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Bird monitoring at offshore wind farms in the Belgian part of the North Sea

Assessing seabird displacement effects

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Samenvatting

Sinds 2005 doet het Instituut voor Natuur- en Bosonderzoek (INBO) onderzoek naar de effecten van offshore windmolenparken op zeevogels. Hierbij wordt in de eerste plaats onderzocht in welke mate de aanwezigheid van windmolens de lokale verspreiding van zeevogels beïnvloedt. Daartoe voert het INBO reeds sinds 2005, drie jaar voor de bouw van de allereerste offshore windturbine, maandelijks gestandaardiseerde zeevogeltellingen uit in de impact- en controlegebieden van de twee momenteel operationele windparken. Het monitoringsonderzoek beantwoordt aldus aan de principes van een zogenaamde BACI monitoring. De resultaten van deze tellingen werden geanalyseerd aan de hand van 'zero-inflated' negatief binomiaal modellen, die rekening houden met de extreme variatie en overmaat aan nul-tellingen eigen aan zeevogeldata. Deze modellering liet ook toe om fictieve datasets te simuleren, en te onderzoeken hoe de 'power' van onze analyse, zijnde de kans om veranderingen in zeevogeldichtheden statistisch op te merken, beïnvloed wordt door soort-specifieke verspreidingskarakteristieken alsook door monitoringsduur en telinspanning.

De power-analyses gaven aan dat het tot tien jaar kan duren eer er voldoende power (90%) is bereikt om veranderingen van 50-75% in het zeevogelbestand statistisch op te merken. Bij heel wat soorten merkten we inderdaad aantalsveranderingen op zonder dat onze impactanalyse een significant effect kon aantonen. Aangehouden monitoring zal op termijn toelaten om beter onderscheid te maken tussen mijd- of aantrekkingsgedrag enerzijds, en indifferentie anderzijds.

Toch zijn er enkele jaren na de bouw van de eerste offshore windparken wel degelijk veranderingen merkbaar. Op de Thorntonbank namen de aantallen dwergmeeuw, visdief en grote stern in de nabijheid van de eerste zes windmolens duidelijk toe. Aangezien de bewuste turbines op één lijn staan, zijn deze resultaten niet zomaar door te trekken naar een situatie met een twee-dimensionele windparkconfiguratie. Indien de gevonden aantrekkingseffecten echter zouden aanhouden, in een ondertussen volledig operationeel windpark van 54 molens, verdient dit onze maximale aandacht gezien de daaruit voortvloeiende verhoogde kans op aanvaringen en het hoge beschermingsstatuut (Bijlage I) van de betrokken soorten. In het windpark op de Blighbank (55 turbines) zijn de resultaten na drie jaar monitoring eenduidiger. Drie soorten bleken het park te mijden en vertoonden een significante daling in aantallen ten opzichte van het controlegebied alsook ten opzichte van de aantallen die in het studiegebied aanwezig waren voor de bouw van het park. Dit zijn met name jan-van-gent, zeekoet en alk. Anderzijds werden twee soorten in significant hogere dichtheden waargenomen, met name zilvermeeuw en kleine mantelmeeuw. Waarom deze soorten precies worden aangetrokken tot de parken is vooralsnog niet gekend. Tot nu toe werd aangenomen dat deze vogels vooral door het fysieke aspect worden aangetrokken en naar de parken komen om te rusten, maar de laatste tijd zijn er ook meer en meer waarnemingen van actief foeragerende vogels, onder meer van kleine mantelmeeuw en drieteenmeeuw. Dit voedt de hypothese dat de toename aan biomassa en biodiversiteit onder water ondertussen is doorgewerkt naar de hogere trofische niveaus en zich vertaald heeft naar een verhoogd voedselaanbod voor zeevogels. Dit is echter nog zeer hypothetisch en de komende jaren zullen hier hopelijk uitsluitsel over brengen. Wat wel zeker is, is dat aantrekking van zeevogels een verhoogd risico op aanvaringen met zich meebrengt. Zo zijn op de Blighbank meeuwen het meest gevoelig voor aanvaringen, en aan de hand van 'collision risk modelling' worden elk jaar 2.4 meeuwenslachtoffers per turbine verwacht.

Abstract

The Research Institute for Nature and Forest (INBO) is in charge of investigating changes in seabird distribution following the offshore wind farm development at the Belgian part of the North Sea. Since 2005, three years before the construction of the very first offshore wind turbine, INBO therefore performs monthly seabird surveys through the impact and control areas of the two operational wind farms, thus following a BACI approach. To statistically discern seabird displacement effects, these count data were analysed through zero-inflated negative binomial modelling. We further investigated how the statistical power of our impact assessment analysis is related to seabird distribution characteristics as well as to survey length and monitoring intensity.

These power analyses showed that five up to ten years of impact monitoring are needed to obtain sufficient power (90%) to detect a decrease in numbers of 50-75%. At both wind farms, numbers of several species indeed appeared to have changed, but without these changes being statistically significant. With more years of monitoring ahead, our data will allow to better distinguish between true displacement and indifference.

Nevertheless, we already found significant displacement effects. At the Thorntonbank, little gull, sandwich tern and common tern were found to be attracted to the immediate surroundings of the six phase I turbines. These results are highly provisory regarding the one-dimensional configuration of the wind farm at the time of the survey. However, if these attraction effects should persist during the now fully operational and two-dimensional phase of 54 turbines, this is of serious conservational concern given the involved species' high protection status and the associated risk of increased mortality. Three years after the completion of the wind farm at the Blighbank (55 turbines), it showed that northern gannet, common guillemot and razorbill avoided the wind farm. Otherwise, numbers of lesser black-backed and herring gull increased significantly. The question whether these birds are attracted to the wind farm from a sheer physical point of view – with the wind farm functioning as a stepping stone or a resting place – or whether birds already learned to exploit the hypothesised increase in food availability, is yet to be answered. What we do know for sure is that attraction of seabirds inevitably results in an increased number of collision fatalities. As such, 'collision risk modelling' learned that gulls in particular are at risk of colliding with the turbine blades at the Blighbank, with up to 2.4 bird strikes per turbine per year.

1 Introduction

In order to meet the targets set by the European Directive 2009/28/EG on renewable energy, the European Union is aiming at a total offshore capacity of 43 GW by the year 2020. Meanwhile, the offshore wind industry is growing fast and by the beginning of 2013, 1,662 offshore wind turbines were already fully grid-connected in European waters, totalling 5.0 GW (EWEA 2013). The Royal Decree of 17 May 2004 assigned a zone for the production of electricity in the Belgian part of the North Sea (BPNS), comprising almost 7% of the waters under Belgian jurisdiction (an area measuring 238 km²). Current plans are to construct seven wind farms on the BPNS, with a maximum number of 530 turbines. In 2008, C-Power installed the first six wind turbines (30 MW) at the Thorntonbank, located 27 km offshore, followed by the construction 48 more turbines in 2012 (295 MW). In 2009, Belwind constructed 55 turbines (165 MW) at the Blighbank, 42 km offshore. At present 72 turbines are being built at the Lodewijckbank, in between the two operational wind farms, 38 km offshore (MUMM 2013).

Offshore wind farm at the Thorntonbank (photo: Hilbran Verstraete)

Despite its limited surface, the BPNS holds internationally important numbers of seabirds. Possible effects of offshore wind farming on seabirds range from direct mortality through collision, to more indirect effects like habitat change, habitat loss and barrier-effects (Exo *et al.* 2003, Langston & Pullan 2003, Fox *et al.* 2006, Drewitt & Langston 2006, Stienen *et al.* 2007). This research focusses on seabird displacement effects induced by the presence of offshore wind farms. To investigate seabird displacement, the Research Institute for Nature and Forest (INBO) designed a BACI monitoring program and delineated impact and control areas for the two operational wind farm projects. Since 2005, 3 years before the construction of the first offshore turbine, INBO performs monthly seabird surveys across these areas, and developed an impact assessment methodology accounting for the statistical problems inherent to ‘seabirds at sea’ (SAS) data. Densities of flying birds as observed during the seabird surveys inside the Blighbank wind farm further allowed to estimate the number of expected collision victims through collision risk modelling (Band 2012).

2 Birds and offshore wind farms: in short, what do we know?

2.1 Collision

Research focusing on the number of birds colliding with wind turbines shows that in most cases the number of victims is relatively low. Therefore, wind farm related bird mortality is often regarded to be insignificant, especially when compared with the number of casualties in for example traffic. But, a common seabird future is that they are long-lived, have delayed maturity and lay small clutches ('K-strategists'), and small changes in adult survivorship may therefore have a substantial impact on a population level (Stienen *et al.* 2007). When looking at the numbers, there are zero to several tens of victims per year per turbine (Erickson *et al.* 2001, Langston & Pullan 2003, Hötker *et al.* 2006, Drewitt & Langston 2006). The chance for a bird to collide with a turbine blade depends on a number of factors, i.e. species-specific characteristics, weather conditions, topography of the wind farm and its surroundings as well as wind farm configuration (Drewitt & Langston 2006). Naturally, the number of casualties will increase with the number of flights crossing the wind farm, and because of this, wind turbines may locally cause an inacceptable number of victims. At Altamont Pass (USA), Navarra and Tarifa (Spain), each year several tens of birds of prey die after colliding with wind turbines (Orloff & Flannery 1992, SEO/BirdLife 1995, Lekuona 2001). Closer by, in the port of Zeebrugge, there are 27 to 34 bird victims per turbine per year (Everaert & Stienen 2007). More than a third of these victims originate from the nearby tern colony, and the resulting additional mortality due to these collisions is 3.0-4.4% for common tern, 1.8-6.7% for little tern & 0.6-0.7% for sandwich tern.

Turbine collision victim at Zeebrugge (common tern) (photo: Eric Stienen)

Very little is known on the actual number of birds colliding with offshore turbines. Offshore wind farm development is still a relatively new phenomenon, presenting serious logistical challenges to the researcher (Drewitt & Langston 2006). Moreover, counting collision victims beneath the turbines – as is often done onshore – is not an option since bird corpses drift away, sink to the sea floor or are readily scavenged by gulls. Luckily, Band (2012) developed a collision risk model (CRM) to estimate bird collision risk based on technical turbine specifications and wind farm configuration, combined with bird-related parameters (wingspan, flight speed & flight height). The few published research on collision risk in offshore wind farms reports on the use of remote techniques, most notably radar, but also of Thermal Animal Detection Systems (TADS). Radar research during two pilot projects in Denmark (Nysted and Horns Rev) showed that migrating eider ducks strongly avoid flying through the farms, and birds that do enter the wind farms appear to prefer the corridors between the turbines. This way, less than 1% of the approaching ducks and geese are at risk of colliding with a turbine (Desholm 2006). Radar- and TADS-based data were used to model the expected number of migrating eider ducks colliding with turbine blades at the Nysted wind farm, resulting in an estimated 44 individuals per autumn season, i.e. 0.02% of the total number passing the area (Petersen *et al*. 2006). Based on the results of radar research and the use of the Band model, Poot *et al*. (2011) made estimates of the expected number of collision fatalities at the OWEZ offshore wind farm in Dutch waters, totalling 581 birds per year, equalling 0.03% of the total flux through the area. The victims would mainly be passerines (53%), gulls (40%) and cormorants (5%). Based on extensive literature research, the same authors built species-specific population models, and made a first attempt to assess the cumulative effect of collision fatalities at multiple wind farms in the Dutch part of the North Sea. The authors found that the effects of multiple offshore wind farms are far away from the levels above which decreasing population trends would occur.

2.2 Habitat loss due to disturbance

Loss of habitat occurs when birds avoid the wind farm area after visual or auditory detection of the turbines. Unfortunately, most studies on habitat loss are inconclusive due to the lack of before-after and control-impact (BACI) data, which would allow the researcher to correct for temporal and natural variations in numbers (Drewitt & Langston 2006). Land-based research shows that highest disturbance occurs outside the breeding season, and mainly in species of open habitats, with disturbance distances up to several hundreds of meters. Breeding birds appear to be less sensitive, due to a high breeding site fidelity (Pedersen & Poulsen 1991, Drewitt & Langston 2006, Hötker *et al*. 2006).

Pilot projects in Denmark (Horns Rev en Nysted) showed that numbers of divers and long-tailed ducks significantly decreased after wind farm construction. The same Danish researchers also found indication of avoidance by scoters and auks, yet without the results being statistically significant (Petersen *et al*. 2006, Petersen *et al*. 2011). Dutch researchers found significant avoidance for divers, grebes, gannets, little gulls, lesser black-backed gulls and both auks at the OWEZ wind farm in Dutch waters, for at least one or more surveys (Leopold *et al.* 2011).

Displacement effects can be expected to be site-specific. Indeed, little gulls were found to avoid the OWEZ wind farm in the Netherlands (Leopold *et al*. 2011), while there was a post-construction increase of the same species at the Horns Rev wind farm in Denmark (Petersen *et al*. 2006). It is also hypothesised that seabirds may habituate to the presence of wind turbines in their foraging areas, as already shown for cormorants, ducks, gulls and terns at several small coastal wind farms (Dierschke & Garthe 2006). Offshore, Petersen & Fox (2007) found that after five years, densities of common scoters at Horns Rev (Denmark) no longer differed outside compared to inside the wind farm. This could potentially be caused by a change in behavioural response towards the wind turbines, but changes in the distribution of food resources is a possible alternative explanation.

2.3 Habitat change

Habitat change due the presence of wind turbines can result in a change in bird presence. At Altamont Pass (USA), researchers found an increase in food availability near the turbines bases, resulting in increased habitat use by birds of prey. Clearly, this brings about a severe increase in collision risk. A comparable scenario is often hypothesised for offshore wind farms, where the turbine bases function as artificial reefs within an often soft-bottom marine ecosystem. This may locally induce an increase in food availability, resulting in attraction of seabirds. Several studies have already demonstrated the development of hard bottom communities and associated fish (Lemming 1999, Leonhard & Pedersen 2004, Reubens *et al.* 2011).

Offshore wind farms have been shown to attract seabirds, and Danish studies demonstrated an increase of gulls (also little gulls), as well as an increased habitat use of terns just outside the wind farm boundaries. At the OWEZ wind farm in the Netherlands, numbers of great cormorants significantly increased after construction, and in several months, attraction of gulls was observed (Leopold *et al*. 2011). These observations however yet do not provide an answer to the question whether birds are attracted to wind farms from a sheer physical point of view, with the wind farm functioning as a stepping stone or a roosting place, or whether they are attracted due to the hypothesised increase in food availability. A good example of an offshore wind farm functioning as a stepping stone is given by Leopold *et al.* (2011). Large numbers of mainland breeding great cormorants exploit the offshore OWEZ and PAWP wind farms for feeding, and use the met-mast and monopile foundations to rest. The presence of above-water structures is a critical side condition for the occurrence of great cormorants that need to dry their feathers after feeding. Without the presence of the wind farms, these areas would simply be off-limit.

2.4 Barrier effect

Lastly, wind farms may prove to be a barrier for migration and local flying movements. Migrating common eiders and other waterfowl tend to change their flight direction at distances of 1-2 km (at Kalmar Sound, Sweden) or 3-5 km (Nysted, Denmark) (Petterson 2005, Petersen 2006). Petersen (2006) suggests that some migrating birds may even react to the wind farm presence up to distances of 10-15 km. On the other hand, this response distance is significantly lower – down to less than 1 km – at night, and during poor visibility. At Nysted & Horns Rev overall migration intensity was reduced with respectively 57% and 75-85% after wind farm construction (Petersen 2006). The number of common eiders entering the wind farm at Tuno Knob in the Kattegat was 50-53% lower compared to the number passing outside the wind farm (Larsen & Guillemette 2007). At the OWEZ wind farm in the Netherlands, there were 18-34% less birds flying inside the wind farm compared to outside, and flight paths were adjusted 1-2 km before the wind farm (Krijgsveld *et al*. 2011).

Flying around wind farms causes an increase in the birds' flying energy expenditure. Masden *et al*. (2009) showed that this is unlikely to have an impact on a population level, at least not for the common eiders studied at Nysted (Denmark). Significant energetic costs due to increased flying distances are probably only to be expected in cases where very large wind farms are developed on the daily foraging route of breeding birds (Fox *et al*. 2006, Poot *et al*. 2011), or in cases where the cumulative impact of several wind farms along a bird migration route leads to increased flying distances of several tens of miles (Langston & Pullan 2003, Hötker *et al*. 2006, Drewitt & Langston 2006). In this respect it is important to note that the Belgian wind farm concession zone is located in the middle of an important migration bottle neck, but is oriented transversely on to the main migration direction over a distance of nearly 40 kilometres.

2.5 Mitigation measures

The configuration of turbines within a wind farm can play an important role towards bird collision risk. Line shaped wind farms as well as corridors in two-dimensional farms should be oriented parallel to the main flight direction of migrating birds. Individual turbines should offer as few roosting possibilities as possible, since at sea, large numbers of birds can be expected to utilize any possible roosting site. Since birds migrating at night are often attracted to light, illumination should be avoided or at least be minimised. Otherwise, during the day, blades can be difficult to see due to their high rotation speed. Marking the blades with a strongly contrasting pattern or with UV paint would strongly improve their visibility (Hötker *et al*. 2006, Drewitt & Langston 2006).

But the best and possibly the only way to avoid large numbers of casualties is well-planned localisation of wind farms, in areas with low numbers of flying birds, well away from migration corridors, bird colonies and other key areas of conservational importance (Erickson *et al*. 2001, Desholm 2006, Hötker *et al*. 2006). The situation in the port of Zeebrugge learns us a different lesson: an artificial breeding site should not be developed close to operational wind turbines, turning it into an ecological pitfall (Everaert & Stienen 2007).

Sandwich tern colony in Zeebrugge (photo: Wouter Courtens)

3 Seabirds in the Belgian part of the North Sea

In this chapter we give a general introduction on the distribution and seasonality of seabirds occurring at the Belgian Part of the North Sea (BPNS), and frame the numbers in an international context. Before doing so we set out our research methods, most notably the principles of 'seabirds at sea' (SAS) surveying.

3.1 Methods: seabirds in the Belgian part of the North Sea

3.1.1 Seabird surveys

Seabird surveys are conducted according to the standardised and internationally applied European Seabirds at Sea (ESAS) method (Tasker *et al.* 1984). The focus is on a 300 m wide transect along one side of the ship's track. While steaming, all birds in touch with the water (swimming, dipping, diving) located within this transect are counted ('transect counts'). The transect count method works perfectly well when considering a 'static' situation, as is the case in swimming or actively foraging seabirds. In contrast, counting all flying birds crossing this same transect would cause an overestimation, and would be a measure of bird flux rather than actual bird density. The birds' flying speed is significantly higher than the ship's movement, and more birds will be flying through the surveyed area in the course of any observation period, than there are present at any one instant (Tasker *et al.* 1984). Flying birds are therefore counted by performing instantaneous counts in one minute intervals ('snapshot counts'). And so, right at the start of each minute we count all birds flying within a quadrant of 300 by 300 m inside the transect. As the ship covers a distance of approximately 300 m per minute (when sailing the prescribed speed of 10 knots), the full transect length is covered by means of these subsequent 'snapshots' (see Figure 1). Taking in account the transect width and distance travelled, the combined result of a transect and snapshot count can be transformed to a number observed per km², i.e. seabird density.

Seabird surveyors Hilbran Verstraete & Peter Adriaens on board of the RV Zeeleeuw (photo: Eric Stienen)

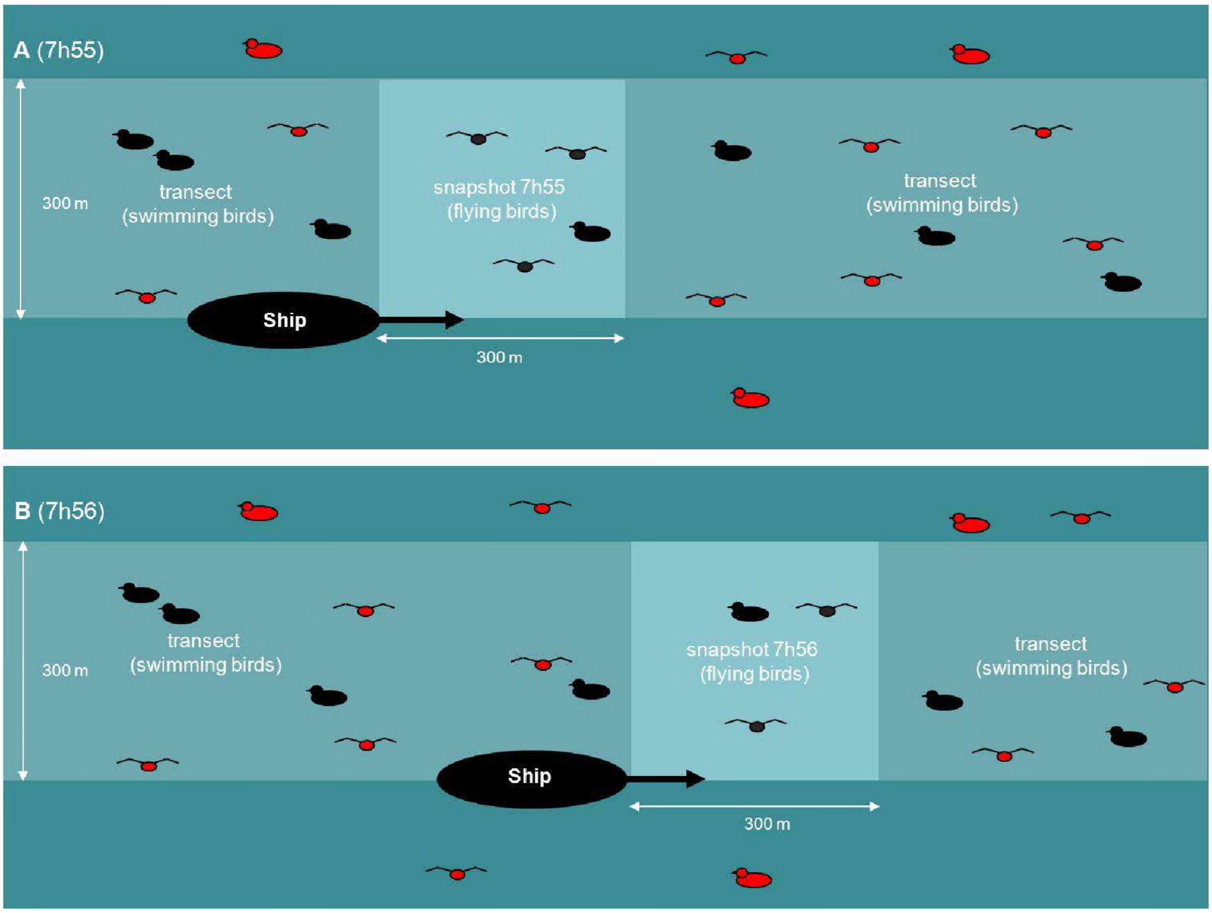


Figure 1. Schematic representation of two subsequent counts (A=7h55 – B=7h56) following the ESAS methodology, in which a transect count is performed for all (stationary) swimming birds, and in which (fast-moving) flying birds are counted by means of one-minute interval snapshot counts (birds indicated in red are thus ignored, at least until the next snapshot count).

In practice, we count all birds observed, but those not satisfying above conditions are given another code and cannot be included in density analyses afterwards. We also note down as much information as possible regarding the birds' age, plumage, behaviour, flight direction and association with objects, vessels or other birds. The distance of the observed bird(s) to the ship is estimated, allowing to correct for decreasing detectability with increasing distance ('distance correction' - see §3.1.2). The transect is therefore divided in four distance categories (A = 0-50 m, B = 50-100 m, C = 100-200 m & D = 200-300 m).

Afterwards, we link observation time to the corresponding GPS-coordinates saved by the ship's board computer, and we aggregate all observations in ten-minute bouts, which are cut off at waypoints. The mean surface counted during a standard ten-minute count is around 1 km² (± 300m/min x 10min x 300m).

3.1.2 Distance analysis

We analysed our transect count results using Distance 6.0. This software program provides a large number of detection functions and adjustment formulas, modelling the relation between distance and detectability. We selected three detection functions which ought to be particularly robust according to Buckland *et al*. (2001):

- Half-normal with hermite polynomial adjustment
- Uniform with cosine adjustment
- Hazard-rate with cosine adjustment

Selection of the most suitable model is based on the corresponding AIC values, and an example of a typical detection function is shown in Figure 6 in the results section. Among other things, the model calculates an 'effective strip width'. The proportion of this value to the actual strip width (equalling 300 m) is a first correction factor, accounting for the decrease in bird detectability with increasing distance.

Seabirds often occur in small to very large clusters, and mostly, the size of the detected seabird clusters also proves to be dependent of the distance to the ship's track. This dependence arises because large clusters are far more easily detected compared to small flocks, and resulting, the latter are under-represented in the sample (Buckland *et al*. 2001). The sample of detected clusters thus exhibits 'size bias', implying that we cannot take the arithmetic mean as an estimate of the cluster size (s), noted as E(s). A method that works particularly well is to regress the logarithm of the cluster size (log(s)) on the detection probability g(x), and to estimate the expected cluster size by the value of log(s) at the point where detection is expected to be certain (where g(x) = 1, i.e. on the ship's track) (Thomas *et al*. 2002, for an example see Figure 7). The arithmetic mean as an estimate for cluster size is only used when the aforementioned regression is not significant (P>0.10).

Summarising, DISTANCE calculates seabird densities as follows:

$$Density = \frac{N(obs)}{L \times ESW} \times ECS$$

with N(obs) = numbers of bird groups ('clusters')
L = length of the sailed transect (m)
ESW = effective strip width (m)
ECS = estimated cluster size

Applying the total numbers of birds (in touch with the water) observed inside the transect during standardised seabird surveys, we calculate distance-corrected bird density according to the following equation:

$$Density = \frac{N(tot)}{L \times TSW} \times C$$

with N(tot) = number of birds observed inside the transect
L = length of the sailed transect (m)
TSW = total strip width (300 m)
C = species-specific distance correction

The species-specific distance correction C is thus calculated knowing that:

$$\frac{N(obs)}{L\times ESW}\times ECS=\frac{N(tot)}{L\times TSW}\times C$$

And so:

$$C=ECS\times\frac{N(obs)}{N(tot)}\times\frac{TSW}{ESW}=\frac{ECS}{MCS}\times\frac{TSW}{ESW}$$

with MCS = (arithmetic) mean cluster size

3.1.3 Calculating seabird numbers at the BPNS

Between September 1992 & December 2012, INBO collected 33,127 ten-minute counts, of which 25,905 are located at the BPNS.

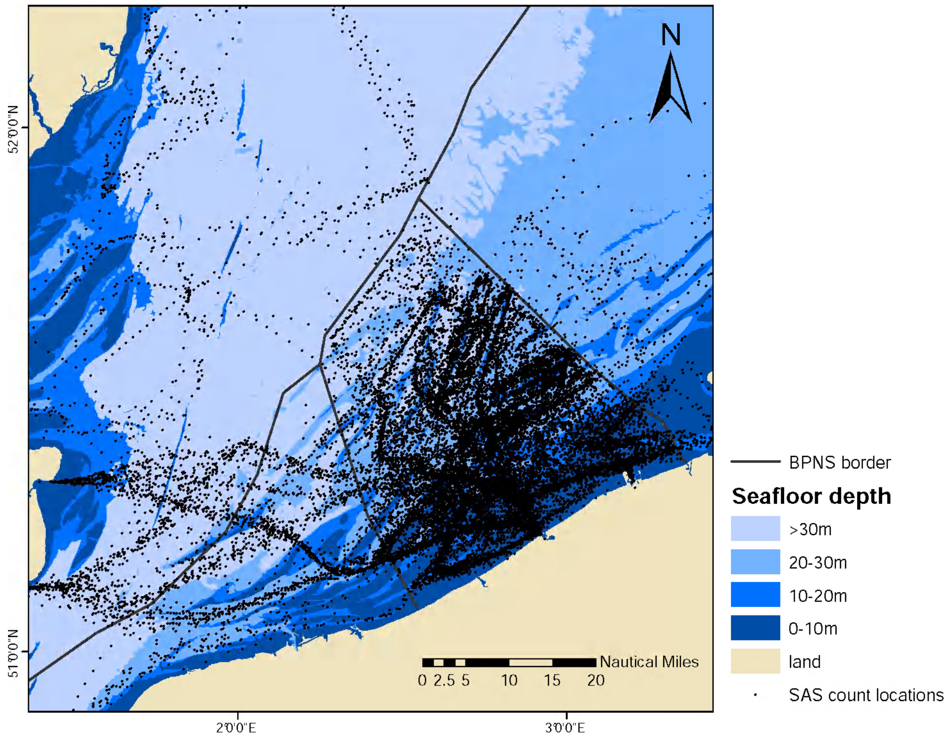


Figure 2. Overview of SAS counts performed by INBO in the period 1992-2012.

As can be seen in Figure 2, count effort is not equally spread over the BPNS (with a lot more counts nearshore compared to farshore). In order to avoid extrapolated densities to be biased towards the most intensely counted areas, we divided the BPNS in three zones. The zones' boundaries are oriented parallel to the coast, roughly 0-10 nautical miles (NM), 10-20 NM & >20 NM away from the coastline (Figure 3). Zone I comprises of the shallow inshore waters and coastal sandbanks (Kustbanken, Vlakte van de Raan & Kwintebank), zone II unites the Thornton- & Gootebank in the east with the Buitenratel, Oostdyck & part of the Westhinder in the west, while zone III comprises of the 'hinderbanken' and the deepwater-zone further out at sea.

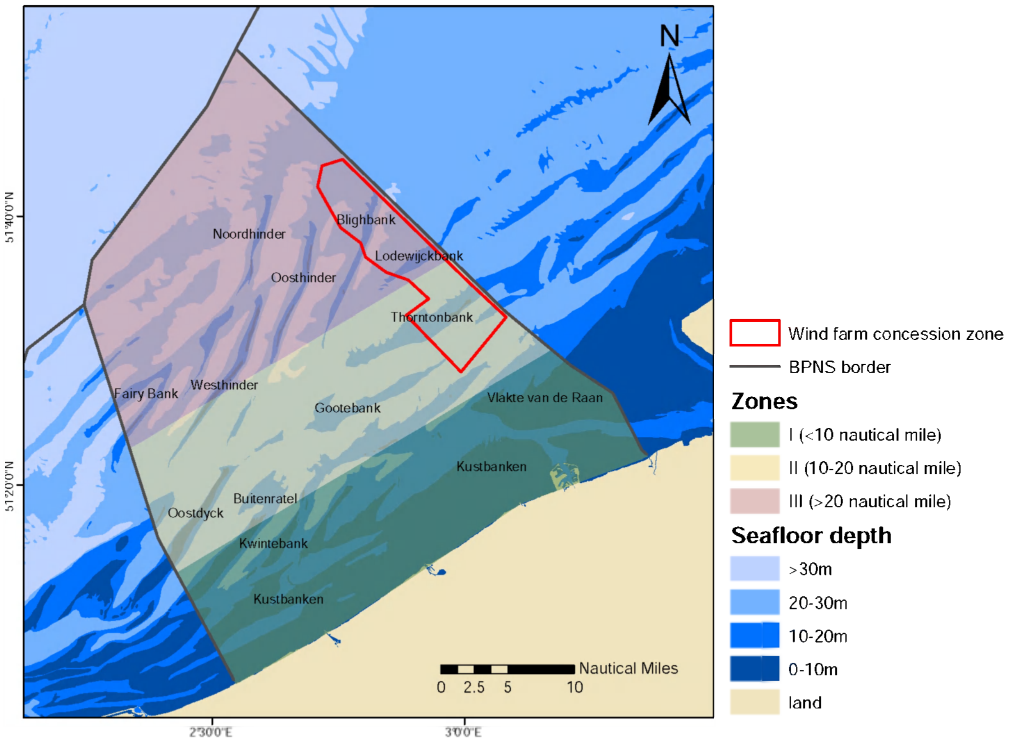


Figure 3. Map of the Belgian Part of the North Sea, with indication of three distance zones applied for calculation of total seabird numbers, and indication of the concession zone for wind energy.

Since 2000, INBO started performing seabird surveys from the RV Zeeleeuw, allowing monthly surveys along fixed monitoring routes throughout the BPNS. Prior to that, seabird surveys were performed on a more irregular base from the RV Belgica as well as from ferries running through the BPNS. From 2008 on, effort was concentrated in the eastern part of the BPNS in favour of the wind farm monitoring program. The calculation of mean numbers of seabirds residing at the BPNS is therefore based on the period 2001-2007, during which surveys were most homogeneously spread over time and space (Figure 4 & Figure 5). The calculation itself is done by aggregating the observed numbers inside the transect during the period 2001-2007 per season and per zone, and dividing these by the number of km² monitored. We then corrected for decreasing detectability with distance (§3.2.1), and multiplied the resulting densities with the respective zones' surfaces.

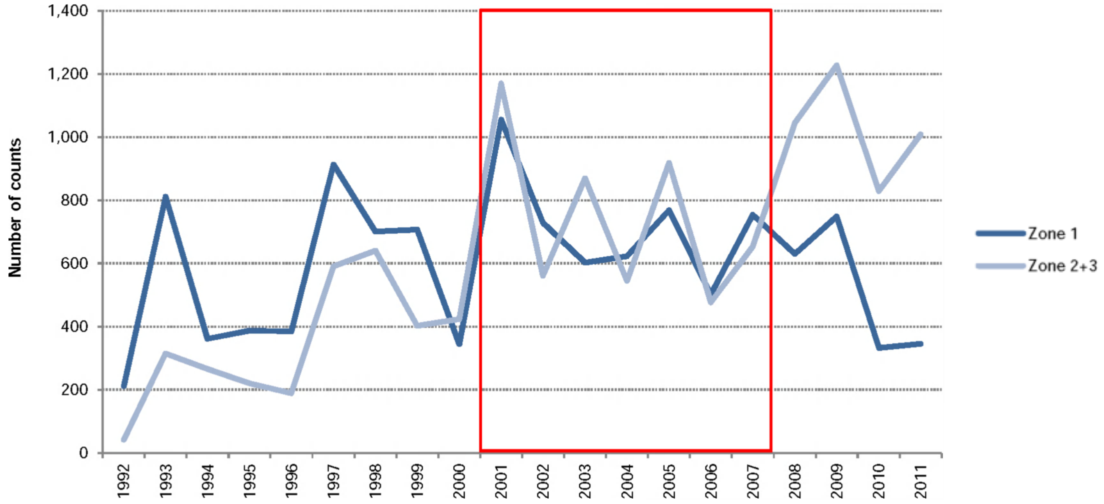


Figure 4. Count effort per zone during the period 1992-2011.

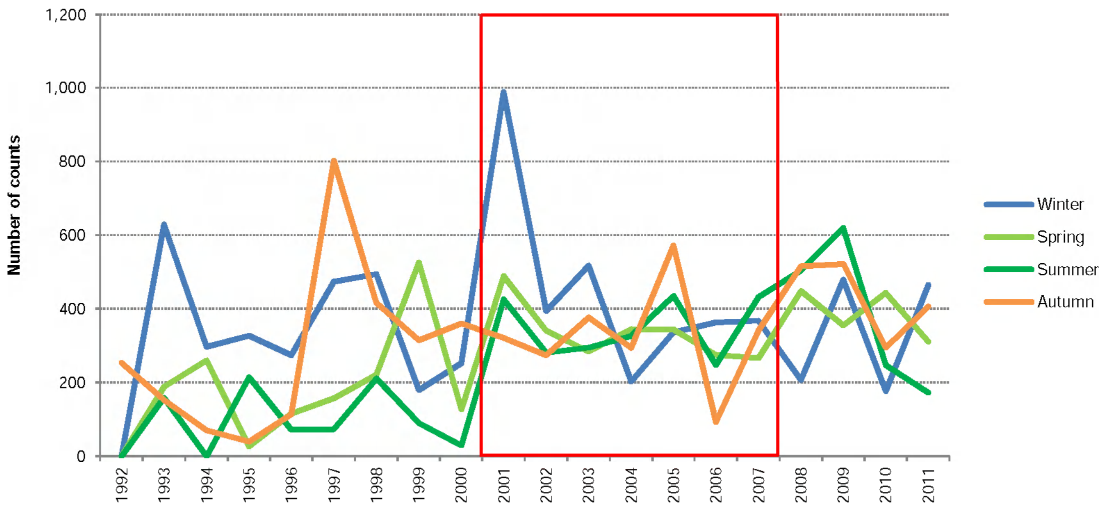


Figure 5. Count effort per season during the period 1992-2011.

3.2 Results: seabirds in the Belgian part of the North Sea

3.2.1 Distance correction

The results of our distance analysis are displayed in Table 1. The values of the ESW demonstrate that bird clusters of all species, except for great cormorant and common scoter, are increasingly difficult to detect with increasing distance. This is especially true (ESW < 170) for the smaller gull species such as black-legged kittiwake, black-headed and little gull, as well as for northern fulmar, common tern and both auks. On the other end of the spectrum are large and conspicuous birds such as northern gannet and great cormorant, or birds that mostly occur in large rafts (increasing detectability as such), i.e. common scoter.

