CHAPTER 8

SEABIRD MONITORING AT THE THORNTON BANK OFFSHORE WIND FARM

FINAL DISPLACEMENT RESULTS AFTER 6 YEARS OF POST-CONSTRUCTION MONITORING AND AN EXPLORATIVE BAYESIAN ANALYSIS OF COMMON GUILLEMOT DISPLACEMENT USING INLA

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Abstract

Since 2005, the Research Institute for Nature and Forest (INBO) has been engaged in a monitoring program aiming to study seabird displacement effects caused by offshore wind farms in the Belgian part of the North Sea. Here we report our findings for the C-Power wind farm at the Thornton Bank after six years of post-construction monitoring. Results showed significant avoidance of the wind farm area by northern gannet, common guillemot and razorbill, these species having dropped in numbers by 98%, 60-63% and 75-80% respectively. In contrast, attraction to the wind farm could be demonstrated for herring and great black-backed gulls, for which our BACI models predicted a factorial change in densities of 3.8-4.9 and 5.3-6.6 respectively. Importantly, most of these effects account for the footprint area only, and were no longer noticeable in the buffer area 0.5-3 km away from the wind farm edge. Great cormorants too showed major attraction effects, amplified by the fact that the species was quasi-absent in the study area prior to wind farm construction. The effects at the Thornton Bank show striking parallels with those observed at the nearby Bligh Bank, and among European studies in general there seems good consistency in the avoidance response of gannets and auks, as well as in the attraction effects observed for great cormorants and great black-backed gulls. A major lack in understanding, however, persists when it comes to the translation of these behavioural responses into displacement impact, considered as any change in individual fitness, reproductive success and survival. Clearly, filling in this wide knowledge gap is crucial for a reliable assessment of the actual and cumulative ecological consequences of extensive offshore wind farm installations, and should therefore be the primary goal of future research.

1. Introduction

In aiming to meet the targets set by the European Directive 2009/28/EG on renewable energy, no fewer than 4,543 offshore wind turbines were fully grid-connected in European waters by the end of 2018, totalling 18.5 GW. In the Belgian part of the North Sea (BPNS), 5 wind farms are currently operational, representing a capacity of 1.2 GW (EWEA 2019).

Since 2005, the Research Institute for Nature and Forest (INBO) has been in charge of studying seabird displacement caused by offshore wind farms (OWFs), applying a before-after control-impact (BACI) strategy. Results after 5 years of post-construction monitoring at the Bligh Bank were presented in Vanermen *et al.* (2016), and this report will discuss the results after 6 years of post-construction data collection at the Thornton Bank. The results will be compared with those obtained at the nearby Bligh Bank and other European OWF sites, and we will continue the discussion by defining important knowledge gaps on wind farm displacement research.

The results presented here can be regarded as final because it is no longer feasible to continue or repeat the monitoring as performed up until now, in which we focused on single isolated wind farm sites surrounded by 3 km buffer zones. However, these buffer areas are now increasingly occupied by wind turbines of newly constructed, adjacent wind farms. From an environmental monitoring perspective, the Belgian offshore wind farm concession zone will soon have to be considered as one large wind farm cluster. Therefore, a new seabird displacement monitoring scheme will start once the concession zone is fully occupied by turbines (expected by 2020), demanding a different and more advanced analysis method. We will explore the possibilities of using an INLA (integrated nested Laplace approximation) approach to detect displacement in seabirds-at-sea monitoring data, based on a post-construction subset of common guillemot data collected at the Thornton Bank. Importantly, this Bayesian analysis method allows to take into account fine-scaled spatial correlation, which has been avoided in our BACI analyses by aggregating the count data to day totals per area, yet hereby strongly limiting the sample size as well as statistical power.

2. Material and methods

2.1. Thornton Bank offshore wind farm

The Thornton Bank wind farm is located 27 km off the coast of Zeebrugge. The wind farm consists of 2 subareas of 10.7 and 9.2 km² occupied with 30 and 24 wind turbines respectively and separated by a 1.7-2.0 km corridor (fig. 1). The water depth of the turbine-built area ranges between 12 and 28 m (C-Power 2019). Distances between the turbines range from 500 up to 900 m.
The wind farm was built in three phases:

- Phase 1: 6 x 5 MW turbines (gravity-based foundations), operational since May 2009
- Phase 2: 30 x 6.15 MW turbines (jacket foundations), operational since October 2012
- Phase 3: 18 x 6.15 MW turbines (jacket foundations), operational since September 2013

2.2. Displacement study

2.2.1. Seabird counting

Ship-based seabird counts were conducted according to a standardised and internationally applied method, combining a "transect count" for birds on the water and repeated "snapshot counts" for flying birds (Tasker *et al.* 1984). We focused on a 300 m wide transect along one side of the ship's track, and while steaming at a speed of about 10 knots, all birds in touch with the water (swimming, dipping, diving) observed within this transect were counted ("transect count"). Importantly, the distance of each observed bird (group) to the ship was estimated, allowing to correct for decreasing detectability with increasing distance afterwards (through distance analysis, see §2.2.2). The transect was thus divided in four distance categories (A = 0-50 m; B = 50-100 m; C = 100-200 m;

D = 200-300 m). Counting all flying birds inside this transect, however, would cause an overestimation and would be a measure of bird flux rather than bird density (Tasker *et al.* 1984). The density of flying birds was therefore assessed through one-minute interval counts of birds flying within a quadrant of 300 by 300 m inside the transect ("snapshot counts"). As the ship covers a distance of approximately 300 m per minute when sailing the prescribed speed of 10 knots, the full transect was covered by means of these subsequent "snapshots".

For data processing, observation time was linked to the corresponding GPS coordinates registered by the ship's board computer. Taking into account the transect width and distance travelled during a certain time interval, the cumulative result of the coinciding transect and snapshot counts could be transformed to a number of birds per km^2, *i.e.* a seabird density. Up to 2012, observations were aggregated in ten-minute bouts, which were cut off to the nearest minute at waypoints. In 2013, resolution was increased and seabird observations were pooled in two-minute bouts ever since, again cut off to the nearest minute at waypoints.

It should be highlighted that in practice we recorded all birds (and sea mammals) observed, but those not satisfying above conditions (*i.e.* not observed inside the transect nor during snapshots) were given another code and could not be included in any analysis using seabird densities (*i.e.* all analyses in this study, except for great cormorants). On board, we further noted as much information as possible regarding the birds' age, plumage, behaviour, flight direction and association with objects, vessels or other birds. Whenever fishing vessels were in view, distance (perpendicular to the monitoring track whenever possible), type and activity of the vessel were assessed and recorded. Finally, observation conditions (wind force, wave height and visibility) were noted at the start of each survey and updated continuously.

2.2.2. Distance analysis

We corrected our transect count numbers for the fact that the probability of detecting birds decreases with distance to the ship (Buckland *et al.* 2001; Thomas *et al.* 2010). The exact relation between distance and detection probability is expected to be species-specific, and further likely to depend on bird group size and observation conditions (Marques & Buckland 2003). Observation conditions were included in the detection models as "wind force" (Beaufort scale) or "wave height" (categorised as 0-0.5 m / 0.5-1.0 m / 1.0-2.0 m / 2.0-3.0 m…), both variables being assessed continuously throughout the surveys.

To look for suitable species-specific detection models, we fitted each of the following "full models" with a half-normal as well as a hazard-rate detection function:

- P(detection) ~ group size + wind force
- P(detection) ~ group size + wave height
- P(detection) ~ log(group size) + wind force
- P(detection) ~ log(group size) + wave height

We did not add cosine or polynomial adjustments to the models as doing so sometimes appeared to result in non-monotonic functions. This would imply that the detection probability *increases* with distance, which is assumed to be highly improbable. The best fitting full model was chosen based on the "Akaike Information Criterion" (AIC), and backward covariate selection was then performed to obtain a parsimonious detection model. In the end, the resulting models were used to predict species-specific detection probabilities varying with the selected covariates, and the counted numbers were corrected accordingly.

Table 1. Definition of the reference, construction and impact periods at the Thornton Bank study area; only the "reference period" and "impact period (phase I, II & III)" were applied in the analyses

Phase	Period
Reference period	< 04/2008
1st construction period	04/2008 > 05/2009 (highly restricted access)
Impact period (phase I)	06/2009 > 04/2011 (6 turbines)
2nd construction period	05/2011 > 09/2012 (variable access)
Impact period (phase I, II & III)	10/2012 > 12/2018 (54 turbines)

2.2.3. Monitoring set-up

The seabird displacement monitoring was performed according to a before-after control-impact (BACI) set-up (fig. 1). The OWF footprint area was surrounded by a buffer zone of 3 km to define the impact area, further distinguishing between the "footprint + 0.5 km" and the "buffer 0.5-3 km" area. Next, we delineated a control area harbouring comparable numbers of seabirds before OWF construction and showing a similar range in water depth and distance to the coast. Meanwhile, the distance between the control and impact area was kept small enough to be able to survey both on the same day by means of a research vessel (Vanermen *et al.* 2005).

Following fixed monitoring tracks, the Thornton Bank study area was counted on a highly regular basis from 2005 until present (figs 1 & 2). During this dedicated monitoring program, the study area should have been visited monthly, but research vessels were not always available and planned trips were regularly cancelled due to adverse weather conditions (characterised by significant wave heights higher than 2 m and/or poor visibility). Prior to this dedicated monitoring program, the study area was counted on a much more irregular base, but we did include surveys dating back to 1993 provided that the control and impact area were visited on the same day.

For our displacement analyses, only data falling within the "reference period" and "impact period (phase I, II & III)" were used (table 1). Note that phase III was not yet operational before September 2013 (§2.1), while the impact period defined in table 1 and as used in the analyses already starts in October 2012 (when phase II became operational). This is justified by the fact that access for monitoring was not allowed where active construction activities of phase III were going on, and data collected between October 2012 and September 2013 thus account for the operational part of the OWF only.

Compared to the previous monitoring report (Vanermen *et al.* 2017), data from 12 more surveys could be added to the dataset. Our dataset now includes 52 post-construction opposed to 65 pre-construction surveys (fig. 2).

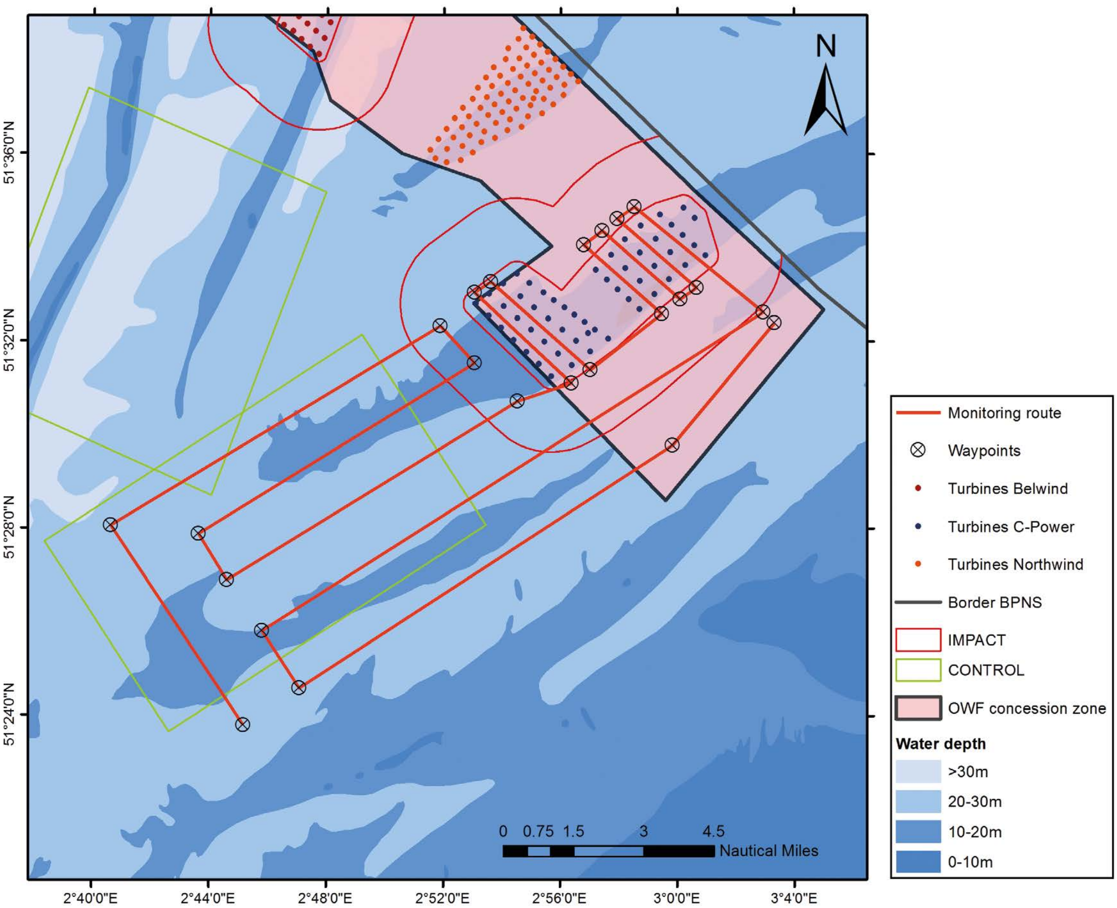

Figure 1. Post-construction monitoring route across the Thornton Bank OWF study area.

