Marine Ecological Research

Marine Mammal Acoustic and Visual Surveys - Analysis of Neart Na Gaoithe data

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1. Methods

Ship based surveys were conducted over two to three days each month from November 2009. Visual data were analysed from November 2009 to October 2011. Acoustic data collection did not start until December 2010. Acoustic data collected between December 2010 and August 2011 have been analysed for this report.

A suite of environmental data (summarised in Table 1) were assembled and a GIS (Manifold) used to assign values to each 1 minute of survey effort allowing the influence of these habitat variables on relative densities and distributions to be explored. However, the survey area was generally rather uniform with respect to bottom topography with depths varying from 31 to 62m and an average slope of 0.15%. 95% of effort was in water depths of 40 to 60m. There was a similar homogeneity in habitat type with 88% of effort being in the same bottom habitat type (Deep circalittoral sand, A5.27).

(Note, similar data collected by EMU as part of this environmental assessment were also analysed. These were collected at a finer scale and probably more accurate, however they had a restricted coverage. None were found to be significant predictors of marine mammal distribution patterns.)

Variable	Source
Bathymetry Depth	Sea Zone Hydrospatial Gridded Offshore Bathymetry
Bathymetry Slope	Derived from Depth
Bathymetry Aspect	Derived from Depth
Feature	SeaZone Feature Description
Benthic Habitat Type	Eunis Predicted Habitats MESH http://www.searchmesh.net
Bottom Type	EMU surveys for Smart Wind (limited spatial coverage)
Time in the “daily” tidal cycle	Tide Table
Time in the “monthly” tidal cycle	Tide Table

Table 1 - Bathymetry and habitat data

Temporally dynamic variables included within models of marine mammal density were, time of day, Julian day, relative time in the “daily” tidal cycle, relative time in the “monthly” tidal cycle and tidal height.

Two visual surveys have been conducted for most months (one in each year). However, acoustic data collection did not start until December 2010 and consequently acoustic data are missing for the autumn months. It is likely that seasonal changes will be more relevant to an environmental assessment than overall trends in numbers. Surveys could take place at different times (e.g. early or late) within a month depending on weather and logistic considerations. To allow for this, Julian day (rather than just month) was used to investigate seasonality and a cyclic cubic regression spline was used to force the beginning and end of the year to be the same. This is equivalent to assuming that any changes observed are related to seasonal effects rather than any long-term trends in numbers

Weather covariates that are likely to influence sightings probability were included in all models. The survey design was such that the same tracks were completed on each monthly survey. Thus, effects of any spatially fixed covariates such as Latitude, Longitude, depth, slope and bottom type can be modelled separately from dynamic covariates. An hour term was included in models to allow for time of day effects on detection probability. It was assumed that time of day affected detection probability rather than that there were diurnal patterns of animal abundance within the area. For visual surveys diurnal changes in detection probability could be an effect of light levels and for acoustics by changes in vocal behaviour of porpoises. Any real changes in animal abundance in the area were assumed to be more likely related to the stage in the tidal cycle. The surveys tended to be conducted in the same pattern with relation to time of day, largely because the vessel left port to arrive at a start point at first light. There was thus a risk that spatial effects could be confounded by any changes in detection probability with time of day.

For analysis, survey effort (i.e. completed trackline) was divided into 1 minute segments; these were approximately 300m at the typical survey speed. Each segment was assigned a value of either a "0" if no animals were present or a "1" when the species of interest was detected in that segment. An acoustic detection always counted as "1" as it was usually not possible to identify group size reliably acoustically. Where group sizes of greater than one individual were recorded in the visual data, these animals were "smeared" across adjacent segments so the total number of animals remained the same reflecting the group size. This approach allowed for groups of more than 1 to contribute the correct number of animals while still maintaining the same (0,1 binomial) modelling approach as used for the acoustic data.

General Additive Models (GAMs) were used for all models with binomial data except for investigations of the relationship between noise levels and depth. Modelling was done using the mgcv package in R (Wood, 2006). Initial modelling explored factors that might affect detection probability. SeaState was found to be a more reliable predictor than WindForce for visual data. (Note: Observers reported that they judged sea state categories according to the Beaufort scale rather than the scale in the SAST manual.) For acoustic data the effects of noise in two 1/3 octave bands 89442-111803Hz (LowFreq) and 111803-141421Hz (HighFreq) which straddle the peak frequency of porpoise clicks, were explored. Time of day was also investigated for both data sets.

There were sufficient sightings and acoustic and visual detections of harbour porpoise and sightings data of grey seals, to allow an analysis to calculate densities and to model distributions and habitat preferences for these two species.

1.1 Estimating Absolute Abundance

We attempted to calculate an estimate of absolute abundance wherever possible. This has rarely been achieved with wind farm baseline survey data. However, there are several advantages to providing estimates of absolute abundance compared to relative indices. As well as being able to provide an estimate of the actual numbers of animals that might be affected by an activity or development, absolute estimates are much easier to compare between surveys and areas, and have greater potential for data validation. For example, if absolute numbers are available from more than one survey method or for subsets of the survey data, these can be directly compared in a way that relative abundance indices cannot.

Line transect methods for calculating absolute abundance require the calculation of a detection function and effective strip width, and a value for the proportion of animals missed on the trackline, often called g(0). For visual detections of porpoises and seals, effective strip width was calculated from the ranges and bearings to sightings measured and estimated by the visual observers using the DISTANCE line transect software package (Thomas et al., 2009). Two different approaches were used for estimating g(0) for seals and for porpoises.

For grey seals g(0) was estimated using data on dive patterns from high resolution GSM/GPS telemetry data kindly made available for this purpose by Bernie McConnell at SMRU. For any diving species, g(0) can be thought of as the product of both an availability bias, the probability that animals are available at the surface to be sighted during the period they are within visual range, and perception bias, the probability that an animal which is at the surface and within range is not seen. Unlike porpoises, seals typically remain continuously visible at the surface between dives. This suggests that, for a seal at the surface, perception bias is quite small. Seabird observers expect to see all seabirds at the surface within 300m, a seal presents as similar visual target and we assume that all seals at the surface within this range would be detected. Telemetry data were used to determine likelihood of being at the surface.

For porpoise visual data the detection function was calculated using observer data for range and bearing. For porpoise acoustic data the detection function was calculated using acoustic bearings and target motion analysis. (Mainstream funded SMRU to develop new functionality into the freeware acoustic analysis program PAMGUARD to facilitate such analysis.)

G(0) for both visual and acoustic porpoise data was calculated using Mark Recapture Distance Sampling (MRDS) techniques. For this, each method was used to generate a set of trials which could then be used to estimate what proportion of these were detected by the other method. The outcome of each trial was a binary result (detected/not detected) and relied on identifying duplicates between visual and acoustic data.

