SIMULATION-BASED IMPACT ASSESSMENT OF OFFSHORE WIND FARMS ON SEABIRDS

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Abstract: Understanding the impact of offshore wind farms on marine fauna is vital for sustainable development of this renewable energy resource. This paper presents an application to real data of a new simulation-based impact assessment method that was developed using artificial data. The method simulates surveys of seabird counts at post-construction survey locations using knowledge obtained from the undisturbed pre-construction phase. Next, using hypothesis-testing it is investigated whether the actually collected post-construction counts are statistically different from the set of simulated surveys of the undisturbed situation. We investigate the applicability of this method in a real case using a dataset that was collected to assess the impact of an offshore wind farm in the North Sea on the seabird species Guillemots (*Uria aalge*). It appeared that several elaborations of the method were needed to accommodate the properties of the dataset at hand. These elaborations included the formulation of an appropriate deterministic model to accommodate for zero-inflation in the species data, transformations of the residual data to be appropriate for the stochastic modelling part, and accommodation of directional spatial correlation in the residuals.

KEYWORDS: autocorrelation, impact assessment, offshore wind farm, seabirds, spatial simulation

Introduction

With the current increase of offshore wind-energy developments, it is essential to assess and monitor their ecological effects (Gill, 2005). Specifically for seabirds, potential effects include mortality due to collision with offshore turbines and the displacement of birds from the wind farm area (Drewitt & Langston, 2006). With the focus on assessing a displacement (hereafter referred to as impact), approaches such as those under the Before-After Control-Impact (BACI) framework (Stewart-Oaten et al., 1986; Stewart-Oaten & Bence, 2001) are generally applied. For example, a BACI approach to investigate impact may rely on comparisons of an indicator variable (such as number of birds) between the pre- and post-construction periods over the wind farm area and a control area (Petersen *et al.,* 2006). The control area is used as a reference to characterise the temporal variability (Stewart-Oaten & Bence,

2001) in bird numbers other than that caused by the man-made construction. Such a comparison may consist of testing for a significant difference between the pre- and post-construction period in the mean number of birds in the impact and control areas (Petersen *et al.,* 2006). A significant difference may then suggest an impact of wind farm construction.

Given that the marine environment is a complex system with many processes interacting in a complex manner, this approach is generally not sufficient. Seabirds are highly-mobile animals, presenting time-varying spatial dependence occurring at various scales. This may be caused by differences in feeding conditions near temperature fronts in the sea water, or by other as yet unknown factors. Also, collected bird counts contain spatial autocorrelation that needs to be accounted for in statistical tests aiming at detecting a significant difference between pre- and post-construction periods. Another complicating factor for applying this statistical testing approach

is that the number and spatial location of the survey points will usually be different for each survey.

An alternative approach to investigate the impact of offshore wind farms on seabirds is the one developed in Pérez-Lapeña *et al.,* (2010). In their approach, the effects of autocorrelation in collected species counts as well as the effect of varying pre- and post-construction environmental conditions and survey effort and design are explicitly taken into account.

The method in Pérez-Lapeña *et al.,* (2010) was developed using artificial data. The objective of this paper is to investigate the applicability of the method by Pérez-Lapeña *et al.,* (2010) in a real case study regarding the impact of an offshore wind farm off the coast of the Netherlands on Guillemots (*Uria aalge*). Guillemots breed on the cliff coasts in the Northern North Sea and Helgoland, visiting the Southern North Sea in the winter. Given the large numbers of this species in Dutch waters during the winter months (Leopold *et al.,* 2004), we choose the month of November for our analysis.

The simulation-based method

The method developed in Pérez-Lapeña *et al.,* (2010) provides a framework to detect, from pre- and post-construction collected data, whether seabirds have been displaced (attracted or driven away) in an area due to offshore wind farm construction (Figure 1).

Using the pre-construction data, a deterministic model and a variogram model is constructed to reflect the spatial autocorrelation in bird counts at two different scales (coarse scale and local scale, respectively). To account for varying environmental conditions between pre- and post-construction periods, the pre-construction situation is re-defined into a so-called 'reference situation' to match the actual environmental conditions of the post-construction survey. By hypothesis-testing, it is assessed whether the actually collected post-construction bird counts are statistically different from the 'reference situation'.