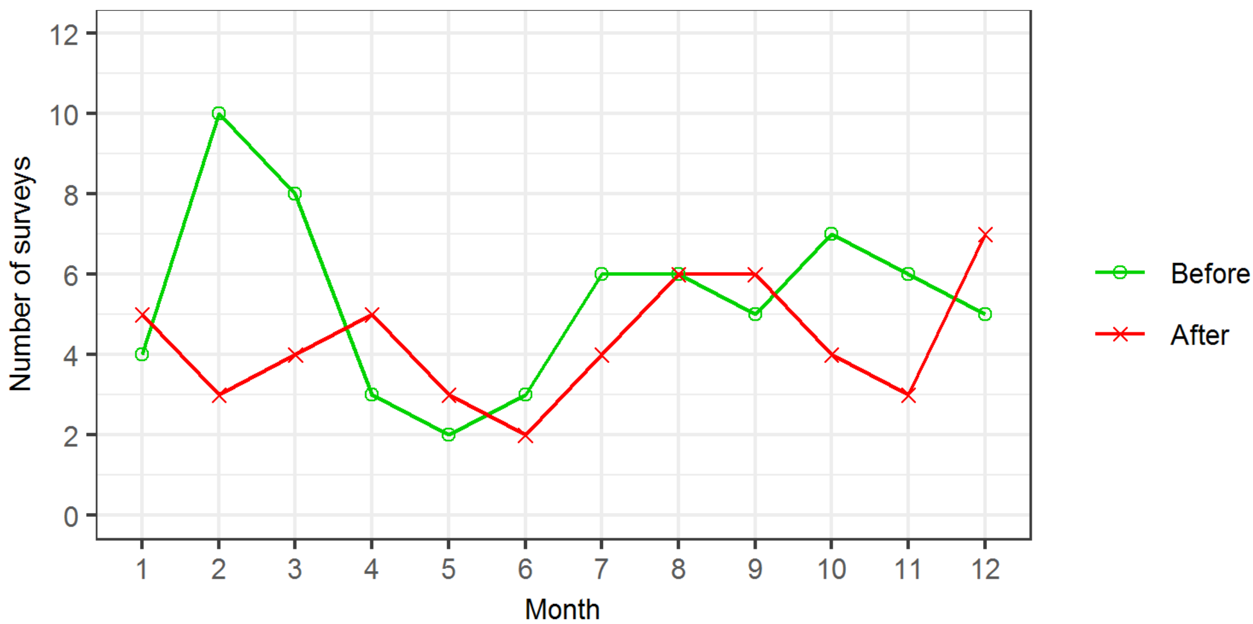

Figure 2. Count effort in the Thornton Bank study area indicated by the number of surveys performed before the construction of the phase I turbines (< April 2008) and after the construction of the phase II turbines (> September 2012).

2.2.4. BACI analysis

Data selection

For the BACI modelling, we aggregated our count data per area (control/impact) and per monitoring day, resulting in day totals for both zones. As such, we avoided spatio-temporal correlation between counts performed within the same day. We further selected only those days on which both the control and impact area were visited, as such excluding day-to-day variation in seabird abundance.

Modelling was performed for thirteen seabird species occurring regularly in the study area, *i.e.* northern fulmar (*Fulmarus glacialis*), northern gannet (*Morus bassanus*), great cormorant (*Phalacrocorax carbo*), great skua (*Stercorarius skua*), little gull (*Hydrocoloeus minutus*), common gull (*Larus canus*), lesser black-backed gull (*Larus fuscus*), herring gull (*Larus argentatus*), great black-backed gull (*Larus marinus*), black-legged kittiwake (*Rissa tridactyla*), Sandwich tern (*Thalasseus sandvicensis*), common guillemot (*Uria aalge*) and razorbill (*Alca torda*). For each of these species, we modelled three different impact datasets differing in the post-construction impact data selection (OWF footprint + 0.5 km, OWF footprint + 3 km, OWF buffer 0.5-3 km, see fig. 3).

Response variable

The response variable (Y) of our displacement models was the number of birds observed inside the transect and during snapshot counts, aggregated per area and per monitoring day. For great cormorants, a different response variable was applied, *i.e.* the number observed per kilometre. This was done because analysing cormorant densities caused analytical problems resulting from extremely low presence rates in the control as well as the impact area before wind farm construction. For the large gull species (herring, lesser black-backed and great black-backed gull), we modelled an "adjusted response variable" on top of the standard response. Because the corridors between the C-Power turbines used during seabird monitoring (fig. 1) vary in width between 650 and 900 m, combined with the fact that the research vessels always aim to sail in the middle of these corridors for security reasons, birds associated with the turbines were by definition outside our 300 m wide transect. To counter this, an adjusted response variable was calculated by adding (i) the number of birds that would have been present inside the transect if the turbine-associated birds had occurred homogenously spread across the area to (ii) the number of birds counted inside the transect and during snapshot counts (*i.e.* the original response variable). This is most easily illustrated with an example: on 28 August 2015 we counted 161 great black-backed gulls resting on the jacket foundations, as opposed to only 1 bird present inside our transect (the original response) despite a survey effort of 7.4 km² inside the impact area. As we checked 43 turbines out of a total of 54 turbines, we estimated the number of turbine-associated great black-backed gulls in the OWF as a whole at 202 birds. The wind farm area surrounded by the 0.5 km wide buffer zone measures 36 km², and the density of turbine-associated great black-backed gulls was thus 5.6 birds/km². If these birds would have occurred homogenously spread across the area, and knowing we counted 7.4 km², the number of birds inside the transect would have been (about) 42, which is our adjusted response. The original and adjusted response variables were always analysed both, and the difference is clearly indicated in all graphs and tables.

Explanatory variables

To account for varying monitoring effort, the number of km² counted was included in the models as an offset-variable (only in case of the great cormorant we used the number of kilometres sailed). The explanatory variables used were (i) a time factor BA (before/after construction), (ii) an area

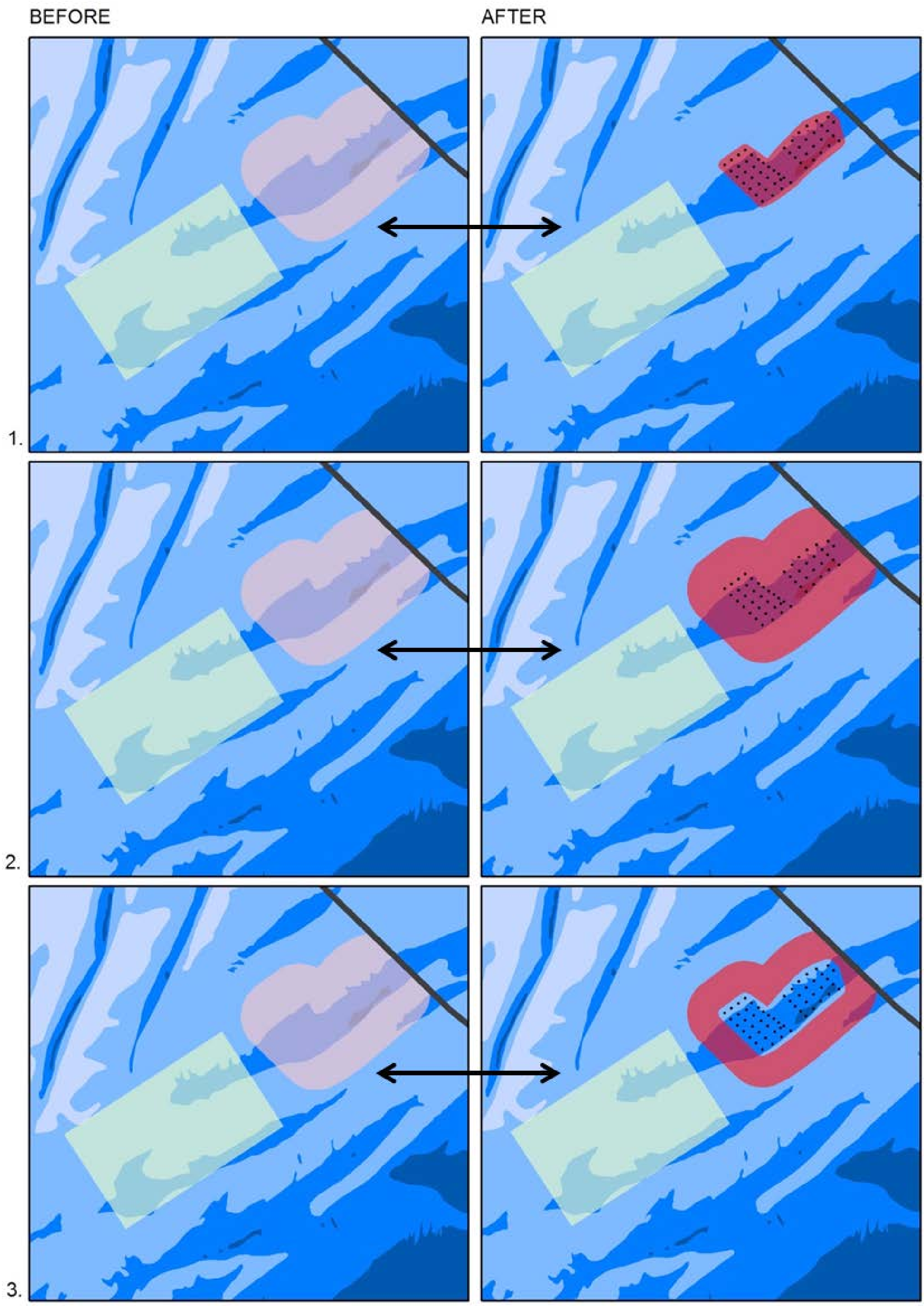

Figure 3. Overview of the BACI polygons used for data selection to study OWF induced seabird displacement at the Thornton Bank (green = control area / red = impact area; 1 = "OWF footprint + 0.5 km", 2 = "OWF footprint + 3 km", 3 = "OWF buffer 0.5-3 km").

factor CI (control/impact area), (iii) an offshore wind farm factor OWF (wind farm present/absent) and (iv) a fishery factor F (fishing vessels present/absent in the wider area). The latter excluded fishing vessels observed beyond 3 km from the monitoring track, and was considered only for those species known to aggregate around fishing vessels (*i.e.* not used for great cormorant, little gull, sandwich tern, common guillemot and razorbill). Finally, the continuous variable month (m) was included to model seasonal fluctuations by fitting a cyclic smoother or alternatively a cyclic sine curve, the latter described through a linear sum of sine and cosine terms (Stewart-Oaten & Bence 2001, Onkelinx *et al.* 2008). Seasonal patterns can often be successfully modelled applying a single sine curve with a period of 12 months, but in some cases adding another sine curve with a period of 6 or 4 months is needed, thus allowing to fit more than one peak in density per year and/or an asymmetric seasonal pattern. Eventually, we considered five different "full" models:

- no seasonal variation
  $Y \sim BA + CI + F + OWF$
- 12 month period sine curve
  $Y \sim BA + CI + F + OWF$
  $+ \sin(2*\pi*m/12) + \cos(2*\pi*m/12)$
- 12 + 6 month period sine curve
  $Y \sim BA + CI + F + OWF$
  $+ \sin(2*\pi*m/12) + \cos(2*\pi*m/12)$
  $+ \sin(2*\pi*m/6) + \cos(2*\pi*m/6)$
- 12 + 4 month period sine curve
  $Y \sim BA + CI + F + OWF$
  $+ \sin(2*\pi*m/12) + \cos(2*\pi*m/12)$
  $+ \sin(2*\pi*m/4) + \cos(2*\pi*m/4)$
- cyclic smoother
  $Y \sim BA + CI + F + OWF + s(m)$

Model selection

In case of a randomly dispersed subject, count results tend to be Poisson-distributed, in which the mean equals the variance (McCullagh & Nelder 1989). Seabirds, however, mostly occur strongly aggregated in (multi-species) flocks, resulting in "over-dispersed" count data which may demand the use of a negative binomial (NB) distribution (Ver Hoef & Boveng 2007; Zuur *et al.* 2009). When the data still exhibit more zeros than can be predicted through a NB distribution, it may be necessary to apply a zero-inflated (ZI) distribution (Potts & Elith 2006; Zeileis *et al.* 2008) which consists of two parts: (i) a "count component" modelling the data according to a Poisson or NB distribution and (ii) a "zero component" modelling the excess in zero counts.

As such, the five different full models were fitted to the "OWF footprint + 3 km" dataset (see fig. 3) applying these four different distributions (Poisson, NB, ZI Poisson, ZI NB). Based on the 20 resulting AIC values, the best fitting full model was selected, which was subsequently fitted to the "OWF footprint + 0.5 km" and "OWF buffer 0.5-3 km" datasets. In the results section we often refer to (i) the OWF coefficient, being the model coefficient of the OWF factor variable and the estimator of the displacement effect, and (ii) the estimated density, being the model prediction for a specific month and factor combination with the number of km^2 fixed at one. Densities in the impact area are further often referred to as X% lower or Y times higher than the "expected value". The latter should be regarded as the post-construction density that would have occurred in the impact area if the numbers had shown the same trend as observed in the control area. Also note that in all models used, the response is related to the linear sum of covariates through a log-link, implying that the OWF coefficient represents a factorial effect after transformation. A coefficient of 0 for example is transformed by calculating the exponential function *e* to the power 0, representing a factorial effect of 1, *i.e.* no effect. On the other hand, a coefficient of 1 is transformed by doing *e* to the power 1, equalling 2.718, implying that (according to the model) post-construction numbers inside the OWF area are almost three times higher than expected based on the trend observed in the control area.

