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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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Abstract

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Introduction

Citizen science has been growing in popularity in recent years, and projects often have hundreds, or thousands of active volunteers collecting data across wide geographical areas and long time periods (Hyder et al., 2015). Long-term monitoring such as this can provide an early warning system of change in the marine environment. Citizen science has been used to study a variety of taxa, for example, birds (e.g. Sullivan et al., 2009), intertidal organisms (e.g. Vermeiren et al., 2016), or record a broad range of animals across taxa and ecosystems (e.g. Postles & Bartlett, 2018). Several citizen science projects collect data on marine mammals, with many of these using shore-based data collection methodologies (Tonachella et al., 2012; Embling et al., 2015). Vessel-based methods are often restricted to ad-hoc data collection of animal presence; however, some studies have successfully used platforms of opportunity (vessels that undertake non-scientific voyages along predetermined routes such as ferries or cruise ships) to undertake citizen science surveys at sea (e.g. Williams, Hedley & Hammond, 2006; Kiszka et al., 2007). The use of such platforms is considerably cheaper than chartering a ship and paying running costs, although surveyors have limited or no control over the journey that the vessel undertakes. Such surveys can be used to investigate animal distribution and abundance.

An understanding of animal distribution and range is critical for potential anthropogenic impacts to be understood, for appropriate conservation management, and spatial planning. Standardised methods can allow for citizen science data to be used in abundance estimates (e.g. Davies et al., 2013), which is key for monitoring species trends in space and time. However, even with standardised methods, it is often challenging for citizen science data to be reliable and accurate enough (Crall et al., 2011) to provide good estimates of abundance due to the difficulties of detecting animals, especially at sea (Buckland et al., 2001). For example, marine mammals spend only a fraction of their time at the surface of the water where they are available to be recorded by vessel-based surveyors (Mate et al., 1995). Animals are also usually less likely to be recorded at increasing distances from the observer, with probability likely to decrease in worsening conditions (Buckland et al., 2001; Buckland et al., 2015), such as higher sea states and swell, reduced visibility, or less experienced surveyors. These uncertain detection
probabilities can be estimated and accounted for with distance sampling analysis (Buckland et al., 2001).

The citizen science charity, ORCA, have been using platforms of opportunity to collect data on cetacean occurrence since 1995, with considerable survey effort being undertaken on-board ferries around the UK and North-Eastern Atlantic. Data are collected following line-transect distance sampling techniques, which can be used in design-based and model-based surveys to estimate the abundance and distribution of cetaceans. Design-based surveys follow randomly-placed systematic transects to provide a representative coverage of the survey area (Thomas et al., 2010). These surveys can be expensive and time-consuming as they use dedicated ships or aircraft to survey large areas (Hammond et al. 2001, 2013, 2017). As a result, they are often carried out infrequently and provide a snapshot of abundance over a short temporal scale. For example, Small Cetaceans in European Atlantic waters and the North Sea (SCANS) surveys are conducted every 10 years but cover expansive areas (Hammond et al., 2001, 2017).

Alternatively, distance sampling surveys can be undertaken with non-random coverage (‘model-based’) from platforms of opportunity. Due to the non-random nature of the transects, results cannot be extrapolated beyond the surveyed area, unlike design-based surveys. Platforms of opportunity often operate year-round however, and data can be collected on a much larger temporal-scales, usually at reduced cost. Results from this type of monitoring are important to understand the impacts of anthropogenic activities on animals, and to assess conservation status and management requirements.

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

This study analyses citizen science data to estimate common dolphin densities in the English Channel, Bay of Biscay and Celtic Sea, accounting for imperfect detection. Results derived from these citizen science data are compared to published results from robust design-based distance
sampling surveys undertaken by professional scientists. Temporal variation in common dolphin
densities is discussed in relation to mass mortality events and bycatch within the study area. The
strengths and limitations of citizen science data are discussed, and recommendations given for
accurate and robust citizen science monitoring data.

Materials & Methods

Survey area

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

Data collection

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

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

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

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

**Density estimation**

GAMs allow for non-normal response data, such as count/abundance of a species, to be related to the predictor variables using non-parametric smooths and were used to model abundance with DSMs, whilst accounting for imperfect detection (Miller et al., 2017). Environmental covariates which have influenced common dolphin occurrence in previous studies were included (Table 1): latitude, longitude (Canadas et al., 2005), depth (Canadas & Hammond, 2008), sea surface temperature (SST; Moura, Sillero & Rodrigues, 2012), distance to coast (Canadas & Hammond,
2008), slope (Canadas, Sagarminaga, & Garcia-Tiscar, 2002), and chlorophyll concentration
\((chl_a; \text{Moura, Sillero} \& \text{Rodrigues}, 2012)\). Transects were segmented into approximately 5 km
lengths using Marine Geospatial Ecology Tools (Roberts \textit{et al.}, 2010) for ArcMap 10.5 (ESRI,
2017), and covariate values were assigned by segment centroids with ncdf4 and raster packages
(Pierce, 2017; and Hijmans, 2017, respectively). Segments were used as a prediction grid in
spatial models, with each cell length equal to approximately 5 km, and width equal to the
truncation distance of the appropriate regions’ detection function.