The null hypothesis (H_0) that is being tested is 'no change' in bird counts between the 'reference' and the post-construction situations, which is stated as:

$$H_0: \ [\mu_{wf} - \mu_c]_{\text{ref}} - [\mu_{wf} - \mu_c]_{\text{post}} = 0$$

where $[\mu_{wf} - \mu_c]_{\text{ref}}$ is the difference between the mean bird count in the wind farm area (μ_{wf}) and control area (μ_c) in the 'reference situation' and $[\mu_{wf} - \mu_c]_{\text{post}}$ is the expected difference in the post-construction survey. The test statistic is defined as $[\bar{\mu}_{wf} - \bar{\mu}_c]_{\text{ref}} - [x_{wf} - x_c]_{\text{post}}$ where the values $\bar{\mu}_{wf}$ and $\bar{\mu}_c$ are estimate of μ_{wf} and μ_c for the reference situation, respectively, and their difference is taken as a constant. The values x_{wf} and x_c are a sample estimate of μ_{wf} and μ_c for the post-construction situation, respectively. The distribution of the test statistic under H_0 (referred to as the null distribution in Figure 1) is constructed by geostatistical simulation. Based on a user-specified significance level the critical regions under the distribution (left and right tail) can be identified for which H_0 will be rejected. Using the post-construction survey data, the actual value of the test statistic is calculated and it can be assessed whether it falls into either of the critical regions. If so, the null hypothesis is rejected and a change in bird numbers between the 'reference' and the post-construction situation is identified. This implies that one can be quite certain (related to the chosen significance level) that birds have been displaced in relation to the wind farm construction.

Guillemot dataset

The study area covers approximately 900 km² which includes the proposed wind farm location (impact area) and a zone around it (hereafter referred as the control area). It is located approximately 14 km distance to the Dutch coast at 17 m water depth.

Count data on Guillemots were collected by Alterra-Texel and Wageningen IMARES under a study commissioned by NoordzeeWind during the pre- and post-construction phase of the offshore wind farm. As described in Leopold *et al.,* (2004), surveys span the main phases of the bird calendar,
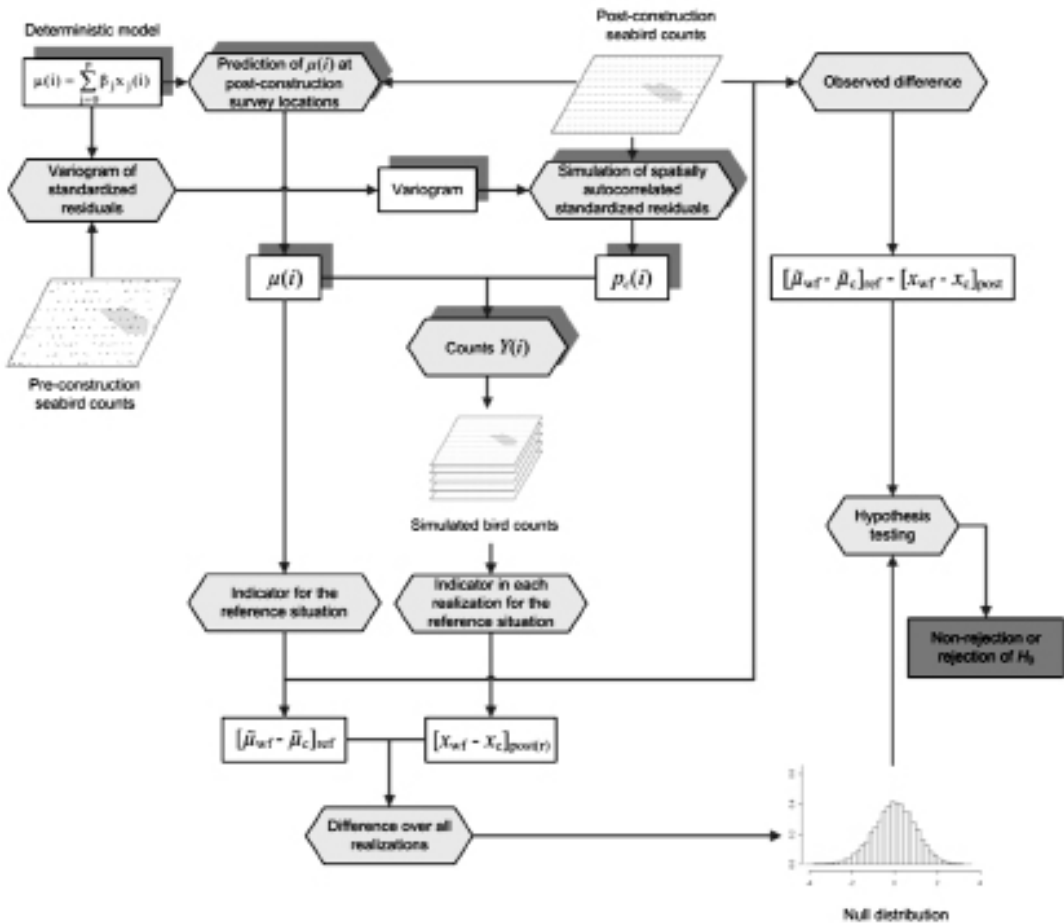
Figure 1. Method for detecting local change in the abundance of a given species (modified after Pérez-Lapeña *et al.,* 2010). The shaded boxes are further elaborated on in section "Investigating impact".