In this report we moved away from further model selection as applied in the previous reports (Vanermen *et al.* 2016, 2017), in which a specific set of nested models was considered and the best-fitting covariate combination was ultimately chosen. Here we used the full model OWF coefficient as a first estimator of the OWF displacement effect. But based on the model selections performed in aforementioned reports, we know that AIC differences between the best-fitting model on the one hand, and the full model or any nested model on the other hand may be very small (< 1), implying that there is actually more than one "good" model, each of them estimating the wind farm effect somewhat (or sometimes quite) differently. Interestingly, the differences in AIC values among a set of candidate models can be used to calculate relative model probabilities ("Akaike weights"), which in turn can be used to calculate a weighted average of any targeted model coefficient. In this study we used the full model and the nested alternatives for the "BA + CI + F" part of the model (always keeping the OWF factor and seasonality part into the model) to obtain a so-called multi-model inferred (MMI) OWF coefficient, as a "second opinion" displacement effect estimator (Burnham & Anderson 2002). For the MMI coefficient, no P-values were provided, but statistical significance could be deducted from the 95% confidence interval and whether or not this included zero (a coefficient of zero implying no effect).

2.2.5. Explorative INLA analysis

Finally, we explored the possibility of detecting displacement in post-construction data making use of the Bayesian "integrated nested Laplace approximation" (INLA) approach. In contrast to the BACI analyses above, we used raw count data (*i.e.* in their original resolution of geo-referenced one- to two-minute counts) allowing to account for spatial correlation. We built a non-convex hull mesh with both maximum edge and cut-off values set at 1.0 km and used a subset of (post-construction) count results of common guillemot, the most common and homogenously distributed seabird in our study area. Survey date was included in the models as a random intercept, and the area surveyed was log-transformed and included as an offset by defining a high-precision prior for its coefficient (a mean of 1 with a precision of 10,000). Another prior was given for the range of spatial correlation, which based on expert judgment was considered unlikely (P = 0.01) to be below 3 km.

Next, we ran Poisson models without spatial correlation, with spatial correlation and with spatial correlation replicated for each survey. Building on the latter, a fourth model included a three-level factor variable assigning counts to either the control, buffer or impact area. Unlike the polygons shown in fig. 3, the impact area in this analysis was confined to the footprint of the wind farm and the buffer area to a 2 km zone outside this footprint. All counts outside these polygons were regarded as control counts.

The resulting models were compared based on the Watanabe-AIC (wAIC) and interpreted by plotting the spatial random field or evaluating the fixed model coefficients. For further model evaluation, simulation exercises were performed to compare the models' data distribution with the original data distribution.

2.3. Statistical software

All data handling and modelling was performed through R.3.5.2 (R Core Team 2018a) in RStudio version 1.1.383 (RStudio Team 2016), making use of the following (randomly ordered) packages: RODBC (Ripley & Lapsley 2017), foreign (R Core Team 2018b), date (Therneau *et al.* 2018), ggplot2 (Wickham 2016), compare (Murrell 2015), reshape (Wickham 2007), MASS (Venables

& Ripley 2002), mgcv (Wood 2011), glmmADMB (Skaug *et al.* 2016), Distance (Miller 2017), mrds (Laake *et al.* 2018), gridExtra (Auguie 2017), MuMIn (Barton 2018), rgdal (Bivand *et al.* 2018), spatialEco (Evans *et al.* 2017), lattice (Sarkar 2008), INLA (Lindgren & Rue 2015), tidyverse (Wickham 2017), plyr (Wickham 2011) and RColorBrewer (Neuwirth 2014).

3. Results

3.1. General observations

Since the Thornton Bank OWF became operational, most of the birds observed inside the OWF footprint area were gulls (91% of all non-passerines – see table 2). Most of these (82%) belong to one of the three “large gull” species, *i.e.* herring, lesser black-backed and great black-backed gull. With over 1800 individuals observed, great black-backed gull was by far the most numerous of all. This species showed a higher preference to the turbine foundations compared to the other two large gulls (89% *versus* 28% and 64% for lesser black-backed and herring gull, respectively). Cormorants too showed strong preference to the turbines, as 95% of the great cormorants and 76% of the European shags were observed roosting on the jacket or gravity-based foundations.

Although gannets and auks generally avoid the wind farm (Vanermen *et al.* 2017), these birds were regularly observed within the OWF boundaries. In total, we observed 47 northern gannets, 104 common guillemots and 59 razorbills.

3.2. Distance analysis

For all species except for great skua, hazard-rate detection models fitted our data better than the half-normal alternative (table 3). In general, either wave height or wind force proved to affect the detectability of seabirds significantly, except in great skua and both tern species. The (natural logarithm of) group size was retained for all species except for great skua. Detection probabilities of single birds during moderate observation conditions (wave height between 0.5 and 1 m or wind force of 4 Beaufort) were predicted to be highest and above 80% for conspicuous birds like great skua and northern gannet, and ranged between 0.54 and 0.71 for all other species. For great cormorants, the numbers observed per kilometre were not distance-corrected as for this species the response also included observations outside the 300 m transect for which detailed distance information was unavailable (see §2.2.1).

Table 2. Numbers of birds and sea mammals observed inside the Thornton Bank wind farm during 873 km of surveying from October 2012 until December 2018

		Total number observed	Number present on turbines	Percentage present on turbines
BIRDS				
Northern fulmar	*Fulmarus glacialis*	1	0	
Northern gannet	*Morus bassanus*	47	0	
Great cormorant	*Phalacrocorax carbo*	150	143	95%
European shag	*Phalacrocorax aristotelis*	17	13	76%
Unidentified cormorant	*Phalacrocorax* sp.	3	1	33%
Eurasian sparrowhawk	*Accipiter nisus*	1	0	
Bar-tailed godwit	*Limosa lapponica*	1	0	
Arctic skua	*Stercorarius parasiticus*	1	0	
Little gull	*Hydrocoloeus minutus*	35	0	
Black-headed gull	*Chroicocephalus ridibundus*	18	0	
Common gull	*Larus canus*	154	3	2%
Lesser black-backed gull	*Larus fuscus*	732	206	28%
Herring gull	*Larus argentatus*	210	135	64%
Yellow-legged gull	*Larus michahellis*	2	0	
Great black-backed gull	*Larus marinus*	1819	1610	89%
Unidentified large gull	*Larus* sp.	577	498	86%
Black-legged kittiwake	*Rissa tridactyla*	528	3	1%
Sandwich tern	*Thalasseus sandvicensis*	19	0	
Common tern	*Sterna hirundo*	1	0	
Common guillemot	*Uria aalge*	104	0	
Unidentified auk	*Alca torda* or *Uria aalge*	20	0	
Razorbill	*Alca torda*	59	0	
Domestic pigeon	*Columba livia "domestica"*	1	0	
Common starling	*Sturnus vulgaris*	122	3	2%
Passerines		28	3	11%
MAMMALS				
Harbour porpoise	*Phocoena phocoena*	6	0	
Grey seal	*Halichoerus grypus*	1	0	

Table 3. Results of the multi-covariate distance analysis for the seabird species targeted in this study; the species-specific detection probabilities account for single birds during moderate observation conditions (wave height between 0.5 and 1 m or wind force of 4 Beaufort)

Species	Detection function	Covariates	Detection probability (single bird)
Northern fulmar	Hazard-rate	log(group size) + wave height	0.54
Northern gannet	Hazard-rate	log(group size) + wave height	0.85
Great skua	Half-normal	/	0.84
Little gull	Hazard-rate	log(group size) + wind force	0.58
Common gull	Hazard-rate	log(group size) + wind force	0.56
Lesser black-backed gull	Hazard-rate	log(group size) + wind force	0.60
Herring gull	Hazard-rate	log(group size) + wind force	0.58
Great black-backed gull	Hazard-rate	log(group size) + wind force	0.71
Black-legged kittiwake	Hazard-rate	log(group size) + wave height	0.55
Sandwich tern	Hazard-rate	log(group size)	0.67
Common tern	Hazard-rate	log(group size)	0.59
Common guillemot	Hazard-rate	group size + wind force	0.54
Razorbill	Hazard-rate	log(group size) + wind force	0.58

3.3. BACI modelling results

3.3.1. Northern fulmar

During the operational phase of the Thornton Bank OWF, the number of northern fulmars was low both in the control and impact area (fig. 4, right panel), in line with an overall decrease in densities in the BPNS. Within the "OWF footprint + 0.5 km" area, no birds were observed at all after wind farm construction, explaining the empty space in the left panel of fig. 4 and the extreme values in table 4 (a strongly negative OWF coefficient of -28.65 combined with a rounded P-value of 1.000). For both the "OWF footprint + 3 km" and "buffer 0.5 - 3 km" areas, the OWF coefficients were negative (-1.44 and -0.77) yet not significantly different from zero, and the same accounted for the MMI coefficient of -1.49 for the buffer area. In conclusion, despite good indications of avoidance of at least the wind farm footprint area no statistically significant effect of the Thornton Bank OWF on the numbers of northern fulmar could be detected.

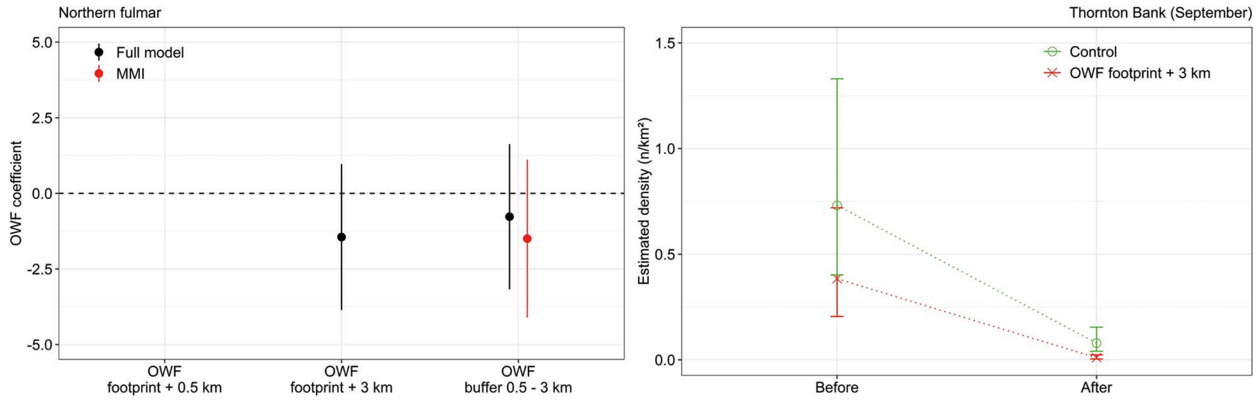

Figure 4. Modelling results for northern fulmar in the Thornton Bank study area with OWF coefficients and their 95% confidence intervals on the left and BACI density estimates (±SE) for the month with maximum numbers on the right.

3.3.2. Northern gannet

Results for northern gannets showed strongly negative and significant MMI and full model OWF coefficients of -4.20 and -4.05 respectively (both implying 98% lower numbers than expected) for the "OWF footprint + 0.5 km" area (fig. 5). OWF coefficients for the buffer area were much less pronounced and not significant, with values of -0.49 and -0.29 estimated through the MMI and full model respectively. Concluding, northern gannets showed strong displacement of the Thornton Bank OWF footprint area, yet this effect was no longer apparent in the surrounding buffer zone.

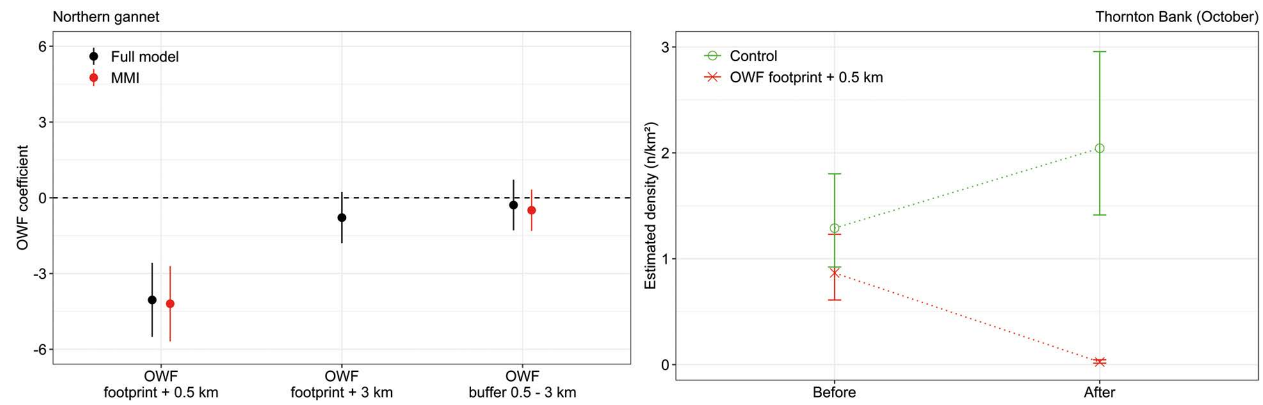

Figure 5. Modelling results for northern gannets in the Thornton Bank study area with OWF coefficients and their 95% confidence intervals on the left and BACI density estimates (± SE) for the month with maximum numbers on the right.

