Methodology for Combining Digital Aerial Survey Data and Passive Acoustic Baseline Data

Final Report

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Methodology for Combining Digital Aerial Survey Data and Passive Acoustic Baseline Data

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Executive Summary

Marine mammal abundance and distribution data form an important part of assessments to estimate the potential effects of proposed offshore wind developments. Therefore, there is a need to ensure that abundance and distribution data are collected and analysed to ensure robust estimates to inform the planning, consenting and licensing processes. There are several sources of information that can contribute to estimating the abundance and distribution of marine mammals. Digital aerial surveys (DAS) and static passive acoustic monitoring (PAM) are two data collection modes, which have been developed relatively recently, compared to standard visual aerial and ship-based surveys used within the UK. Both digital aerial and static PAM surveys can collect data on fine temporal and spatial scales, though they have their strengths and limitations. Aerial surveys typically provide better spatial survey coverage than static acoustic recorders, while acoustic recorders generally provide improved temporal coverage. The overarching goals of this project were to: (1) produce a modelling framework integrating DAS and PAM data; (2) produce a test case study on harbour porpoise to validate the methods; and (3) provide recommendations on standards for static PAM and DAS data collection.

This project ran from January 2023 – February 2024 and a series of technical meetings were held by the project team to review data integration methods, available software to assist data integration and survey design considerations and recommendations. A dataset from the Moray Firth, Scotland, was prepared and analysed for the case study. The main deliverables were this final report and accompanying analysis code.

Multiple methods to integrate DAS and PAM data were assessed. The selected method for the case study used a Bayesian model to calibrate the PAM data using absolute densities derived from the DAS data. This method allows uncertainty to be propagated in all elements of the density estimators for both the DAS and PAM data. Currently available tools to assist with DAS and PAM data integration were also assessed. R-based MRSea software was used for the spatial modelling components of the case study analysis, and the project also identified how other R-based tools can be used for survey design (dssd/dsims) and to assess power to detect changes in density/abundance (MRSeaPower/AVADECAF). All assessed software packages have potential for extensions, which would ultimately aid data integration, though these were outside the scope of this project. Discussions about software concluded that clear documentation and long-term support are key features of any software used for analysis so should be considered a priority in any future software development.

The case study used PAM and DAS data in the Moray Firth from August and September 2010 to assess the distribution and abundance of harbour porpoise (*Phocoena phocoena*). The analysis demonstrated the use

of Bayesian data integration following methods in Jacobson et al. (2017). A parameter combining detection probability of harbour porpoise clicks and probability of clicking was estimated, with associated uncertainty. The estimation of this parameter enabled absolute density to be estimated from the PAM data, including during time periods where no DAS were flown. This is the primary benefit of implementing this method: long-term time series of PAM data can be used to estimate absolute densities, assuming that the parameters estimated from the combined DAS and PAM data are representative across the time periods analysed. Density surfaces were also estimated from the calibrated PAM data, showing spatial changes in absolute density. This approach is likely to be of most practical use in applications to support offshore wind development, where DAS data are able to provide an estimate of the absolute density of cetaceans (albeit with some limitations) and the PAM data play a supporting role by collecting continuous data across the time period of interest. Relevant code and data used for the case study are available on GitHub. Finally, survey design discussions within the project team highlighted key topics such as (1) defining project goals, (2) addressing survey design principles such as replication and coverage at the survey design stage using available software tools, (3) using best available data regarding required parameters for density/abundance estimation and (4) specific considerations relating to DAS-PAM data integration. Future survey design-related research steps were also outlined, focusing on assessing how the number of PAM instruments and DAS flights influence precision and accuracy in the resulting calibrated PAM data.

In conclusion, the following survey design recommendations were suggested:

- Clearly identify the goals of a survey to ensure that the survey design will meet the needs of the survey goals. Goals may need to be prioritised where there are several competing goals and/or target species.
- Follow existing guidance for line and point placement for separate DAS and PAM surveys, though more research is needed to understand survey design requirements for an integrated survey.
- Use existing tools where possible to aid survey design, including assessing the power of the survey to detect changes in density and abundance. More software tool development is required specifically for integrated surveys.
- Consider the benefits of collecting data from more than one type of surveying platform. Different platform types offer different advantages; in this study combining DAS and PAM data led to a time series of estimated absolute densities that would not have been practically possible from one platform alone. More research is required, however, to determine how many DAS flights are required, and at what intervals, to optimally calibrate the PAM data.

Finally, the following future research directions across the project were identified and summarised:

- There is a need to develop a software tool to design combined DAS and PAM surveys, which could be an extension of existing tools.
- Several extensions to the case study analysis would be beneficial including:
  - Explore variability in the vp parameter via extended modelling and simulation.
  - Compare the calibration approach with other reviewed data integration methods.
  - Explore the effects on precision and accuracy of estimated parameters when including acoustic detection probability and cue production rates as informed priors.
  - Use simulation (based on the case study data) to assess how many PAM instruments and how many DAS surveys are required to achieve negligible bias and a suitable level of uncertainty in the resulting abundance estimates.
- Continued research into estimating detection probability and availability parameters for DAS data is important, given the need to estimate absolute density from the DAS data when using the calibration method. This research may also include extracting group size information from DAS data.

Introduction

Within the marine renewables industry, regulators need to make decisions regarding the consenting of proposed offshore wind developments. As part of Environmental Impact Assessments (EIA), Habitat Regulation Appraisals (HRA) and Strategic Environmental Assessments (SEA) there is a requirement to assess the potential impacts to marine mammals from the development of marine renewable sites. Marine mammal abundance and distribution data form an important part of assessments to determine the potential effect of such activities. Therefore, there is a need to ensure that abundance and distribution data are collected and analysed to ensure robust estimates to inform the planning, consenting and licensing processes.

There are several sources of information that can contribute to estimating the abundance and distribution of marine mammals. The current standard within the UK is to use density and abundance estimates for cetaceans from aerial and ship-based visual surveys conducted under the SCANS programme (Gilles et al., 2023; Hammond et al. 2002; 2013; 2021) to define reference populations, against which the likely effects at development sites can be gauged. Such surveys are conducted infrequently over large spatial scales, and so abundance and distribution data at a finer scale are not available for the development sites (Hague et al. 2020). As part of EIA processes, there is a need to both characterise the development site and provide baseline density and abundance estimates for eventual pre- to post-impact monitoring. Digital aerial surveys (DAS) have become the offshore industry standard primarily for offshore ornithology studies. However, the method is not taxon-specific and data on marine megafauna, including cetaceans, are also collected. Static passive acoustic monitoring (PAM) is an alternative method of data collection that detects the presence of vocalising animals. While there are other types of acoustic surveying platforms, such as ship-based towed arrays or glider-mounted hydrophones, these mobile acoustic monitoring platforms are not the focus of this study. Both digital aerial and static PAM surveys can collect data on fine temporal and spatial scales, though they have their strengths and limitations. Aerial surveys can typically provide better spatial survey coverage than static acoustic recorders, while acoustic recorders generally provide improved temporal coverage owing to their extensive deployment durations and ability to collect data during hours of darkness and poor weather. Static PAM surveys can be, however, spatially constrained when compared to dynamic surveys such as DAS.

Absolute animal abundance and density can be estimated from both aerial and static passive acoustic data (e.g., Buckland et al., 2015; Marques et al., 2013). Abundance and density estimation methods for both survey modes share many of the same survey design and analysis attributes but differ in some key aspects, as reviewed below.

All absolute animal abundance methods such as distance sampling (e.g., Buckland et al., 2015) and spatial capture-recapture (e.g., Borchers, 2012) require various inputs (both known constants and parameters that need to be estimated). These inputs form an estimator, an equation designed to convert detections of the target species into an estimate of absolute abundance. A general estimator may take the form (Eqn 1.)

$$\widehat{\mathrm{N}} = \frac{\mathrm{n}}{\widehat{\mathrm{P}}.\mathrm{m}} \qquad \text{(Eqn. 1),}$$

where $\widehat{\mathrm{N}}$ is the estimated abundance, n is the number of detections, $\widehat{\mathrm{P}}$ is the estimated probability of detecting the target species and m is a general term for other multiplying terms that are needed to estimate abundance e.g., group size if n is the number of detected groups or cue production rate if n is the number of detected acoustic cues (see below for more detail).

Further, if the monitored survey area is quantified, then animal density, $\widehat{\mathrm{D}}$, can be estimated (Eqn. 2):

$$\widehat{\mathrm{D}} = {}^{\widehat{\mathrm{N}}}/_{\mathrm{A}} \qquad \text{(Eqn. 2),}$$

where A is the size of the surveyed area. If the monitored area was selected at random within a wider survey area, abundance estimates can be obtained for the wider survey area by using the random properties of the design. Such estimates are known as design-based estimates. If not, model-based approaches, where density is modelled over space as a function of spatially explicit covariates, might be useful (e.g., Miller et al. 2013).

The probability of detection, P, is a key parameter for abundance/density estimation methods, correcting for objects of interest (i.e., individual animals, animal groups, or cues the animals produce such as sounds) that were available to be detected but were missed during a survey. In other words, the detection probability corrects for perception bias, which would, if ignored, cause density/abundance to be underestimated. Estimating detection probability is an essential step for absolute abundance estimation. Without P, or other required parameters (such as probability of detection on the transect line or call production rate) an estimator might be interpreted as a relative index of abundance. Relative indices of abundance rely on the major assumption that the missing parameter(s) remain constant so that temporal or spatial changes in the relative measure are due to real changes in the abundance or density, and not changes in the parameter(s) missing from the estimator. Therefore, absolute measures of density or abundance should be estimated when possible (e.g., Anderson 2001).

In addition to detection probability, both aerial and acoustic density estimators require additional parameters that are challenging to estimate. Aerial survey data analyses require an estimated availability parameter, which in the marine context accounts for diving animals that are missed on the survey trackline because they are unavailable to be detected (e.g., Borchers et al., 2013). By estimating the probability of detecting an animal on the trackline, often described using the notation g(0) in the distance sampling literature, potential availability bias is corrected for, which would otherwise cause density/abundance to be underestimated. Passive acoustic data analyses require a parameter to account for animals' vocal behaviour e.g., the number of calls produced per minute, or the proportion of time that an animal is acoustically active, discussed in Marques et al. (2013).

Often, data do not exist to directly estimate detection probability, the availability parameter or the call production parameter. In these cases, to avoid a relative abundance index, data from two survey modes may be combined. This was the motivation for this project, which had the following goals:

1. Produce a modelling framework integrating DAS data and PAM data, including the ability to incorporate seasonal and diurnal uncertainty.

2. Produce a test case study on harbour porpoise to validate the methods, producing density maps for a specified site in Scotland.

3. Provide recommendations on standards for static PAM and DAS data collection.

These goals were achieved by completing the following tasks over the project's 1-year timeline:

Task 1: A technical meeting was held to discuss available methods for data integration (Section 1).

Task 2: A second technical meeting was held to assess how existing software tools developed within CREEM could be adjusted for combined data types (Section 2).

Task 3: Based on discussions in Task 2, a comprehensive roadmap of how the available software tools could be extended was produced (Section 2).

Task 4: A dataset was selected and prepared for the case study (Section 3).

Task 5: The case study analysis was completed to produce density maps of harbour porpoise for the selected Scottish study site (Section 3).

Task 6: The R-based dssd/dsims survey design tools were used for survey planning recommendations. Tracklines for digital aerial surveys and the placement of acoustic instruments for an integrated survey were designed, using the same location as the case study (Section 4).

Task 7: Finally, this report summarises all objectives and deliverables across the project.

Section 1: Review of Methods to Integrate Passive Acoustic and Digital Aerial Data

Integrating data from different survey platforms can be broadly separated into three categories:

1. Combining results from multiple survey platforms once the same metric (e.g., absolute abundance) is estimated from the data sets.
2. Using an estimate of absolute abundance/density from one survey platform to estimate parameters required to estimate absolute abundance from the other platform i.e., one dataset is used to calibrate the other.
3. Integrating both datasets, each with missing information about specific parameters, but both sharing other parameters, enabling the missing parameters to be estimated for each dataset, leading to an estimate of absolute abundance/density.

NB: the second category can be considered a special case of the third category.

Examples of each category are given below before a concluding section that summarises why one particular method was chosen over the other approaches for the case study.

Category 1: Combining data from different platforms using the same metric

Examples of combining estimates of data that have been analysed to produce the same metric are given here. Passive acoustic detections and visual sightings of Dall's porpoise (*Phocoenoides dalli*) from a Pacific ship-based survey were combined in spatial modelling analyses (Fleming et al., 2018). The data were combined as encounter rates, given the limitation that absolute density could not be estimated from the acoustic data alone. Frasier et al. (2021) independently estimated animal densities from both fixed (seafloor-mounted) acoustic and ship-based visual data for multiple species: Cuvier's beaked whales (*Ziphius cavirostris*), Risso's dolphin (*Grampus griseus*) and sperm whales (*Physeter macrocephalus*). Spatial models were then estimated using both a Generalised Additive Model (GAM) and a Neural Network (NN) framework. Models incorporating PAM data were preferred to models using the visual data alone (for both GAM and NN frameworks and based on selecting models with minimum root mean square error values). Fitting a model with joint PAM and visual data (rather than PAM-only or visual-only models) was the preferred model for all species using GAMs, while PAM-only NN models were preferred for Cuvier's beaked whales and Risso's dolphin, though a joint PAM and visual NN model was selected for sperm whales.

