Citizen science in the marine environment: A case-study estimating common dolphin densities in the north-east Atlantic

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Background. Citizen science is increasingly popular and has the potential to collect extensive datasets at lower costs than traditional surveys. Ferries have been used to collect data on cetacean populations for decades, providing long-term time series allowing for monitoring of cetacean populations. One cetacean species of concern is the common dolphin, which have been found stranded around the north-east Atlantic in recent years, with high numbers on French coasts being attributed to fisheries bycatch. We estimate common dolphin densities in north-east Atlantic and investigate the power of citizen science data to identify changes in marine mammal densities and areas of importance.

Materials & Methods. Data were collected by citizen scientists on ferries between April and October in 2006 - 2017. Common dolphin sightings data from two ferry routes in the Bay of Biscay (n= 569), Celtic Sea (n= 260), and English Channel (n= 75) were used to estimate detection probabilities with detection functions. Density Surface Models estimated density across ferry routes, accounting for the influence of environmental (chlorophyll a, sea surface temperature, depth, and slope), spatial (latitude and longitude) and temporal terms (year and Julian day).

Results. Overall detection probability was highest in the English Channel (0.384) and Bay of Biscay (0.348), and lowest in the Celtic Sea (0.158). Common dolphins were estimated to occur in higher densities in the Celtic Sea (0.400 per km) and the Bay of Biscay (0.319 per km), with low densities in the English Channel (0.025 per km). Densities in the Celtic Sea have been relatively stable on the ferry route since 2006 with a slight decrease in 2017. Densities peaked in the Bay of Biscay in 2013 with lower numbers since. The general trend in the English Channel is for increasing densities of common dolphins over time since 2009.

Discussion. This study highlights the effectiveness of citizen science data to investigate the distribution and density of cetaceans. The densities and temporal changes shown by this study are representative of those from wider-ranging robust estimates. We highlight the ability of citizen science to collect data over extensive periods of time which complements traditional surveys. Such long-term data are important to identify changes within a population; however, citizen science data may, in some situations, present challenges. We provide recommendations to ensure high-quality data which can be used to inform management and conservation of cetacean populations.

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13 **Abstract**

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16 populations for decades, providing long-term time series allowing for monitoring of cetacean
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18 stranded around the north-east Atlantic in recent years, with high numbers on French coasts
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30 Biscay (0.348), and lowest in the Celtic Sea (0.158). Common dolphins were estimated to occur
31 in higher densities in the Celtic Sea (0.400 per km) and the Bay of Biscay (0.319 per km), with
32 low densities in the English Channel (0.025 per km). Densities in the Celtic Sea have been
33 relatively stable on the ferry route since 2006 with a slight decrease in 2017. Densities peaked in

34   the Bay of Biscay in 2013 with lower numbers since. The general trend in the English Channel is

35   for increasing densities of common dolphins over time since 2009.

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37   distribution and density of cetaceans. The densities and temporal changes shown by this study

38   are representative of those from wider-ranging robust estimates. We highlight the ability of

39   citizen science to collect data over extensive periods of time which complements traditional

40   surveys. Such long-term data are important to identify changes within a population; however,

41   citizen science data may, in some situations, present challenges. We provide recommendations to

42   ensure high-quality data which can be used to inform management and conservation of cetacean

43   populations.

Introduction

44

45   Citizen science has been growing in popularity in recent years, and projects often have hundreds,

46   or thousands of active volunteers collecting data across wide geographical areas and long time

47   periods (Hyder *et al.*, 2015). Long-term monitoring such as this can provide an early warning

48   system of change in the marine environment. Citizen science has been used to study a variety of

49   taxa, for example, birds (e.g. Sullivan *et al.*, 2009), intertidal organisms (e.g. Vermeiren *et al.*,

50   2016), or record a broad range of animals across taxa and ecosystems (e.g. Postles & Bartlett,

51   2018). Several citizen science projects collect data on marine mammals, with many of these

52   using shore-based data collection methodologies (Tonachella *et al.*, 2012; Embling *et al.*, 2015).

53   Vessel-based methods are often restricted to ad-hoc data collection of animal presence; however,

54   some studies have successfully used platforms of opportunity (vessels that undertake non-

55   scientific voyages along predetermined routes such as ferries or cruise ships) to undertake citizen

56   science surveys at sea (e.g. Williams, Hedley & Hammond, 2006; Kiszka *et al.*, 2007). The use

57   of such platforms is considerably cheaper than chartering a ship and paying running costs,

58   although surveyors have limited or no control over the journey that the vessel undertakes. Such

59   surveys can be used to investigate animal distribution and abundance.

60   An understanding of animal distribution and range is critical for potential anthropogenic impacts

61   to be understood, for appropriate conservation management, and spatial planning. Standardised

62   methods can allow for citizen science data to be used in abundance estimates (e.g. Davies *et al.*,

63   2013), which is key for monitoring species trends in space and time. However, even with

64   standardised methods, it is often challenging for citizen science data to be reliable and accurate

65   enough (Crall *et al.*, 2011) to provide good estimates of abundance due to the difficulties of

66   detecting animals, especially at sea (Buckland *et al.*, 2001). For example, marine mammals

67   spend only a fraction of their time at the surface of the water where they are available to be

68   recorded by vessel-based surveyors (Mate *et al.*, 1995). Animals are also usually less likely to be

69   recorded at increasing distances from the observer, with probability likely to decrease in

70   worsening conditions (Buckland *et al.*, 2001; Buckland *et al.*, 2015), such as higher sea states

71   and swell, reduced visibility, or less experienced surveyors. These uncertain detection

72   probabilities can be estimated and accounted for with distance sampling analysis (Buckland *et*
73   *al.*, 2001).

74   The citizen science charity, ORCA, have been using platforms of opportunity to collect data on
75   cetacean occurrence since 1995, with considerable survey effort being undertaken on-board
76   ferries around the UK and North-Eastern Atlantic. Data are collected following line-transect
77   distance sampling techniques, which can be used in design-based and model-based surveys to
78   estimate the abundance and distribution of cetaceans. Design-based surveys follow randomly-
79   placed systematic transects to provide a representative coverage of the survey area (Thomas *et*
80   *al.*, 2010). These surveys can be expensive and time-consuming as they use dedicated ships or
81   aircraft to survey large areas (Hammond *et al.* 2001, 2013, 2017). As a result, they are often
82   carried out infrequently and provide a snapshot of abundance over a short temporal scale. For
83   example, Small Cetaceans in European Atlantic waters and the North Sea (SCANS) surveys are
84   conducted every 10 years but cover expansive areas (Hammond *et al.,* 2001, 2017).
85   Alternatively, distance sampling surveys can be undertaken with non-random coverage ('model-
86   based') from platforms of opportunity. Due to the non-random nature of the transects, results
87   cannot be extrapolated beyond the surveyed area, unlike design-based surveys. Platforms of
88   opportunity often operate year-round however, and data can be collected on a much larger
89   temporal-scales, usually at reduced cost. Results from this type of monitoring are important to
90   understand the impacts of anthropogenic activities on animals, and to assess conservation status
91   and management requirements.