3.3.3. Great cormorant

With only 9 observations of 1 to 4 birds prior to April 2008, great cormorants were virtually absent in the study area before wind farm construction. Post-construction observations were much more numerous but largely limited to turbine-associated birds in the impact area (143 individuals, see table 2) and to only 6 observations of 1 to 5 birds in the control area. Not unexpectedly, this species showed strongly positive and significant displacement coefficients. For the footprint area, MMI and full model OWF coefficients equalled 3.69 and 3.77, representing an increase in numbers with factors 40 and 43 respectively. For the buffer zone, a 17-fold increase in numbers was predicted by the full model (OWF coefficient = 2.86). Great cormorants were thus found to be strongly attracted to the Thornton Bank wind farm area and its immediate surroundings (fig. 6).

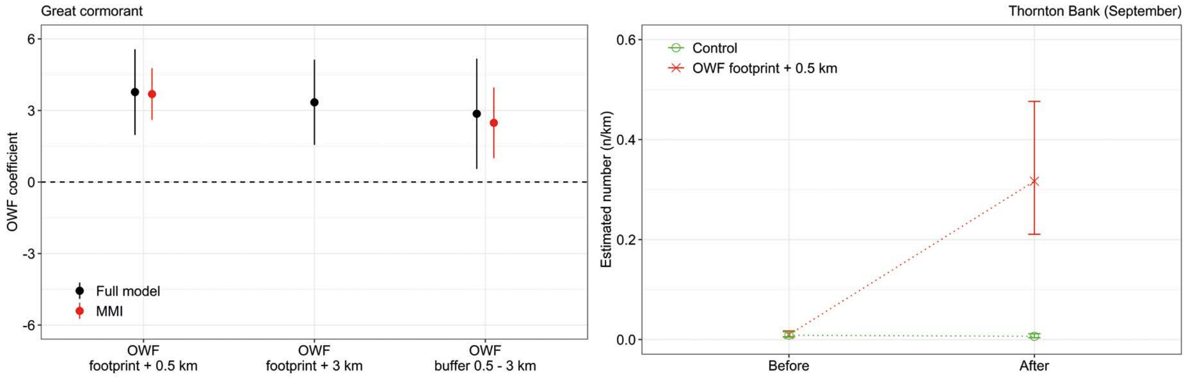

Figure 6. Modelling results for great cormorants in the Thornton Bank study area with OWF coefficients and their 95% confidence intervals on the left and BACI estimates of the number observed per km (± SE) for the month with maximum occurrence on the right.

3.3.4. Great skua

As for northern fulmar, no great skuas were observed inside the wind farm, hampering meaningful statistics and explaining the empty space in the left panel of fig. 7. All other coefficients were found positive, but only the full model OWF coefficient of 2.54 for the buffer area appeared to be statistically significant. The results thus indicate avoidance of the footprint area (no post-construction observations!) combined with attraction towards the immediate surroundings of the wind farm. But considering the generally very low encounter rate in the study area (0.014 birds per km²), combined with a lack of consistency between MMI and full model coefficient significance, the results for great skua should be interpreted with care and firm conclusions are difficult to draw.

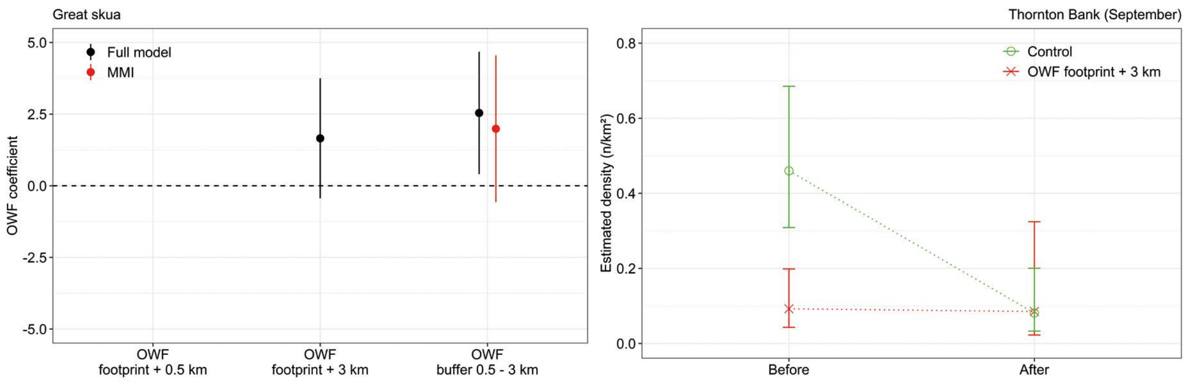

Figure 7. Modelling results for great skua in the Thornton Bank study area with OWF coefficients and their 95% confidence intervals on the left and BACI density estimates (± SE) for the month with maximum numbers on the right (but note that the zero inflation of 71% is not accounted for in these estimates).

3.3.5. Little gull

As in previous reports, the results for little gull showed an interesting pattern of avoidance of the OWF footprint area (negative coefficients of -1.64 and -1.75 for the full model and MMI alternative), opposed to attraction to the surrounding buffer zone (positive coefficients of 1.12 and 1.03) (fig. 8). Neither full model nor MMI OWF coefficients, however, proved statistically significant, leaving the results for little gull inconclusive.

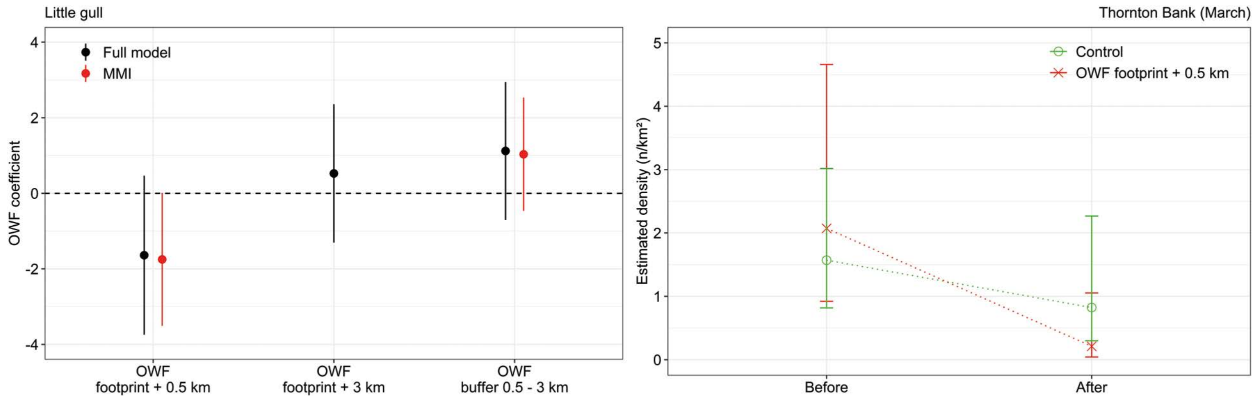

Figure 8. Modelling results for little gull in the Thornton Bank study area with OWF coefficients and their 95% confidence intervals on the left and BACI density estimates (±SE) for the month with maximum numbers on the right.

3.3.6. Common gull

Between the reference and impact period, numbers of common gull in the study area increased (fig. 9, right panel). This increase, however, was less prominent in the wind farm area and its immediate surroundings, resulting in negative full model OWF coefficients ranging between -1.25 and -0.61 for all three data selections. None of these, however, nor the highly similar MMI coefficients, significantly differed from zero and no firm conclusions on the effect of the Thornton Bank OWF on the presence of common gulls can therefore be drawn.

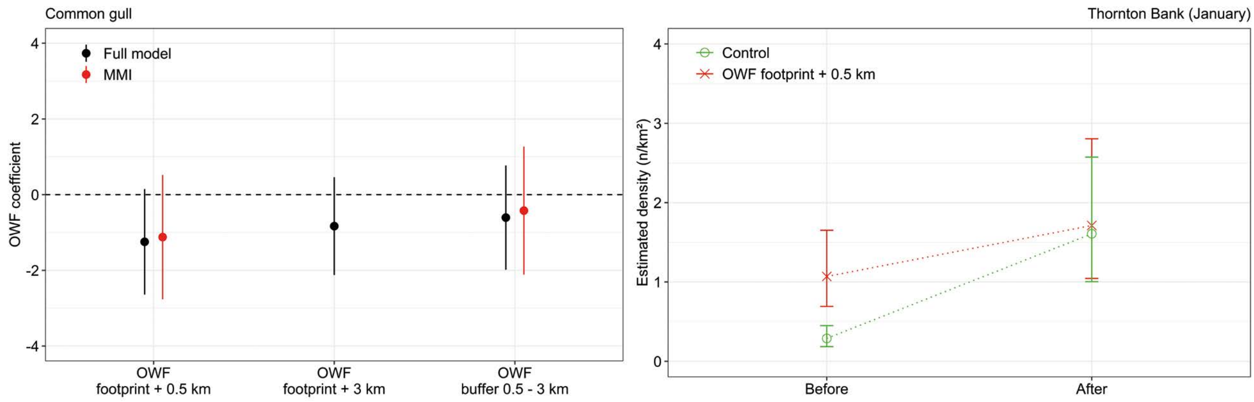

Figure 9. Modelling results for common gull in the Thornton Bank study area with OWF coefficients and their 95% confidence intervals on the left and BACI density estimates (± SE) for the month with maximum numbers on the right.

3.3.7. Lesser black-backed gull

The full model OWF coefficients for lesser black-backed gull were all found to be above zero, ranging between 0.40 and 0.81, with little variation caused by including or excluding turbine-associated birds. The MMI coefficients were slightly lower with values between 0.22 and 0.48 (fig. 10). None of these coefficients, however, significantly differed from zero, leaving the results for lesser black-backed to be inconclusive.

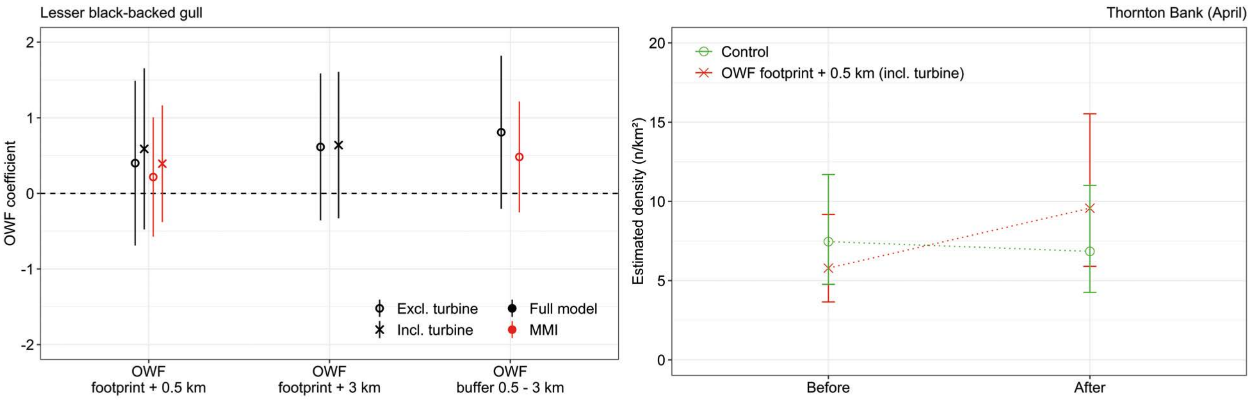

Figure 10. Modelling results for lesser black-backed gull in the Thornton Bank study area with OWF coefficients and their 95% confidence intervals on the left and BACI density estimates (± SE) including turbine-associated birds for the month with maximum numbers on the right.

3.3.8. Herring gull

Positive MMI and full model OWF coefficients were found for all data selections, suggesting an overall attraction of herring gulls to the wind farm area (fig. 11). These effects were generally not statistically significant, except when modelling the adjusted response (including turbine-associated birds) for the “OWF footprint + 0.5 km” area. For the latter, the full model predicts a density 4.9 times higher compared to the value expected based on the trend in the control area (OWF coefficient = 1.58). The MMI alternative prediction also differed significantly from zero, representing a factorial effect of 3.8 (MMI OWF coefficient = 1.33). In conclusion, a significant attraction effect of herring gulls to the footprint area of the Thornton Bank wind farm could be demonstrated, provided birds associated with the turbines are included in the analysis.