Category 2: Calibration of one dataset with the other

In this approach, an estimate of absolute density/abundance from one platform can help to infer the missing parameters needed for density/abundance estimation from the other platform. For example, if D_a and D_p refer to density estimates derived from aerial and passive acoustic data, respectively, then D_a can be used to estimate the call production rate, r, required for D_p. Let D_{pc} be estimated call density from the acoustic data and assume that a robust estimate of D_a is available:

$$\widehat{D_a} = \widehat{D_p} = \frac{\widehat{D_{pc}}}{\hat{r}} \qquad \text{(Eqn. 3).}$$

Therefore,

$$\hat{r} = \frac{\widehat{D_{pc}}}{\widehat{D_a}} \qquad \text{(Eqn. 4).}$$

This ratio estimator is one way in which acoustic and aerial data could be integrated and would provide an estimate of call production rate suitable for estimating the absolute abundance of all animals (not just vocalising animals) from passive acoustic data. There are other possibilities to integrate data, such as using the acoustic data as a second platform in a double platform mark-recapture framework to estimate the availability parameter for a digital aerial survey (e.g., Rankin et al., 2020). To date, several studies have combined passive acoustic data and some form of visual data (whether from aerial surveys or ship-based surveys) to estimate missing parameters.

Perhaps the most relevant study in relation to the planned case study in this project is Jacobson et al., (2017), who used aerial survey data (from visual, not digital, sightings) to estimate a parameter combining both the effective detection area (EDA) of passive acoustic recorders for a harbour porpoise (*Phocoena phocoena*) survey and the probability of a porpoise clicking in a 1-second time period. The passive acoustic survey was comprised of a grid of 11 cetacean click detectors (CPODs; Chelonia Ltd.) deployed between August 2013 and January 2014 using a systematic, random design off the Californian coast in Monterey Bay. The study area was 370 km^2. Fine-scale aerial surveys were flown on three days during October 2013 covering 20 transect lines over the same survey area. The CPOD data were processed to determine the proportion of porpoise-positive-seconds (PPS) in a 12-hour period during daylight hours. PPS was the preferred metric for two reasons. First, a porpoise detection in a 1-second time period is more likely to be a single animal than porpoise detections within a 1-minute time period (a standard CPOD data output), meaning that group size is not required in the density estimation equation for the acoustic data. Secondly, using a 1-second time window allows the assumption that the animal is conceptually stationary, which is an important assumption for density estimation methods. PPS were calculated over daylight hours only so that the acoustic detections best matched the aerial detections. The aerial data were divided into ~1 km segments and a detection function was fitted to the perpendicular distances between the detections and the transect lines using the Distance R-package (Miller, 2015). Beaufort sea state was included in the detection function model as a potential covariate affecting detectability. Then, segment-specific density estimates were derived from the aerial data. Availability bias was accounted for by using an estimate for the detection probability on the trackline, g(0), from a previous study (Laake et al., 1997). Porpoise densities were then estimated at the specific CPOD locations using Gauss-Markov smoothing. Gauss-Markov smoothing was chosen as a method to prevent over-smoothing when interpolating the aerial data, thereby preserving observed patchiness in harbour porpoise distribution.

A ratio estimator was used to link the aerial density estimates with the acoustic data as follows:

$$\frac{\widehat{\mathrm{D}}_{\mathrm{l,d}}}{\hat{\mathrm{g}}(0)} = \frac{\mathrm{n}_{\mathrm{l,d}}}{\mathrm{T}_{\mathrm{l,d}}\widehat{\mathrm{vp}}} \qquad \text{(Eqn. 5),}$$

where $\widehat{\mathrm{D}}_{\mathrm{l,d}}$ is the estimated harbour porpoise density at each CPOD location, l, on each of the three days (d). $\mathrm{n}_{\mathrm{l,d}}$ are the number of PPS recorded on each instrument on each day. $\mathrm{T}_{\mathrm{l,d}}$ is the corresponding time (in seconds) that each CPOD monitored for each day in the designated 12-hour time period. Finally, vp is a combined parameter of the effective detection area of the CPOD, and the probability that a harbour porpoise echolocates in a 1-sec period. The equation was re-arranged to produce:

$$\mathrm{n}_{\mathrm{l,d}} = \frac{\widehat{\mathrm{D}}_{\mathrm{l,d}}}{\hat{\mathrm{g}}(0)} \times \mathrm{T}_{\mathrm{l,d}} \times \widehat{\mathrm{vp}} \qquad \text{(Eqn. 6).}$$

A Bayesian model was used to estimate the parameters in the model, using the PPS and $\mathrm{T}_{\mathrm{l,d}}$ as input data. $\widehat{\mathrm{D}}_{\mathrm{l,d}}$ was treated as a parameter to also be estimated, with the $\widehat{\mathrm{D}}_{\mathrm{l,d}}$ estimates and errors being included in the model as highly informed priors. g(0) was also included as an informed prior. Markov Chain Monte Carlo (MCMC) methods were used in the R-package R2jags (Su & Yajima, 2022) to fit the model.

Key results from the Monterey Bay study were that nine CPODs returned data, yielding 640 high-quality echolocation click trains, totalling 15,717 clicks, during the daylight hours on the three days when the aerial surveys were flown. The PPS per instrument per day ranged between 0 and 114 s. The aerial surveys covered 1,228 km of on-effort transect lines and 245 groups of harbour porpoise were seen, with a mean group size of two animals.

The estimated and interpolated density estimates from the aerial data resulted in estimated densities at each CPOD location that correlated with the recorded PPS (see Fig. 5 in Jacobson et al., 2017). The resulting estimated abundance using the acoustic data with the estimated vp parameter gave similar means to the aerial-derived estimates, though with larger confidence intervals. Abundance was also estimated for the whole CPOD dataset, including months where no aerial data were collected, by assuming that vp remained constant over time. Jacobson et al. (2017) also noted that if trend in abundance, rather than absolute abundance, was of key concern, then the uncertainty associated with vp could be ignored when interpreting the abundance trends over time (see Fig. 9 in Jacobson et al., 2017). Assessing population trends, rather than absolute abundance, in this way still relies on the assumption that vp remains constant over time (and space). Jacobson et al. (2017) also noted that estimating the EDA for each CPOD separately would be preferable and may reduce the uncertainty. This would require more aerial surveys; Jacobson et al. (2017) suggested that 10 surveys would be required.

A similar ratio estimator approach was taken in Gerrodette et al. (2011) where visual sightings data from a ship-based line transect survey for vaquita (*Phocoena sinus*) was combined with passive acoustic data from a separate ship-towed acoustic array (also conducting a line transect survey) to estimate the acoustic g(0). Both the visual and acoustic surveys estimated distances to detections, so distance sampling could be used to analyse both datasets. The estimator used for both datasets was:

$$\widehat{N} = \frac{n\hat{s}A}{2WL\widehat{P}\hat{g}(0)} \qquad \text{(Eqn. 7)},$$

where A is the study area, L is the on-effort trackline length, W is the truncation distance of the trackline, n is the number of detections, s is the estimated mean group size, P is the estimated probability of detection and $\hat{g}(0)$ is the estimated probability of detecting a group on the trackline.

The visual estimate of $\hat{g}(0)$ was estimated using a double-observer protocol during the survey (Jaramillo-Legorreta et al., 1999). To estimate the acoustic $\hat{g}(0)$, simultaneous acoustic and visual datasets were compared using a ratio estimator. The estimators for absolute density were set equal to each other (with subscript v and a denoting parameters and constants relating to visual and acoustic estimators, respectively):

$$\frac{n_v\hat{s}A}{2W_vL_{vl}\widehat{p_v}\widehat{g_v}(0)} = \frac{n_a\hat{s}A}{2W_aL_a\widehat{p_a}\widehat{g_a}(0)} \quad \text{(Eqn. 8)},$$

which was re-arranged to solve for acoustic availability:

$$\widehat{g_a}(0) = \frac{n_a W_v L_v \widehat{p_v} \widehat{g_v}(0)}{n_v W_a L_a \widehat{p_a}} \qquad \text{(Eqn. 9).}$$

Any uncertainty in the parameter estimates were combined using the Delta method to estimate an overall CV for $\widehat{g_a}(0)$ (Seber, 1982). Simultaneous surveys occurred over 8 days and covered an area of 613 km^2 (L_v = 165 km and L_a = 132 km). There were 28 visual sighting and two acoustic detections in the calibration survey. These data were used to estimate $\widehat{g_a}(0)$ = 0.413 (CV: 108%). The high CV was due to the low number of encounters during the calibration survey.

Mark Recapture Distance Sampling (MRDS) is another method that has been used to combine passive acoustic and visual data (as opposed to ratio estimators as used in the two studies described above). During a visual ship-based survey of rough-toothed dolphins (*Steno bredanensis*) in the Pacific in 2007, Rankin et al. (2020) used passive acoustic detections from a towed hydrophone array as the second platform in an MRDS analysis, which enabled $\hat{g}(0)$ to be estimated (for the visual team and the acoustic team separately, and also when the platforms were combined). This study relied, however, on visual and acoustic detections being matched, which is not a requirement for the presented ratio estimator approaches.

Category 3: Integrated models with missing parameters in both datasets

Extending the second category to allow both datasets to have missing parameters results in integrated modelling approaches such as the method outlined in Doser et al. (2021). Here, visual survey data were integrated with acoustic data in a Bayesian framework, where a joint likelihood was written to accommodate detection probability in both datasets, as well as both a false positive rate and call production rate in the acoustic data. Simulations were first performed, fitting the visual and acoustic data separately, as well as an integrated model, using MCMC methods in the R package jagsUI (Kellner, 2018). A case study was also performed using survey data of Eastern Wood-Pewee (*Contopus virens*). The case study dataset used recordings from 14 days in June, at four sites, across three separate years (2013 – 2015). Results showed that the integrated model performed better than models with one source of data (Doser et al. 2021). Another study recently combined visual aerial and PAM data for North Atlantic right whale (*Eubalaena glacialis*) abundance estimation using a spatial point pattern approach (Schliep et al., 2023). Simulations were conducted first, before a two-day data set from Cape Cod Bay collected in April 2009 was used to implement the method. One of the surveyed days allowed a direct comparison between a joint acoustic and visual model and a visual-only model. On this day, 46 whales were visually observed and 486 calls were recorded. Results showed that the uncertainty in the resulting abundance estimate was lower when using two data sources.

Conclusions

Based on the review of available methods and the discussions at a project meeting focussed on methods to integrate data, the calibration approach outlined in Category 2 was pursued for the case study. The rationale behind the choice of method was not driven by the temporal or spatial coverage of the available data for the case study but was dependent on whether absolute densities could be estimated from either platform. It was not possible to estimate densities from the CPOD data alone using methods such as distance sampling or capture-recapture, given that there was no fine scale spatial information (e.g., ranges or locations) available about the detections in relation to each of the CPODs. Other density estimation methods are available (e.g., reviewed in Marques et al., 2013) though these require more auxiliary data and assumptions, and are generally more labour-intensive to implement. Therefore, we discounted estimating densities directly from the CPOD data for this case study. This is a practical consideration that other monitoring programs will have to evaluate: whether absolute density is estimable from the PAM data. Density estimation from PAM data is dependent on the deployed PAM instruments and their configuration, the target species and whether all auxiliary data required for absolute density estimate is available or can be estimated. This is applicable to any survey using PAM instrumentation, not just CPODs. In the case study dataset, absolute densities could be estimated from the DAS surveys using a plot sampling method (where detection probability within the surveyed area is assumed to be certain) combined with an estimate for g(0) (for case study details see Section 3). Therefore, Category 1 methods were not appropriate, given that data from only one of the survey platforms could be used to estimate densities (so combining absolute abundance estimates derived separately from the aerial and acoustic platforms was not an option) and simply combining encounter rate data (as demonstrated in Fleming et al., 2018) would not achieve the project goal of estimating absolute abundance. The methods described in Category 3 assumes that data from both platforms are missing key parameters whereas, in the case study, absolute densities could be estimated from the DAS data. The most uncertain parameter required for absolute density estimation from the DAS data is the g(0) estimate, though the chosen Category 2 method based on Jacobson et al. (2017) allows previous information about g(0) to be included as an informed prior and g(0) estimated (with associated uncertainty). Further, Jacobson et al. (2017) provided a comparable study using the same instrumentation and surveying the same target species as our case study. Whilst the methods in category 3 could be applied here, implementing the Category 2 Jacobson et al. (2017) method was considered a natural starting point, given that the results between the two studies could be compared.