Next, we estimated the cluster size using Distance 6.0, by regressing the logarithm of the detected cluster size to the detection probability. For great cormorant and common scoter, the detection probability function is a constant (resulting in an ESW of 300 m), which cannot be regressed. Resulting, for these two species cluster size was estimated by the arithmetic average. The same was done for great skua, as there was no significant relation between cluster size and detection probability (P>0.10), undoubtedly resulting from the fact that this is a highly solitary species, and observations of more than one bird at the same time are rare. For all other species, cluster size was significantly related to detection probability, and the proportion of estimated cluster size to mean cluster size (ECS/MCS) is generally disproportional to the degree of clustering, with values of 0.89-0.95 for auks, and values < 0.6 for all gulls except little gull.

The resulting correction factors, calculated by multiplying TSW/ESW by ECS/MCS (see Table 1), are highest in auks (1.7), great skua (1.5) and little gull (1.4), while they are lowest and smaller than 1.0 for common, lesser black-backed, herring and great black-backed gull. For these latter species, the increasing overrepresentation of large clusters with distance is so strong that it overcompensates decreasing detectability, resulting in correction factors below 1.

Table 1. Results of the distance analysis of SAS data collected at the BPNS since 2001.

Species	Model	ESW (m)	TSW/ESW	ECS/MCS	**Correction**
Red-throated diver (*Gavia stellata*)	Uniform/Cosine	203	1.48	0.71	**1.1**
Great crested grebe (*Podiceps cristatus*)	Hazard/Cosine	209	1.44	0.81	**1.2**
Northern fulmar (*Fulmarus glacialis*)	Uniform/Cosine	156	1.93	0.69	**1.3**
Northern gannet (*Morus bassanus*)	Hazard/Cosine	232	1.29	0.83	**1.1**
Great cormorant (*Phalacrocorax carbo*)	Uniform/Cosine	300	1.00	1.00	**1.0**
Common scoter (*Melanitta nigra*)	Uniform/Cosine	300	1.00	1.00	**1.0**
Great skua (*Stercorarius skua*)	Uniform/Cosine	206	1.45	1.00	**1.5**
Little gull (*Hydrocoloeus minutus*)	Hazard/Cosine	169	1.78	0.78	**1.4**
Black-headed gull (*Chroicocephalus ridibundus*)	Hazard/Cosine	137	2.19	0.47	**1.0**
Common gull (*Larus canus*)	Hazard/Cosine	173	1.74	0.47	**0.8**
Lesser black-backed gull (*Larus fuscus*)	Hazard/Cosine	187	1.61	0.42	**0.7**
Herring gull (*Larus argentatus*)	Hazard/Cosine	191	1.57	0.52	**0.8**
Great black-backed gull (*Larus marinus*)	Hazard/Cosine	204	1.47	0.49	**0.7**
Black-legged kittiwake (*Rissa tridactyla*)	Hazard/Cosine	151	1.99	0.57	**1.1**
Sandwich tern (*Sterna sandvicensis*)	Uniform/Cosine	195	1.54	0.67	**1.0**
Common tern (*Sterna hirundo*)	Hazard/Cosine	162	1.85	0.58	**1.1**
Common guillemot (*Uria aalge*)	Hazard/Cosine	155	1.94	0.89	**1.7**
Razorbill (*Alca torda*)	Hazard/Cosine	167	1.80	0.95	**1.7**
Auk (common guillemot + razorbill)	Hazard/Cosine	156	1.92	0.90	**1.7**
Large gull (LBB + herring + GBB gull)	Hazard/Cosine	191	1.57	0.43	**0.7**

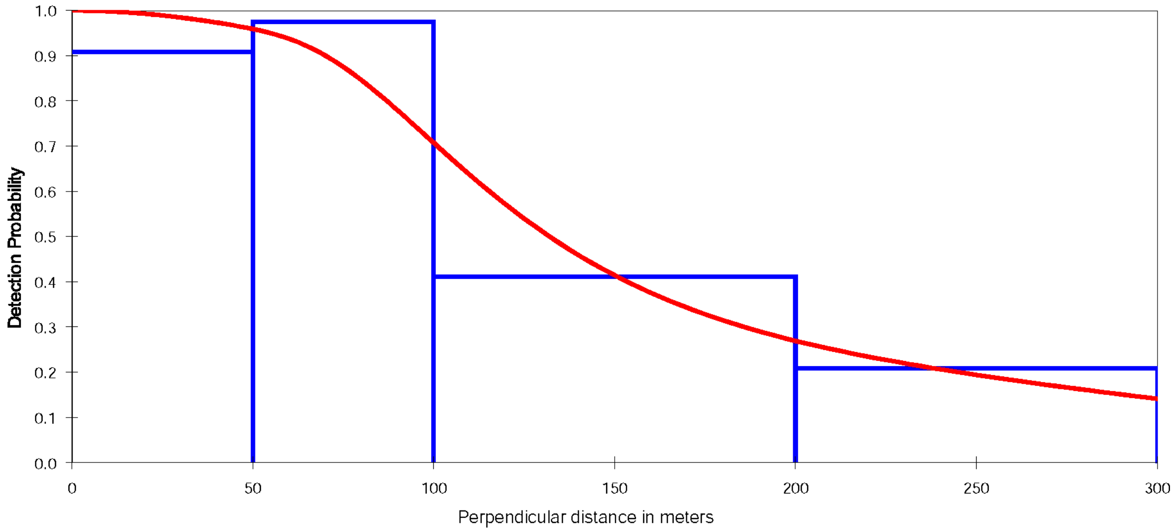


Figure 6. Hazard-rate detection function with cosine adjustment for auks (common guillemot + razorbill) observed inside the transect at the BPNS.

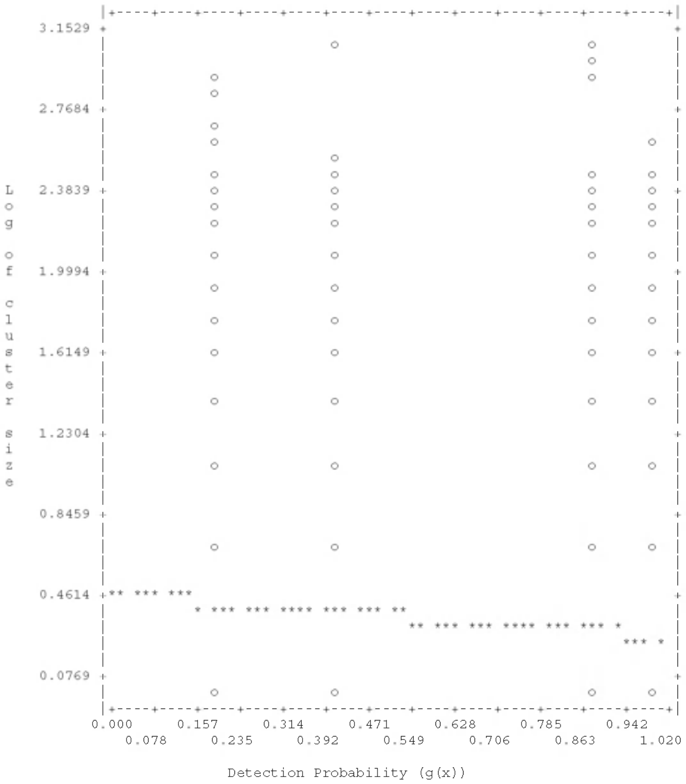


Figure 7. Regression of the cluster sizes (log-transformed) on the modelled detection probability of auks (common guillemot + razorbill) observed inside the transect.

3.2.2 Seabird numbers at the BPNS

We estimated seasonal numbers occurring at the BPNS based on data collected during the period 2001-2007, during which seabird surveys were well spread over time and space (Table 2). During winter, maximum numbers are present with over 46,000 seabirds, of which more than 20,000 auks. Offshore, the wintering community is dominated by common guillemots, razorbills and black-legged kittiwakes. Meanwhile, large numbers of grebes, scoters and divers reside nearshore. In summer, fewer birds are present (on average 15,000), but high numbers of terns and gulls exploit the area in support of their breeding colony located in the port of Zeebrugge. It must be stressed that the resulting totals are values averaged over 7 years of time, offering no more than a first impression of the seasonality and magnitude of numbers residing at the BPNS. As such, the numbers listed in Table 2 & Table 3 do not give insight in the temporary maxima, nor in the number of seabirds spending at least a little part of their lives at the BPNS, resulting from high turnover during migration. Migrating seabirds do not necessarily cross the BPNS overnight, but in contrast, exploit the area for sleeping as well as foraging. Stienen *et al*. (2007) estimated the percentages of the biogeographical seabird populations annually migrating through the southern North Sea, based on the numbers in wintering areas, the position of the breeding grounds in respect to these wintering grounds and the number of birds seen during land-based observations (seawatch data). This study highlighted the extreme importance of the southern North Sea towards great skua, little gull, common tern and sandwich tern, as the major part of these species' biogeographic populations migrates through this area each year.

Table 2. Seasonal (distance-corrected) numbers residing at the BPNS based on the results of seabird surveys between 2001 & 2007 (summer population indicated by x^S, migratory and/or wintering population by x^M, figures indicated in yellow exceed the 1%-threshold) (threshold values based on Mitchell *et al*. 2004 & Wetlands International 2013).

Species	Subspecies / Population	1%-threshold	Mean numbers BPNS 2001-2007			
			Winter	Spring	Summer	Autumn
Red-throated diver	NW Europe (winter)	2,600	966	86	0	209
Diver sp.	-	-	34	1	0	6
Black-throated diver	N Europe + W Siberia	3,500	6	0	0	56
Great crested grebe	NW + W Europe	3,500	1,458	66	1	186
Northern fulmar	NE Atlantic	30,000	2,575	1,405	808	8,098
Northern gannet	NE Atlantic	3,100	1,799	737	556	4,990
Great cormorant	N + C Europe	3,900	246	86	209	98
Common scoter	ssp. *nigra*	5,500	1,089	3,656	119	85
Great skua	NE Atlantic	160	52	37	109	152
Little gull	C & E Europe	1,100	503	2,128	174	969
Black-headed gull	W Europe	42,100	388	1,289	321	1,442
Common gull	NW & C Europe	16,400	3,599	1,806	19	764
Lesser black-backed gull	ssp. *graellsii* + *intermedius*	$(5{,}500^S + 3{,}800)^M$	418	8,595	6,271	3,076
Herring gull	*ssp. argenteus* + *argentatus*	$(10{,}200^S + 20{,}100)^M$	1,844	3,124	2,621	874
Great black-backed gull	N & W Europe	4,200	5,092	590	90	3,850
Black-legged kittiwake	NE Atlantic	66,000	6,310	542	58	5,015
Sandwich tern	W Europe	1,700	0	627	987	113
Common tern	S/W Europe + N/E Europe	$(1{,}800^S + 9{,}800)^M$	0	2,431	2,638	286
Common guillemot	NE Atlantic	23,500	16,121	2,174	3	5,044
Unidentified auk	-	-	1,077	216	0	324
Razorbill	NE Atlantic	5,700	2,907	481	0	1,205
Total			46,451	30,077	14,985	36,839

Table 2 further shows that throughout the year, the BPNS hosts internationally important seabird numbers. During winter, great black-backed gull exceeds the 1%-threshold of its biogeographic population. This threshold is also exceeded by little gull during spring migration, and by northern gannet during autumn migration. Lastly, (summer) population thresholds are exceeded for common tern and lesser black-backed gull. However, this result is hard to interpret as breeding and migration seasons partly overlap, and to unravel this we actually need a higher time resolution.

When the same calculations are done by aggregating per month instead of per season (Table 3), the resulting numbers are based on a smaller sample size (inducing broader confidence intervals), but display more information on the birds' seasonality patterns and timing of migration peaks. Because migration of some species is strongly clustered in time, the maximum monthly mean is often a multitude of the maximum seasonal mean. Conclusions however are more or less the same, confirming the occurrence of internationally important numbers of northern gannet, little gull and great black-backed gull. Added to this, numbers of great skua exceed the 1%-threshold in October (Figure 8).

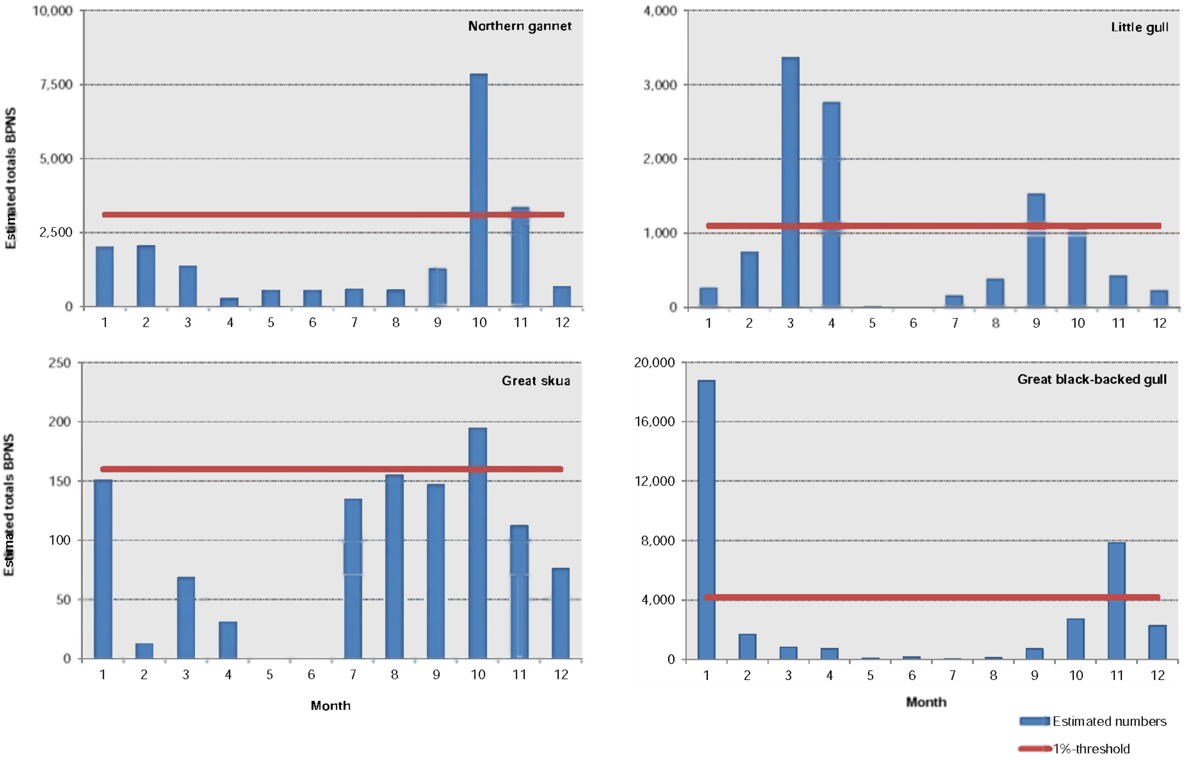


Figure 8. Monthly (distance-corrected) numbers of 4 species of seabird at the BPNS with indication of the 1%-threshold of their biogeographic populations.

By splitting up per month, we can now also see that May numbers of lesser black-backed gull exceed the combined 1%-threshold value of the *graellsi* and *intermedius* population (Figure 9). In June & July, when migration intensity is minimal, the numbers exceed the *graellsi* 1%-threshold. In May and August, numbers of common tern reach maximum values, due to the presence of local breeding birds as well as migrants from the N/E population. Despite these increased numbers, the combined 1%-threshold of 11,600 is not exceeded. However, in June and July numbers of common tern at the BPNS do exceed the S/W European 1%-threshold of 1,800 birds (Figure 9).

Northern gannet (photo: Hilbran Verstraete)

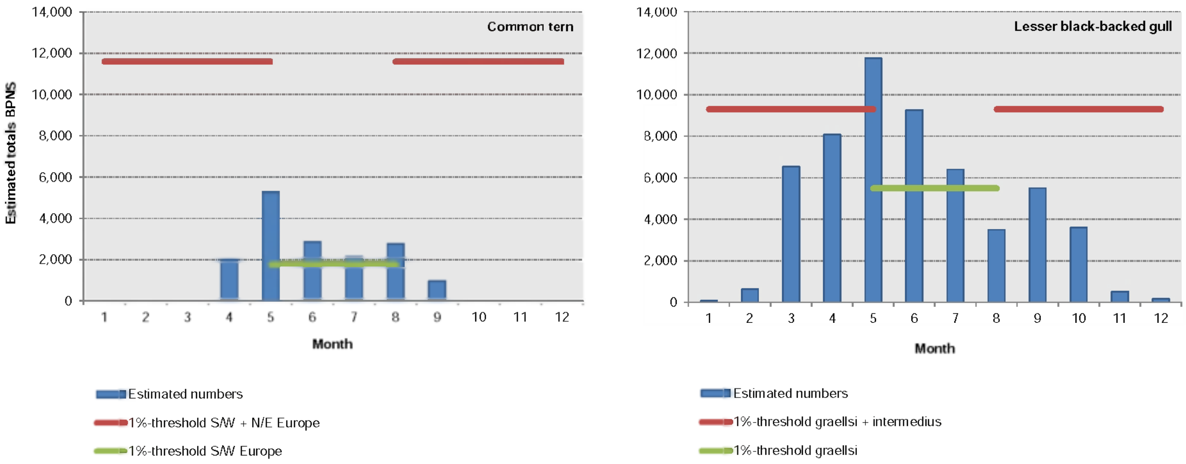
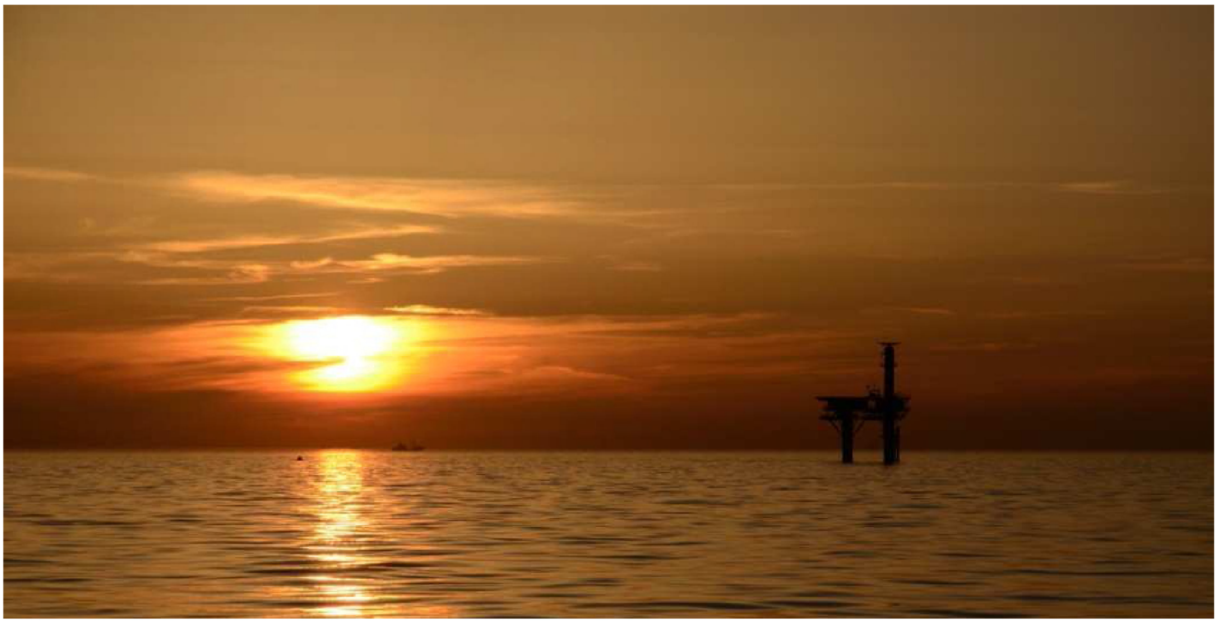


Figure 9. Monthly (distance-corrected) numbers of common tern and lesser black-backed gull at the BPNS with indication of the 1%-threshold of their biogeographic populations.

Table 3 further shows several rather unrealistically high totals, namely for great black-backed gull in January (>18,000), northern fulmar in November (>21,000) and common scoter in May (>5,700). These totals are determined by 1 or 2 counts during which extremely high numbers were concentrated inside the transect. Omitting these single counts from the calculations, numbers drop to more realistic values, i.e. 6,752 for great black-backed gull, 5,233 for northern fulmar and 132 for common scoter.



Sunset near the Oostdyck helicopter deck at the BPNS (photo: Nicolas Vanermen)

Table 3. Monthly (distance-corrected) numbers residing at the BPNS based on the results of seabird surveys between 2001 & 2007 (summer population indicated by x^S, migratory and/or wintering population by x^M, figures indicated in yellow exceed the 1%-threshold) (threshold values based on Mitchell *et al*. 2004 & Wetlands International 2013).

Species	Subspecies/Population	1%-threshold	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Red-throated diver	NW Europe (winter)	2,600	1,874	534	206	36	3	0	0	0	0	37	530	638
Diver sp.	-	-	15	24	3	0	0	0	0	0	0	0	16	74
Black-throated diver	N Europe + W Siberia	3,500	16	0	0	0	0	0	0	0	0	3	160	8
Great crested grebe	NW + W Europe	3,500	1,982	1,330	102	0	94	3	0	0	0	23	482	1,095
Northern fulmar	NE Atlantic	30,000	4,717	1,176	2,078	1,226	670	1,580	469	476	550	1,516	(21,842)	5,034
Northern gannet	NE Atlantic	3,100	2,025	2,046	1,375	264	541	541	585	548	1,263	7,838	3,345	676
Great cormorant	N + C Europe	3,900	435	92	30	115	124	288	239	104	118	72	102	356
Common scoter	ssp. *nigra*	5,500	236	1,801	4,970	130	(5,742)	144	71	138	41	64	140	555
Great skua	NE Atlantic	160	151	13	68	31	0	0	135	155	147	194	112	76
Little gull	C & E Europe	1,100	260	747	3,365	2,756	28	0	152	374	1,523	1,081	423	224
Black-headed gull	W Europe	42,100	646	334	3,069	89	642	570	138	242	3,279	341	1,010	186
Common gull	NW & C Europe	16,400	6,611	2,530	3,167	2,199	10	17	24	17	181	1,010	1,002	2,235
Lesser black-backed gull	ssp. *graellsii* + *intermedius*	(5,500^S + 3,800)^M	86	638	6,532	8,086	11,758	9,262	6,390	3,495	5,500	3,597	513	168
Herring gull	*ssp. argenteus* + *argentatus*	(10,200^S + 20,100)^M	2,106	1,873	4,743	2,406	2,105	3,715	2,753	1,424	1,069	411	1,155	1,371
Great black-backed gull	N & W Europe	4,200	(18,739)	1,674	823	710	57	138	20	107	717	2,713	7,855	2,276
Black-legged kittiwake	NE Atlantic	66,000	12,390	3,478	1,155	288	91	35	107	33	168	5,105	8,428	6,964
Sandwich tern	W Europe	1,700	0	0	170	966	638	1,522	912	522	383	3	0	0
Common tern	S/W Europe + N/E Europe	(1,800^S + 9,800)^M	0	0	6	2,005	5,294	2,869	2,150	2,776	963	24	0	0
Common guillemot	NE Atlantic	23,500	15,067	17,416	5,312	679	24	9	0	0	37	3,773	9,809	13,192
Auk sp.	-	-	702	1,025	465	122	0	0	0	0	0	342	494	1,541
Razorbill	NE Atlantic	5,700	2,400	3,303	1,097	220	0	0	0	0	8	1,163	2,211	2,130

3.2.3 Seabird profiles: distribution versus seasonality

Characterised by their seasonal occurrence and spatial distribution at the BPNS, we can categorize aforementioned seabird species in different groups.

3.2.3.1 Widespread winter visitors

At the BPNS, great black-backed gull, black-legged kittiwake, common guillemot and razorbill all occur in highest densities during winter, while they are as good as absent during summer (breeding season) (Figure 10). Peak densities are generally around 2-3 birds/km², with razorbill being the least common (0.3-0.6 birds/km²). Their occurrence is homogenously spread over the BPNS, yet with a preference to zones II and III. Also, autumn numbers are much higher than spring numbers owing to an early return to their northern breeding grounds.

Common gull (not displayed in Figure 10) too is a true winter visitor, but with relatively high spring numbers due to intense migration in March & April, and a preference to zone I.

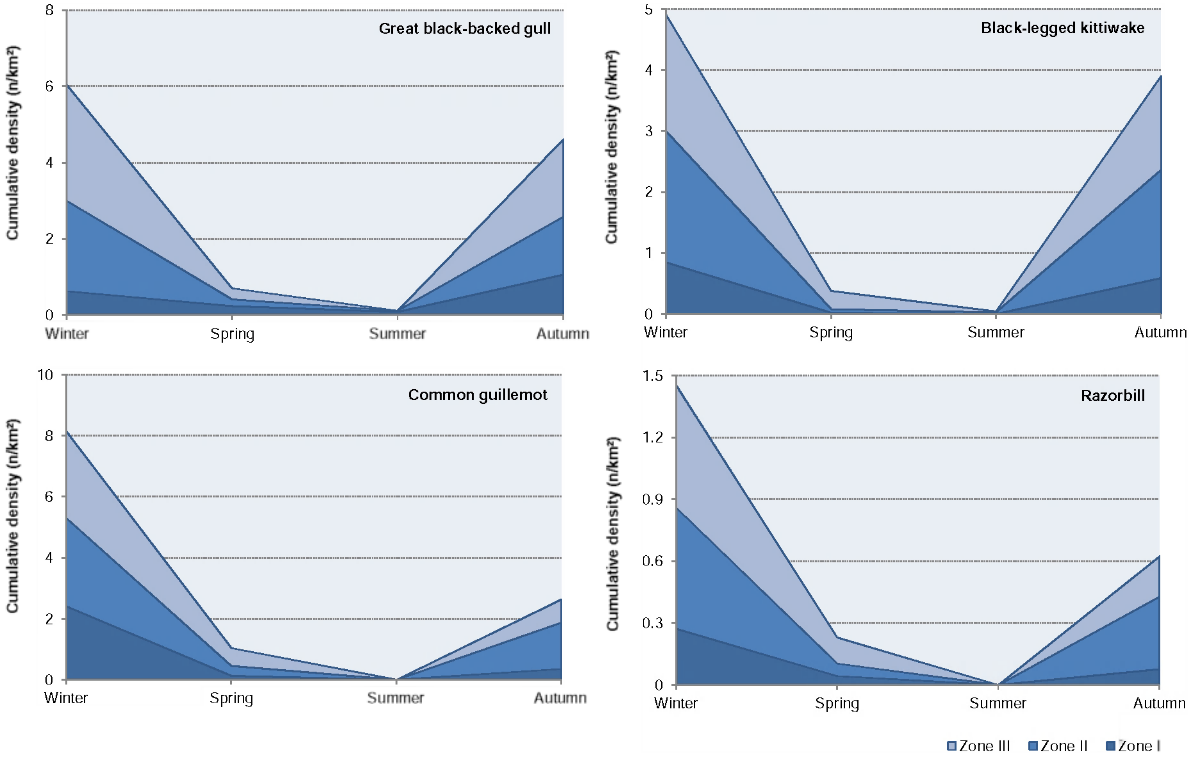


Figure 10. Cumulative density plots of four common winter visitors at the BPNS (zone I: 0-10 NM, zone II: 10-20 NM & zone III: >20 NM offshore).

3.2.3.2 *Inshore species*

In contrast to the previously discussed species, red-throated diver & great crested grebe display a strongly coast bound distribution. Seasonality shows a high density peak in winter, and very low numbers during the rest of the year (Figure 11). In case of great crested grebe, numbers are highly variable with distinct peaks during prolonged periods of frost when inland water bodies have become frozen.

Apart from black-headed gull which is discussed further on, only two other species show a comparable coast-bound distribution, being common scoter and great cormorant (Figure 11). Great cormorants occur year-round in fairly low numbers (<0.3 birds/km²), concentrated in the inshore zone west of Ostend, while common scoter is a winter visitor in highly varying densities, often peaking in early spring (March). Before 2002, wintering numbers of scoters regularly exceeded 10,000 individuals, but after that, numbers dropped down to less than 1,000 birds in most winters (Courtens & Stienen 2012).

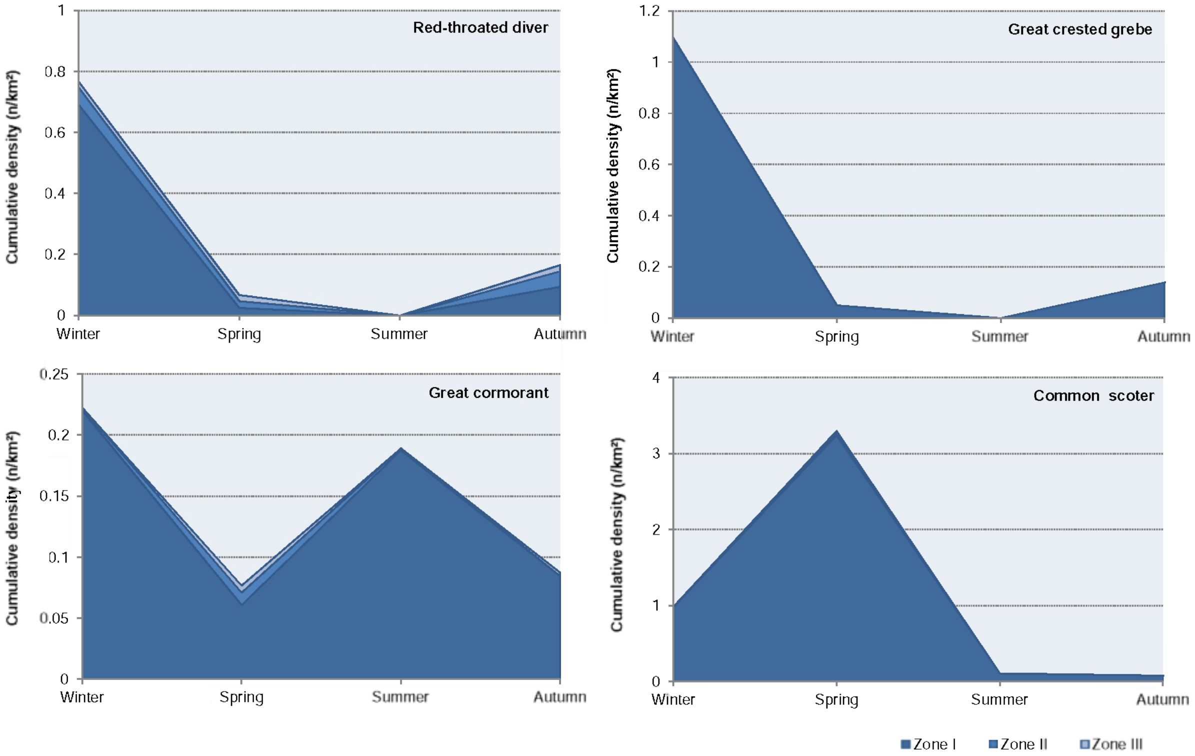


Figure 11. Cumulative density plots of four typically inshore species (zone I: 0-10 NM, zone II: 10-20 NM & zone III: >20 NM offshore).

3.2.3.3 *Local breeding birds*

Two of the most common species on the BPNS are lesser black-backed and herring gull, occurring in densities of 3-5 birds/km² in zone I. While herring is present year-round, most lesser black-backed gulls winter further south. A very large mixed breeding colony is located in the port of Zeebrugge (up to 7,843 breeding pairs in 2012), explaining the spring and summer peaks in density. In summer, the distribution of herring gull is highly coast-bound, but the species is present throughout the BPNS during winter months. In comparison, lesser back-backed gull is much less reluctant to go further out at sea and especially during spring migration, high numbers are present in zone II between 10 & 20 NM from the coast (6 birds/km²) (Figure 12).

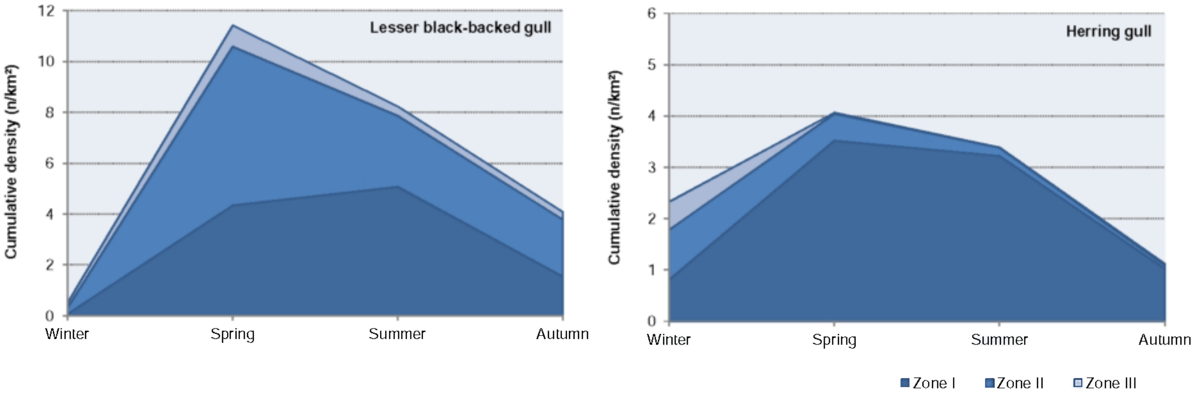


Figure 12. Cumulative density plots of lesser black-backed and herring gull (zone I: 0-10 NM, zone II: 10-20 NM, zone III: >20 NM offshore).

Being fully absent from November to February, sandwich and common tern are true summer visitors, that spend the winter along W and S African coasts (Figure 13). Both species are included on the Annex I of the Bird Directive. At the BPNS, the inshore zone sees peak densities during the breeding season (May-June), when varying numbers breed at the colony in Zeebrugge (up to 4,067 breeding pairs of sandwich tern and 3,052 pairs of common tern in 2004). During migration, the occurrence of both species is less coast bound, with small density peaks in zone II during migration in March-April and July-August. The southern North Sea is of high conservational value to both sandwich and common tern, as an estimated 67 and 56% of their respective European populations migrate through each year (Stienen *et al*. 2007).

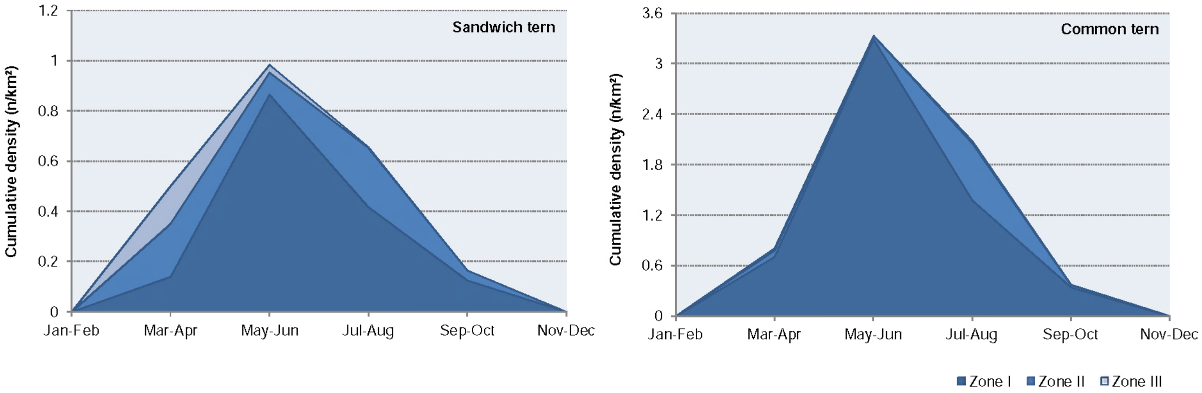


Figure 13. Cumulative density plots of sandwich and common tern (zone I: 0-10 NM, zone II: 10-20 NM, zone III: >20 NM offshore).

3.2.3.4 Offshore migrants

Another distinct profile is that of three 'true' seabird species, i.e. northern gannet, northern fulmar & great skua (Figure 14). These birds clearly prefer offshore waters, with highest densities occurring in zone III (>20 NM offshore). Northern gannets are present year-round, with particularly high numbers during autumn, when an estimated at 4-7% of the NE Atlantic population migrates through the southern North Sea bottleneck (Stienen *et al.* 2007). Northern fulmar shows a very similar seasonal pattern, but displays an even more offshore distribution. Its occurrence on the BPNS is erratic, and year-to-year variability in numbers is very high.

The world population of great skua is confined to merely 16,000 breeding pairs (Mitchell *et al.* 2004), and an estimated 60% of the NW European population (Icelandic birds excluded) migrates through the southern North Sea (Stienen & Kuijken 2003). At the BPNS, great skua is the least abundant species discussed in this chapter, with mean densities not even exceeding 0.05 birds/km². This species too reaches highest numbers during autumn, but compared to the two other offshore migrants, relatively high densities occur during summer. Indeed, during August and September internationally important numbers are known to reside in the southern North Sea (Camphuysen & Leopold 1994).