92   This study focuses on short-beaked common dolphins (*Delphinus delphis, Linnaeus*; hereafter
93   referred to as common dolphins*)*, in the English Channel, Bay of Biscay, and Celtic Sea.
94   Previous studies suggest that common dolphins are most abundant in the Bay of Biscay, with
95   fewer recorded in the Celtic Sea and English Channel (MacLeod, Brereton & Martin, 2009;
96   Hammond *et al.*, 2017). There is concern about common dolphins in these waters due to an
97   increasing number stranding on European Atlantic beaches in recent years, with many likely to
98   be a result of fisheries bycatch in the Bay of Biscay and Celtic Sea (Crosby *et al.*, 2016; Peltier *et*
99   *al.*, 2016; Peltier *et al.*, 2017). Common dolphins are one of the most frequently bycaught
100   species in north-east Atlantic fisheries (De Boer *et al.*, 2008; Peltier *et al.*, 2016), particularly
101   reported in pelagic fisheries targeting sea bass or albacore tuna in the English Channel and Bay
102   of Biscay (Rogan & Mackey, 2007; Spitz *et al.*, 2013). Analysis derived from stranding records
103   and accounting for drift dynamics estimated between 2250 and 5750 animals are bycaught per
104   year in the north-east Atlantic (Peltier *et al.*, 2016). Given the infrequency of design-based
105   surveys in this these areas of numerous strandings and high bycatch rate, citizen science is an
106   ideal method to collect longer term data on the distribution and densities of common dolphins in
107   this vulnerable area.

108   This study analyses citizen science data to estimate common dolphin densities in the English
109   Channel, Bay of Biscay and Celtic Sea, accounting for imperfect detection. Results derived from
110   these citizen science data are compared to published results from robust design-based distance

111   sampling surveys undertaken by professional scientists. Temporal variation in common dolphin
112   densities is discussed in relation to mass mortality events and bycatch within the study area. The
113   strengths and limitations of citizen science data are discussed, and recommendations given for
114   accurate and robust citizen science monitoring data.

Materials & Methods

116   *Survey area*

117   Our study regions include the Bay of Biscay, a heterogeneous area incorporating relatively
118   shallow coastal areas, the continental shelf edge, and deep-water canyons (Certain *et al.*, 2008); a
119   relatively shallow area of the Celtic Sea between Cornwall and the Isles of Scilly; and the
120   English Channel, a busy shipping region (McClellan *et al.*, 2014), with relatively shallow waters.
121   Surveys cover ferry routes of Brittany Ferries' Pont-Aven (21.6 m bridge height) which leaves
122   Portsmouth, travels through the English Channel and across the Bay of Biscay to Santander, and
123   then returns to Plymouth (Figure 1). No survey effort was undertaken on the southern edge of the
124   continental shelf due to the ferry crossing this area at night. The Isles of Scilly Travel's
125   Scillonian III *(*10 m bridge height) crosses from Penzance to St Mary's on the Scilly Isles in the
126   Celtic Sea (Figure 1).

127   *Data collection*

128   Data were collected by trained citizen scientists between 2006 - 2017, with survey effort
129   concentrated between April - October, and no surveys conducted between November - February.
130   Only data collected during April - October were used in the analysis due to a similar number of
131   surveys throughout this period. Frequency of surveys varied across the study period but averaged
132   once per month on the Plymouth - Santander - Portsmouth route and twice a month on the
133   Penzance - Isles of Scilly route. Trained surveyors were deployed on ferries by ORCA
134   (www.orcaweb.org.uk) and collected data from the forward-facing bridge of vessels according to
135   standard distance sampling methodologies (Buckland *et al.*, 2001, 2015). Survey teams
136   comprised of four surveyors on the Pont-Aven (at least three of which were experienced),
137   allowing for 30-minute rest breaks to avoid observer fatigue, and three on the Scillonian III (at
138   least two of which were experienced) due to shorter survey lengths. Two observers scanned the
139   forward 180 degrees (100 degrees each, with a 10-degree crossover at the bow). The data
140   recorder collected effort data, including environmental conditions (glare, sea state, swell,
141   precipitation, and visibility) at a minimum of 30-minute intervals, and sighting event details on
142   cetacean species. Group sizes were estimated, and angles from the ships' bow to animals were
143   recorded using an angle board. Radial distances were calculated from reticle binoculars where
144   possible, or alternatively estimated by eye.

145   *Data analysis & detection function modelling*

146 Observer experience was calculated as a proxy of the number of sightings they had over the total
147 distance in km travelled while on effort during surveys. Observer eye height (height of reticle
148 from the sea), was determined to be the height of the platform in addition to the height of the
149 average UK adult (1.68 m). Distances calculated from reticle readings were used to calculate
150 perpendicular distance where available; however, distances estimated by eye were also included
151 only if closer than 250 m, due to distance estimation being difficult at sea, especially at greater
152 distances (Gordon, 2001). Perpendicular distances from the trackline were over-inflated at 0 m
153 (i.e. on the trackline) due to a prevalence of angles being rounded to 0 degrees. As a result, exact
154 perpendicular distances were converted into 'bins', e.g. all sightings between 0 and 268 m are in
155 the first 'bin', with 'cutpoints' at 0 and 268 m.

156 Distance sampling analysis was carried out in R (R Core Team, 2017) to calculate the probability
157 of detecting animals at distance y from the trackline (Buckland *et al.*, 2001). Detection functions
158 were calculated (distance package; Miller, 2017), including conditions recorded by observers to
159 test their influence on detection (platform height, vessel speed, group size, sea state, visibility,
160 and observer experience). It was assumed that common dolphins were always observed on the
161 trackline, g(0) =1, or close enough to have little impact on the results, based on quick dive times,
162 and often clear surface behaviours (Hammond *et al.,* 2001; Canadas & Hammond, 2008; Becker
163 *et al.*, 2010).

164 Detection functions were originally fitted for a single dataset with all routes combined; however,
165 region was found to alter detectability, likely due to varying platform heights. As a result,
166 regions (as defined by OSPAR sea regions: English Channel, Celtic Sea, and Bay of Biscay &
167 Iberian Coast) were stratified, and detection functions and density surface models were fitted for
168 each region separately. A range of detection function models were calculated including hazard
169 rate, and half normal forms, and including up to three covariates that may influence detection
170 probability: group size; region (when the entire dataset was modelled as a whole); sea state;
171 precipitation, visibility, vessel speed; platform height; and observer experience. The effect of
172 truncation distances and cut points on the detection functions was also investigated. Subsets of
173 detection functions were selected that were deemed to have an adequate fit, based on chi squared
174 goodness of fit tests. The best model for each region was selected based on minimising the
175 Akaike Information Criterion (AIC) score. The final models were used to calculate the effective
176 strip width (ESW).

177 *Density estimation*

178 GAMs allow for non-normal response data, such as count/abundance of a species, to be related
179 to the predictor variables using non-parametric smooths and were used to model abundance with
180 DSMs, whilst accounting for imperfect detection (Miller *et al.*, 2017). Environmental covariates
181 which have influenced common dolphin occurrence in previous studies were included (Table 1):
182 latitude, longitude (Canadas *et al.*, 2005), depth (Canadas & Hammond, 2008), sea surface
183 temperature (SST; Moura, Sillero & Rodrigues, 2012), distance to coast (Canadas & Hammond,

184 2008), slope (Canadas, Sagarminaga, & Garcia-Tiscar, 2002), and chlorophyll concentration
185 (*chl$_a$*; Moura, Sillero & Rodrigues, 2012). Transects were segmented into approximately 5 km
186 lengths using Marine Geospatial Ecology Tools (Roberts *et al.*, 2010) for ArcMap 10.5 (ESRI,
187 2017), and covariate values were assigned by segment centroids with ncdf4 and raster packages
188 (Pierce, 2017; and Hijmans, 2017, respectively). Segments were used as a prediction grid in
189 spatial models, with each cell length equal to approximately 5 km, and width equal to the
190 truncation distance of the appropriate regions' detection function.