Duplicates cannot be identified with absolute certainty because there are a number of factors that could lead to either selecting false duplicates or missing real ones. For visual data there may be errors in the recorded time of the cue and associated location. In particular angles and distances are notoriously difficult to estimate to sightings at sea and so an allowance for location has to be made based on the likely magnitude of errors (Leaper et al., 2011). Animals may also move considerably between the visual sighting and the acoustic detection. Animal movement will affect the accuracy of perpendicular distances from acoustic data derived from target motion analysis. In higher density areas there is a possibility that detections of different animals by the two methods would be classified as duplicates. To avoid this, conservative criteria for a detection to be considered a suitable trial were applied. These included that no other detections had been made by the method setting up the trial for five minutes either side of the trial detection time.

Once a set of suitable trials had been selected these were investigated for possible duplicate detections by the other method. The speed of the vessel, the estimated distance ahead of the vessel and the length of the hydrophone towing astern of the vessel are used to estimate the expected time delay between the sighting and the acoustic detection coming abeam of the hydrophone. If there is a detection with the pod coming abeam within a time window of a certain time period either side of this delayed time then that is classified as a duplicate. To determine the most appropriate time period, the number of duplicates can be plotted by time relative to the predicted delay. The expected shape of this plot is for a peak at zero time delay dropping away to either side followed by 'noise' from false duplicates at longer time intervals. However, this relies on sufficient numbers of duplicates to generate an informative plot.

The estimate for g(0) suggested by Buckland et al (1993) where g(0) for method *A* is given by

$$g_A(0) = \frac{n_{AB} w_B}{n_B w_{AB}}$$

Where n_{AB} is the number of duplicates detected by both methods, n_B is the number of trials based on detections by method *B*, w_{AB} is the strip width of the duplicated data and w_B is the strip width of the trial data. This method is simple and easy to apply but does rely on a sufficient number of duplicates to estimate a strip width for the duplicate detections.

2. Results

2.1 Factors affecting detection probability

2.1.1 Acoustic data

There is an expectation (based on signal processing theory) that increasing levels of noise in the frequency band of porpoise clicks will reduce detection rates through masking and interference effects. In fact, against expectation, detection rates increased slightly with increasing noise. We found, however, that there was a strong correlation between noise and water depth (Figure 1). This may occur because boat and surface noise is reflected from the bottom and the travel path to the hydrophones is shorter when water depths are shallower. Thus, the interaction between depth and noise may have confounded the detection of any relationship between density and depth in the acoustic data.

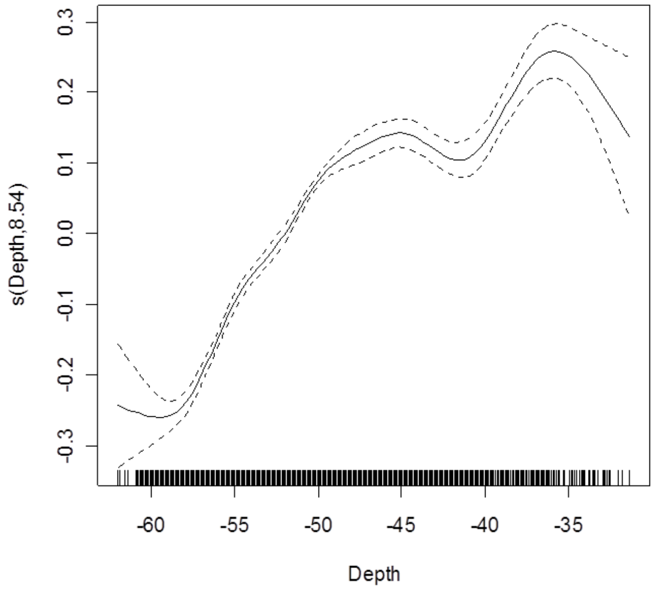

Figure 1 - Change ambient noise in 1/3 octave band 89442Hz to 11803Hz with depth

Time of day also appeared to affect acoustic detection rates (Figure 2).

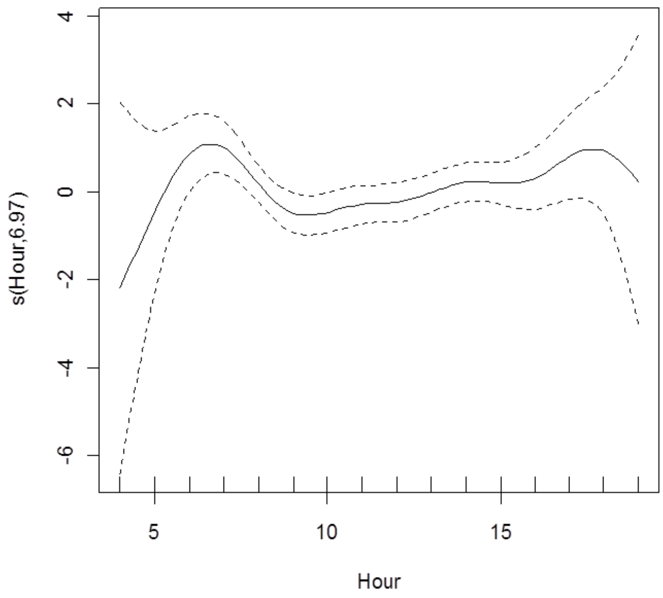

Figure 2 - Variation in acoustic detection rates with time of day from fitted GAM

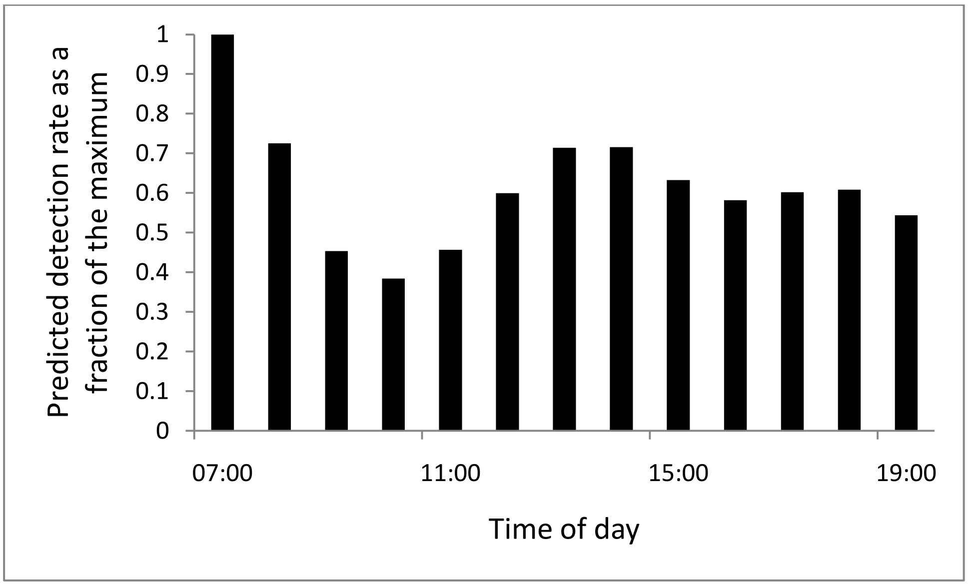

Figure 3 - Changes in harbour porpoise acoustic detection rate with time of day predicted from the GAM.