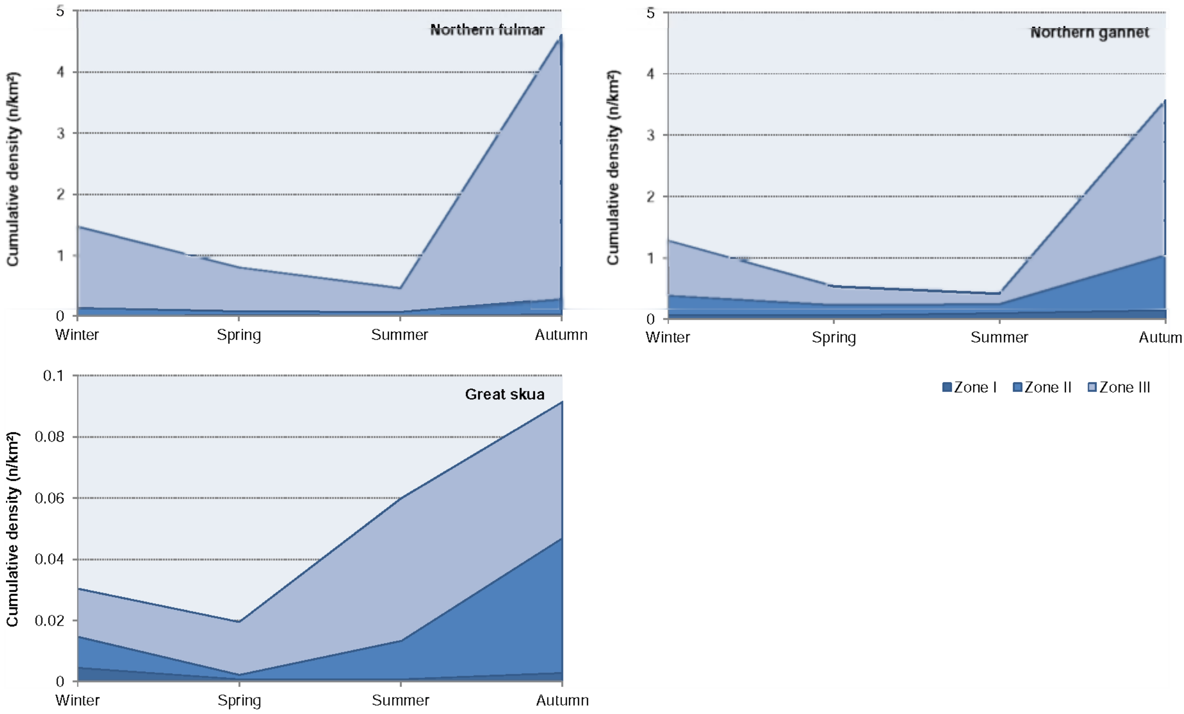


Figure 14. Cumulative density plots of northern fulmar, northern gannet and great skua, three offshore migrants (zone I: 0-10 NM, zone II: 10-20 NM, zone III: >20 NM offshore).

3.2.3.5 *Nearshore migrants*

Little and black-headed gull both show a very distinct double-peaked seasonal pattern due to intense migration both in spring and autumn (Figure 15). Little gull is a species of high conservational concern (Annex I), of which an estimated 40-100% of the total European population annually migrates through the southern North Sea bottle neck (Stienen *et al*. 2007). Their migration occurs concentrated along the continental coast (Stone *et al*. 1995) and the Belgian waters are thus of high value to this species.

Figure 15 shows that the migration of little gull is indeed concentrated within zone I, with decreasing numbers further out at sea. Small numbers spend the winter at the BPNS, with fairly equal densities in zone I & II. Interestingly, spring migration of little gull at the BPNS appears to be more intense compared to autumn migration. This is in contrast to what is found in literature, as both Camphuysen & Leopold (1994) and Stone *et al*. (1995) report larger numbers during autumn than during spring migration, in Dutch and southeast North Sea waters respectively. This is also what one would expect based on the simple fact that in autumn bird populations are supplemented with their recent offspring. Even more so since according to Cramp (1983), a higher percentage of birds migrate overland during spring compared to autumn.

Migration of black-headed gull occurs almost exclusively within zone I (<10 NM from the coast). While little gulls are fully absent during breeding season, black-headed gulls are present in small numbers year-round, and variable numbers breed at the seabird colony in Zeebrugge (up to 2,390 breeding pairs in 2001).

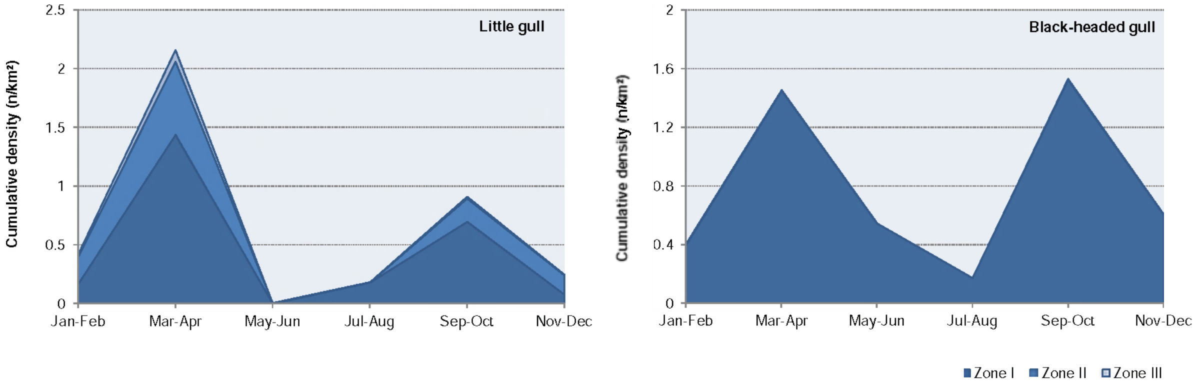


Figure 15. Cumulative density plots of little and black-headed gull, two nearshore migrants (zone I: 0-10 NM, zone II: 10-20 NM, zone III: >20 NM offshore).

Razorbill, a common winter visitor at the BPNS (photo: Hilbran Verstraete)

4 Seabirds in the Belgian concession zone for wind energy before wind farm construction

In the following chapter we describe the numbers and seasonality of seabirds occurring in the several wind farm areas before the first turbines were built, i.e. during the so-called reference period. The analysis is based on the results of standardised 'seabirds at sea' (SAS) surveys (see §3.1.1). The same reference database is applied to perform a 'wind farm sensitivity analysis'. This integrated method allows to identify areas particularly sensitive to wind farm development, which may serve as input for future spatial planning on the BPNS.

4.1 Methods: reference analysis for the concession zone & impact areas

4.1.1 Selectivity Index

Based on the mean number of birds exploiting the concession zone for wind energy compared to the numbers present at the BPNS as a whole, we calculate a bird's preference to the area as follows (Jacobs 1974):

$$\text{Selectivity Index SI} = (r - p) / (r + p - 2rp)$$

In which:

- r = the proportion of the mean number of birds inside the concession zone on to the total number of birds occurring on the BPNS
- p = the proportion of the surface of the concession zone on to the total surface of the BPNS

This calculation results in index values ranging from -1 to +1. When birds occur homogeneously dispersed, with an equal density in both areas, a SI of 0 is obtained, while 100% preference to the concession zone results in a value of +1 and full avoidance in -1 (for a hypothetical example, see Figure 16).

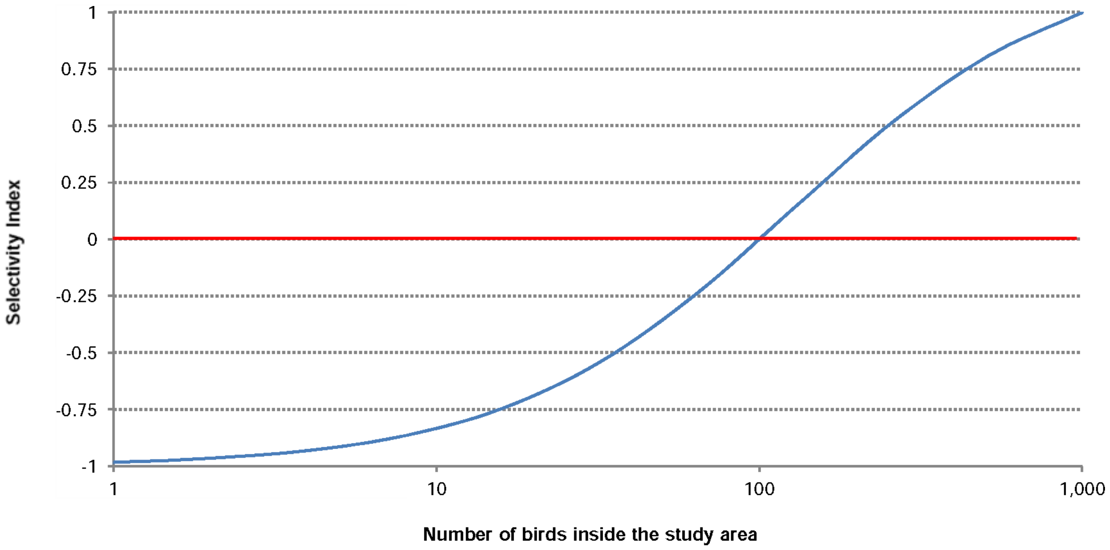


Figure 16. Example of selectivity index values in the hypothetical case where the total population numbers 1,000 birds, and the concession zone surface is 10% of the BPNS.

Due to seasonal variation in numbers, this method can result in extreme SI values at a time when the total number of birds is actually very low and results are thus less relevant. We therefore only present SI values for seasons/months when the number residing at the BPNS is at least 10% of the maximum periodic number (see Table 2 & Table 3).

4.1.2 Reference situation in the concession zone & impact areas

Based on the results gathered during the Danish research project on seabird displacement effects at offshore wind farms (Petersen *et al.* 2006), we surrounded the future wind farm areas at the BPNS by a buffer zone of 3 km to define the impact areas (Figure 17), i.e. the zones where effects of turbine presence can be expected. These impact polygons were thus used as a base for our reference analysis.

First we compared the seabird densities inside the concession zone with the densities at the BPNS (§4.3.1). We applied the same method as set out in §3, taking account of distance correction. Due to the different wind farm construction time lines, we considered the part of the concession zone overlapping with zone II (reference period defined as 2001-2007) separate from the part overlapping with zone III (reference period defined as 2001-2009), and summed the two resulting totals afterwards.

Next we performed separate analyses per impact area (§4.3.2-§4.3.4), with the reference period varying between areas:

- Thorntonbank: < April 2008
- Blighbank: < September 2009
- Lodewijckbank: < January 2013

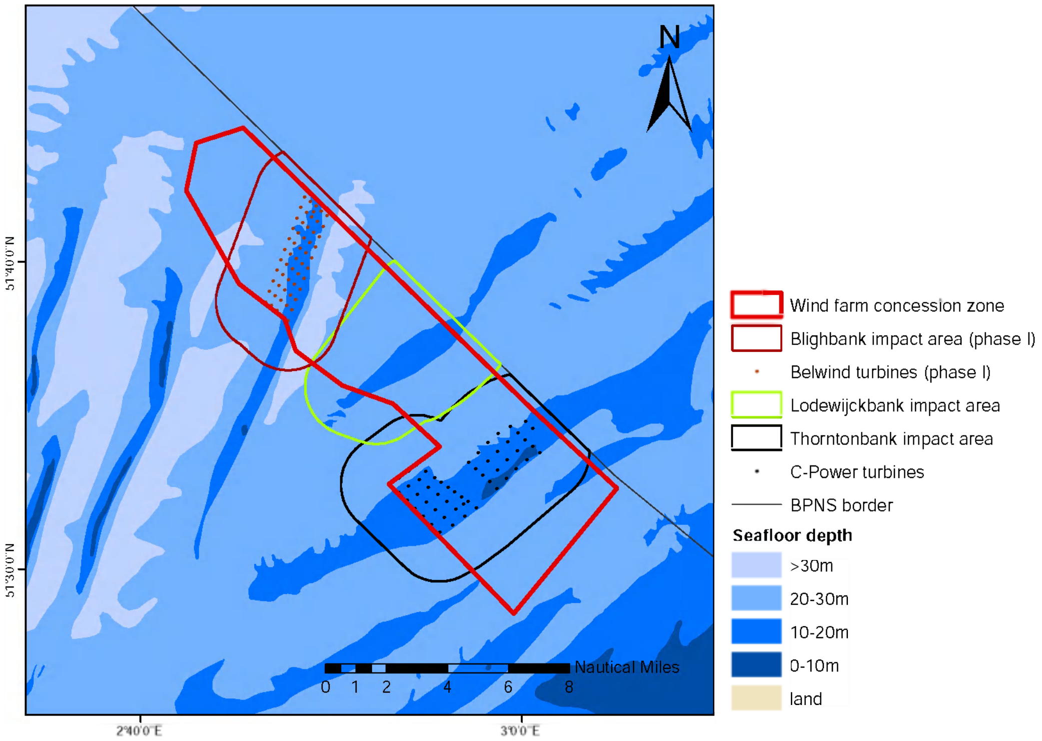


Figure 17. Impact area polygons, i.e. the (planned) wind farm sites surrounded by a 3 km wide buffer zone.

Ideal observation conditions and a happy researcher at the Thorntonbank study area (photo: Klaas Debusschere)

4.2 Methods: wind farm sensitivity analysis

Garthe & Hüppop (2004) suggested a valuable and integrated approach to assess the wind farm sensitivity of different seabird species. The wind farm sensitivity is calculated by combining nine factors given a score from 1 to 5 according to a species' supposed vulnerability to certain aspects of wind farm presence. These nine vulnerability factors are aggregated into three categories, referring to (A) flight behaviour, (B) disturbance and/or displacement related behaviour & (C) population level and/or protection status:

A (flight behaviour)
- a= flight manoeuvrability
- b= flight altitude
- c= percentage of time flying
- d= nocturnal flight activity

B (disturbance/displacement)
- e= sensitivity to disturbance
- f= flexibility in habitat use

C (population level/protection status)
- g= biogeographical population size
- h= adult survival rate
- i = European threat & conservation status

The average scores for A, B & C are multiplied by each other to obtain the 'species sensitivity index' (SSI):

$$SSI = A \times B \times C = \frac{(a+b+c+d)}{4} \times \frac{(e+f)}{2} \times \frac{(g+h+i)}{3}$$

Following, the 'wind farm sensitivity index' (WSI) for a certain area is calculated by:

$$\mathrm{WSI} = \Sigma_{\mathrm{species}}(\ln(\mathrm{density}_{\mathrm{species}} + 1) \times \mathrm{SSI}_{\mathrm{species}})$$

While we took over the methodology of Garthe & Hüppop (2004) for the major part, we introduced some slight changes, based on new insights (Furness *et al*. 2013) and our own SAS data:

- We eliminate nocturnal flight activity (d) since this factor is the least reliable, considering the few scientific knowledge on the matter;
- In this study, the score for conservation status (i) is set to 5 when it concerns species included in the Annex I of the Bird Directive – for example, Garthe & Hüppop set (i) for common tern to 1 based on its 'secure' population status, but since it is an Annex I – species, this study sets (i) to 5;
- Disturbance sensitivity factor (e) was increased for both diver species and great crested grebe, analogue to Furness *et al*. (2013);
- The 'percentage of time flying' (c) can be expected to be highly site-specific (e.g. when comparing areas mainly used for foraging vs. areas used for migration). Therefore we use our own SAS data to estimate this value, yet with the same cut-off values as determined by Garthe & Hüppop (2004) (0-20%=1, 20-40%=2,…).
- Lastly, we revised the score for flight height (b) based on our own SAS data and recent review literature (Cook *et al*. 2012, Furness *et al*. 2013). Ever since 2008, we visually estimated the flight height of birds observed during ship-based seabird counts to be below (<30m), at (30-150m) or above (>150m) rotor height, resulting in species-specific percentages flying at rotor height. We considered these values together with percentages given by Cook *et al*. (2012) and Furness *et al*. (2013), and converted the 'worst case scenario' value to score (b) according to following cut-off values:
    - 0-1% -> 1
    - 2-5% -> 2
    - 6-10% -> 3
    - 11-20% -> 4
    - >20% -> 5

Finally, we overlaid the BPNS with a 6x6 km² grid, and we calculated 4 seasonal WSI values as well as their mean for each grid cell based on SAS count data collected in the period 2001-2007 (zone I & II) and the period 2001-2009 (zone III), i.e. before wind farm development in the respective zones. Grid cells where seasonal monitoring effort was less than 10 km² were omitted from the calculations.

4.3 Results: reference analysis for the concession zone & impact areas

4.3.1 Reference situation in the wind farm concession zone

Figure 18 compares the overall seabird density between the concession zone and the BPNS before wind farm construction. The two line graphs show remarkable resemblance, and diverge only in summer when seabird density in the concession zone was less than half the density at the BPNS. This can be explained by the fact that seabird distribution in summer is much more coast bound compared to other seasons. Seabird density is highest in winter with more than 12 birds/km², meaning the concession zone hosts on average around 3,000 wintering seabirds.

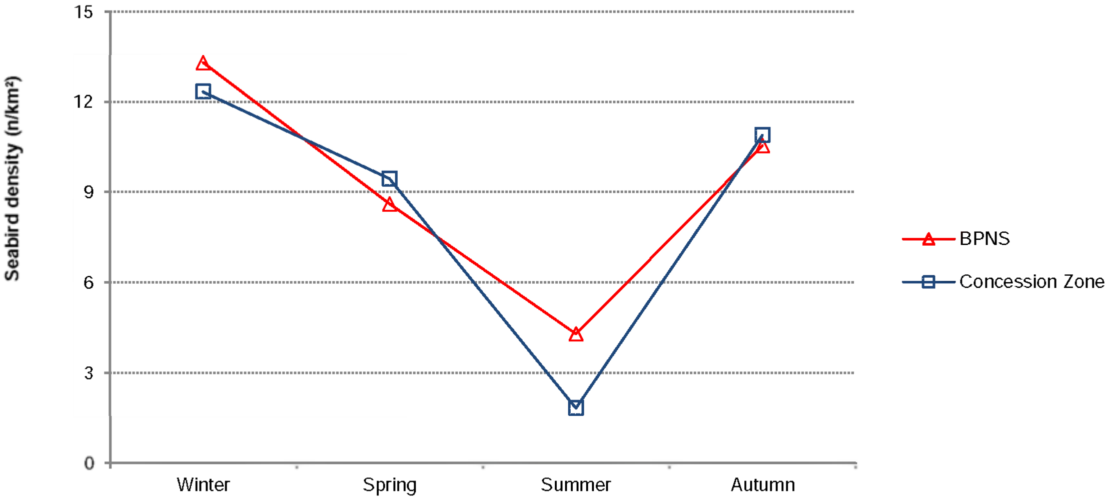


Figure 18. Seasonal (distance-corrected) seabird densities residing at the BPNS and in the concession zone for wind energy prior to wind farm construction.

Looking at the results presented in Table 4, we see that several species showed no preference to the wind farm concession zone at all. This is not surprising since most of these species display an inshore distribution while the wind farm concession zone is located more than 12 NM offshore. Because of this, divers, grebes, scoters, cormorants, black-headed gulls and terns all show strongly negative SI's. On the other hand, no less than 9 species do show positive SI's, indicating preference to the concession area by northern gannet, great skua and lesser black-backed gull in spring/summer and by little gull, herring gull, great black-backed gull, black-legged kittiwake, common guillemot and razorbill in autumn/winter.

Table 4. Selectivity indices at the wind farm concession zone for 18 seabird species (only calculated for those seasons during which numbers at the BPNS exceed 10% of the maximum seasonal numbers as indicated in Table 2 - positive values indicating preference are shown in green).

Species	Winter	Spring	Summer	Autumn
Red-throated diver	-0.81			-0.71
Great crested grebe	-1.00			-1.00
Northern fulmar	-0.63	-0.77		-0.68
Northern gannet	-0.10	**0.00**	**0.06**	-0.17
Great cormorant	-1.00	-1.00	-1.00	-1.00
Common scoter	-0.88	-1.00		
Great skua	-0.05	-1.00	**0.11**	-0.35
Little gull	**0.72**	-0.08		**0.04**
Black-headed gull	-1.00	-1.00	-1.00	-1.00
Common gull	-0.32	-0.97		-0.44
Lesser black-backed gull		**0.59**	-0.15	**0.01**
Herring gull	**0.01**	-0.78	-0.97	-0.93
Great black-backed gull	-0.13	-0.61		**0.12**
Black-legged kittiwake	**0.19**			**0.38**
Sandwich tern		-0.44	-0.69	-1.00
Common tern		-0.84	-0.87	-0.69
Common guillemot	0.00	-0.06		**0.36**
Razorbill	**0.07**	-0.26		**0.35**

Previous studies (Vanermen *et al*. 2006, Vanermen & Stienen 2009) pointed out that the wind farm areas could be of special interest to several species of high conservational concern, i.e. great skua, little gull, common tern & sandwich tern. This is only partly confirmed by the results in Table 4. During winter (and to a lesser extent also in autumn), little gulls do seem to concentrate in the concession zone, and the same accounts for great skua in summer. But the strongly negative SI's as found for both tern species are not in line with what was found earlier. This may be due to the fact that counted numbers were aggregated for the whole concession zone and per season, as a result of which finer scaled spatial and/or temporal patterns remain hidden. In the next paragraphs (§4.3.2-§4.3.4), we split up the concession zone in the respective impact areas, and aggregated the numbers per month instead of per season for all four species of interest.

INBO at work on top of the monkey bridge
at the RV Zeeleeuw (photo: Marc Van de walle)

Blighbank wind farm (photo: Hilbran Verstraete)

4.3.2 Reference situation in the Thorntonbank impact area

The Thorntonbank impact area was found to be important to seabirds during reference years, hosting high numbers of seabirds, in densities well above those at the BPNS as a whole (Figure 19). From September to February, the area sees good numbers of wintering great black-backed gulls, kittiwakes and auks, added with northern gannets during autumn migration. In spring and summer, diversity proved to be much lower, and was dominated by lesser black-backed gull. The latter species occurred in very high densities of over 15 birds/km² in spring.

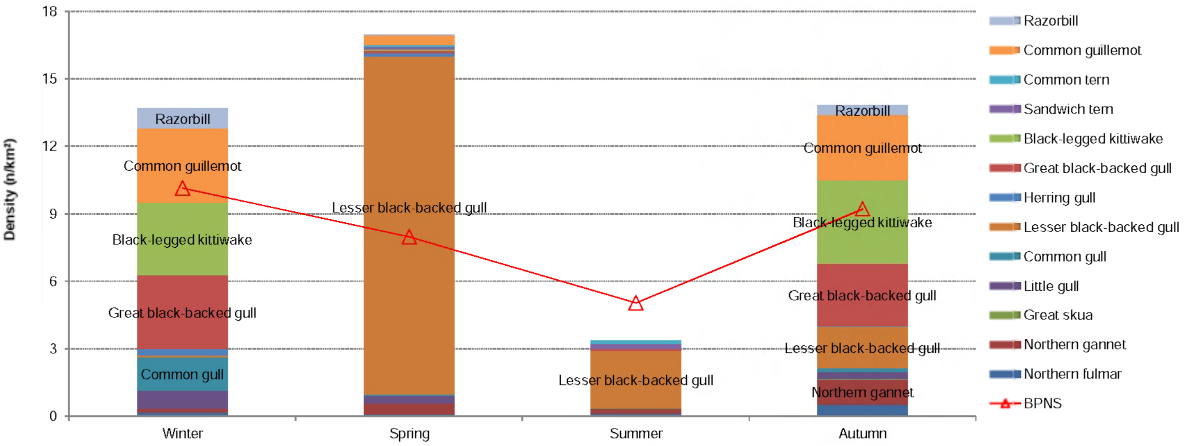


Figure 19. Seasonal densities of seabirds in the impact area at the Thorntonbank before wind farm construction (<04/2008), with indication of the cumulative seabird density at the BPNS.

For the four species of conservational concern occurring at the Thorntonbank, we calculated monthly selectivity indices (Table 5). Results show that during August great skua occurred in increased numbers in the Thorntonbank wind farm area (SI=0.45), and the same accounts for little gulls from October-February (SI=0.08-0.82). Sandwich tern appeared to prefer the area during the migration months April (SI=0.09) and August (SI=0.55). In contrast, and despite regular observations, common terns did not concentrate in the area resulting in highly negative SI values.

Table 5. Monthly selectivity indices at the Thorntonbank impact area for four seabird species of conservational concern (only shown for those months during which numbers at the BPNS exceed 10% of the maximum monthly numbers as shown in Table 3).

Species	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Great skua	-1.00		-1.00	-1.00			-1.00	**0.45**	-1.00	-1.00	-0.06	-1.00
Little gull		**0.82**	-0.04	-0.48				-1.00	-0.86	**0.08**	**0.77**	
Sandwich tern			-1.00	**0.09**	-1.00	-1.00	-0.21	**0.55**	-0.36			
Common tern				-0.32	-1.00	-1.00	-0.82	-0.40	-0.66			

4.3.3 Reference situation in the Blighbank impact area

Compared to the Thorntonbank, seabird densities at the Blighbank were much lower, not exceeding 5 birds/km², which is far beneath the overall density at the BPNS (Figure 20). During winter, only common guillemot and black-legged kittiwake were observed in considerable numbers. Densities in spring and summer were very low (<1.5 bird/km²), increasing back again in the course autumn due to moderate numbers of northern gannets, great black-backed gulls and kittiwakes.

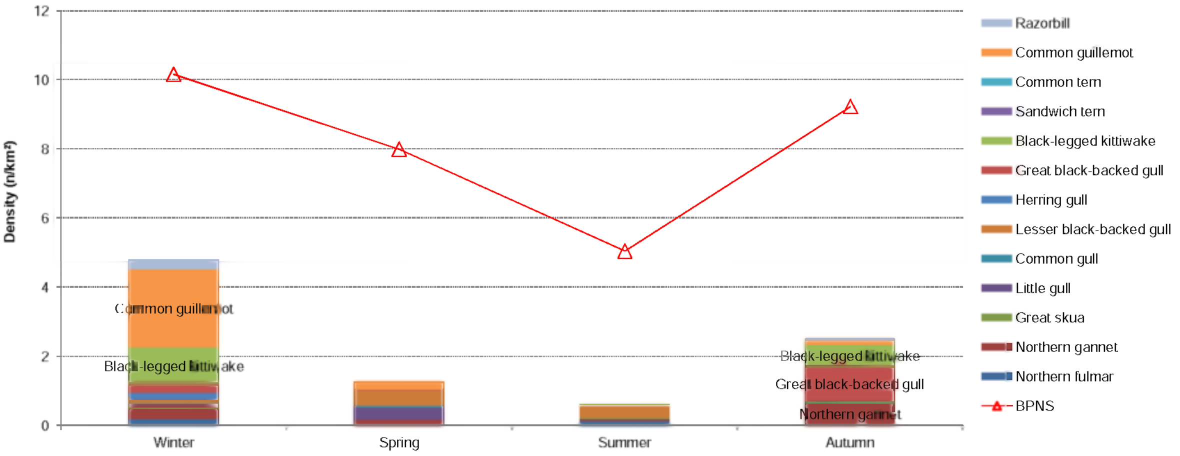


Figure 20. Seasonal densities of seabirds in the impact area at the Blighbank before wind farm construction (<09/2009), with indication of the cumulative seabird density at the BPNS.

As for the Thorntonbank in the previous paragraph, we investigated the possible preference to this area by four species of conservational concern (Table 6). Due to its far offshore location, the impact area at the Blighbank was not expected to be important to sandwich and common terns, which is confirmed by the strongly negative SI's. In contrast, increased numbers of great skua were observed in the area during 4 months between August & December (SI=0.02-0.71). Vanermen & Stienen (2009) already suggested the area to be valuable to migrating little gulls in spring. Indeed, coinciding with the spring migration peak at the BPNS, numbers of little gull were found to concentrate in the Blighbank area in March, illustrated by a well positive SI of 0.26.

Table 6. Monthly selectivity indices at the Blighbank impact area for four seabird species of conservational concern (only shown for those months during which numbers at the BPNS exceed 10% of the maximum monthly numbers as shown in Table 3).

Species	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Great skua	-1.00		-1.00	-1.00			-1.00	**0.49**	-1.00	**0.02**	**0.67**	**0.71**
Little gull		-1.00	**0.26**	-0.84				-1.00	-1.00	-1.00	-1.00	
Sandwich tern			-1.00	-1.00	-1.00	-1.00	-1.00	-1.00	-1.00			
Common tern				-1.00	-1.00	-1.00	-1.00	-0.89	-1.00			

4.3.4 Reference situation in the Lodewijckbank impact area

Conform the location, seabird densities in the impact area at the Lodewijckbank held the middle between those at the other two sites. The total winter density was just above 10 birds/km², including the usual auks and kittiwakes, but added with surprisingly high densities of herring and lesser black-backed gulls. As in the other two impact areas, lowest densities were observed in spring and summer, with again lesser black-backed gull being the dominant species. In autumn, high numbers of kittiwakes and auks were supplemented with migrating northern gannets.

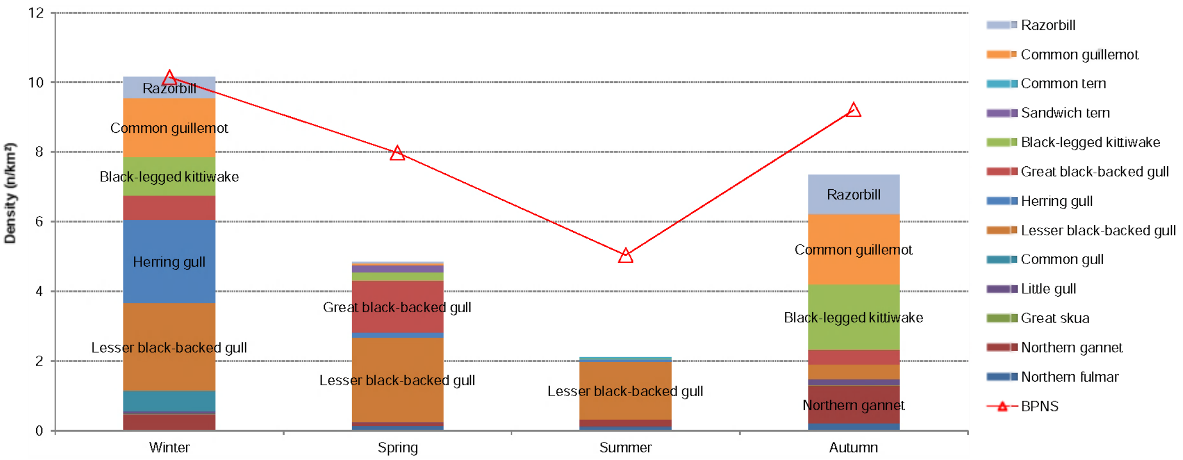


Figure 21. Seasonal densities of seabirds in the impact area at the Lodewijckbank before wind farm construction, with indication of the cumulative seabird density at the BPNS.

Analogue to the previous paragraphs, we calculated the preference of great skua, little gull and both tern species to the Lodewijckbank impact area relative to the BPNS as a whole. Based on the figures in Table 7 we see that the area was preferred by great skuas and little gulls in November. Sandwich terns migrated through the area in high numbers in April (SI=0.43), while for common tern again no positive SI values were found.

Table 7. Monthly selectivity indices at the Lodewijckbank impact area for four seabird species of conservational concern (only shown for those months during which numbers at the BPNS exceed 10% of the maximum monthly numbers as shown in Table 3).

Species	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Great skua	-1.00		-1.00	-1.00			-1.00	-1.00	-1.00	-1.00	**0.58**	-1.00
Little gull		-0.01	-1.00	-0.80				-1.00	-1.00	-0.43	**0.81**	
Sandwich tern			-1.00	**0.43**	-1.00	-1.00	-1.00	-1.00	-1.00			
Common tern				-1.00	-1.00	-1.00	-0.63	-1.00	-1.00			

4.3.5 Summary: seabirds in the Belgian concession zone for wind energy

Based on data collected during reference years, it can be concluded that the concession zone for wind energy at the BPNS is an important area to seabirds. Except during summer, mean local densities were comparable to those at the rest of the BPNS (Figure 18), and several species of high conservational value were shown to prefer the area during at least part of the year.

Regarding common seabirds we conclude that:

- within the concession zone, seabird densities strongly decreased with increasing distance to the coast;
- the area held relatively high numbers of wintering seabirds such as great black-backed gull, black-legged kittiwake, common guillemot and razorbill – these birds arrived in the course of autumn, and stayed until February-March;
- the concession zone was a preferred staging area for lesser black-backed gull in spring;
- during summer, the area was mostly devoid of birds, but lesser black-backed gulls resided in small numbers.

Based on a thorough analysis of the densities of four species of high conservational value we found that:

- from August to December, relatively high numbers of great skua occurred in the area, chiefly in north-western part (the Blighbank impact area);
- the full concession zone lies within the spring migration route of little gulls, and concentrated migration took place during February-March, while the Thorntonbank was a preferred staging area during winter months;
- in April and August, there were increased numbers of sandwich tern, due to concentrated migration over the Thornton- & Lodewijckbank;
- the wind farm concession zone cannot be regarded as particularly important to common tern, despite small numbers migrating through the south-eastern part of the area.

First winter black-legged kittiwake and company (photo: starlingreizen.be)

4.4 Results: wind farm sensitivity analysis

4.4.1 Input values

For several species, the flight height data collected at the BPNS are in concordance with at least one of the review results presented by Cook *et al*. (2012) & Furness *et al*. (2013). This is the case in red-throated diver, great crested grebe, northern fulmar, common scoter, great skua and both auk species. Our own estimated percentages of gannets, gulls and terns flying at rotor height however are consistently lower than the percentages reported in the review literature. This is partly caused by the fact that rotor height by aforementioned authors is defined as 20-150 m above sea level (instead of 30-150 m as used in this study), but we cannot rule out the possibility that flight altitudes at the BPNS were consistently underestimated.

We therefore applied the 'worst case scenario principle' and used the highest of the three reported values to define score (b) for the SSI calculation (Table 8). With one exception however, according to Cook *et al*. (2012), their modelled value of 13% for common tern is of low confidence, and this value is therefore ignored (resulting in a score of 3 instead of 4).

Table 8. Flight altitude scores (b) used for calculation of the SSI - based on percentages of birds flying at rotor height as observed at the BPNS in the period 2008-2012 (rotor height defined as 30-150 m) and as reported in review literature (rotor height defined as 20-150 m).

	N	BPNS (%)	Cook (2012) (%)	Furness (2013) (%)	**Score (b)**
Red-throated diver	506	4	2	5	**2**
Great crested grebe	175	0	0	4	**2**
Northern fulmar	810	0	0.2	1	**1**
Northern gannet	3713	5	10	16	**4**
Great cormorant	1216	8	-	4	**3**
Common scoter	1453	2	1	3	**2**
Great skua	192	5	4	10	**3**
Little gull	4090	2	6	-	**3**
Black-headed gull	2413	6	8	18	**4**
Common gull	8648	15	23	23	**5**
Lesser black-backed gull	14919	22	25	30	**5**
Herring gull	4518	15	28	35	**5**
Great black-backed gull	2330	20	33	35	**5**
Black-legged kittiwake	9310	9	16	16	**4**
Sandwich tern	2111	2	4	7	**3**
Common tern	4112	1	(13)	7	**3**
Common guillemot	995	0	0	1	**1**
Razorbill	937	0	0.4	1	**1**

Despite the slight changes in vulnerability scores, the eventual SSI values presented in Table 9 are highly similar to those presented by Garthe & Hüppop (2004). The largest difference is seen in common tern due to the strong increase in the factor (i) related to conservation status.

Herring gull flying at rotor height in the Blighbank wind farm (photo: Hilbran Verstraete)

Table 9. Species-specific input scores for calculation of the species sensitivity index (SSI) – scores in grey are revised regarding to those reported by Garthe & Hüppop (2004).

	a	b	c	e	f	g	h	i	
	Flight manouvr.	Flight altitude	% flying	Disturb. sensitivity	Habitat flexibility	Population size	Adult survival	Conserv. Status	**SSI**
Red-throated diver	5	2	1	5	4	5	3	5	**52.0**
Black-throated diver	5	2	1	5	4	4	3	5	**48.0**
Sandwich tern	1	3	5	2	3	4	4	5	**32.5**
Common tern	1	3	5	2	3	3	4	5	**30.0**
Great cormorant	4	3	2	4	3	4	3	1	**28.0**
Great black-backed gull	2	5	1	2	2	4	5	2	**19.6**
Great crested grebe	4	2	1	4	4	4	1	1	**18.7**
Razorbill	4	1	1	3	3	2	5	2	**18.0**
Northern gannet	3	4	2	2	1	4	5	3	**18.0**
Little gull	1	3	2	1	3	5	2	5	**16.0**
Common scoter	3	2	1	5	4	2	2	1	**15.0**
Common gull	1	5	2	2	2	2	2	4	**14.2**
Lesser black-backed gull	1	5	1	2	1	4	5	2	**12.8**
Common guillemot	4	1	1	3	3	1	4	1	**12.0**
Great skua	1	3	2	1	2	5	4	2	**11.0**
Herring gull	2	5	1	2	1	2	5	1	**10.7**
Black-headed gull	1	4	2	2	2	1	3	1	**7.8**
Black-legged kittiwake	1	4	2	2	2	1	3	1	**7.8**
Northern fulmar	3	1	1	1	1	1	5	1	**3.9**

4.4.2 Wind farm sensitivity maps

For the German part of the North Sea (GPNS), Garthe & Hüppop (2004) set the level of concern at the 60 percentile of the average WSI frequency distribution, according with a WSI of 24. The level of major concern was set at the 80 percentile, equalling a WSI of 43. Applying these same values on the seasonal WSI values at the BPNS, we found that 90% of the investigated grid cells would be of major concern during at least one season, strongly emphasising the importance of the BPNS to seabirds. Compared to the BPNS, the GPNS includes a huge offshore area hosting relatively few birds, explaining the difference in gravity point of the respective frequency distributions. In the sense of spatial planning, using the German WSI thresholds at the BPNS has little value. Therefore we use the same percentile cut-offs instead of the absolute values, allowing to identify the 20 and 40% most sensitive areas at the BPNS.