191 One-way thin plate regression smooths and two-way tensor smooths were used to model
192 abundance with the spatial covariates, with a one-way smooth of environmental covariates, using
193 mgcv (Wood, 2006). Models were compared between those based on a negative binomial
194 distribution and a Tweedie distribution which adequately handles zero-inflated spatial models
195 (Miller *et al.*, 2013). The number of allowed knots (k) in the smooth was varied up to k=15 to
196 investigate the best model fit, whilst EDF were considered in order to avoid overfitting models.
197 The best model was selected based on minimising the AIC score, including only those variables
198 that were significant to $p < 0.05$ according to step-wise model selection. Residuals were checked
199 for normality, auto-correlation and homoscedasticity. Abundance was estimated with a Horvitz-
200 Thompson-like estimator which accounts for detection probabilities arising from count data
201 (Miller *et al.*, 2018). Abundance estimates and survey effort, calculated in Europe albers equal
202 conic area projection, were used to calculate density per km. For each estimate, the coefficient of
203 variance (CV) and 95% confidence intervals (95% CI) were calculated by variance propagation,
204 including uncertainty arising from the detection function, and GAMs (Miller *et al.*, 2013).
205 Density estimates for the Celtic Sea were compared to those from models that only included the
206 outward leg from Penzance to St Mary's, but not the return) to investigate whether returning
207 across the same area in quick succession influenced results, and to check model performance.

208 Results

209 There were 969 sightings of 11,993 common dolphins during the 68,206 km of effort undertaken
210 by citizen scientists between March and October 2006 - 2017. The amount of effort and sightings
211 fluctuated considerably between years, with a generally increasing trend in the amount of effort
212 over time (Table 2). The majority of sightings were in the Bay of Biscay (Figure 2), with 611
213 sightings, of 8,287 animals (group size range = 1-1000, median = 8). There were 273 sightings of
214 2,516 animals in the Celtic Sea (group size range =1-150, median = 6), and 85 sightings of 1,190
215 animals in the English Channel (group size range = 1-200, median = 6).

216 Probability of detection & density estimates

217 English Channel

218 A total of 24,262 km of effort was undertaken in the English Channel, with at least 2,000 km in
219 most years, with reduced effort (less than 2,000 km) in 2006-2008, and 2016 (Table 2). The best
220 detection function was a half-normal, including 75 sightings within the truncation distance of

221   1,250 m (Table 3). Vessel speed, sea state, and group size were retained in the model as they
222   affected detection probabilities, with higher vessel speeds, higher sea state, and lower group sizes
223   resulting in reduced probability of detection. This resulted in a probability of detection of 0.384
224   within the truncation distance (Figure 3). The best density surface model included a 2-way
225   smooth of longitude and latitude (p<0.05) and year (p<0.05), explaining a relatively low 13.2%
226   of deviance but passed model checks for fit, normality, auto-correlation and homoscedasticity.
227   Density was estimated to be 0.025 common dolphins per km (0.016 - 0.04 95% CI), with a
228   coefficient of variation (CV) of 0.229.

229   Higher densities were predicted to occur ~20 km north of the Finistere region of Brittany (Figure
230   4A). Variation between years is uncertain due to wide confidence intervals; however, it appears
231   that densities decreased from 2006 to 2009 and have been increasing since (Figure 5).

232   *Celtic Sea*

233   A total of 15,915 km was travelled whilst searching for cetaceans in the Celtic Sea, with reduced
234   effort in 2006 - 2009 (Table 2). The best hazard-rate detection function included 260 sightings
235   within the truncation distance of 1000 m (Table 3). Group size and sea state were retained, with
236   larger group sizes, and lower sea states resulting in improved detection probabilities. The overall
237   detection probability was relatively low compared to other regions at 0.158 (Figure 2); however
238   SCANS-III calculated a similar probability of detection for common and striped dolphins
239   combined of 0.13, also assuming g(0)=1.

240   The best density surface model included a 2-way smooth of latitude and longitude (p<0.01), and
241   1-way smooths of chlorophyll (p < 0.01), year (p < 0.01) and Julian day (p <0.01) explaining
242   23.2% of deviance. There was an estimated density of 0.40 common dolphins per km (CI: 0.305
243   - 0.524), with a coefficient of variation of 0.139. The highest densities were predicted to occur in
244   the middle of the route, ~20 km east of the Isles of Scilly (Figure 4B). Densities have been fairly
245   stable over time, with a decrease in 2017 (Figure 6b). Densities decreased towards winter, with
246   stable numbers throughout summer (Figure 6a). The influence of chlorophyll concentrations was
247   significant, with a slight decrease in density associated with higher concentrations, however
248   confidence intervals are wide, resulting in a high degree of uncertainty (Supporting Figure 6).
249   Densities were similar between models that included both the onward and return journey (0.4
250   dolphins per km), and models that only included a single leg (0.39 per km), suggesting suitable
251   performance and limited influence of repeated journeys within quick succession.

252   *Bay of Biscay*

253   A total of 28,029 km of effort was undertaken in the Bay of Biscay from 2006 - 2017, with
254   reduced effort in 2006 and 2016 (Table 2). The best model was a hazard-rate key function, with
255   569 sightings included within the truncation distance of 1,250 m (Table 3). Speed, sea state, and
256   group size were retained in the detection function as they affected detection probability, with

257 higher speeds, higher sea states, and smaller group sizes reducing detection probabilities. The
258 probability of detection was 0.348 within the truncation distance (Figure 2).

259 Depth (p < 0.001), distance to coast (p < 0.001), Julian day (p <0.001), and year (p < 0.001) were
260 all retained in the DSM. The model explained a relatively low percentage of the deviance
261 (13.3%) but passed model checks with a total CV of 0.072. There was an estimated density of
262 0.319 common dolphins per km (0.277 - 0.367 95% CI). The highest densities were predicted to
263 be towards the northern end of the surveyed region, close to the continental shelf edge with
264 lower densities towards the Santander coast (Figure 4C). The effects of depth and distance to
265 coast are less clear due to wide confidence intervals; however, density increases with increasing
266 distance from the coast (Supplementary Figure 4), and up to 2000 m depth, then decreases at
267 greater depths (Supplementary Figure 5). Similar to the Celtic Sea, numbers decrease towards
268 winter (Figure 7a). Densities increased between 2006 and 2013 and have decreased since (Figure
269 7b).

Discussion

271 *Common dolphin densities & trends*

272 The highest densities of common dolphins were found in the small area surveyed in the Celtic
273 Sea between Penzance and the Isles of Scilly, with an estimate of 0.4 per km (0.305 - 0.524 95%
274 CI). This is similar to the overall density estimated for the wider area of the Celtic Sea surveyed
275 by SCANS-III in 2016 of 0.374 (0.09 - 0.680 95% CI) (Hammond *et al.*, 2017). The mean group
276 size is also similar between the two studies (9.68 in our study, and 10 in SCANS-III). The Bay of
277 Biscay was estimated to have similarly high densities of common dolphins (0.319, with 0.277 -
278 0.367 95% CI), but this is lower than that estimated by SCANS-III (0.784, with 0.445 - 1.26 95%
279 CI). This is likely to be due to the limited extent of the Bay of Biscay covered by the ferry route
280 in comparison to the SCANS surveys which covered more of the off-shore waters and
281 continental shelf edge - areas frequented by common dolphins and other cetacean species due to
282 higher productivity along the shelf-edge (Hammond *et al.*, 2009).