Section 2: Available Software Tools to Assist Data Integration

A goal of the project was to provide software to aid data integration, so existing tools were evaluated that the project team had ready access to i.e., developed by several of the CREEM project team members, to see how these tools could either (1) be directly used in or (2) adapted for the selected modelling framework. Therefore, we do not suggest that these are the only tools available to practitioners, though many of the tools described below were developed to address specific research gaps and/or are now widely used by a variety of stakeholders (details given below for each described tool). We also note that this software review was not focussed on abundance and density estimation software such as the R packages Distance (Miller et al., 2019), dsm (Miller et al., 2022) and ascr (Stevenson et al., 2015) but specifically on the survey design and power analysis tools available. There are relevant features in these packages, however, particularly the spatial modelling capabilities in the dsm package.

First a generic survey design, monitoring, and analysis workflow is outlined (Fig. 1), before a description of the evaluated survey design and power analysis software tools and how these tools would fit in the described workflow is provided. An overview of possible extensions that could be developed in the future is also included, highlighting the extensions that would particularly benefit the integration of PAM and DAS data (summarised in Table 1). A specific workflow for the category 2 data integration method chosen for the case study is then described, demonstrating where the software tools fit within the workflow (Fig 2).

Section 2a: Survey Design and Analysis Workflow

A typical survey design workflow might be as follows (summarised in Fig. 1):

1. Establish project goals and research questions (e.g., baseline monitoring of target species by obtaining absolute abundance, where end products are density surfaces of target species with associated uncertainty).

2. Design a survey to meet these goals considering:
    a. Survey platform(s) and survey methods to be used.
    b. Spacing of transect lines/point transects to achieve desired survey coverage/effort.
    c. For PAM surveys, number, configuration, and capabilities of deployed instrumentation; can detection probability be estimated from each monitoring station?
    d. Does the survey design have enough statistical power to detect change in abundance at the required spatial and temporal scales?

e. Where spatial modelling is required, are relevant environmental covariates also available or being collected e.g., sea surface temperature, primary productivity data.

NB: in the survey design phase, any existing relevant data e.g., pilot survey data or data from a similar study will provide valuable information and help to optimise the survey design.

3. Data collection

4. Data analysis and survey design feedback
    a. After initial data collection, perform preliminary analyses of collected data to ensure that the assumptions of the survey design are realistic. Analysis steps will include:
        i. Process survey data (visual/digital and/or acoustic).
        ii. Estimate absolute densities from the data where possible.
        iii. Perform spatial modelling to produce density surfaces (with associated uncertainties).
    b. Adjust the survey design if needed (re-considering points 2a – e as needed).
    c. On completion of data collection analyse whole dataset, following steps 4ai – iii.

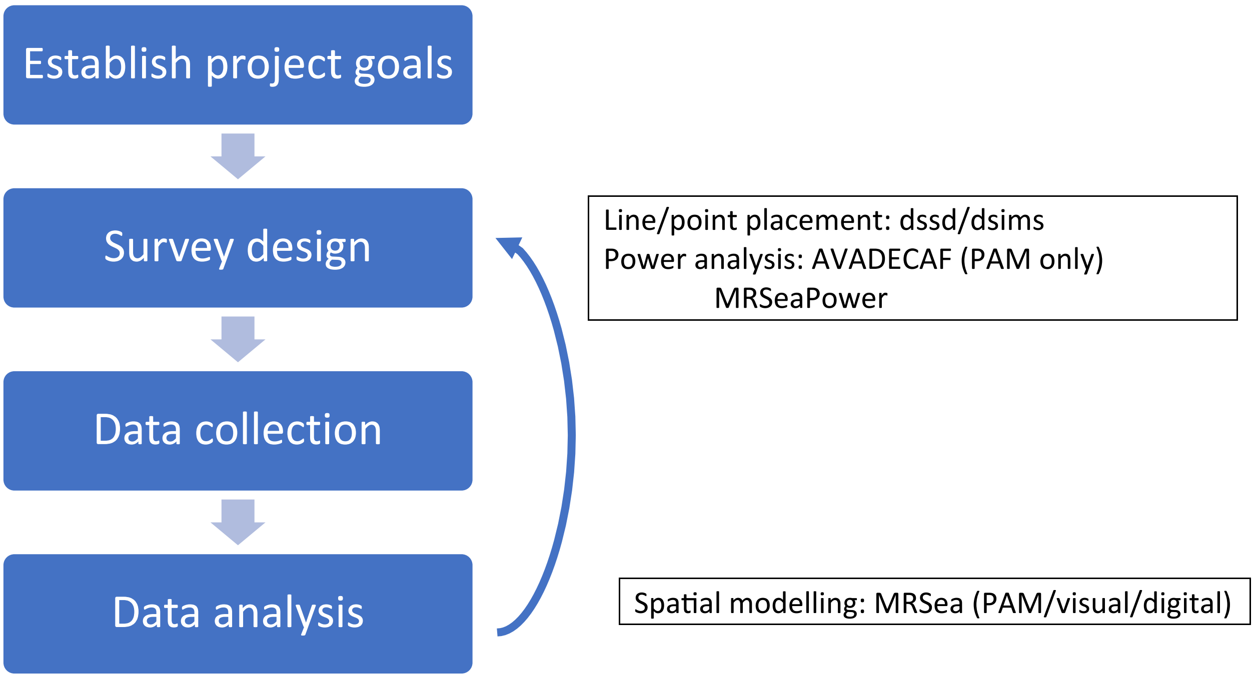


Fig. 1 Generic survey design, data collection and analysis workflow, with available software tools developed within CREEM

Section 2b: Evaluated Software Tools

1. dssd and dsims

The R package “dssd”is a distance sampling survey design package used to define designs and generate transects (Marshall, 2022a) and “dsims” is a simulation R package which extends “dssd” to additionally simulate populations of interest and subsequent surveys to allow better assessment of design properties (Marshall, 2022b). These can be used to design optimal line and point transect surveys and so are relevant to the design of both DAS and PAM surveys. The simulation package currently focusses on design-based estimation (Buckland et al., 2015).

Possible future extensions to dsims are given below, with the extensions most useful to PAM/DAS data integration highlighted by “(PAM-aerial)” notation, though all extensions are relevant:

- Include space-filling designs, which use an algorithm to achieve even placement of a given number of instruments within a study area, though uniform coverage may be lost (PAM-aerial, specifically for PAM data).
- Facilitate cue-based analyses (PAM-aerial, specifically for PAM data).
- Include designs with combined lines and points (PAM-aerial).
- Implement downsampling to assess effect of fewer lines/points on coverage. (PAM-aerial).
- Combine dssd/dsims and MRSea (see below). (PAM-aerial).
- Incorporate model-based density estimation options.
- Generate the population only in the covered areas, not the whole study area. This should speed simulations up and allow larger population sizes to be simulated.

2. AVADECAF

AVADECAF (Booth et al., 2017) is a set of R functions that perform a power analysis to address the question whether a given acoustic survey design will allow a change in animal density to be identified for a species of interest. Several input parameters are required to set up the power analysis such as the expected densities (e.g., via a density surface), detection probability estimates and parameters related to acoustic behaviour of the target species. Survey data are simulated and analysed, then a Generalised Linear Model (GLM) is fitted to the resulting density estimates to see whether estimates are changing over time (by fitting year or season as a covariate in the GLM).

Possible future extensions to AVADECAF are:

- Enable an existing survey design to be uploaded, rather than generating one in the software (PAM-aerial).

- Include variable spatial density surfaces to incorporate the uncertainty in the density surface estimates. Currently, only one density surface is generated per power analysis.

3. MRSea and MRSea Power

MRSea and MRSeaPower are R packages that allow the fitting of spatially adaptive models and spatially-explicit power analysis (Mackenzie et al., 2013, Scott-Hayward et al., 2021).
The MRSea package fits Generalised Additive Models (GAMs) to survey data and includes functionality to account for spatial and temporal correlation in observed data, and can be used to compare different surfaces (e.g., between years or construction phases). MRSea is very flexible and can be used to model different data types e.g., PAM, visual, digital, telemetry data. In particular, it is the recommended approach by NatureScot for analysing aerial survey data for baseline site characterisation for marine ornithology (e.g., one survey a month over two years) (NatureScot, 2023).

MRSeaPower is an extension of MRSea that enables a simulation-based approach to power analysis with spatially explicit outcomes (power to detect change can be visualised across a study area).
Possible future extensions to MRSea/MRSeaPower relevant to this work include:

- Link with the dssd/dsims packages by (1) providing MRSea density surfaces to be used in dsims and/or (2) using dssd survey designs in MRSeaPower. (1) allows a real density surface to be used to determine the best survey design (PAM or DAS) and (2) allows spatially explicit power to be estimated for a variety of survey designs. In principle this can be done with the existing packages but has not been tried or tested. Further work would allow seamless integration and user documentation. (PAM-aerial).
- Include ways to propagate uncertainty from machine learning species classification from DAS/PAM data.

Section 2c: Conclusions of Available Software Review and Implications for Case Study

The review identified that existing spatial modelling software (MRSea) could be used for the spatial modelling components of the case study analysis, and that other R-based tools can be used for survey design (dssd/dsims) and to assess power to detect changes in density/abundance (MRSeaPower/AVADECAF). How these software tools fit into the workflow for the category 2 method is given in Fig. 2. However, it was concluded that there was no available software that could readily combine PAM and DAS data, nor future extensions that could be implemented within the timeframe of the project. The review outlined where existing tools could be extended in the future to facilitate (1) survey design of monitoring programs in general and (2) specifically combining data from PAM and aerial platforms (summarised in Table 1). Finally, discussions about software concluded that clear documentation and long-term support are key features of any software used for analysis so should be considered a priority in any future software development.

Table 1: Roadmap of the capabilities of CREEM-developed software tools potentially useful for integration of PAM and DAS data.

Capabilities	dssd/dsims	MRSea	MRSea Power	AVADECAF
Create survey design	Yes	No	No	Yes
Upload existing design for use in analysis	Yes	n/a	Yes	No
Spatial modelling capabilities	No	Yes	No	No
Power analysis (PA) capabilities	No	No	Yes	Yes
Spatially referenced power outputs	n/a	n/a	Yes	No
Declines can be assessed in PA	n/a	n/a	Yes	Yes
Spatial redistributions can be assessed in PA	n/a	n/a	Yes	Yes
Changes in survey design can be assessed in PA	n/a	n/a	Yes	Yes
Can work with non-density data (i.e. detection-only) for PA	n/a	n/a	Yes	No
Future potential extensions to aid data integration	Yes	Yes	Yes	Yes
Main future extension(s) to aid data integration	Space-filling designs Cue-based analyses Combined lines/point designs Enable downsampling Link with MRSea/MRSeaPower	Link with dssd/dsims	Link with dssd/dsims	Enable existing survey design upload