from breeding to migration and wintering periods. Survey transects were approximately 2.5 km apart, providing 10 equidistant transects over the total study area in each survey. Seabird count data were collected from a ship using the strip-transect methodology (Tasker *et al.,* 1984). Guillemots were counted during periods of 5 minutes from the two sides of the ship. Within this time frame, the surface area surveyed was approximately 0.5 km². Bird counts were then spatially referenced to the central position of the counting strips. Collected Guillemot counts for the month of November 2003 (pre-construction) are shown in Figure 2.

In general, we might expect the Guillemot count data to follow a Poisson distribution, because Guillemot count data are bounded by zero, as one cannot observe a negative number of birds, and have no upper limit on how large an observed count can be. However, the histogram shown in Figure 3 reveals this is not the case. Figure 3 shows the sample-based distribution (from data in Figure 2) of the square root of the collected count values. In case counts were indeed following a Poisson distribution, the distribution of the square root of the counts would approximate the normal distribution. Obviously, this is not the case.

From the histogram, we observe that there is a larger proportion of zeros than the one from a pure Poisson process. This property is referred to as 'zero-inflation' (Tu, 2002). Zero-inflation
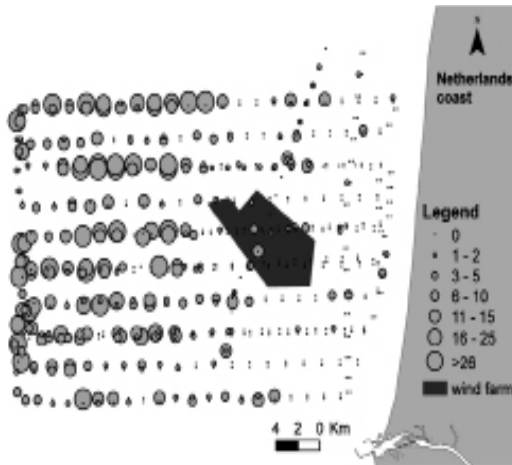
Figure 2. Observed Guillemot density (birds/km²) during November 2003.

Figure 3. Sample-based histogram of collected Guillemot counts (square root).

may arise from an excess of true and false zeros (Martin *et al.,* 2005). A true zero count occurs because, for example, the bird is absent at the survey location, due to poor habitat whereas a false zero count occurs because, even though the habitat may be suitable, one fails to record birds.

Deterministic model

In the applied method, we separate spatial autocorrelation in Guillemot counts into two components, deterministic and stochastic. The deterministic component reflects spatial autocorrelation in bird counts at coarse scales and arises from birds responding to coarse-scale external environmental factors. The stochastic component reflects residual spatial correlation at local scales and may arise from birds responding to as yet unknown factors that have not been incorporated in the deterministic model.

Coarse-scale environmental factors can influence the numbers of birds that are observed at different spatial locations (Suryan & Irons, 2001; Poot *et al.,* 2004; Garthe, 1997; Hunt Jr, 1997). Water depth and the location of temperature fronts, for example, have been identified as having a correlation with the number of seabirds (Markones, 2007). The reasons for the apparent relationship are not known but it has been hypothesised that seabirds may select certain
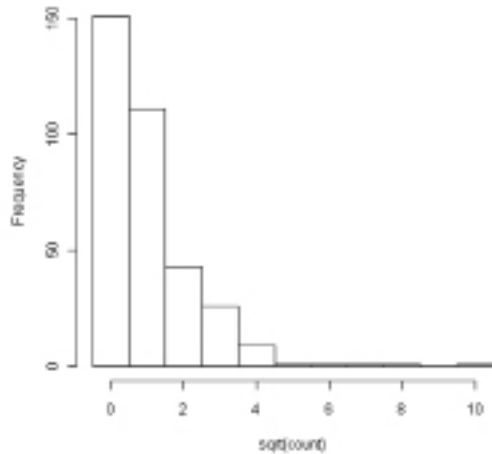
areas where physical conditions enhance the probability of finding prey (Wright & Begg, 1997).