283 Common dolphins are infrequent visitors to the English Channel, as demonstrated by the low
284 density estimated in this study (0.036 animals per km with 0.024 - 0.05 95% CI), and lack of
285 common dolphins recorded during the SCANS-III survey (Hammond et al., 2017). The role and
286 importance of regular citizen science data collection is demonstrated particularly clearly here,
287 allowing for the detection and monitoring of species in low-density areas which infrequent but
288 extensive surveys may miss. This could be especially useful for endangered species, where low-
289 densities may require important conservation action that could be critical to their continued
290 presence. Platforms of opportunity facilitate regular monitoring that is unlikely to be practical
291 with traditional means and can be used to survey data-deficient areas if infrastructure and
292 logistics allow.

293   Densities of common dolphins on the Celtic Sea route have been relatively stable since 2006,
294   however density decreased in 2017. This was also the year with the highest number of stranded
295   common dolphins on the Cornish coast in the past 15 years. The decline in density in 2017 could
296   be a result of the mass mortality of common dolphins before the start of the survey season or
297   show a movement away from the survey area which may also be linked to the mass mortality
298   event. But given the limited extent of the survey, it may just indicate a slight shift in distribution
299   within the Celtic Sea rather than a large scale change in distribution. If the decline continues, it
300   may suggest that further studies are needed to widen the data collection further into the Celtic
301   Sea to explore these changes in density in more detail (e.g. extending survey effort to the
302   Roscoff-Cork ferry route).

303   In the Bay of Biscay, higher densities were predicted in waters up to 2500 m deep, with lower
304   densities closer to the Santander coast, which agree with previous studies (Kiszka *et al.*, 2007;
305   Hammond *et al.*, 2009). Densities increased between 2006 and 2016, which is also supported by
306   results from SCANS-II and SCANS-III (Hammond *et al.*, 2017). However, our results show a
307   decline from 2013 onwards which is similarly reported in Authier *et al.* (2018). These
308   decreasing or increasing trends as demonstrated by our data and supported by other studies,
309   shows the importance of long-term and frequent monitoring that can be provided by citizen
310   science data, as infrequent surveys are not able to identify finer-scale temporal changes in
311   density and distribution.

312   Wide-scale infrequent surveys, such as the SCANS surveys (Hammond et al., 2001; 2017) can
313   provide robust estimates of abundance which are essential for estimating the impacts of bycatch.
314   These surveys also provide a complete snapshot of the distribution of the entire population at the
315   time of survey (depending on the extent of the survey). However finer-scale spatial or temporal
316   changes require additional monitoring. Without ongoing monitoring, which can be provided by
317   citizen scientists or local dedicated projects, changes in distribution or abundance may remain
318   unnoticed for an extensive period. Ongoing monitoring has the potential to highlight changes and
319   act as an early warning system, especially for a species such as common dolphins that are
320   vulnerable to bycatch. Up-to-date information on distribution and trends is critical for
321   appropriate and timely management of anthropogenic activities to ensure the conservation of
322   vulnerable species.

323   *Benefits of citizen science data*

324   Citizen science programmes have the potential to collect large quantities of data over a long
325   period of time, and/or a wide area. The collection of long-term time series such as in this study is
326   often not feasible for designed surveys which can be expensive, especially when chartering ships
327   and paying running costs. Using platforms of opportunity such as ferries and cruise ships can
328   make long-term surveys more affordable. Non-random survey designs, such as those imposed
329   when surveying from ferries, limit inferences that can be made due to limited survey area;
330   however, they are repeatedly sampled providing extensive information on changes across that

331 area. Temporal changes in density do need be considered conservatively, especially in fixed
332 areas covered by platforms of opportunity, as small-scale movements away from or into the
333 survey area could influence these estimates considerably. However, these datasets can be
334 important to inform wider-ranging survey design and form an early warning system about
335 changes in the marine environment. Spatial and temporal trends identified by citizen science
336 projects such as this study can also be used by professional surveyors to determine suitable
337 survey areas and times to survey their target species.

338 Conservation management benefits from up-to-date information to best conserve species. Many
339 designed surveys are conducted infrequently, and citizen science data may allow regular
340 evaluation of populations to inform policy makers and legislators. This is particularly relevant to
341 species which don't often warrant targeted surveys but face inter-annual variability of threats.
342 One such example is the expected inter-annual changes in habitat use of common dolphins, and
343 therefore variable overlap with fisheries that may lead to fluctuating bycatch rates. Whilst it is
344 unlikely citizen science surveys will rival designed surveys for robust data collection, the two
345 methodologies complement each other, with citizen science data filling in the gaps between
346 design-based surveys.

347 *Recommendations for high quality citizen science data*

348 Citizen science can be a powerful monitoring tool; however, some datasets may possess certain
349 challenges. To maximise the usability and power of citizen science datasets, simple measures can
350 be taken. The following recommendations for high quality citizen science data are based on the
351 authors' experience working with citizen science data and are provided to hopefully improve the
352 quality of similar data.

353 It is important to identify incomplete data or errors early in the data life-cycle. Early
354 identification facilitates timely communication with the data collectors to correct the data where
355 possible or provide further training to improve future data. To maintain quality, data should be
356 checked for accuracy as it is collected in the field, with further exploration for broader patterns
357 soon after the survey. If surveys are conducted as a team, an experienced individual should be
358 responsible for checking that data are logical (e.g. angles are between $0 - 359$), and accurate (e.g.
359 distances and angles are not rounded). A short cross-over period between recorders can be
360 factored into the protocol, e.g. when the survey team cycles through roles, the old recorder can
361 discuss the current environmental conditions with the new observer to ensure consistency
362 between recorders and continue training if required. When data are collected by lone citizen
363 scientists without *in-situ* discussion and checking of the data by others, further data validation
364 rules may be required after collection. If the project allows, photographs of a subset of animals
365 could be taken to confirm identification skills, or alternatively a digital quiz could be created to
366 test survey skills and reinforce training.

367   Discussion should be nurtured, and the views of less experienced individuals should be
368   welcomed. This allows their surveying techniques to be evaluated for accuracy; conversely
369   inexperienced individuals are more likely to have recently undertaken structured training
370   courses. If experienced recorders miss on-going training, then there is a chance they could
371   develop bad habits that vary from the intended protocol. It is important for citizen scientists to
372   have a support network with ongoing training and avenues for queries to be addressed.
373   Continued support could be in the form of face-to-face training days with active citizen
374   scientists, mid-season reminders of successes and best practise, or annual training events.

375   In some cases, citizen science data can lack complete spatial coverage of the study area;
376   however, there are often similar projects researching the same species. Coverage can be
377   improved by combining similar datasets, for example the Joint Cetacean Protocol (Paxton *et al.*,
378   2016) and the European Cetacean Monitoring Coalition (previously ARC; Brereton *et al.*, 2001)
379   join data from many smaller-scale groups. Once data are converted into a shared format, an
380   extensive dataset can be analysed with greater spatial coverage. Collaborations such as these can
381   be powerful and enhance monitoring to drive conservation of key species.