2.1.2 Visual data

The dominant factor affecting visual detection probability in surveys is usually wind and resulting sea state. In these data, we found that, Sea State gave a better model with a lower UBRE than did Wind Force, explaining more of the deviance (8.4% for Seas State compared to 3.2% for Wind Force). Swell Height and Visibility did not have significant effects on sightings rates of seals or porpoises. However, for both grey seals and porpoises, sighting rates dropped steadily with Sea State. For harbour porpoise, sightings rates dropped most sharply between seas state 1 and 2.

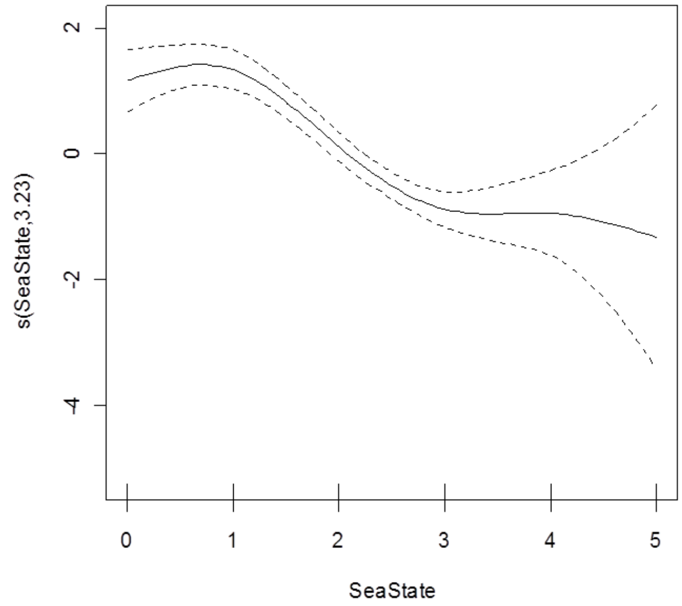

Figure 4 - Sighting rates of harbour porpoise in relation to sea state.

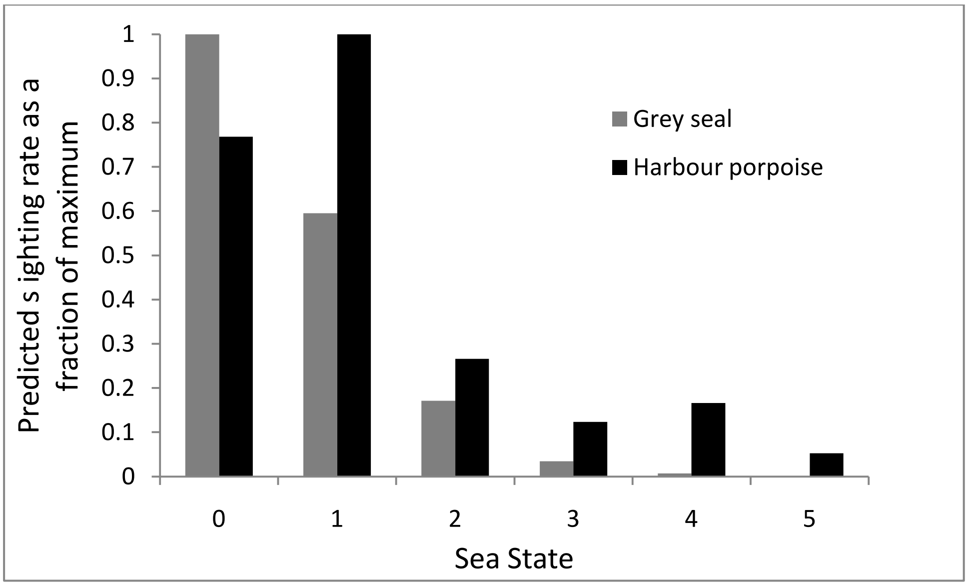

Figure 5 - Predicted changes in sighting rates of grey seal and harbour porpoise from GAM. The largest change from sea state 0 and 1 to 2 and above for harbour porpoise is consistent with other studies. The small sample sizes in this study probably account for the higher sighting rates in sea state 1 than 0 for harbour porpoise.