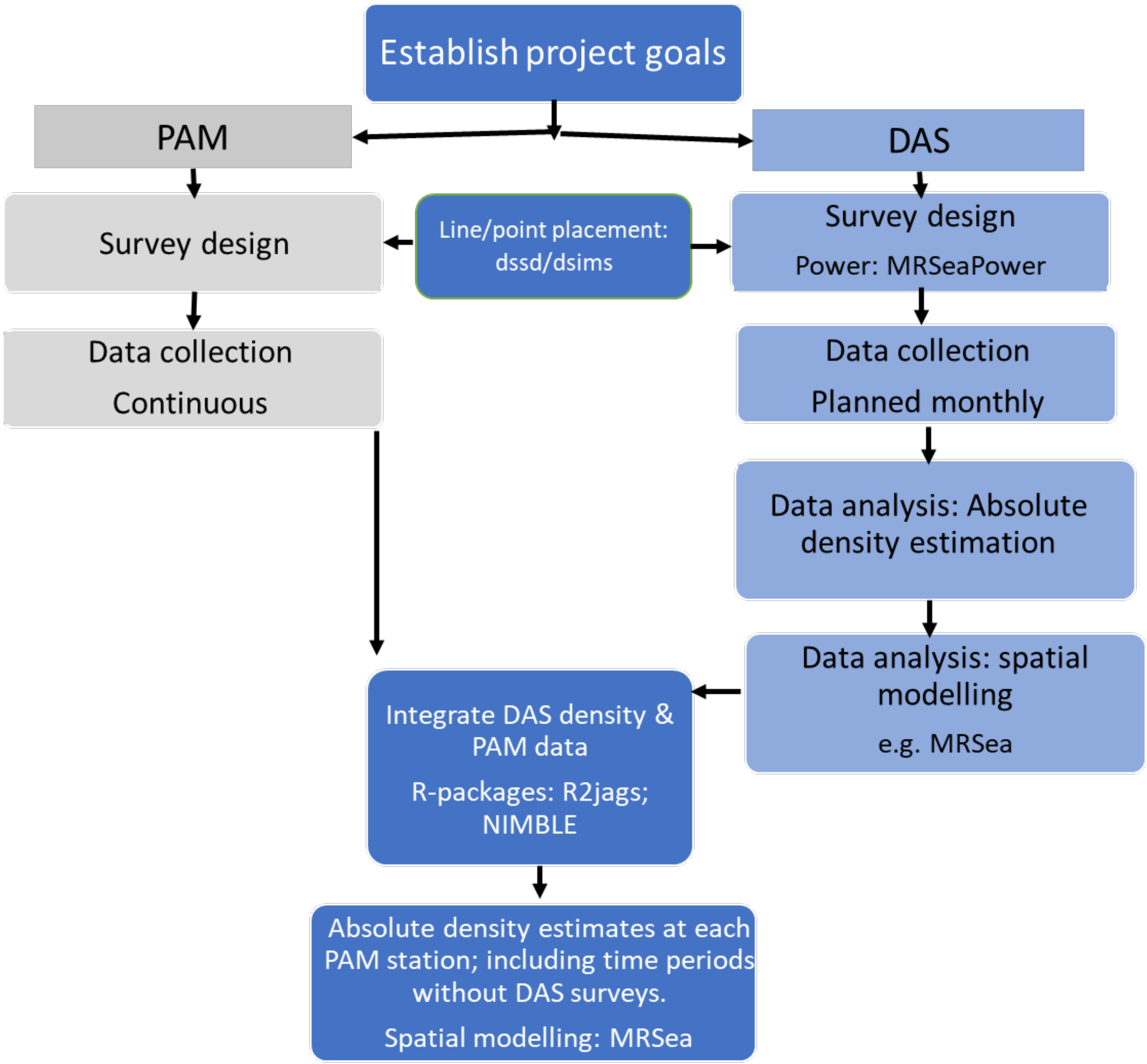


Fig. 2 Survey design, data collection and analysis workflow with the aim of integrating DAS and PAM data using the calibration method demonstrated in this case study.

Section 3: Case Study - Estimating Harbour Porpoise Density in the Moray Firth

Various datasets were considered for the case study, yet concurrently collected DAS and PAM data in 2010 in the Moray Firth were the only data that met the project requirements to focus on (1) PAM and DAS data (2) with harbour porpoise as the target species (3) in Scotland. Therefore, this dataset became the focus of the project case study. The data were previously presented in both Thompson et al. (2013) and Williamson et al. (2016).

Data overview and previous work

Thompson et al. (2013) used an extensive deployment of 70 CPODs in 2010 to assess the response of harbour porpoise to seismic surveys, focussing on two 25 x 25 km study blocks in the Moray Firth. Williamson et al. (2016) then used the CPOD data to compare these PAM data with density estimates derived from visual-aerial surveys, and compared the visual-aerial density estimates with those derived from DAS data. The aerial surveys occurred between August and September 2010. Visual-aerial surveys were conducted on ten days during the Aug-Sept 2010 survey period, and the DAS surveys occurred on four days. The majority of CPODs were deployed between June and November 2010. The main details of the CPOD and DAS data are given in the Materials and Methods section, though further details are given in Williamson et al. (2016).

Williamson et al. (2016) compared typical CPOD data outputs e.g., detections per minute, and other coarser time resolutions, with the density estimates from both sets of aerial data. The density estimates produced from the DAS data in Williamson et al. (2016) were considered to be relative estimates as no estimate of g(0) was available from the survey data to correct for availability bias, though a parameter from Hammond et al. (2013) was applied to the visual-aerial data. Therefore, the visual-aerial data were used to estimate absolute abundance estimates. Density surface modelling using GAMs in the R package dsm (Miller et al., 2022) was conducted using the visual- and the digital-aerial data separately. Candidate environmental variables used in spatial modelling were depth, slope, sediment type (proportion of sediment that was sand or gravelly sand) and distance from the coast. The comparison of the density surfaces yielded similar patterns. Correlation was also evident between the CPOD data and corresponding absolute densities from the visual-aerial data (Williamson et al., 2016).

Materials and Methods

As described in Williamson et al. (2016), the DAS data were collected by HiDef Aerial Surveying Ltd on 4 days in Aug – Sept 2010 (28 Aug, 19 Sept, 26 Sept, 27 Sept) between 10:00 and 16:00 depending on the surveyed day. On each day, a randomly selected route was chosen, along planned transect lines (Fig. 3). Flight height varied between 244 and 457 m depending on cloud height, resulting in a strip width between 80 – 150 m. Detectability was assumed to be certain across the whole strip width. The effective strip half widths of the surveys were therefore between 40 – 75 m.

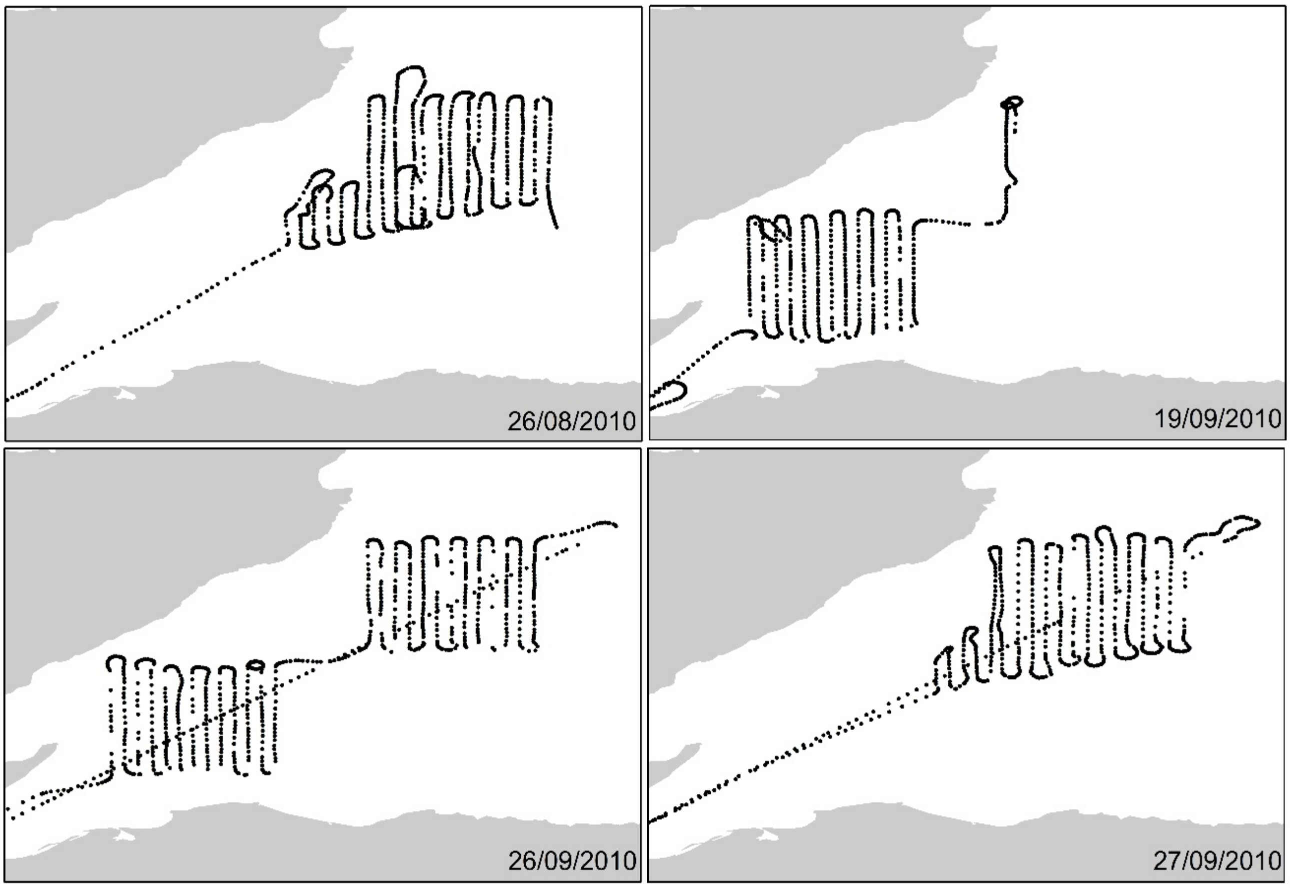


Fig. 3 Track lines flown during digital aerial surveys on four days in 2010.

We used similar methods as applied in Jacobson et al. (2017), with the following workflow.

Absolute density estimation (DAS)

- Estimate a density surface using the DAS data. Jacobson et al. (2017) used Gauss-Markov smoothing to prevent over-smoothing and retain observed patchiness in harbour porpoise distribution. Here, MRSea was used, which fits spatially adaptive GAMs, with targeted flexibility, to also preserve any patchiness in porpoise distribution. Any other appropriate spatial modelling approach could be used at this stage. This analysis used processed data where the sightings were represented by the mid-point of a 4 x 4 km grid in the area. The same grid was also used as a prediction grid.

- Ideally, a separate model would be fitted to each DAS survey. However, the number of sightings from the first and second survey days were not sufficient to obtain density surfaces and both survey areas were not always surveyed on each separate day (Fig. 3). Therefore, one model was fitted to data from all four surveys to produce an average density surface across the period of the DAS surveys. The analysis was performed with the MRSea package, using the number of sightings per 4 x 4 km grid cell from DAS as a response variable.
- A set of one dimensional (water depth and slope) candidate smooth explanatory variables were associated with the centroid of each grid. A range of models was fitted using both natural cubic and quadratic B-splines for these univariate terms with the number of internal knots set between one and four. Additionally, a bivariate smooth of x and y coordinates (the centroid of each grid) was added to the model and implemented using a Gaussian radial basis function. This spatial smooth was parameterised with a minimum of 2 and maximum 15 knots. For both the uni- and bi-variate splines knot number and location was chosen using the spatially adaptive local smoothing algorithm (SALSA) implemented in MRSea (Walker et al., 2010).
- Models using both a quasi-Poisson and a Tweedie distribution framework were trialled and an offset for effort at each grid (in km^2) was included. The assumed mean-variance relationship was assessed through diagnostic plots to be best for the Tweedie distribution and so this was used for subsequent analysis.
- Model selection for covariates and their flexibility (using SALSA) was conducted using Akaike's Information Criterion (AIC).
- Model diagnostics included assessing residual correlation and relationship between fitted and observed residuals to ensure the assumptions of the models were not violated and to assess model fit.
- Uncertainties (expressed as coefficient of variation, CV) around predictions at each grid cell were obtained using a parametric bootstrap (500 samples). This process resampled coefficients of the best fitting model, made predictions using the resampled coefficients and calculated a standard deviation for each grid cell.
- The best fitting model was used with a prediction grid (also of size 4 x 4 km) to estimate densities at each of the CPOD locations.
- Using an assumed value of g(0), all DAS-derived estimates could be converted to absolute density estimates for comparison to the PAM-derived estimates. Data from Teilman et al. (2013) (see the PAM calibration section below for more detail) was used to provide an estimate of g(0).

PAM data preparation

- The CPOD data were initially processed by customised software (CPOD.exe, vs 2.025) provided by Chelonia Ltd. Files (specifically .CP3 files) available to this project enabled further processing using software version 2.048 to match the data inputs used in Jacobson et al. (2017). For each available CPOD, details of high confidence, narrow-band high frequency click trains detected in each minute of the data were extracted. Specifically, the start in microseconds within each minute and the duration of each click train were stored, as well as the amount of time within a given minute that was lost due to data saturation (a CPOD can only store so much data, and so cannot record more data in a given minute if that threshold is exceeded). These metrics enabled the number of seconds in each minute that contained porpoise click trains to be recorded, as well as a measure of recording effort for each minute.
- The number of porpoise positive seconds (PPS) from the PAM data, between 0600 and 1800 over the four days of data collection, were extracted. The calculation of PPS during daylight hours was so that the densities derived from the DAS data were linked to the same time period for the CPOD data (as in Jacobson et al., 2017).

PAM calibration

- The relative DAS densities, as well as the number of PPS from PAM were used as the data inputs for the integration analysis.
- The Bayesian model was used to estimate the following parameters $\widehat{\mathrm{D}}_{\mathrm{l,d}}$, $\hat{\mathrm{g}}(0)$ and $\widehat{\mathrm{vp}}$ following Eqn 6:
  - $\widehat{\mathrm{D}}_{\mathrm{l,d}}$ were the relative DAS-derived densities and were included as highly informed priors, assuming a lognormal distribution.
  - $\hat{\mathrm{g}}(0)$ for the DAS data was included as an informed prior, assuming a beta distribution with shape parameters (47.6, 45.9) following data from Teilman et al. (2013) where the median estimate of porpoise availability (time spent at 0-2 m depth) was 0.58.
  - $\widehat{\mathrm{vp}}$ was to be estimated by the model with a Uniform prior between 0 and 0.003 (based on results from Jacobson et al., 2017).
  - $\mathrm{n}_{\mathrm{l,d}}$ were the number of PPS observed between 0600 and 1800 summed over 4 days.
  - $\mathrm{T}_{\mathrm{l,d}}$ was included as the summed number of seconds surveyed by the CPODs over the 4 days.
- Markov Chain Monte Carlo methods were used in the R-packages nimble (NIMBLE Development Team, 2023) and runjags (Denwood, 2016) to fit and evaluate the model. Four chains of 250,000 iterations with a burn-in period of 200,000 iterations was used, with a thinning rate of 10.