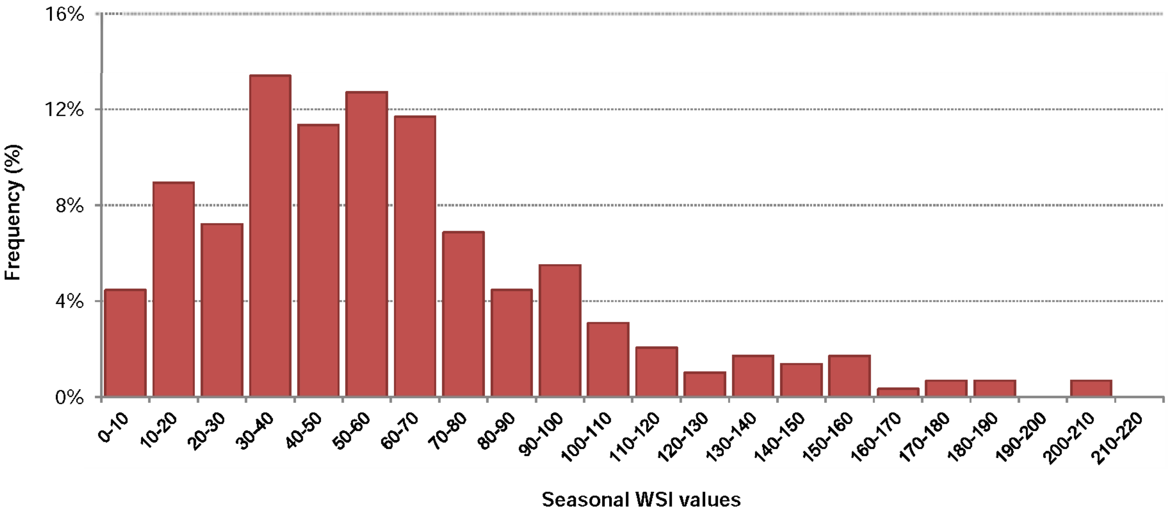


Figure 22. Average frequency plot of seasonal WSI values in 6x6 km² grid cells as found at the BPNS.

Overlaying the BPNS with a 6x6 km² grid, and calculating the mean of the 4 seasonal WSI values per grid cell, we obtain the map visualised in Figure 23. The 20% most sensitive areas are all located within 6 NM from the coast, except for one grid cell on the northern border of the Vlakte van de Raan. The areas with highest WSI's thus largely overlap with the zones designated as Special Protection Areas by Haelters *et al*. (2004). The major part of the area further offshore (>6 NM) appears to be of relatively low concern regarding wind farm development, but several scattered grid cells do show a WSI above the 60 percentile. Interestingly, a zone of more than 100 km² in the Thornton- and Lodewijckbank area classifies as sensitive (>60 percentile). In contrast, WSI values in the north western part of the wind farm concession zone (Blighbank) are low. This is in line with the results of the reference analyses (§4.3), which demonstrated that the Thorntonbank area holds much higher numbers and a greater diversity of seabirds than the Blighbank.

As could be expected, wind farm sensitivity shows strong seasonal variation (see Figure 24). In winter, wind farm sensitivity is high throughout the BPNS, with particularly high WSI's along the west coast, around the Hinderbanken and near the Thornton- and Lodewijckbank. During spring and summer, the offshore area (>10 NM) shows low sensitivity (being particularly low during summer), but high WSI's occur throughout zone I (<10 NM), especially around the port of Zeebrugge. In autumn also, wind farm sensitivity is fairly low throughout most of the BPNS, yet with increased sensitivity along the west coast and around the Thorntonbank.

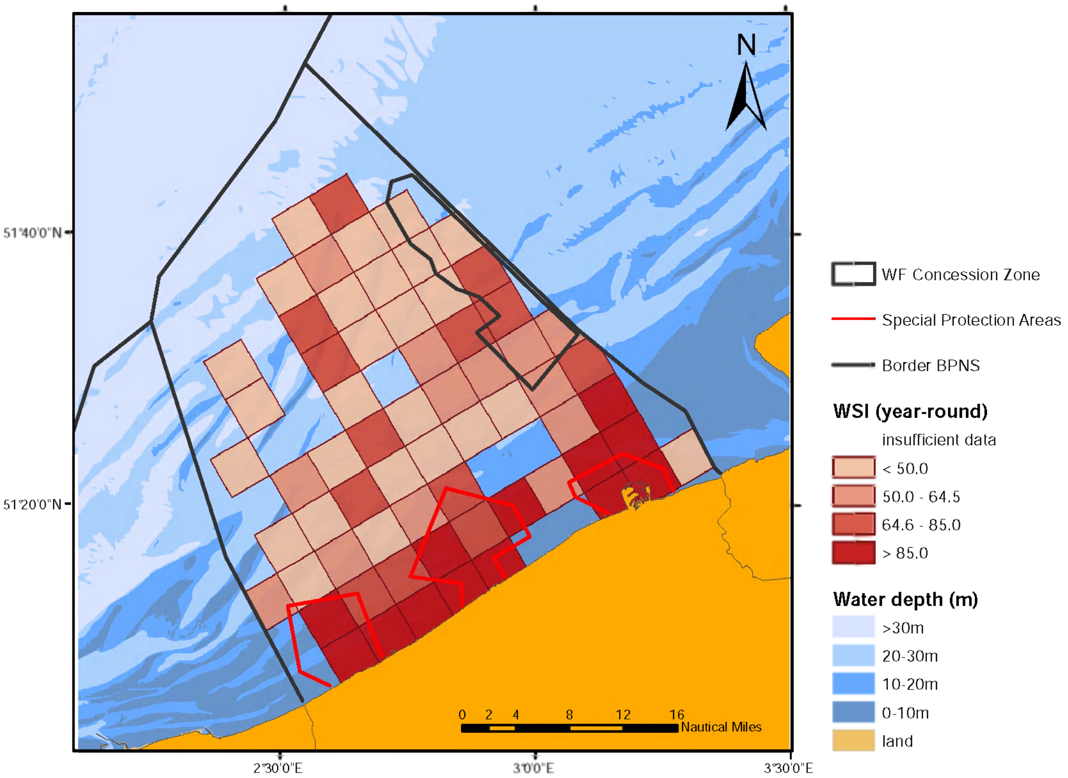


Figure 23. Map of the BPNS with 6x6 km² grid cells colour-scaled according to average wind farm sensitivity (legend cut-offs corresponding to the 40, 60 & 80 percentiles of the frequency distribution of the mean WSI values).

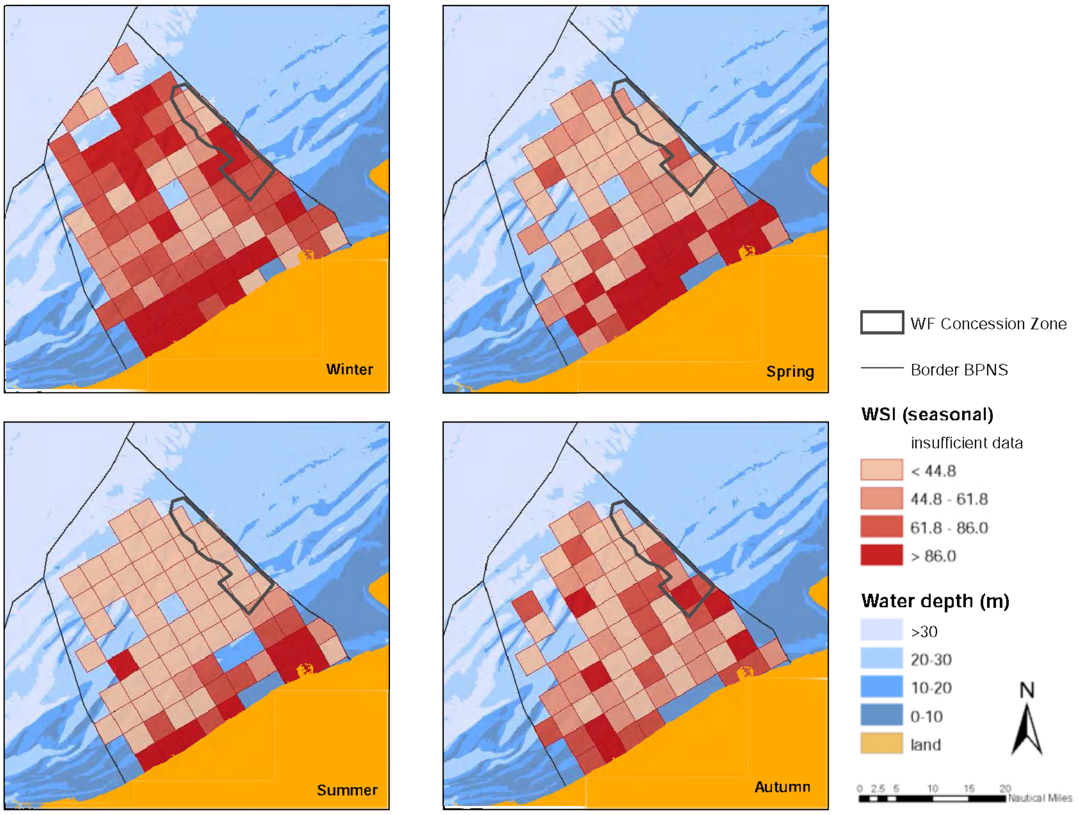


Figure 24. Maps of the BPNS with 6x6 km² grid cells colour-scaled according to seasonal wind farm sensitivity (legend cut-offs based on the 40, 60 & 80 percentiles of the frequency distribution of the seasonal WSI values – see Figure 22).

5 Monitoring seabird displacement: a modelling approach

In this chapter, we describe the BACI monitoring set-up and the process of data handling for assessing seabird displacement effects caused by offshore wind farms. Seabird presence in the study area was modelled supposing that our 'seabirds at sea' (SAS) data follow a (zero-inflated) negative binomial distribution and taking account of seasonal variation in seabird numbers. To study the statistical value of our data, we performed extensive power analyses. Among other things, power results learn us how long monitoring programs should be continued in order to be able to discern certain effects (e.g. a decrease in seabird density of 25%). Lastly, we report on the results of the impact models, and discuss which species were found to be displaced to or out from the wind farm study areas, and hypothesise on the ecological processes behind observed patterns.

5.1 Methods: monitoring seabird displacement

5.1.1 BACI set-up

Stewart-Oaten & Bence (2001) reviewed various approaches for environmental impact assessment, differing in goals and time series available. When 'before' data are available and the inclusion of a suitable control is possible, before/after control/impact (BACI) assessment is the suggested approach. While the importance of temporal replication in BACI assessments is widely recognised, there is disagreement on the role of spatial replication, i.e. the inclusion of several control locations (Bernstein & Zalinski 1983, Stewart-Oaten *et al*. 1986, Underwood 1994, Underwood & Chapman 2003, Stewart-Oaten & Bence 2001). In a SAS context, including more than one control area is often not feasible, considering budgetary constraints and/or limited availability of research vessels. In this respect, Stewart-Oaten & Bence (2001) argue that when the goal of the assessment is to detect a particular change at a predefined, non-random location (e.g. the Blighbank wind farm), variation among control sites is irrelevant to the assessment problem. The authors conclude that multiple controls are not needed, but can be useful for insurance, model checking and causal assessment.

Seabird monitoring from the RV Belgica near the Blighbank wind farm
(photo: Nicolas Vanermen)

As explained in §4.1.2, we surrounded every wind farm area with a buffer zone of 3 km to define the 'impact area', being the zone where effects of the wind farm presence can be expected. Next, a more or less equally large control area was delineated, harbouring comparable numbers of seabirds, showing similar environmental conditions, and enclosing a high number of historical count data (Vanermen *et al*. 2010) (see Figure 25 & Figure 26). Considering the large day-to-day variation in observation conditions and seabird densities, the distance between control and impact areas was chosen to be small enough to be able to survey both on the same day by means of a research vessel. As a result, control and impact areas are only 1.5 km apart, equalling half the mean distance sailed during a ten-minute count (the standard unit in our SAS database).

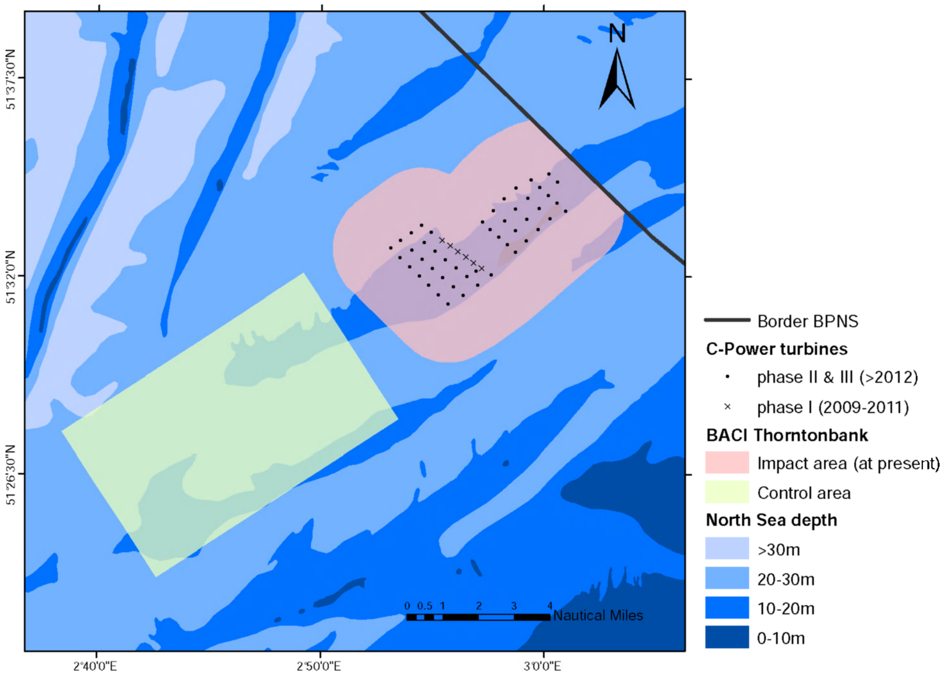


Figure 25. Control and impact area of the C-Power wind farm at the Thorntonbank.

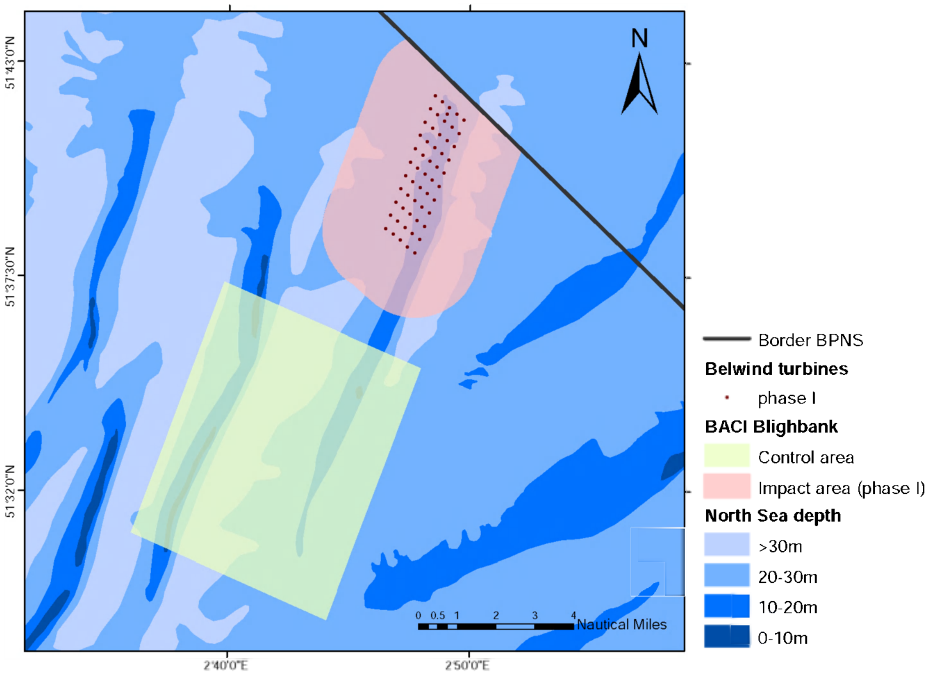


Figure 26. Control and impact area of the Belwind wind farm at the Blighbank.

While the extent of the control areas is fixed, the exact size and shape of the impact areas varies according to the progress of the wind farm construction. Hence the BACI lay-outs shown in Figure 25 & Figure 26 represent the ideal case in which a complete wind farm is being built overnight. In practice, wind farms are constructed in separate phases and construction plans change over time. While C-Power originally planned to build 60 turbines at the Thorntonbank, they ended up placing 54 higher-powered turbines, built over a wider space. For a long time however only 6 turbines were present at the site. Therefore different 'impact polygons' are in use, depending on the time period considered.

Table 10 gives an overview of the reference, construction and impact periods at the two operational wind farms as applied in our analyses. Data collected during the 1st construction period of both wind farms were not used for impact assessment analyses, because access to the study areas was mostly restricted to the surroundings, hampering adequate monitoring. In contrast, during the construction of phase II & III of the C-Power wind farm, access to the area was facilitated, allowing for a separate impact analysis.

Table 10. Definition of the reference, construction and impact periods at the Thorntonbank and Blighbank study areas as applied in the impact analyses.

	Thorntonbank (C-Power)	Blighbank (Belwind)
Reference period	< 04/2008	< 09/2009
1st Construction period	04/2008 – 05/2009 (highly restricted access)	09/2009 – 08/2010 (highly restricted access)
Impact period	06/2009 – 04/2011 (6 turbines)	09/2010 – on-going (55 turbines)
2nd Construction period	05/2011 – on-going (variable access)	

To model displacement effects, we used data on thirteen seabird species occurring regularly in the respective wind farm areas (listed in Table 11, see also §4.3).

Table 11. Species included for modelling displacement effects caused by wind turbines.

Species	Thorntonbank	Blighbank
Northern fulmar (*Fulmarus glacialis*)	X	X
Northern gannet (*Morus bassanus*)	X	X
Great skua (*Stercorarius skua*)	X	X
Little gull (*Hydrocoloeus minutus*)	X	X
Common gull (*Larus canus*)	X	X
Lesser black-backed gull (*Larus fuscus*)	X	X
Herring gull (*Larus argentatus*)	X	X
Great black-backed gull (*Larus marinus)*	X	X
Black-legged kittiwake (*Rissa tridactyla*)	X	X
Sandwich tern (*Sterna sandvicensis*)	X	
Common tern (*Sterna hirundo*)	X	
Common guillemot (*Uria aalge*)	X	X
Razorbill (*Alca torda*)	X	X

5.1.2 BACI seabird surveys

Monitoring was performed through monthly ship-based seabird counts along fixed monitoring routes (Figure 27), which were conducted according to the internationally applied ESAS method (§3.1.1). The applied count unit in our seabird database is the result of so-called 'ten-minute counts'. Stewart-Oaten *et al*. (1986) state that in BACI assessments, any information gained from replicates taken at the same time is not useful, and that it is better to consider one summarised value. Accordingly, we summed our count data per area (control/impact) and per monitoring day, resulting in day-totals. This way, we avoided pseudo-replication resulting from autocorrelation between subsequent ten-minute counts, and minimised overall variance. We also included only those days during which both areas were visited, minimising additional variation due to short-term temporal changes in seabird abundance as well as in weather and observation conditions. Today, the monitoring routes always include both of these areas, but this was not always the case in our historical surveys.

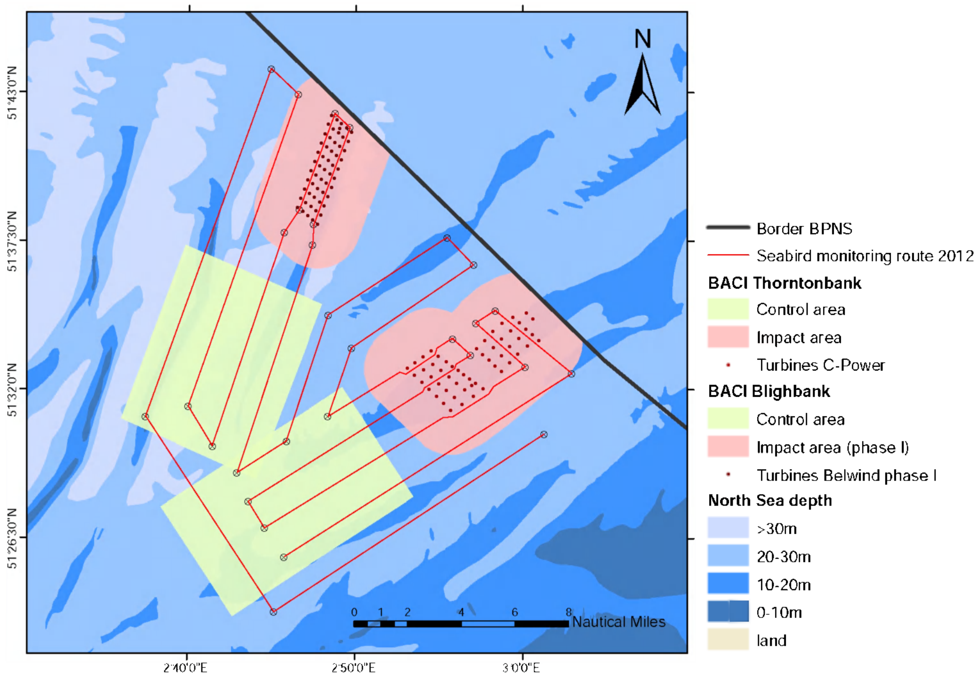


Figure 27. Wind farm monitoring route as performed from 2012 onwards.

Common guillemot (photo: Hilbran Verstraete)

5.1.3 Survey effort

The first turbine foundations at the Thorntonbank were installed in April 2008, and the reference period therefore includes all data collected until March 2008. INBO started monthly monitoring of the study area in 2005, but has data available dating back to 1993. In total, 66 surveys were included in the reference dataset - with one day total per area (control/impact) per survey this results in a sample size (N) of 132. Construction activities continued until May 2009, and during that time access to the area was highly restricted. Impact data include all observations collected from June 2009 to April 2011 (33 impact surveys – N=66), after which the construction of phase II & III was started up, and access was restricted again. Despite on-going construction activities, access to the area was facilitated from January 2012 on, and for this period, a separate impact analysis will be performed, in order to investigate the effects of construction activities on seabird presence.

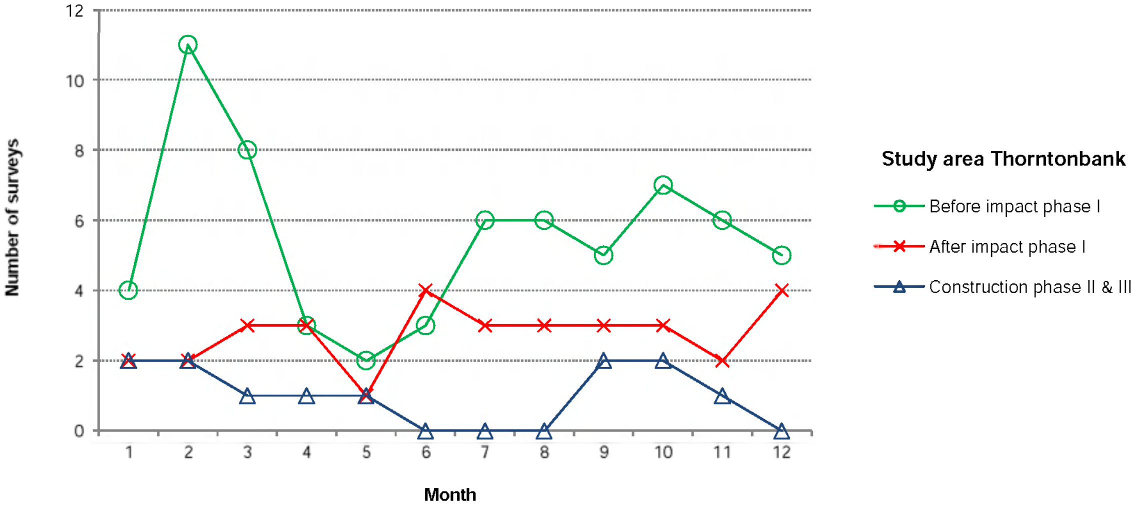


Figure 28. Count effort in the Thorntonbank study area, with indication of the number of surveys performed before and after the construction of the phase I turbines, as well as during the construction of phase II & III.

Nicolas Vanermen and Eric Stienen busy counting seabirds from the
RV Belgica at the Thorntonbank wind farm (photo: Bob Rumes)

At the Blighbank, construction activities were started up in September 2009, prior to which INBO performed 63 reference surveys (N=126). The last of 55 turbines was built in September 2010, and from that time on, monthly impact monitoring was performed inside the wind farm boundaries. All data collected from September 2010 to December 2012 (totalling 30 surveys – N=60) were defined as 'impact data', and were used to assess the effect of the operational Blighbank wind farm on local seabird distribution.

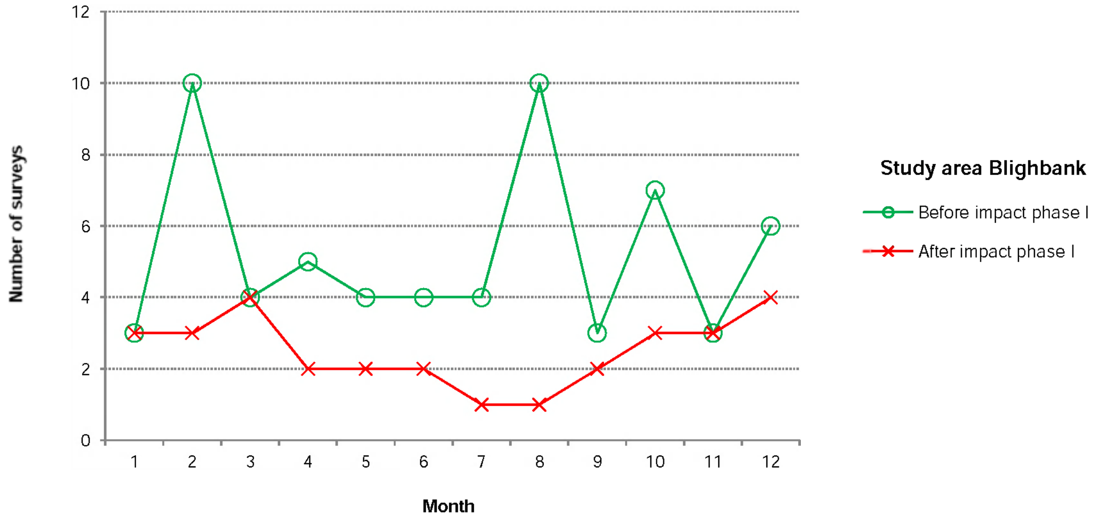


Figure 29. Count effort in the Blighbank study area, with indication of the number of surveys performed before and after the construction of the phase I turbines.

Morning glory at the Thorntonbank wind farm (photo: Nicolas Vanermen)

5.2 Methods: modelling seabird displacement

5.2.1 Modelling SAS data

There are several ways in which SAS data can be modelled, using generalised linear models (Leopold *et al*. 2004, Maclean *et al*. 2006 & 2007), quasi-likelihood estimation (McDonald *et al*. 2000), generalised additive models (Clarke *et al*. 2003, Karnovsky *et al*. 2006, Huettmann & Diamond 2006, Certain *et al*. 2007), or combining one of these with geostatistics (Pebesma *et al*. 2000, Pérez-Lapeña *et al*. 2010 & 2011). When a counted subject is randomly dispersed, count results tend to be Poisson-distributed, in which the mean equals the variance (McCullagh & Nelder 1989). Seabirds however often occur strongly aggregated in (multi-species) flocks, typically resulting in a high proportion of zero counts and relatively few but sometimes very high positive counts. Not surprisingly, the variance of seabird count results exceeds the mean without exception, and such data are called 'over-dispersed'. The greatest challenge in dealing with SAS data for impact assessment purposes is thus to correctly handle this inherent high variance. The most common approach to do so is to apply a generalised linear model with a quasi-poisson (QP) or a negative binomial (NB) distribution (Ver Hoef & Boveng 2007). Here we applied a NB distribution, since this distribution is to be preferred over a QP in case of highly over-dispersed data (Zuur *et al*. 2009).

The variance function of a negative binomial distribution is of the following form:

$$V(\mu) = \mu + \frac{\mu^2}{\theta} = \left(1 + \frac{\mu}{\theta}\right) \times \mu \qquad \text{(Eq. 1)}$$

And the over-dispersion parameter φ thus equals:

$$\phi = \frac{V(\mu)}{\mu} = 1 + \frac{\mu}{\theta} \qquad \text{(Eq. 2)}$$

As can be seen, the over-dispersion parameter is inversely proportional to the theta value. Despite accounting for over-dispersion, data may still exhibit more zeros than predicted through NB modelling. In these cases, 'zero-inflated models' (ZI) offer a way out (Potts & Elith 2006, Zeileis *et al.* 2008). This type of model consists of two parts, (1) a 'zero component' modelling the additional chance (p) of *not* encountering birds applying a logistic regression, and (2) a 'count component' modelling the count data (λ) according to a NB distribution with probability (1-p). Hence, the so-called ZINB model predicts the expected number of birds Y encountered as follows (Potts & Elith 2006):

$$Y \sim \begin{cases} 0, & \text{with probability p} \\ \text{NB}(\lambda), & \text{with probability (1-p)} \end{cases}$$

5.2.2 Reference modelling

Since seabird occurrence is subject to large seasonal fluctuations we first added *seasonality* as a covariate to the models. Most seasonal patterns can be described by a cyclic sine curve, which can be written as a linear sum of sine and cosine terms (Stewart-Oaten & Bence 2001, Onkelinx *et al.* 2008), allowing to include *month* as a continuous variable. This method performed much better compared to the inclusion of *month* as a factor variable which actually splits the dataset in twelve subsets, resulting in high standard errors and unreliable coefficient estimates. Whether data were collected in the control or impact area was included in the model through the factor variable *CI*. We did not allow for interaction between *CI* and *seasonality* since differences in seasonal patterns are not expected to occur at such a small spatial scale.

The response variable equals the total number of birds observed (inside the transect) during one monitoring day in either the control or impact area. To correct for varying monitoring effort, the number of km² counted is included in the model as an offset-variable. The reference model (or at least the count component) is thus of the following form:

$$\log(response) = offset(\log(km^2)) + a_1 + a_2.\sin\left(2\Pi\frac{month}{12}\right) + a_3.\cos\left(2\Pi\frac{month}{12}\right) + a_6.CI$$

(Eq. 3)

In Eq. 3, *seasonality* is modelled as a sine curve with a period of 12 months (Figure 30). Several migratory species however show two peaks in density per year (Figure 31). To describe such a seasonal pattern, another sine curve with a period of 6 months can be added, and the reference model is then written as:

$$\log(response) = offset(\log(km^2)) + a_1 + a_2.\sin\left(2\Pi\frac{month}{12}\right) + a_3.\cos\left(2\Pi\frac{month}{12}\right) + a_4.\sin\left(2\Pi\frac{month}{6}\right) + a_5.\cos\left(2\Pi\frac{month}{6}\right) + a_6.CI$$

(Eq. 4)

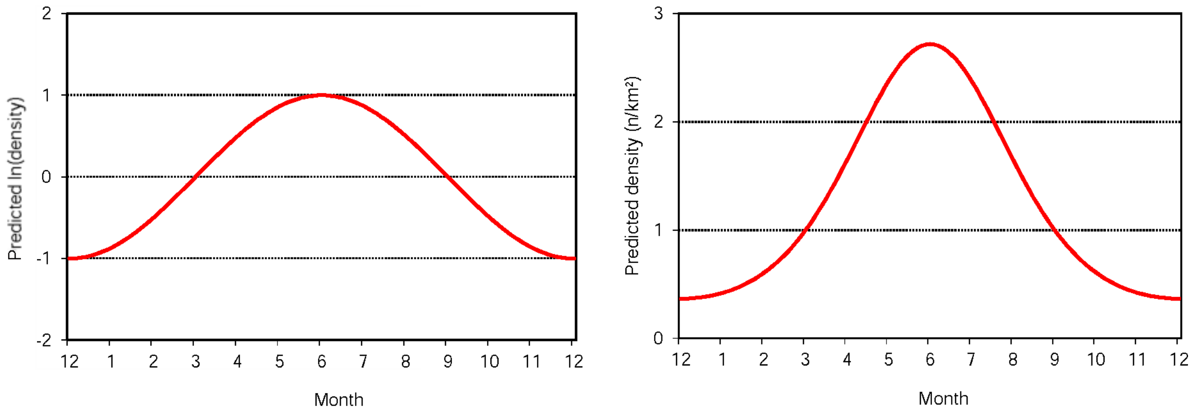


Figure 30. Example of a sine curve with a period of 12 months in the logarithmic scale (left) and the same curve after transformation into the linear scale (right).

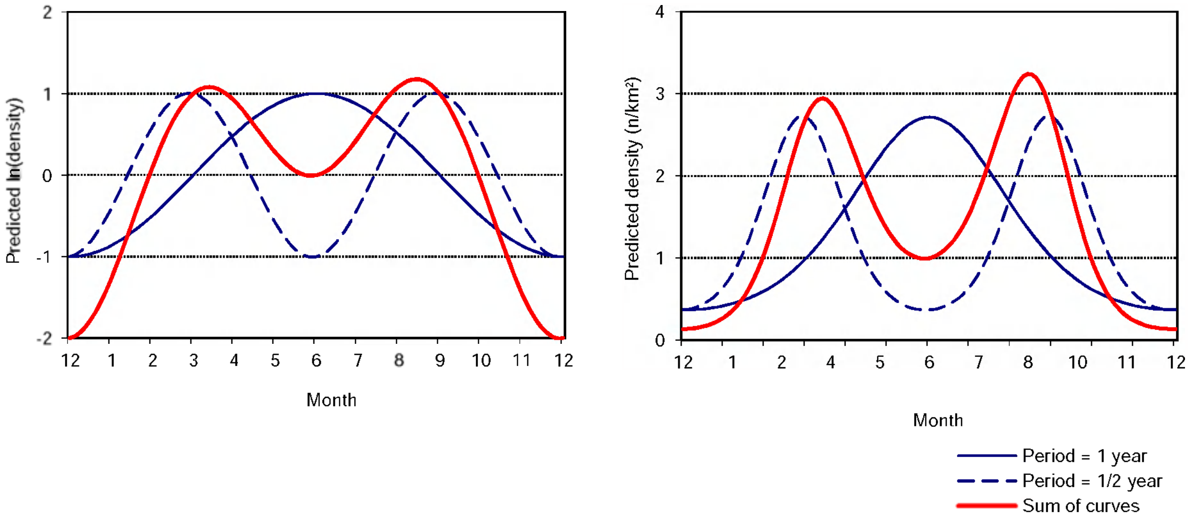


Figure 31. Example of a double-peaked sine curve obtained through combination of two curves with different periods (12 & 6 months), in the logarithmic scale (left) and after transformation into the linear scale (right).

The reference model is then selected through backward model selection, first testing for the area effect *CI*, and then testing for the effect of *seasonality*, comparing the different models using a Wald-test and considering their respective AIC values.

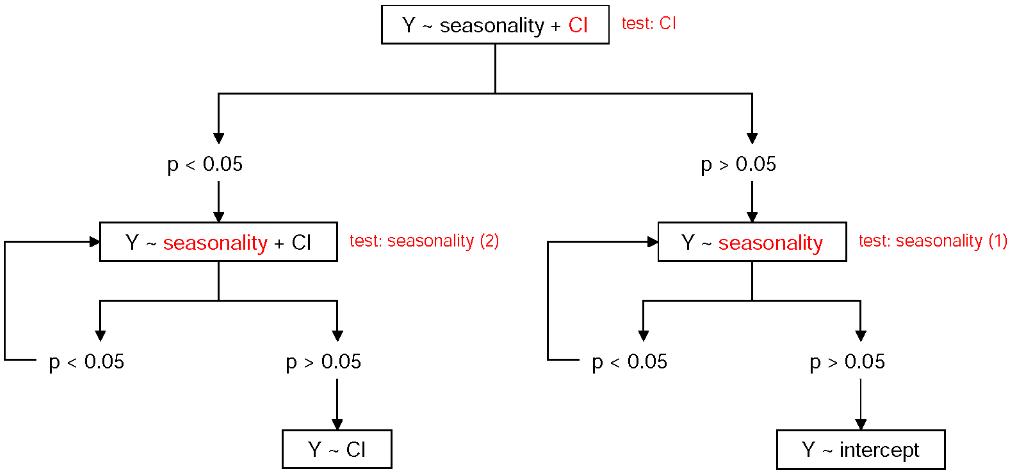


Figure 32. Reference model selection flowchart.

When applying a ZINB model, the zero-component was built up solely from an intercept (b_1), linked to the response by a logit-function. Back-transformation of this intercept results in the chance of encountering an additional zero-value (e.g. an intercept of 1 corresponds to a chance of 73.1%).