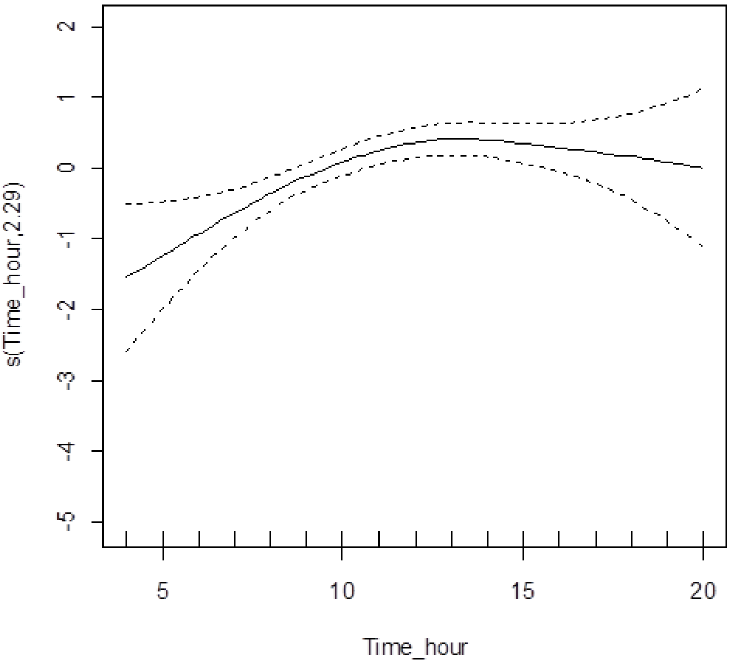

Figure 6 - Sighting rates of harbour porpoise with time of day

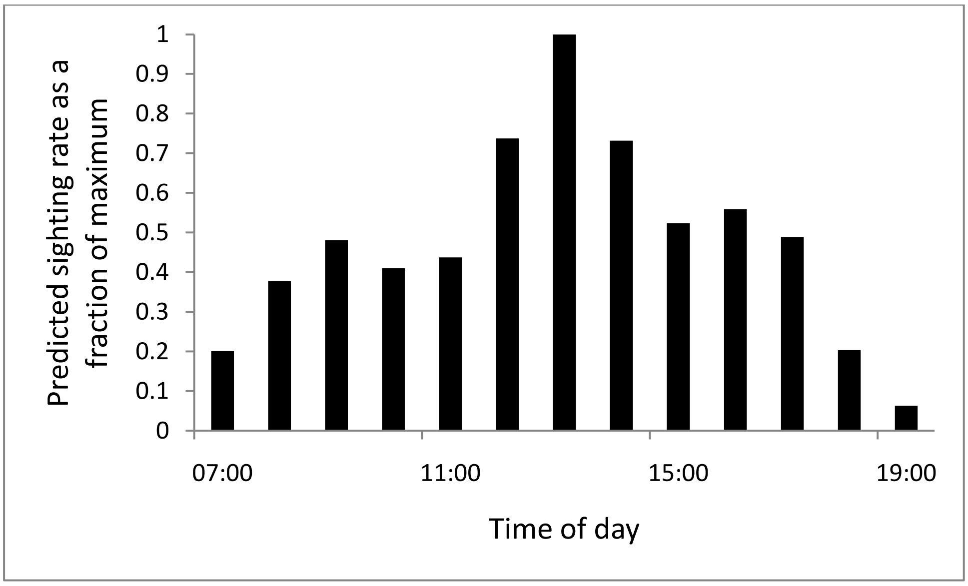

Figure 7 - Changes in harbour porpoise sighting rate with time of day predicted from the GAM.

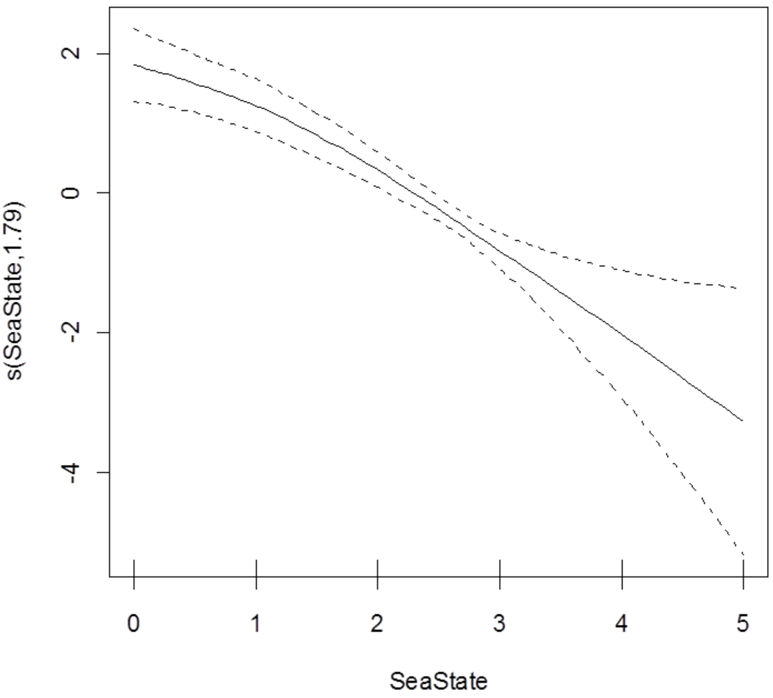

Figure 8 - Sighting rates of grey seals in relation to sea state.

The magnitude of the diurnal changes in sightings rate are higher than might be expected. This could be related to confounding effects between distribution patterns and generally starting the surveys at the same location. However, the opposite effect observed within the acoustics would suggest that this cannot explain these effects completely. There may also be a combination of behavioural changes that affect porpoise detectability and diurnal changes that affect observer performance e.g. light levels or fatigue. It should also be noted that the model is based on rather small sample sizes and so these results should be interpreted with caution. Qualitatively the shape of both plots is what might be expected, higher sighting rates in the middle of the day related to the best light conditions and more porpoise acoustic activity towards dawn and dusk.

2.1.3 Effects of Spatial and Temporal Variables on Densities and Distributions

The covariates used in exploratory and final models are given in Tables 2 a-d. These are divided into temporal and spatial categories since the main interests are how animal distribution varies across the whole area seasonally (temporal) and how average distribution within the area varies spatially. In each case both the full set of covariates explored using GAMs and those retained in the best fitting model are shown. Covariates related to detectability were important in all cases. The only spatial covariate retained in the best fitting models were longitude for porpoise sighting data and both longitude and latitude in seal sighting data. The only temporal covariate retained in all “best” models (apart from time of day which is believed to primarily affect detection probability) was Julian Day indicating significant seasonal variation. Tidal covariates did not show any significant effects.

	Detection		**Spatial**					
	Time of day	**Sea State**	**Latitude**	**Longitude**	**Depth**	**Slope**	**Aspect**	**Bottom Type (EUNIS Habitat)**
Harbour porpoise								
Co-variates included in exploratory models	x	x	x	x	x	x	x	x
Co-variates included in 'best' model (selected on basis of minimum UBRE)	x	x	x	x				
Grey seal								
Co-variates included in exploratory models	x	x	x	x	x	x	x	x
Co-variates included in 'best' model (selected on basis of minimum UBRE)		x	x	x				

Table 2a - Range of detection and spatially related covariates modelled for harbour porpoise and grey seal sightings data.

	Detection		**Temporal**					
	Time of day	**Sea State**	**Julian Day**	**Wind Direction**	**Tidal Height**	**Tidal Phase**	**Current Speed**	**Current Direction**
Harbour porpoise								
Co-variates included in exploratory models	X	x	X	x	x	x	x	x
Co-variates included in 'best' model (selected on basis of minimum UBRE)	x	x	X					
Grey seal								
Co-variates included in exploratory models	x	x	X	x	x	x	x	x
Co-variates included in 'best' model (selected on basis of minimum UBRE)		x	X					

Table 2b - The range of detection and temporally related covariates modelled for harbour porpoise and grey seal sightings data.

	Detection		**Spatial**					
Spatial	**Time of day**	**Noise**	**Latitude**	**Longitude**	**Depth**	**Slope**	**Aspect**	**Bottom Type (EUNIS Habitat)**
Harbour porpoise								
Co-variates included in exploratory models	x	x	x	x	x	x	x	x
Co-variates included in 'best' model (selected on basis of minimum UBRE)	x							

Table 2c - Range of detection and spatially related covariates modelled for harbour porpoise acoustic detection data.

