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Further use of aerial surveys to detect bird displacement by offshore windfarms

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Executive Summary

- Offshore windfarms are likely to become one of Europe's most extensive technical interventions in marine habitats. The areas in which windfarms are located often coincide with areas favoured by large concentrations of seabirds. The UK Government has a legal obligation to monitor the impact windfarms might have on seabirds.
- This report follows a previous report commissioned by COWRIE (Maclean *et al.* 2006), in which the extent to which BERR (formally DTI) aerial survey protocol allows changes in bird numbers to be detected, was examined using power analysis. Changes in bird numbers can be hard to detect due to natural fluctuations in bird numbers. Power analysis allows a statistical assessment to be made of the probability that such changes could be distinguished from background fluctuations.
- Several issues are assessed in more detail than in the previous report. Rather than using data collected in many areas to estimate variability by assuming that the extent to which birds fluctuate in numbers is broadly similar (relative to the mean number present) across all sites, we select a few areas for which a long time-series of data exists and analyse these data exclusively. Additionally, rather than assuming a uniform decline within any given area, we explore one method of allowing for a gradient of decline, such that declines after windfarm construction are greatest closest to the windfarm. Lastly, we investigate the effects of using simple spatial variables (water depth, seabed slope gradient, seabed aspect, distance from land, distance from shallow water and seabed complexity) on the ability to detect changes in bird numbers. As with the previous report, four taxa were selected for analysis: red-throated diver (*Gavia stellata*), common scoter (*Melanitta nigra*), sandwich tern (*Sterna sandvicensis*) and lesser and great black-backed gull (*Larus fuscus* and *L. marinus*).
- Using long time-series of data rather than assuming equal proportional variability across many sites has no appreciable difference on the likelihood of being able to detect declines in bird numbers of 50% or less. The statistical power of being able to detect such changes remains low (< 0.8) for all species irrespective of the length of time over which monitoring is carried out.
- Analysing data by assuming a gradient of decline generally results in a lower power to detect changes in numbers, but can sometimes improve power if declines are particularly severe. This is unsurprising given that the over-riding effect of using a gradient of decline, rather than uniform decline to estimate variability, is to increase the variability. Again, the statistical power of being able to detect such changes remains low (< 0.85) for all species irrespective of the length of time over which monitoring is carried out.
- Using spatial variables to account for some of the variability in bird numbers does not improve the statistical power of being able to detect changes. Again this is unsurprising given that the low likelihood of being able to detect change is caused by temporal rather than spatial variability in numbers. As previously, the statistical power of being able to detect such changes remains low (< 0.85) for all species irrespective of the length of time over which monitoring is carried out.
- Similar conclusions are drawn in this report compared with the previous displacement report. The statistical power of being able to detect changes in bird numbers is lower than desirable. This is primarily because there are large inter-annual fluctuations in numbers. In our opinion, the only way in which changes in numbers could be detected with a high degree of certainty would be to find ways of explaining some of this temporal variation, such as through the incorporation of dynamic ocean variables into analysis. Failing this, we caution that an inability to detect changes in numbers post windfarm construction should not be taken to mean that no such changes are occurring.

Glossary

Accuracy - a term which refers to how closely an estimated value agrees with the correct value (a count of 55 birds is accurate but an estimate of 103 is not if in reality 56 birds are present).

Akaike's Information Criterion (AIC) - a statistic that assesses how well a statistical model fits, developed by Professor Akaike (Akaike 1976). Using a rigorous framework of information analysis, it also takes into account that a simpler model, i.e. one with fewer explanatory variables is generally better. In the context of this study it is used to determine which combination of variables best explains bird count data and is calculated from the log-likelihood ratios obtained when undertaking generalized linear modelling, but also weights the statistic by the number of explanatory variables in the model.

Bathymetry – mean water depth.

Degrees of Freedom - the number of independent pieces of information on which a parameter estimate is based and is a measure of the precision of the variance. The degrees of freedom for an estimate equals the number of observations (values) minus the number of additional parameters estimated for that calculation. As one has to estimate more parameters, the degrees of freedom that are available decrease. It can also be thought of as the number of observations (values) which are freely available to vary given the additional parameters estimated.

Explanatory variable - this variable (also called the independent variable) is the variable that is manipulated or selected by the experimenter to determine its relationship to an observed phenomenon (the response or dependent variable). In other words, a study will attempt to find evidence that the values of the explanatory variables determine the values of the response variable (which is what is being measured). The explanatory variable can be changed as required, and its values do not represent a problem requiring explanation in an analysis, but are taken simply as given. In the context of this report, season, site or any of the spatial variables are explanatory variables.

Generalized linear model - a statistical technique that allows one to calculate expected values from a set of observed values. In the context of this report it is used to estimate counts at any given site in any given year from observed data. The technique differs from ordinary regression techniques in that it allows the relationship between response variables and explanatory variables to be non-linear and can accommodate the response probability distribution being non-normally distributed as any member of an exponential family of distributions. Examples of the distributions that can be accommodated include negative binomial, Poisson, binomial and normal.

Log-likelihood ratio - A statistical test relying on a computed test statistic, used in the context of this study to investigate how closely the observed counts in any given month at any given site compare to those predicted by a generalized linear model. It can be conveniently expressed using a simple formula including the Pearson's Chi-squared statistic.

P-scale factor - when undertaking generalized linear modelling using a Poisson distribution (which assumes that the variance and mean are equal), it allows one to estimate the extent to which the variance may differ from the mean and thus the variance to mean ratio of a datasets (in context of this report, the inter-annual variance in count data in any given month at any given site), as the P-scale factor is the square-root of the variance to mean ratio. It is estimated from the ratio of the Pearson Chi-Square statistic to its degrees of freedom.

Parameter estimate - When undertaking statistical modelling, such as generalized linear modelling, the relationship between a response variable and one or more explanatory variables is sought. The parameter estimates are constants that give the extent to which the response varies as a result of changes in the explanatory variables.

Pearson Chi-Square statistic - is a value derived from one of the variety of statistical tests commonly used to evaluate how well observed values compare to predicted values. In the context of this report, it is a measure of how closely the observed counts in any given month at any given site compare to those predicted by a generalized linear model.

Power analysis - an analytical technique used to determine statistical power. There are a number of ways in which it can be calculated, for example by rearranging the equation of a statistical test (see Cohen 1988 for a review of methods). In this study it is calculated by generating random datasets with the same characteristics (i.e. response probability distribution, mean and variance) as real data, specifying a change in numbers (by adjusting the mean and variance), statistically analysing each dataset as if it were real data and then calculating the proportion of times that the statistical tests are significant.

Response probability distribution - the mathematical distribution of the response variable. Essentially when data are presented in a frequency histogram, if they approximate to a symmetrical bell-shaped curve they can often be assumed to be normally distributed. If the data are asymmetrical and positively skewed and the variance of the numbers is greater than the mean then they can often be said to have a negative binomial distribution. A Poisson distribution is a special case of a negative binomial distribution in which the mean and variance are equal.

Response variable - this variable (also called the dependent variable) is the variable that is being measured and is affected by explanatory variables. In other words, a study will attempt to find evidence that the values of the explanatory variables determine the values of the response variable. In the context of this report bird counts are considered to be response variables.

Season effect - the influence a season has on bird numbers**.** It is estimated using the generalized linear modelling procedure and enables expected counts to be calculated for any given season.

Site effect - The influence a site has on bird numbers**.** It is estimated using the generalized linear modelling procedure and enables expected counts to be calculated for any given site.

Spatial-autocorrelation - Spatial autocorrelation is a measure of the extent to which spatial observations are dependent on one another. For many statistical tests there is an assumption of independence. In the context of this report it is taken to mean that if counts of a particular species are high at a particular location, then counts in neighbouring areas are also likely to be high. This has a potentially important bearing on power analysis as it would mean that counts in one area could be partially explained by counts in neighbouring areas.

Statistical Power – or just power, is the probability of detecting a specified change in numbers. One minus the power (or beta) is the probability of falsely concluding that no decline has occurred when in fact a decline has occurred. In general results are expressed as a percentage that refers to the probability of detecting changes.

Statistical significance (alpha) – the probability of committing a ‘Type 1’ error, that is rejecting the null hypothesis (in this case of no changes in numbers) when it is in fact true.

Variance - A measure of the spread of the values in a group of numbers. The larger the variance, the larger the distance of the individual numbers from the group mean.

Variance to mean ratio - the variance divided by the mean. A frequency histogram of two sets of numbers with different means, but the same mean to variance ratio will have the same shape; only the one with the larger mean will be larger in size than the other. When performing statistical tests, to determine differences between two sets of numbers (e.g. bird numbers before and after the construction of a windfarm), statistical significance is affected by three things: (1) the sample size, (2) the amount of difference and (3) the variance to mean ratio.

Acronyms

AIC – Aikake's Information Criterion

BERR - Department for Business, Enterprise and Regulatory Reform (formally known as DTI)

BTO – British Trust for Ornithology

COWRIE – Collaborative Offshore Wind Research Into the Environment

DHI – DHI Water and Environment (formerly Danish Hydraulic Institute)

DTI – Department of Trade and Industry (now known as BERR)

JNCC - Joint Nature Conservation Committee

SNH – Scottish Natural Heritage

Units

Km – Kilometres

M – Metres

H – Hour

1. Introduction

Within the framework of the United Nations Climate Convention, industrial nations agreed in the 1997 Kyoto Protocol to reduce their greenhouse gas emissions by an average of 5% (compared to 1990) by 2012. The UK government is committed to obtaining 10% and 20% of the UK's electricity from renewable sources by 2010 and 2020 respectively. Suitable land locations have become very limited and consequently major plans for offshore windfarms have been announced (Innogy 2003). According to current plans, within about 10 years, windfarms with a combined output of 40,000 megawatts will be installed in European seas, requiring an area of about 13,000 km^2 (Exo *et al.* 2003; Wind Directions 2003). Thus offshore windfarms are likely to become one of Europe's most extensive technical interventions in marine habitats (Merck and von Nordheim 2002; Exo *et al.* 2003).

Although windfarms could be viewed as beneficial to wildlife because they contribute to reducing climate change, they are also of potential detriment as they displace wildlife from favoured areas. The taxonomic group most likely to be affected in this way is birds (Exo *et al.* 2003; Garthe and Hüppop 2004; JNCC 2004; Desholm and Kahlert 2005) as aggregations of large numbers of seabirds may be found in UK offshore waters throughout the year (Skov *et al.* 1995; JNCC 2004). In the UK, all wild birds have a level of protection under the 1981 Wildlife and Countryside Act. Additionally, European inshore coastal and offshore marine waters support globally significant numbers of seabirds (Carter *et al.* 1993; Skov *et al*. 1995) and European Union Member States are obliged to protect populations of these species, under the EU Directive on the Conservation of Wild Birds (79/409/EEC, the Birds Directive) and the Ramsar Convention on Wetlands (Ramsar Convention Bureau 1988). These international agreements, together with the United Nations law of the Seas (United Nations 1982) and the EU Directive on the Assessment of the Effects of Certain Plans and Programmes on the Environment (2001/42/EC, the SEA Directive) require that states accept responsibility for assessing the effects of major offshore development on the environment. Governments are thus legally obliged to monitor the effects of offshore windfarms on birds.

One of the most frequently used method of monitoring birds offshore is by aerial survey. The speed of aircraft guarantees rapid, near-simultaneous coverage of large areas, to provide a snapshot of distribution and density. It is also often cheaper to survey large areas by air than by boat. Aircrafts are also suitable as, for the most part, they enable survey without causing excessive disturbance or attraction and can be used to survey areas inaccessible to boats. In general, aeroplanes provide efficient coverage with a variable degree of error of most species groups over the large areas being developed for wind energy, while boats provide more accurate coverage of seabirds and their behavioural reactions within the smaller impacted area of each offshore windfarm (Camphuysen *et al.* 2004; JNCC 2004). However, seabird numbers are often highly variable and it is often assumed rather than tested, that changes induced by the presence of windfarms could be distinguished from natural fluctuations in numbers.

This report follows from a previous report (Maclean *et al*. 2006), in which power analyses were used to assess whether the current BERR aerial survey scheme can distinguish changes in bird numbers induced by windfarms from background fluctuations. Four taxa were selected for analysis: red-throated diver (*Gavia stellata*), common scoter (*Melanitta nigra*), sandwich tern (*Sterna sandvicensis*) and lesser and great black-backed gull (*Larus fuscus* and *L. marinus*). Aerial surveyors are not usually able to distinguish between these two large gull species. In Maclean *et al*. (2006) a critical (albeit necessary) assumption was made, that data from all sites have approximately the same mean-to-variance ratio and as such data from all sites can be pooled to reveal an average mean-to-variance ratio (the critical factor in determining statistical power). In so doing, there are some issues associated with data being spatially auto-correlated and as such, the estimates of variance may be slightly high and that of power slightly low. In this report, insight into the extent of this problem is gained by analysing continuous runs of data from the small number of locations from where such data are available. In this report we also investigate the effects on power of using a gradient of decline, in which birds are displaced in greater number immediately adjacent to the windfarm. Lastly, we investigate the effects on power of using static environmental data (bathymetry, slope, gradient, aspect, distance to land and shallow water, seabed complexity) instead of a site factor to explain spatial variance.