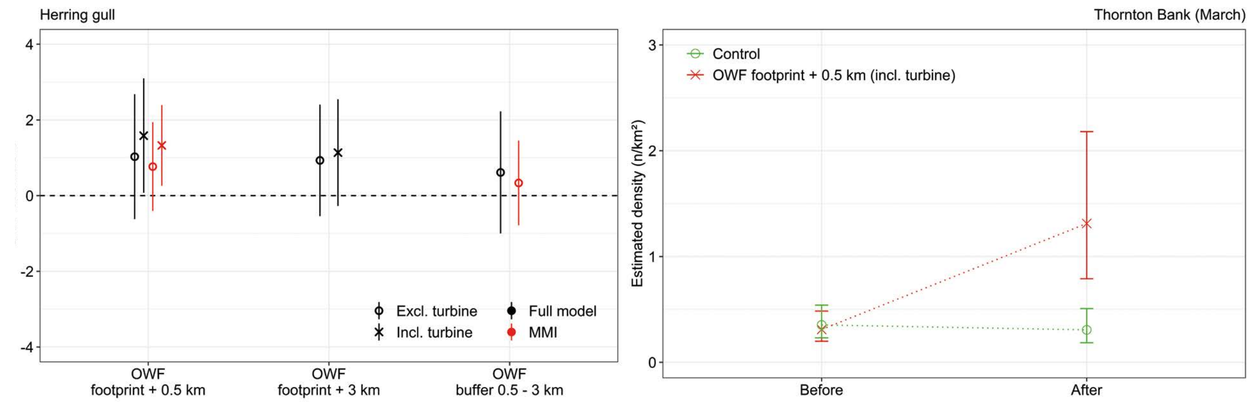

Figure 11. Modelling results for herring gull in the Thornton Bank study area with OWF coefficients and their 95% confidence intervals on the left and BACI density estimates (± SE) including turbine-associated birds for the month with maximum numbers on the right.

3.3.9. Great black-backed gull

Highly positive and significant OWF coefficients were found for great black-backed gull occurrence inside the wind farm footprint, provided birds roosting on the turbines were included in the analysis (*i.e.* applying the adjusted response variable). For the footprint area, the full model OWF coefficient equalled 1.67, implying a 5.3 times higher density than expected, with the MMI coefficient being even more pronounced with a value of 1.89 and a factorial effect of 6.6 (fig. 12). Interestingly, model coefficients when not including turbine-associated birds as well as those obtained for the buffer area all approached zero, emphasising the important role of turbine-association in the observed attraction effect of great black-backed gulls towards the Thornton Bank wind farm.

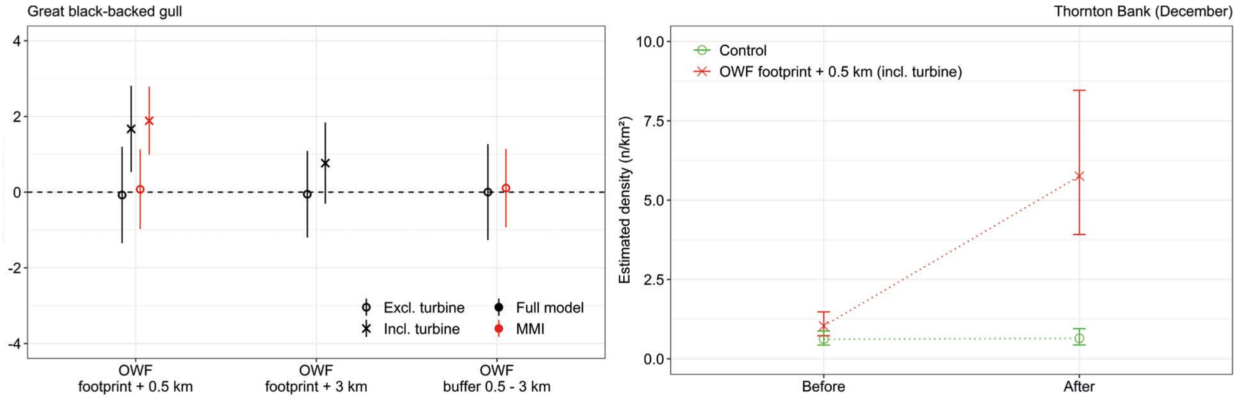

Figure 12. Modelling results for great black-backed gull in the Thornton Bank study area with OWF coefficients and their 95% confidence intervals on the left and BACI density estimates (± SE) including turbine-associated birds for the month with maximum numbers on the right.

3.3.10. Black-legged kittiwake

Results for this species showed comparison with those for little gull, indicating avoidance of the footprint area opposed to attraction to the buffer zone (fig. 13). For the footprint area, only the MMI effect appeared significant (MMI coefficient = -1.16, *i.e.* a 69% decrease), while for the buffer area this was exclusively so for the full model OWF coefficient (= 1.54, *i.e.* a 4.7 factorial increase). Due to inconsistency between the significance levels of the MMI and full model OWF coefficients, the results for black-legged kittiwake should yet be regarded as inconclusive.

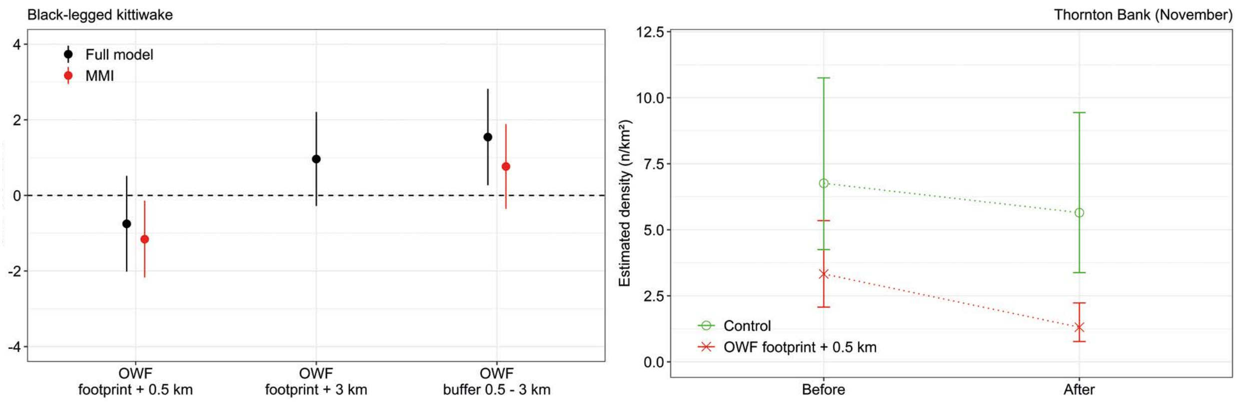

Figure 13. Modelling results for black-legged kittiwake in the Thornton Bank study area with OWF coefficients and their 95% confidence intervals on the left and BACI density estimates (± SE) for the month with maximum numbers on the right.

3.3.11. Sandwich tern

Due to fitting problems, we only used Sandwich tern data collected from March till September, and no longer considered seasonal variation in the model. Sandwich terns showed a steady trend in the impact area compared to a strong decrease in the control area, resulting in positive OWF coefficients for all three data selections, varying between 1.10 and 2.11 (fig. 14). Only for the buffer zone, the full model OWF coefficient of 2.11 and the MMI coefficient of 1.70 were significantly different from zero, corresponding to factorial changes of 8.2 and 5.5 respectively. The results for Sandwich tern thus suggest attraction at least to the wind farm surroundings, yet should be interpreted with care considering the low number of positive counts after impact (only 10 post-construction observations of 1 up to 17 birds per observation).

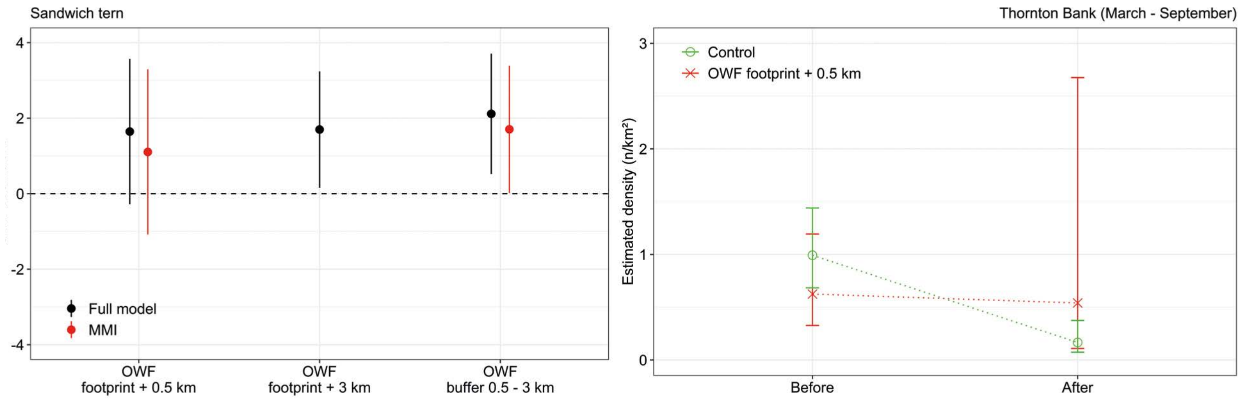

Figure 14. Modelling results for Sandwich tern in the Thornton Bank study area with OWF coefficients and their 95% confidence intervals on the left and BACI density estimates (± SE) for the period March to September on the right (but note that the zero inflation of 77% is not accounted for in these estimates).

3.3.12. Common guillemot

For the "OWF footprint + 0.5 km" area, significantly negative values of -0.92 and -1.00 (corresponding to 60 and 63% decreases) were found for the full model and MMI OWF coefficient respectively (fig. 15). In the buffer zone, these coefficients approached zero. The results for common guillemot thus demonstrate clear displacement of the Thornton Bank wind farm itself, but no such effect in the surrounding buffer zone.

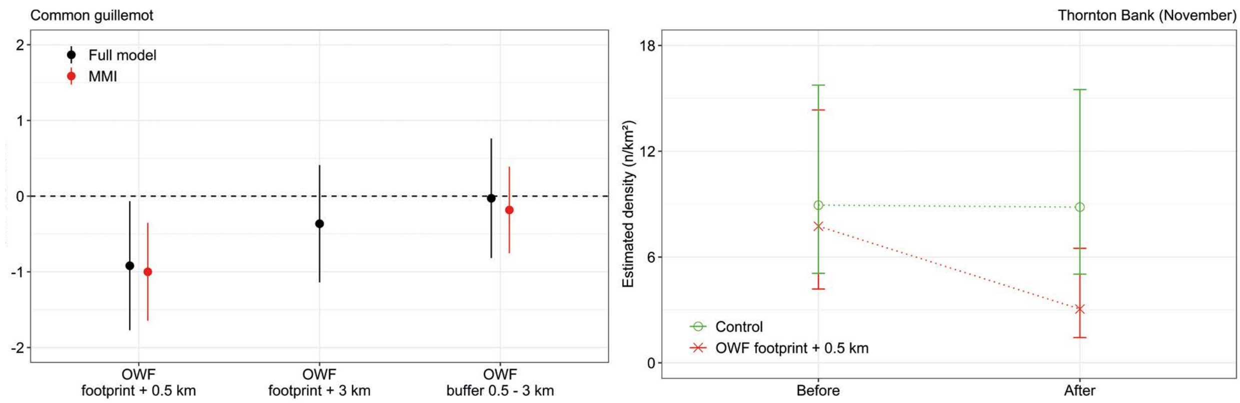

Figure 15. Modelling results for common guillemot in the Thornton Bank study area with OWF coefficients and their 95% confidence intervals on the left and BACI density estimates (± SE) for the month with maximum numbers on the right (but note that the zero inflation of 10% is not accounted for in these estimates).

3.3.13. Razorbill

For razorbill, a highly comparable pattern was found as for common guillemot, with significantly negative footprint coefficients opposed to buffer coefficients approaching zero (fig. 16). The coefficients for the “OWF footprint + 0.5 km” area were estimated at -1.38 and -1.62 through MMI and the full model respectively, corresponding to 75% and 80% lower numbers than expected. As for common guillemot, a clear displacement of razorbills occurred from the Thornton Bank wind farm itself, with no observable effect in the 0.5-3 km buffer zone.

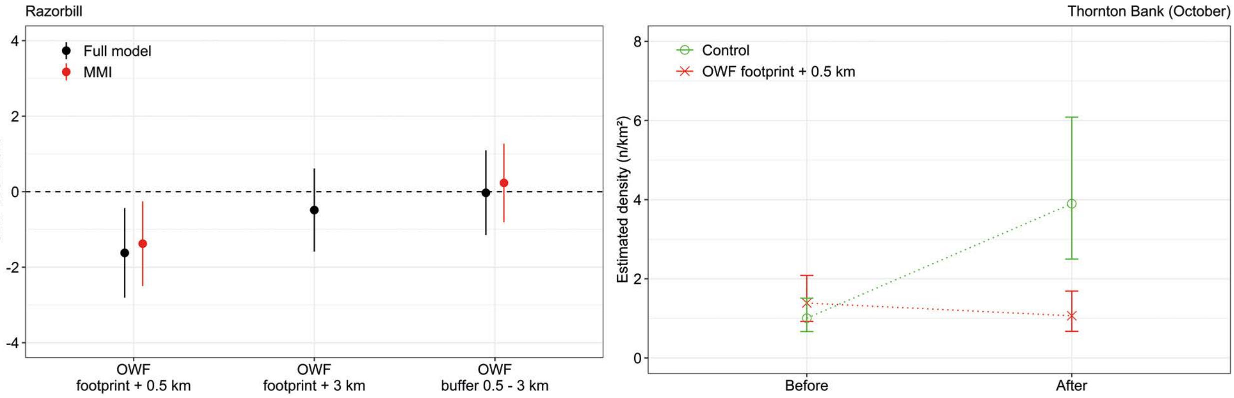

Figure 16. Modelling results for razorbill in the Thornton Bank study area with OWF coefficients and their 95% confidence intervals on the left and BACI density estimates (± SE) for the month with maximum numbers on the right.