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

\textbf{Results}

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

\textbf{Probability of detection & density estimates}

\textit{English Channel}

A total of 24,262 km of effort was undertaken in the English Channel, with at least 2,000 km in
most years, with reduced effort (less than 2,000 km) in 2006-2008, and 2016 (Table 2). The best
detection function was a half-normal, including 75 sightings within the truncation distance of
Vessel speed, sea state, and group size were retained in the model as they affected detection probabilities, with higher vessel speeds, higher sea state, and lower group sizes resulting in reduced probability of detection. This resulted in a probability of detection of 0.384 within the truncation distance (Figure 3). The best density surface model included a 2-way smooth of longitude and latitude (p<0.05) and year (p<0.05), explaining a relatively low 13.2% of deviance but passed model checks for fit, normality, auto-correlation and homoscedasticity. Density was estimated to be 0.025 common dolphins per km (0.016 - 0.04 95% CI), with a coefficient of variation (CV) of 0.229.

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

**Celtic Sea**

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

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

**Bay of Biscay**

A total of 28,029 km of effort was undertaken in the Bay of Biscay from 2006 - 2017, with reduced effort in 2006 and 2016 (Table 2). The best model was a hazard-rate key function, with 569 sightings included within the truncation distance of 1,250 m (Table 3). Speed, sea state, and group size were retained in the detection function as they affected detection probability, with...
higher speeds, higher sea states, and smaller group sizes reducing detection probabilities. The probability of detection was 0.348 within the truncation distance (Figure 2).

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

**Discussion**

**Common dolphin densities & trends**

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

Common dolphins are infrequent visitors to the English Channel, as demonstrated by the low density estimated in this study (0.036 animals per km with 0.024 - 0.05 95% CI), and lack of common dolphins recorded during the SCANS-III survey (Hammond et al., 2017). The role and importance of regular citizen science data collection is demonstrated particularly clearly here, allowing for the detection and monitoring of species in low-density areas which infrequent but extensive surveys may miss. This could be especially useful for endangered species, where low-densities may require important conservation action that could be critical to their continued presence. Platforms of opportunity facilitate regular monitoring that is unlikely to be practical with traditional means and can be used to survey data-deficient areas if infrastructure and logistics allow.
Densities of common dolphins on the Celtic Sea route have been relatively stable since 2006, however density decreased in 2017. This was also the year with the highest number of stranded common dolphins on the Cornish coast in the past 15 years. The decline in density in 2017 could be a result of the mass mortality of common dolphins before the start of the survey season or show a movement away from the survey area which may also be linked to the mass mortality event. But given the limited extent of the survey, it may just indicate a slight shift in distribution within the Celtic Sea rather than a large scale change in distribution. If the decline continues, it may suggest that further studies are needed to widen the data collection further into the Celtic Sea to explore these changes in density in more detail (e.g. extending survey effort to the Roscoff-Cork ferry route).

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

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

**Benefits of citizen science data**

Citizen science programmes have the potential to collect large quantities of data over a long period of time, and/or a wide area. The collection of long-term time series such as in this study is often not feasible for designed surveys which can be expensive, especially when chartering ships and paying running costs. Using platforms of opportunity such as ferries and cruise ships can make long-term surveys more affordable. Non-random survey designs, such as those imposed when surveying from ferries, limit inferences that can be made due to limited survey area; however, they are repeatedly sampled providing extensive information on changes across that
area. Temporal changes in density do need be considered conservatively, especially in fixed areas covered by platforms of opportunity, as small-scale movements away from or into the survey area could influence these estimates considerably. However, these datasets can be important to inform wider-ranging survey design and form an early warning system about changes in the marine environment. Spatial and temporal trends identified by citizen science projects such as this study can also be used by professional surveyors to determine suitable survey areas and times to survey their target species.