Conclusions

383   We have demonstrated that citizen science data collected from platforms of opportunity have an
384   important role to play in the continued monitoring of cetaceans. Many of the results are similar
385   to those derived from wide-scale and robust, but infrequent surveys. Therefore, citizen science
386   can complement traditional scientific monitoring by continuing monitoring between these
387   surveys. If used appropriately, citizen science data can be used to identify changes in distribution
388   or density which have conservation implications such as changing distributions that may cause
389   an overlap with anthropogenic stressors.

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Figure 1

The ferry routes travelled between Plymouth - Santander - Portsmouth through the English Channel and Bay of Biscay, and from Penzance - St Mary's in the Celtic Sea.

Black lines indicate the line of ferry travel when surveyors are actively searching for dolphins. Bathymetry is indicated with light blue to dark blue in order of increasing depth. *(Bathymetry vector courtesy of Natural Earth: www.naturalearthdata.com).*
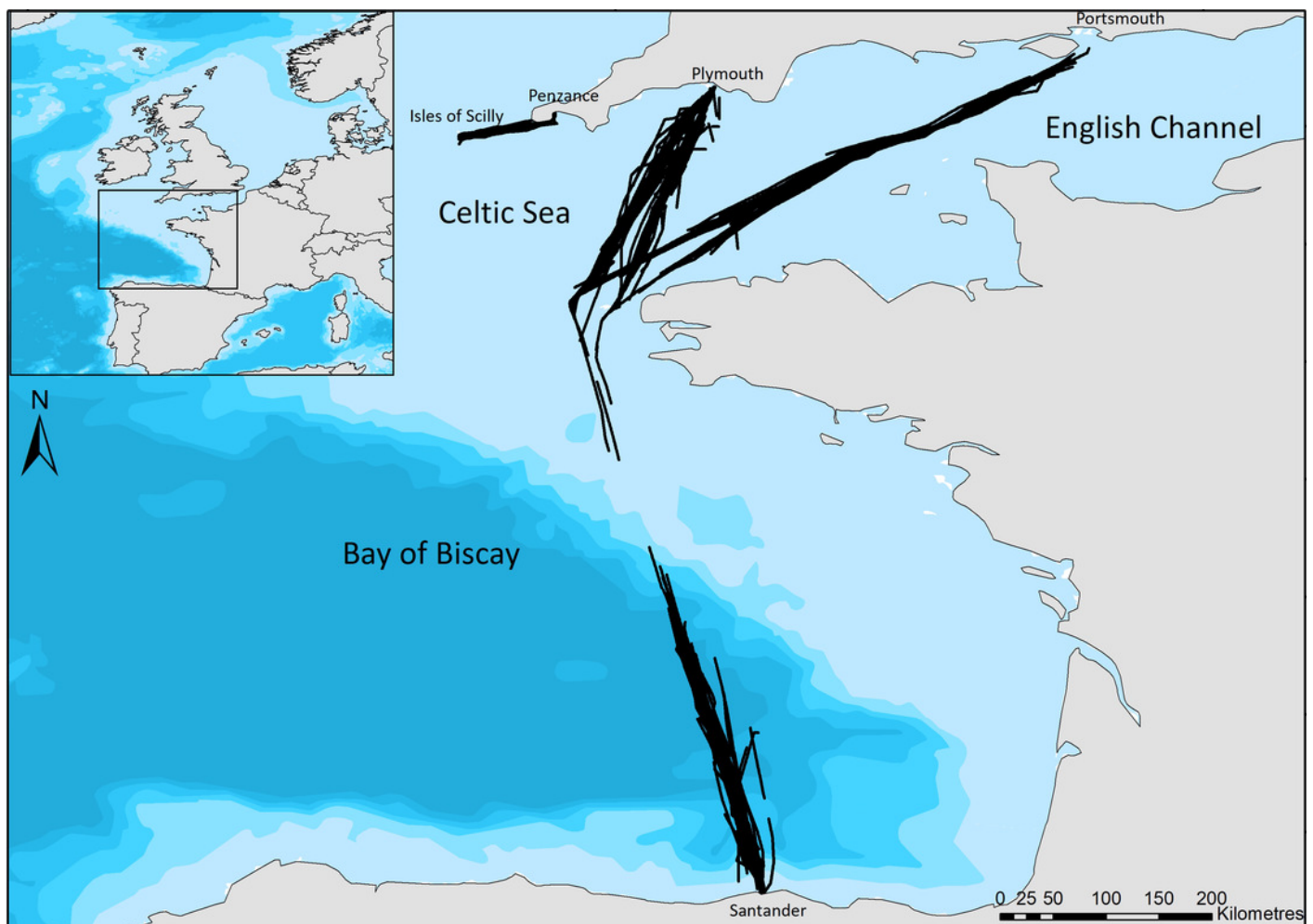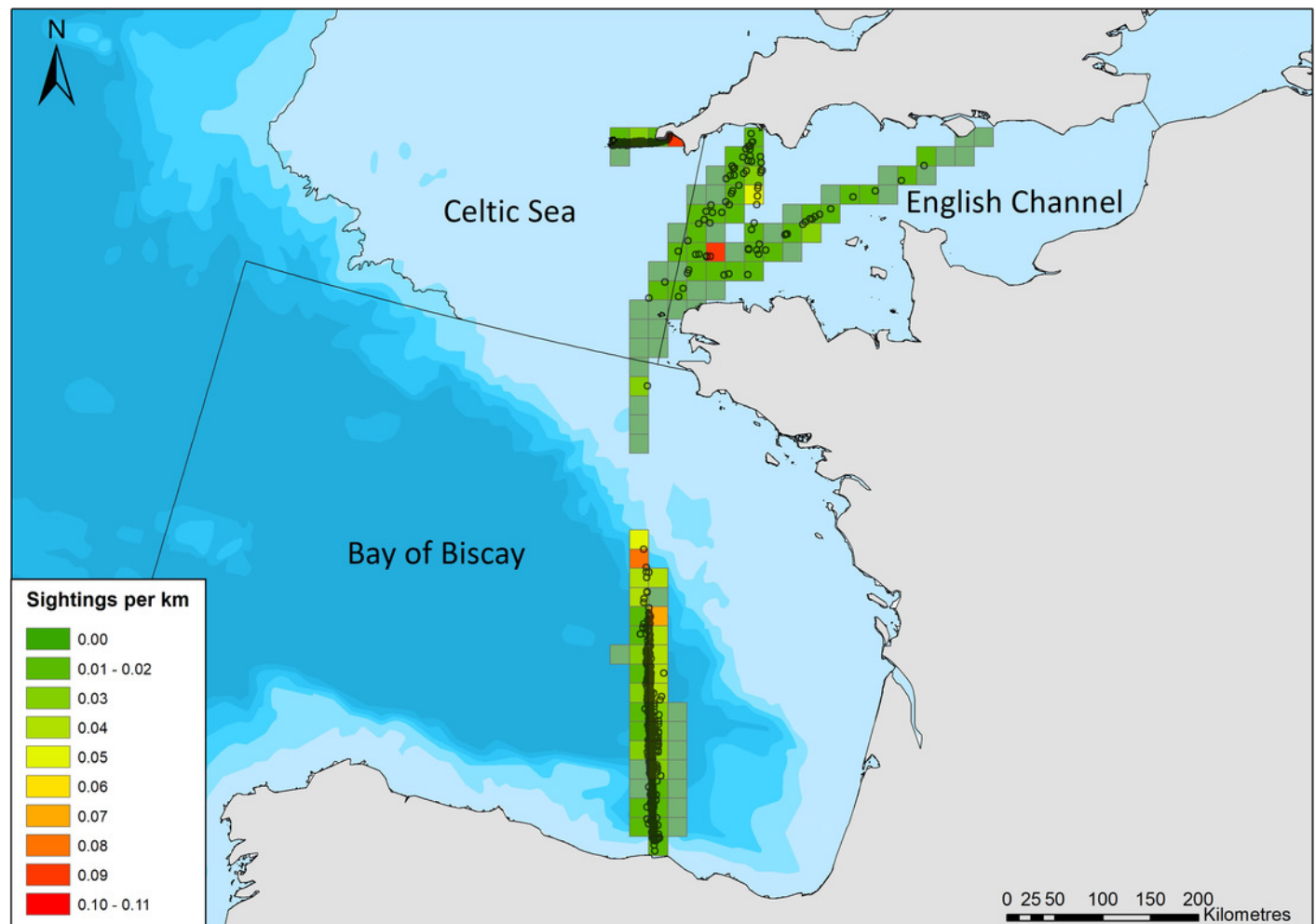
Figure 2