	Detection		**Temporal**					
Temporal	**Time of day**	**Noise**	**Julian Day**	**Wind Direction**	**Tidal Height**	**Tidal Phase**	**Current Speed**	**Current Direction**
Harbour porpoise								
Co-variates included in exploratory models	x	x	x	x	x	x	x	x
Co-variates included in 'best' model (selected on basis of minimum UBRE)	x		x					

Table 2d - Range of detection and temporally related covariates modelled for harbour porpoise acoustic detection data.

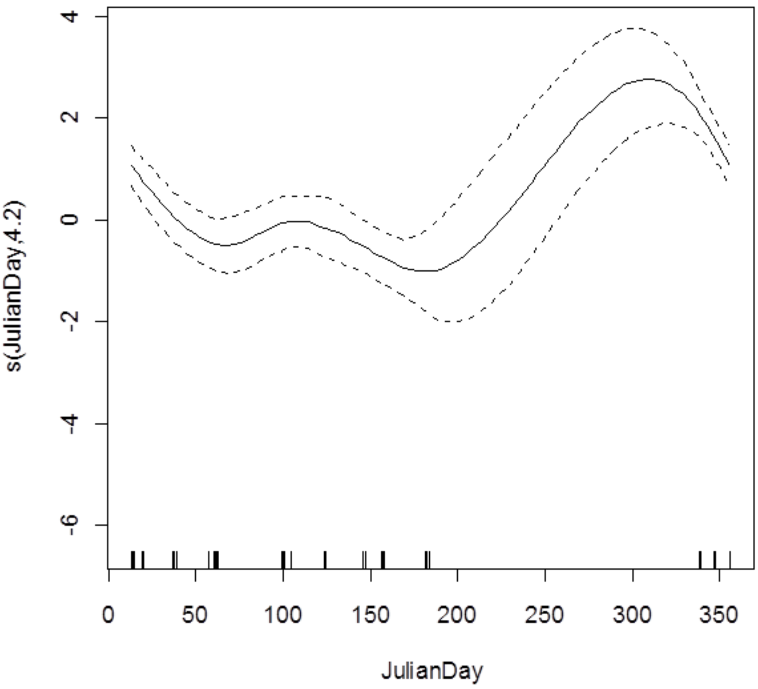

Figure 9 - Seasonal changes in acoustic detection rates of harbour porpoise

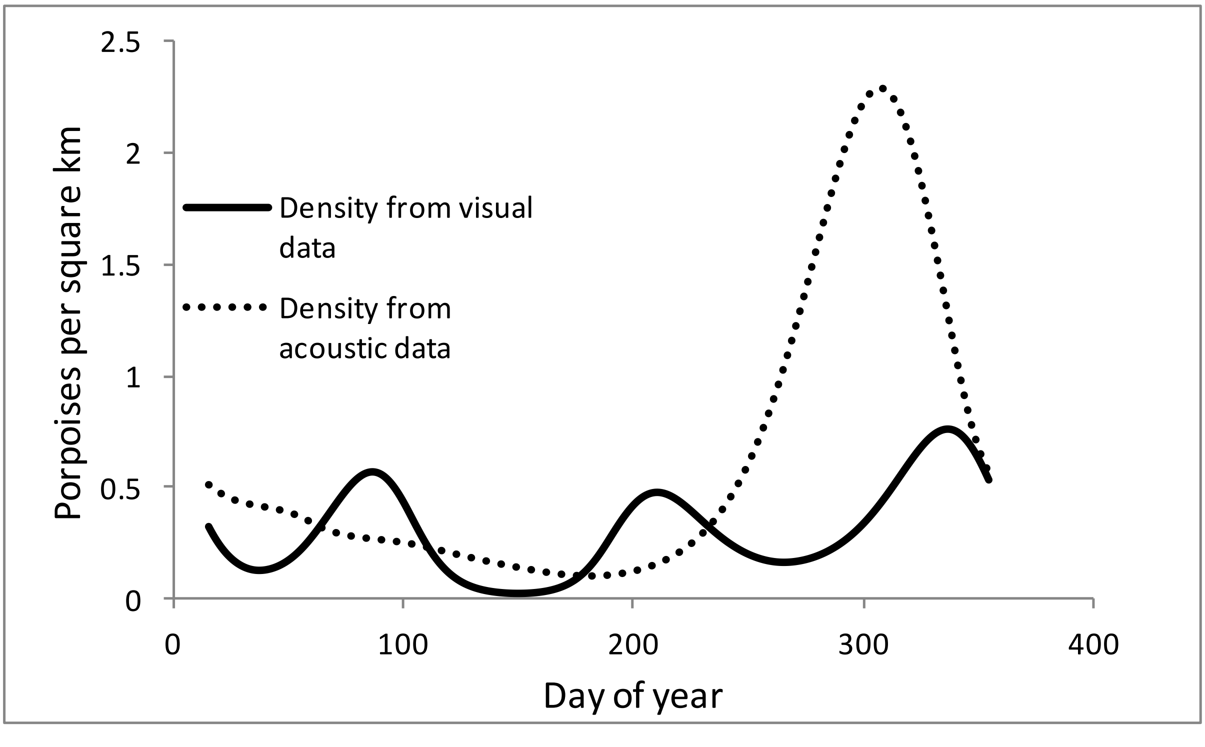

Figure 10 - Seasonal changes in porpoise density predicted from GAM. Note that the autumn peak in the acoustic data is largely an artefact of the model because there was no survey data for this period.

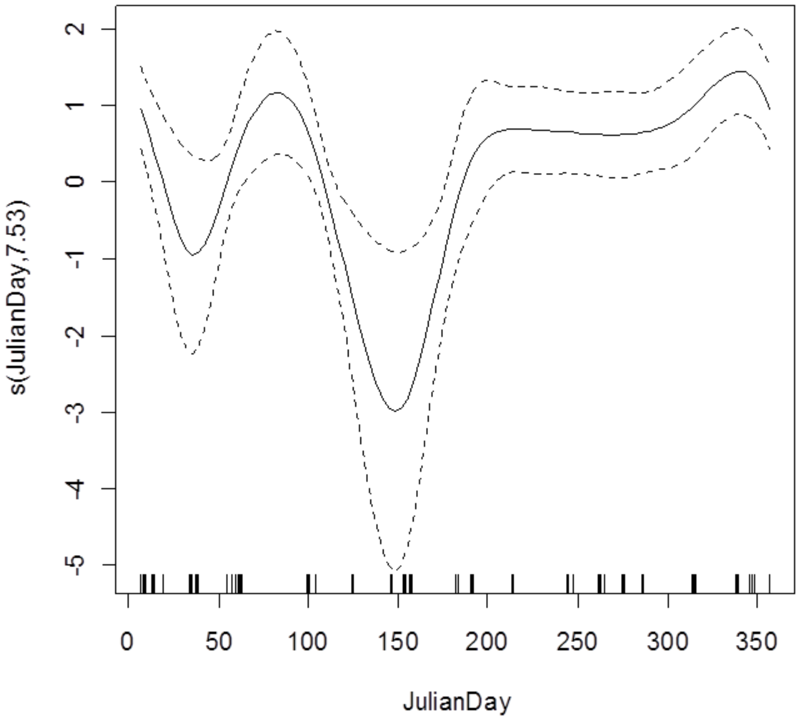

Figure 11 – Seasonal changes in visual sightings of harbour porpoise

2.2 Absolute Density Estimates Distance Analysis

Figures 12, 13 and 14 show detection functions for harbour porpoise and grey seal visual detection, and for porpoise acoustic detections respectively. Important data from these are summarised in Table 3