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

**Recommendations for high quality citizen science data**

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

It is important to identify incomplete data or errors early in the data life-cycle. Early identification facilitates timely communication with the data collectors to correct the data where possible or provide further training to improve future data. To maintain quality, data should be checked for accuracy as it is collected in the field, with further exploration for broader patterns soon after the survey. If surveys are conducted as a team, an experienced individual should be responsible for checking that data are logical (e.g. angles are between 0 – 359), and accurate (e.g. distances and angles are not rounded). A short cross-over period between recorders can be factored into the protocol, e.g. when the survey team cycles through roles, the old recorder can discuss the current environmental conditions with the new observer to ensure consistency between recorders and continue training if required. When data are collected by lone citizen scientists without *in-situ* discussion and checking of the data by others, further data validation rules may be required after collection. If the project allows, photographs of a subset of animals could be taken to confirm identification skills, or alternatively a digital quiz could be created to test survey skills and reinforce training.
Discussion should be nurtured, and the views of less experienced individuals should be welcomed. This allows their surveying techniques to be evaluated for accuracy; conversely inexperienced individuals are more likely to have recently undertaken structured training courses. If experienced recorders miss on-going training, then there is a chance they could develop bad habits that vary from the intended protocol. It is important for citizen scientists to have a support network with ongoing training and avenues for queries to be addressed. Continued support could be in the form of face-to-face training days with active citizen scientists, mid-season reminders of successes and best practise, or annual training events.

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

Conclusions

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

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References


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.
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.
<table>
<thead>
<tr>
<th>Covariate</th>
<th>Source</th>
<th>Approximate Resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Depth at mean tide height</td>
<td>EMODNET Bathymetry Consortium, 2016</td>
<td>463 m²</td>
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<tr>
<td>Sea surface temperature</td>
<td>MODIS Aqua level 3; NASA, 2017</td>
<td>4 km²</td>
</tr>
<tr>
<td>Chlorophyll</td>
<td>MODIS Aqua level 3, OCI algorithm; NASA, 2017</td>
<td>4 km²</td>
</tr>
<tr>
<td>Distance to coast</td>
<td>Calculated with Albers equal European projection in ArcMap (ESRI, 2017)</td>
<td></td>
</tr>
<tr>
<td>Slope</td>
<td>Calculated from min &amp; max depth values</td>
<td>463 m²</td>
</tr>
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</table>
Table 2 (on next page)

Number of sightings and effort to the nearest km for each survey region and year.
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<tr>
<th></th>
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<tbody>
<tr>
<td>English Channel</td>
<td>Effort</td>
<td>640</td>
<td>1183</td>
<td>1529</td>
<td>2507</td>
<td>2404</td>
<td>2661</td>
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<td>4</td>
<td>6</td>
<td>9</td>
<td>11</td>
<td>3</td>
<td>9</td>
<td>34</td>
<td>85</td>
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<tr>
<td>Celtic Sea</td>
<td>Effort</td>
<td>274</td>
<td>196</td>
<td>138</td>
<td>783</td>
<td>2005</td>
<td>1603</td>
<td>1507</td>
<td>1671</td>
<td>1959</td>
<td>2011</td>
<td>1768</td>
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<td>15915</td>
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<tr>
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<td>3</td>
<td>5</td>
<td>4</td>
<td>18</td>
<td>14</td>
<td>49</td>
<td>14</td>
<td>74</td>
<td>79</td>
<td>12</td>
<td>273</td>
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<tr>
<td>Bay of Biscay</td>
<td>Effort</td>
<td>1200</td>
<td>2173</td>
<td>2808</td>
<td>2766</td>
<td>2276</td>
<td>2797</td>
<td>2618</td>
<td>2212</td>
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<td>2391</td>
<td>1721</td>
<td>2643</td>
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<tr>
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<td>Sightings</td>
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<td>2</td>
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<tr>
<td></td>
<td>Sightings per km</td>
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<td>0.0179</td>
<td>0.0142</td>
<td>0.0007</td>
<td>0.0026</td>
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Table 3 (on next page)

Final detection function models for the English Channel, Celtic Sea, and Bay of Biscay.
<table>
<thead>
<tr>
<th>Region</th>
<th>Model</th>
<th>Truncation distance (# sightings)</th>
<th>p (SE)</th>
<th>ESW (SE)</th>
<th>% CV</th>
<th>Variables</th>
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</thead>
<tbody>
<tr>
<td>English Channel</td>
<td>Half-normal</td>
<td>1250 m (75)</td>
<td>0.384 (0.04)</td>
<td>480 (50.62)</td>
<td>10.6</td>
<td>Vessel speed + sea state + group size</td>
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<tr>
<td>Celtic Seas</td>
<td>Hazard-rate</td>
<td>1000 m (260)</td>
<td>0.158 (0.019)</td>
<td>158 (19)</td>
<td>12.2</td>
<td>Sea state + group size</td>
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<tr>
<td>Bay of Biscay</td>
<td>Hazard-rate</td>
<td>1250 m (569)</td>
<td>0.348 (0.02)</td>
<td>435 (2.5)</td>
<td>5.9</td>
<td>Vessel speed, sea state + group size</td>
</tr>
</tbody>
</table>