2. Method

Overview

We selected four taxa for analysis: red-throated diver, common scoter, black-backed gulls and sandwich tern. As the majority of divers are unidentified to species level during aerial surveys, we added a proportion of the unidentified divers to the counts of red-throated diver equivalent to the proportion of positively identified red-throated diver relative to other identified diver species. The vast majority of scoter species were recorded as common scoter, presumably because although this species can be difficult to distinguish from other scoter species from the air, the areas surveyed are known to contain only small numbers of velvet scoter (*Melanitta fusca*). Thus additional unidentified scoters were not added to common scoter counts, although in reality the numbers of these are such that doing so would not have made any appreciable difference. Although not all terns were identified to species level, unidentified terns were not added to the sandwich tern counts, firstly because the number of unidentified terns was also relatively small compared to the number of sandwich tern and secondly because most unidentified terns are likely to refer to either common tern (*Sterna hirundo*), arctic tern (*S. paradisaea*) or roseate tern (*S. dougallii*) as these three species are much harder to tell apart from each other than they are from sandwich tern, which have a diagnostic structure in flight (Blomdahl *et al.* 2003). Since distinctions between lesser and great black-backed gull are rarely made by aerial observers, all observations referring to either one of these species and those referring to identified black-backed gulls were pooled.

For an evidence-based assessment of whether existing aerial survey programmes are suitable to determine whether windfarms affect bird distributions, it was necessary to determine by how much bird numbers and distributions fluctuate, as any change in distribution will have to be identified against this background of fluctuating counts. To perform such analysis, existing aerial survey data were used. We opted to use raw counts rather than data corrected for distance bias using DISTANCE (Buckland *et al.* 2001) to avoid introducing another element of uncertainty into the analyses and thus reducing statistical power. In so doing, we make the assumption that the probability of detecting birds does not differ appreciably in relation to the number of birds present.

Long time-series of data

In the context of this study, statistical power is essentially the probability of being able to detect a specified change in numbers, in this case a change in bird numbers due to the construction of an offshore windfarm. Although there are a number of ways in which it can be calculated (see Innogy 2003 for an example relating to offshore windfarms and Cohen 1988 for a more general discussion), one common way of undertaking power analysis is to generate a series of random datasets with the same characteristics (i.e. statistical distribution, and hence mean and variance) as real data, specify a change in numbers (by adjusting the mean and variance), analysing each dataset as if it were real data and then calculate the proportion of times that the statistical tests are significant (Cohen 1988).

To estimate variability in bird numbers, we selected data from a small number of areas for which long time-series of data exist (see Figure 2.1 and Table 2.1). Bird numbers vary according to season. To help explain some of the variation in bird numbers (and thus improve power) we divided up the data into the following seasons: early-winter (1 Dec to 10 Jan), late-winter (11 Jan to 20 Feb), early-spring (21 Feb to 31 Mar), late-spring (1 April to 31 May), Summer (1 Jun to 15 Aug), early-Autumn (15 Aug to 14 Oct) and late Autumn (15 Oct to 30 Nov). In order to estimate the mean and variance of the real count data in any given season a generalized linear model was employed. To fit the model, log-likelihood ratios (derived from Pearson's Chi-Square statistic), were used. The relationship between expected counts and explanatory variables was assumed to be linear using a logarithmic scale, which makes the assumption that predicted counts for any given season are related to the exponential of the season effects, thus constraining the predicted counts so that they cannot be negative. Count data were fitted with a Poisson model, but the degree of over-dispersion (i.e. the extent to which the count variances might be greater than the mean) was calculated from the ratio of the Pearson Chi-Square statistic to the degrees of freedom and is hereafter referred to as the P-scale factor. Season was considered to be a categorical rather than continuous variable. The mean count for every season was calculated using the estimates for the season effects and the variance from the P-scale factor and mean as follows:

$$Variance = \frac{kq}{p^2} \qquad \text{Equation 1}$$

where :

$$k = \frac{\mu p}{q},\ q = 1 - p \text{ and } p = \frac{1}{D^2} \qquad \text{Equation 2}$$

where *D* is the P-scale factor and *μ* is the mean, given by exp (season effect).

Figure 2.1. Location of the three areas from where long time-series of data exist.

Table 2.1. Season and year in which areas shown in Figure 2.1. were counted (dark grey).

Year	Location	Late Winter	Early Spring	Late Spring	Summer	Early Autumn	Late Autumn	Early Winter[1]
1988	Thames							■
	NW England	■	■	■			■	
	Wales	■		■			■	
1989	Thames			■	■	■	■	
	NW England		■	■	■	■		
	Wales				■	■		
1991	Thames							
	NW England							
	Wales		■					
2002	Thames					■		
	NW England					■		■
	Wales							
2003	Thames						■	■
	NW England							
	Wales							
2004	Thames	■					■	■
	NW England	■	■				■	
	Wales				■	■	■	
2005	Thames	■	■				■	■
	NW England	■		■	■		■	■
	Wales	■			■		■	■
2006	Thames	■	■					
	NW England	■						
	Wales	■	■					

[1] Counts conducted between 1st and 10th of January have been assigned to the previous year as this season runs from 1st December to 10th January.

In contrast to the previous report (Maclean *et al.* 2006), we performed separate analyses for each site, thus not making the assumption that the variance to mean ratio is constant across all sites. To simulate real data and thus perform power analysis we randomly selected one site and calculated the season effect and variance to mean ratio of data for this site. We then generated random counts for each season and year. To represent data in years prior to construction, counts were generated using the season effect calculated from real data and by assuming a negative binomial distribution. To represent data in post-construction years, the mean and variance were adjusted by specified declines (50%, 25% and 10%). The process was repeated 1,000 times (each time randomly selecting a site) and statistical power calculated by undertaking generalized linear modelling on each of the randomly generated datasets and then calculating the proportion of times that specified declines could be detected as significantly different from zero, using a range of significance levels (0.05, 0.1, 0.2). Again, a logarithmic link-function and Poisson distribution with P-scaling was specified. Modelling using a Poisson distribution with P-scaling, accounts for the extent to which the variance may not be equal to the mean (Zar 1988). We specify two spatial scales: 2 km x 2km and 5 km x 5km. All computations were carried-out using SAS (SAS Institute, Cary, NC, USA). For a flow chart of methods, see Figure 2.2.

Gradients of decline

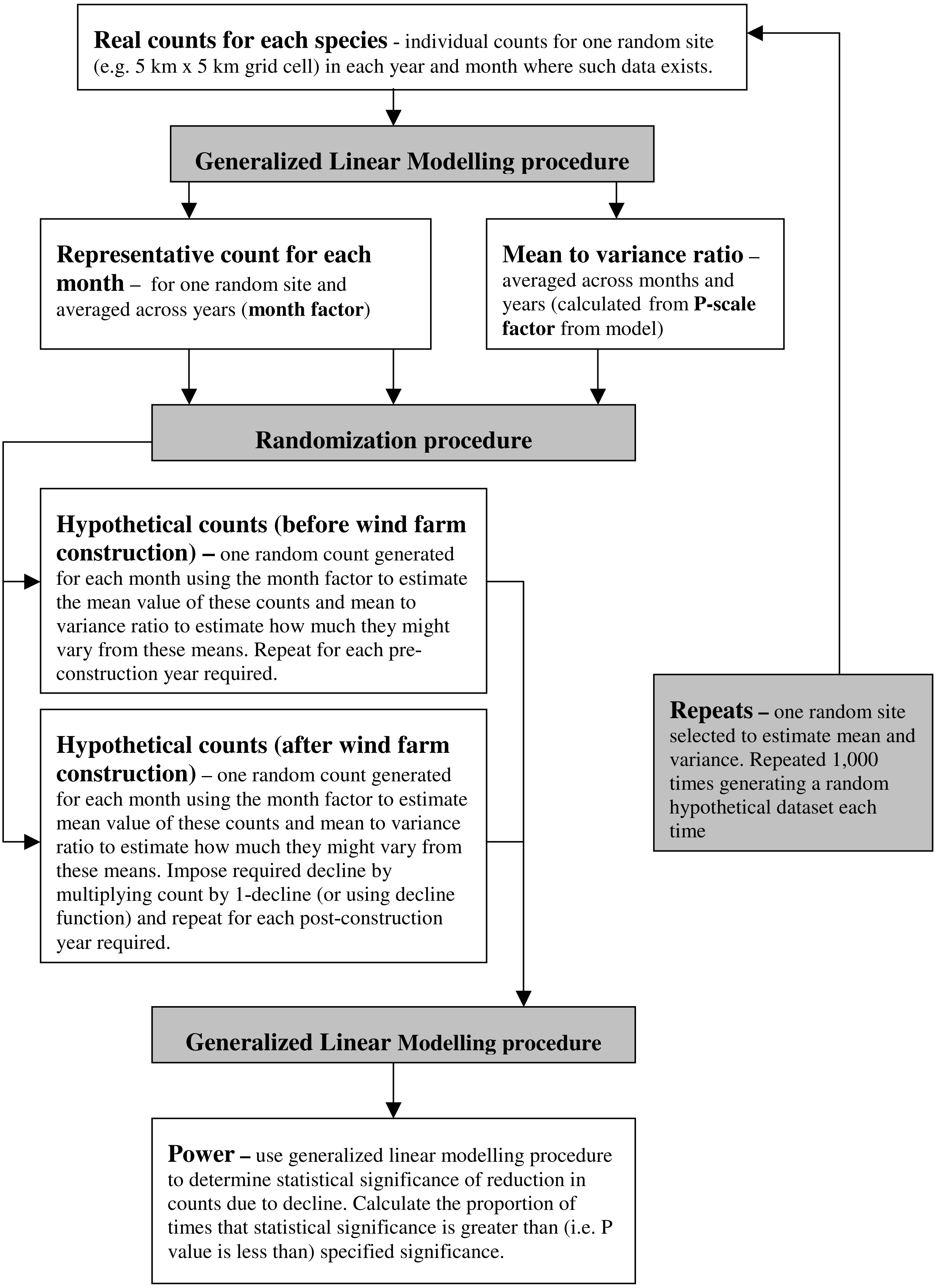
Thus far, and in the previous report (Maclean *et al.* 2006) we assume a uniform decline throughout a specified grid cell representing each site. In reality declines are more likely to be non-uniform, declining by most close to the windfarm and declining by less, or even increasing (because of displaced birds) at distances further away. For the purposes of power analysis, there are two ways in which this gradient of decline could be modelled. Firstly, by adopting a finer grid cell resolution, assuming uniform decline in each of these smaller grids and then looking for the greater declines within the small grids located towards the location of the windfarm (as represented in Figure 2.3). The issue then becomes one of scale and equivalency in declines, an issue which was examined in detail in the previous report (Maclean *et al.* 2006) and is consequently not examined here. The other method is to mimic the gradient during the repeat procedure (see Figure 2.2), when generating the random datasets. Thus during some iterations, much larger declines are imposed (thus representing birds occurring near to the windfarm), whereas in other iterations, smaller declines are imposed (representing birds more distant from the windfarm), such that on average, the declines still equate to pre-specified declines (in this case, 50%, 25% and 10% overall).

Mathematically this can be achieved by randomly drawing numbers from a uniform distribution with the extremities zero and one (i.e. randomly selecting any number between zero and one, such that all are equally likely), applying the following mathematical transform to calculate the proportional decline:

$$1 - decline = \frac{1}{1 + \exp(b \times rand - a)} \qquad \text{Equation 3}$$

and then adjusting counts after windfarm construction by the specified decline. In the above equation *decline* is a value between 0 and 1, such that all counts after windfarm construction are multiplied by 1 - *decline* (and is thus on average equivalent to the overall required decline), *rand* is the random number between 0 and 1 and *a* and *b* are parameter values which must be chosen to represent the overall decline and extent to which decline varies with distance (*a* has more affect on the latter and *b* on the former, but if one is altered, the other needs to be adjusted too). The above equation is analogous to a decline with distance if *rand* is substituted by a variable *distance*. Conceptually, *rand* is similar to the distance from a windfarm, except that it is scaled such that its maximum is one and minimum is zero. Mathematically, this is helpful, as the average decline then becomes one minus the area under the curve represented by equation 3 (see Figure 2.4).

We opted to model six scenarios: overall declines representing 50%, 25% and 10% and for each, a gradient whereby the extent of decline changes rapidly with distance from the windfarm and a gradient whereby declines change less rapidly with distance. The shape of these functions and the corresponding *a* and *b* parameter values in Equation 3 are shown in Figure 2.4.



Real counts for each species - individual counts for one random site (e.g. 5 km x 5 km grid cell) in each year and month where such data exists.