5.2.3 Impact modelling

The impact model is a simple extension of the count component of the reference model by the factor variables *BA* (before/after turbine construction) and/or *T* (turbine absence/presence), depending on the outcome of the reference model selection:

reference model		impact model	
Y ~ seasonality + CI	→	Y ~ seasonality + CI + BA + BA:CI	(Eq. 5)
Y ~ CI	→	Y ~ CI + BA + BA:CI	(Eq. 6)
Y ~ seasonality	→	Y ~ seasonality + BA + T	(Eq. 7)
Y ~ intercept	→	Y ~ BA + T	(Eq. 8)

Here, *seasonality* is the sine wave as described earlier (§5.2.2). The effect of wind farm presence on the number of seabirds is estimated by the coefficient of the interaction term *BA:CI* (Eq. 5 & 6), or by the coefficient of the factor variable *T* (Eq. 7 & 8), of which the significance is tested based on the value of the corresponding *z* statistic.

How the value of this coefficient relates to the impact of wind farm presence on seabirds is illustrated in Figure 33. A negative model coefficient value indicates that birds are avoiding the wind farm, resulting in habitat loss yet a decreasing number of collision fatalities, while a positive value suggests attraction of seabirds and increased bird mortality. The exponential relation between the model coefficient and the number of collision fatalities is explained by the logarithmic link between the response and the linear regression equation incorporated in the NB model structure (see Eq. 3 & 4).

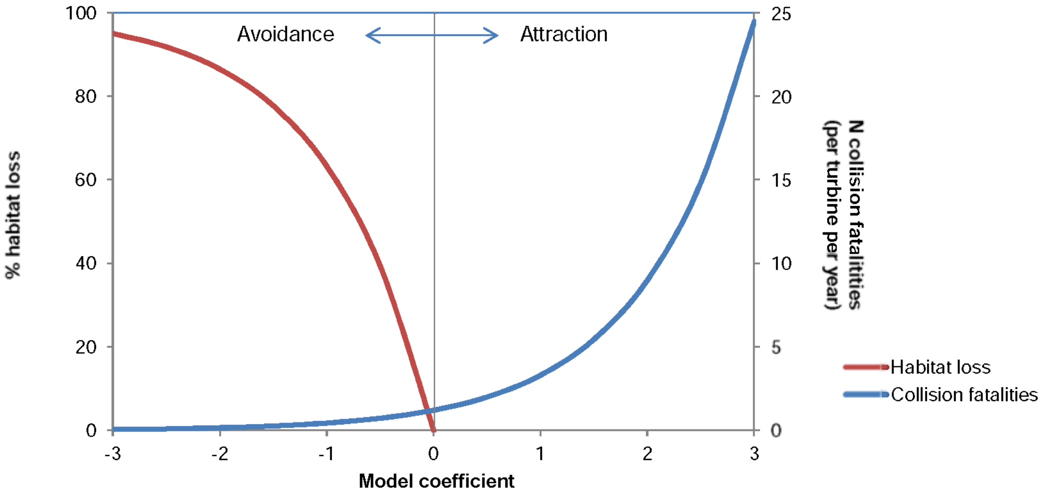


Figure 33. Relation between the displacement-related model coefficient and the anticipated negative impact on seabirds (estimation of collision fatalities being based on the characteristics of lesser black-backed gull and a hypothetical density of 0.02 birds/km^2 at rotor height).

For reference modelling and power analysis purposes, we applied a ZINB model for all species. In the impact modelling stage however, we considered each species separately whether to use a NB or ZINB model. In theory, this can be done based on two criteria:

- The P-value of the zero-component intercept: the null hypothesis of the z-test testing for the effect of the intercept is that b_1 equals zero. Back-transformation of an intercept value of zero however corresponds to a chance of 50%, which can already be classified as a high degree of zero-inflation.

- A Vuong test (Vuong, 1989): a test that compares non-nested models, as is the case here with a NB model and its zero-inflated analogue. The sign (+/-) of the test-statistic indicates which model is superior over the other in terms of probability. However, in most cases, the corresponding P-value appeared to be indecisive.

Hence, none of these two options gave distinct results. We therefore defined our own criterion and calculated the lower boundary of the 95% confidence interval of the zero-component intercept: when this lower boundary exceeds -2.2 (corresponding to an additional 10% chance to encounter zero birds), we decided to hold on to the ZINB model.

5.2.4 Power analysis

To investigate the statistical value of our data, we performed an extensive power analysis. In our impact assessment, the power reflects the chance of statistically detecting a certain change in seabird numbers, which of course one wants to be as high as possible. The power is estimated by simulating random BACI datasets with pre-defined characteristics, i.e. the model parameters as found during the reference modelling (§5.2.2), and imposing a hypothetical change on the post-construction numbers. The imposed change in numbers is supposed to occur immediately after the impact and throughout the impact area, and to persist as long as turbines are present (‘press disturbance’ – Underwood & Chapman 2003). Our analysis is based on the reference data collected in the Thorntonbank study area and the associated reference models.

5.2.4.1 Testing the effect of model parameters

We first modelled the reference data applying one and the same base model for all species (analogous to Eq. 3 in §5.2.2). This exercise revealed empirical coefficient ranges, i.e. the intercept (a_1), the amplitude of *seasonality* (equalling the square root of the sum of squares of a_2 & a_3), the effect of *CI* (a_6), theta θ (related to the data variance – see Eq. 1) and the amount of zero-inflation (b_1). Next, we varied all of these coefficient values within these empirical ranges, resulting in 159 scenarios (see Annex I - Figure 50). At this stage, the monitoring set-up characteristics were held constant, with a reference and impact period of both 5 years, one survey per month with an effort of 10 km² per area, a post-construction decrease in numbers of 50% and a significance level of 10%. The latter represents the chance of wrongly concluding that the turbines are causing an impact, while in fact they are not (‘type I error’). Power was assessed by simulating each scenario 1,000 times, and calculating the percentage of times the z-test of our impact analysis resulted in a P-value less than 10% for the *BA:CI* or *T* term.

5.2.4.2 Testing the effect of survey duration and degree of seabird displacement

In a second step we calculated powers based on the coefficient estimates of species-specific reference models (§5.2.2, Figure 32), this time varying monitoring set-up characteristics, more precisely the decrease in numbers in the impact area to be detected (25, 50 & 75%) and the monitoring period (5 years before versus 1, 3, …, 15 years after impact). Again, each scenario was simulated 1,000 times, resulting in 1,000 impact model outputs per scenario, with the power equalling the percentage of times that the z-test revealed significance for the *BA:CI* or *T* term.

5.2.5 Statistics

All data handling and modelling was performed in R.2.15.0 (R Core Team 2012), making use of the following packages:

- lmtest (Zeileis & Hothorn 2002)
- MASS (Venables & Ripley 2002)
- reshape (Wickham 2007)
- pscl (Zeileis *et al*. 2008, Jackman 2011)
- foreign (R Core Team 2011)
- RODBC (Ripley 2012)

5.3 Results: power analysis

5.3.1 Effect on power by model parameters

We calculated the power for 159 scenarios varying the intercept, seasonal amplitude, theta and amount of zero-inflation within empirical coefficient ranges (see Annex I, Figure 50 & Table 23 → Table 25).

Zero-inflation has a strong negative effect on the power of our impact study (Figure 34). When inducing zero-inflation by setting $b_1=0$ & $b_1=1$, power drops from 78% in the non-zero-inflated scenario to 50% and 36% respectively. Despite overall power being low, the ZINB model performs slightly better than the NB model when considering zero-inflated data.

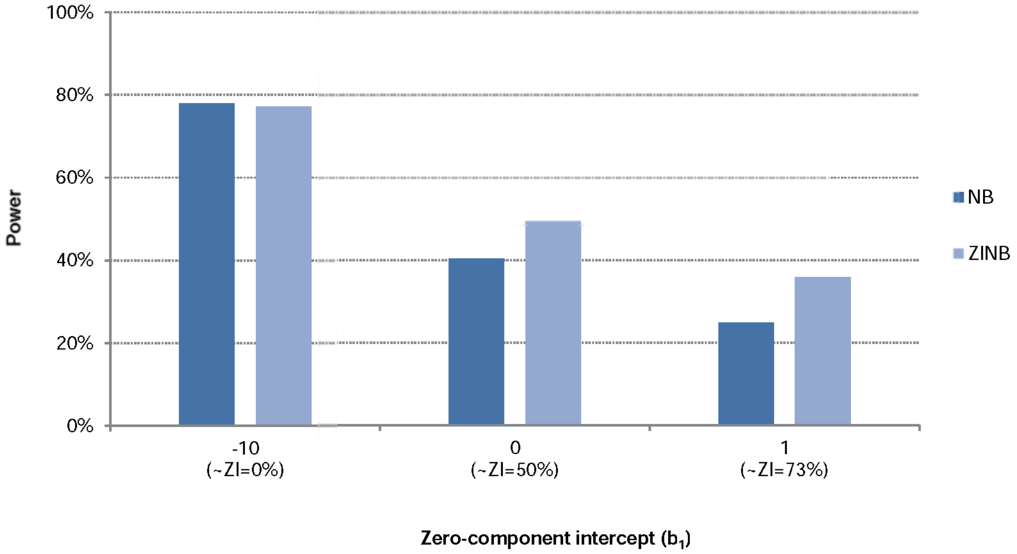


Figure 34.Comparison of the power to detect a 50% decrease in numbers based on a NB and a ZINB model, for several levels of zero-inflation (data simulations based on coefficients $a_1=-1$, $a_2=1$, $a_3=0$, $a_6=0$, $\theta=0.5$).

Theta θ is another parameter strongly influencing the power of our impact analysis (Figure 35). For the regarded monitoring set-up, a theta of 0.2 or less inevitably results in low power (<60%), and a value of more than 0.6 is needed to obtain a power of 90% after five years of post-impact monitoring, provided data are not zero-inflated. Base modelling (see Annex I) showed that the reference data of several species combine zero-inflation with a favourable theta (>0.4), suggesting that the over-dispersion is (at least partly) captured by the zero-component. When comparing the power-curve for the scenario's 'θ=0.2 / ZI=0%' and 'θ=0.6 / ZI=73%' in Figure 35, it shows that the benefit gained from a seemingly favourable theta does not compensate for the loss of power due to zero-inflation. As θ continues to rise (illustrated by scenario 'θ=1.2 / ZI=73%'), power results do start to catch up.

Based on Figure 35, we also learn that the intercept is positively correlated with resulting power, which is particularly true for intercepts ranging from -4 to 0. The increase in power levels off when the intercept exceeds zero, corresponding to a seabird density of 1 bird/km². On the other hand, the amplitude of *seasonality* appears to have a limited effect on the power to detect a change in numbers.

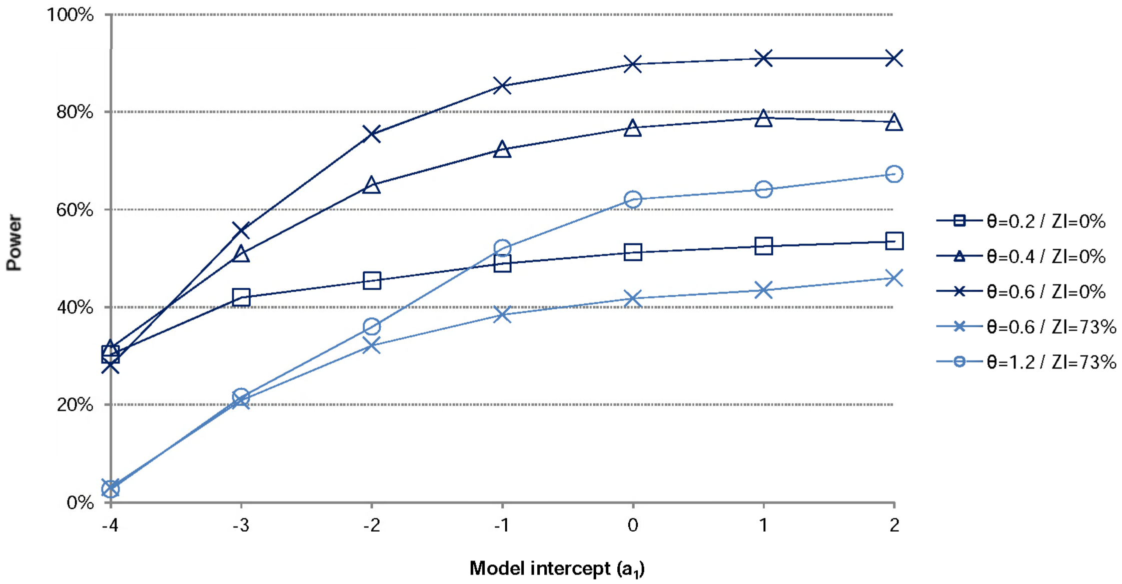


Figure 35. Effect of the model intercept (a_1), theta (θ) and the amount of zero-inflation (ZI) on the power to detect a 50% decline in numbers (data simulations based on a seasonal amplitude equalling zero: a_2=0 & a_3=0).

Finally, we investigated the effect of the area factor (*CI*). For the same relative decrease in numbers (50%), we simulated datasets with varying *CI* coefficients (a_6). When there is no statistical difference in the numbers of seabirds occurring in the control and impact area during reference years, the *CI* factor can be excluded (Eq. 7), thus gaining a degree in freedom as opposed to a model that does include *CI* (Eq. 5). This is reflected by better power, equalling 75% for a scenario with no area effect, versus powers of 53 & 60% for scenarios with the *CI* coefficient a_6 equalling -1 & +1 respectively (Figure 36).

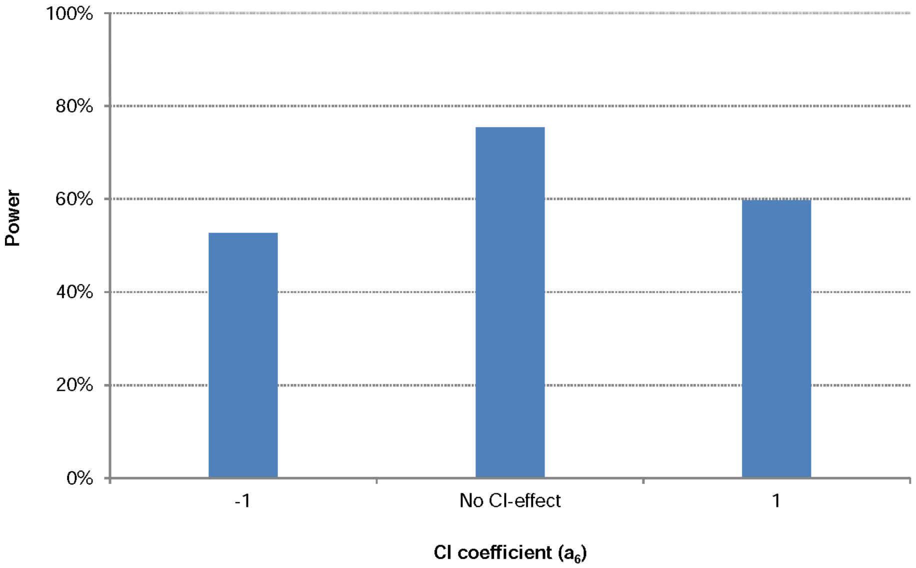


Figure 36. Comparison of the power to detect a 50% in numbers for several levels of the area-coefficient a_6 (data simulations based on coefficients a_1=-1, a_2=1, a_3=0, θ=0.5).

5.3.2 Effect on power by survey duration and degree of seabird displacement

Based on the empirical coefficient estimates of species-specific reference models (Table 22 – Annex I), we studied how power varies among species and how it is related to survey duration (Figure 37, and see also Table 26 & Table 27 in Annex I).

We found that for none of the 12 seabird species under study, we will be able to detect a decline of 25% with a power of more than 55%, not even after 15 years of impact monitoring. In contrast, a 50% change in numbers should be detectable within less than 10 years with a chance of >90% in northern gannet and common guillemot. The reference models of these two species showed a favourable combination of a relatively high intercept (>-1.5) and theta (>0.3), as well as lack of zero-inflation (<-10). Within the same time frame of 10 years of impact monitoring, we will be able to detect a decrease in numbers of 75% with a power of >90% in all species, except for common gull and black-legged kittiwake. The reference data of these species are indeed far from ideal, both showing a significant area effect and a low theta (<0.3) (Table 22 in Annex I).

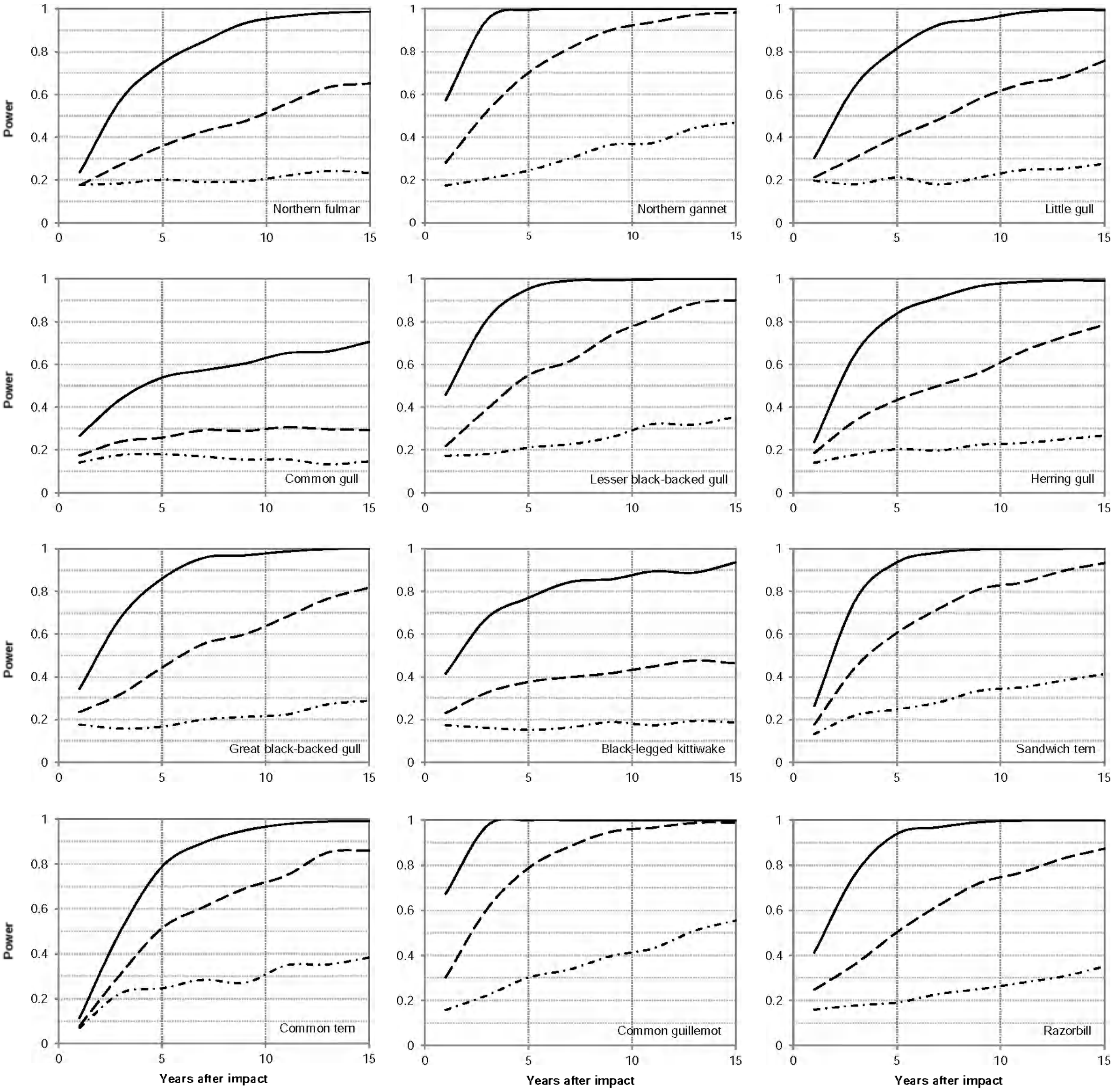


Figure 37. Power results for 12 seabird species for an impact study with a monitoring intensity of one survey of 10 km² per month per area, and 5 years of reference monitoring (significance level = 0.10).

5.3.3 Discussion: power analysis

We modelled the reference data collected in the Thorntonbank study area, which resulted in empirical coefficient ranges. Next, we defined numerous scenarios varying the model coefficients within these given ranges. For each scenario we performed 1,000 data simulations, allowing us to investigate how the different model parameters affect the power of detecting a certain change in numbers. Each of these parameters appears to interact with one another, so unambiguous conclusions are difficult to draw. Nevertheless, it could be shown that for the given monitoring set-up (5 years before / 5 year after the impact with a survey effort of 10 km² per month per area), count data subject to zero-inflation and/or characterised by a low theta (<0.3) can hardly be of any value in impact monitoring. Ideally, the reference data show no zero-inflation ($b_1<-5$), a moderately negative or even positive intercept ($a_1>-2$), a favourable theta (>0.3) and no significant area effect.

According to Underwood & Chapman (2003), power is strongly affected by the variability of the measurements. In a negative binomial distribution, the variance is negatively correlated with theta (θ) and indeed, we found that power strongly increases with increasing theta. A low theta value depicts over-dispersion, which in this case might arise from high year-to-year variability in observed seabird numbers or from strong spatial aggregation of seabirds. It is closely related to the amount of unexplained data variance, implying that building a good reference model, i.e. a model explaining as much biologically relevant variation as possible, is of key importance to the final impact assessment results.

Our analysis illustrated the importance of selecting a well-considered control area. Ideally, this area hosts seabird numbers comparable to the wind farm site, allowing us to perform the impact assessment with more degrees of freedom, reflected by better power. It was also shown that when data are subject to an excess in zero-counts, it is recommended to use the ZINB model, since this results in better power compared to a standard NB model.

By far the easiest way to enhance the power of any impact analysis is to apply a higher significance threshold (α) (as illustrated by the results in Table 26 & Table 27 – Annex I). In this context, a higher α increases the chance of wrongly concluding that the turbines are causing an impact, while in fact they are not ('type I error'). However, a stringent significance level goes at the expense of the power, resulting that certain impact effects may go unnoticed ('type II error'). For decision-making, ecological studies commonly set the probability of a type I error (α) to 5%, and the probability of a type II error (β) to 20%. However, this choice tends to be arbitrary and implies that the acceptable risk of committing a type II error is four times higher than the risk of a type I error (Pérez-Lapeña *et al*. 2011). This is contradictory to the fact that most impact studies are meant to function as an early warning system and to detect potential negative effects as soon as possible. In this paper, the risk of making a type I error α was therefore set to 10% (instead of the conventional 5%), and we use 90% as a boundary for sufficient power (1-β), thus equalling acceptable levels for both risks (α=β). Nevertheless, it would even be better for these values to be determined by predefined management objectives (Pérez-Lapeña *et al*. 2011) and an approach to set acceptable values for α and β based on costs (in economic, political, environmental and social terms) is proposed by Mapstone (1995).

In a second step we calculated powers based on species-specific reference models of twelve seabird species, as observed in the Thorntonbank study area prior to the construction of wind turbines in 2008. To detect a of 50% decrease in numbers, a power of 90% is reached within 10 years for two seabird species only, i.e. northern gannet and common guillemot. Within the same time frame, power to detect a 75% decrease in numbers exceeds 90% for all species, except for common gull and black-legged kittiwake, partly caused by a significant difference in abundance between control and impact area during reference years.

The reported results are based on a monitoring set-up in which there is one monthly survey, with an effort of 10 km² in both the control and impact area, and as was shown, power is strongly enhanced by counting for a longer period of time, due to the increase in sample size (Underwood & Chapman 2003, Pérez-Lapeña *et al*. 2011). One could argue that the timeframe needed to reach a certain power can be halved by performing two monitoring surveys each month. This is in fact true, but surveys then need to be sufficiently spread over time to avoid temporal autocorrelation. Contrastingly, doubling the effort by counting 20 km² per survey per area - instead of 10 km² - does not result in enhanced power, at least not in a direct way. However, it can yield more reliable count results, influencing the parameter estimates. Doubling the count effort for example might temper the level of over-dispersion or zero-inflation, positively affecting the statistical power as such. It would be very interesting to know how the count effort per survey relates to the variation/robustness of parameter estimates.

Maclean *et al.* (2013) conducted a comparable study on long-time series of aerial survey count data of four seabird taxa (scoters, northern gannet, divers & sandwich tern), collected in the UK North Sea waters. The authors also assume a ZINB distribution, and estimated the power of being able to detect various declines in seabird numbers (10-50%) and assessed the effect of survey duration, survey frequency, spatial scale and variability in bird numbers. Maclean *et al*. (2013) conclude that the statistical power to detect a 50% change in bird numbers remains low (<80%) for all species irrespective of the length of time over which monitoring is carried out, even for a significance level of 0.20. The authors state that the primary reason for this low power is the fact that seabird numbers fluctuate greatly at any given location, and that the only way likely to improve the power would be for some of this variance to be explained, by for example hydrodynamic data. Lapeña *et al*. (2011) performed power analyses generating simulated seabird count datasets, mimicking real surveys as reported in Leopold *et al*. (2004), and investigated the role of spatial factors in the statistical detection of seabird displacement. The authors identified the environmental conditions at the time of survey as the most influential factor on the statistical power, followed by survey effort and species abundance. The power results presented here are clearly higher than those presented by Maclean *et al*. (2013). One crucial difference between both studies is that Maclean *et al*. (2013) divide the year in 7 periods and include these in the model as a fixed factor. Compared to the inclusion of a sine curve, this strategy absorbs much more degrees of freedom resulting in higher standard errors, which in turn may explain poor power.

5.4 Results: impact analysis

5.4.1 Thorntonbank: reference modelling

We built species-specific reference models (§5.2.2) based on the reference data collected in the Thorntonbank study area (Figure 25). Table 12 lists all estimated coefficients, and the corresponding model predictions are displayed in Figure 38. Considering their specific seasonal occurrence in the study area, we used a double sine curve to explain the seasonal variation in numbers for four species, being northern gannet, little gull, sandwich tern and common tern. The occurrence of all other species was described by using a single sine curve.

In two out of thirteen species, we retained a significant area-effect i.e. for great skua (a_6=-1.55) and common gull (a_6=1.27). Back-transformation of the intercept values b_1 of the model's zero component (IntZero) learns that zero-inflation is present in the data of northern fulmar (33.6%), great skua (61.6%), little gull (23.4%), sandwich tern (53.0%) and common tern (76.5%). At the same time, theta values for great skua and the two tern species are high (respectively $3.5*10^4$, 4.8 and 26.1), suggesting that most of the over-dispersion is captured by the zero-component. In all other species zero-inflation is very close to 0%. In terms of expected power, the most favourable coefficients combined with lack of zero-inflation are seen in common guillemot (θ=0.67), followed by razorbill (θ=0.38) and northern gannet (θ=0.34).

Table 12. Model coefficients of the selected reference models at the Thorntonbank.

	IntCount a_1	Sin(1yr) a_2	Cos(1yr) a_3	Sin(1/2yr) a_4	Cos(1/2yr) a_5	CI a_6	IntZero b_1	θ
Northern fulmar	-1.23	-0.97	0.27				-0.68	0.16
Northern gannet	-0.85	-0.61	0.26	-0.60	-0.53		-10.35	0.34
Great skua	-2.80	-1.74	0.04			-1.55	0.47	$3.47*10^4$
Little gull	-3.04	1.63	3.53	-1.15	-0.75		-1.18	0.28
Common gull	-4.41	1.98	3.30			1.27	-11.23	0.20
Lesser black-backed gull	0.11	1.04	-2.46				-11.74	0.21
Herring gull	-2.75	1.74	0.80				-8.12	0.19
Great black-backed gull	-1.57	-0.30	2.37				-10.15	0.17
Black-legged kittiwake	-0.62	-1.04	1.78				-11.21	0.25
Sandwich tern	-9.16	0.45	-11.29	1.16	-6.65		0.12	4.80
Common tern	-10.13	-1.36	-13.12	-1.05	-6.97		1.18	26.12
Common guillemot	-1.35	0.59	3.63				-13.81	0.67
Razorbill	-2.57	0.06	3.29				-10.23	0.38

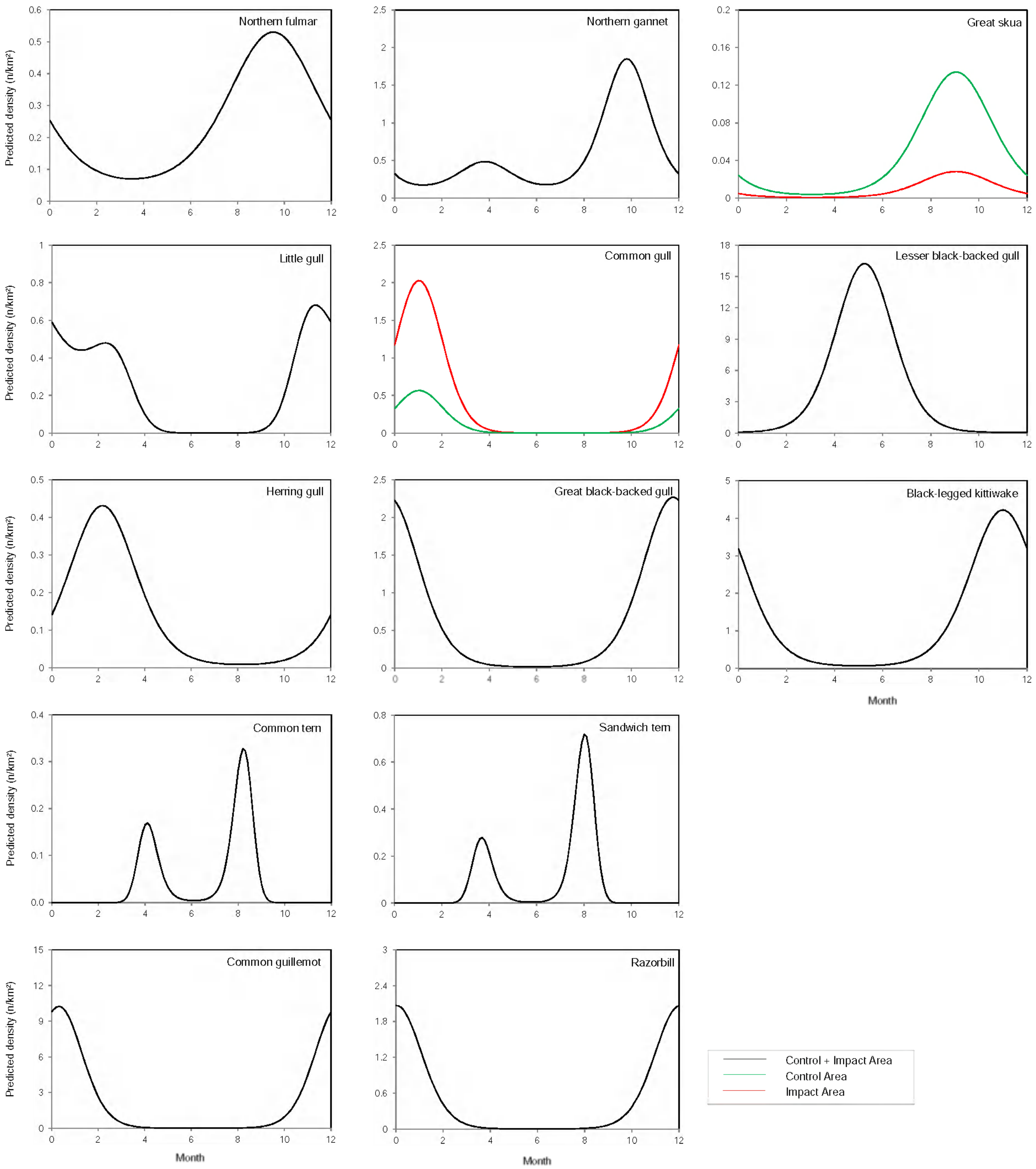


Figure 38. Modelled densities of 13 seabird species, based on data collected at the Thorntonbank study area prior to the construction of the wind farm (<04/2008).

5.4.2 Thorntonbank: impact assessment (operation phase I)

In order to include enough data for the construction of reliable reference models, we used the full extent of the (present) wind farm plus a 3 km buffer wide buffer zone. A different polygon however was applied to select impact data, i.e. the phase I wind farm of six turbines surrounded by a 3 km buffer zone (Figure 39). Cleary, it is impossible to count 'inside' a one-dimensional wind farm, so this analysis actually presents the results of displacement into & out of the wind farm buffer zone.

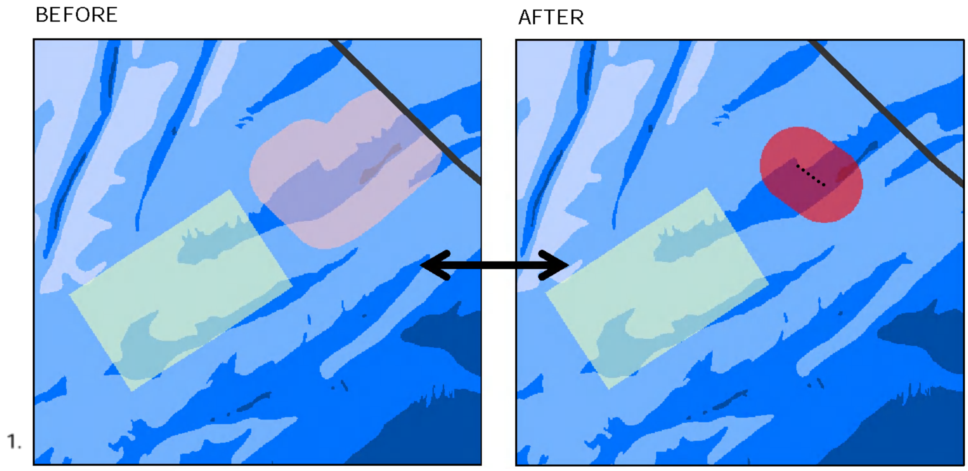


Figure 39. Overview of the polygons used for impact assessment of the operational phase I of the C-Power wind farm at the Thorntonbank.

Four species occurred in significantly higher numbers in the impact area after the construction of the phase I turbines and opposed to the numbers in the control area, i.e. little gull, great black-backed gull, sandwich tern and common tern (see Table 13 & Figure 40). Impact modelling further revealed that common gull avoided the area during the time of our research. The BACI graph in Figure 41 however nuances the model result, as numbers in the impact area actually remained at the same level throughout the period, opposed to a strong increase in the control area. Furthermore, densities in the impact and control area after turbine construction are highly comparable. It can therefore be suspected that the modelled displacement effect results from abnormal low numbers in the control area before wind farm construction rather than from true avoidance behaviour of common gulls.

The turbine effect coefficients found for the other species depict avoidance by northern gannet, lesser black-backed gull and common guillemot, and attraction of great skua, herring gull, black-legged kittiwake and razorbill, yet these changes were not statistically significant (P>0.1). For northern fulmar, the P-value of the turbine coefficient equals 1, implying that the uncertainty of the obtained result is 100%.

Table 13. Impact modelling results for the operational phase I of the Thorntonbank wind farm, with indication of the displacement-related model coefficients and their respective P-values.

	WF + buffer (3 km)	
	Coefficient	P-Value
Northern fulmar	-32.76	1.000
Northern gannet	-0.70	0.141
Great skua	2.12	0.186
Little gull	**1.22**	**0.093**
Common gull	**-1.45**	**0.097**
Lesser black-backed gull	-0.14	0.797
Herring gull	0.38	0.566
Great black-backed gull	**1.50**	**0.024**
Black-legged kittiwake	0.63	0.272
Sandwich tern	**2.46**	**0.001**
Common tern	**2.32**	**0.027**
Common guillemot	-0.17	0.698
Razorbill	0.41	0.477

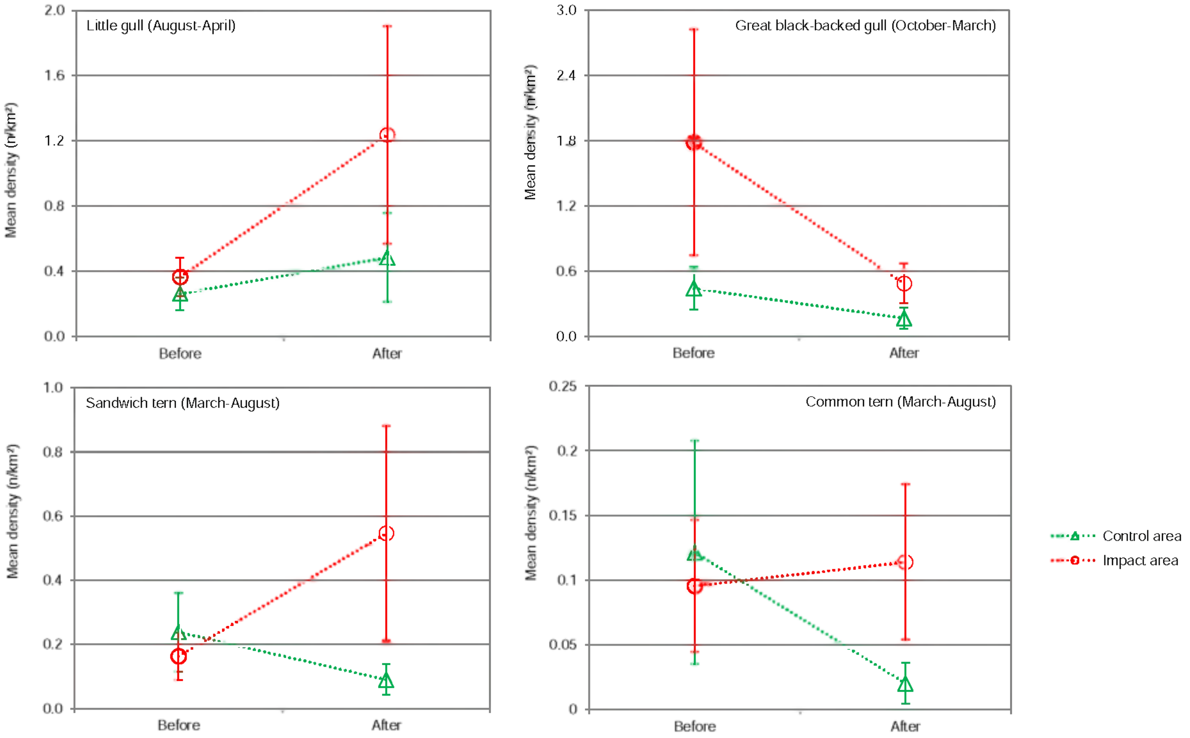


Figure 40. Mean seabird densities (+/- std. errors) in the control and impact area (WF + 3 km buffer zone) of four species found to be attracted to the phase I turbines at the Thorntonbank.

