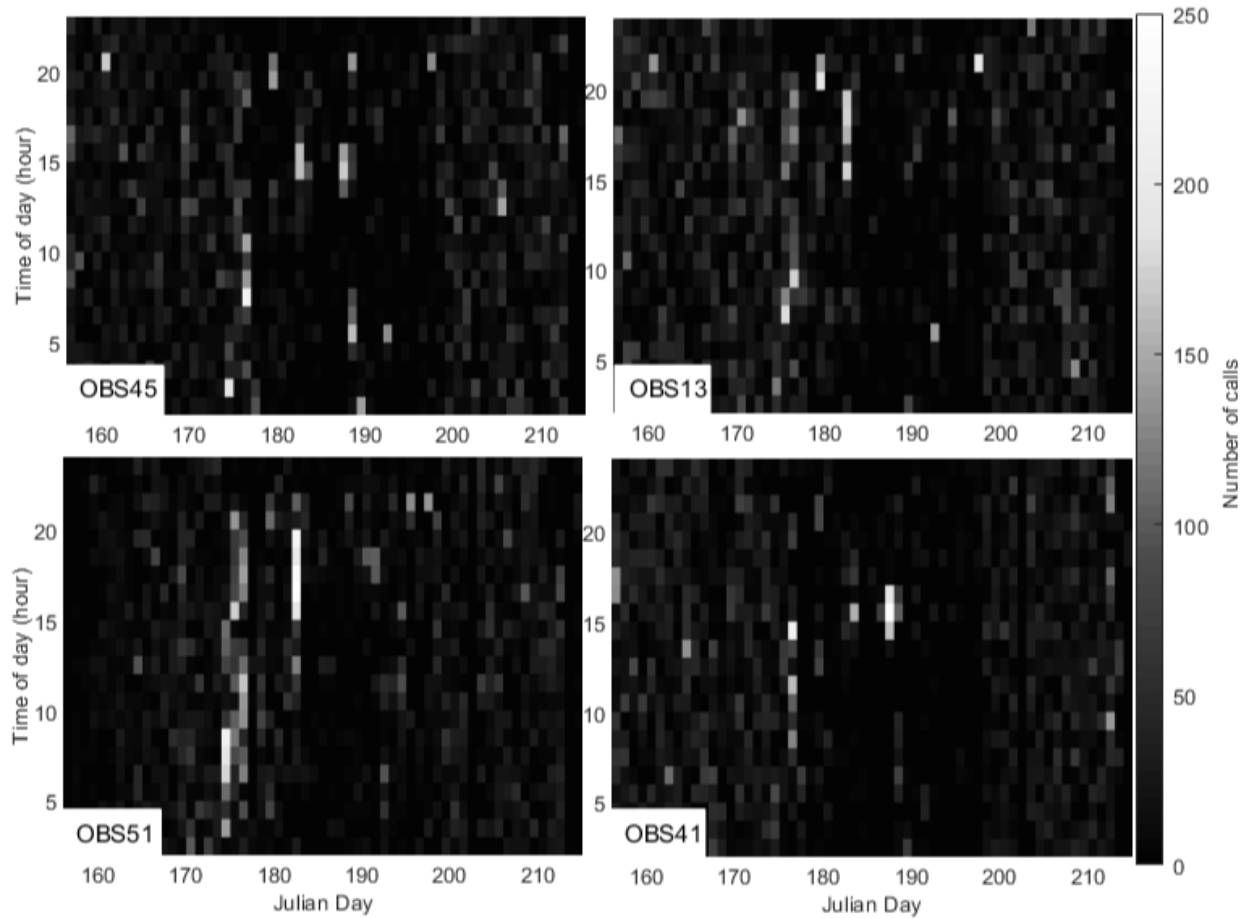
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Black and white versions of colour figures





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