Data set	Model	Number of observations	ESW	CV	95% CU
Harbour porpoise visual	Half-normal	84	180m	8.1	154-212m
Grey seal visual	Half-normal	86	215m	8.6	181-255m
Harbour porpoise acoustic	Half-normal	189	416m	15.8	305-567m

Table 3 - Summary of Detection function data for harbour porpoise and grey seals

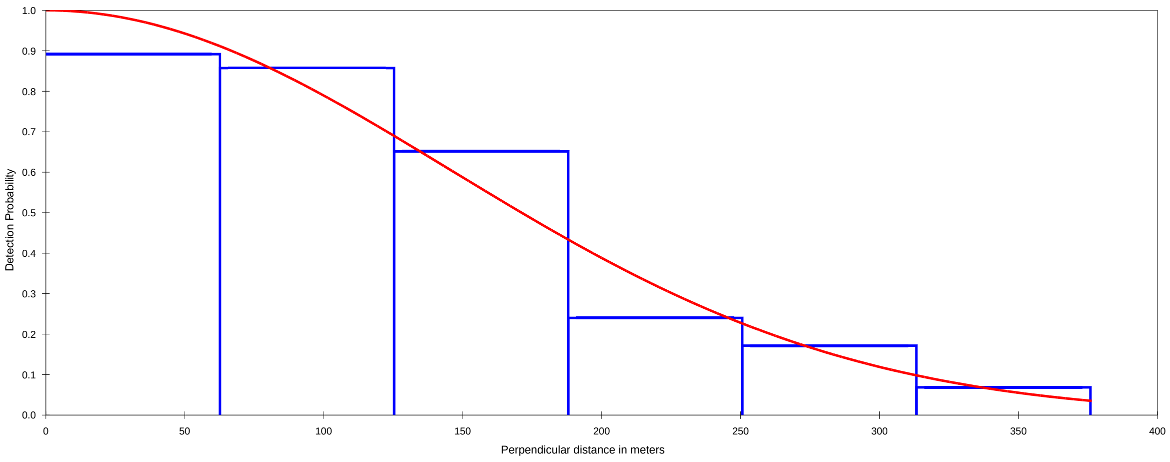

Figure 12 - Harbour porpoise visual detection function

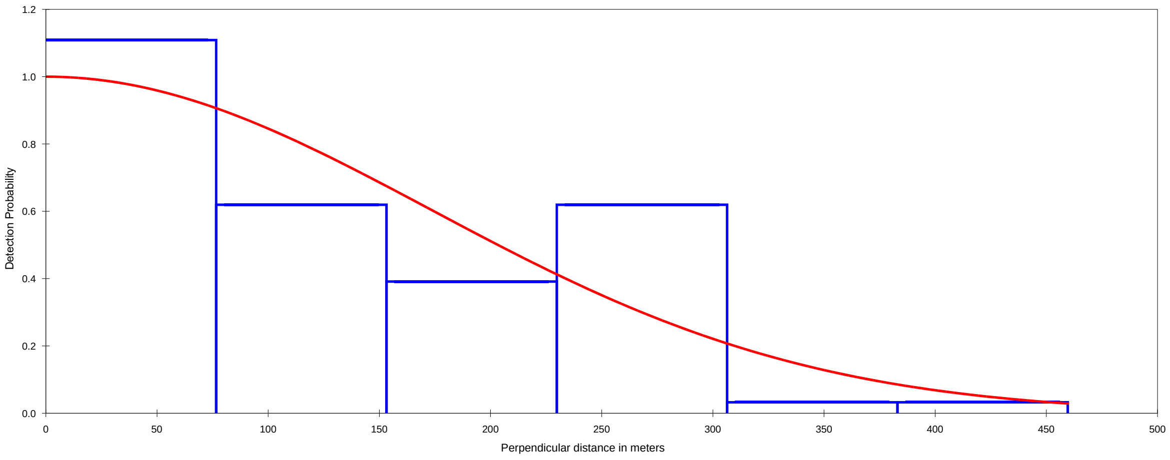

Figure 13 – Grey seal visual detection function

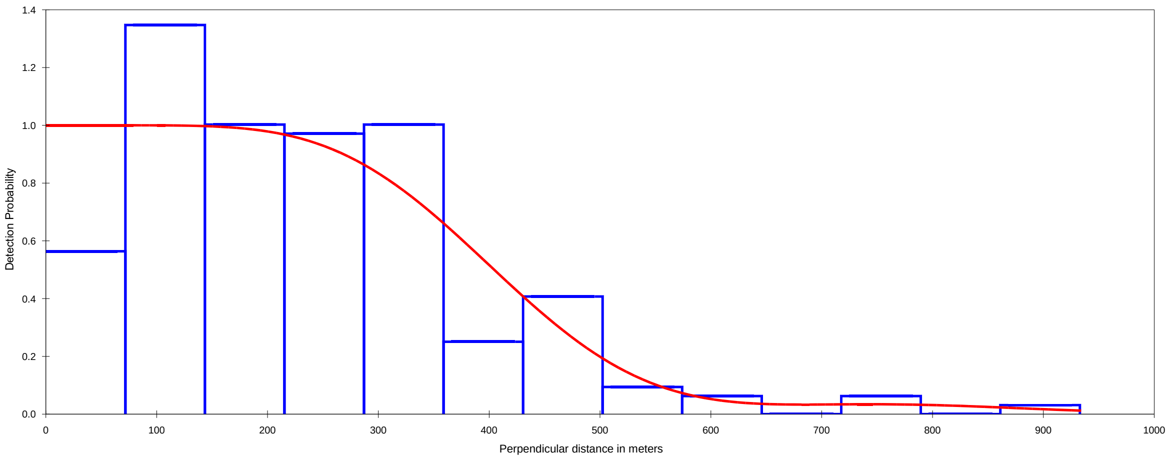

Figure 14 – Harbour porpoise acoustic detection function

2.2.1 Porpoise Acoustic data

As it is not possible to accurately determine group size from the acoustic data we recorded acoustic detections of porpoise pods and scaled these using visual data on pods size. There was no significant difference between visual estimates of group size for pods that were detected acoustically (1.47) and those not detected acoustically (1.38). Thus, the overall mean visually determined group size of 1.43 was used to convert acoustic encounters into individuals.