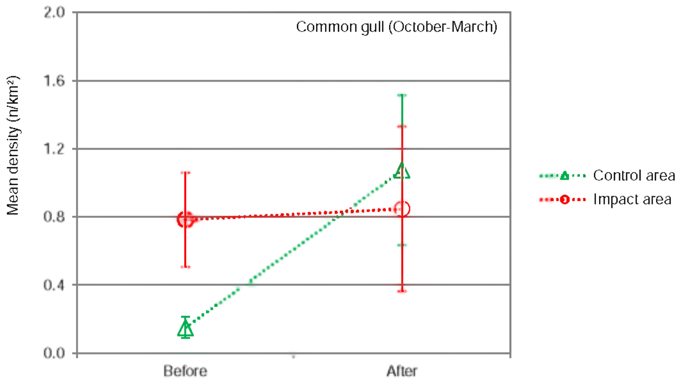


Figure 41. Mean densities (+/- std. errors) of common gull in the control and impact area (WF + 3 km buffer zone), a species found to avoid the phase I turbines at the Thorntonbank.

Sandwich tern near the Thorntonbank wind farm
(photo: Geert Beckers)

5.4.3 Thorntonbank: impact assessment (construction phase II & III)

For the impact assessment of the construction period we considered three polygons as a base for data selection, i.e. the wind farm area in its final configuration of 54 turbines added with a 0.5 km wide buffer zone (the area considered to be under direct influence of the turbines), the wind farm area added with a 3 km wide buffer zone, and the buffer zone itself (0.5 - 3 km of the nearest turbine) (Figure 42).

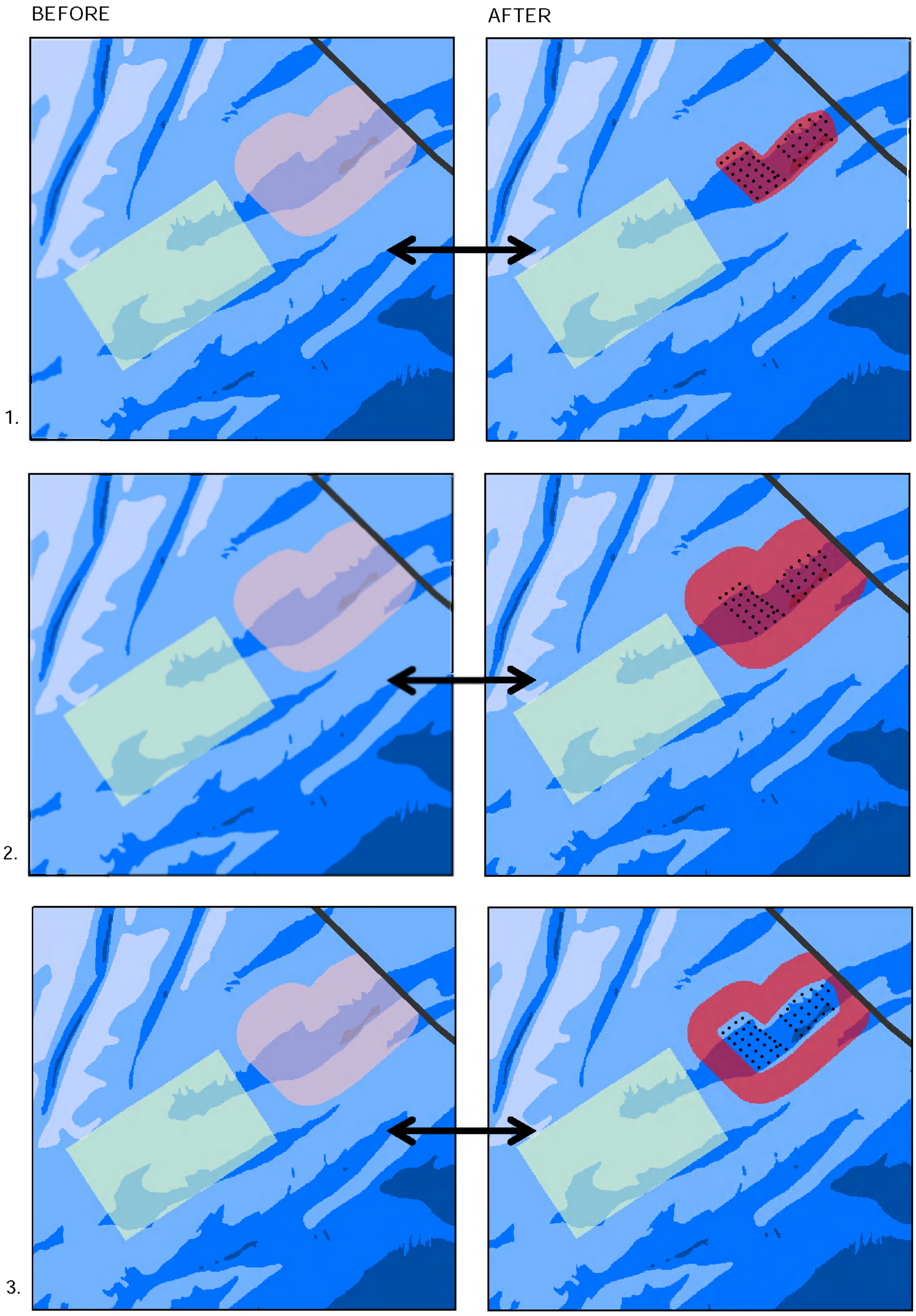


Figure 42. Overview of the polygons used for impact assessment of the construction of phase II & III of the C-Power wind farm at the Thorntonbank.

During construction of phase II & III of the C-Power wind farm, regular surveys could be performed throughout the year 2012, and during that time 14 seabird species were observed within the wind farm boundaries (Table 14). The area was regularly visited by gulls (especially lesser black-backed gull) which were often seen resting on the (yet) turbine-free jacket foundations (Table 14 – right column). Except for gulls, there were regular observations of sandwich tern and both auk species.

Table 14. Number of birds observed during 108 km of seabird surveying within the Thorntonbank wind farm boundaries during the construction of phase II & III (Jan 2012 - Dec 2012) (the number of birds resting on turbine foundations or transformation platform is shown separately).

	Observed species	Wind farm	Turbines
Construction phase II & III Thorntonbank	Northern gannet	2	0
	Great cormorant	10	1
	Shag (*Phalacrocorax aristotelis*)	0	1
	Great skua	2	0
	Little gull	14	0
	Common gull	40	0
	Lesser black-backed gull	178	36
	Herring gull	11	2
	Yellow-legged gull (*Larus michahellis*)	1	0
	Great black-backed gull	24	53
	Unidentified large gull	2	99
	Black-legged kittiwake	25	0
	Sandwich tern	75	3
	Common guillemot	21	0
	Auk (common guillemot / razorbill)	12	0
	Razorbill	44	0

Shag on the turbine base of a phase I turbine at the Thorntonbank
(photo: Hilbran Verstraete)

When we look at the results of the impact assessment modelling we see few significant effects ($P<0.1$). Importantly, the results presented in Table 15 should be regarded as indicative, since the analysis is based on a limited dataset, with a low statistical power as a result (§5.3). Unfortunately, this is inherent to the temporary nature of any construction phase.

During the construction period, sandwich terns were observed regularly inside the wind farm during spring migration, resulting in a highly significant attraction effect. Meanwhile there was significant avoidance of the area within the wind farm boundaries by lesser black-backed gulls. This is a quite unexpected result since it is the most commonly observed species inside the wind farm (Table 14). Great skua, little gull, common gull, herring gull and great black-backed gull all occurred in increased numbers inside the wind farm during construction, while there was a decrease in numbers of black-legged kittiwake, common guillemot and razorbill, but for all of these species, the effect of the displacement-related model coefficient was not significant.

Table 15. Impact modelling results for the construction period of phase II & III of the Thorntonbank wind farm, with indication of the displacement-related model coefficients and their respective P-values.

	WF		WF + buffer (3 km)		Buffer (3 km)	
	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value
Northern fulmar	-35.59	1.000	-36.26	1.000	-35.97	1.000
Northern gannet	-28.64	1.000	0.50	0.539	0.68	0.405
Great skua	3.01	0.129	1.67	0.267	1.34	0.423
Little gull	1.82	0.237	1.14	0.308	1.38	0.218
Common gull	2.87	0.113	2.45	0.139	2.37	0.148
Lesser black-backed gull	**-2.13**	**0.052**	-0.46	0.600	-0.25	0.782
Herring gull	1.66	0.274	0.87	0.529	0.42	0.777
Great black-backed gull	0.92	0.457	0.69	0.508	0.52	0.628
Black-legged kittiwake	-0.79	0.439	-0.44	0.596	-0.45	0.586
Sandwich tern	**2.23**	**0.001**	**1.24**	**0.064**	-0.89	0.333
Common tern	0.77	1.000	16.34	0.993	16.66	0.994
Common guillemot	-1.31	0.118	-0.31	0.599	-0.24	0.686
Razorbill	-1.41	0.146	-0.56	0.427	-0.49	0.490

5.4.4 Blighbank: reference modelling

Due to its specific seasonal occurrence in the study area, we used a double sine curve to explain seasonal variation in numbers of northern gannet. Reference modelling revealed a significant area-effect in two species, i.e. common and lesser black-backed gull (0.99 & -1.08 respectively). Also, for the latter, as well as for great skua, no significant seasonality pattern could be discerned in the reference data. Zero-inflation is present in the reference data of northern gannet (15.3%), great skua (77.4%), little gull (21.8%), common gull (82.9%) and lesser black-backed gull (48.5%). Great skua and common gull further combine zero-inflation with high theta values (8.41 & $5.26*10^4$), suggesting that most of the over-dispersion is captured by the zero-component. As in the reference data of the Thorntonbank (§5.4.1), common guillemot shows the most favourable theta value (0.64) in combination with near to 0% zero-inflation, with black-legged kittiwake as second-best (0.37). Model predictions based on the coefficients in Table 16 are shown in Figure 43.

Table 16. Model coefficients of the selected reference models at the Blighbank.

	IntCount a_1	Sin(1yr) a_2	Cos(1yr) a_3	Sin(1/2yr) a_4	Cos(1/2yr) a_5	CI a_6	IntZero b_1	θ
Northern fulmar	-2.01	0.31	0.76				-7.63	0.16
Northern gannet	-1.46	-0.15	1.28	0.01	-0.58		-1.71	0.63
Great skua	-1.68						1.23	8.41
Little gull	-27.36	27.57	-0.78				-1.28	0.11
Common gull	-3.18	1.31	2.85			0.99	1.58	$5.26*10^4$
Lesser black-backed gull	-0.43					-1.08	-0.06	0.48
Herring gull	-4.25	2.25	1.21				-8.12	0.20
Great black-backed gull	-2.17	0.65	2.26				-9.61	0.10
Black-legged kittiwake	-1.74	0.67	2.25				-10.72	0.37
Common guillemot	-1.87	1.05	3.06				-11.82	0.64
Razorbill	-4.30	1.68	3.57				-9.01	0.23

Northern gannet (photo: starlingreizen.be)

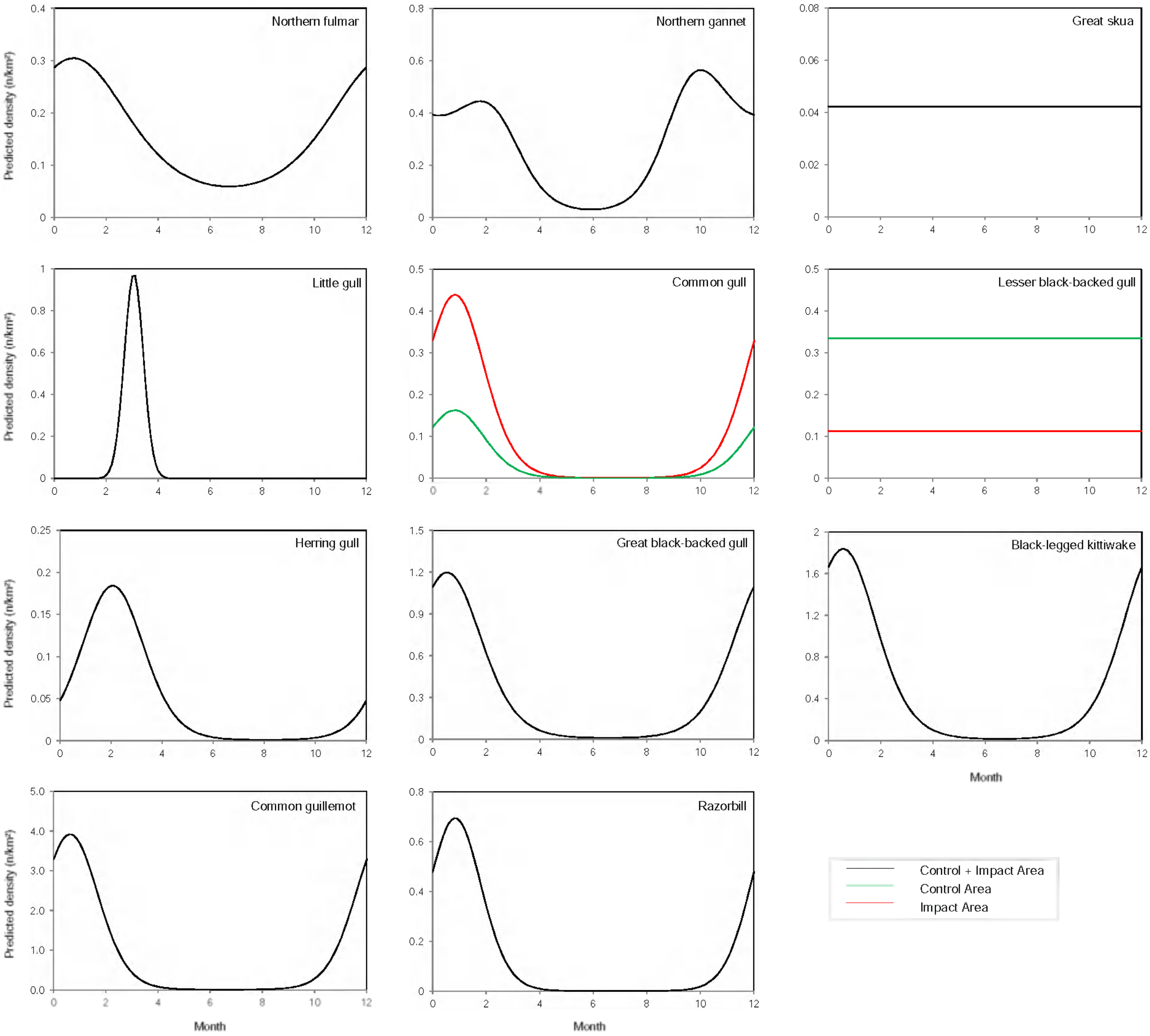


Figure 43. Modelled densities of 11 seabird species, based on data collected at the Blighbank study area prior to the construction of the wind farm (<09/2009).

5.4.5 Blighbank: impact assessment (operation phase I)

We considered three polygons applied for data selection for the impact assessment of the operational phase I of the Belwind wind farm. These are 1) the wind farm area in its phase I configuration of 55 turbines with a 0.5 km wide buffer zone, 2) the wind farm area surrounded by a 3 km wide buffer zone and 3) the buffer zone itself (the area within 0.5 - 3 km of the nearest turbine) (Figure 44).

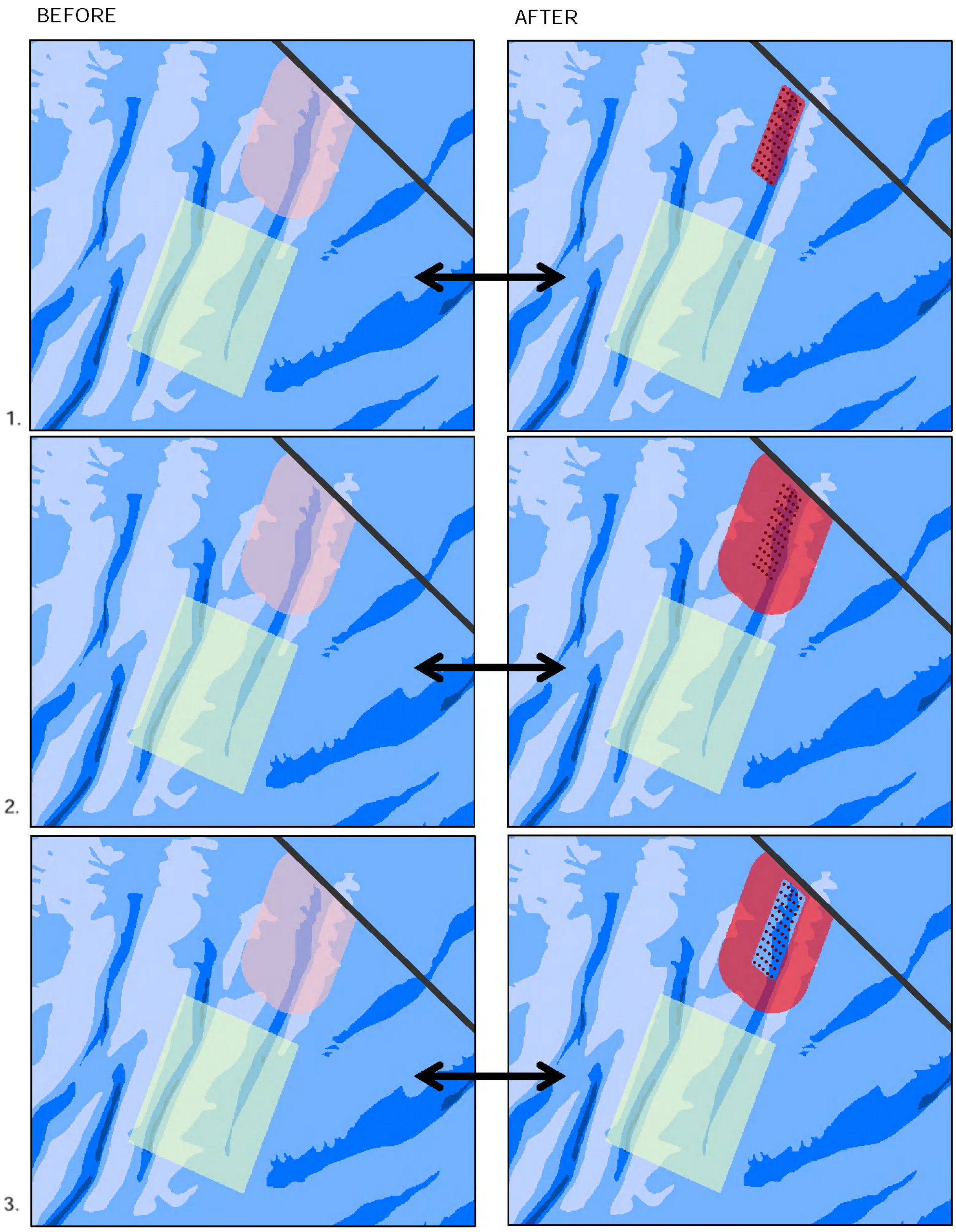


Figure 44. Overview of the polygons used for impact assessment of the operational phase I of the Belwind wind farm at the Blighbank.

The most commonly observed seabird species inside the Blighbank wind farm were common gull and black-legged kittiwake, followed by the three large gull species (herring, lesser & great black-backed gull). With 138 observed individuals, common guillemot and razorbill were also present in relatively high numbers (Table 17). The numbers of two gull species however are strongly determined by the results of only one survey (20/12/2010). That day, no less than 98% & 94% of all common and herring gulls were counted, implying that despite the high numbers observed, these two species were generally scarce.

The relative number of birds resting on turbine bases was much lower at the operational Blighbank wind farm, compared to those observed during the construction period of phase II & III at the Thorntonbank (Table 14). Not only were the jacket foundations in the latter area yet free of rotating turbines, the jacket foundation type also offers more roosting possibilities.

Interestingly, sea mammals too were regularly encountered inside the wind farm's boundaries, and in total we observed 35 harbour porpoises (*Phocoena phocoena*). There was also an observation of a pack of 5 white-beaked dolphins (*Lagenorhynchus albirostris*) and of a single grey seal (*Halichoerus grypus*) associated to a turbine base.

Table 17. Number of birds and sea mammals observed during 297 km of seabird surveying within the Blighbank wind farm boundaries during the operation of phase I (Sept 2010 - Dec 2012) (the number of birds resting on turbine foundations and transformation platform are shown separately).

	Observed species	Wind farm	Platform	Turbines
Operational phase I Blighbank	Northern gannet	18	0	0
	Shag	2	0	0
	Common gull	1,564	0	0
	Lesser black-backed gull	278	0	5
	Herring gull	193	1	1
	Yellow-legged gull	1	0	0
	Great black-backed gull	151	67	28
	Unidentified large gull	7	0	0
	Black-legged kittiwake	711	0	0
	Unidentified gull	34	0	0
	Sandwich tern	4	0	0
	Common guillemot	61	0	0
	Auk (common guillemot + razorbill)	18	0	0
	Razorbill	59	0	0
	Atlantic puffin	1	0	0
	White-beaked dolphin	5	0	0
	Harbour porpoise	35	0	0
	Grey seal	1	0	0

5.4.5.1 Seabirds

When analysing the impact dataset (reference data + results of 3 years of impact monitoring), several significant displacement effects were found. Three species appeared to avoid the wind farm area, i.e. northern gannet and both auk species. For razorbill, this effect was limited to the wind farm area itself, while the other two species avoided the whole area up to at least 3 km from the nearest turbines. Results for little gull also suggest avoidance, but the effect was not statistically significant. For northern fulmar and great skua the coefficients are highly negative, suggesting a decrease. These results however are extremely unreliable, indicated by the P-values leaning towards 1 and due to a very limited number of positive observations in both impact and control area in recent years.

Lesser black-backed gulls and herring gulls showed a significant increase in number inside the impact area after the wind farm construction and opposed to the numbers in the control area. For lesser black-backed gull the attraction effect was significant for up to at least 3 km from the wind farm, which was not the case for herring gull. Increased numbers were also observed in three other gull species: common gull, great black-backed gull and black-legged kittiwake, yet these effects were not found to be statistically significant.

Figure 45 & Figure 46 show the mean densities observed in the reference and impact area, before and after wind farm construction, for all five species for which we found a significant displacement effect. The distribution maps show that the avoidance by northern gannet was almost absolute while common guillemot, despite its avoidance behaviour, was regularly observed inside the wind farm (Figure 47). The attraction of herring gulls is nicely illustrated by the distribution pattern in Figure 48, with high numbers being observed exclusively near or inside the wind farm. In contrast, the distribution pattern of lesser black-backed gull (Figure 48) suggests indifference rather than attraction.

Table 18. Impact modelling results for the operation of phase I of the Belwind wind farm at the Blighbank, with indication of the displacement-related model coefficients and their respective P-values.

	WF		WF + buffer (3 km)		Buffer (3 km)	
	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value
Northern fulmar	-32.38	1.000	-33.08	1.000	-32.51	1.000
Northern gannet	**-1.83**	**0.000**	**-1.52**	**0.000**	**-1.32**	**0.003**
Great skua	-15.03	0.993	-15.94	0.992	-15.37	0.992
Little gull	-1.12	0.423	-0.32	0.793	0.13	0.912
Common gull	2.61	0.110	1.80	0.195	0.91	0.413
Lesser black-backed gull	**1.57**	**0.059**	**2.39**	**0.004**	**2.37**	**0.006**
Herring gull	**3.97**	**0.000**	1.26	0.111	0.83	0.269
Great black-backed gull	1.08	0.127	0.47	0.447	0.54	0.428
Black-legged kittiwake	0.25	0.605	0.50	0.264	**0.78**	**0.092**
Common guillemot	**-1.26**	**0.003**	**-0.87**	**0.015**	**-0.69**	**0.059**
Razorbill	**-1.10**	**0.063**	-0.90	0.107	-0.53	0.359

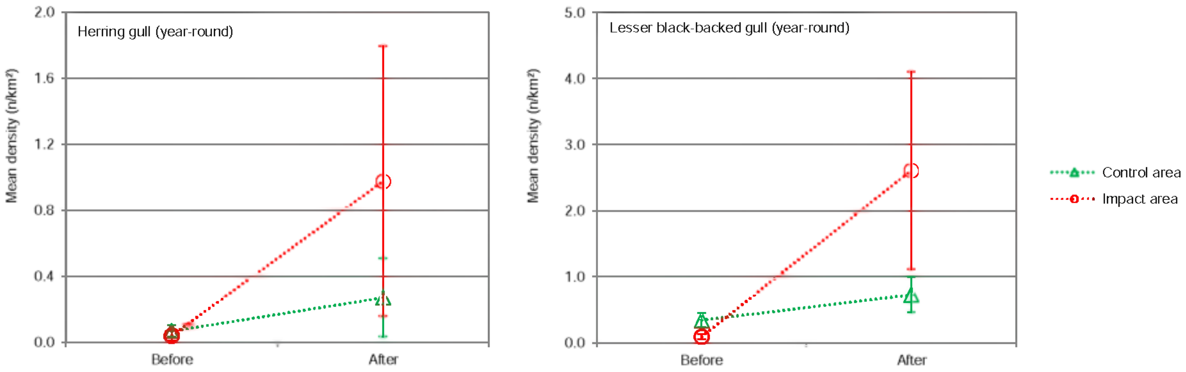


Figure 45. Mean seabird densities (+/- std. errors) in the control and impact area (WF + 3 km buffer zone) of two species found to be attracted to the wind farm at the Blighbank.

Common guillemots near the Blighbank wind farm (photo: Johan Buckens)

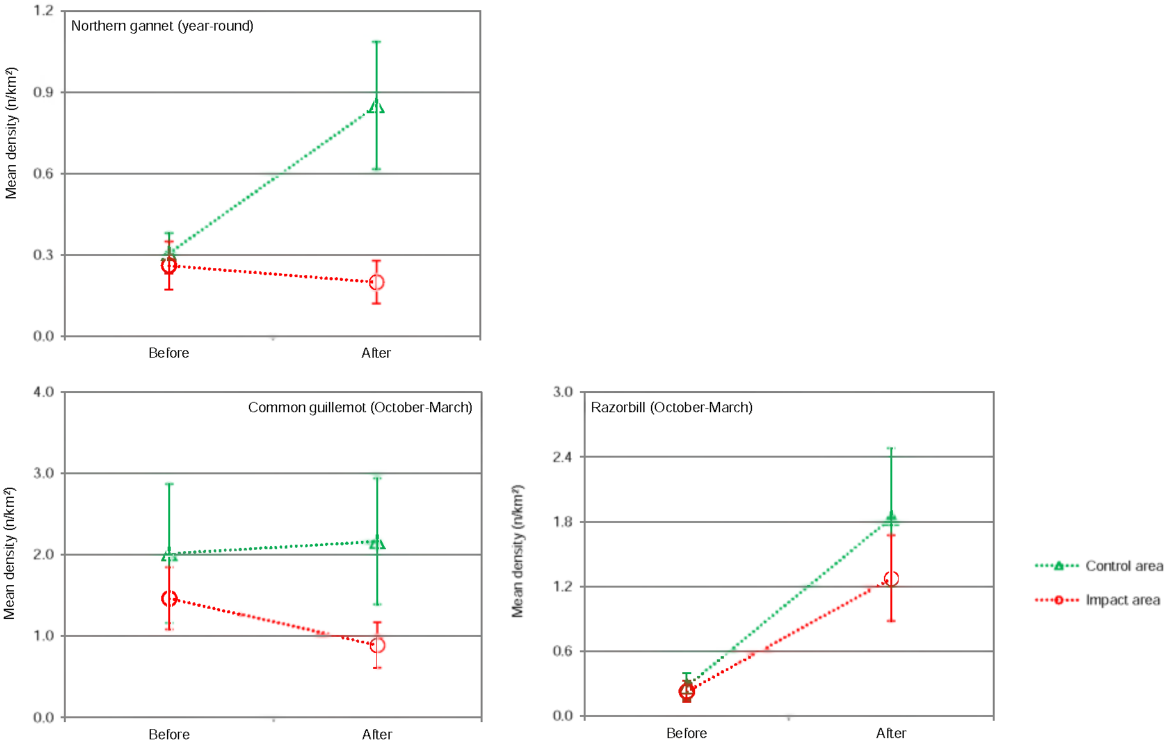


Figure 46. Mean seabird densities (+/- std. errors) in the control and impact area (WF + 3 km buffer zone) of three species found to avoid the wind farm at the Blighbank.

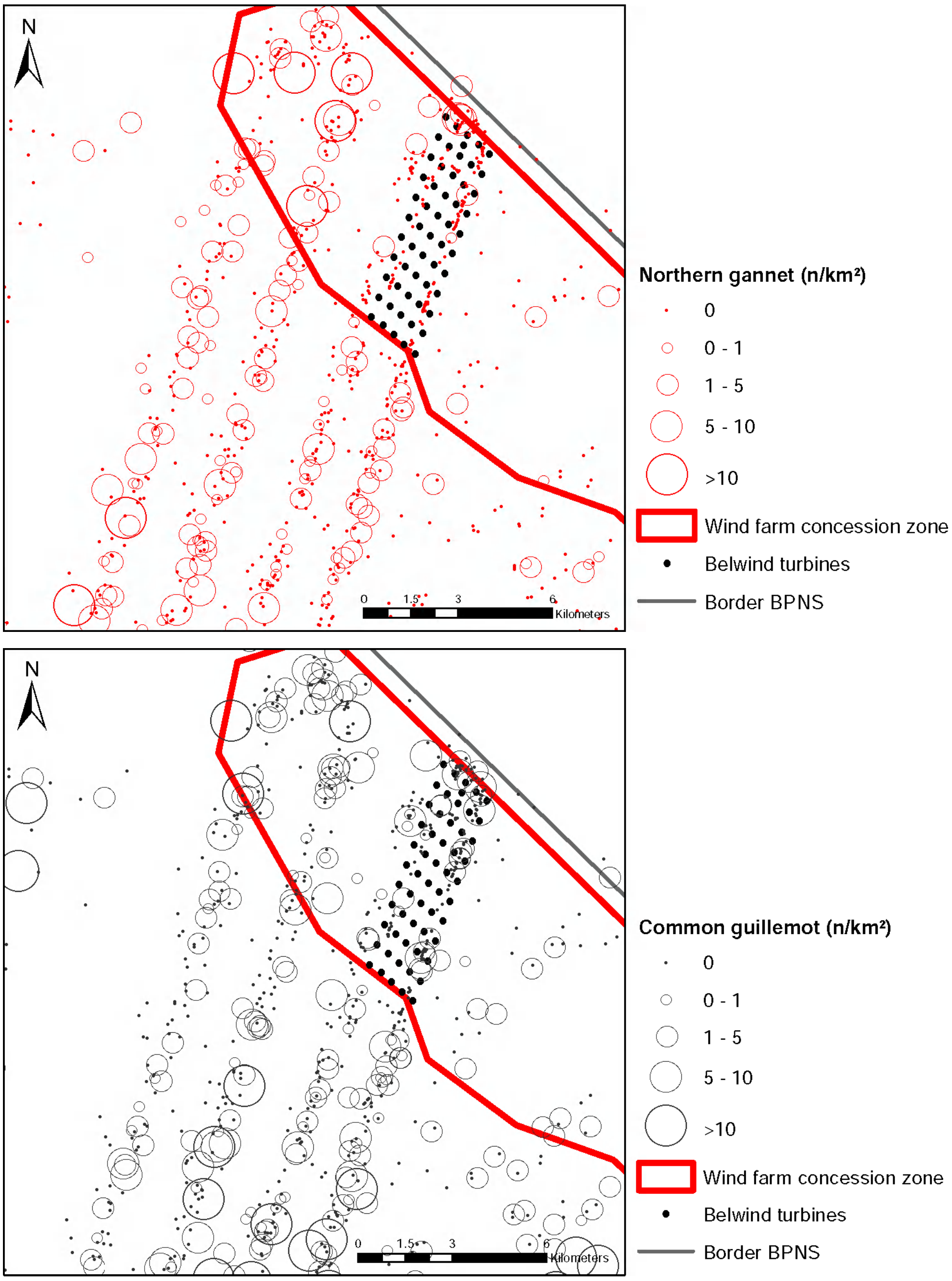


Figure 47. Observations of northern gannet and common guillemot during the seabird monitoring program at the Blighbank after wind farm construction.

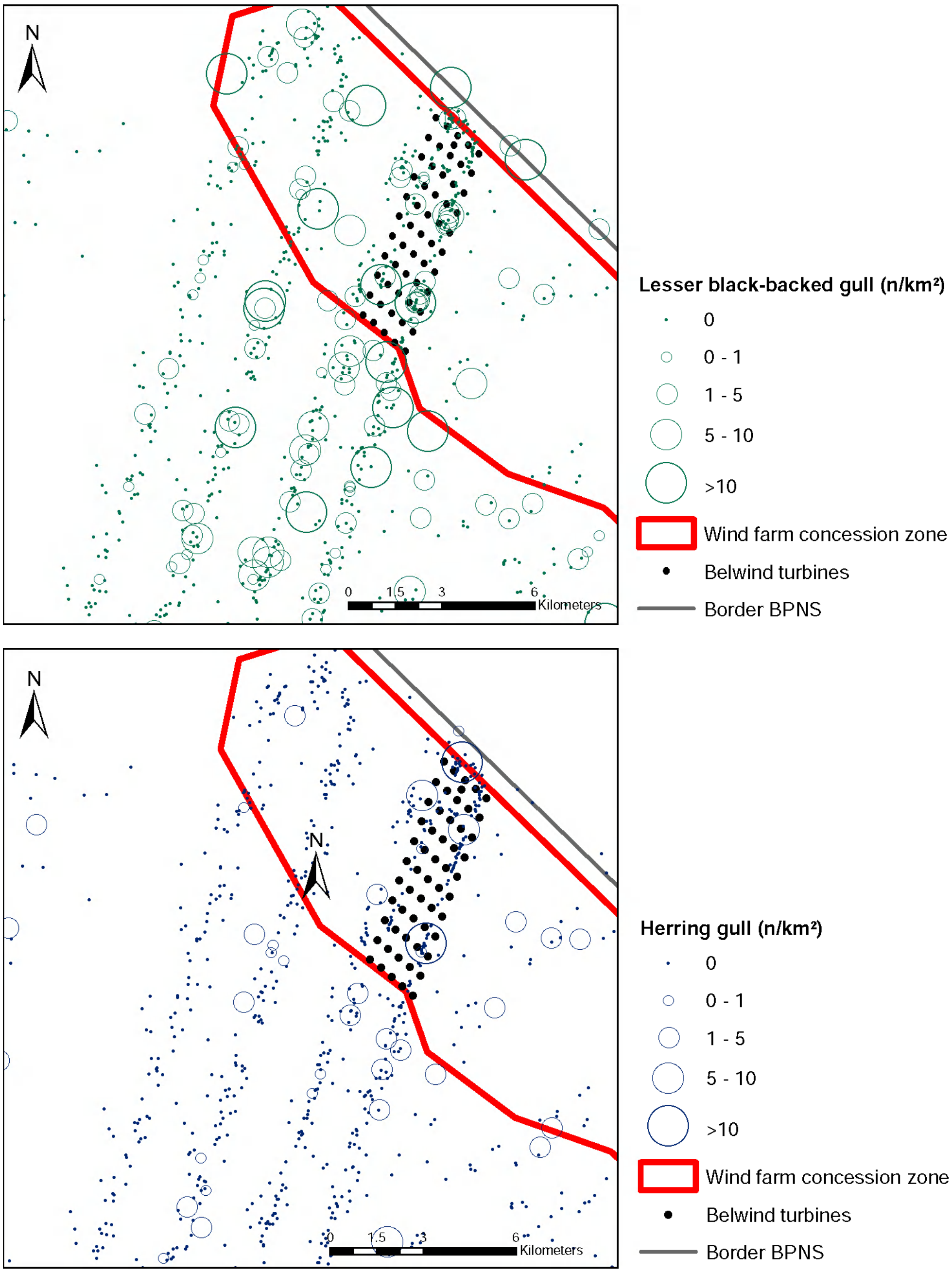


Figure 48. Observations of lesser black-backed and herring gull during the seabird monitoring program at the Blighbank after wind farm construction.