Generalized Linear Modelling procedure

Representative count for each month – for one random site and averaged across years (**month factor**)

Mean to variance ratio – averaged across months and years (calculated from **P-scale factor** from model)

Randomization procedure

Hypothetical counts (before wind farm construction) – one random count generated for each month using the month factor to estimate the mean value of these counts and mean to variance ratio to estimate how much they might vary from these means. Repeat for each pre-construction year required.

Hypothetical counts (after wind farm construction) – one random count generated for each month using the month factor to estimate mean value of these counts and mean to variance ratio to estimate how much they might vary from these means. Impose required decline by multiplying count by 1-decline (or using decline function) and repeat for each post-construction year required.

Repeats – one random site selected to estimate mean and variance. Repeated 1,000 times generating a random hypothetical dataset each time

Generalized Linear Modelling procedure

Power – use generalized linear modelling procedure to determine statistical significance of reduction in counts due to decline. Calculate the proportion of times that statistical significance is greater than (i.e. P value is less than) specified significance.

Figure 2.2. Flow chart of method used to determine statistical power in instances where either a site factor was used or oceanographic data were used to determine typical counts at any given location.

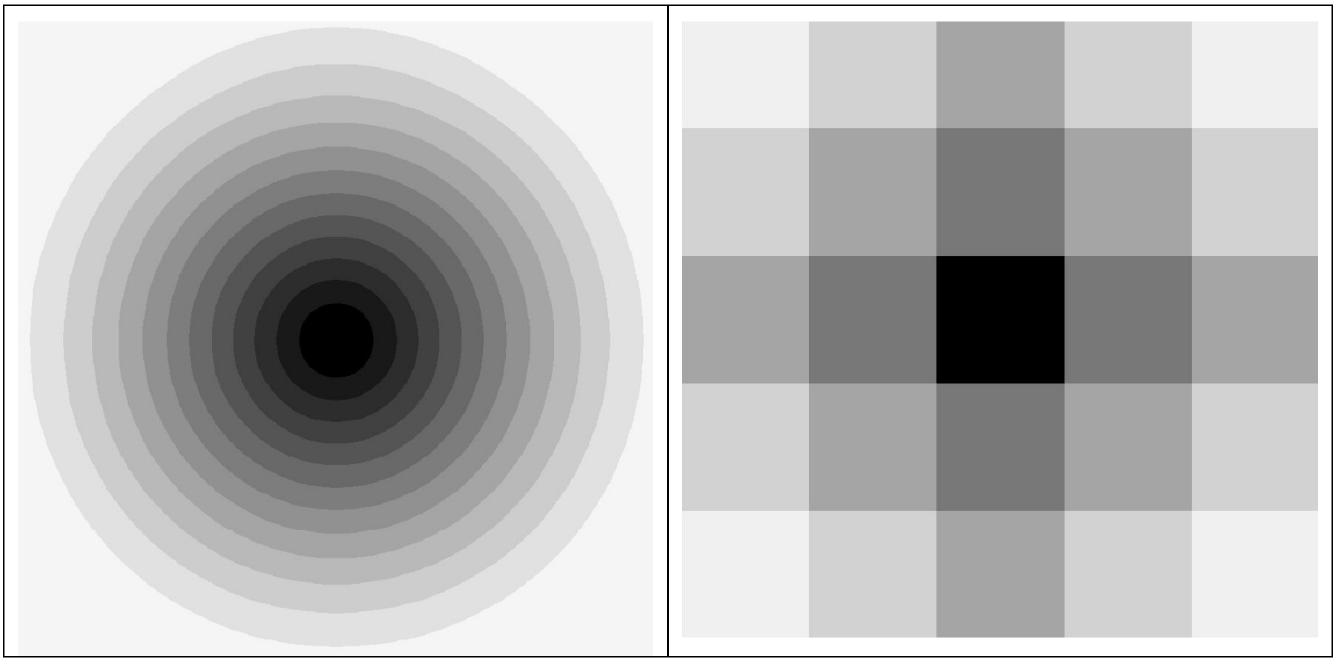


Figure 2.3. 5 km × 5 km area in which the highest declines (darkest tone of shading) occur at the centre of the grid in which it is assumed that a windfarm is located (left). Declines of this nature could be modelled by subdividing the grid into twenty-five 1km × 1 km grids, assuming uniform decline in each of these smaller grids and then looking for the greater declines within the small grids located towards the centre.

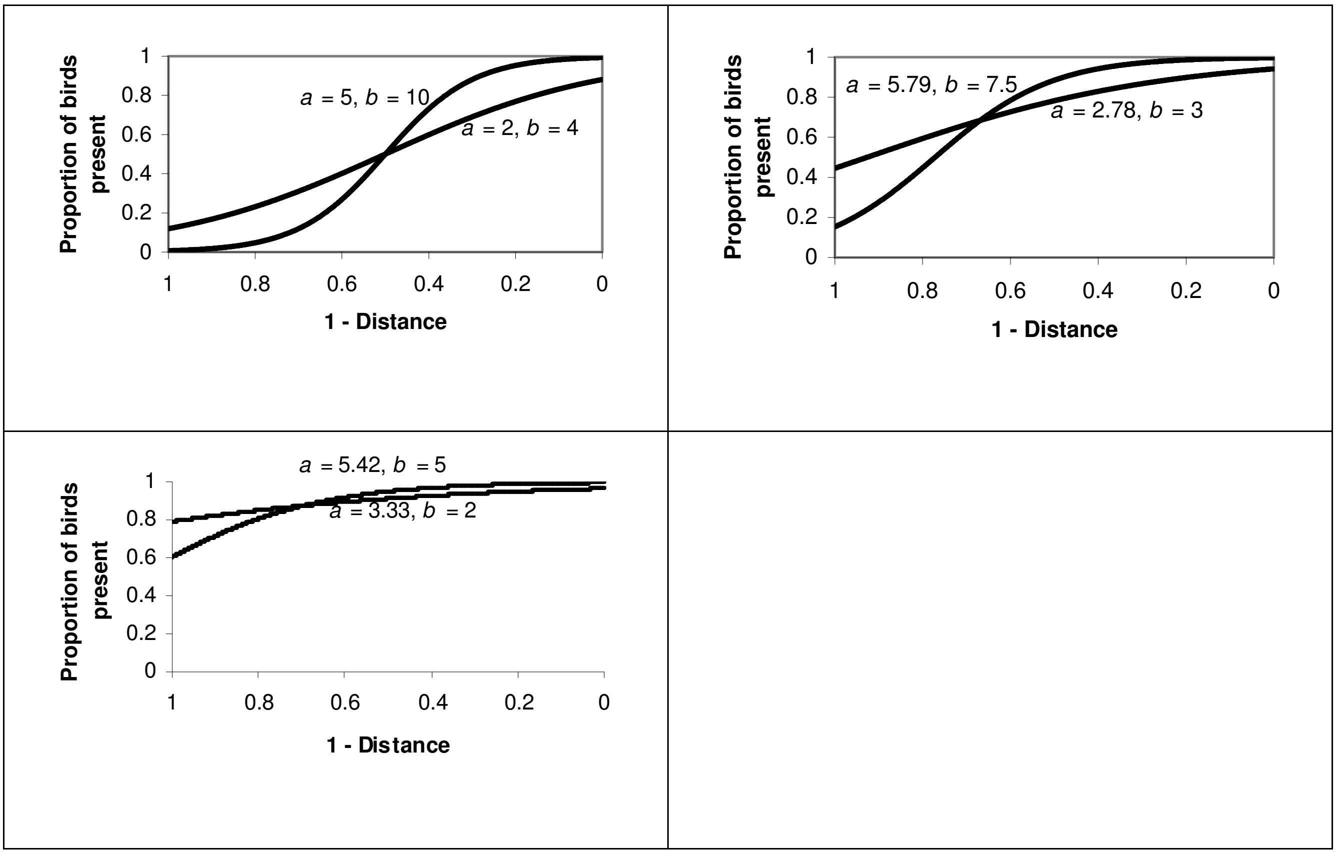


Figure 2.4. Two different scenarios, one in which the level of decline changes rapidly with distance from the windfarm (a > 5) and one whereby declines change less rapidly with distance (a < 5) for a 50% decline (top-left), a 25% decline (top-right) and a 10% decline (bottom-left). The corresponding *a* and *b* parameter values (see Equation 3) are also shown for each curve. The proportion of bird present is equivalent to 1 – the proportional decline.

Spatial oceanographic variables

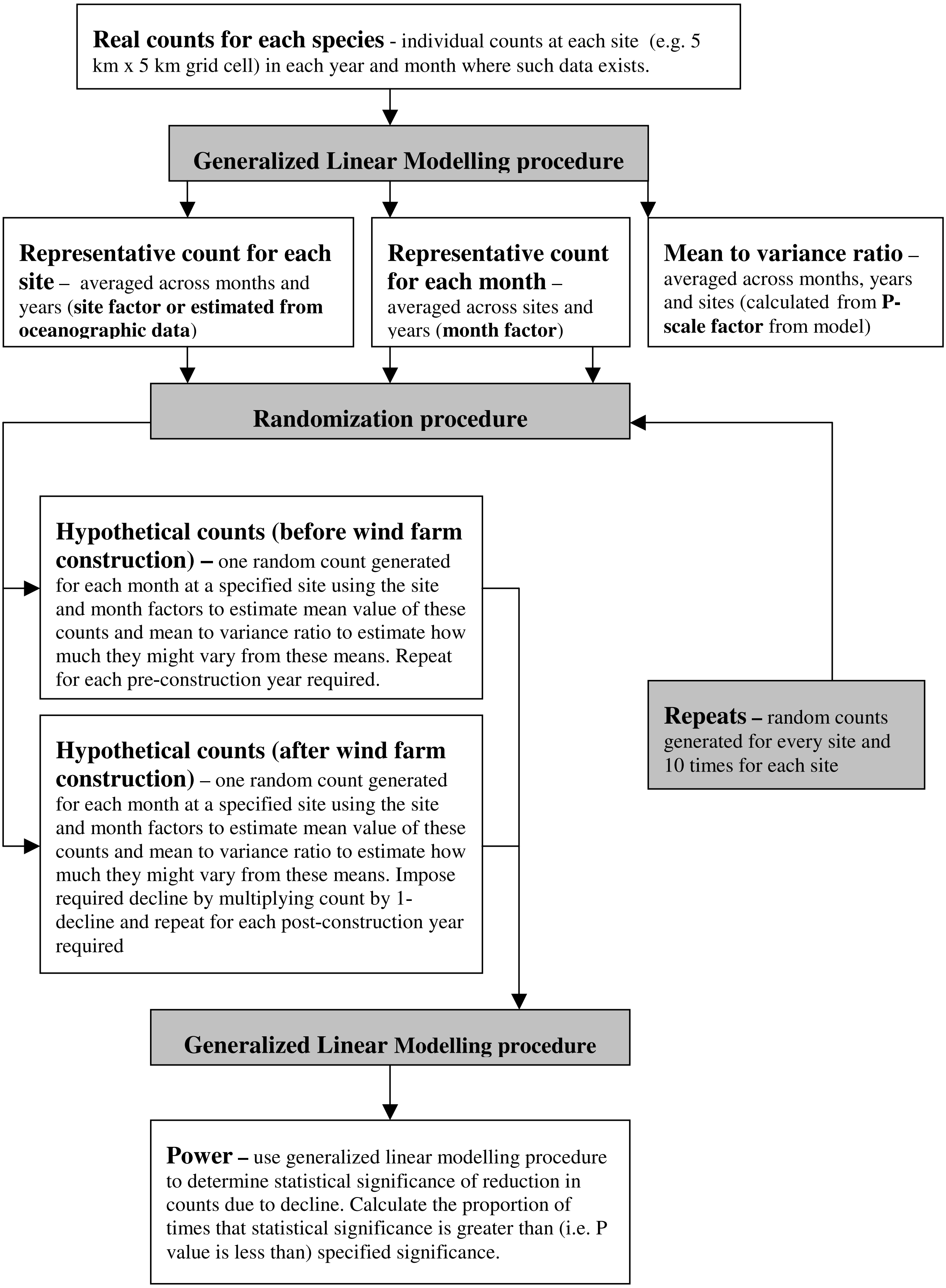
We also investigate whether several spatial oceanographic variables (bathymetry, distance to land, distance to shallow water less than 10 m in depth, northward slope gradient, eastward slope gradient and seabed complexity) help to explain some of the variation in count data. Since such data do not vary through time at a specific location they cannot be used to explain variation in counts at a specific location. Their use is restricted to determining power in instances where variance-to-mean ratios are assumed to be constant across all sites as they were in Maclean *et al* (2006). In such instances they could be used instead of site effects, i.e. - the influence a site has on bird numbers. In general, although one would expect individual site effects to better explain variance, it is conceivable that there may be a moderate improvement in power due to the lower number of degrees of freedom (i.e. independent pieces of information on which parameter estimates are based) when using continuous rather than categorical variables.