Detection Function

DISTANCE software (Thomas, 1999) was used to analyse acoustically derived estimates of range from the trackline to calculate an acoustic detection function Figure (10). This gave an acoustic strip width of 416m (95% CI of 305 to 567).

g(0) estimation

There were a total of 30 sightings of harbour porpoise groups during combined visual and acoustic effort that could potentially be considered as trials for acoustic detections. . Of these, all were within perpendicular distance of 200m. For 16 of these there was an acoustic detection within 10 minutes of the visual sighting. This number of detections was too small to determine an estimate of the time window around the expected delay between the visual sighting and the acoustic detection based on the data. Several of the 30 sightings were also close to each other in timing making it difficult to associate an acoustic detection with a particular sighting. Rejecting sightings for trials if there were any others within 5 minutes resulted in 20 trials. Of these, 12 were detected acoustically with 9 within a window of 200 seconds of the expected time delay. Based on this small number of duplicates it was not possible to estimate a strip width for the duplicates but given the greater strip width for acoustics it would be reasonable to expect the strip width for the duplicates to be similar to that for the visual estimates. Hence our best estimate of g(0) was therefore 9/20 or 0.45. A simple binomial distribution variance for this estimate would give a CV of 0.25, however this does not take into account the uncertainties in duplicate identification or strip width estimation, and this estimate of g(0) should be considered very preliminary.

Acoustic density estimates for harbour porpoise are given in Table 4.

2.2.2 Porpoise Visual data

g(0)

There were f 99 acoustic detections that provided suitable trials for visual detections. Of these 7 were seen with 5 minutes of the expected time delay window. This number was not sufficient to estimate the strip width for duplicates but because of the much greater acoustic strip width it was assumed that these would be a random sample from the visual sightings and could thus be represented by the same detection function. Visual observers only watch one side of the vessel whereas the acoustics detect animals on both sides and so the acoustic strip width needs to be multiplied by 2.

Hence g(0) could be approximated by 7/99*2*ESWacoustic/ESWvisual = 0.33

A simple binomial distribution variance for the trial detections would give a CV for the g(0) estimate of 0.37 but this does not capture the full range of uncertainty with this estimate because of the duplicate identification uncertainty and variance associated with the strip width estimation.

Visual density estimates for harbour porpoise are given in Table 4.

2.2.3 Grey Seal Visual Data

Estimating G(0)

Telemetry data from tags were used to estimate the effect of availability bias on g(0) for grey seals. A dataset for 9 tagged grey seals was provided by Bernie McConnell at SMRU. Data were restricted to dives conducted during daylight hours(08:00 to 20:00) and within the visual survey study area leaving data for 1551 dive cycles; 60% of surfacing periods were between 15 and 45 seconds with a median of 40s. Dive times were more widely distributed (Figure 11) with a maximum of 496s.

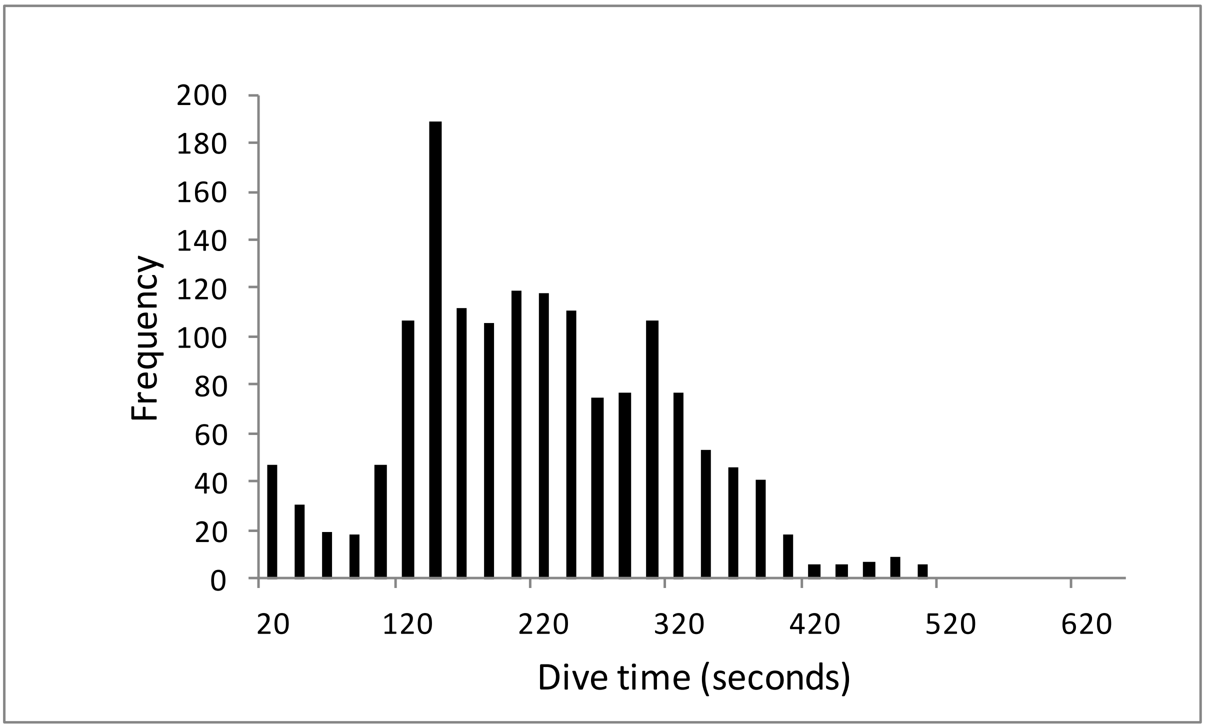

Figure 11 - Frequency of observed dive times for grey seals within the NnG study area during approximate daylight hours (08:00-20:00).

A crude model for estimating the likely effects of availability bias on g(0) is to assume a hard-edged detection distance, *s*, ahead of the vessel within which any seal directly on the trackline would be detected and outside which detection probability is zero. For a vessel travelling at 5ms^{-1}, (average survey speed) the time t for which a seal could surface and be detected is given by t=s/5. For a dive of duration d, the probability p_d that the seal will not surface at some time within distance s ahead of the vessel is $p_d=(d-t)/d$ if d>t and $p_d=0$ if $d \leq t$.