5.4.5.2 Harbour porpoise

Harbour porpoises were regularly observed inside the Blighbank wind farm. Since these animals are counted in the exact same standard way like seabirds, we were also able to analyse whether harbour porpoise distribution has changed after wind farm construction.

During the reference model selection process we could not discern a seasonality nor an area effect, resulting in an intercept model (see Eq. 8 - §5.2.3). Analysing the full impact dataset learned that numbers of harbour porpoise have increased inside the impact area compared to the numbers in the control area and the numbers present before wind farm construction. However this change in porpoise density was not significant. The distribution maps in Figure 49 show how numbers have increased overall (confirmed by the significantly positive *BA* model coefficient, P=0.035, see Annex IV), but also how porpoise numbers appear to concentrate inside the Blighbank wind farm (lower panel of Figure 49).

Table 19. Impact modelling results of harbour porpoise for the operation of phase I at the Blighbank.

	WF		WF + buffer (3 km)		Buffer (3 km)	
	Coeff	P-Value	Coeff	P-Value	Coeff	P-Value
Harbour porpoise	0.79	0.354	0.65	0.392	0.63	0.356

Harbour porpoise swimming inside the Blighbank wind farm (photo: Hilbran Verstraete)

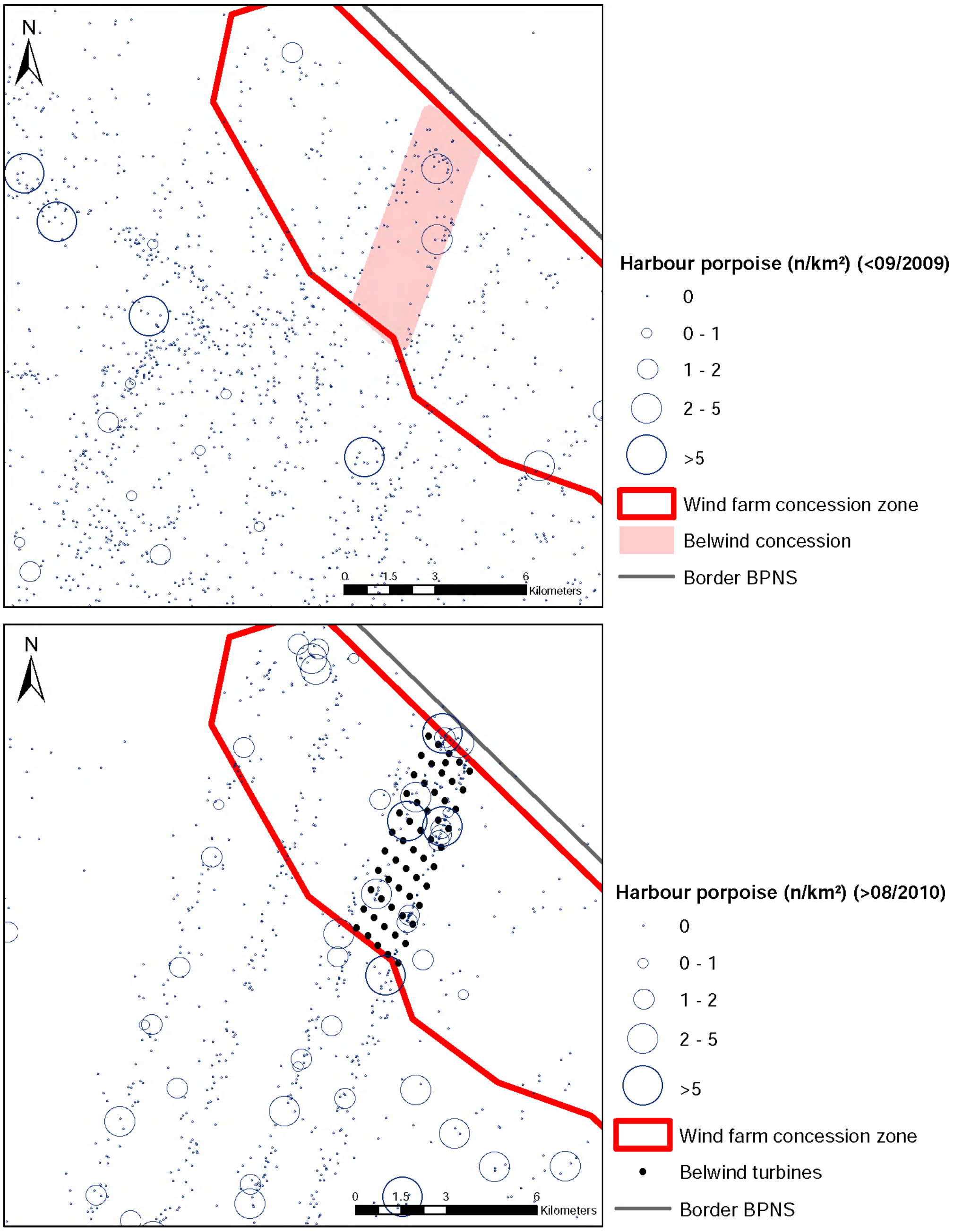


Figure 49. Observations of harbour porpoise in the study area before and after wind farm construction at the Blighbank.

5.5 Discussion: monitoring seabird displacement

Possible effects of offshore wind farms on seabirds range from indirect effects (habitat change, habitat loss and barrier-effects) to direct mortality through collision (Exo *et al.* 2003, Langston & Pullan 2003, Fox *et al.* 2006, Drewitt & Langston 2006). The installation of an offshore wind farm indeed changes the impacted area drastically, not only because of the impressive physical appearance in the wide open seascape, but also due to the underwater changes following the introduction of hard substrates in an often soft-bottom marine ecosystem. On the one hand, some seabirds can be expected to avoid the huge vertical structures in much the same way as they avoid the coast or are scared off by ship traffic. As such, seabirds can be displaced out from an area which was used for foraging prior to the construction of the wind farm, resulting in habitat loss. In an offshore context, the impacted area is generally surrounded by a huge surface of turbine-free marine habitat, which however does not necessarily include equally suitable feeding grounds. Birds bound to shallow waters are thus the most at risk of losing large areas of valuable and irreplaceable habitat, since wind farms too are generally built on shallow sandbanks. On the other hand however, there are numerous examples of seabirds being attracted to offshore constructions, as for example gas platforms. Mostly, this attraction effect is hypothesised to result from increased food availability and roosting possibilities (Tasker *et al.* 1986, Wiese *et al.* 2001). The same off course can be expected to happen at offshore wind farms. But with wind farms acting as a magnet to seabirds, more birds face the risk of colliding with the turbine blades. Importantly, as seabirds are long-lived species with a delayed maturity and small clutch size, even the smallest change in adult survival may have a substantial impact at a population level (Stienen *et al.* 2007).

The wind farm monitoring program at the BPNS revealed significant attraction of large gulls towards the Blighbank wind farm. This was rather surprising since at-sea gull distribution is strongly determined by the presence of fishing trawlers. The main anticipated effect of wind farms on gull distribution patterns was thus a decrease in densities resulting from the prohibition for trawlers to fish inside the farm boundaries. Accordingly, no clear-cut attraction effects were found for large gulls during the Danish and Dutch monitoring programs (Petersen *et al.* 2006, Leopold *et al.* 2011). For common gull and black-legged kittiwake our impact modelling did not reveal unambiguous effects, and both species were regularly observed between the turbines, suggesting indifference towards wind farm presence. On the other hand, three species displayed avoidance, being northern gannet, common guillemot and razorbill. Importantly, strong avoidance by gannets and auks was reported by the Dutch researchers at the OWEZ wind farm (Leopold *et al.* 2011, Krijgsveld *et al.* 2011) and avoidance by auks was also found by Petersen *et al.* (2006) at the Horns Rev wind farm in Denmark.

We further found significant attraction effects of three Annex I species (i.e. little gull, common tern and sandwich tern) to the operational phase I at the Thorntonbank. Importantly, high proportions of the biogeographical populations of all three species migrate through the southern North Sea (Stienen *et al.* 2007). Clearly it is impossible to count 'inside' a one-dimensional farm of six turbines, and the revealed attraction effects account for the wind farm buffer zone, rather than the wind farm area itself. These findings nevertheless agree well with findings done by the Danish researchers Petersen *et al.* (2006), who observed a significant post-construction increase in numbers of little gull just outside the Horns Rev wind farm boundaries (up to 2 km), and a slight (non-significant) increase in numbers inside the wind farm. The same authors found a clear post-construction increase in numbers of common tern in the immediate vicinity of the farm (1 to 8 km), opposed to a total absence of the species inside the wind farm up to 1 km of its boundaries. Similarly, increased presence of sandwich terns foraging on the borders of the OWEZ wind farm was observed by our Dutch colleagues. Apart from this, Krijgsveld *et al.* (2011) report both tern species and little gull to regularly enter the wind farm, with little gull being observed in higher numbers inside compared to outside OWEZ. Unfortunately, densities of all three species were too low to draw firm conclusions on displacement effects (Leopold *et al.* 2011).

Power analyses showed that even for quite substantial changes in seabird densities (e.g. a decrease of 75%), up to ten years of monitoring may be needed to obtain sufficient statistical power. Indeed, at both wind farms we saw numbers of several seabird species to have changed, without the difference in density being statistically significant. With more years of monitoring ahead of us, our data will allow to better distinguish between true displacement and indifference. Long-term monitoring at the various wind farm sites is also needed to anticipate the possible habituation of seabirds to the presence of wind turbines (temporal variation) or the fact that displacement effects may differ between wind farm sites (spatial variation). The results from the Dutch and Danish research programs further show that the occurrence of increased numbers just outside an offshore wind farm (as was found near the single row of turbines at the Thorntonbank) cannot be extrapolated to the wind farm area itself. Continuing to monitor seabird presence in the now fully operational (and two-dimensional) Thorntonbank wind farm is therefore highly important. Clearly, if the attraction effects as found in this study persist during the coming years, the associated increased collision risk is of serious conservational concern considering the involved species' high protection status.

Gulls resting on a jacket foundation at the Thorntonbank during construction of phase II & III (photo: Hilbran Verstraete)

Attraction hypothesis

The introduction of hard substrate in a sandy soft-bottom ecosystem brings about a cascade of environmental changes, most notably organic enrichment and the attraction of hard-substrate fish (the so-called 'reef effect' - Degraer *et al.* 2011). Another important factor in this respect is the exclusion of fishery activities, allowing the soft-bottom ecosystem in between the turbine foundations to recover from decennia of heavy beam trawling impact. The most important question yet to be answered is whether birds are attracted to wind farms from a sheer physical point of view, with the wind farm functioning as a stepping stone or a resting place, or whether they already learned to exploit the hypothesised increase in food availability.

Initially, birds occurring inside the Belgian offshore wind farms (mainly gulls) were only observed resting on the water or on top of the transformation platform, strongly supporting the idea that their presence was to be interpreted in the view of roosting possibilities. Since October 2012 however, flocks of black-legged kittiwakes are regularly observed foraging inside the Blighbank wind farm. Strikingly, the percentage of kittiwakes displaying active foraging behaviour inside the wind farm appears to be much higher than in the control area (5.9% versus 0.3%). In subzone B of the Thorntonbank wind farm (operational since the beginning of 2013), good numbers of lesser black-backed gulls were observed foraging near the jacket foundations during the surveys of April and May 2013. It should also be mentioned that compared to gannets, auks are much less reluctant to enter the wind farms, and during 2012 in particular, both auk species were observed in relatively good numbers. These observed behavioural changes may not be coincidental, but might well be a reflection of the delayed increase in food availability to seabirds following initial reef effects. Assuming that (in time) offshore wind farms offer increased feeding possibilities, seabird attraction effects too are expected to increase. Not only are seabirds known to readily exploit any area with high and predictable food availability, improved foraging conditions might also strongly speed up the habituation process for birds that are now still reluctant to enter the wind farms. We will continue to monitor seabird presence inside the Belgian offshore wind farms, with increased attention to their behavioural and foraging-related actions. To further investigate the hypothesised link between seabird presence and food availability, it would be very interesting to conduct research on pelagic fish communities occurring in- and outside the wind farms. To what extent improved foraging conditions benefit seabirds on a population level is very hard to assess. The benefits gained on a population level however are unlikely to weigh up to the costs of additional mortality, as an increased number of flight movements inside the wind farms inevitably results in an increase of collision fatalities, potentially turning the situation into an ecological pitfall.

First winter black-legged kittiwake (photo: Hilbran Verstraete)

6 Bird collision rates

6.1 Methods: bird collision rate estimation

For obvious reasons it is difficult to assess the number of collision victims at an offshore wind farm. Corpse searches as often performed onshore are not an option, since bird corpses drift away, sink to the sea floor or are readily scavenged by gulls. Band (2012) however developed a collision risk model (CRM) to estimate the bird collision risk based on local seabird densities, technical turbine specifications, wind farm configuration and bird-related parameters. The ‘snapshot counts’ (§3.1.1) as performed during standardised seabird counts allowed estimating densities of flying birds within the Blighbank wind farm. Beside absolute densities, species-specific flight height is of large influence on the expected collision risk. During seabird surveys, the flight height of all observed seabirds was therefore categorised as ‘in’, ‘under’ or ‘above’ the rotor sweep zone (30-150 m) (results shown in Table 8 - §4.4.1). For this study, data on wingspan and flying speed were taken from Cramp (1977-1985) and Alerstam (2007).

Lastly, the CRM includes a micro-avoidance rate, accounting for last-minute avoidance actions. This factor is hard to assess, but is considered to be very high and is generally set to at least 95% (Chamberlain *et al.* 2006). Importantly, the number of estimated victims is proportional to the percentage of birds that *do not* perform avoidance actions (= 1 - % micro-avoidance). A relatively small difference in avoidance rate between 95% and 99.5% therefore results in a factor 10 difference in terms of estimated collision victims. In this study we applied the micro-avoidance value of 97.6% as found by Krijgsveld *et al.* (2011) based on their extensive radar research.

Lesser black-backed gull approaching the rotor sweep zone
in the Blighbank wind farm (photo: Nicolas Vanermen)

6.2 Results: bird collision rate estimation

Based on the density assessment of flying birds during our ship-based surveys inside the Blighbank wind farm and the corresponding CRM results, we expect one or more casualties per year for six seabird species (northern gannet and five species of gull), up to more than one victim per turbine per year for lesser black-backed gull. For all other species occurring in the study area, the density of individuals flying at rotor height was close to zero and the number of expected collision fatalities is regarded to be insignificantly low. In total, the number of gull victims is estimated at 134 per year (2.4 per turbine), which is less than half the number obtained by Poot *et al.* (2011), reporting an estimated 243 gull victims at the OWEZ wind farm (6.8 per turbine). This substantial difference in estimated collision rate can partly be explained by the far more offshore location of the Blighbank compared to the OWEZ wind farm, respectively 40 versus 10 km from the coast, which is inevitably reflected in lower gull densities.

Table 20. Estimated collision victims based on observed densities of flying birds inside the Blighbank wind farm and an assumed micro-avoidance rate of 97.6%.

	Northern gannet	Common gull	Lesser black-backed gull	Herring gull	Great black-backed gull	Black-legged kittiwake
Winter	0	3	0	3	3	19
Spring	0	0	40	3	4	10
Summer	0	0	22	0	0	0
Autumn	1	0	3	0	21	3
Number/year	1	3	65	6	28	32
Number/(turbine*year)	0.02	0.05	1.18	0.11	0.51	0.58

6.3 Extrapolating bird collision rate estimates

In January 2013, 1,662 offshore turbines were already installed in European waters, and the European Union aims at an offshore capacity of 43 GW, which is equivalent to more than 14,000 3 MW turbines (EWEA 2013). The number of offshore turbines still to be installed is thus enormous, and their distribution will no longer be limited to the nearshore zone. Even at the Doggerbank in the central part of the North Sea, plans exist to build a 9 GW wind farm. Concluding, all North Sea seabirds will be confronted with the presence of offshore turbines. Considering the future large-scale exploitation, it is interesting to extrapolate the results as found at the BPNS and frame them into an international context. The latter can be done by weighing the expected wind farm induced mortality on a North Sea scale to the natural mortality within the involved species' biogeographical populations. The results based on such an extrapolation should be interpreted very carefully, since the numbers of estimated collision victims as presented in Table 20 are without any doubt highly site-specific, largely reflecting the local seabird community. But for two species in particular, this exercise definitely holds sense. Outside the breeding season, black-legged kittiwake and northern gannet both occur widely and homogenously spread over the entire North Sea. Moreover, densities in the study area before wind farm construction were highly comparable to those in the North Sea as a whole, with respectively 0.6 versus 0.3 northern gannets per km^2 in autumn, and 1.1 versus 1.3 black-legged kittiwakes per km^2 during winter (Stone *et al*. 1995).

In their research on wind farm induced mortality in German waters, Dierschke *et al*. (2003) regard an increase of the existing mortality rate by less than 5% as acceptable. For Flanders, Everaert (2013) also sets the acceptable level at 5%, with a more stringent threshold of 1% for threatened species or species facing population decline. When extrapolating the expected number of victims per turbine at the Blighbank wind farm (Table 19) for a scenario of 10,000 turbines, we outreach the 5% limit for the two black-backed gull species. Black-legged kittiwake too shows a relevant increase of the existing adult mortality by 1.5%. The other three species regarded here are at the safe side of the mortality threshold (Table 21). Importantly, these thresholds are indicative values set to function as an 'early warning system', rather than true critical thresholds, which will depend on species-specific population dynamics (Dierschke e*t al*. 2003). Nevertheless, the results presented here show that the cumulative impact of large scale wind farm development can cause a considerable increase in bird mortality levels, potentially putting specific seabird populations under pressure.

Table 21. Estimation of the additional mortality per 10,000 offshore turbines and a micro-avoidance of 97.6%, based on an extrapolation of the CRM results for the Blighbank study area (Mitchell *et al.* 2004[a], Wetlands International 2013[b]; BTO 2013[c] and Poot *et al.* 2011[d]).

Species	Biogeographical population	Population level	Yearly mortality	Number of collisions	Additional mortality
Northern gannet	NE Atlantic	310,000 [a]	8.1% [c]	182	0.7%
Common gull	NW & C Europe	1,640,000 [b]	14.0% [c]	545	0.2%
LBB gull	ssp. *graellsii + intermedius*	930,000 [b]	8.7% [c]	11,818	14.6%
Herring gull	ssp. *argenteus + argentatus*	3,030,000 [b]	12.0% [c]	1,091	0.3%
GBB gull	N & W Europe	420,000 [b]	16.5% [d]	5,091	7.3%
BL kittiwake	NE Atlantic	6,600,000 [b]	5.9% [c]	5,818	1.5%

6.4 Discussion

For bird collision rate estimates two techniques can be used. Visual censuses from research vessels aim at estimating local seabird densities, and provide a high taxonomic resolution and direct information on seabird behaviour, but is restricted by the availability of research vessels and associated budgetary constraints. In practice, ship-based visual censuses were limited to single day-time visits per month, and so the chance of missing short-lived but massive migration events is very high. In contrast, radar research (as presently performed by the Management Unit of the North Sea Mathematical Models - MUMM) provides continuous observations, yet with a significantly lower taxonomic resolution. Applying both techniques is thus invaluable for an integrated assessment of bird mortality caused by offshore wind farms. Unfortunately, the radar research first had to cope with various technical and analytical problems, but nevertheless, the first promising results were recently reported in Vanermen *et al*. (2013). To further improve the outcome of the CRM, radar observations should be combined as much as possible with simultaneous visual observations from a fixed point inside the wind farm (preferably the radar location itself), not only to calibrate radar data and to filter birds from clutter, but also to assess species-specific flight heights and avoidance rates.

Regarding bird collision rates at offshore wind farms, two important knowledge gaps remain. Since the CRM is a theoretical model, there is still need for devices that measure actual collision rate (e.g. TADS, WT-Bird, DTBird,…) allowing good calibration of the models. And secondly, to well interpret the consequences of bird collisions on a population level, the expected number of casualties needs to be framed in a population perspective. Therefore, wind farm related research should also focus on setting species- and population-specific thresholds of acceptable additional mortality levels, a first onset of which is given by Poot *et al*. (2011).

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Annex I. Power analysis - model coefficient inputs & results

1. *Input for power analysis: coefficient estimates through 'base modelling'*

Based upon the empirical coefficient ranges resulting from the base models (§5.2.4.1), we defined unique coefficient combinations, which were used for data simulation. As such, the intercept a_1 of the count component was varied stepwise from -4 to 0. The amplitude was varied by setting a_3 to zero and varying a_2 from 1 to 4, again in discrete steps of one. Figure 50 displays the empirical model coefficients, as well as the ones used for the data simulation. Despite being largely outside the empirical coefficient range, we also combined an amplitude of 0 with an intercept varying from -4 to 2, in order to be able to fully exclude the effect of seasonality. Next, we defined an empirical range for theta (related to data variance) as well as for b_1 (indicating zero-inflation). The base modelling revealed some sort of interaction between the theta value and the amount of zero-inflation. For data showing no zero-inflation (b_1<-5), theta was without exception small, varying between 0.18 and 0.66, while in data subject to zero-inflation (b_1>0.5), theta values were clearly higher, ranging from 0.48 to 1.40. This implies that in the latter case, over-dispersion is (at least partly) captured by the zero-component. For data simulation we thus combined a b_1 value of -10 (zero-inflation=0%) with a theta varying by 0.2, 0.4 & 0.6, and a b_1 value of 1 (zero-inflation=73%) with a theta varying by 0.6 & 1.2.

We further investigated the role of zero-inflation by varying b_1 by -10, 0 & 1, for a limited selection of scenario's (a_1=-1 & -2, a_2=1 & 2, a_3=0, a_6=0, theta=0.5), and compared powers resulting from a NB and a ZINB model.

Until now, the area-coefficient a_6 was fixed at zero. Base models however showed this coefficient to vary between -1.02 and 1.25. Lastly, we investigated the effect of the CI-factor on the resulting power by varying a_6 with -1, 0 & 1, again for a limited selection of scenario's (a_1=-1 & -2, a_2=1 & 2, a_3=0, b_1=-10, theta=0.5).

Adding up all of these parameter combinations, we end up with 159 theoretical scenarios, enabling us to isolate and explore the effect of the different model parameters on the power of our impact analysis, given a certain monitoring set-up (i.e. to detect a decrease in numbers of 50% after 10 years of monitoring, i.e. 5 year before and 5 years after the impact). Power was assessed by simulating each scenario 1,000 times, and calculating the percentage of times our impact analysis detected a significant change in numbers.

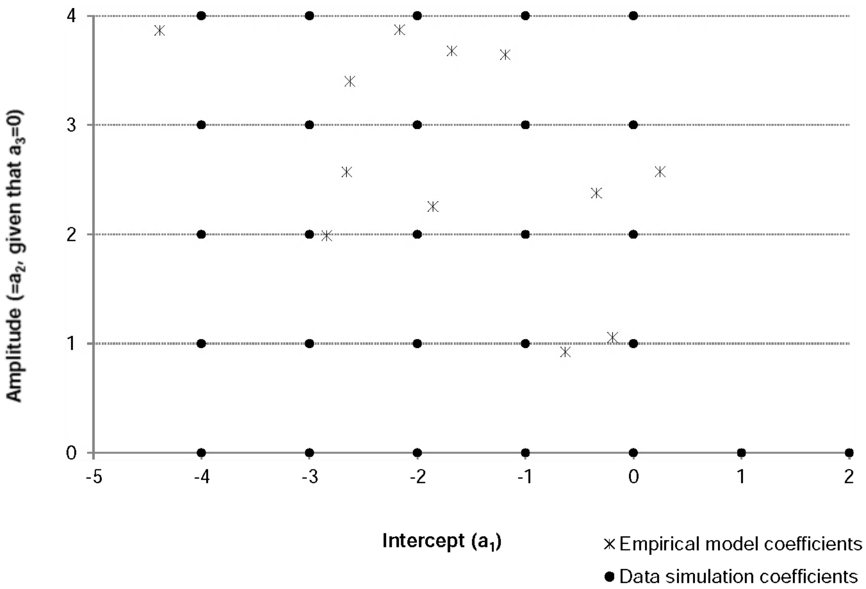

Figure 50. Values for the intercept (a_1) and amplitude (equalling a_2 as a_3 is set to zero) as used for data simulations and subsequent power analyses, plus indication of the empirical coefficient values as found by modelling the reference data collected in the Thorntonbank study area according to a standard 'base model'.

Since all of these model coefficient values are linked to the response variable by a logarithmic link function, they can be difficult to interpret. For 8 unique combinations of intercept and amplitude, we therefore visualize the corresponding predicted densities in Figure 51.

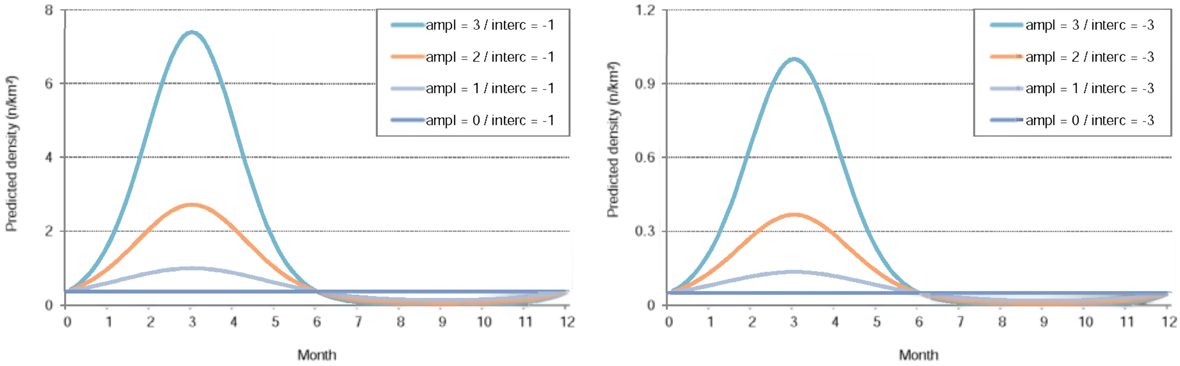

Figure 51. Predicted densities (n/km²) based on 8 unique combinations of intercept and amplitude values as input for the base models.

2. Input for power analyses: coefficient estimates through ‘species-specific modelling’

In 2011, we built species-specific models (as set out in §5.2.4.2) based on data collected in the Thorntonbank wind farm area following the (former) BACI set-up as delineated Figure 52. This resulted in the model coefficients as displayed in Table 22. Considering their specific seasonal occurrence in the study area, we used a double sine curve to explain seasonal variation in numbers for four species, i.e. northern gannet, little gull, sandwich tern and common tern. The occurrence of all other species was described by using a single sine curve. In only two out of twelve species, we retained a significant area-effect i.e. for common gull (a_6=1.25) and black-legged kittiwake (a_6=-0.87). Back-transformation of the intercept values b_1 of the zero components (IntZero) shown in Table 22 learns that zero-inflation occurs in the data of northern fulmar (54.0%), sandwich tern (52.2%) and common tern (74.8%). For the two latter species, theta values are high (3.68 & 11.05), suggesting that most of the over-dispersion is captured by the zero-component. In all other species zero-inflation is very close to 0%.

Be aware of the fact that these model coefficients differ slightly from the ones used in the eventual reference modelling in §5.4.1 due to a different BACI set-up, resulting from the fact that C-Power revised their wind farm configuration and extended their concession area. When compared to the values shown in Table 12 however, model predictions in Table 22 prove to be extremely similar, the only important difference being the fact that for black-legged kittiwake, we no longer found an area-effect in the revised reference dataset.

Table 22. Model coefficients used as input for data simulations and subsequent power analyses as found through species-specific reference modelling of the reference data collected in the Thorntonbank study area.

	IntCount a_1	Sin(1yr) a_2	Cos(1yr) a_3	Sin(1/2yr) a_4	Cos(1/2yr) a_5	CI a_6	IntZero b_1	θ
Northern fulmar	-0.82	-1.06	0.18				0.16	0.27
Northern gannet	-0.90	-0.80	0.29	-0.56	-0.43		-11.71	0.38
Little gull	-3.34	1.72	3.78	-1.31	-0.88		-2.86	0.23
Common gull	-4.39	2.01	3.30			1.25	-8.88	0.20
Lesser black-backed gull	0.08	1.12	-2.35				-10.92	0.22
Herring gull	-2.74	1.80	0.78				-7.82	0.20
Great black-backed gull	-1.52	-0.30	2.31				-10.28	0.18
Black-legged kittiwake	-0.34	-1.07	2.12			-0.87	-12.74	0.26
Sandwich tern	-8.82	0.53	-10.87	1.23	-6.36		0.09	3.68
Common tern	-10.48	-1.21	-13.51	-0.89	-7.22		1.09	11.05
Common guillemot	-1.26	0.58	3.60				-10.39	0.66
Razorbill	-2.48	-0.15	3.36				-11.35	0.32

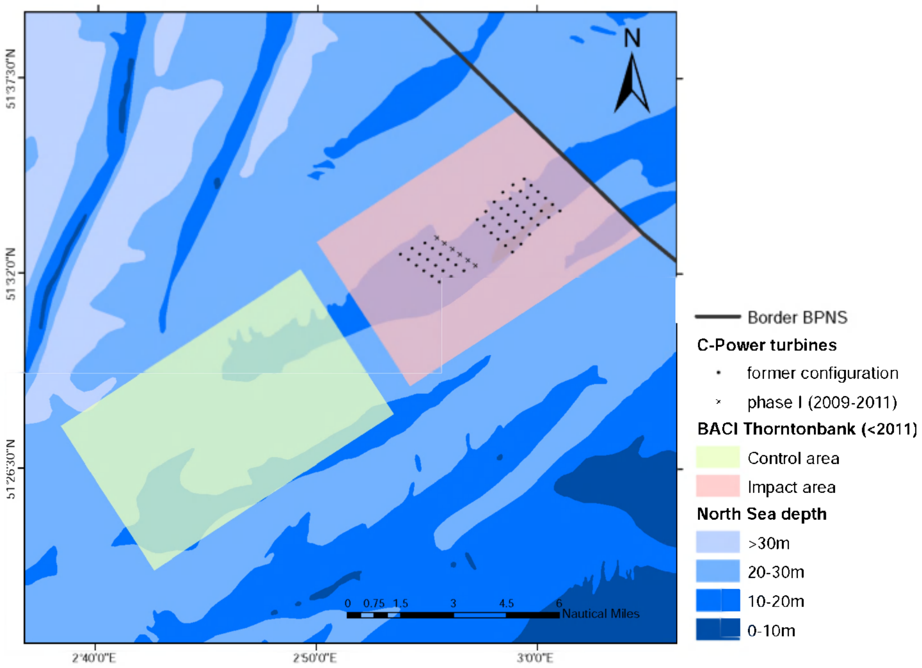

Figure 52. BACI set-up as applied for reference data selection and modelling as input for data simulations and power analyses.

3. *Power results*

Table 23. Power results to detect a decrease in numbers of 50% after 10 years of monitoring (5 year before and 5 years after impact) for 135 different coefficient combinations within empirical ranges (a_3=0, a_6=0, significance level=0.10).

Amplitude a_2	Intercept a_1	ZI=0% (b_1=-10)			ZI=73% (b_1=1)	
		θ=0.2	θ=0.4	θ=0.6	θ=0.6	θ=1.2
0	-4	0.30	0.32	0.28	0.03	0.03
0	-3	0.42	0.51	0.56	0.21	0.22
0	-2	0.45	0.65	0.76	0.32	0.36
0	-1	0.49	0.72	0.85	0.39	0.52
0	0	0.51	0.77	0.90	0.42	0.62
0	1	0.53	0.79	0.91	0.44	0.64
0	2	0.54	0.78	0.91	0.46	0.67
1	-4	0.31	0.34	0.37	0.07	0.04
1	-3	0.42	0.50	0.59	0.23	0.26
1	-2	0.47	0.66	0.74	0.35	0.40
1	-1	0.51	0.73	0.83	0.38	0.49
1	0	0.52	0.77	0.87	0.38	0.57
2	-4	0.34	0.43	0.46	0.17	0.16
2	-3	0.40	0.52	0.64	0.31	0.36
2	-2	0.46	0.60	0.76	0.34	0.41
2	-1	0.53	0.68	0.82	0.36	0.50
2	0	0.52	0.77	0.86	0.36	0.57
3	-4	0.35	0.43	0.52	0.29	0.28
3	-3	0.40	0.52	0.64	0.30	0.37
3	-2	0.45	0.61	0.70	0.32	0.44
3	-1	0.45	0.64	0.76	0.35	0.50
3	0	0.51	0.74	0.85	0.36	0.54
4	-4	0.34	0.51	0.56	0.33	0.39
4	-3	0.38	0.51	0.63	0.32	0.37
4	-2	0.41	0.59	0.71	0.29	0.38
4	-1	0.41	0.64	0.79	0.31	0.45
4	0	0.47	0.69	0.80	0.35	0.50

Table 24. Effect of a varying area (CI) coefficient (a_6) and the applied impact model on the power to detect a 50% decrease in numbers after 10 years of monitoring (5 year before & 5 years after impact) for a limited number of scenario's (a_3=0, b_1=-10, θ=0.5, significance level=0.10).

Impact model	Amplitude	Intercept	Area coefficient		
	a_2	a_1	a_6=-1	a_6=0	a_6=1
Excl. CI (Eq.7)	1	-2	1.00	0.71	0.28
	2	-2	1.00	0.65	0.28
	1	-1	1.00	0.75	0.27
	2	-1	1.00	0.78	0.29
Incl. CI (Eq.5)	1	-2	0.40	0.48	0.52
	2	-2	0.41	0.47	0.48
	1	-1	0.53	0.56	0.60
	2	-1	0.48	0.56	0.54

Table 25. Effect of a varying zero-inflation (b_1) and the applied impact model on the power to detect a 50% decrease in numbers after 10 years of monitoring (5 year before & 5 years after impact) for a limited number of scenario's (a_3=0, a_6=0, θ=0.5, significance level=0.10).

Impact model	Amplitude	Intercept	Zero-inflation coefficient		
	a_2	a_1	b_1=-10	b_1=0	b_1=1
NB	1	-2	0.70	0.40	0.24
	2	-2	0.69	0.36	0.23
	1	-1	0.78	0.40	0.25
	2	-1	0.74	0.35	0.24
ZINB	1	-2	0.71	0.45	0.33
	2	-2	0.70	0.42	0.31
	1	-1	0.77	0.49	0.36
	2	-1	0.76	0.47	0.34

Table 26. Power results to detect a varying decrease in numbers after 5 years of reference monitoring and 1 to 15 years of impact monitoring, based on species-specific coefficient estimates (significance level=0.05).