3.3.14. Summarising tables

Our BACI monitoring results are summarised in table 4, listing the OWF coefficients and corresponding P-values as estimated throughout the modelling process. The full range of impact model coefficient estimates is listed in table 6 in the appendix.

After six years of post-impact monitoring at the Thornton Bank OWF, the impact area appeared to be avoided by three species, *i.e.* northern gannet, common guillemot and razorbill. In the “OWF footprint + 0.5 km” area, these species dropped in numbers by 98%, 60-63% and 75-80% respectively (the ranges originating from variation between the full model and MMI coefficient estimates). Strikingly, none of these three species appeared to be displaced from the wind farm buffer zone 0.5-3 km away from the wind farm edge. Black-legged kittiwakes too showed avoidance of the wind farm footprint area, yet only the MMI coefficient proved statistically significant.

Attraction to the wind farm footprint area could be demonstrated for herring and great black-backed gulls, for which the BACI models predicted a factorial change in densities of 3.8-4.9 and 5.3-6.6 respectively. These results only account for models including turbine-associated birds by applying the adjusted response variable. Both species were indeed often observed associated with the turbines (table 2). Occurrence of great cormorants too was concentrated on or near the jacket-turbine foundations, and despite their rather low numbers, the species showed major attraction effects and an increase with a factor 40-43 (amplified by the fact that great cormorants were quasi-absent in the study area before wind farm construction). Except for great cormorants aforementioned attraction effects were limited to the wind farm footprint area.

Table 4. BACI monitoring results for the C-Power wind farm at the Thornton Bank after 6 years of operation, listing full model OWF coefficients (and their P-values) and MMI coefficients; model results based on the adjusted response variable for the three large gull species are indicated by "(T)" in the species column; cells in bold indicate a statistically significant model coefficient, while coloured text indicates consistency in significance between the full model and MMI coefficient

	OWF footprint + 0.5 km			**OWF footprint + 3 km**		**OWF buffer 0.5-3 km**		
SPECIES	Full model	P-Value	MMI	Full model	P-Value	Full model	P-Value	MMI
Northern fulmar	-28.65	1.000	/	-1.44	0.240	-0.77	0.529	-1.49
Northern gannet	**-4.05**	**0.000**	**-4.20**	-0.78	0.129	-0.29	0.573	-0.49
Great cormorant	**3.77**	**0.000**	**3.69**	**3.34**	**0.000**	**2.86**	**0.015**	**2.48**
Great skua	-114.17	0.998	/	1.66	0.121	**2.54**	**0.020**	1.99
Little gull	-1.64	0.127	-1.75	0.52	0.574	1.12	0.229	1.03
Common gull	-1.25	0.079	-1.12	-0.83	0.207	-0.61	0.387	-0.42
Lesser black-backed gull	0.40	0.471	0.22	0.61	0.215	0.81	0.117	0.48
Lesser black-backed gull (T)	0.59	0.278	0.39	0.64	0.196			
Herring gull	1.03	0.221	0.77	0.93	0.216	0.61	0.455	0.34
Herring gull (T)	**1.58**	**0.040**	**1.33**	1.14	0.114			
Great black-backed gull	-0.08	0.907	0.07	-0.05	0.926	0.00	0.998	0.11
Great black-backed gull (T)	**1.67**	**0.004**	**1.89**	0.77	0.160			
Black-legged kittiwake	-0.75	0.245	**-1.16**	0.96	0.129	**1.54**	**0.018**	0.77
Sandwich tern	1.64	0.094	1.10	**1.70**	**0.031**	**2.11**	**0.009**	**1.70**
Common guillemot	**-0.92**	**0.034**	**-1.00**	-0.36	0.357	-0.03	0.943	-0.18
Razorbill	**-1.62**	**0.007**	**-1.38**	-0.49	0.387	-0.03	0.960	0.23

Interestingly, some species showed (indications of) attraction to the surrounding buffer area, *i.e.* great skua, little gull, black-legged kittiwake and Sandwich tern, which except for the latter coincided with (indications of) avoidance of the footprint area. The OWF coefficients obtained for these species, however, were mostly not significant. Only for Sandwich tern we found consistency in statistical significance between the full model and MMI coefficients estimating the observed attraction to the wind farm buffer zone.

3.4. Explorative INLA analysis

3.4.1. Data selection

Five post-construction surveys were selected based on their coverage of the study area, the total number of guillemots counted and the proportion of non-zero counts. As such, numbers counted inside the transect varied from 93 to 173 and the proportion of non-zero counts between 29 and 46% (fig. 17).

3.4.2. INLA model results

We fitted four different Poisson models using INLA: one without spatial correlation, one with spatial correlation (estimated across surveys), one with replicated spatial correlation (estimated for each survey) and a last one with replicated spatial correlation including an area factor assigning counts to either the control, buffer or impact area. Doing so, we observed strong successive decreases in the wAIC values of the fitted models (table 5) implying that

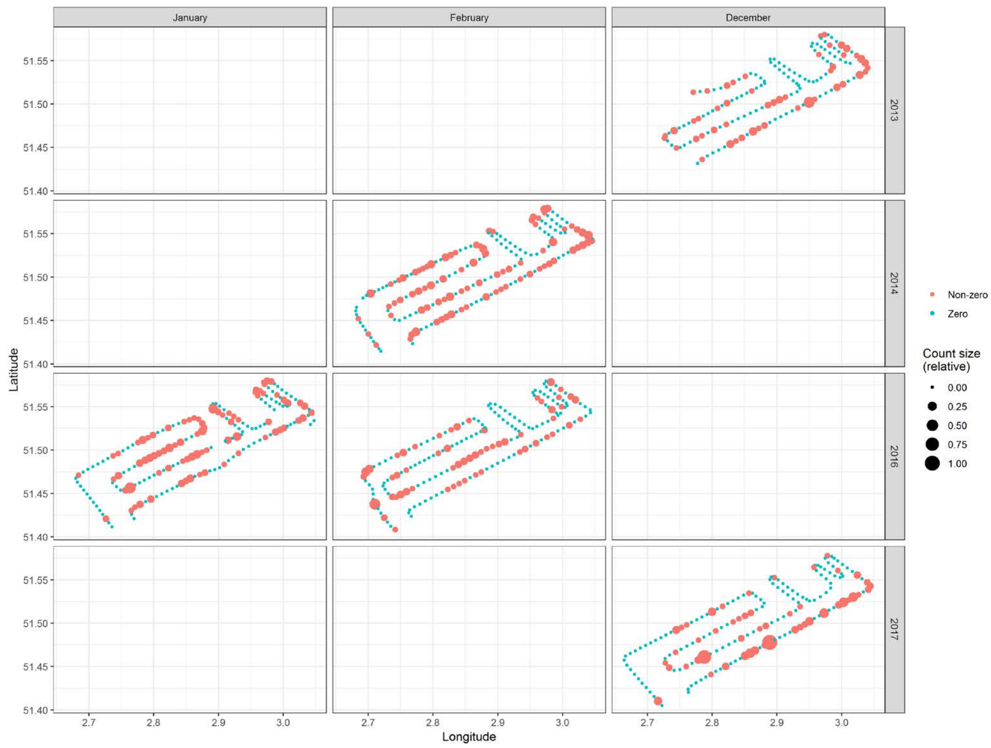

Figure 17. Count results for common guillemot during the five post-construction surveys used in the explorative INLA analysis (coloured red symbols indicate positive observations and symbol size indicates count size relative to the maximum single count of 24 guillemots in the data subset).

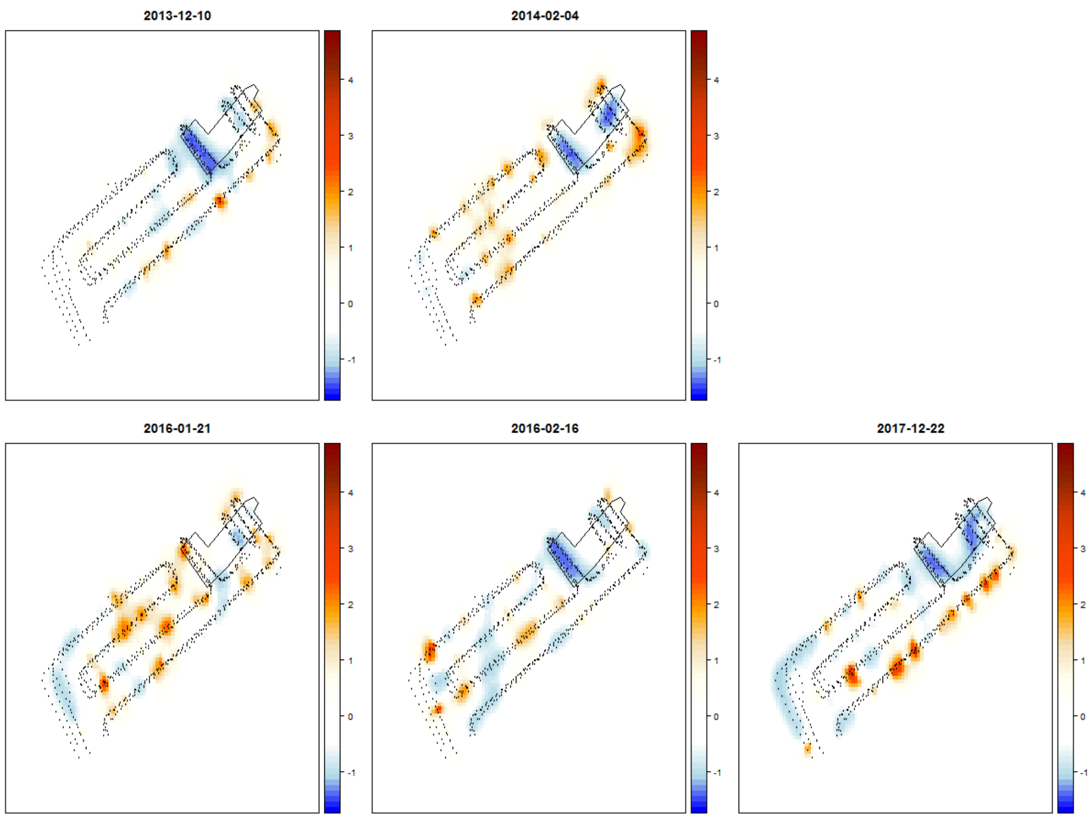

Figure 18. Spatial random field values (projected on a 100 x 100 dimension grid) as obtained through the “Poisson + repl. SRF” model of common guillemot numbers encountered during five surveys in the Thornton Bank study area (with the wind farm border indicated by the black polygon).

Table 5. INLA models results in terms of wAIC values (SRF = spatial random field)

Model type	wAIC
Poisson	2604.2
Poisson + SRF	2205.0
Poisson + replicated SRF	1839.7
Poisson (incl. area factor) + replicated SRF	1822.1

accounting for spatial correlation, especially when replicated for the different surveys, resulted in major model improvement.

A distribution plot of the "Poisson + repl. SRF" spatial random field across the study area (fig. 18) can be regarded as a heat map of unexplained variance, with blue areas (~ negative values of the spatial random field) delineating zones where occurrence appeared to be lower than expected by the (fixed part of the) model, whereas red areas highlight zones with higher occurrence. Looking at fig. 18, interestingly, this pattern of hot and cold spots varies strongly between surveys, except for the clear and recurrent cold spots prevailing inside the wind farm boundaries in 4 out of 5 surveys, which provides strong indication of a wind farm displacement effect.

To quantitatively estimate this wind farm displacement effect, we plotted density plots of the spatial random field values obtained at grid locations falling within the wind farm boundaries (fig. 19). These plots show that most values are indeed below zero, with a mean of -0.60 across surveys, representing 45% lower numbers of common guillemot inside compared to outside the wind farm.

When including an area factor in the model, the recurrent cold spots inside the wind farm are no longer visible when plotting the spatial random field (fig. 20), as the effect is absorbed by the factor variable in the fixed part of the model. Instead, we obtained an "important" coefficient value of -1.50 for the impact area, corresponding to 78% lower numbers. Note that in Bayesian analyses, a coefficient is regarded as "important" when the 95% credible interval of its posterior probability distribution does not contain zero (which would imply no effect) (fig. 21).

As a final step, we performed a simulation exercise to compare the models' data distribution with the original data distribution. For this specific "high count" data subset, a Poisson distribution performed quite well in predicting the number of zeros present in the original data (fig. 22).