- Using the estimated $\widehat{vp}$ values, density estimates could be derived from the PAM data. Daily PPS counts from the 1st August to 1st October 2010 were extracted to create a time series of daily absolute density estimates. Variances of the daily density estimates were estimated using the Delta method to combine all sources of uncertainty.
- Finally, a new absolute density surface was estimated from the resulting density estimates based on the PAM data. The same model fitting, model selection and model prediction approaches were used as for the spatial modelling based on DAS data only. If more than one CPOD overlapped with a given grid cell, a mean value of the devices was used as an input to the modelling. The same covariates as the DAS-only model were fitted to the resulting densities for one of the days when DAS was conducted (19 September) and to a day outside that period (01 October) to show the utility of the calibration method. A quasi-Poisson distribution was assumed for the response variable as the response variable was not count (as in case of DAS-based modelling) but density. Bootstrapping was used as described above for the DAS spatial models to estimate spatial modelling uncertainty around the generated density surfaces. Further bootstrapping routines would be required to include additional uncertainty from the vp estimation.

Results

Estimating density using DAS

Over the 4 days, a total of 2,155 km of completed DAS transect lines resulted in 97 observations of individual harbour porpoises. Specifically, 17, 11, 41, and 28 observations of individual porpoises were made on each of the separate survey days. The corresponding DAS-only absolute density estimate was 0.67 animals/km^{-2} (95% confidence interval: 0.53 – 0.86 animals/km^{-2}).

The best model fitted to the DAS data used a Tweedie distribution and included coordinates, depth and slope as natural cubic splines. The mean DAS-derived density across the whole prediction grid was 0.52 animals/km^{-2}. The DAS-derived densities assigned to the CPOD locations ranged between 0 and 2.0 animals/km^{-2}, with a mean of 0.57 animals/km^{-2} (95% confidence interval: 0.43 – 0.95 animals/km^{-2}) (Fig 4). These estimates were comparable to those in Williamson et al. (2016).

Estimating density using DAS and PAM

CPOD data were available from 43 CPODs. Between 06:00 and 18:00, the mean number of PPS on the CPODs (summed across the four days of surveying) was 107, ranging between 0 and 613 PPS.

The model estimated the median value of vp to be 0.0012 (95% credible interval: 0.00094 – 0.0015) (Fig. 5). The estimate of g(0) was very similar to the assumed prior distribution; the median value was estimated to be 0.51 (95% credible interval: 0.42 – 0.61) (Fig. 6).

Using the estimates of vp and g(0), separate density estimates could be derived for each day from 1st Aug – 1st Oct 2010, including days where no DAS data were available. The median densities (averaged across all CPODs) for each day ranged between 0.24 and 0.83 animals/km^{-2} (Fig. 7). The daily surfaces fitted using the calibrated PAM data showed differing daily patterns (Fig. 8).

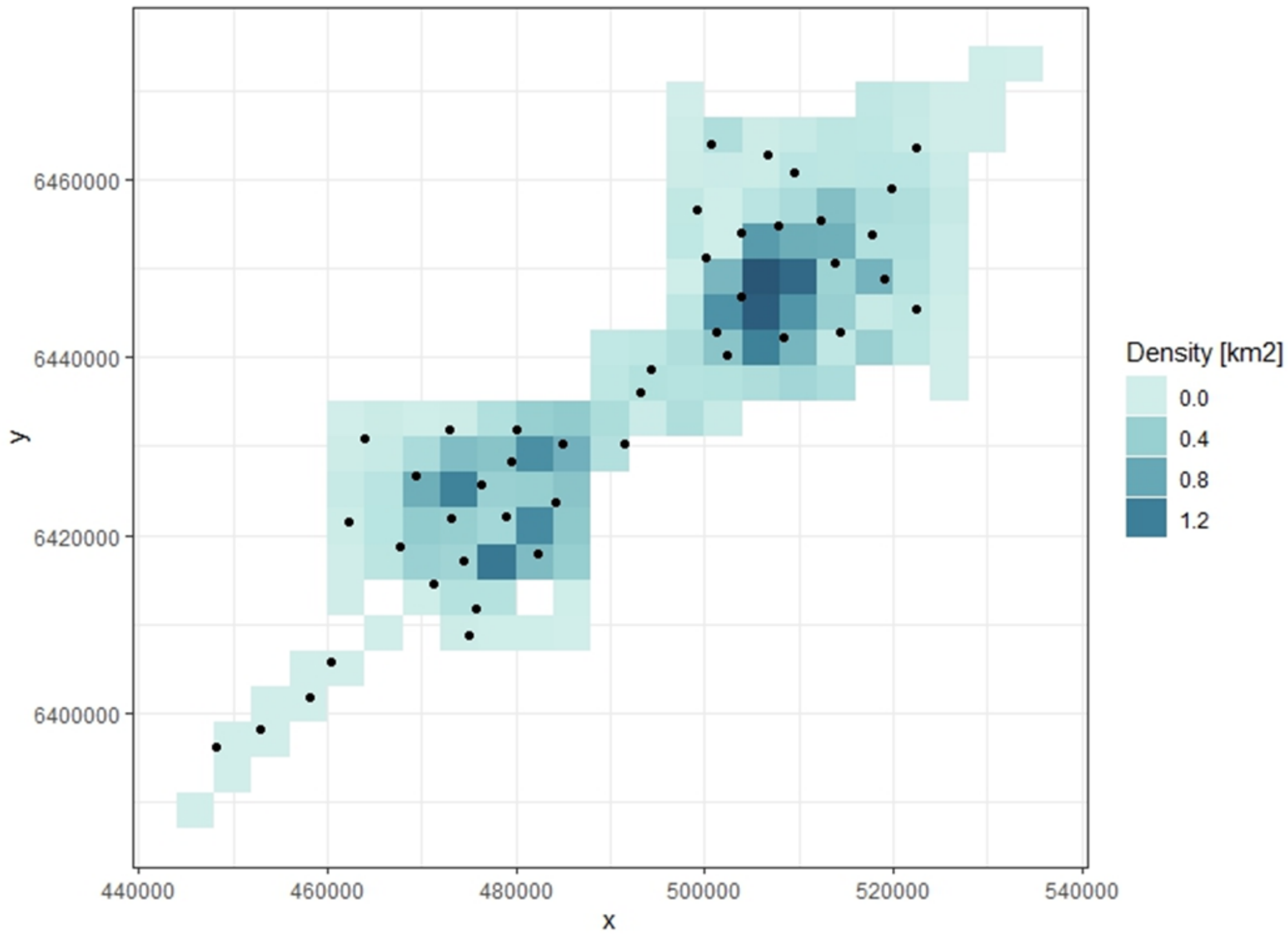


Fig. 4: Estimated relative density surface using the DAS data (not corrected for g(0)). The black dots denote CPOD locations.

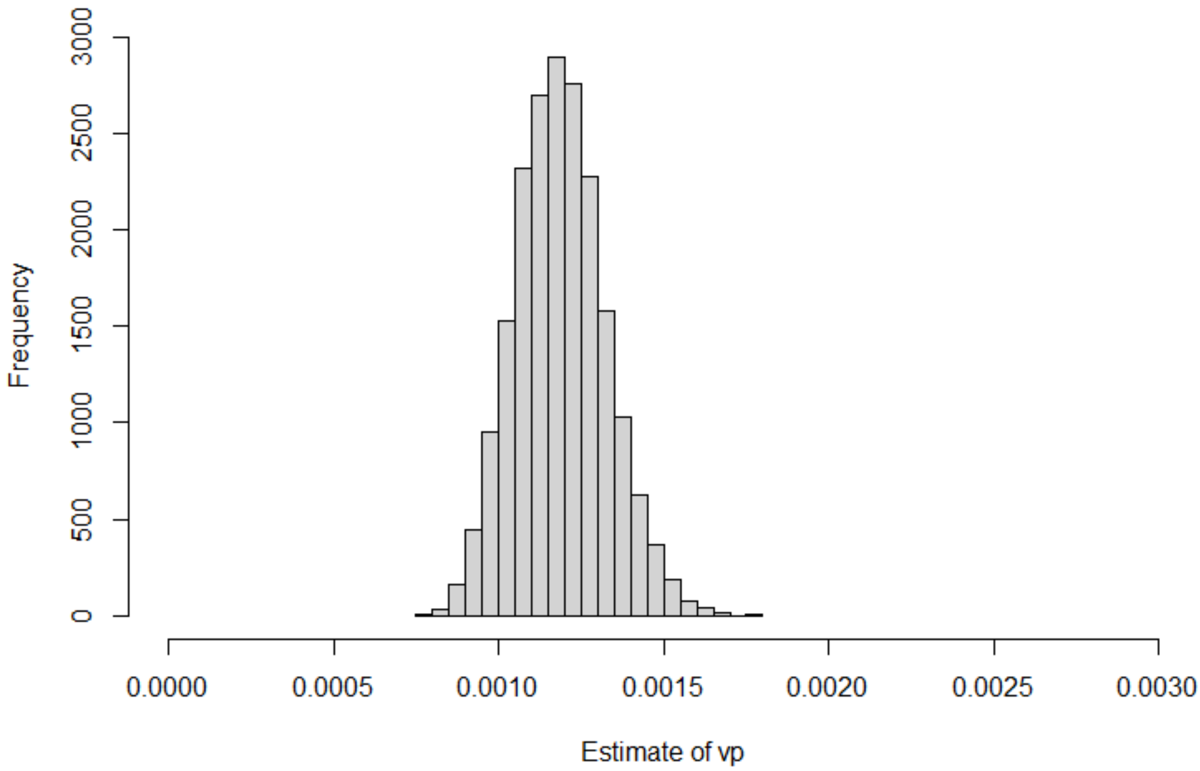


Fig. 5 Posterior distribution showing estimated values of vp.

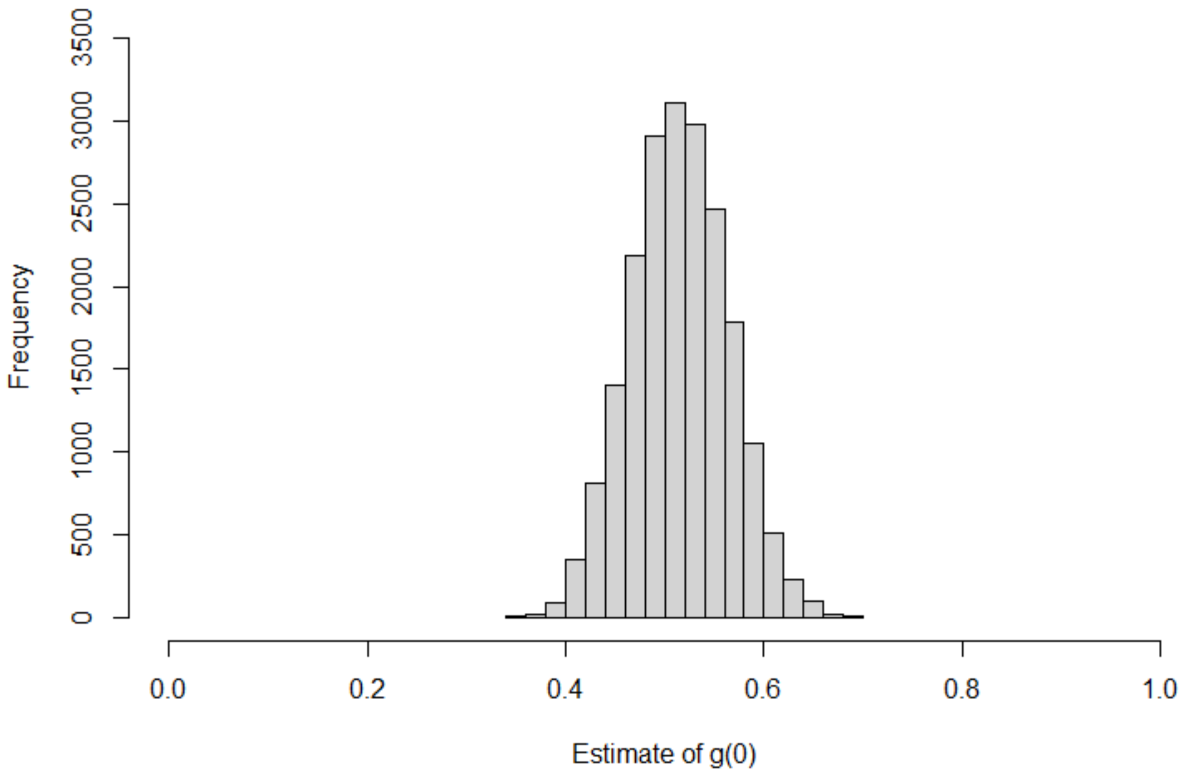


Fig. 6 Posterior distribution showing estimated values of g(0).