We selected water depth as the explanatory variable in the constructed deterministic model given that datasets with time-varying environmental variables (such as sea surface temperature) were not available for the moment of the surveys. The deterministic model is constructed using Guillemot counts collected in the pre-construction period.

As shown in the previous section, the Guillemot dataset is zero-inflated. In this study, we assume that this is due to an excess of only true zeros. Given this assumption, we expand the method proposed in Pérez-Lapeña *et al.,* (2010) by using a two-part deterministic model.

In a two-part model (Welsh *et al.,* 1996; Mullahy, 1986) the first part is a binomial model. Using logistic regression (Agresti, 2002), one can determine the probability of observing at least one bird given the value of the explanatory variable (water depth). To construct this model, counts are divided into presence and absence, where presence observations are those having a count larger than zero and absence are those with a true zero count. The second part is a zero-truncated model. Using zero-truncated regression (Welsh et al., 1996), one can determine the mean bird count

given that at least one bird is present. To construct this model, only positive counts are used because zero counts have already been taken into account in the binomial model. In addition, the expected number of birds predicted from this model is the mean bird count (using non-zero bird counts) in the area as the binomial model accounts for the probability of observing at least one bird given values of coarse-scale explanatory factors (water depth in this case).

Logistic regression

Let $p(x_i)$ be the probability of observing at least one bird at observation location i given the explanatory variable x. The distribution for modelling the presence/absence data is:

$$P(y_i = q \mid x_i) = \begin{cases} p(x_i) & q > 0 \\ 1 - p(x_i) & q = 0 \end{cases} \qquad (1)$$

The logit model (Agresti, 2002) fitted to the Guillemot counts converted to presence/absence for the month of November using water depth x as explanatory variable is:

$$logit(p(x_i)) = -8.08 + 0.44\, x_i \qquad (2)$$

with both significant coefficients (p<0.001), and using water depth as predictor fits significantly better than a model with just an intercept.

The probability $p(x_i)$ is estimated by:

$$p(x_i) = \frac{exp(-8.08 + 0.44\, x_i)}{1 + exp(-8.08 + 0.44\, x_i)} \qquad (3)$$

Zero-truncated Poisson regression

Let λ be the mean of a Poisson distribution fitted to non-zero counts q. The distribution for modelling the zero-truncated observations is (Yee, 2008):

$$P(y_i = q \mid \lambda) = \begin{cases} \dfrac{exp(-\lambda)\, \lambda^q}{q!\,(1 - exp(-\lambda))} & q > 0 \\ 0 & q = 0 \end{cases} \qquad (4)$$

The Poisson model fitted to the non-zero Guillemot counts is:

$$log(\lambda) = 1.61 \qquad (5)$$

The estimated mean μ from the zero-truncated Poisson model (Welsh et al., 1996) at locations with non-zero bird counts for the month of November is:

$$\mu(i) = \frac{exp(1.61)}{1 - exp(-exp(1.61))} \qquad (6)$$

Stochastic model

Once the deterministic model reflecting the spatial autocorrelation in bird counts due to coarse scale factors (water depth) has been constructed, we model residual spatial autocorrelation in bird counts at a local scale using a variogram. The variogram measures the degree of spatial autocorrelation between pairs of observations at different separation distances. It is a measure of variability: the semivariance increases as observations become more dissimilar (Gringarten & Deutsch, 2001). As this model requires the residual to be a stationary normal random variable, the residuals from the deterministic model are standardised.

Standardised residuals from logistic regression

Let φ_i be a presence ($\varphi_i = 1$) or absence observation ($\varphi_i = 0$) at location i and $p(x_i)$ be the predicted probability of presence for a given water depth x calculated using logistic regression.

Let $p(x_i)[1 - p(x_i)]$ be the variance of the binomial distribution (Agresti, 2002).

We calculate the standardised residuals $p_l(i)$ as:

$$p_l(i) = \frac{\varphi_i - p(x_i)}{\sqrt{p(x_i)[1 - p(x_i)]}} \qquad (7)$$

The empirical variogram of the standardised residuals is shown in Figure 4.