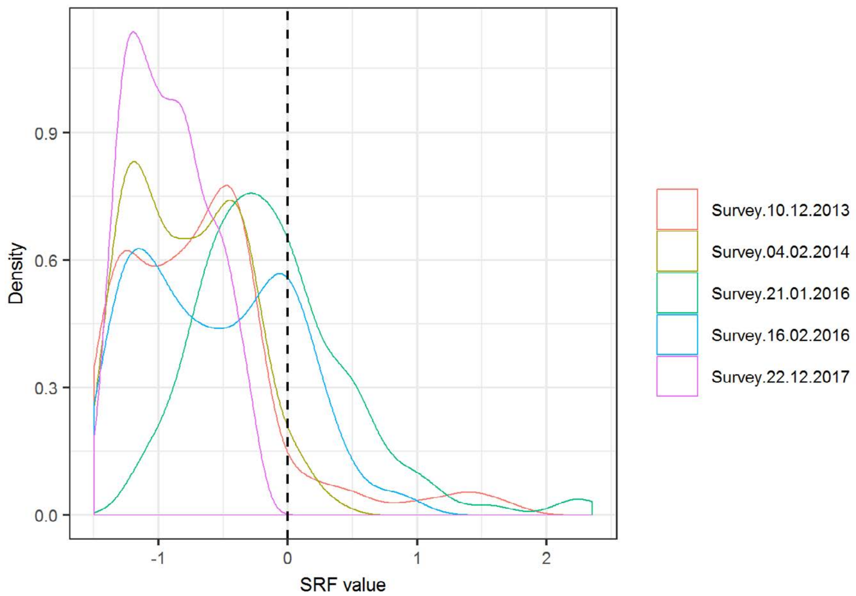

Figure 19. Density-plots of the spatial random field values within the wind farm boundaries for each of the five surveys.

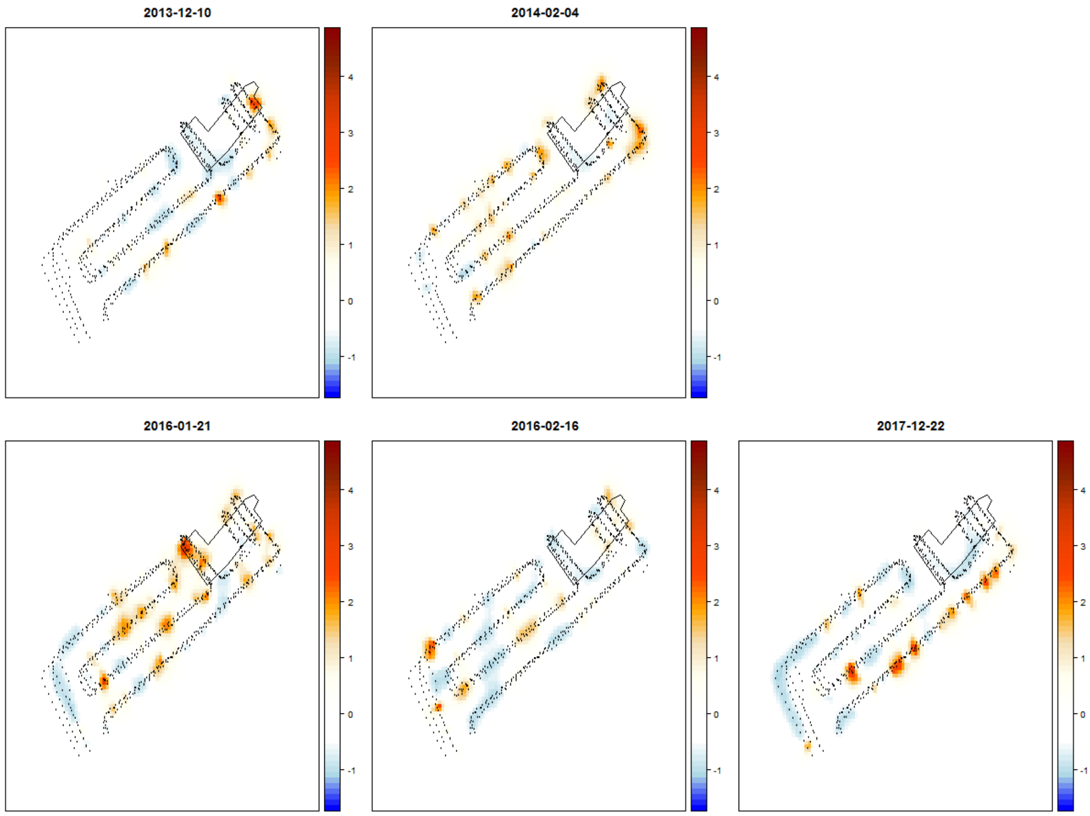

Figure 20. Spatial random field (projected on a 100 x 100 dimension grid) as obtained through the "Poisson (incl. area factor) + repl. SRF" model of common guillemot numbers encountered during five surveys in the Thornton Bank study area (with the wind farm border indicated by the black polygon).

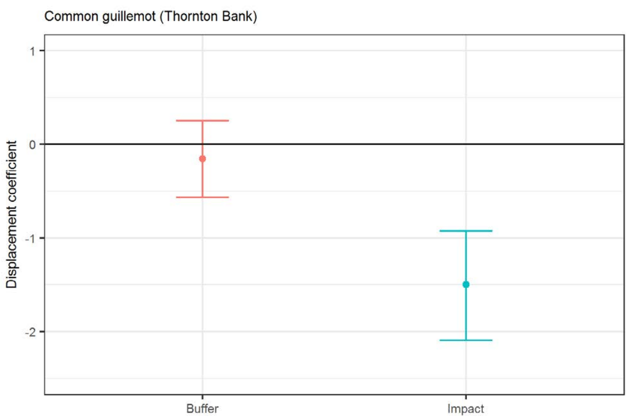

Figure 21. Posterior mean coefficient estimates for the area factor as estimated by the "Poisson (incl. area factor) + repl. SRF" model with indication of the 95% credible interval.

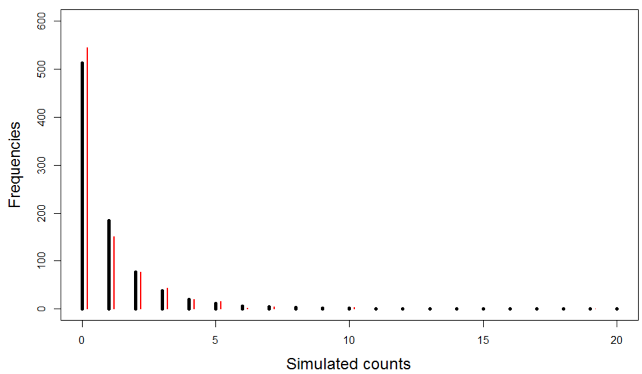

Figure 22. Average frequency table of simulated bird counts based on the "Poisson (incl. area factor) + repl. SRF" model (200 simulations – black bars) opposed to the original data histogram (red bars).

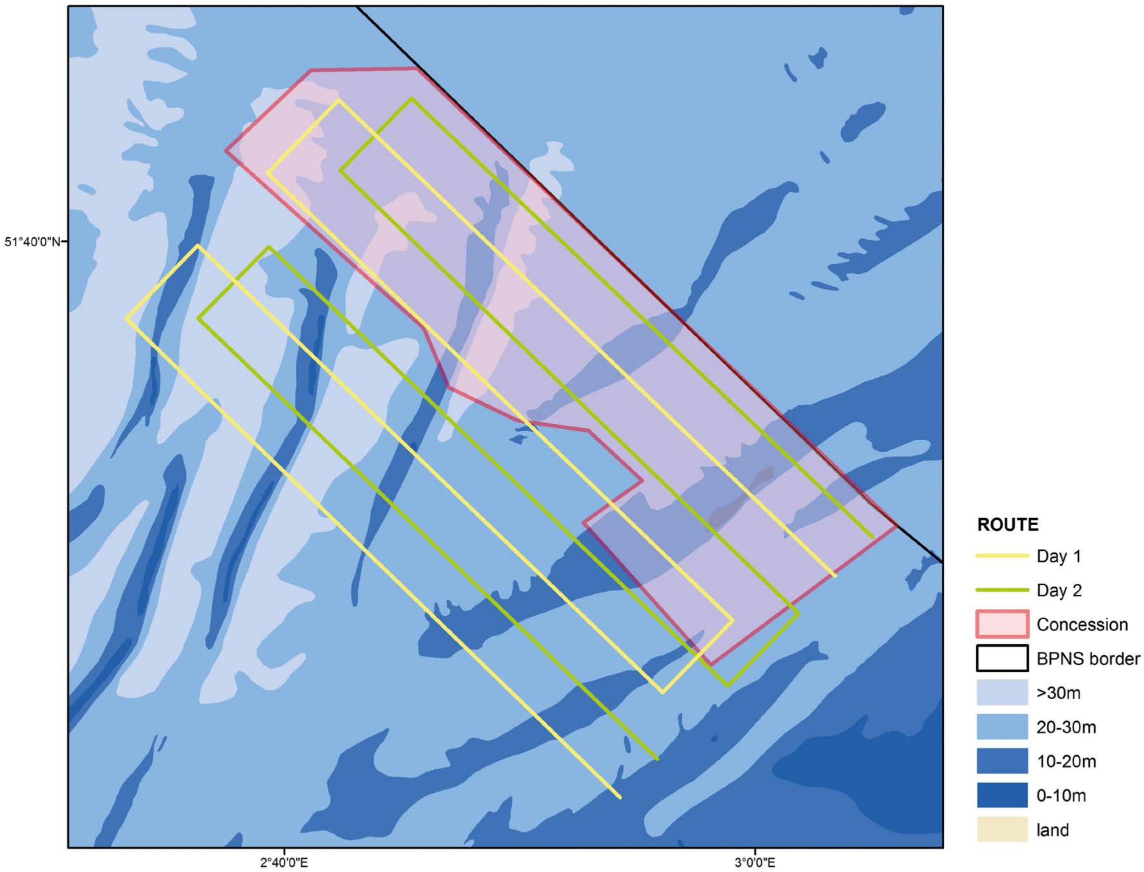

Figure 23. Proposal for a two-day concession-wide seabird displacement monitoring scheme.

3.4.3. Conclusions and future prospects

Depending on the strategy followed, modelling (a subset of) our data in their original resolution and taking into account the spatial correlation predicted common guillemot displacement levels of 45 to 78%, which is comparable to the 63% figure obtained through BACI modelling of day totals per area (yet applying the full dataset including pre-construction data). While the INLA modelling strategy probably needs some fine-tuning (*e.g.* by defining more informative priors), this exercise already illustrates how displacement can successfully be detected using a rather limited set of post-construction data. This offers interesting perspectives towards future monitoring, which will be reoriented towards assessing concession-wide displacement. Up until now our research focused on single isolated wind farm sites surrounded by 3 km buffer zones, but these buffer areas are now increasingly occupied by wind turbines of newly constructed, adjacent wind farms. From a seabird displacement monitoring perspective, the Belgian OWF concession zone should therefore better be considered as one large wind farm cluster from now on. Taking into account the vast area of the concession zone itself, and the need to monitor an equally wide reference area, we propose a two-day monitoring scheme as illustrated in fig. 23. Interestingly, this monitoring scheme can take full account of inshore-offshore gradients in seabird distribution (and possibly in displacement levels), and may also allow to detect other variability in species-specific displacement levels resulting from differences in wind farm configuration.

4. Discussion

4.1. Local displacement results in a wider perspective

We have now conducted 5 and 6 years of post-construction monitoring in and around the Bligh Bank and Thornton Bank offshore wind farms respectively. Compared to the Thornton Bank OWF, the Bligh Bank OWF is located further offshore (46 km) and consists of smaller and more closely spaced 3 MW turbines built on monopile foundations. Yet the results of both displacement studies are highly similar (compare Vanermen *et al.* 2016). In both wind farm areas, northern gannet, common guillemot and razorbill showed a marked and significant decrease in numbers, while the opposite was observed for herring and great black-backed gulls. Only for lesser black-backed gulls, results differed markedly, with a strong attraction effect at the Bligh Bank opposed to non-significant, moderate attraction effects at the Thornton Bank. The estimated effect sizes too are surprisingly alike, *e.g.* avoidance estimates of 82% *vs.* 98% for northern gannet, 75% *vs.* 63% for common guillemot and 67% *vs.* 75% for razorbill, next to factorial increases of 4.3 *vs.* 3.8 for herring gull and 3.6 *vs.* 6.6 for great black-backed gull at the Bligh Bank and Thornton Bank respectively. Avoidance effects at the Thornton Bank were limited to the "footprint + 0.5 km" area, while at the Bligh Bank, common guillemots were also displaced from the "buffer 0.5-3 km" zone.

The wind farm displacement effects found in the BPNS correspond well to other European study results. Based on a comparison of 16 European studies (Vanermen & Stienen 2019), avoidance was reported in 7 out of 9 studies on northern gannet, and wherever detected, displacement seemed to be strong and comparable with Belgian results, *e.g.* reductions of 93% at PAWP, 74% at OWEZ, 95% at Greater Gabbard and 79% at Alpha Ventus (Leopold *et al.* 2013; APEM 2014; Welcker & Nehls 2016). For auks, displacement was confirmed in 5 out of 7 studies on common guillemot, in 6 out of 7 studies on razorbill and in 3 out of 3 studies on auks as a species group. Levels of change were generally less pronounced compared to Belgian results, yet still amounted to 45 and 24% decreases of common guillemots at the Dutch PAWP and OWEZ wind farms, an 80% reduction of razorbills at PAWP and a 75% lower number of auks (common guillemot + razorbill) at the German Alpha Ventus wind farm (Leopold *et al.* 2013; Welcker & Nehls 2016). Great black-backed gulls were found to be attracted to 5 out of 8 study sites, yet the increase in numbers was nowhere as high and pronounced as in the two Belgian wind farms. Lastly, for great cormorants, 4 out of 5 European studies demonstrated strong attraction effects. Results for herring gull, on the other hand, showed inconsistency between European studies, as was the case for quite a number of (mainly gull) species.