To investigate the effects of including oceanographic data, we compared the results presented in the previous report (Maclean *et al.* 2006), with those obtained by using oceanographic data instead of a site effect. These were obtained from DHI's depth model covering the sites at a resolution of 10 km x 10 km and matched spatially to count data also at a spatial resolution of 10 km x 10 km using ArcView (ESRI, Redlands, CA, USA). Slope was estimated from the depth data by determining the slope of each depth grid cell based on the cell resolution and the values of the immediate neighbouring cells to the top, bottom, left and right of the cell in question using the following formula (Monmonier 1982):

$$Tan\_slope = 2 \times \sqrt{\left(\frac{right - left}{2 \times res}\right) + \left(\frac{top - bottom}{2 \times res}\right)}$$

where *Tan_slope* is the tangent of the angle that has the maximum downhill slope; *left*, *right*, *top* and *bottom* are the attributes of the neighbouring cells and *res* is the cell resolution.

The northward slope aspect was calculated as the sine of the direction of the maximum slope values, while the eastward slope aspect was calculated as the cosine of the direction of the maximum slope values. The complexity of the seabed was calculated using a 5x5 kernel: F = (n-1)/(c-1) Where n = number of different classes present in the kernel, c = number of cells. To determine which combination of variables were most appropriate to use for each species, models with all potential combinations of variables were tested and that yielding the lowest AIC selected (Akaike 1976). Using the minimum AIC, red-throated diver counts were assumed to be best explained by bathymetry, seabed complexity, distance from land and northern slope aspect. For common scoter counts were best explained by bathymetry, seabed complexity, eastward slope aspect and northward slope aspect. For black-backed gulls the counts were best explained by bathymetry, distance from land, northward slope aspect and distance from shallow water. For sandwich tern counts were best explained by seabed complexity, northward slope aspect and distance from shallow water.



Real counts for each species - individual counts at each site (e.g. 5 km x 5 km grid cell) in each year and month where such data exists.

Generalized Linear Modelling procedure

Representative count for each site – averaged across months and years (**site factor or estimated from oceanographic data**)

Representative count for each month – averaged across sites and years (**month factor**)

Mean to variance ratio – averaged across months, years and sites (calculated from **P-scale factor** from model)

Randomization procedure

Hypothetical counts (before wind farm construction) – one random count generated for each month at a specified site using the site and month factors to estimate mean value of these counts and mean to variance ratio to estimate how much they might vary from these means. Repeat for each pre-construction year required.

Hypothetical counts (after wind farm construction) – one random count generated for each month at a specified site using the site and month factors to estimate mean value of these counts and mean to variance ratio to estimate how much they might vary from these means. Impose required decline by multiplying count by 1-decline and repeat for each post-construction year required

Repeats – random counts generated for every site and 10 times for each site

Generalized Linear Modelling procedure

Power – use generalized linear modelling procedure to determine statistical significance of reduction in counts due to decline. Calculate the proportion of times that statistical significance is greater than (i.e. P value is less than) specified significance.

Figure 2.5. Flow chart of method used to determine statistical power in instances where either a site factor was used or oceanographic data were used to determine typical counts at any given location.

3. Results

Count data

Species varied between seasons and by species, but overall relatively low numbers were recorded within each of the 2 km x 2 km or 5 x 5 km grid cells. The mean number of birds recorded per grid cell for each of the species together with the mean of the inter-annual standard deviation of birds in each grid cell for each species, is listed in Table 3.1.

Table 3.1 Mean (mean of mean within each grid cell) and standard deviation (mean of standard deviation within each grid cell) number of each species in each of the seasons used in analyses.

Species	Period	Mean count		Mean inter-annual variability (standard deviation)	
		2 km x 2 km	5 km x 5 km	2 km x 2 km	5 km x 5 km
Red-throated diver	Autumn	0.00	0.00	0.00	0.00
	Winter 1	0.07	0.21	0.13	0.39
	Winter 2	0.54	1.74	0.69	2.06
	Winter 3	1.14	3.68	1.92	5.13
	Winter 4	0.98	3.16	1.58	4.38
	Spring	0.00	0.00	0.00	0.00
	Summer	0.00	0.00	0.00	0.00
Common scoter	Autumn	0.19	0.60	0.50	1.74
	Winter 1	1.55	4.84	3.97	13.12
	Winter 2	1.50	4.88	2.81	8.78
	Winter 3	5.04	15.46	11.39	33.72
	Winter 4	2.96	9.39	6.42	20.99
	Spring	0.02	0.04	0.03	0.09
	Summer	0.14	0.34	0.47	1.16
Black-backed gulls	Autumn	0.03	0.10	0.06	0.20
	Winter 1	0.08	0.26	0.20	0.52
	Winter 2	0.32	0.93	0.53	1.48
	Winter 3	0.62	1.83	1.24	3.42
	Winter 4	0.47	1.43	0.98	2.90
	Spring	0.01	0.04	0.04	0.09
	Summer	0.05	0.15	0.16	0.39
Sandwich tern	Autumn	0.01	0.03	0.02	0.05
	Winter 1	0.00	0.00	0.00	0.00
	Winter 2	0.00	0.00	0.00	0.00
	Winter 3	0.00	0.00	0.00	0.00
	Winter 4	0.00	0.00	0.00	0.00

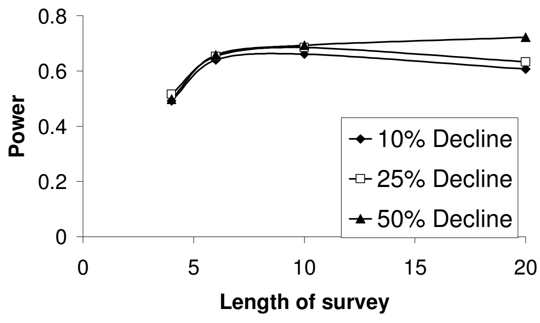
	Spring	0.06	0.23	0.13	0.39
	Summer	0.09	0.33	0.22	0.57

Long time-series of data

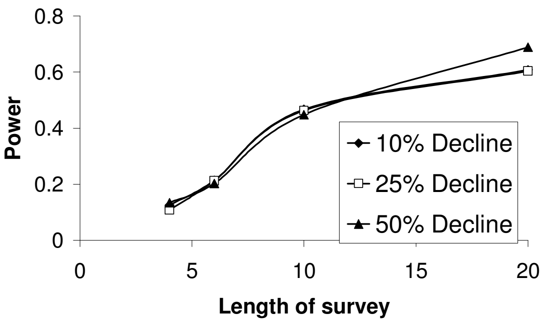
Across all species there is a relatively low power of detecting change irrespective of the length of time over which surveys are conducted or the spatial scale used for analysis. The maximum power attained for any species was 0.793 in the case of black-backed gulls surveyed for 10-years prior to construction and 10-years after construction and using a spatial scale of 5 km × 5 km (Figure 3.1.2).

In almost all instances, there is an increase in statistical power with increased survey duration. For red-throated diver (both scales), common scoter (5 km × 5 km) and black-backed gulls (5 km × 5 km) the greatest proportional improvement in power is achieved by increasing the survey duration from 2 years pre- and post-construction (4-years) to 3-years pre- and post-construction (6-years). In all other instances, the greatest proportional improvement in power is achieved by increasing the survey duration from 3 years pre- and post-construction (6-years) to 5-years pre- and post-construction (10-years) (see parts of lines with steepest slope in Figures 3.1.1 and 3.1.2).

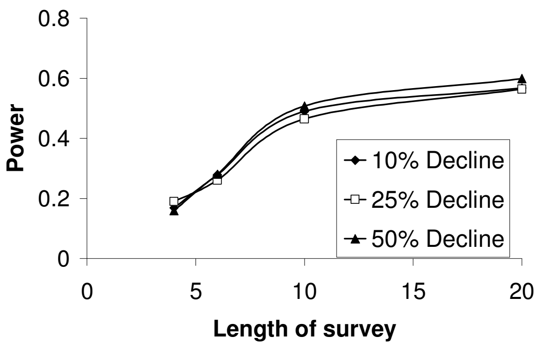
For all species, a slightly higher statistical power is attained using a spatial-scale of 5 km by 5 km rather than 2 km by 2 km. Results are broadly similar to those presented in the last report (Maclean *et al.* 2006) in which it was assumed that data from all sites have approximately the same mean-to-variance ratio, thus suggesting that spatial-autocorrelation does not significantly confound the results of the previous report (see also Figures 3.1.1 and 3.1.2 in this report).



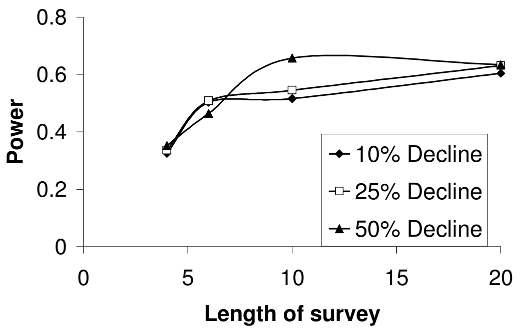
Red-throated diver



Common scoter

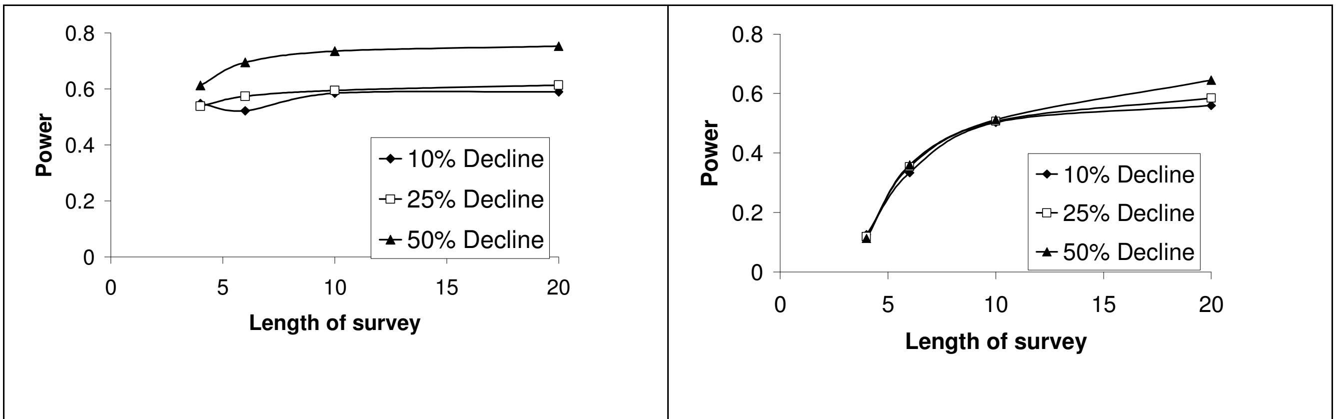


Black-backed gulls



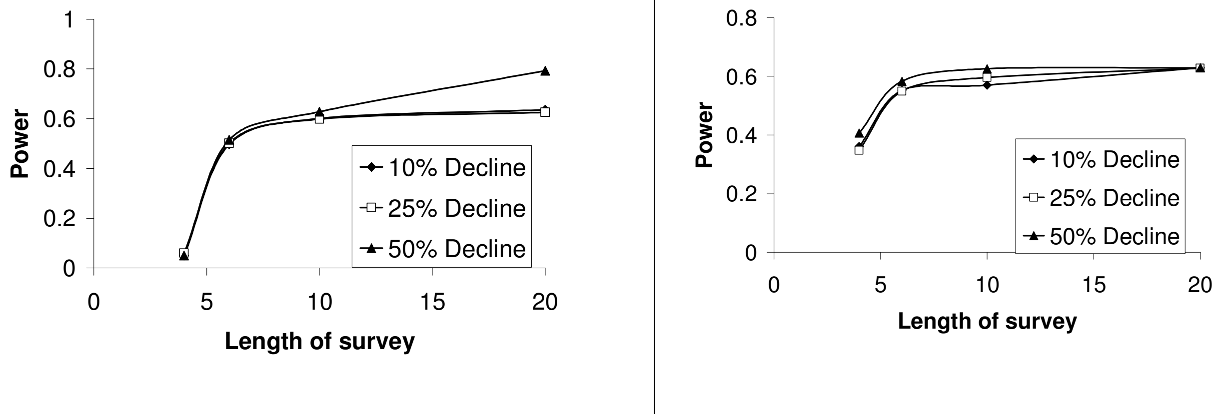
Sandwich tern

Figure 3.1.1. Statistical power as a function of survey duration for each of the three decline scenarios (10%, 25% and 50%), for red-throated diver (top-left), common scoter (top-right), black-backed gulls (bottom-left) and sandwich tern (bottom-right). Spatial-scale of analysis is 2 km × 2 km and P = 0.2.