Common dolphin sightings across the study area.

Black lines crossing water depict region boundaries for the English Channel, Celtic Sea, and Bay of Biscay. Open circles show locations of common dolphin groups. Grid cell colour represents common dolphin groups per km of effort. Bathymetry is shown, with sightings in shallow water (light blue), through to waters up to 4000 m deep (dark blue). *Bathymetry vector courtesy of Natural Earth: www.naturalearthdata.com .*
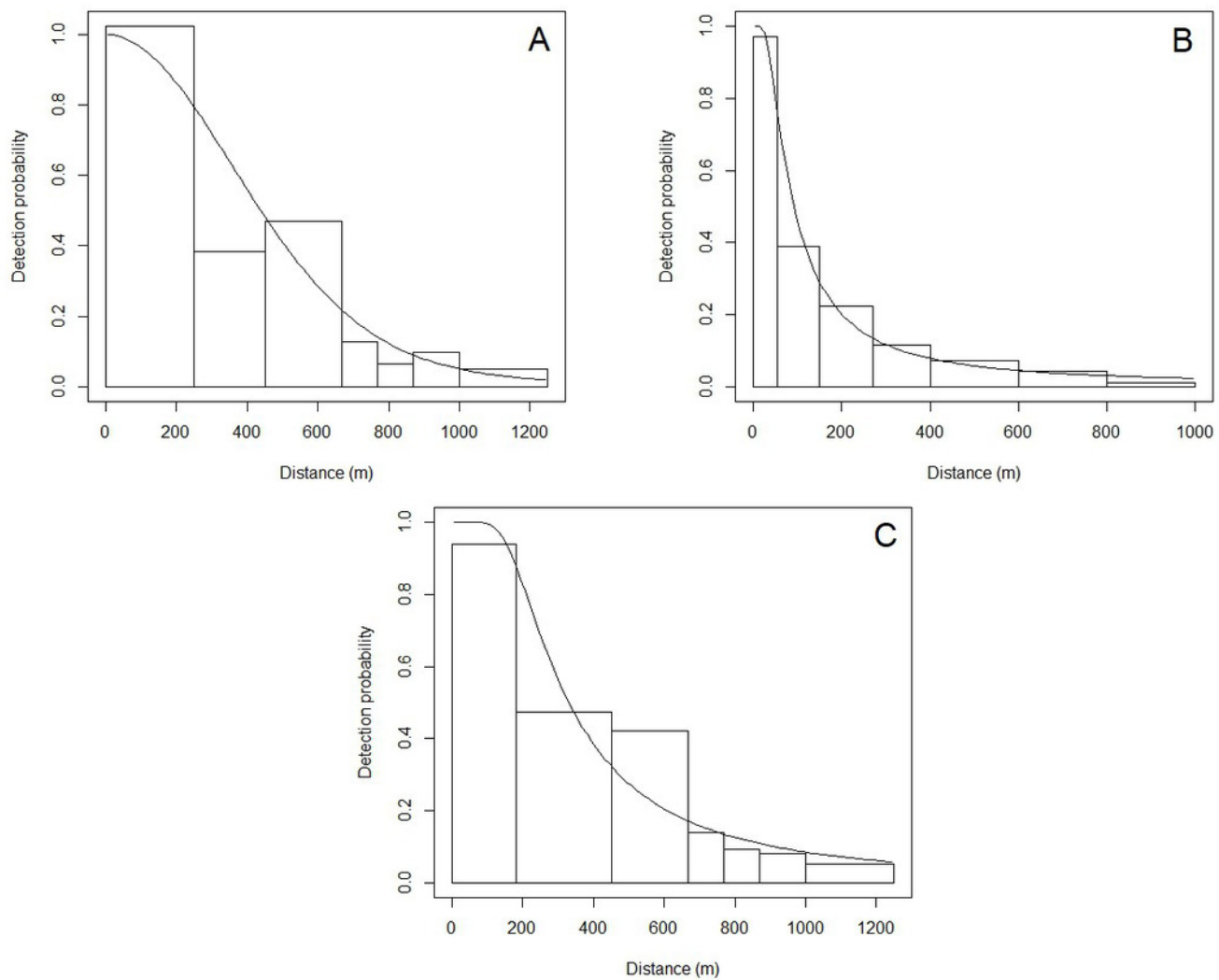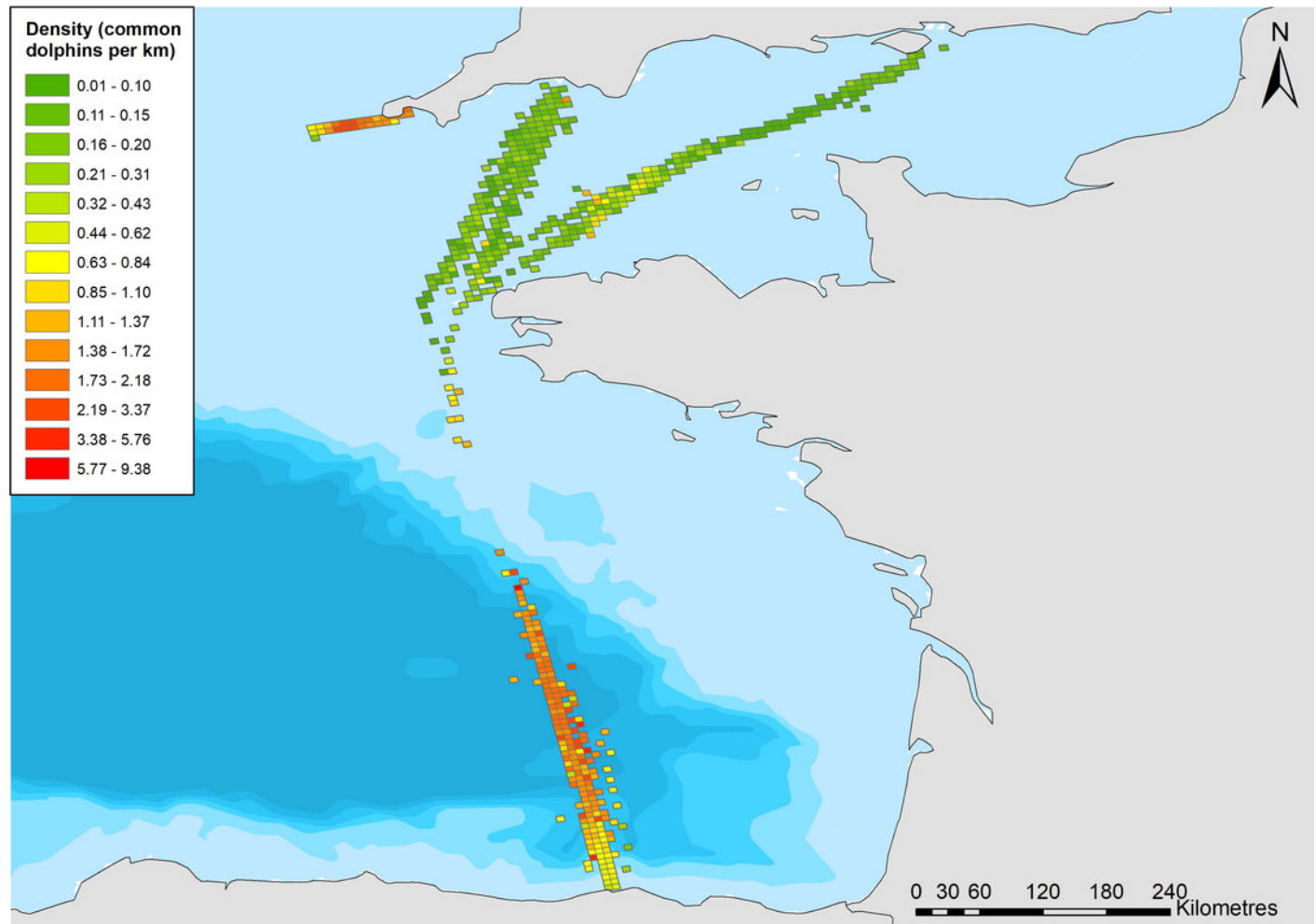
Figure 3