In conclusion, offshore displacement studies have thus shown quite good consistency in results for at least some species, opposed to major differences in study outcomes for others. Local parameters such as food abundance in and outside the impacted area, the location of the OWF relative to the colony or feeding grounds and wind farm configuration might all be important in explaining the observed (differences in) responses but are mostly not accounted for in current studies. There is also likely to be a seasonal aspect in a bird's reaction towards wind farms. The Robin Rigg study site for example is the only one included by Vanermen & Stienen (2019) where common guillemots are more abundant during the breeding season than during winter, and one of the few not finding an avoidance response. In winter, common guillemots occur widespread and can be expected to be quite flexible in compensating habitat loss by moving elsewhere to forage (Dierschke *et al.* 2016). Breeding common guillemots, however, become central-place foragers and are more constrained in terms of distribution and habitat choice. As resources become limited, individuals may be prepared to take more risks and be more tolerant of the presence of wind farms (Hötker 2017). Another temporal aspect regarding displacement effects relates to the fact that OWFs are still a relatively new phenomenon, and in time seabirds might habituate to their presence (*e.g.* Drewitt & Langston 2006; Fox *et al.* 2006; Petersen & Fox 2007). The occurrence of common scoters in and around Horns Rev 2 provides a good example of potential habituation. Although assumed to be displaced based on the first three years after wind farm construction, Petersen & Fox (2007) reported common scoters to occur in numbers higher than ever before in the fourth year post-construction, with a maximum of no fewer than 4,624 birds within the wind farm footprint. It was hypothesised that this strong change in distribution suggesting habituation might as well have been due to an unknown shift in food abundance, again emphasising the importance of accounting for local factors such as food availability to increase the reliability of conclusions drawn on wind farm induced seabird displacement.

4.2. Displacement effect versus impact

Importantly, a displacement effect, *i.e.* a change in distribution or numbers, should not be regarded synonymous with a displacement *impact*, which rather refers to changes in fitness and survival (Masden *et al.* 2010a). Birds subject to OWF displacement might respond by flying or swimming around rather than entering the wind farm and/or by spending time searching for alternative foraging habitat, all implying increased energetic costs. The alternative foraging areas may prove to be of minor quality, or may be subject to increased inter- and intraspecific competition due to the inflow of displaced birds, resulting in decreased food intake. Initial behavioural displacement responses may thus eventually lead to decreased body condition, increased mortality and/or decreased productivity (Fox *et al.* 2006; Petersen *et al.* 2014). Importantly, displacement impact is likely to vary with the different stages in the species' annual life cycle, *i.e.* breeding, non-breeding and dispersal/migration periods. During the breeding season, birds suffering from poor body condition due to the displacement may abandon ongoing breeding efforts or not even attempting to breed in a particular year or an even longer period (Furness 2013). Displacement from OWFs within the foraging range of a colony could also result in longer foraging flights, leading to decreased chick provisioning and/or increased chick predation both resulting in reduced chick survival (Searle *et al.* 2014). Crucially, seabirds commuting daily between their breeding colony and feeding grounds may interact with OWFs several times a day and are therefore suspected to be particularly vulnerable to displacement impact (Masden *et al.* 2010b), despite the possibility of being less susceptible to avoidance responses as outlined above. During the non-breeding season, seabirds are no longer constrained to feeding grounds near the colony. On the other hand, mortality of seabirds is often highest in winter, and displacement effects will be additive to other factors causing this annual survival bottleneck. Due to carry-over effects, displacement during winter might further lead to a poor body condition at the onset of the breeding season, again affecting productivity (Dierschke & Garthe 2006; Furness 2013).

The quantitative translation of a displacement effect into its ultimate impact in terms of reproductive success or chances of survival, however, is highly challenging (Fox *et al.* 2006). Crucial parameters to feed population models needed to unravel displacement impact on demographic parameters often lack empirical evidence (Green *et al.* 2016). In the case of seabirds, density-dependency, seabird population carrying capacities as well as spatio-temporal variation in habitat quality are all important knowledge gaps. Seabird colony size for example is considered to be limited by intraspecific competition for food within the foraging range (Furness & Birkhead 1984), highlighting the potential ecological consequences of reducing the foraging habitat available to a specific colony. But while there is (some) evidence of density-dependency affecting seabird populations during the breeding season, there is virtually no mentioning of such mechanisms occurring during the non-breeding season, which is no surprise as seabirds are much more difficult to study in their extensive offshore winter ranges (Busch *et al.* 2015). The assessment of relative habitat quality is also key to reliably assess displacement impacts on seabirds as displacement from poor instead of high-quality habitat is anticipated having less impact (Furness 2013; Warwick-Evans *et al.* 2017). Another knowledge gap highlighted by Searle *et al.* (2014) is the relationship between adult body mass and expected survival over the following year, which would help to quantify aforementioned carry-over effects, and accordingly, there is very few empirical information on the effect of fledging chick mass on post-fledging survival.

While a single OWF generally affects only small numbers of birds relative to their population sizes, the cumulative impact of all current and future developments may be severe and potentially even greater than the sum of single wind farm impacts (Masden *et al.* 2010a). Displacement affecting birds during the non-breeding season at a location several thousands of kilometres away from the colony may have fitness consequences that only become apparent a few months later during the breeding season or even in the years thereafter. Ideally, a cumulative impact assessment therefore includes all existing and new wind farm developments within the year-round distribution range of the species or population under study. Several cumulative impact assessments based on individual-based models have been conducted so far (Topping *et al.* 2011; Searle *et al.* 2014; Warwick-Evans *et al.* 2017), all showing that displacement effects may indeed have consequences for individual fitness and survival, which may ultimately lead to seabird population declines. The models applied, however, still rely on numerous assumptions on key seabird ecology aspects. Filling in the knowledge gaps highlighted in this discussion would support a more reliable assessment of the actual and cumulative ecological consequences of extensive offshore wind farm installations and should be the primary goal of future research.

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Appendix

Table 6. Impact model coefficients for all species studied in the Thornton Bank OWF study area (zero-inflation shown in the response scale, all other coefficients in the link scale)

Species	Impact polygon	Intercept	Sin (1yr)	Cos (1yr)	Sin (1/2yr)	Cos (1/2yr)	Sin (1/4yr)	Cos (1/4yr)	BA	CI	Fishery	OWF	Theta	Zero-inflation
Northern fulmar (GLM NB)	OWF footprint + 0.5 km	-1.37	-0.83	0.51					-2.39	-0.62	0.99	-28.65	0.08	
	OWF footprint + 3 km	-1.29	-0.98	0.11					-2.22	-0.64	0.76	-1.44	0.07	
	OWF buffer 0.5 - 3 km	-1.30	-0.99	0.12					-2.22	-0.64	0.76	-0.77	0.07	
Northern gannet (GAM NB)	OWF footprint + 0.5 km	-0.47	s(month)						0.46	-0.40	0.34	-4.05	0.32	
	OWF footprint + 3 km	-0.40	s(month)						0.03	-0.48	0.27	-0.78	0.31	
	OWF buffer 0.5 - 3 km	-0.43	s(month)						0.05	-0.46	0.29	-0.29	0.31	
Great cormorant (GLM NB)	OWF footprint + 0.5 km	-6.15	-0.03	0.86	0.11	-1.36			-0.29	0.12		3.77	0.47	
	OWF footprint + 3 km	-6.31	-0.10	1.18	0.09	-1.49			-0.29	0.16		3.34	0.46	
	OWF buffer 0.5 - 3 km	-6.53	0.39	1.85	-0.34	-1.81			-0.42	-0.25		2.86	0.16	
Great skua (ZIP)	OWF footprint + 0.5 km	-2.40	-1.50	-0.02					-1.68	-1.64	-0.26	-114.17		0.66
	OWF footprint + 3 km	-2.28	-1.51	0.16					-1.73	-1.61	-0.50	1.66		0.71
	OWF buffer 0.5 - 3 km	-2.29	-1.59	0.22					-1.67	-1.59	-0.57	2.54		0.73
Little gull (GLM NB)	OWF footprint + 0.5 km	-2.57	2.31	2.29	-1.90	-0.70			-0.65	0.28		-1.64	0.12	
	OWF footprint + 3 km	-2.65	2.30	2.40	-1.95	-0.70			-0.63	0.31		0.52	0.12	
	OWF buffer 0.5 - 3 km	-2.63	2.29	2.39	-1.94	-0.71			-0.63	0.30		1.12	0.12	
Common gull (GLM NB)	OWF footprint + 0.5 km	-4.35	2.53	3.15	-0.86	-0.28			1.72	1.31	0.50	-1.25	0.29	
	OWF footprint + 3 km	-4.38	2.39	3.26	-0.70	-0.40			1.61	1.39	0.20	-0.83	0.30	
	OWF buffer 0.5 - 3 km	-4.35	2.34	3.21	-0.57	-0.37			1.65	1.45	0.02	-0.61	0.26	
Lesser black-backed gull (GAM NB)	OWF footprint + 0.5 km	-0.31	s(month)						-0.08	-0.24	0.69	0.40	0.31	
	OWF footprint + 0.5 km (T)	-0.23	s(month)						-0.14	-0.27	0.65	0.61	0.33	
	OWF footprint + 3 km	-0.20	s(month)						-0.20	-0.36	0.67	0.81	0.30	
	OWF footprint + 3 km (T)	-0.31	s(month)						-0.09	-0.25	0.68	0.59	0.32	
	OWF buffer 0.5 - 3 km	-0.23	s(month)						-0.14	-0.27	0.65	0.64	0.33	

Species	Impact polygon	Intercept	Sin (1yr)	Cos (1yr)	Sin (1/2yr)	Cos (1/2yr)	Sin (1/4yr)	Cos (1/4yr)	BA	CI	Fishery	OWF	Theta	Zero-inflation
Herring gull (GLM NB)	OWF footprint + 0.5 km	-2.27	1.24	0.12					-0.14	-0.12	0.71	1.03	0.15	
	OWF footprint + 0.5 km (T)	-2.28	1.19	0.29					-0.31	-0.18	0.80	0.93	0.17	
	OWF footprint + 3 km	-2.39	1.38	0.46					-0.24	-0.24	0.99	0.61	0.15	
	OWF footprint + 3 km (T)	-2.28	1.24	0.17					-0.14	-0.13	0.72	1.58	0.18	
	OWF buffer 0.5 - 3 km	-2.26	1.17	0.29					-0.33	-0.18	0.79	1.14	0.19	
Great black-backed gull (GAM NB)	OWF footprint + 0.5 km	-1.93	s(month)						-0.11	0.49	1.46	-0.08	0.25	
	OWF footprint + 0.5 km (T)	-2.14	s(month)						-0.15	0.51	1.51	-0.05	0.29	
	OWF footprint + 3 km	-2.19	s(month)						-0.15	0.52	1.56	0.00	0.24	
	OWF footprint + 3 km (T)	-1.84	s(month)						0.04	0.52	1.48	1.67	0.31	
	OWF buffer 0.5 - 3 km	-1.95	s(month)						-0.07	0.53	1.44	0.77	0.32	
Black-legged kittiwake (GAM NB)	OWF footprint + 0.5 km	-0.14	s(month)						-0.18	-0.71	0.72	-0.75	0.24	
	OWF footprint + 3 km	-0.15	s(month)						-0.65	-0.92	0.48	0.96	0.22	
	OWF buffer 0.5 - 3 km	-0.11	s(month)						-0.70	-0.95	0.43	1.54	0.20	
Sandwich tern (ZINB)	OWF footprint + 0.5 km	-0.01	/						-1.79	-0.46		1.64	2.11	0.77
	OWF footprint + 3 km	-0.05							-1.93	-0.44		1.70	1.72	0.75
	OWF buffer 0.5 - 3 km	-0.04							-1.92	-0.45		2.11	1.73	0.77
Common guillemot (ZINB)	OWF footprint + 0.5 km	-2.79	1.67	6.57	-1.27	-1.94			-0.01	-0.14		-0.92	0.91	0.10
	OWF footprint + 3 km	-2.97	1.81	6.83	-1.41	-2.11			-0.14	-0.14		-0.36	0.91	0.11
	OWF buffer 0.5 - 3 km	-3.05	1.89	6.95	-1.49	-2.14			-0.13	-0.15		-0.03	0.89	0.10
Razorbill (GAM NB)	OWF footprint + 0.5 km	-4.13	s(month)						1.36	0.32		-1.62	0.40	
	OWF footprint + 3 km	-4.90	s(month)						1.08	0.30		-0.49	0.41	
	OWF buffer 0.5 - 3 km	-4.82	s(month)						1.05	0.29		-0.03	0.40	