Red-throated diver

Common scoter



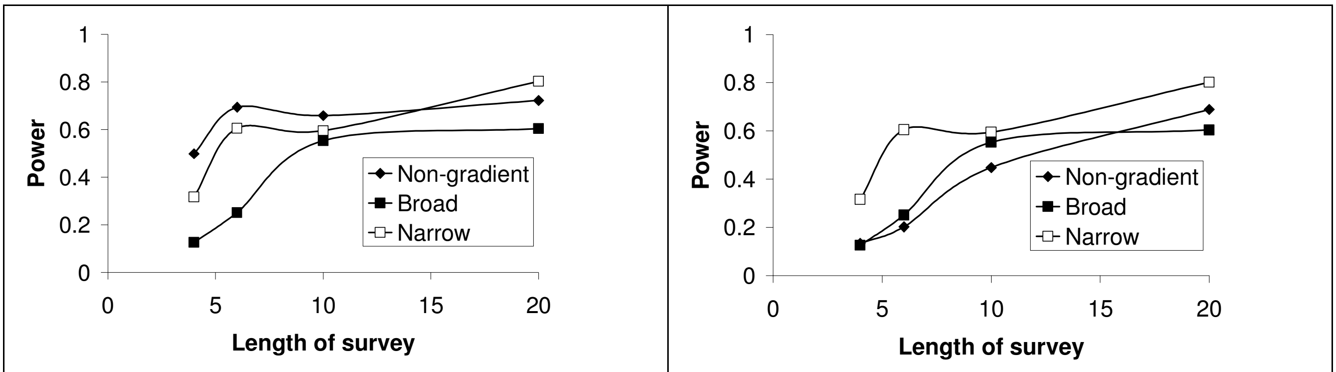
Black-backed gulls

Sandwich tern

Figure 3.1.2. Statistical power as a function of survey duration for each of the three decline scenarios (10%, 25% and 50%), for red-throated diver (top-left), common scoter (top-right), black-backed gulls (bottom-left) and sandwich tern (bottom-right). Spatial-scale of analysis is 5 km × 5 km and P = 0.2.

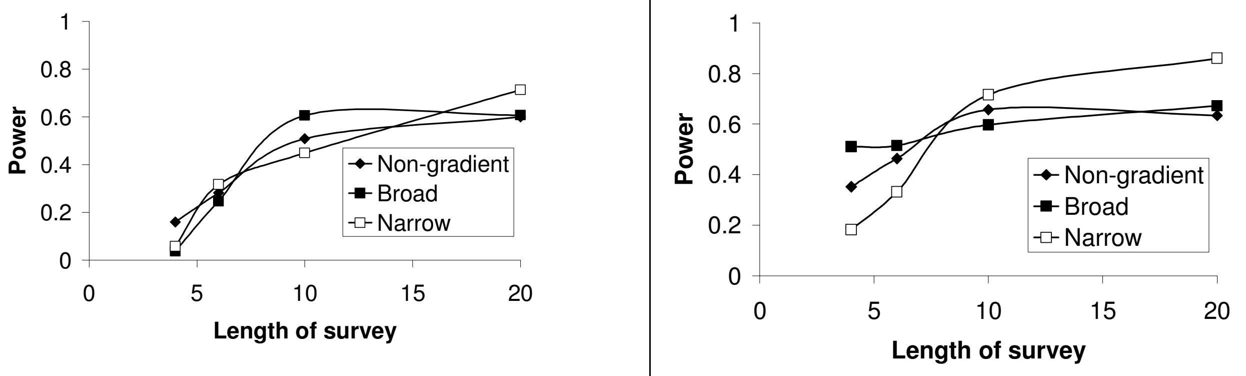
Gradients of decline

In general, it is difficult to determine whether assuming a gradient of decline such that declines are highest near a windfarm has any discernible influence on the power of being able to detect changes. There is some evidence of improved power if a gradient is assumed and the survey is carried out for a long period of time and a fairly large reduction in power if survey durations are short (Figures 3.2.1 and 3.2.2). Overall, power appears to be slightly lower if a gradient is assumed, with these effects is more pronounced if a "narrow" (i.e. extent of decline changes rapidly with distance from windfarm) rather than "broad" (i.e. extent of decline changes gradually with distance from windfarm) gradient is assumed (Figures 3.2.1 and 3.2.2). The opposite is true for common scoter however, where some improvement in power was observed in instances where a gradient of decline is imposed. Spatial-scale appears to have little bearing on the extent to which power is affected by the gradient of decline. Overall there is quite a moderate degree of random variation in power and it is thus difficult to discern real patterns from spurious ones (Appendix 2).



Red-throated diver

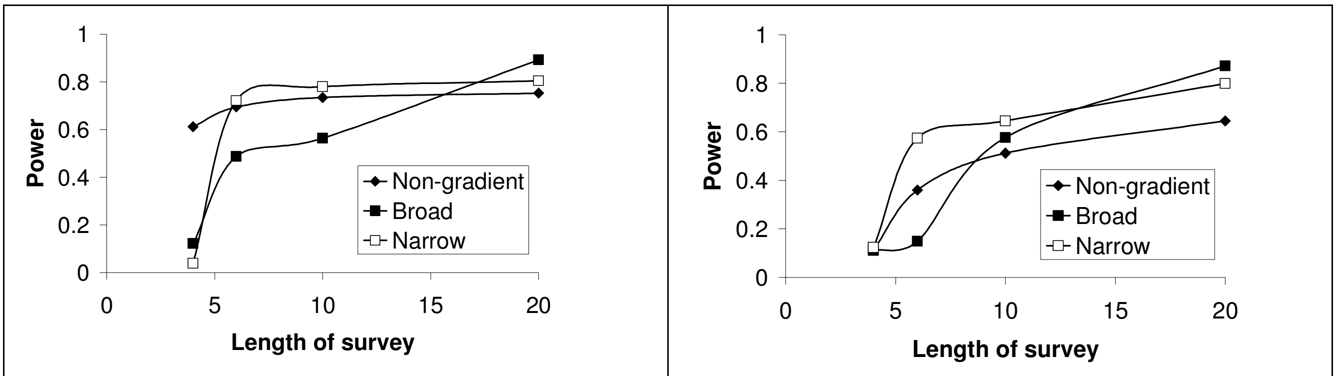
Common scoter



Black-backed gulls

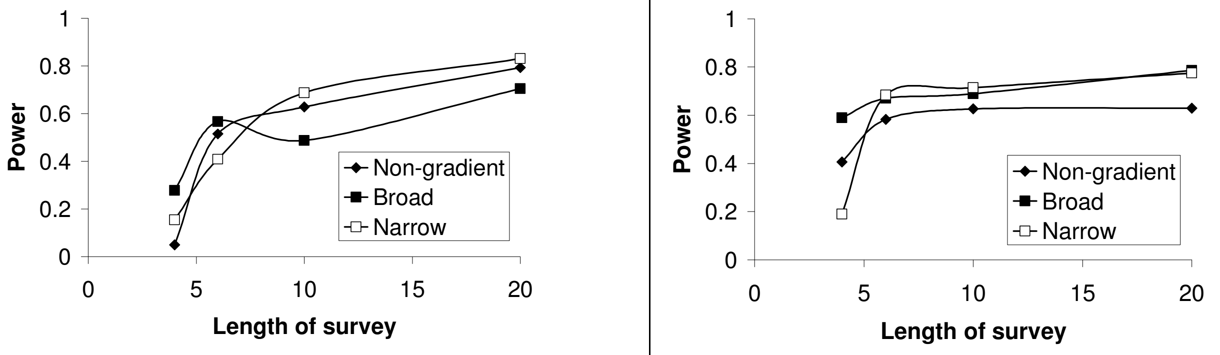
Sandwich tern

Figure 3.2.1. Statistical power as a function of survey duration assuming either a gradient of decline whereby bird declines are greatest close to a windfarm and declines are gradual (broad), a gradient of decline whereby declines are fairly rapid (narrow) and where declines are constant throughout the grid cell used in analysis (non-gradient), for red-throated diver (top-left), common scoter (top-right), black-backed gulls (bottom-left) and sandwich tern (bottom-right). Only 50% declines are shown, spatial-scale of analysis is 2 km × 2 km and P = 0.2.



Red-throated diver (50% decline, 2 km × 2 km, P = 0.02)

Common scoter (50% decline, 2 km × 2 km, P = 0.02)



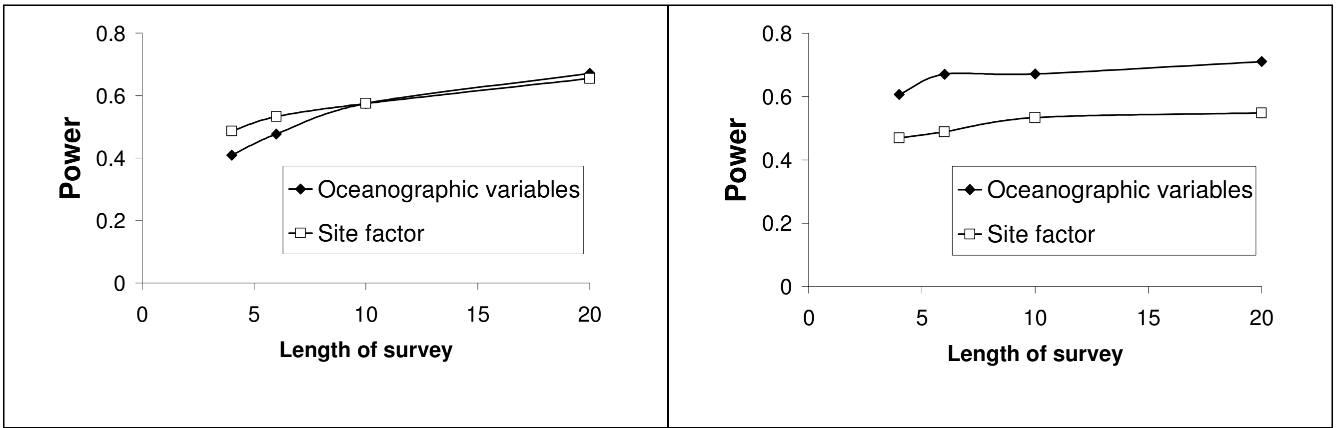
Black-backed Gulls (50% decline, 2 km × 2 km, P = 0.02)

Sandwich Tern (50% decline, 2 km × 2 km, P = 0.02)

Figure 3.2.2. Statistical power as a function of survey duration assuming either a gradient of decline whereby bird declines are greatest close to a windfarm and declines are gradual (broad), a gradient of decline whereby declines are fairly rapid (narrow) and where declines are constant throughout the grid cell used in analysis (non-gradient), for red-throated diver (top-left), common scoter (top-right), black-backed gulls (bottom-left) and sandwich tern (bottom-right). Only 50% declines are shown, spatial-scale of analysis is 5 km × 5 km and P = 0.2.

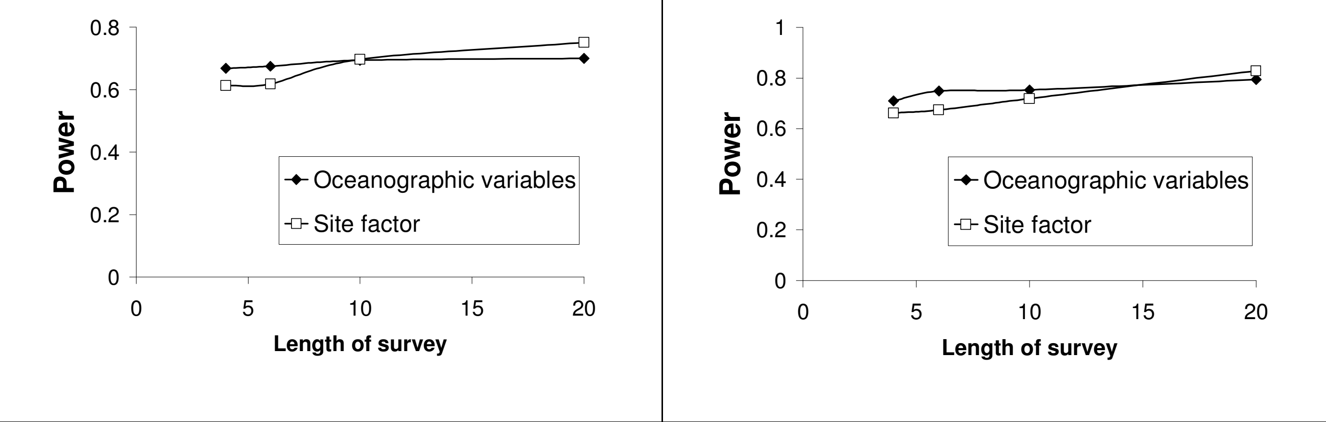
Spatial oceanographic variables

Using spatial oceanographic variables as opposed to a site factor to account for spatial variation does not have the effect of significantly increasing the power of detecting declines in bird numbers (Figures 3.3.1 and 3.3.2), although in some instances it can result in moderate improvements. This is most evident for common scoter, where 10-15% improvements in power resulted. Although this effect is fairly non-uniform in-so-far as different scenarios result in different differences in power, there is no overall pattern discernible (see Appendix 3) and the variations in difference are probably due to the random nature of performing power analysis using only ten iterations (although averaged across all sites, resulting in an average derived from several thousand individual values). As with the previous report (Maclean *et al.* 2006), it was not possible to perform a greater number of iterations within the time-frame of this study.