Detection functions showing the detection probability of common dolphins at perpendicular distances (m)

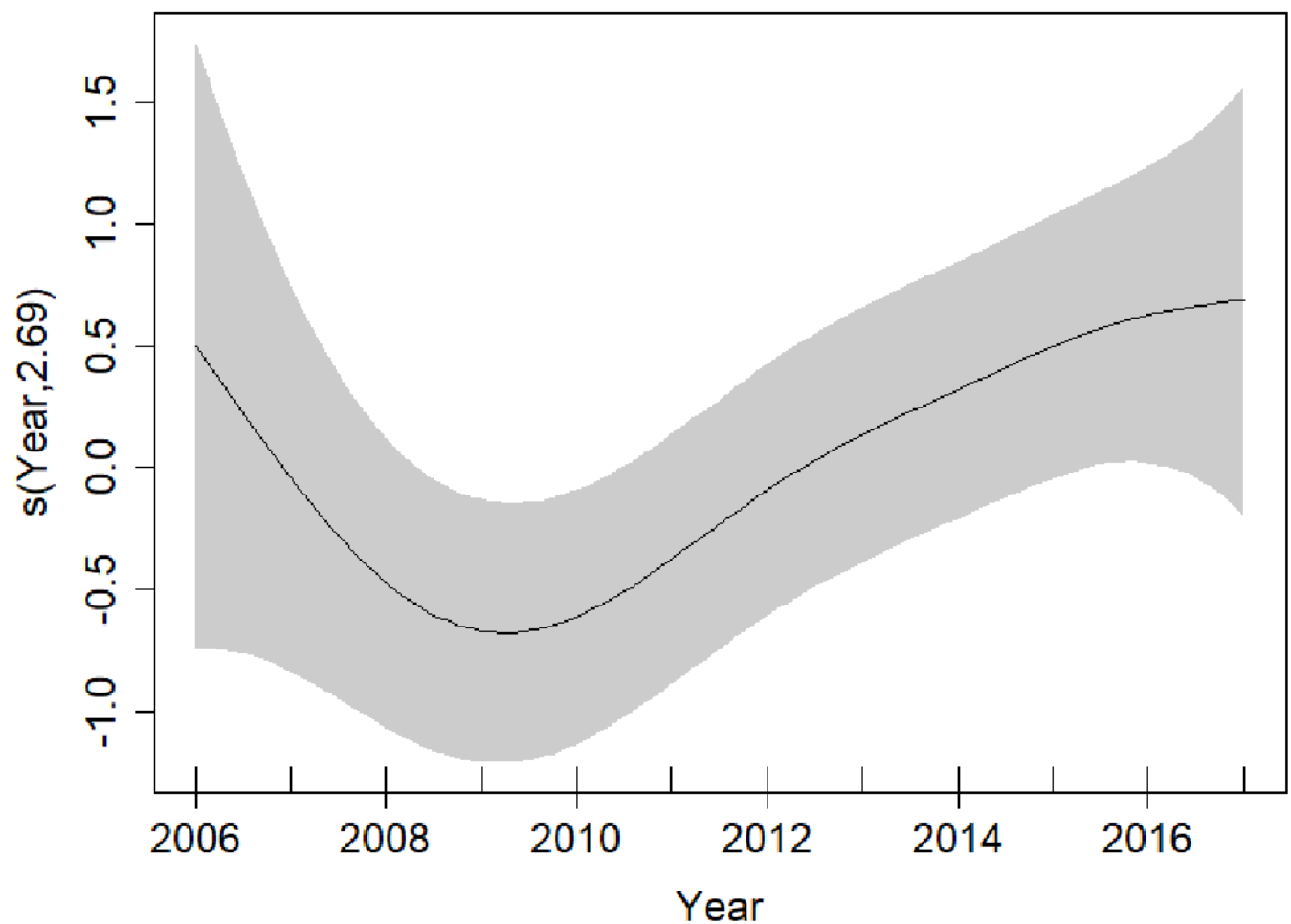A) English Channel, B) Celtic Sea, C) Bay of Biscay

Figure 4

Density of common dolphins (per km) across the study area.