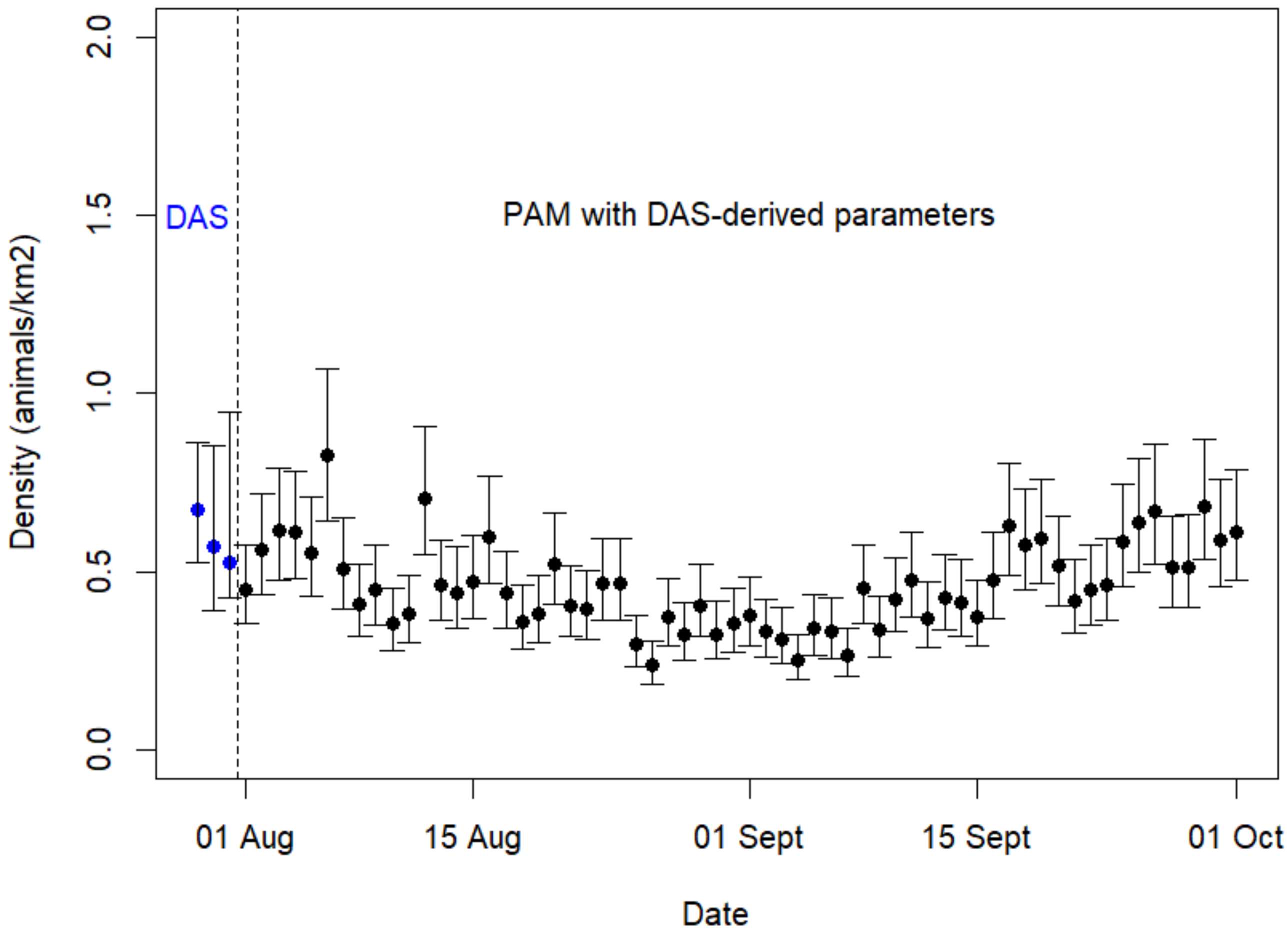
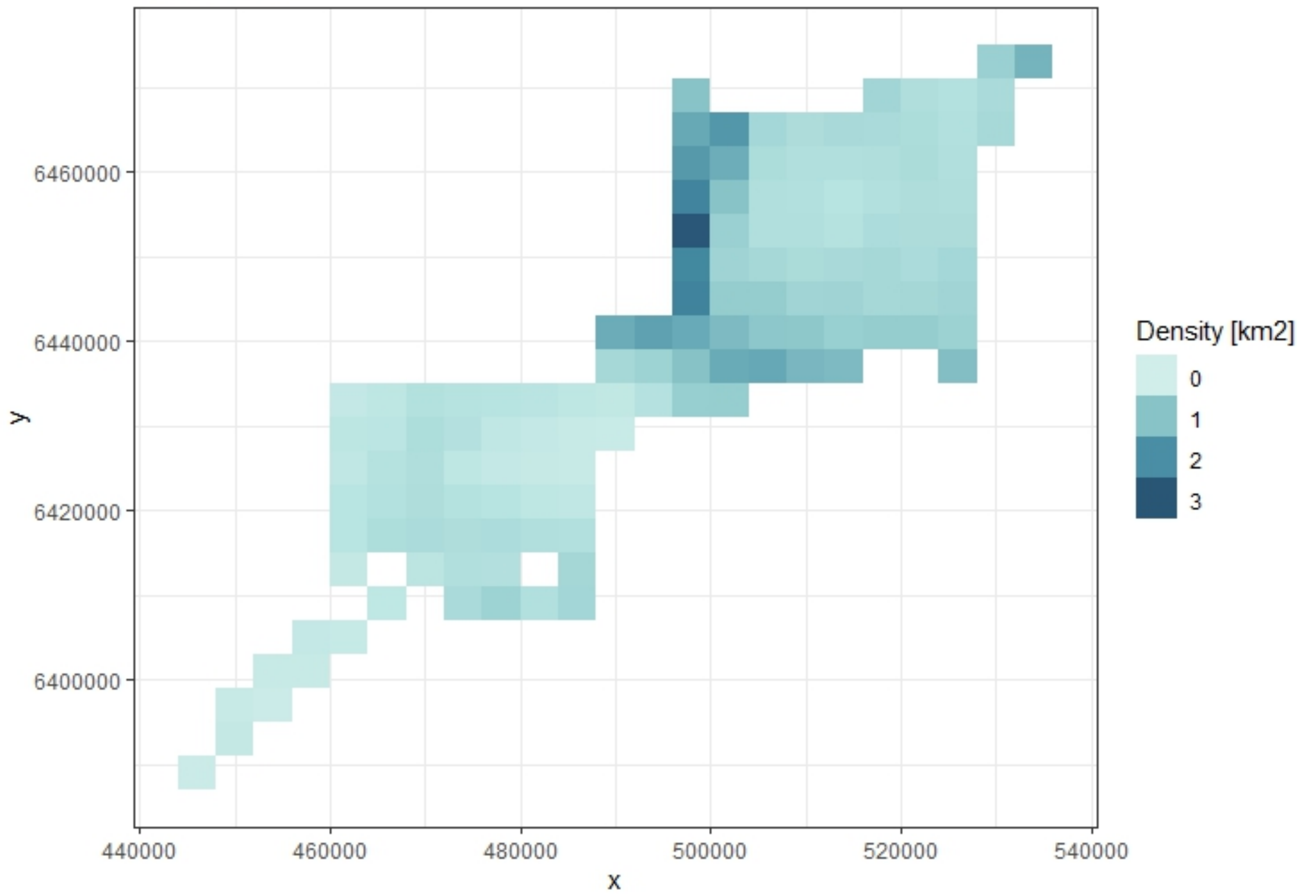


Fig. 7. A comparison of, to the left of the vertical dashed line, the DAS-derived density estimates (the first estimate is a mean design-based estimate, the second estimate is the mean density derived from the spatial model across the whole prediction grid and the third estimate is the mean density derived from the spatial model at the CPOD locations only) and, to the right of the vertical dashed line, the PAM-derived density estimates using the estimated values of vp for all days between 1st Aug 2010 and 1st Oct 2010. Confidence intervals (95%) are also shown for all estimates.

19/09/2010



01/10/2010

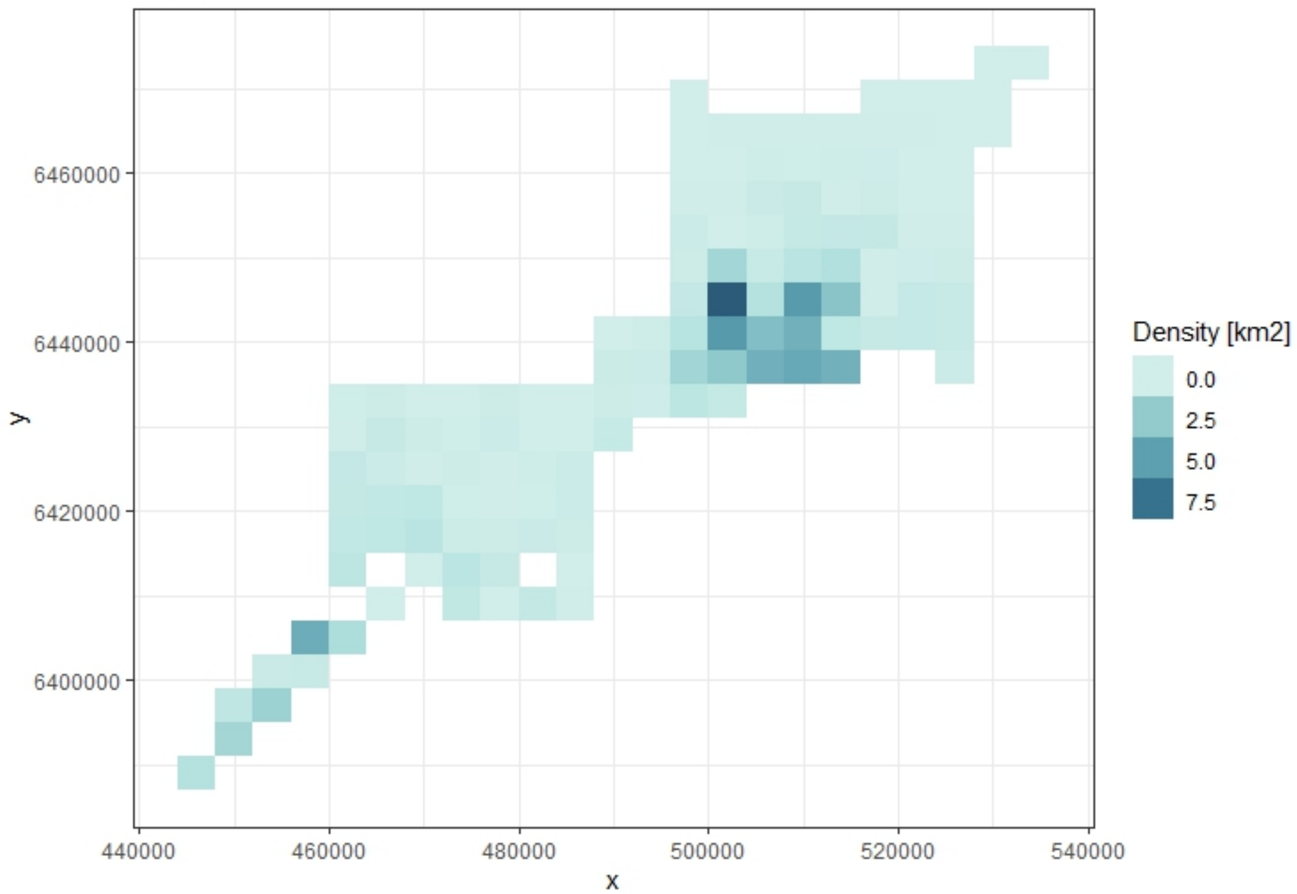


Fig. 8: Estimated absolute density surfaces using the calibrated PAM data on two example days. 19/09/10 (when there was a DAS) and 01/10/10 (when there was no DAS).

Discussion

The case study implemented a Bayesian data integration method based on the methods in Jacobson et al. (2017). By estimating a parameter combining detection probability of harbour porpoise clicks and probability of clicking (vp), as well as g(0), PAM data could be converted to absolute density at a daily resolution, including days when the DAS data were not being collected (Figs 7 and 8). All daily estimates from the PAM data were on the same order of magnitude as the DAS-derived estimates (Fig 7). The method also accounts for uncertainty propagation (where included in the model) allowing confidence intervals to be estimated for all density estimates. In this analysis, uncertainty in g(0) and the DAS-derived estimates was included by incorporating these inputs as informed priors in the model.