Red-throated diver

Common scoter



Black-backed gulls

Sandwich tern

Figure 3.3.1. Statistical power as a function of survey duration in instances where a site factor was used to account for spatial variation (see Maclean *et al.* 2006) and where spatial oceanographic variables have been used to account for spatial variation, for red-throated diver (top-left), common scoter (top-right), black-backed gulls (bottom-left) and sandwich tern (bottom-right). Only 50% declines are shown, spatial-scale of analysis is 10 km × 10 km and P = 0.2.

4. Discussion

Long time-series of data

Selecting the few sites for which there are continuous data and performing power analysis exclusively on these sites does not, in most cases improve the power of detecting changes in bird numbers. For example, using a spatial-scale of 5 km x 5 km and assuming four years of monitoring (2-years pre and 2-years post-construction), the power of detecting a 50% decline in common scoter (assuming a statistical significance of 0.2) for common scoter is 0.113 and compared to 0.448 obtained using the method outlined in Maclean *et al.* (2006). For black-backed gulls, the corresponding results are 0.050 and 0.569, and for sandwich tern 0.342 and 0.557, suggesting a substantial reduction in the ability to detect changes in bird numbers. However, increasing the survey duration from 4 to 6 years increases the power of detecting change to slightly more than 50%, making the results comparable to those obtained using the previous method. Nevertheless, for red-throated diver there were moderate improvements in power even when only short survey durations are simulated. For example, using a spatial-scale of 5 km x 5km and assuming four years of monitoring (2-years pre and 2-years post-construction), the power of detecting a 50% decline for red-throated diver (assuming a statistical significance of 0.2) is 0.613 using the method adopted in this report, but 0.453 using the method in the previous report (Maclean *et al.* 2006).

For all species, there is an increase in statistical power with increased survey duration. Although the extent to which power increases with survey duration is species and scale-specific, on average, the best improvements are obtained by increasing the survey duration from 4 years to 6 years, and at least 6-years of survey are needed for all species except red-throated diver if one is to have even a 20% chance of detecting large declines in numbers. For all species, there is generally a slightly higher chance of detecting changes in bird numbers if larger spatial-scales are used, although the results are less pronounced than in Maclean *et al.* (2006). Nevertheless, the same conclusions can be drawn regarding spatial-scale of analysis as in the previous report: data should be analysed at the same spatial-scale at which one expects broadly consistent declines to occur as this maximises the probability of detecting them.

All in all, the results obtained using the method presented in this report are broadly comparable to those presented in the previous report, thus suggesting that issues associated with spatial-autocorrelation do not confound the results presented in the previous report and that across all species there is a relatively low power of detecting change irrespective of the length of time over which surveys are conducted or the spatial scale used for analysis. Indeed, the maximum power attained for any species was 0.793 in the case of black-backed gulls surveyed for 10-years prior to construction and 10-years after construction and using a spatial scale 5 km × 5 km.

Gradients of decline

Using the method adopted, in which gradients of decline are mimicked during the randomisation procedure, assuming a gradient of decline rather than constant decline throughout an area makes little difference. Although moderate improvements in power might be attained in instances where the survey duration approaches 20-years, in general there is a slightly lower probability of detecting changes in bird numbers if a gradient rather than a constant decline is assumed. This is as one would expect given that the effect of assuming a gradient of decline is to increase the variability in post-construction count data.

A more sensible approach to account for gradients of decline, both intuitively and practically, is to examine data using higher spatial resolutions. This issue was discussed in considerable detail in the previous report (Maclean *et al.* 2006). In essence, analysing data at the same resolution over which one expects approximately uniform declines to occur maximises the power of detecting changes in bird numbers. Since, by definition, a gradient of decline would mean that declines are not uniform within any given area, the best option would be to analyse data at as fine a resolution as possible. In practice, the resolution of data analysis is thus restricted by the resolution at which it is collected. Although aerial surveyors record the approximate distance birds are away from the aircraft by assigning birds to a distance band, and although cross-referencing the time of observation with the onboard GPS enables the precise distance along a transect to be determined (Camphuysen *et al.* 2003), in practice declining detectability with distance from the plane is such that the finest resolution that can be adopted is 2 km × 2 km, because if a finer resolution is adopted, some counts will represent birds detected at different distances from the surveyors and thus may have a different probability of detection resulting in incomparable numbers (Camphuysen *et al*. 2003). Since a gradient of decline is more realistic than assuming uniform decline over a larger area, we recommend that data are analysed at this resolution.

Spatial oceanographic data

Using spatial oceanographic variables as opposed to a site factor to account for spatial variation in some instances resulted in some improvements in statistical power, particularly for common scoter, where a clear improvement was observed. This is unexpected given that one would expect a site-factor, calculated separately for each site, to provide greater information on variability in numbers at that site. However, in the context of this report the statistical significance of declines will depend on three factors: the degree of difference between pre- and post-construction counts, the variability in counts and the amount of independent pieces of information needed to estimate parameter values (see Akaike 1976 for a detailed explanation of the trade-offs between the complexity of information and the extent to which information explains modelled results). The results of our analysis thus suggest that the benefit of having tailored site factors which better explain count variance is in some instances outweighed by the benefit of having a continuous rather than class (i.e. categorical) variable and thus using a lower number of independent pieces of information to make predictions. Since such circumstances are only likely to occur when continuous variables are highly predictive (Zar 1998), our results suggest that spatial oceanographic variables explain a high proportion of the spatial variation in bird numbers.

Nevertheless, even using oceanographic data, only moderate improvements in power were achieved and primarily for common scoter. In no instance, did power exceed 0.8, even if surveys were assumed to have been carried-out for 10 years prior to construction and 10-years after construction. Thus in general, whilst the results of this exercise suggest that incorporation of static spatial oceanographic variables into modelling processes can help to explain a lot of the spatial variation in numbers, it does not increase power to adequate levels and cannot, by definition, be used to account for temporal variation in numbers, which is the primary determinant of the statistical power of being able to detect changes.

The results suggest that red-throated divers prefer shallow water with a sloped and complex seabed, generally situated further offshore. This may be related to this species’ preference for the boundary zone between outer estuaries and open water, which provide rich feeding grounds for this species (Skov and Prins 2001). Common scoter prefer shallow water with a sloped, but uncomplex seabed. This is likely to be related to food availability as such areas are favoured by their bivalve prey (Kaiser *et al.* 2006). The relationship with shallow water may also be influenced by their inability to dive to he bottom in deep water, as their prey are bottom-dwelling. Black-backed gulls prefer deeper water situated further offshore, but generally close to shallow water and where the seabed is not sloped. This is broadly consistent with findings by Garthe (1997), which highlights the trade-off between better feeding conditions often found in deeper water (they feed on fish and crustaceans), and the need to be colonies, although Garthe’s study also highlights the importance of trawlers. Sandwich terns prefer areas with a more complex, but flatter seabed located far from shallow water. This is likely to be related to food availability, but few studies examining offshore foraging in UK waters have been conducted.

Conclusions

The conclusions to this report are similar to the previous one. The statistical power of being able to detect changes in bird numbers is lower than desirable. This is primarily because there are large inter-annual fluctuations in numbers. In our opinion, the only way in which changes in numbers of the study species could be detected with a high degree of certainty would be to find ways of explaining some of this temporal variation, such as through the incorporation of dynamic ocean variables into analyses. Failing this, we caution that an inability to detect changes in numbers post windfarm construction should not be taken to mean that no such changes are occurring.

5. Appendices

Appendix 1 - Long time-series of data

5.1.1 Red-throated diver

Table 5.1.1.1. Statistical power for 50%, 25%, and 10% declines in red-throated diver using a spatial scale of 2 km x 2 km, for a range of significance levels (*P* = 0.2, 0.1 and 0.05). Time periods = 2-years pre-construction and 2-years post-construction (4-years), 3-years pre-construction and 3-years post-construction (6-years), 5-years pre-construction and 5-years post-construction (10-years) and 10-years pre-construction and 10-years post-construction (20-years).

Length of survey	Decline	*P*=0.2	*P*=0.1	*P*=0.05
4-years	10%	0.492	0.363	0.303
	25%	0.516	0.316	0.398
	50%	0.498	0.398	0.316
6-years	10%	0.661	0.590	0.556
	25%	0.685	0.576	0.576
	50%	0.693	0.623	0.621
10-years	10%	0.640	0.568	0.504
	25%	0.653	0.581	0.536
	50%	0.658	0.607	0.563
20-years	10%	0.607	0.525	0.427
	25%	0.633	0.527	0.384
	50%	0.722	0.631	0.565

Table 5.1.1.2. Statistical power for 50%, 25%, and 10% declines in red-throated diver using a spatial scale of 5 km x 5 km, for a range of significance levels (*P* = 0.1, 0.1 and 0.05). Time periods = 2-years pre-construction and 2-years post-construction (4-years), 3-years pre-construction and 3-years post-construction (6-years), 5-years pre-construction and 5-years post-construction (10-years) and 10-years pre-construction and 10-years post-construction (20-years).

Length of survey	Decline	*P*=0.2	*P*=0.1	*P*=0.05
4 years	10%	0.548	0.420	0.339
	25%	0.539	0.447	0.371
	50%	0.613	0.494	0.440
6 years	10%	0.552	0.462	0.371
	25%	0.574	0.489	0.395
	50%	0.695	0.588	0.496
10 years	10%	0.585	0.456	0.350
	25%	0.595	0.513	0.406
	50%	0.735	0.673	0.606
20 years	10%	0.590	0.546	0.439
	25%	0.614	0.557	0.485
	50%	0.753	0.657	0.566

5.1.2 Common scoter

Table 5.1.2.1. Statistical power for 50%, 25%, and 10% declines in common scoter using a spatial scale of 2 km x 2 km, for a range of significance levels (*P* = 0.1, 0.1 and 0.05). Time periods = 2-years pre-construction and 2-years post-construction (4-years), 3-years pre-construction and 3-years post-construction (6-years), 5-years pre-construction and 5-years post-construction (10-years) and 10-years pre-construction and 10-years post-construction (20-years).

Length of survey	Decline	*P*=0.2	*P*=0.1	*P*=0.05
4 years	10%	0.125	0.112	0.113
	25%	0.108	0.098	0.103
	50%	0.134	0.099	0.111
6 years	10%	0.213	0.192	0.098
	25%	0.212	0.193	0.093
	50%	0.202	0.178	0.098
10 years	10%	0.467	0.355	0.261
	25%	0.463	0.321	0.262
	50%	0.448	0.376	0.278
20 years	10%	0.608	0.503	0.401
	25%	0.604	0.519	0.437
	50%	0.689	0.583	0.523

Table 5.1.2.2. Statistical power for 50%, 25%, and 10% declines in common scoter using a spatial scale of 5 km x 5 km, for a range of significance levels (*P* = 0.1, 0.1 and 0.05). Time periods = 2-years pre-construction and 2-years post-construction (4-years), 3-years pre-construction and 3-years post-construction (6-years), 5-years pre-construction and 5-years post-construction (10-years) and 10-years pre-construction and 10-years post-construction (20-years).

Length of survey	Decline	*P*=0.2	*P*=0.1	*P*=0.05
4 years	10%	0.126	0.101	0.075
	25%	0.119	0.084	0.079
	50%	0.113	0.086	0.066
6 years	10%	0.334	0.272	0.206
	25%	0.354	0.291	0.167
	50%	0.360	0.334	0.188
10 years	10%	0.503	0.367	0.295
	25%	0.507	0.383	0.298
	50%	0.512	0.374	0.279
20 years	10%	0.560	0.476	0.398
	25%	0.585	0.490	0.406
	50%	0.645	0.481	0.406

5.1.3. Black-backed gulls

Table 5.1.3.1. Statistical power for 50%, 25%, and 10% declines in black-backed gulls using a spatial scale of 2 km x 2 km, for a range of significance levels (*P* = 0.1, 0.1 and 0.05). Time periods = 2-years pre-construction and 2-years post-construction (4-years), 3-years pre-construction and 3-years post-construction (6-years), 5-years pre-construction and 5-years post-construction (10-years) and 10-years pre-construction and 10-years post-construction (20-years).

Length of survey	Decline	*P* = 0.2	*P* = 0.1	*P* = 0.05
4 years	10%	0.169	0.124	0.066
	25%	0.190	0.127	0.072
	50%	0.160	0.140	0.056
6 years	10%	0.279	0.227	0.228
	25%	0.261	0.215	0.235
	50%	0.281	0.251	0.254
10 years	10%	0.490	0.355	0.324
	25%	0.465	0.342	0.305
	50%	0.508	0.362	0.351
20 years	10%	0.568	0.461	0.393
	25%	0.564	0.472	0.388
	50%	0.599	0.483	0.428

Table 5.1.3.2. Statistical power for 50%, 25%, and 10% declines in black-backed gulls using a spatial scale of 5 km x 5 km, for a range of significance levels (*P* = 0.1, 0.1 and 0.05). Time periods = 2-years pre-construction and 2-years post-construction (4-years), 3-years pre-construction and 3-years post-construction (6-years), 5-years pre-construction and 5-years post-construction (10-years) and 10-years pre-construction and 10-years post-construction (20-years).