Figure 5

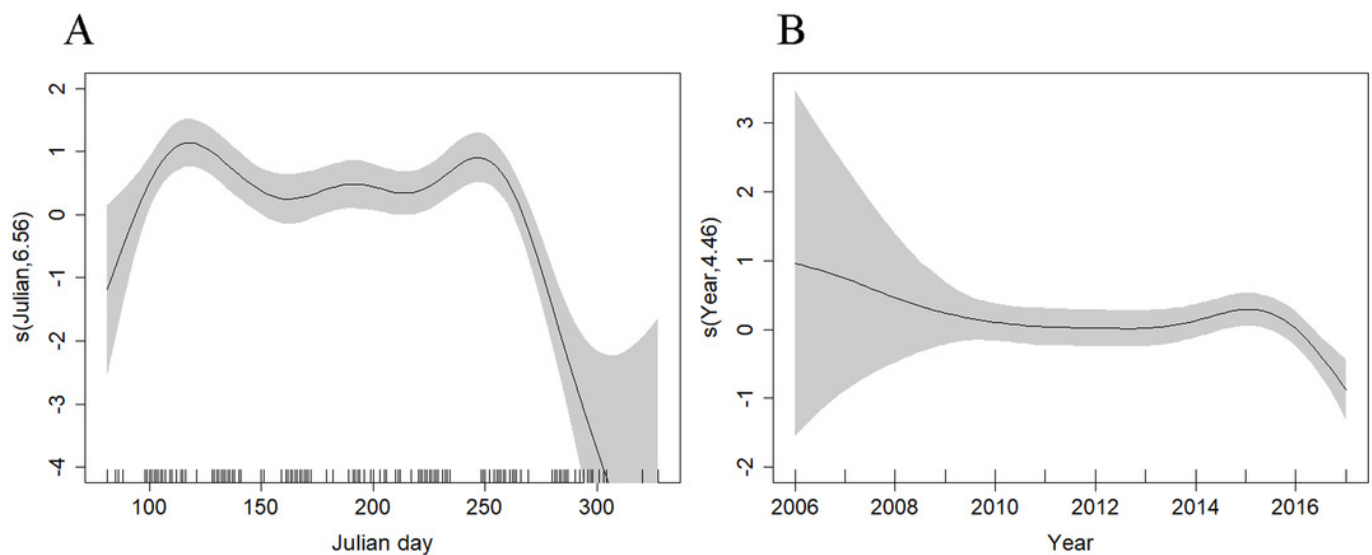Plots of the GAM smooth fit of abundance between years in the English Channel.

Solid line represents the best fit, with the grey shaded area representing the 95% confidence intervals. Vertical lines on the x-axis are the observed data values.

Figure 6

Plot of the GAM smooth fit of abundance between A) Julian days, and B) Years in the Celtic Sea.

The solid line represents the best fit, with the grey shaded area representing the 95% confidence intervals which are wide between 2006 – 2008 and early spring and late autumn when effort is low. Vertical lines on the x-axis are the observed data values.

Figure 7

Plot of the GAM smooth fit of abundance across A) Julian days and B) Years in the Bay of Biscay.

The solid line represents the best fit, with the grey shaded area representing the 95% confidence intervals. Vertical lines on the x-axis are the observed data values.
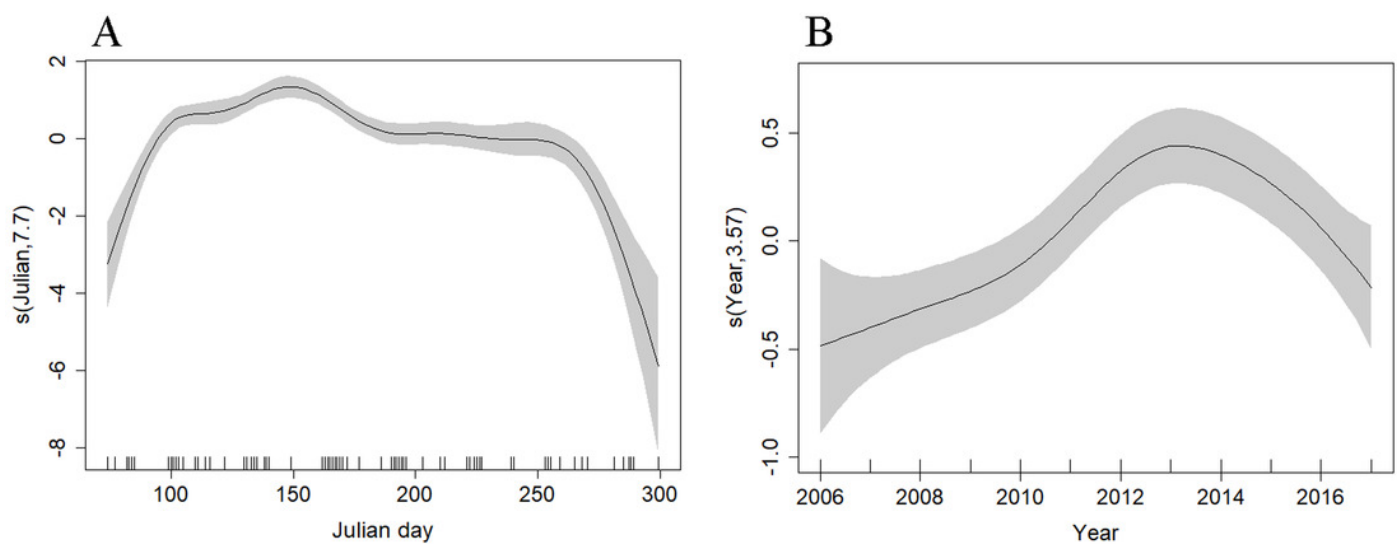
Table 1(on next page)

Summary of the key environmental covariates used in the DSM, their source and resolution.

SST and chlorophyll data are monthly composites for the appropriate year.

Covariate	Source	Approximate Resolution
Depth at mean tide height	EMODNET Bathymetry Consortium, 2016	463 m^2
Sea surface temperature	MODIS Aqua level 3; NASA, 2017	4 km^2
Chlorophyll	MODIS Aqua level 3, OCI algorithm; NASA, 2017	4 km^2
Distance to coast	Calculated with Albers equal European projection in ArcMap (ESRI, 2017)	
Slope	Calculated from min & max depth values (EMODNET Bathymetry Consortium, 2016)	463 m^2

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Table 2(on next page)

Number of sightings and effort to the nearest km for each survey region and year.

Survey region	Data	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Total
English Channel	Effort	640	1183	1529	2507	2404	2661	2390	2091	2726	2261	1705	2167	24262
	Sightings	1	2	5	0	1	4	6	9	11	3	9	34	85
	Sightings per km	0.0015	0.0016	0.0032	0	0.0004	0.0015	0.0025	0.0043	0.0040	0.0013	0.0052	0.0156	0.0035
Celtic Sea	Effort	274	196	138	783	2005	1603	1507	1671	1959	2011	1768	1997	15915
	Sightings	0	1	3	5	4	18	14	49	14	74	79	12	273
	Sightings per km	0	0.0051	0.0217	0.0063	0.0019	0.0112	0.0092	0.0293	0.0071	0.0367	0.0446	0.0060	0.0171
Bay of Biscay	Effort	1200	2173	2808	2766	2276	2797	2618	2212	2424	2391	1721	2643	28029
	Sightings	25	39	40	2	6	49	65	75	78	110	53	69	611
	Sightings per km	0.0208	0.0179	0.0142	0.0007	0.0026	0.0175	0.0248	0.0339	0.0321	0.0460	0.0307	0.0261	0.0217

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Table 3(on next page)

Final detection function models for the English Channel, Celtic Sea, and Bay of Biscay.

Region	Model	Truncation distance (# sightings)	p (SE)	ESW (SE)	% CV	Variables
English Channel	Half-normal	1250 m (75)	0.384 (0.04)	480 (50.62)	10.6	Vessel speed + sea state + group size
Celtic Seas	Hazard-rate	1000 m (260)	0.158 (0.019)	158 (19)	12.2	Sea state + group size
Bay of Biscay	Hazard-rate	1250 m (569)	0.348 (0.02)	435 (2.5)	5.9	Vessel speed, sea state + group size

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