From the computed empirical variogram, we conclude that the residuals are not spatially autocorrelated given that the semivariances at different distances fluctuate around the variance of the calculated standardised residuals. This value is called the sill and represents the variogram value that corresponds with zero autocorrelation (Gringarten & Deutsch, 2001).
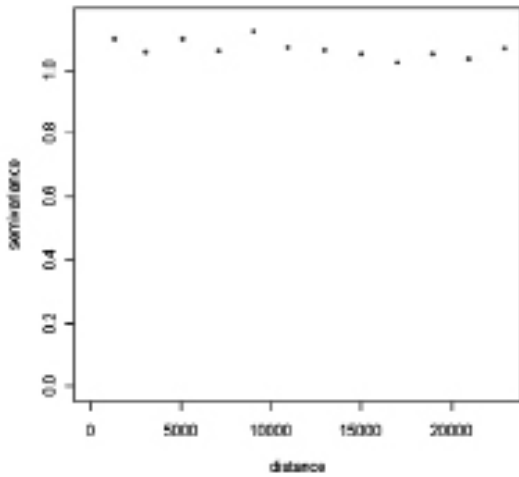
Figure 4. Empirical variogram of standardised residuals from logistic regression model (distance in m).

Therefore, given the absence of spatial autocorrelation in the standardised residuals from the logistic model, the overall spatial autocorrelation in Guillemots absence/presence has been captured by the logistic model.

Standardised residuals from Zero-truncated Poisson regression

Let obs_i be the observed non-zero bird count at location *i*. Let μ be the predicted mean bird count calculated from zero-truncated Poisson regression. Let:

$$\frac{\lambda \, exp(\lambda)\,[-1+exp(\lambda)-\lambda]}{(exp(\lambda)-1)^2} \tag{8}$$

be the variance of the zero-truncated Poisson distribution (Yee, 2008).

We calculate the standardised residuals $p_t(i)$ as:

$$p_t(i) = \frac{obs_i - \mu(i)}{\sqrt{\dfrac{\lambda \, exp(\lambda)\,[-1+exp(\lambda)-\lambda]}{(exp(\lambda)-1)^2}}} \tag{9}$$

In order to investigate residual spatial autocorrelation, we first transform the residuals so that these are normally distributed with mean $\mu=0$ and variance $\sigma^2=1$ using the normal score transform (Goovaerts & Jacquez, 2004). The
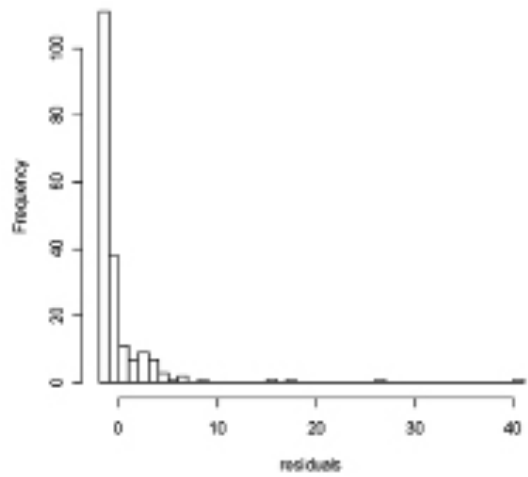

Figure 5. Histogram of standardised residuals from the zero-truncated Poisson model.

reason for the transformation is two-fold. On the one hand, the distribution of the residuals is skewed with very large values at the right end of the tail (Figure 5). This would produce an erratic variogram (Gringarten & Deutsch, 2001), inflating the semivariance for pairs of observations containing such extreme values. On the other hand, the simulation procedure presented in Pérez-Lapeña *et al.*, (2010) simulates standardised residuals from a standard normal distribution ($\mu=0$ and variance $\sigma^2=1$).

To investigate the effect of ordering in the data to perform the normal score transform, and to estimate the variogram, we apply the normal score transform to 1000 random orders in the residuals. We choose the 12° azimuth and 102° azimuth direction as having the higher and the lower degree of spatial autocorrelation respectively after constructing a rose diagram at 12° azimuth intervals for each of the 1000 normal score transforms. The average rose diagram is shown in Figure 6.

The rose diagram shows, for a given set of directions (azimuths), the approximated variogram ranges derived by linear interpolation between the values in the empirical variogram. The range of a variogram is the separation distance at which spatial correlation is no longer present (Gringarten & Deutsch, 2001). From the
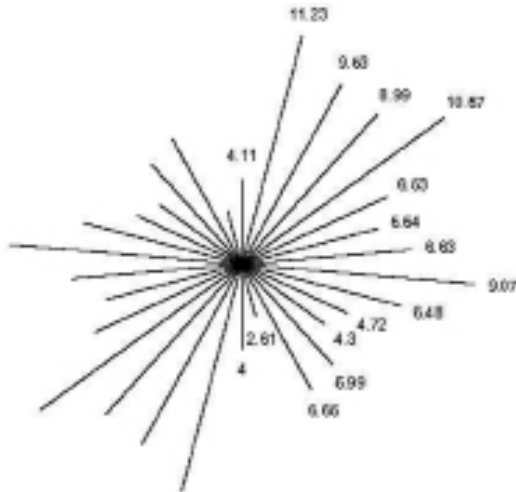
Figure 6. Average rose diagram at intervals of 12° azimuth for the 1000 normal score transformations. The numbers refer to the approximated ranges (in km) where the semivariance reaches a sill of 1.