A key aspect of this model is that the average estimates for vp and g(0) are assumed to be constant both over the period considered and over space (albeit with uncertainty). This is especially important for using the parameter estimates to estimate densities from the PAM data; a decision must be taken about how reasonable it is to use the estimates on days where there were no DAS surveys. The parameter of vp is a combination of CPOD EDA and the probability that a porpoise is vocally active in a 1-second time period. Due to changes in oceanographic conditions, it is possible that the EDA of a CPOD will change under differing ambient noise conditions, which may change seasonally. Therefore, despite the CPODs being deployed for several months, densities were only estimated between 01 Aug 10 and 01 Oct 10, given that the DAS surveys occurred in August and September, and assuming that conditions remained similar throughout this period. A next research step would be to alter the model to estimate vp for individual CPODs as suggested by Jacobson et al. (2017), and potentially as a function of date to more accurately predict vp for other dates, though more calibration DAS flights would likely be needed.

The average vocal behaviour of a porpoise is also assumed to remain constant over the survey time being considered (in this case 01 Aug – 01 Oct 2010). We do note in this study that seismic survey activity occurred during the data collection period and, if such activity altered harbour porpoise vocal behaviour, then the estimate of vp applied to days with seismic activity could be biased. Therefore, it is important to consider how representative the estimated parameters are of the wider dataset, especially when deciding which PAM data to apply the parameters to.

We also limited the CPOD data to daylight hours, to better match the DAS survey data. This means that our estimate of vp contains information about porpoise vocal behaviour specifically in daylight hours. However, we could readily include all CPOD data across all hours each day; the only assumption we would have to make is that the DAS-derived densities from daylight hours are applicable to hours of darkness as well. This may be reasonable to assume unless porpoises consistently migrated in or out of the survey area in hours of darkness. In that case, a more fine-scale study would be needed to understand potential diurnal changes in porpoise density and distribution, if such fine-scale changes needed to be understood for a given study (e.g., Williamson et al., 2022).

This case study focused on harbour porpoise using CPODs and DAS surveys. However, there is no reason why the same framework could not be implemented for other cetacean species, using different PAM instrumentation and even aerial surveys using human observers. However, the method is likely to be more successful for some species than others. Cetaceans with seasonal vocal behaviour (such as some baleen whales) may not make enough calls at a daily scale to calibrate effectively (the variability may be too high), but it is likely that the method will work well for other echolocating odontocetes, provided that the aerial surveys can provide robust estimates for calibration. Therefore, the calibration method may be a challenge for deep-diving odontocete species such as beaked whales, where visual-based estimates often have high uncertainty due to low sample sizes. Further, details of the method e.g., the specific acoustic unit of detection used for the PAM survey, will differ between species.

Finally, there are other data integration methods available as reviewed in Section 1. Therefore, a next research step would be to compare other reviewed methods with the calibration approach to assess the various strengths and limitations of the different methods. This would be an important step before recommending a standard approach to data integration.

Relevant code and data used for the case study are available on GitHub.

Section 4: Survey design recommendations

The discussions within the final technical meeting covered various aspects of survey design for both DAS and PAM surveys but ultimately considered those that would enable data integration for estimation of absolute abundance using PAM. The main discussion points are summarised below. Many discussion points relate to both DAS and PAM surveys, though points specific to DAS or PAM are highlighted.

Goals of a survey

Firstly, it is important to define the aims of any survey because the ultimate project goal will determine the survey design required. For example, a PAM survey designed to estimate absolute density or abundance from PAM data alone will need to consider detection probability estimation (and cue production information). In PAM surveys, this will often lead to a specific instrument configuration and will likely require more instrumentation overall (to create instrument arrays for animal localisation, for example). More complex data processing will also be required to estimate detection probability from PAM data. Further, if a survey is designed to detect a response to some disturbance, then particular designs e.g., gradient designs (as used in Thompson et al., 2013) may be required. In this project, the role of the PAM data was to supplement the absolute density estimates from the DAS data by providing data at a finer temporal resolution. Therefore, detection probability estimation and cue production information from the PAM data was not required (though see below for an extended discussion about detection probability estimation).

Survey effort

Sufficient replication of transect lines/points and obtaining uniform survey coverage are two important components of survey design (e.g., Buckland et al., 2001). Guidance is given in Buckland et al. (2001; 2015) regarding the number of lines/points required to achieve a desired level of variance (a minimum of 10 – 20 lines or points should be considered for an individual line- or point-transect survey). Tools such as dssd and dsims can also be used to design surveys for both line (for DAS surveys) and point (for stationary PAM surveys) transects. They can help to assess a number of design options, for example, whether the number of lines/points will achieve a reliable estimate of the encounter rate variance, whether the coverage probability within the survey area is uniform or whether stratification can help achieve more precise estimates. Using such tools as part of any survey design exercise is recommended. An example for one of the surveyed areas in the case study is presented in Appendix 1.

A further step would be to conduct a power analysis to investigate whether the survey design in question has enough power to detect changes in density/abundance (if that is the goal of a given project) using tools such as MRSeaPower or AVADECAF.

Required parameters for density/abundance estimation

There are several required parameters for absolute density/abundance estimation. These parameters will fundamentally affect precision and accuracy in density and abundance analyses. Therefore, it is recommended that studies attempt to estimate these parameters where practical, rather than relying on literature values, which may introduce bias due to geographical and temporal variability. More detailed comments on specific parameters are given below.

Detection probability: it is generally assumed that a digital aerial platform detects all animals available for detection within the surveyed strip but this may not always be the case. Detectability can be estimated for DAS data (likely using distance sampling) and this is an active area of research. Regarding PAM data, there are several ways to estimate detection probability (Marques et al., 2013) though, as discussed above, this has implications for survey design. In this project, a method is demonstrated that does not require detection probability to be directly estimated from the CPOD data, though prior information about detection probability could be included in the Bayesian model, if known. Further work via simulation is required to ascertain how the inclusion of detection probability as an informed prior would affect the precision and accuracy of the estimated parameters.

Group size: group size information from the DAS data might lead to insights about demography of the target species but is also linked to estimating availability (see next discussion point). Therefore, extracting group size information from DAS data could be useful.

Availability: estimation of availability parameters of relevance to DAS data is an active research topic. While instantaneous availability estimates are available for harbour porpoise from dive tag data (Teilmann et al. 2013), their application has limitations (e.g. unvalidated assumptions regarding animal visibility at depth), and efforts are underway to address these. Work is also ongoing by HiDef to generate estimates of availability based on a tandem aircraft approach.

Cue production rate (or similar vocal behaviour-linked parameters): again, this is an active area of research (for example ACCCURATE project, University of St Andrews). Similar to detection probability, a future research step would be to assess how the inclusion of prior information about the cue production rate of the target species affects the precision and accuracy of the estimated parameters.

Considerations specific to combining DAS and PAM data

It is important to note that by combining DAS and PAM data in this project, there was no requirement to estimate absolute density directly from the PAM data. Therefore, the survey design principles outlined above may not be strictly required for a combined DAS-PAM survey of this nature. So, while a conservative approach to the PAM survey design should start using the guidance referenced above (e.g., Buckland, 2001; 2015) about number of instruments, it is possible that some of the survey design principles can be relaxed when the PAM data only support the DAS data. However, this would require a dedicated down-sampling analysis, where instruments are removed in a simulation analysis to assess how many are required to still achieve the scientific objectives. This would be a natural next research step for this topic and similar exercises have been undertaken for other data integration methods (e.g., Schliep et al., 2023). Given the need to estimate absolute density from the DAS data then, when using the calibration method, efforts must be made to collect the most robust DAS data including data required for additional parameters as discussed above. Further, another next step would be to use simulation studies to assess how many DAS surveys would be required to adequately calibrate the PAM data i.e., how many flights, and at what intervals, are required to avoid bias and maintain an acceptable level of uncertainty in the calibrated PAM data.

Project Conclusions and Future Research Directions

This project addressed three main goals:

1. Produce a modelling framework integrating DAS data and PAM data, including the ability to incorporate seasonal and diurnal uncertainty.

2. Produce a test case study on harbour porpoise to validate the methods, producing density maps for a specified site in Scotland.

3. Provide recommendations on standards for static PAM and DAS data collection.

The first two goals were addressed through the review of available data integration methods and selecting a method for implementation in a case study. A calibration method was chosen and applied to a combined DAS and PAM dataset collected in the Moray Firth in 2010. By integrating DAS and PAM data, the different strengths of the data – the broader spatial coverage of aerial surveys and the long-duration, continuous monitoring of PAM surveys – were combined. The immediate benefit of combining the data was the conversion of the timeseries of PAM data into estimated absolute densities with associated uncertainty, including days when the DAS surveys were not operating. This may make it possible to investigate animal densities at a finer temporal resolution than with DAS data alone. In the case study, density surfaces were also estimated from the calibrated PAM data, showing spatial changes in absolute density. It is also potentially possible to apply this method to data already collected (as was demonstrated in the case study), assuming that an estimate of absolute abundance can be estimated from one of the survey platforms.

The key assumption is, however, that the parameters estimated from the combined DAS and PAM data are representative across the time period analysed. For example, in the case study, the DAS surveys were conducted on two dates in August 2010 and two dates in September 2010. It is therefore assumed that the corresponding estimated parameter, vp, combining the average effective detection area of the CPODs and the average probability of an animal clicking in a 1-second time period on those four days is representative of vp throughout all dates in August and September 2010. Further, the application of the combined parameter vp across the daily PAM dataset assumes that the average value of vp is constant across the time period being analysed and does not change from one day to the next. If this assumption is not true, then individual daily PAM estimates could be biased. Two next research steps would be to (1) assess through simulation studies how unaddressed variability in vp would impact the bias and precision of resulting abundance estimates and (2) compare the calibration approach with different data integration approaches (three broad categories were identified in the methods review) to better understand the advantages and disadvantages of the various methods.

Regarding the final goal, survey design considerations and recommendations were outlined for both DAS and PAM data separately, before considering survey design specifically for an integrated survey. The software review also highlighted that tools already exist to (1) aid DAS and PAM survey design and (2) assess the power of survey designs to detect change in trends in abundance and/or density (for both DAS and PAM surveys). These discussions led to identifying two further research steps: (1) there is a need to investigate how a dedicated integrated survey design would differ from the recommendations for individual DAS and PAM surveys, specifically regarding the number of PAM instruments and DAS flights required and (2) there is a need for a software tool to design a combined DAS and PAM survey, which could be an extension of existing tools.

Current survey design recommendations are to:

- Clearly identify the goals of a survey to ensure that the survey design will meet the needs of the survey goals. Goals may need to be prioritised where there are several competing goals and/or target species.
- Follow existing guidance for line and point placement for separate DAS and PAM surveys, though more research is needed to understand survey design requirements for an integrated survey.
- Use existing tools where possible to aid survey design, including assessing the power of the survey to detect changes in density and abundance. More software tool development is required specifically for integrated surveys.

In summary, data integration of DAS and PAM data is possible, providing a time series of absolute abundance estimates (with associated assumptions) that would not be possible using DAS data alone. Therefore, a further recommendation is to:

- Consider the benefits of collecting data from more than one type of surveying platform. Different platform types offer different advantages; in this study combining DAS and PAM data led to a time series of estimated absolute densities that would not have been practically possible from one platform alone. More research is required, however, to determine how many DAS flights are required, and at what intervals, to optimally calibrate the PAM data.

The demonstrated calibration method is flexible and so could be considered for use with other species and other surveying platforms (such as DAS using still images, ship-based surveys or autonomous vehicles).

However, there are likely to be specific considerations for each type of surveying platform, which may require adjustments to the data integration method. Ultimately, data integration from several surveying platforms has the potential to impact survey design and data collection recommendations, which in turn may influence required survey effort and, therefore, survey costs.

Future Research Directions

Each stage of the project highlighted future research steps, as summarised here.

- The software review highlighted that there is a need for a software tool to design a combined DAS and PAM survey, which could be an extension of existing tools.
- Several extensions to the case study analysis would be beneficial:
  - Explore variability in the vp parameter as a function of space and time.
  - Assess via simulation how unaddressed variability in vp would impact the bias and precision of resulting abundance estimates.
  - Compare other reviewed methods with the calibration approach to assess the various strengths and limitations of the different methods.
  - Further work via simulation is required to ascertain how the inclusion of acoustic detection probability and cue production rates as informed priors, if available, would affect the precision and accuracy of the estimated parameters.
  - Survey design considerations could be tested via simulation (based on the case study data) by (1) performing a down-sampling analysis to assess how many PAM instruments are required to avoid bias and achieve a suitable level of uncertainty in the resulting abundance estimates and (2) assess how many DAS surveys would be required to adequately calibrate the PAM data.
- Continued research into estimating (1) detection probability and (2) availability parameters for DAS data is important, given the need to estimate absolute density from the DAS data when using the calibration method. In addition, extracting group size information from DAS data might also be useful as it is linked to detection and availability parameters.