A more complex approach would be to model the detection probability as a function of radial distance and combine this with the dive data into a full model incorporating availability bias. This is difficult because of the limited number of sightings on which to base a radial distance model. In addition, the observers tend to focus on the area 300m ahead of the vessel for bird observations. This is likely to result in a sharper drop in detection probability at distances greater than 300m than might be expected with other observation protocols. Of the 86 grey seal sightings 92% were within a distance ahead of the vessel along the trackline of 300m, with the peak in radial distances at 250m. Based on this, and the scanning patterns of the observers, a hard-edged detection limit of 300m ahead of the vessel seems a reasonable assumption for estimating the effects of availability bias on g(0).

The total probability, *P* that a seal would not be available for detection was calculated as

$$P = \frac{1}{T}\sum_{d} p_d \, n_d t_d$$

Where there were 1551 observed dives with n_d dives falling within each 20 second time band category with mid point t_d, shown in Figure 11 and *T* is the total observation period i.e. the sum of all surface and dive intervals. The proportion of total time spent performing dives in duration band d is thus given by

$$\frac{n_d \, t_d}{T}$$

For *s*=300m this gave *P*=0.54 resulting in g(0) =0.46 if no correction is made for perception bias.

Based on this, assumption the density of grey seals in the survey area is 0.125 individuals per km^{-2} (Table 5). We have had to make several assumptions to arrive at this estimate, in particular that there is no perception bias. If a significant perception bias is present then the true density estimate will be higher than the value provided here.

	Harbour porpoise acoustic (all detections)	Harbour porpoise visual (same effort as acoustics)	Harbour porpoise visual, all data
Effort in minutes	8272	8272	22754
Mean speed	10.1	10.1	10.1
Estimated Strip half width (m)	416	180	180
Total strip width	832	180	180
Track surveyed (km)	2579	2579	7094
Area surveyed (km^2)	2140	464	1277
Group size (average total for all surveys)	1.43	1.43	1.43
Groups detected	184	30	113
Individuals detected	263	43	161
g(0)	0.45	0.33	0.33
Density (individuals km^{-2})	0.27	0.28	0.38

Table 4 – Visual sightings, acoustic detections and density estimates for harbour porpoise

	Grey seal (positive id)	Grey seal (including pro rated seal sp)	Common seal
Effort in minutes	22754	22754	22754
Mean speed	10.1	10.1	10.1
Estimated Strip half width (m)	215	215	215
Total strip width	215	215	215
Track surveyed (km)	7094	7094	7094
Area surveyed (km^2)	1525	1525	1525
Group size (average total for all surveys)	1.02	1.02	
Groups detected	86		
Individuals detected	88	95	16
g(0)	0.46	0.46	
Density (individuals km^{-2})	0.13	0.14	

Table 5 – Sightings and density estimates for seals

3. Discussion

Initial exploratory spatial models for harbour porpoise showed significant variation in density with latitude and longitude but with patterns that rather conflicted between visual and acoustic data. These models did not include a time of day term. When time of day was included latitude and longitude were no longer significant in the acoustic model suggesting that apparent spatial variability could be explained by acoustic detection probability. Other studies have found greater numbers of acoustic detections at night(Todd et al., 2009) and this is reflected in this study with peaks at the beginning and end of the day. This could confound the detection of any spatial variation because the surveys tended to be conducted in the same pattern with respect to time of day. Some spatial variation was apparent in the visual data and it may be possible that this was not apparent in the acoustic dataset because of the low number of acoustic compared to visual surveys. The lack of strong spatial patterns in distribution is also not surprising given the uniform bottom topography and small size of the survey area.

The spatial patterns of grey seal distribution were more pronounced than those for harbour porpoise with highest densities in the NW and lowest in the SE of the survey region. However, grey seals showed little seasonal variation in density.

Seasonal variation in density was pronounced for harbour porpoise with lowest numbers in May. The acoustic and visual data gave a broadly consistent picture of seasonal distribution but this was limited by the number of acoustic surveys which only spanned 9 months.

The crude estimates of g(0) presented for harbour porpoise should be considered very preliminary and will have quite a high variance due to the small numbers of duplicate detections. Nevertheless the values of 0.45 for acoustics and 0.33 for visual are reasonably consistent with other studies. The acoustic strip width was rather greater than for the larger vessels used on the SCANSII survey but the vessel used for this study did appear to be relatively quiet. Data collection is ongoing and should allow more precise estimates of g(0) because the sample sizes used in this study were really too small for reliable estimates. These estimates might also become more precise if data from the same vessel using similar teams of observers were combined between different projects.

Effects of Observing on only one side of the vessel

If (as was the case on this survey), observations are only made on one side of the transect line then random animal movement will result in more animals being seen within the observation area than half of what would be expected to be detected within the total strip width from observations both sides of the vessel[1]. The size of this effect will depend on swim speed of the animals relative to survey speed, the probability of detecting any surfacing event and the diving pattern of the animals. A general sighting simulation model (see Leaper et al. 2011) was used to estimate bias for different combinations of swim speed and dive time. Animals were assumed to move in straight lines and so the results will generally overestimate the effects of random animal movement. Responsive animal movement was not investigated but the relatively low number of detections close to the track line in the acoustic detection function shows some evidence of responsive movement occurring. Parameters were tuned to give a similar strip width to the observed data, in this case slightly greater than the observed at 415m. Further simulation runs could be conducted for different combinations of parameters but it seems likely that the bias would be around 10% for typical swim speeds and dive times (Table 6).

Swim speed (ms^{-1})	Ship speed (ms^{-1})	Mean dive duration (s)	Number of surfacings between dives	Ratio of density estimated from observations on one side to both sides
1	5	120	3	1.09
1	5	60	3	1.11
2	5	120	3	1.14
2	5	60	3	1.18

Table 6 - Simulation results to investigate bias in density estimation caused by random animal movement if observations are only made on one side of the vessel.

This issue has generally not arisen with previous analyses of similar data sets because only relative estimates of density were generated. In this case it is worth considering the bias because the dual platform data allows an estimate of g(0) and thus the calculation of absolute density.

Based on the crude g(0) estimates, the average densities of harbour porpoise are between 0.27 0.38 porpoises km^{2}. The latter estimate is for the whole year whereas the former is for the 9months including April to June which had the lowest densities. The estimates of 0.27 from acoustic and 0.28 from visual for the same surveys are consistent and not significantly different from the overall estimate for SCANSII block V of 0.294 (0.37) porpoises km^{2}. The SCANSII survey did however report higher mean group sizes 2.37(0.22), compared to 1.43 in this study.

The value of g(0) used for seals should also be treated as a preliminary. If accepted with caution however, it provides the first values we are aware for offshore densities for this species in this region of 0.13 seals per km^{2}.

4. References

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