rose diagram in Figure 6, we observe that, as the direction changes, the variogram range changes, drawing an elliptical shape. The minor and major axis of such an ellipse represents the approximated directions having the lower and the higher degree of spatial correlation.

Given that the normal score residuals have a variance of 1, we expect that the sills in the 12° and 102° azimuths remain similar. This variogram behaviour is called geometric anisotropy (Gringarten & Deutsch, 2001). To fit the theoretical variogram, we find the anisotropy ratio between the ranges in both directions (Hengl, 2009). The estimated anisotropy ratio is approximately 0.5.

The fitted directional variograms, for each of the 1000 normal score transformations in the 12° azimuth and 102° azimuth directions, are shown in Figure 7. The average variogram is superimposed in Figure 7 in black colour.

The average-fitted exponential variograms have a partial sill = 0.5, nugget = 0.55, and the range in the 12° azimuth direction equals to 15.5 km and in the 102° azimuth direction equals to 7.5 km.
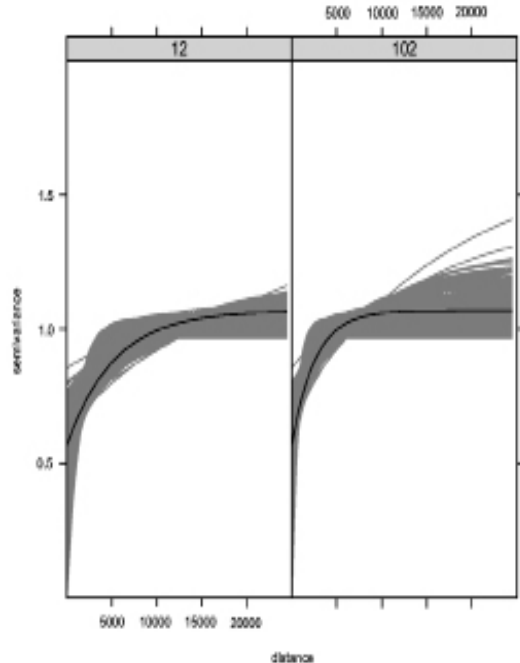

Figure 7. Fitted directional variograms (normal score) standardised residuals, for each of the 1000 normal score transformations, in the 12° azimuth (left-hand panel) and 102° azimuth (right-hand panel) directions (distance in m). The semivariances are calculated at a lag of 2.3 km.

Investigating impact

Once the spatial autocorrelation in bird counts has been modelled by i) the two-part deterministic model and ii) the directional variogram of the (normal score) standardised residuals, we have statistically described the pre-construction period. Using the two-part deterministic model, we re-define the pre-construction situation into the 'reference situation' given the actual environmental conditions and the survey effort and design of the post-construction survey.

Using the two-part deterministic and stochastic models, we generate realisations of possible post-construction bird counts by means of geostatistical simulation. Simulated counts are used to construct the null distribution of the test statistic $[\mu;\bar{}_{wf} - \mu;\bar{}_{c}]_{\text{ref}} - [x_{wf} - x_{c}]_{\text{post}}$ for hypothesis-testing.

The simulation procedure, with extended steps from Pérez-Lapeña *et al.,* (2010) schematised in Figure 9 (steps 1-7), is summarised as follows:

1. Using the logistic model, we predict the probability of observing at least one bird ($p(x_i)$ in equation 3) at post-construction survey locations given water-depth values at those locations. Using the zero-truncated Poisson model, we predict the mean number of birds ($\mu(i)$ in equation 6) at post-construction survey locations. Multiplying $\mu(i)$ by $p(x_i)$ we obtain expected bird counts at post-construction survey locations and define the 'reference' situation. Using the expected bird counts, the indicator for the 'reference' situation $[\mu;\overline{}_{wf}\text{-}\mu;\overline{}_c]_{\text{ref}}$ is calculated.

2. Realisations of (normal score) standardised residuals of the zero-truncated Poisson model at post-construction survey locations are simulated. This is achieved by assigning standard normal random variables (μ=0 and variance σ^2=1) to each spatial location with values in each realisation sampled from the standard normal distribution.