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Appendix 1 - Survey design and simulation using dsims

This exercise used dsims to design (1) a line transect survey and (2) a point transect survey for one of the 25 km x 25km monitoring areas from the case study (Fig. A1). In each case, the design was created using guidance from Buckland et al. (2001) regarding the number of recommended lines and points i.e., between 10 and 20. The coverage of the designs was then assessed using the simulation capabilities in dsims.

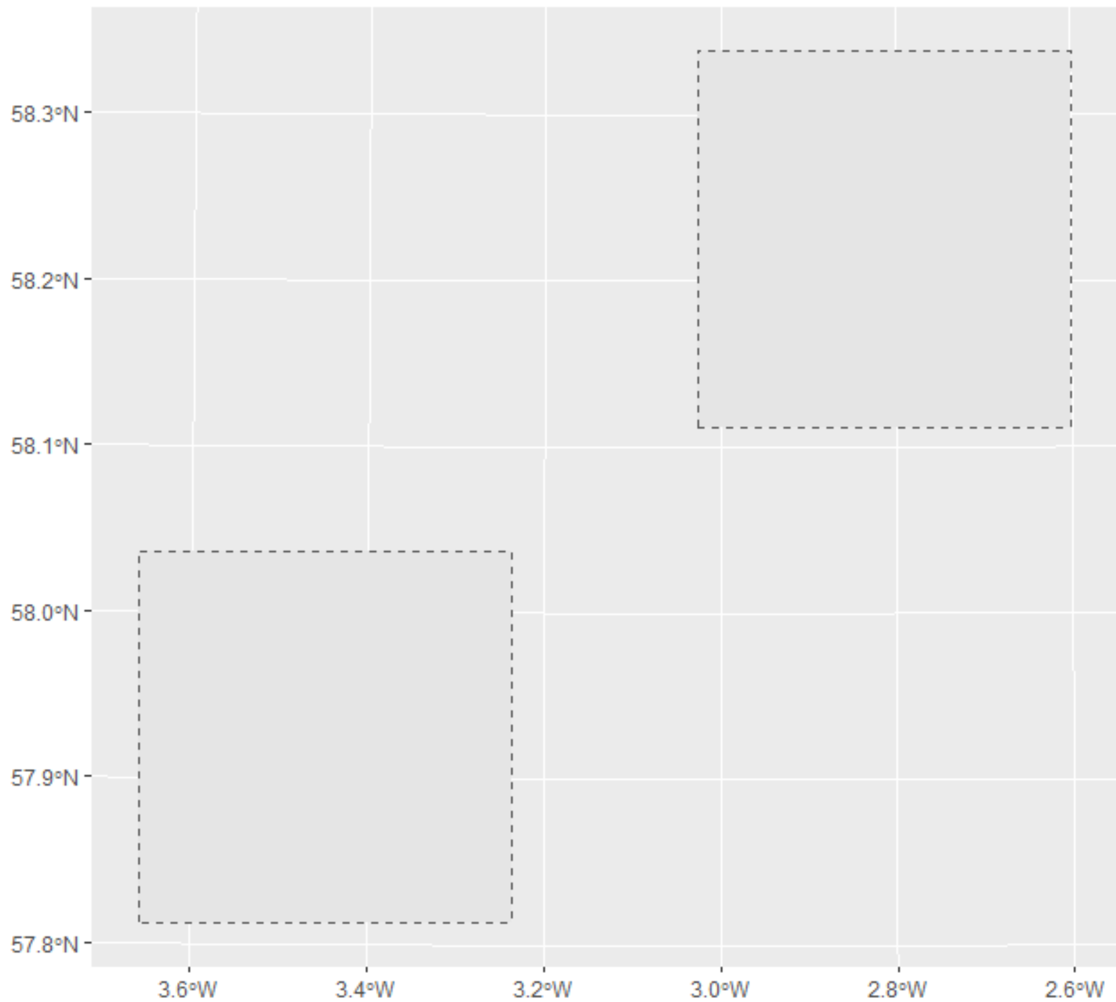

Fig. A1 The two main monitored areas from the case study. The design exercise was completed for one of the areas as a demonstration of the dsims package capability.

Methods

The line transect design assumed a spacing of 1,500 m and generated systematically-placed parallel lines with a random start point, which resulted in a design with 16 transect lines across the area. Line strip width was assumed to be 100 m. Coverage was assessed by generating 100 examples of the survey design and then using 1,000 grid points overlaid onto the survey area to quantify the number of times each point was covered by a survey (generating a coverage score per grid point). The point transect analysis assumed 20 monitoring points arranged in a systematic grid with a random start point. A monitoring radius of 100 m was also assumed. Coverage was assessed in the same way as the line transect survey.

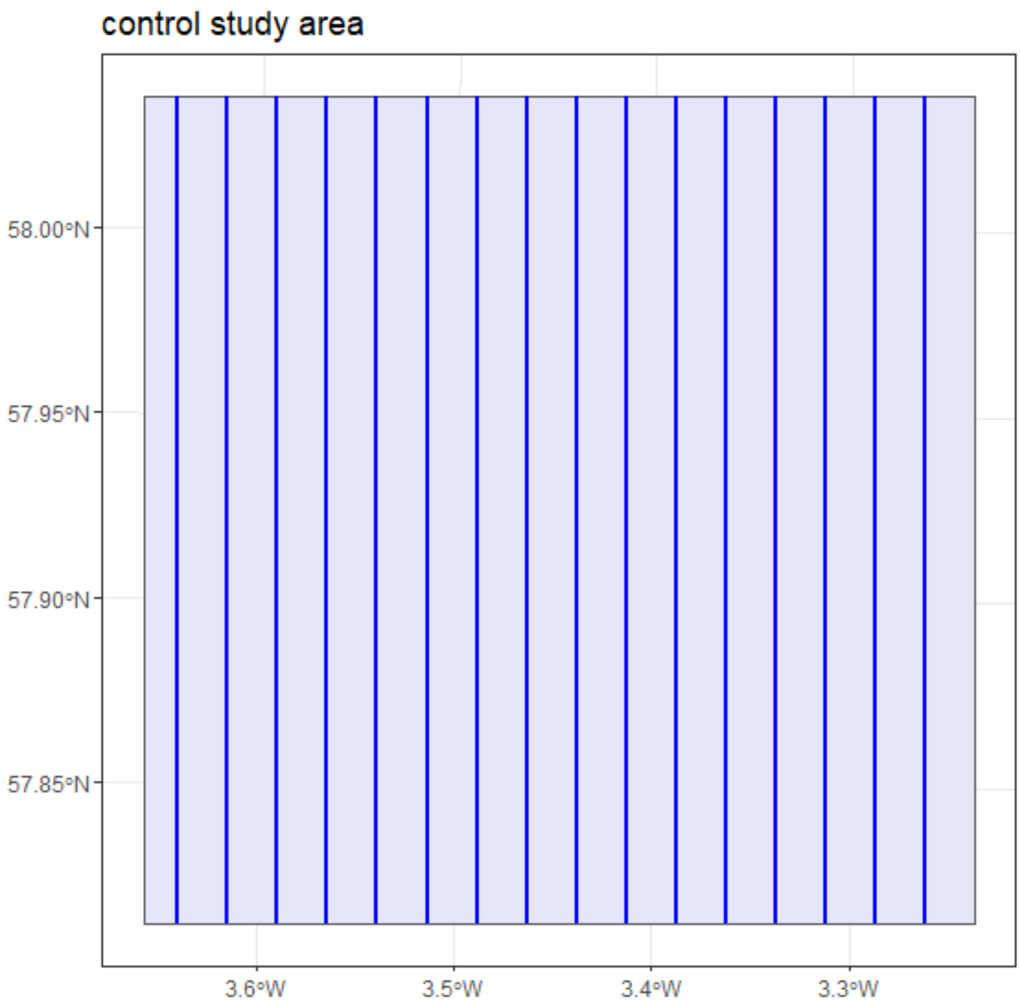

Fig. A2 A line transect design from one of the case study monitored areas.

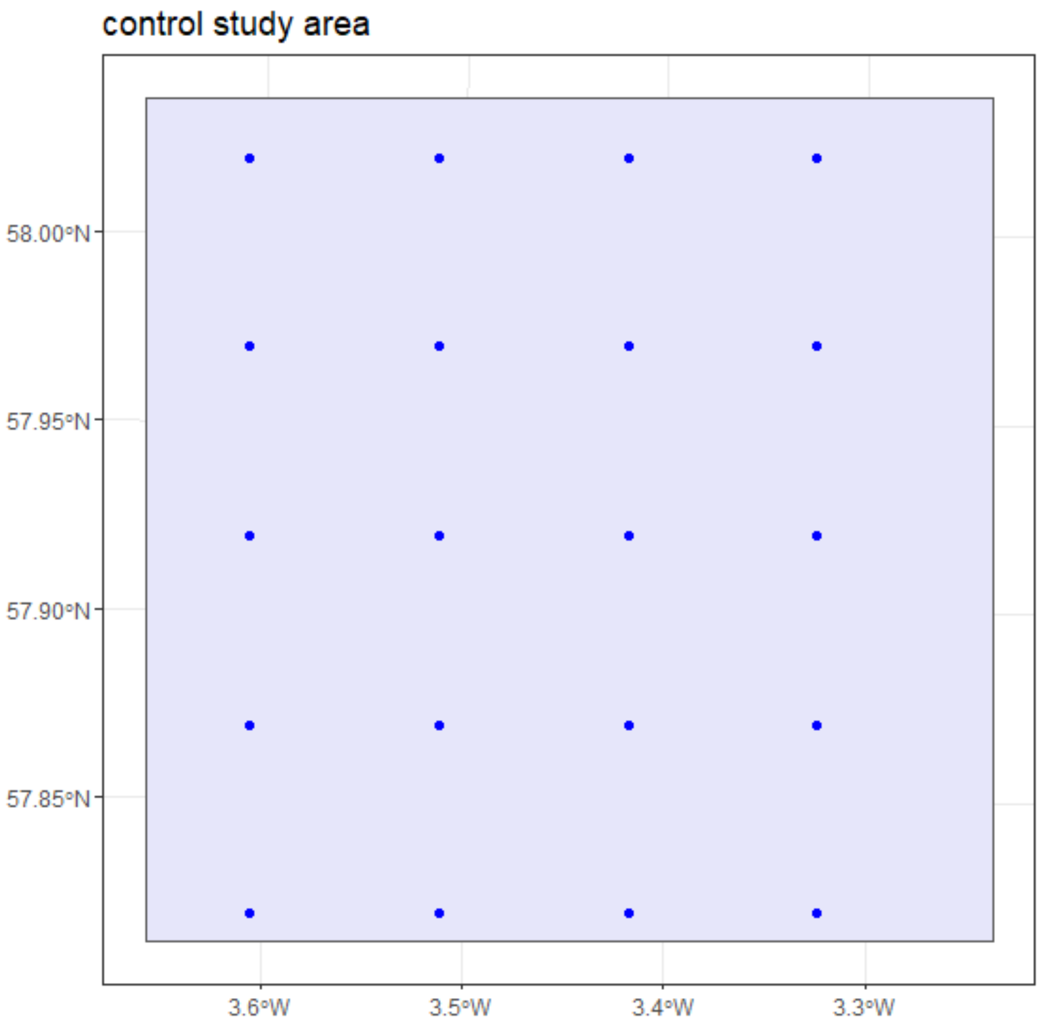

Fig. A3 A point transect design from one of the case study monitored areas.

Results

The resulting designs are shown in Figs A2 and A3. The coverage assessment resulted in a mean coverage of 13.3% for the line transect design, with individual coverage scores ranging between 0.09 and 0.2. Coverage was much lower for the point transect design with only 0.1% of the survey area being monitored. Corresponding coverage scores were also very low; the majority of points did not have any coverage across the 100 replicates of the design and the remaining coverage scores ranged between 0.01 and 0.02.

Conclusions

The results of the simulated analyses demonstrated the differences between the coverage of the line transect survey compared to the point transect survey. This is not surprising as CPODs (on which this simulation was based) typically have small detection ranges (and associated detection probability). This is an important consideration for survey design because the encounter rate variance can be affected by small sample sizes, which may result from very low coverage. dsims provides the opportunity to (1) design both line and point transect surveys and (2) assess their coverage. Further, dsims can be used to (3) simulate distance sampling analyses to assess many other aspects of the survey design (not demonstrated here) including encounter rate variance and bias in resulting abundance/density estimates. Therefore, dsims is a useful survey design tool, with several potential future extensions (see Section 2) being particularly relevant for integrated data analyses including (but not limited to) PAM and DAS data.

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