Length of survey	Decline	*P*=0.2	*P*=0.1	*P*=0.05
4 years	10%	0.050	0.047	0.034
	25%	0.060	0.033	0.039
	50%	0.050	0.049	0.031
6 years	10%	0.479	0.373	0.291
	25%	0.501	0.377	0.287
	50%	0.515	0.380	0.292
10 years	10%	0.601	0.532	0.425
	25%	0.599	0.518	0.413
	50%	0.628	0.532	0.492
20 years	10%	0.636	0.523	0.400
	25%	0.626	0.575	0.428
	50%	0.793	0.728	0.680

5.1.4 Sandwich tern

Table 5.1.4.1. Statistical power for 50%, 25%, and 10% declines in sandwich tern using a spatial scale of 2 km x 2 km, for a range of significance levels (*P* = 0.1, 0.1 and 0.05). Time periods = 2-years pre-construction and 2-years post-construction (4-years), 3-years pre-construction and 3-years post-construction (6-years), 5-years pre-construction and 5-years post-construction (10-years) and 10-years pre-construction and 10-years post-construction (20-years).

Length of survey	Decline	*P*=0.2	*P*=0.1	*P*=0.05
4 years	10%	0.325	0.276	0.186
	25%	0.336	0.271	0.208
	50%	0.352	0.275	0.203
6 years	10%	0.503	0.368	0.324
	25%	0.508	0.327	0.320
	50%	0.464	0.328	0.335
10 years	10%	0.516	0.437	0.344
	25%	0.545	0.449	0.412
	50%	0.657	0.542	0.470
20 years	10%	0.604	0.519	0.470
	25%	0.631	0.503	0.447
	50%	0.634	0.567	0.476

Table 5.1.4.2. Statistical power for 50%, 25%, and 10% declines in sandwich tern using a spatial scale of 5 km x 5 km, for a range of significance levels (*P* = 0.1, 0.1 and 0.05). Time periods = 2-years pre-construction and 2-years post-construction (4-years), 3-years pre-construction and 3-years post-construction (6-years), 5-years pre-construction and 5-years post-construction (10-years) and 10-years pre-construction and 10-years post-construction (20-years).

Length of survey	Decline	*P*=0.2	*P*=0.1	*P*=0.05
4 years	10%	0.361	0.292	0.245
	25%	0.348	0.294	0.196
	50%	0.407	0.316	0.212
6 years	10%	0.552	0.475	0.381
	25%	0.549	0.484	0.373
	50%	0.583	0.494	0.364
10 years	10%	0.570	0.538	0.509
	25%	0.596	0.526	0.500
	50%	0.626	0.526	0.502
20 years	10%	0.629	0.527	0.424
	25%	0.628	0.527	0.491
	50%	0.629	0.527	0.424

Appendix 2 - Gradients of decline

5.2.1 Red-throated diver

Table 5.2.1.1. Statistical power for 50%, 25%, and 10% declines in red-throated diver using a spatial scale of 2 km x 2 km, for a range of significance levels (*P* = 0.2, 0.1 and 0.05) and assuming a gradient of decline such that declines decrease gradually with distance from the windfarm. Time periods = 2-years pre-construction and 2-years post-construction (4-years), 3-years pre-construction and 3-years post-construction (6-years), 5-years pre-construction and 5-years post-construction (10-years) and 10-years pre-construction and 10-years post-construction (20-years).

Length of survey	Decline	*P*=0.2	*P*=0.1	*P*=0.05
4 years	10%	0.214	0.150	0.127
	25%	0.197	0.160	0.095
	50%	0.126	0.093	0.053
6 years	10%	0.356	0.260	0.214
	25%	0.318	0.306	0.207
	50%	0.251	0.204	0.162
10 years	10%	0.516	0.427	0.326
	25%	0.506	0.422	0.331
	50%	0.553	0.446	0.361
20 years	10%	0.615	0.484	0.421
	25%	0.696	0.616	0.564
	50%	0.604	0.496	0.407

Table 5.2.1.2. Statistical power for 50%, 25%, and 10% declines in red-throated diver using a spatial scale of 2 km x 2 km, for a range of significance levels (*P* = 0.2, 0.1 and 0.05) and assuming a gradient of decline such that declines decrease rapidly with distance from the windfarm. Time periods = 2-years pre-construction and 2-years post-construction (4-years), 3-years pre-construction and 3-years post-construction (6-years), 5-years pre-construction and 5-years post-construction (10-years) and 10-years pre-construction and 10-years post-construction (20-years).

Length of survey	Decline	*P*=0.2	*P*=0.1	*P*=0.05
4 years	10%	0.531	0.436	0.427
	25%	0.395	0.351	0.366
	50%	0.316	0.254	0.253
6 years	10%	0.569	0.426	0.351
	25%	0.571	0.484	0.368
	50%	0.605	0.526	0.421
10 years	10%	0.636	0.542	0.500
	25%	0.637	0.573	0.495
	50%	0.595	0.593	0.536
20 years	10%	0.529	0.403	0.316
	25%	0.599	0.497	0.434
	50%	0.802	0.759	0.686

Table 5.2.1.3. Statistical power for 50%, 25%, and 10% declines in red-throated diver using a spatial scale of 5 km x 5 km, for a range of significance levels (*P* = 0.2, 0.1 and 0.05) and assuming a gradient of decline such that declines decrease gradually with distance from the windfarm. Time periods = 2-years pre-construction and 2-years post-construction (4-years), 3-years pre-construction and 3-years post-construction (6-years), 5-years pre-construction and 5-years post-construction (10-years) and 10-years pre-construction and 10-years post-construction (20-years).

Length of survey	Decline	*P*=0.2	*P*=0.1	*P*=0.05
4 years	10%	0.210	0.180	0.143
	25%	0.197	0.171	0.118
	50%	0.122	0.111	0.068
6 years	10%	0.537	0.469	0.481
	25%	0.514	0.472	0.404
	50%	0.488	0.401	0.339
10 years	10%	0.567	0.452	0.369
	25%	0.576	0.455	0.412
	50%	0.564	0.439	0.379
20 years	10%	0.639	0.532	0.465
	25%	0.714	0.619	0.559
	50%	0.893	0.845	0.805

Table 5.2.1.4. Statistical power for 50%, 25%, and 10% declines in red-throated diver using a spatial scale of 5 km x 5 km, for a range of significance levels (*P* = 0.2, 0.1 and 0.05) and assuming a gradient of decline such that declines decrease rapidly with distance from the windfarm. Time periods = 2-years pre-construction and 2-years post-construction (4-years), 3-years pre-construction and 3-years post-construction (6-years), 5-years pre-construction and 5-years post-construction (10-years) and 10-years pre-construction and 10-years post-construction (20-years).

Length of survey	Decline	*P*=0.2	*P*=0.1	*P*=0.05
4 years	10%	0.042	0.047	0.050
	25%	0.055	0.053	0.059
	50%	0.039	0.023	0.034
6 years	10%	0.601	0.505	0.415
	25%	0.616	0.535	0.452
	50%	0.722	0.643	0.574
10 years	10%	0.548	0.462	0.384
	25%	0.610	0.539	0.440
	50%	0.780	0.710	0.652
20 years	10%	0.639	0.571	0.497
	25%	0.680	0.599	0.562
	50%	0.805	0.757	0.709

5.2.2 Common Scoter

Table 5.2.2.1. Statistical power for 50%, 25%, and 10% declines in common scoter using a spatial scale of 2 km x 2 km, for a range of significance levels (*P* = 0.2, 0.1 and 0.05) and assuming a gradient of decline such that declines decrease gradually with distance from the windfarm. Time periods = 2-years pre-construction and 2-years post-construction (4-years), 3-years pre-construction and 3-years post-construction (6-years), 5-years pre-construction and 5-years post-construction (10-years) and 10-years pre-construction and 10-years post-construction (20-years).

Length of survey	Decline	*P*=0.2	*P*=0.1	*P*=0.05
4 years	10%	0.112	0.105	0.121
	25%	0.114	0.123	0.100
	50%	0.074	0.059	0.059
6 years	10%	0.248	0.192	0.105
	25%	0.263	0.183	0.131
	50%	0.210	0.134	0.089
10 years	10%	0.592	0.529	0.461
	25%	0.630	0.539	0.456
	50%	0.643	0.531	0.447
20 years	10%	0.590	0.497	0.444
	25%	0.587	0.503	0.427
	50%	0.549	0.458	0.434

Table 5.2.2.2. Statistical power for 50%, 25%, and 10% declines in common scoter using a spatial scale of 2 km x 2 km, for a range of significance levels (*P* = 0.2, 0.1 and 0.05) and assuming a gradient of decline such that declines decrease rapidly with distance from the windfarm. Time periods = 2-years pre-construction and 2-years post-construction (4-years), 3-years pre-construction and 3-years post-construction (6-years), 5-years pre-construction and 5-years post-construction (10-years) and 10-years pre-construction and 10-years post-construction (20-years).

Length of survey	Decline	*P*=0.2	*P*=0.1	*P*=0.05
4 years	10%	0.120	0.122	0.095
	25%	0.092	0.08	0.098
	50%	0.050	0.044	0.066
6 years	10%	0.680	0.592	0.548
	25%	0.704	0.653	0.536
	50%	0.727	0.639	0.583
10 years	10%	0.717	0.563	0.535
	25%	0.713	0.608	0.534
	50%	0.776	0.702	0.641
20 years	10%	0.590	0.467	0.409
	25%	0.618	0.530	0.467
	50%	0.789	0.697	0.640

Table 5.2.2.3. Statistical power for 50%, 25%, and 10% declines in common scoter using a spatial scale of 5 km x 5 km, for a range of significance levels (*P* = 0.2, 0.1 and 0.05) and assuming a gradient of decline such that declines decrease gradually with distance from the windfarm. Time periods = 2-years pre-construction and 2-years post-construction (4-years), 3-years pre-construction and 3-years post-construction (6-years), 5-years pre-construction and 5-years post-construction (10-years) and 10-years pre-construction and 10-years post-construction (20-years).

Length of survey	Decline	*P*=0.2	*P*=0.1	*P*=0.05
4 years	10%	0.191	0.167	0.096
	25%	0.194	0.153	0.087
	50%	0.111	0.104	0.054
6 years	10%	0.255	0.254	0.257
	25%	0.163	0.161	0.143
	50%	0.149	0.108	0.074
10 years	10%	0.563	0.468	0.368
	25%	0.584	0.462	0.395
	50%	0.576	0.428	0.357
20 years	10%	0.631	0.529	0.441
	25%	0.701	0.616	0.552
	50%	0.872	0.867	0.820

Table 5.2.2.4. Statistical power for 50%, 25%, and 10% declines in common scoter using a spatial scale of 5 km x 5 km, for a range of significance levels (*P* = 0.2, 0.1 and 0.05) and assuming a gradient of decline such that declines decrease rapidly with distance from the windfarm. Time periods = 2-years pre-construction and 2-years post-construction (4-years), 3-years pre-construction and 3-years post-construction (6-years), 5-years pre-construction and 5-years post-construction (10-years) and 10-years pre-construction and 10-years post-construction (20-years).

Length of survey	Decline	*P*=0.2	*P*=0.1	*P*=0.05
4 years	10%	0.197	0.357	0.280
	25%	0.190	0.405	0.320
	50%	0.123	0.543	0.440
6 years	10%	0.626	0.182	0.098
	25%	0.599	0.147	0.091
	50%	0.574	0.099	0.066
10 years	10%	0.469	0.488	0.415
	25%	0.555	0.527	0.410
	50%	0.645	0.485	0.427
20 years	10%	0.690	0.648	0.553
	25%	0.718	0.653	0.576
	50%	0.799	0.745	0.681

5.2.3. Black-backed gulls

Table 5.2.3.1. Statistical power for 50%, 25%, and 10% declines in black-backed gulls using a spatial scale of 2 km x 2 km, for a range of significance levels (*P* = 0.2, 0.1 and 0.05) and assuming a gradient of decline such that declines decrease gradually with distance from the windfarm. Time periods = 2-years pre-construction and 2-years post-construction (4-years), 3-years pre-construction and 3-years post-construction (6-years), 5-years pre-construction and 5-years post-construction (10-years) and 10-years pre-construction and 10-years post-construction (20-years).