3. The simulated (normal score) standardised residuals of the zero-truncated Poisson model are correlated satisfying the computed directional spatial autocorrelation (using the Cholesky decomposition).

4. The correlated (normal score) residuals are backtransformed into correlated residuals ($p_t(i)$ in equation 9).

5. Using the formula of the standardised residuals from the zero-truncated Poisson model, we obtain count values (obs_i in equation 9).

6. We simulate realisations of presence (value of 1) and absence (value of 0) at post-construction survey locations with probability $p(x_i)$. This is achieved by generating random variables at each spatial location with values in each realisation sampled from a binomial distribution with probability $p(x_i)$.

7. For each realisation *r*, we multiply at each survey location the count values obtained in step 5, by the presence/absence values obtained in step 6.

8. For each realisation *r*, we calculate the difference between $[\mu;\overline{}_{wf}\text{-}\mu;\overline{}_c]_{\text{ref}}$ (from step 1) and $[x_{wf}\text{-}x_c]_{post(r)}$ where x_{wf} and x_c are the mean bird count in the wind farm and control area respectively (calculated from count values in step 7). With the calculated differences over all realisations, we derive the null distribution to be used in hypothesis-testing.

The distribution of the test statistic under H_0 (null distribution) is shown in Figure 9. The null distribution represent possible values of the test statistic $[\mu;\overline{}_{wf}\text{-}\mu;\overline{}_c]_{\text{ref}}-[x_{wf}\text{-}x_c]_{\text{post}}$ that could arise given the stochasticity in bird counts, when the wind farm does not displace birds. In order to test whether the difference between the 'reference situation' and the post-construction survey is statistically significant, we calculate the test statistic using the post-construction data. The observed value of the test statistic is 0.75. With this value, we fail to reject H_0 at a significance level of α=0.05, suggesting that there is no evidence that the wind farm did have a positive or negative effect on the number of Guillemots using the wind farm area.

Discussion

Applying the method developed by Pérez-Lapeña *et al.,* (2010) in a real case showed that properties of the dataset at hand will dictate case-specific elaborations of the method, such as the formulation of an appropriate deterministic model, or case-specific transformation of the residual data to be appropriate for the stochastic modelling part. In the following we will discuss some implications of the presented elaborations.

In the presented deterministic model, we have only accounted for static explanatory factors affecting the number of birds observed. The time-varying location of water masses and temperature fronts, for example, are known to affect the collected counts (Markones, 2007). Given that impact is based on comparisons between the 'reference' and post-construction situations and
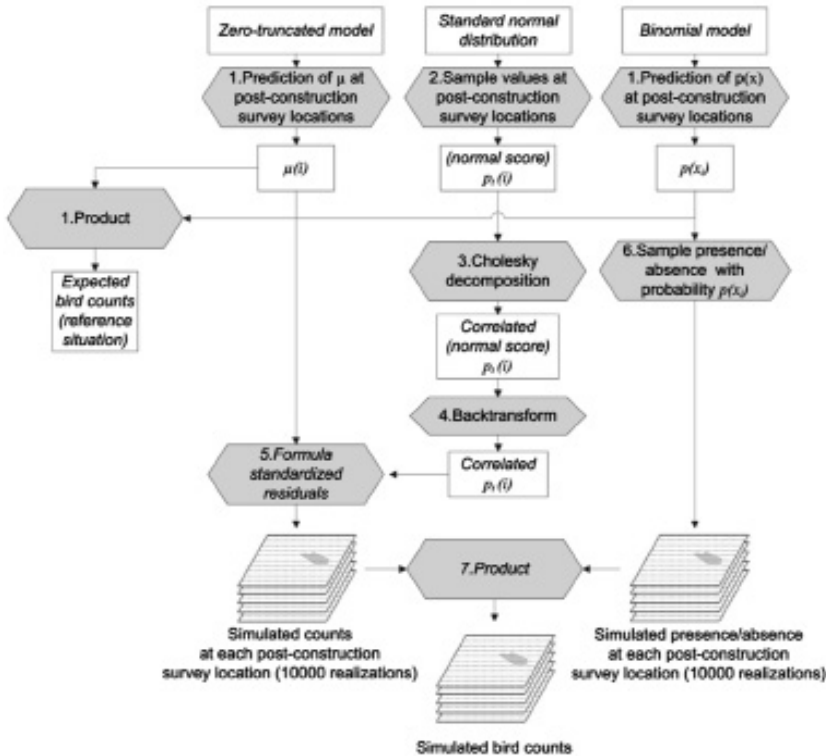
Figure 8. Simulation procedure to obtain post construction realisations of Guillemots counts, expanded from Pérez-Lapeña *et al.,* (2010). Numbers refer to the steps described in section 'Investigating impact'.