Length of survey	Decline	*P*=0.2	*P*=0.1	*P*=0.05
4 years	10%	0.060	0.064	0.065
	25%	0.063	0.048	0.054
	50%	0.037	0.034	0.035
6 years	10%	0.380	0.281	0.216
	25%	0.335	0.284	0.212
	50%	0.246	0.213	0.152
10 years	10%	0.602	0.527	0.431
	25%	0.631	0.528	0.454
	50%	0.605	0.514	0.441
20 years	10%	0.621	0.547	0.470
	25%	0.685	0.571	0.531
	50%	0.607	0.560	0.448

Table 5.2.3.2. Statistical power for 50%, 25%, and 10% declines in black-backed gulls using a spatial scale of 2 km x 2 km, for a range of significance levels (*P* = 0.1, 0.1 and 0.05) and assuming a gradient of decline such that declines decrease rapidly with distance from the windfarm. Time periods = 2-years pre-construction and 2-years post-construction (4-years), 3-years pre-construction and 3-years post-construction (6-years), 5-years pre-construction and 5-years post-construction (10-years) and 10-years pre-construction and 10-years post-construction (20-years).

Length of survey	Decline	*P*=0.2	*P*=0.1	*P*=0.05
4 years	10%	0.129	0.118	0.051
	25%	0.089	0.086	0.039
	50%	0.057	0.048	0.020
6 years	10%	0.394	0.352	0.263
	25%	0.372	0.304	0.233
	50%	0.316	0.238	0.190
10 years	10%	0.524	0.438	0.368
	25%	0.514	0.391	0.371
	50%	0.448	0.413	0.314
20 years	10%	0.532	0.380	0.296
	25%	0.523	0.432	0.337
	50%	0.713	0.639	0.555

Table 5.2.3.3. Statistical power for 50%, 25%, and 10% declines in black-backed gulls using a spatial scale of 5 km x 5 km, for a range of significance levels (*P* = 0.1, 0.1 and 0.05) and assuming a gradient of decline such that declines decrease gradually with distance from the windfarm. Time periods = 2-years pre-construction and 2-years post-construction (4-years), 3-years pre-construction and 3-years post-construction (6-years), 5-years pre-construction and 5-years post-construction (10-years) and 10-years pre-construction and 10-years post-construction (20-years).

Length of survey	Decline	*P*=0.2	*P*=0.1	*P*=0.05
4 years	10%	0.361	0.279	0.310
	25%	0.321	0.229	0.174
	50%	0.278	0.204	0.118
6 years	10%	0.479	0.400	0.301
	25%	0.523	0.416	0.343
	50%	0.567	0.493	0.435
10 years	10%	0.503	0.388	0.348
	25%	0.541	0.437	0.341
	50%	0.488	0.393	0308
20 years	10%	0.622	0.463	0.394
	25%	0.586	0.472	0.446
	50%	0.705	0.608	0.504

Table 5.2.3.4. Statistical power for 50%, 25%, and 10% declines in black-backed gulls using a spatial scale of 5 km x 5 km, for a range of significance levels (*P* = 0.1, 0.1 and 0.05) and assuming a gradient of decline such that declines decrease rapidly with distance from the windfarm. Time periods = 2-years pre-construction and 2-years post-construction (4-years), 3-years pre-construction and 3-years post-construction (6-years), 5-years pre-construction and 5-years post-construction (10-years) and 10-years pre-construction and 10-years post-construction (20-years).

Length of survey	Decline	*P*=0.2	*P*=0.1	*P*=0.05
4 years	10%	0.281	0.211	0.166
	25%	0.200	0.202	0.120
	50%	0.155	0.129	0.096
6 years	10%	0.466	0.366	0.272
	25%	0.477	0.343	0.249
	50%	0.409	0.336	0.249
10 years	10%	0.442	0.364	0.270
	25%	0.565	0.445	0.317
	50%	0.688	0.594	0.537
20 years	10%	0.646	0.545	0.484
	25%	0.704	0.609	0.553
	50%	0.831	0.787	0.747

5.2.4. Sandwich Tern

Table 5.2.4.1. Statistical power for 50%, 25%, and 10% declines in sandwich tern using a spatial scale of 2 km x 2 km, for a range of significance levels (*P* = 0.1, 0.1 and 0.05) and assuming a gradient of decline such that declines decrease gradually with distance from the windfarm. Time periods = 2-years pre-construction and 2-years post-construction (4-years), 3-years pre-construction and 3-years post-construction (6-years), 5-years pre-construction and 5-years post-construction (10-years) and 10-years pre-construction and 10-years post-construction (20-years).

Length of survey	Decline	*P*=0.2	*P*=0.1	*P*=0.05
4 years	10%	0.517	0.444	0.334
	25%	0.538	0.408	0.356
	50%	0.511	0.428	0.319
6 years	10%	0.539	0.438	0.378
	25%	0.526	0.445	0.364
	50%	0.515	0.441	0.351
10 years	10%	0.574	0.426	0.358
	25%	0.572	0.403	0.319
	50%	0.597	0.501	0.396
20 years	10%	0.643	0.560	0.505
	25%	0.633	0.544	0.497
	50%	0.672	0.567	0.475

Table 5.2.4.2. Statistical power for 50%, 25%, and 10% declines in sandwich tern using a spatial scale of 2 km x 2 km, for a range of significance levels (*P* = 0.1, 0.1 and 0.05) and assuming a gradient of decline such that declines decrease rapidly with distance from the windfarm. Time periods = 2-years pre-construction and 2-years post-construction (4-years), 3-years pre-construction and 3-years post-construction (6-years), 5-years pre-construction and 5-years post-construction (10-years) and 10-years pre-construction and 10-years post-construction (20-years).

Length of survey	Decline	*P*=0.2	*P*=0.1	*P*=0.05
4 years	10%	0.334	0.284	0.187
	25%	0.278	0.267	0.135
	50%	0.182	0.167	0.094
6 years	10%	0.418	0.346	0.255
	25%	0.390	0.325	0.238
	50%	0.332	0.243	0.181
10 years	10%	0.613	0.513	0.427
	25%	0.641	0.548	0.435
	50%	0.716	0.638	0.550
20 years	10%	0.768	0.685	0.650
	25%	0.806	0.730	0.698
	50%	0.860	0.826	0.779

Table 5.2.4.3. Statistical power for 50%, 25%, and 10% declines in sandwich tern using a spatial scale of 5 km x 5 km, for a range of significance levels (*P* = 0.1, 0.1 and 0.05) and assuming a gradient of decline such that declines decrease gradually with distance from the windfarm. Time periods = 2-years pre-construction and 2-years post-construction (4-years), 3-years pre-construction and 3-years post-construction (6-years), 5-years pre-construction and 5-years post-construction (10-years) and 10-years pre-construction and 10-years post-construction (20-years).

Length of survey	Decline	*P*=0.2	*P*=0.1	*P*=0.05
4 years	10%	0.579	0.478	0.397
	25%	0.598	0.520	0.456
	50%	0.589	0.474	0.368
6 years	10%	0.635	0.539	0.390
	25%	0.600	0.510	0.411
	50%	0.670	0.563	0.497
10 years	10%	0.602	0.524	0.434
	25%	0.621	0.460	0.365
	50%	0.689	0.603	0.479
20 years	10%	0.677	0.561	0.476
	25%	0.660	0.577	0.524
	50%	0.786	0.739	0.676

Table 5.2.4.4. Statistical power for 50%, 25%, and 10% declines in sandwich tern using a spatial scale of 5 km x 5 km, for a range of significance levels (*P* = 0.1, 0.1 and 0.05) and assuming a gradient of decline such that declines decrease rapidly with distance from the windfarm. Time periods = 2-years pre-construction and 2-years post-construction (4-years), 3-years pre-construction and 3-years post-construction (6-years), 5-years pre-construction and 5-years post-construction (10-years) and 10-years pre-construction and 10-years post-construction (20-years).

Length of survey	Decline	*P*=0.2	*P*=0.1	*P*=0.05
4 years	10%	0.262	0.229	0.227
	25%	0.230	0.212	0.192
	50%	0.190	0.168	0.138
6 years	10%	0.657	0.532	0.433
	25%	0.659	0.521	0.440
	50%	0.683	0.610	0.536
10 years	10%	0.621	0.495	0.446
	25%	0.646	0.548	0.458
	50%	0.714	0.645	0.588
20 years	10%	0.667	0.562	0.500
	25%	0.719	0.647	0.529
	50%	0.775	0.705	0.646

5.1 Appendix 3 – Oceanographic variables

5.3.1 Red-throated diver

Table 5.3.1.1. Statistical power for 50%, 25%, and 10% declines in red-throated diver using a spatial scale of 10 km x 10 km, for a range of significance levels (*P* = 0.1, 0.1 and 0.05). Oceanographic variables (bathymetry, seabed complexity, distance from land and northern slope gradient) where used to help explain count variation. Time periods = 2-years pre-construction and 2-years post-construction (4-years), 3-years pre-construction and 3-years post-construction (6-years), 5-years pre-construction and 5-years post-construction (10-years) and 10-years pre-construction and 10-years post-construction (20-years).

Length of survey	Decline	*P*=0.2	*P*=0.1	*P*=0.05
4 years	10%	0.359	0.344	0.306
	25%	0.366	0.329	0.295
	50%	0.410	0.391	0.321
6 years	10%	0.464	0.418	0.350
	25%	0.491	0.4132	0.360
	50%	0.477	0.437	0.387
10 years	10%	0.564	0.472	0.419
	25%	0.573	0.501	0.434
	50%	0.575	0.529	0.458
20 years	10%	0.617	0.552	0.474
	25%	0.637	0.540	0.477
	50%	0.671	0.614	0.532

5.3.2 Common scoter

Table 5.3.2.1. Statistical power for 50%, 25%, and 10% declines in common scoter using a spatial scale of 10 km x 10 km, for a range of significance levels (*P* = 0.1, 0.1 and 0.05). Oceanographic variables (bathymetry, seabed complexity, eastern slope gradient and northern slope gradient) where used to help explain count variation. Time periods = 2-years pre-construction and 2-years post-construction (4-years), 3-years pre-construction and 3-years post-construction (6-years), 5-years pre-construction and 5-years post-construction (10-years) and 10-years pre-construction and 10-years post-construction (20-years).

Length of survey	Decline	*P*=0.2	*P*=0.1	*P*=0.05
4 years	10%	0.578	0.479	0.421
	25%	0.577	0.496	0.402
	50%	0.607	0.530	0.431
6 years	10%	0.582	0.542	0.429
	25%	0.616	0.532	0.444
	50%	0.671	0.564	0.453
10 years	10%	0.642	0.519	0.460
	25%	0.637	0.525	0.457
	50%	0.672	0.596	0.492
20 years	10%	0.603	0.501	0.431
	25%	0.628	0.518	0.421
	50%	0.711	0.598	0.555

5.3.3. Black-backed gulls

Table 5.3.3.1. Statistical power for 50%, 25%, and 10% declines in black-backed gulls using a spatial scale of 10 km x 10 km, for a range of significance levels (*P* = 0.1, 0.1 and 0.05). Oceanographic variables (bathymetry, distance from land, northern slope gradient and distance from shallow water) where used to help explain count variation. Time periods = 2-years pre-construction and 2-years post-construction (4-years), 3-years pre-construction and 3-years post-construction (6-years), 5-years pre-construction and 5-years post-construction (10-years) and 10-years pre-construction and 10-years post-construction (20-years).

Length of survey	Decline	*P*=0.2	*P*=0.1	*P*=0.05
4 years	10%	0.522	0.411	0.325
	25%	0.546	0.477	0.342
	50%	0.668	0.536	0.459
6 years	10%	0.586	0.481	0.374
	25%	0.586	0.494	0.405
	50%	0.675	0.563	0.475
10 years	10%	0.643	0.538	0.459
	25%	0.646	0.542	0.476
	50%	0.694	0.605	0.531
20 years	10%	0.454	0.325	0.248
	25%	0.492	0.374	0.276
	50%	0.700	0.578	0.473

5.3.4. Sandwich tern

Table 5.3.4.1. Statistical power for 50%, 25%, and 10% declines in sandwich tern using a spatial scale of 10 km x 10 km, for a range of significance levels (*P* = 0.1, 0.1 and 0.05). Oceanographic variables (seabed complexity, northern slope gradient and distance from shallow water) where used to help explain count variation. Time periods = 2-years pre-construction and 2-years post-construction (4-years), 3-years pre-construction and 3-years post-construction (6-years), 5-years pre-construction and 5-years post-construction (10-years) and 10-years pre-construction and 10-years post-construction (20-years).

Length of survey	Decline	*P*=0.2	*P*=0.1	*P*=0.05
4 years	10%	0.614	0.492	0.447
	25%	0.636	0.530	0.421
	50%	0.710	0.643	0.526
6 years	10%	0.613	0.546	0.511
	25%	0.629	0.599	0.525
	50%	0.749	0.676	0.604
10 years	10%	0.608	0.478	0.400
	25%	0.615	0.513	0.434
	50%	0.753	0.694	0.568
20 years	10%	0.592	0.507	0.418
	25%	0.624	0.549	0.499
	50%	0.794	0.731	0.707

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