that the spatial distribution of these explanatory factors may vary over time, an observed difference in bird counts between the wind farm and control areas may be erroneously attributed to the wind farm construction. Therefore, ideally, dynamic explanatory factors should have been incorporated in the deterministic model as well. In the current case, data on such dynamic factors were not available. Note, however, that if the spatial pattern of dynamic explanatory factors induce a consistent spatial correlation scale, these will be (partially) accounted for in the stochastic part of the model.

The relationship between bird abundance and coarse-scale environmental factors (water depth in this case) has been modelled solely in the binomial model. This implies that the preference of Guillemots for certain water depths, hence certain locations in the study area, is only modelled as a probability of 'bird presence', not as 'bird numbers'. To obtain actual estimates of the mean
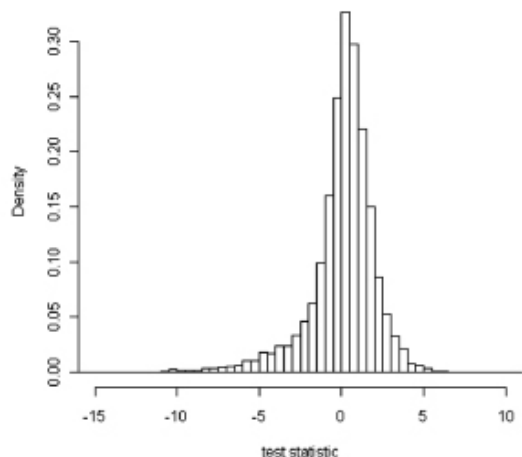

Figure 9. Null distribution for the test statistic $[\mu;\bar{}_{wf} - \mu;\bar{}_c]_{\mathrm{ref}} - [x_{wf} - x_c]_{\mathrm{post}}$.

number of birds in the impact and control area, required for defining the 'reference' situation, the overall average number of birds present in the pre-construction period has been used. This

essentially implies we assumed no year-to-year variability in the number of birds using the study area. When this is not a suitable assumption, another test statistic can be considered, e.g. the difference between the ratios of the mean number of birds in the wind farm area to the mean number of birds in the control area for the reference and the post-construction situation, respectively.

By using a two-part model with a zero-truncated Poisson distribution, we have assumed that the zeros in the dataset are true zeros. That is, a zero count occurs because the bird is not there due to, for example, poor habitat. False zeros will be present in reality as detection errors in collected data occur, e.g. a bird may be present but at the moment of the observation is under water catching prey. How the occurrence of false zeros affects the assessment and whether they should be included in the analysis procedure is the subject of further study.

The Guillemot count data in the month of November consisted of data collected over a four-day period. In our analysis we considered the observations as a 'snapshot' of the situation in that month, and as such we neglected the variability in bird abundance patterns between and within days. As a result, to calculate the residual spatial autocorrelation in bird numbers using the variogram, we may have used pairs of observations that are close in space but that may be three days apart. A further spatio-temporal analysis should follow in order to justify the aggregation of data over the four-day period or otherwise, account for variability using, for example, different semivariograms for modelling the spatial correlation at different times during a day.

Finally, the conclusion of impact is based on the result of a hypothesis test. Therefore, failure to reject H_0 can be wrongly interpreted as acceptance of H_0 (Ludwig et al., 2001), i.e. that an impact has not occurred. If the results of the study were to be used in an environmental monitoring context, a subsequent power analysis would have been required. In this manner, the suitability of the survey design to detect impacts possibly occurring could have been assessed.

Conclusion

This study investigated the applicability of the method developed in Pérez-Lapeña *et al.,* (2010) in a real case, consisting of offshore wind farm impact on Guillemots. The method indeed provided a suitable framework for these type of impact studies and proved to be flexible enough to incorporate extensions at several steps of the analyses that had to be made to be suited for the case at hand. The method needed to be extended to include a two-part deterministic model to account for the zero-inflation present in the bird-count dataset. Also, anisotropic variograms could be accommodated to account for the directional spatial correlation in the residuals. Finally, due to the skewness present in the residual data, with many low values but few very large values, a data transformation was applied to approach normality in the data, avoiding possible erratic behaviour in the constructed variograms.

Acknowledgements

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