Years after impact	Decrease	Northern fulmar	Northern gannet	Little gull	Common gull	LBB gull	Herring gull	GBB gull	BL kittiwake	Sandwich tern	Common tern	Common guillemot	Razorbill
1	0.25	0.10	0.10	0.13	0.08	0.11	0.07	0.11	0.10	0.09	0.04	0.09	0.10
3	0.25	0.12	0.14	0.11	0.11	0.10	0.11	0.10	0.10	0.15	0.14	0.14	0.09
5	0.25	0.13	0.16	0.13	0.12	0.13	0.13	0.11	0.09	0.18	0.16	0.20	0.11
7	0.25	0.12	0.21	0.12	0.11	0.14	0.13	0.12	0.10	0.19	0.21	0.22	0.16
9	0.25	0.12	0.25	0.14	0.10	0.18	0.14	0.14	0.11	0.23	0.20	0.27	0.16
11	0.25	0.14	0.28	0.17	0.09	0.22	0.15	0.15	0.11	0.26	0.25	0.33	0.19
13	0.25	0.16	0.33	0.16	0.08	0.23	0.16	0.17	0.13	0.27	0.26	0.38	0.21
15	0.25	0.16	0.35	0.18	0.09	0.24	0.17	0.19	0.11	0.31	0.29	0.44	0.25
1	0.50	0.11	0.21	0.14	0.12	0.15	0.10	0.15	0.15	0.12	0.06	0.21	0.16
3	0.50	0.19	0.42	0.21	0.17	0.29	0.22	0.23	0.23	0.34	0.22	0.48	0.25
5	0.50	0.27	0.60	0.31	0.19	0.42	0.33	0.34	0.28	0.49	0.39	0.70	0.39
7	0.50	0.32	0.73	0.37	0.21	0.51	0.39	0.43	0.30	0.62	0.50	0.82	0.50
9	0.50	0.36	0.84	0.45	0.21	0.64	0.45	0.48	0.30	0.73	0.60	0.90	0.61
11	0.50	0.43	0.89	0.52	0.22	0.71	0.54	0.57	0.33	0.76	0.66	0.94	0.67
13	0.50	0.51	0.94	0.57	0.21	0.79	0.61	0.68	0.36	0.85	0.78	0.97	0.73
15	0.50	0.53	0.97	0.65	0.18	0.84	0.67	0.72	0.33	0.88	0.81	0.98	0.81
1	0.75	0.15	0.45	0.22	0.20	0.34	0.14	0.24	0.32	0.20	0.08	0.58	0.30
3	0.75	0.47	0.91	0.54	0.33	0.73	0.54	0.58	0.55	0.68	0.41	0.95	0.66
5	0.75	0.66	0.99	0.73	0.42	0.92	0.75	0.80	0.67	0.89	0.71	1.00	0.88
7	0.75	0.76	1.00	0.87	0.46	0.98	0.87	0.93	0.76	0.97	0.85	1.00	0.95
9	0.75	0.89	1.00	0.92	0.51	0.99	0.94	0.95	0.78	0.98	0.92	1.00	0.99
11	0.75	0.93	1.00	0.97	0.54	1.00	0.97	0.98	0.84	1.00	0.96	1.00	0.99
13	0.75	0.97	1.00	0.99	0.55	1.00	0.99	0.99	0.83	1.00	0.98	1.00	1.00
15	0.75	0.97	1.00	0.99	0.60	1.00	0.99	0.99	0.89	1.00	0.99	1.00	1.00

Table 27. Power results to detect a varying decrease in numbers after 5 years of reference monitoring and 1 to 15 years of impact monitoring, based on species-specific coefficient estimates (significance level of 0.10).

n years after impact	decrease	Northern fulmar	Northern gannet	Little gull	Common gull	LBB gull	Herring gull	GBB gull	BL kittiwake	Sandwich tern	Common tern	Common guillemot	Razorbill
1	0.25	0.18	0.18	0.20	0.14	0.17	0.14	0.18	0.17	0.13	0.07	0.16	0.16
3	0.25	0.19	0.21	0.18	0.18	0.18	0.18	0.16	0.16	0.22	0.23	0.22	0.18
5	0.25	0.20	0.25	0.21	0.18	0.21	0.20	0.17	0.15	0.25	0.25	0.30	0.19
7	0.25	0.19	0.30	0.18	0.17	0.23	0.20	0.20	0.16	0.28	0.29	0.34	0.23
9	0.25	0.19	0.37	0.21	0.16	0.26	0.23	0.21	0.19	0.34	0.27	0.40	0.25
11	0.25	0.22	0.37	0.25	0.16	0.32	0.23	0.22	0.17	0.35	0.35	0.43	0.28
13	0.25	0.24	0.44	0.25	0.13	0.32	0.25	0.27	0.19	0.38	0.35	0.51	0.31
15	0.25	0.23	0.47	0.28	0.15	0.36	0.27	0.29	0.19	0.41	0.38	0.56	0.35
1	0.50	0.18	0.28	0.21	0.17	0.22	0.19	0.24	0.23	0.18	0.08	0.30	0.25
3	0.50	0.27	0.52	0.31	0.24	0.39	0.34	0.32	0.33	0.45	0.31	0.61	0.36
5	0.50	0.36	0.70	0.40	0.26	0.55	0.43	0.45	0.38	0.61	0.52	0.79	0.50
7	0.50	0.43	0.82	0.48	0.29	0.62	0.50	0.56	0.40	0.72	0.61	0.88	0.62
9	0.50	0.48	0.90	0.58	0.29	0.74	0.56	0.60	0.42	0.81	0.69	0.95	0.72
11	0.50	0.56	0.94	0.65	0.31	0.81	0.66	0.68	0.45	0.84	0.75	0.97	0.77
13	0.50	0.63	0.97	0.68	0.30	0.89	0.73	0.77	0.48	0.90	0.85	0.99	0.83
15	0.50	0.65	0.98	0.76	0.29	0.90	0.79	0.82	0.46	0.93	0.86	0.99	0.87
1	0.75	0.24	0.57	0.30	0.27	0.46	0.24	0.34	0.42	0.26	0.11	0.67	0.41
3	0.75	0.58	0.95	0.64	0.44	0.81	0.65	0.68	0.68	0.76	0.51	0.98	0.76
5	0.75	0.75	1.00	0.82	0.54	0.95	0.84	0.86	0.77	0.94	0.79	1.00	0.94
7	0.75	0.85	1.00	0.93	0.57	0.99	0.91	0.96	0.84	0.98	0.90	1.00	0.97
9	0.75	0.94	1.00	0.95	0.61	1.00	0.97	0.97	0.86	1.00	0.95	1.00	0.99
11	0.75	0.97	1.00	0.98	0.65	1.00	0.99	0.99	0.89	1.00	0.98	1.00	1.00
13	0.75	0.98	1.00	1.00	0.66	1.00	0.99	1.00	0.89	1.00	0.99	1.00	1.00
15	0.75	0.99	1.00	1.00	0.71	1.00	0.99	1.00	0.94	1.00	0.99	1.00	1.00

Annex II. BACI graphs

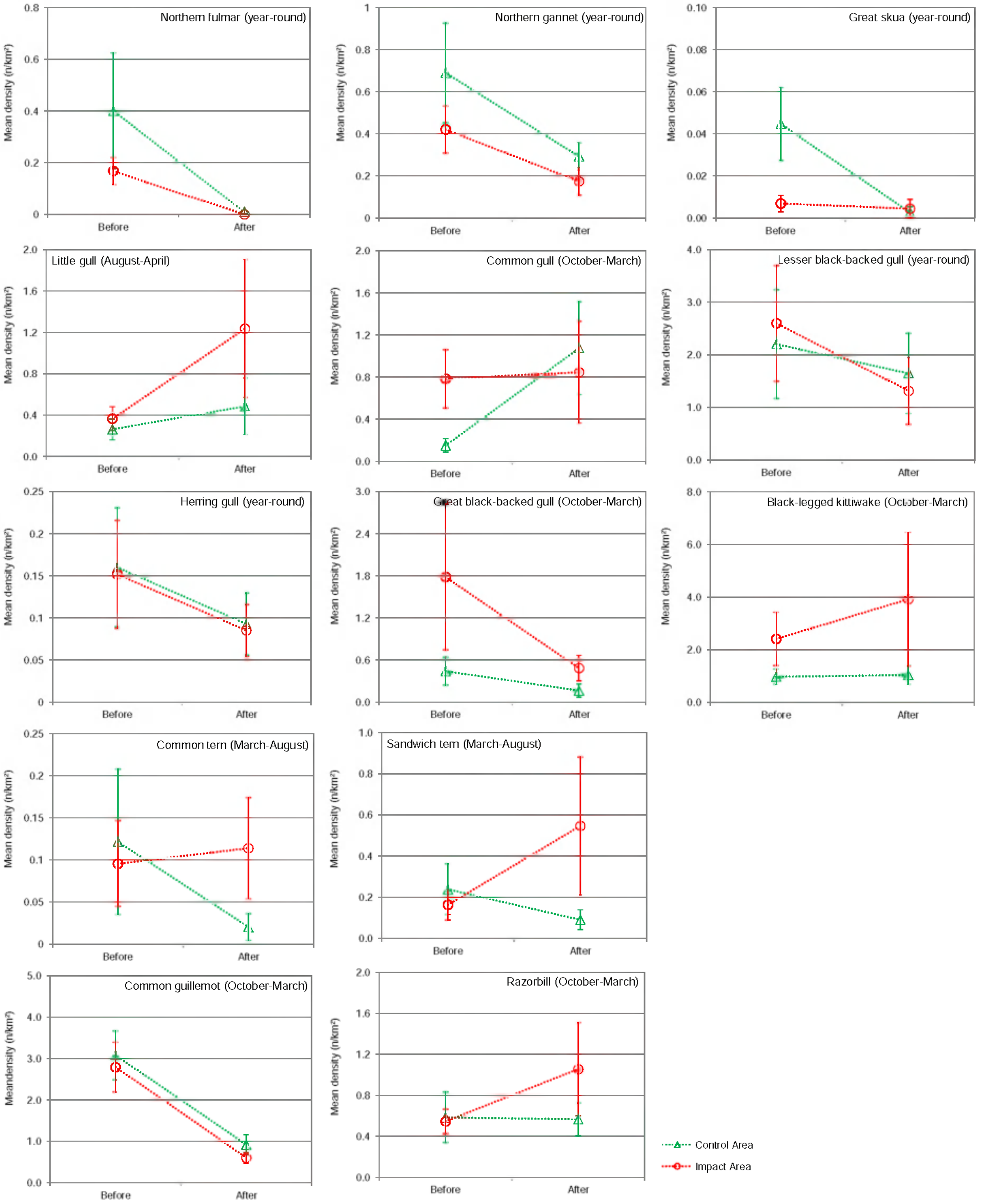

Figure 53. Mean seabird densities (+/- std. errors) in the control and impact area (phase I WF + 3 km buffer zone) of thirteen seabird species at the Thorntonbank.

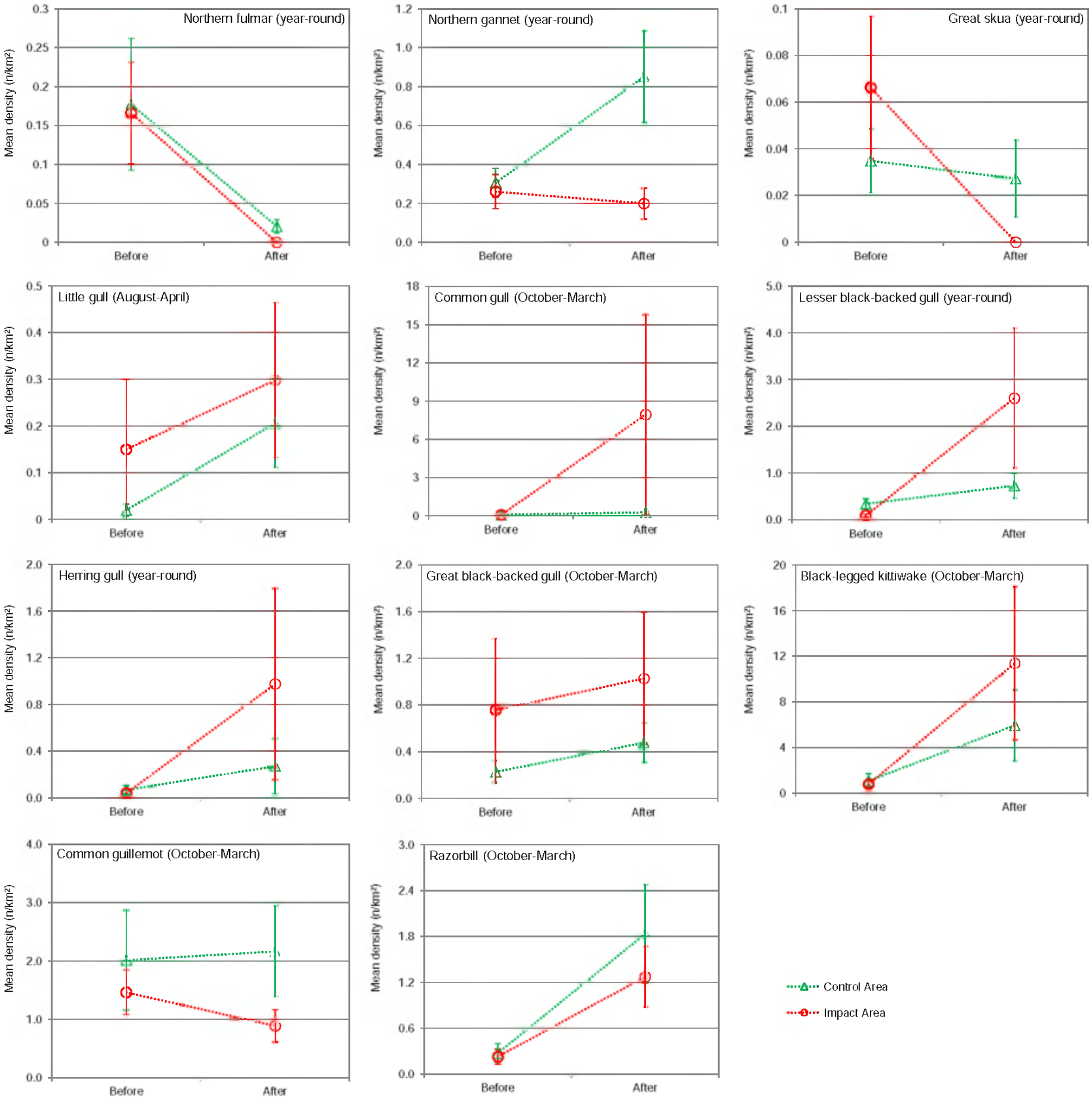

Figure 54. Mean seabird densities (+/- std. errors) in the control and impact area (WF + 3 km buffer zone) of eleven seabird species at the Blighbank.

Annex III. Impact model summaries Thorntonbank (phase I)

Wind farm + 3 km buffer

```
> summary(northern_fulmar <- NB.NSV3.imp)

Call:
glm.nb(formula = NSV ~ offset(log(KM2)) + sin(2 * pi * (MONTH/12)) + 
    cos(2 * pi * (MONTH/12)) + BA + Turbines, data = TTB.DD, link = log, 
    init.theta = 0.09607397564)

Deviance Residuals: 
    Min       1Q   Median       3Q      Max  
-0.9032  -0.6869  -0.4316   0.0000   1.9331  

Coefficients:
                           Estimate Std. Error z value Pr(>|z|)    
(Intercept)              -1.622e+00  3.113e-01  -5.210 1.89e-07 ***
sin(2 * pi * (MONTH/12)) -9.621e-01  3.966e-01  -2.426 0.015258 *  
cos(2 * pi * (MONTH/12))  1.595e-01  4.432e-01   0.360 0.718910    
BATRUE                   -3.290e+00  9.777e-01  -3.365 0.000766 ***
TurbinesTRUE             -3.276e+01  6.550e+06   0.000 0.999996    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for Negative Binomial(0.0961) family taken to be 1)

    Null deviance: 97.616  on 197  degrees of freedom
Residual deviance: 66.426  on 193  degrees of freedom
AIC: 281.04

Number of Fisher Scoring iterations: 1


              Theta:  0.0961 
          Std. Err.:  0.0242 

 2 x log-likelihood:  -269.0410 
```

```
> summary(northern_gannet <- NB.JVG3.imp)

Call:
glm.nb(formula = JVG ~ offset(log(KM2)) + sin(2 * pi * (MONTH/12)) + 
    cos(2 * pi * (MONTH/12)) + sin(2 * pi * (MONTH/6)) + cos(2 * 
    pi * (MONTH/6)) + BA + Turbines, data = TTB.DD, link = log, 
    init.theta = 0.3847832551)

Deviance Residuals: 
     Min        1Q    Median        3Q       Max  
-1.54155  -1.05259  -0.67000  -0.06239   2.60195  

Coefficients:
                         Estimate Std. Error z value Pr(>|z|)    
(Intercept)               -0.8329     0.1654  -5.035 4.78e-07 ***
sin(2 * pi * (MONTH/12))  -0.5111     0.1798  -2.842  0.00449 ** 
cos(2 * pi * (MONTH/12))   0.3935     0.2065   1.906  0.05668 .  
sin(2 * pi * (MONTH/6))   -0.4083     0.1950  -2.094  0.03630 *  
cos(2 * pi * (MONTH/6))   -0.3594     0.1876  -1.916  0.05542 .  
BATRUE                    -0.3995     0.3531  -1.131  0.25787    
TurbinesTRUE              -0.7009     0.4762  -1.472  0.14108    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for Negative Binomial(0.3848) family taken to be 1)

    Null deviance: 206.85  on 197  degrees of freedom
Residual deviance: 171.89  on 191  degrees of freedom
AIC: 690.84

Number of Fisher Scoring iterations: 1

              Theta:  0.3848 
          Std. Err.:  0.0592 

 2 x log-likelihood:  -674.8360 
```

```
> summary(great_skua  <- zeroinfl.GJ4.imp)

Call:
zeroinfl(formula = GJ ~ offset(log(KM2)) + sin(2 * pi * (MONTH/12)) + cos(2 * pi * (MONTH/12))
+ BA + CI + BA:CI | 1, data = TTB.DD, dist = "negbin")

Pearson residuals:
     Min       1Q   Median       3Q      Max
-0.70643 -0.25234 -0.13331 -0.06905  4.23454

Count model coefficients (negbin with log link):
                         Estimate Std. Error z value Pr(>|z|)
(Intercept)              -2.90910    0.53457  -5.442 5.27e-08 ***
sin(2 * pi * (MONTH/12)) -1.88489    0.57693  -3.267  0.00109 **
cos(2 * pi * (MONTH/12)) -0.01253    0.42278  -0.030  0.97635
BATRUE                   -2.62194    1.09046  -2.404  0.01620 *
CITRUE                   -1.57912    0.64626  -2.443  0.01455 *
BATRUE:CITRUE             2.11558    1.59991   1.322  0.18606
Log(theta)               13.20855         NA      NA       NA

Zero-inflation model coefficients (binomial with logit link):
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.3831     0.5480   0.699    0.485
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Theta = 545003.8652
Number of iterations in BFGS optimization: 39
Log-likelihood: -48.1 on 8 Df
```

```
> summary(little_gull <- NB.DWM3.imp)

Call:
glm.nb(formula = DWM ~ offset(log(KM2)) + sin(2 * pi * (MONTH/12)) +
    cos(2 * pi * (MONTH/12)) + sin(2 * pi * (MONTH/6)) + cos(2 *
    pi * (MONTH/6)) + BA + Turbines, data = TTB.DD, link = log,
    init.theta = 0.2024762453)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-1.23050  -0.89833  -0.32003  -0.03433   1.84122

Coefficients:
                         Estimate Std. Error z value Pr(>|z|)
(Intercept)               -3.3237     0.5686  -5.845 5.07e-09 ***
sin(2 * pi * (MONTH/12))   2.5029     0.5043   4.963 6.93e-07 ***
cos(2 * pi * (MONTH/12))   3.2644     0.7840   4.164 3.13e-05 ***
sin(2 * pi * (MONTH/6))   -1.8644     0.4949  -3.767 0.000165 ***
cos(2 * pi * (MONTH/6))   -0.8921     0.4209  -2.120 0.034026 *
BATRUE                    -0.2262     0.5856  -0.386 0.699317
TurbinesTRUE               1.2205     0.7259   1.681 0.092675 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for Negative Binomial(0.2025) family taken to be 1)

    Null deviance: 179.65  on 197  degrees of freedom
Residual deviance: 100.90  on 191  degrees of freedom
AIC: 462.57

Number of Fisher Scoring iterations: 1


              Theta:  0.2025
          Std. Err.:  0.0381
Warning while fitting theta: alternation limit reached

 2 x log-likelihood:  -446.5700
```

```
> summary(common_gull <- NB.STM4.imp)

Call:
glm.nb(formula = STM ~ offset(log(KM2)) + sin(2 * pi * (MONTH/12)) + 
    cos(2 * pi * (MONTH/12)) + BA + CI + BA:CI, data = TTB.DD, 
    link = log, init.theta = 0.2428992068)

Deviance Residuals: 
    Min       1Q   Median       3Q      Max  
-1.4115  -0.7441  -0.2878  -0.1059   2.4239  

Coefficients:
                         Estimate Std. Error z value Pr(>|z|)    
(Intercept)               -4.4109     0.5389  -8.184 2.73e-16 ***
sin(2 * pi * (MONTH/12))   2.0570     0.3552   5.790 7.02e-09 ***
cos(2 * pi * (MONTH/12))   3.1360     0.4685   6.694 2.17e-11 ***
BATRUE                     1.7190     0.6382   2.694  0.00707 ** 
CITRUE                     1.3729     0.5263   2.609  0.00909 ** 
BATRUE:CITRUE             -1.4515     0.8759  -1.657  0.09747 .  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for Negative Binomial(0.2429) family taken to be 1)

    Null deviance: 204.270  on 197  degrees of freedom
Residual deviance:  91.801  on 192  degrees of freedom
AIC: 407.77

Number of Fisher Scoring iterations: 1


              Theta:  0.2429 
          Std. Err.:  0.0495 

 2 x log-likelihood:  -393.7750 
```

```
> summary(LBB_gull <- NB.KLM3.imp)

Call:
glm.nb(formula = KLM ~ offset(log(KM2)) + sin(2 * pi * (MONTH/12)) + 
    cos(2 * pi * (MONTH/12)) + BA + Turbines, data = TTB.DD, link = "log", 
    init.theta = 0.2531513255)

Deviance Residuals: 
    Min       1Q   Median       3Q      Max  
-1.6535  -1.0080  -0.7401  -0.2342   2.9166  

Coefficients:
                         Estimate Std. Error z value Pr(>|z|)    
(Intercept)                0.1296     0.1874   0.691    0.489    
sin(2 * pi * (MONTH/12))   0.8962     0.2061   4.348 1.37e-05 ***
cos(2 * pi * (MONTH/12))  -2.2276     0.2348  -9.486  < 2e-16 ***
BATRUE                    -0.4157     0.4161  -0.999    0.318    
TurbinesTRUE              -0.1363     0.5308  -0.257    0.797    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for Negative Binomial(0.2532) family taken to be 1)

    Null deviance: 259.56  on 197  degrees of freedom
Residual deviance: 172.24  on 193  degrees of freedom
AIC: 895.93

Number of Fisher Scoring iterations: 1


              Theta:  0.2532 
          Std. Err.:  0.0331 

 2 x log-likelihood:  -883.9330 
```

```
> summary(herring_gull  <- NB.ZM3.imp)

Call:
glm.nb(formula = ZM ~ offset(log(KM2)) + sin(2 * pi * (MONTH/12)) + 
    cos(2 * pi * (MONTH/12)) + BA + Turbines, data = TTB.DD, link = log, 
    init.theta = 0.2606233045)

Deviance Residuals: 
    Min       1Q   Median       3Q      Max  
-1.2994  -0.7244  -0.4296  -0.2675   2.5666  

Coefficients:
                         Estimate Std. Error z value Pr(>|z|)    
(Intercept)               -2.6550     0.2642 -10.048  < 2e-16 ***
sin(2 * pi * (MONTH/12))   1.5997     0.2844   5.625 1.86e-08 ***
cos(2 * pi * (MONTH/12))   0.6561     0.2989   2.195   0.0282 *  
BATRUE                    -0.2312     0.5245  -0.441   0.6593    
TurbinesTRUE               0.3783     0.6595   0.574   0.5662    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for Negative Binomial(0.2606) family taken to be 1)

    Null deviance: 141.56  on 197  degrees of freedom
Residual deviance: 103.91  on 193  degrees of freedom
AIC: 351.29

Number of Fisher Scoring iterations: 1


              Theta:  0.2606 
          Std. Err.:  0.0594 

 2 x log-likelihood:  -339.2910 


> summary(GBB_gull  <- NB.GM3.imp)

Call:
glm.nb(formula = GM ~ offset(log(KM2)) + sin(2 * pi * (MONTH/12)) + 
    cos(2 * pi * (MONTH/12)) + BA + Turbines, data = TTB.DD, link = log, 
    init.theta = 0.2110276727)

Deviance Residuals: 
    Min       1Q   Median       3Q      Max  
-1.3735  -0.8725  -0.5548  -0.3011   2.5676  

Coefficients:
                         Estimate Std. Error z value Pr(>|z|)    
(Intercept)               -1.4467     0.2291  -6.314 2.72e-10 ***
sin(2 * pi * (MONTH/12))  -0.4561     0.2441  -1.869  0.06167 .  
cos(2 * pi * (MONTH/12))   2.0124     0.2953   6.814 9.49e-12 ***
BATRUE                    -1.5464     0.5447  -2.839  0.00452 ** 
TurbinesTRUE               1.5018     0.6666   2.253  0.02426 *  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for Negative Binomial(0.211) family taken to be 1)

    Null deviance: 196.18  on 197  degrees of freedom
Residual deviance: 128.87  on 193  degrees of freedom
AIC: 542.69

Number of Fisher Scoring iterations: 1


              Theta:  0.2110 
          Std. Err.:  0.0360 

 2 x log-likelihood:  -530.6930 
```

```
> summary(BL_kittiwake <- NB.DTM3.imp)

Call:
glm.nb(formula = DTM ~ offset(log(KM2)) + sin(2 * pi * (MONTH/12)) + 
    cos(2 * pi * (MONTH/12)) + BA + Turbines, data = TTB.DD, link = log, 
    init.theta = 0.2477481728)

Deviance Residuals: 
    Min       1Q   Median       3Q      Max  
-1.5922  -0.9219  -0.6240  -0.4043   5.0698  

Coefficients:
                         Estimate Std. Error z value Pr(>|z|)    
(Intercept)               -0.6371     0.2005  -3.177 0.001488 ** 
sin(2 * pi * (MONTH/12))  -0.7578     0.2152  -3.521 0.000429 ***
cos(2 * pi * (MONTH/12))   2.2913     0.2554   8.972  < 2e-16 ***
BATRUE                    -1.0137     0.4526  -2.240 0.025116 *  
TurbinesTRUE               0.6294     0.5726   1.099 0.271664    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for Negative Binomial(0.2477) family taken to be 1)

    Null deviance: 236.09  on 197  degrees of freedom
Residual deviance: 158.97  on 193  degrees of freedom
AIC: 771.3

Number of Fisher Scoring iterations: 1


              Theta:  0.2477 
          Std. Err.:  0.0348 
Warning while fitting theta: alternation limit reached 

 2 x log-likelihood:  -759.2960 
```

```
> summary(sandwich_tern  <- zeroinfl.GS3.imp)

Call:
zeroinfl(formula = GS ~ offset(log(KM2)) + sin(2 * pi * (MONTH/12)) + cos(2 * pi * (MONTH/12))
+ sin(2 * pi * (MONTH/6)) + cos(2 * pi * 
    (MONTH/6)) + BA + Turbines | 1, data = TTB.DD, dist = "negbin")

Pearson residuals:
       Min         1Q     Median         3Q        Max 
-0.5902216 -0.3468134 -0.0251771 -0.0001776  4.0943564 

Count model coefficients (negbin with log link):
                         Estimate Std. Error z value Pr(>|z|)    
(Intercept)               -7.3571     1.7885  -4.114 3.90e-05 ***
sin(2 * pi * (MONTH/12))   0.4589     0.5325   0.862 0.388826    
cos(2 * pi * (MONTH/12))  -9.3142     2.3615  -3.944 8.01e-05 ***
sin(2 * pi * (MONTH/6))    1.1233     0.5554   2.023 0.043120 *  
cos(2 * pi * (MONTH/6))   -4.1768     1.2679  -3.294 0.000987 ***
BATRUE                    -1.1544     0.6597  -1.750 0.080133 .  
TurbinesTRUE               2.4598     0.7147   3.442 0.000578 ***
Log(theta)                -0.0608     0.7583  -0.080 0.936095    

Zero-inflation model coefficients (binomial with logit link):
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.1752     0.6478   -0.27    0.787
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 

Theta = 0.941 
Number of iterations in BFGS optimization: 20 
Log-likelihood: -107.2 on 9 Df
```

```
> summary(common_tern  <- zeroinfl.VD3.imp)

Call:
zeroinfl(formula = VD ~ offset(log(KM2)) + sin(2 * pi * (MONTH/12)) + cos(2 * pi * (MONTH/12))
+ sin(2 * pi * (MONTH/6)) + cos(2 * pi *
    (MONTH/6)) + BA + Turbines | 1, data = TTB.DD, dist = "negbin")

Pearson residuals:
       Min         1Q     Median         3Q        Max
-5.258e-01 -2.817e-01 -6.515e-03 -4.707e-05  4.020e+00

Count model coefficients (negbin with log link):
                         Estimate Std. Error z value Pr(>|z|)
(Intercept)               -8.4907     2.8919  -2.936  0.00332 **
sin(2 * pi * (MONTH/12))  -1.0470     1.1343  -0.923  0.35599
cos(2 * pi * (MONTH/12)) -11.2795     3.9891  -2.828  0.00469 **
sin(2 * pi * (MONTH/6))   -0.5320     1.1561  -0.460  0.64539
cos(2 * pi * (MONTH/6))   -4.9307     1.7641  -2.795  0.00519 **
BATRUE                    -2.3261     0.9089  -2.559  0.01049 *
TurbinesTRUE               2.3165     1.0503   2.206  0.02741 *
Log(theta)                 1.2104     1.5997   0.757  0.44925

Zero-inflation model coefficients (binomial with logit link):
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.8626     0.5411   1.594    0.111
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Theta = 3.3549
Number of iterations in BFGS optimization: 33
Log-likelihood: -60.43 on 9 Df
```

```
> summary(common_guillemot  <- NB.ZK3.imp)

Call:
glm.nb(formula = ZK ~ offset(log(KM2)) + sin(2 * pi * (MONTH/12)) +
    cos(2 * pi * (MONTH/12)) + BA + Turbines, data = TTB.DD, link = "log",
    init.theta = 0.7928235808)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.2911  -0.8895  -0.3819  -0.1061   2.7243

Coefficients:
                         Estimate Std. Error z value Pr(>|z|)
(Intercept)               -1.3030     0.1766  -7.376 1.63e-13 ***
sin(2 * pi * (MONTH/12))   0.5870     0.1520   3.861 0.000113 ***
cos(2 * pi * (MONTH/12))   3.5248     0.2496  14.119  < 2e-16 ***
BATRUE                    -1.4406     0.3237  -4.450 8.59e-06 ***
TurbinesTRUE              -0.1717     0.4429  -0.388 0.698266
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for Negative Binomial(0.7928) family taken to be 1)

    Null deviance: 479.76  on 197  degrees of freedom
Residual deviance: 154.28  on 193  degrees of freedom
AIC: 764.35

Number of Fisher Scoring iterations: 1


              Theta:  0.793
          Std. Err.:  0.123

 2 x log-likelihood:  -752.355
```

```
> summary(razorbill <- NB.ALK3.imp)

Call:
glm.nb(formula = ALK ~ offset(log(KM2)) + sin(2 * pi * (MONTH/12)) + 
    cos(2 * pi * (MONTH/12)) + BA + Turbines, data = TTB.DD, link = "log", 
    init.theta = 0.3933525335)

Deviance Residuals: 
    Min       1Q   Median       3Q      Max  
-1.6979  -0.7304  -0.3369  -0.1291   4.1676  

Coefficients:
                         Estimate Std. Error z value Pr(>|z|)    
(Intercept)               -2.6933     0.2806  -9.600   <2e-16 ***
sin(2 * pi * (MONTH/12))   0.3311     0.2225   1.488    0.137    
cos(2 * pi * (MONTH/12))   3.5492     0.3743   9.483   <2e-16 ***
BATRUE                    -0.3558     0.4463  -0.797    0.425    
TurbinesTRUE               0.4088     0.5741   0.712    0.477    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for Negative Binomial(0.3934) family taken to be 1)

    Null deviance: 233.58  on 197  degrees of freedom
Residual deviance: 117.90  on 193  degrees of freedom
AIC: 509.05

Number of Fisher Scoring iterations: 1


              Theta:  0.3934 
          Std. Err.:  0.0702 

 2 x log-likelihood:  -497.0510 
```

Annex IV. Impact model summaries Blighbank

Wind farm + 0.5 km buffer

```
> summary(northern_fulmar <- NB.NSV3.imp)

Call:
glm.nb(formula = NSV ~ offset(log(KM2)) + sin(2 * pi * (MONTH/12)) + 
    cos(2 * pi * (MONTH/12)) + BA + Turbines, data = BB_DD, link = "log", 
    init.theta = 0.17268541)

Deviance Residuals: 
    Min       1Q   Median       3Q      Max  
-1.0488  -0.6925  -0.5020   0.0000   2.2115  

Coefficients:
                           Estimate Std. Error z value Pr(>|z|)    
(Intercept)              -2.001e+00  2.621e-01  -7.633 2.29e-14 ***
sin(2 * pi * (MONTH/12))  3.506e-01  3.275e-01   1.071  0.28437    
cos(2 * pi * (MONTH/12))  6.702e-01  3.608e-01   1.858  0.06319 .  
BATRUE                   -2.040e+00  6.768e-01  -3.014  0.00258 ** 
TurbinesTRUE             -3.238e+01  4.691e+06   0.000  0.99999    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for Negative Binomial(0.1727) family taken to be 1)

    Null deviance: 99.305  on 179  degrees of freedom
Residual deviance: 75.453  on 175  degrees of freedom
AIC: 260.32

Number of Fisher Scoring iterations: 1


              Theta:  0.1727 
          Std. Err.:  0.0471 

 2 x log-likelihood:  -248.3210 
```

```
> summary(northern_gannet <- NB.JVG3.imp)

Call:
glm.nb(formula = JVG ~ offset(log(KM2)) + sin(2 * pi * (MONTH/12)) + 
    cos(2 * pi * (MONTH/12)) + sin(2 * pi * (MONTH/6)) + cos(2 * 
    pi * (MONTH/6)) + BA + Turbines, data = BB_DD, link = log, 
    init.theta = 0.4612040949)

Deviance Residuals: 
     Min        1Q    Median        3Q       Max  
-1.72927  -0.94179  -0.53346   0.02261   2.25653  

Coefficients:
                         Estimate Std. Error z value Pr(>|z|)    
(Intercept)              -1.62322    0.18692  -8.684  < 2e-16 ***
sin(2 * pi * (MONTH/12)) -0.05908    0.19451  -0.304 0.761325    
cos(2 * pi * (MONTH/12))  1.28977    0.23971   5.381 7.43e-08 ***
sin(2 * pi * (MONTH/6))  -0.04290    0.20311  -0.211 0.832731    
cos(2 * pi * (MONTH/6))  -0.58909    0.21784  -2.704 0.006847 ** 
BATRUE                    1.04698    0.34703   3.017 0.002553 ** 
TurbinesTRUE             -1.82552    0.52071  -3.506 0.000455 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for Negative Binomial(0.4612) family taken to be 1)

    Null deviance: 190.89  on 179  degrees of freedom
Residual deviance: 138.78  on 173  degrees of freedom
AIC: 544.74

Number of Fisher Scoring iterations: 1


              Theta:  0.4612 
          Std. Err.:  0.0895 

 2 x log-likelihood:  -528.7390 
```

```
> summary(great_skua <-  zeroinfl.GJ0.imp)

Call:
zeroinfl(formula = GJ ~ offset(log(KM2)) + BA + Turbines | 1, data = BB_DD, dist = "negbin")

Pearson residuals:
    Min      1Q  Median      3Q     Max 
-0.4350 -0.3386 -0.2698 -0.1298  5.4193 

Count model coefficients (negbin with log link):
             Estimate Std. Error z value Pr(>|z|)    
(Intercept)   -1.6780     0.3932  -4.268 1.98e-05 ***
BATRUE        -1.1970     0.6629  -1.806    0.071 .  
TurbinesTRUE -15.0255  1763.1789  -0.009    0.993    
Log(theta)     2.3407     4.7518   0.493    0.622    

Zero-inflation model coefficients (binomial with logit link):
            Estimate Std. Error z value Pr(>|z|)  
(Intercept)   1.2196     0.4876   2.501   0.0124 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 

Theta = 10.3889 
Number of iterations in BFGS optimization: 20 
Log-likelihood: -69.53 on 5 Df
```

```
> summary(little_gull <- NB.DWM3.imp)

Call:
glm.nb(formula = DWM ~ offset(log(KM2)) + sin(2 * pi * (MONTH/12)) + 
    cos(2 * pi * (MONTH/12)) + BA + Turbines, data = BB_DD, link = log, 
    init.theta = 0.05793804049)

Deviance Residuals: 
    Min       1Q   Median       3Q      Max  
-0.8990  -0.5080  -0.1980  -0.0419   2.1076  

Coefficients:
                         Estimate Std. Error z value Pr(>|z|)    
(Intercept)               -5.5466     0.9845  -5.634 1.76e-08 ***
sin(2 * pi * (MONTH/12))   3.7273     0.9727   3.832 0.000127 ***
cos(2 * pi * (MONTH/12))   2.0023     0.8120   2.466 0.013671 *  
BATRUE                     2.8671     1.1606   2.470 0.013500 *  
TurbinesTRUE              -1.1225     1.4002  -0.802 0.422727    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for Negative Binomial(0.0579) family taken to be 1)

    Null deviance: 56.316  on 179  degrees of freedom
Residual deviance: 32.980  on 175  degrees of freedom
AIC: 166.85

Number of Fisher Scoring iterations: 1


              Theta:  0.0579 
          Std. Err.:  0.0191 

 2 x log-likelihood:  -154.8500 
```

```
> summary(common_gull <- zeroinfl.STM4.imp)

Call:
zeroinfl(formula = STM ~ offset(log(KM2)) + sin(2 * pi * (MONTH/12)) + cos(2 * pi * 
(MONTH/12)) + BA + CI + BA:CI | 1, data = BB_DD, 
    dist = "negbin")

Pearson residuals:
     Min       1Q   Median       3Q      Max 
-0.28817 -0.26882 -0.16602 -0.03737  6.14512 

Count model coefficients (negbin with log link):
                         Estimate Std. Error z value Pr(>|z|)    
(Intercept)               -4.9811     1.3289  -3.748 0.000178 ***
sin(2 * pi * (MONTH/12))   1.7798     0.5832   3.052 0.002276 ** 
cos(2 * pi * (MONTH/12))   3.4869     0.9806   3.556 0.000376 ***
BATRUE                     1.3504     1.0858   1.244 0.213613    
CITRUE                     0.1993     1.0300   0.193 0.846584    
BATRUE:CITRUE              2.6113     1.6320   1.600 0.109592    
Log(theta)                -2.4807     1.2577  -1.972 0.048566 *  

Zero-inflation model coefficients (binomial with logit link):
            Estimate Std. Error z value Pr(>|z|)
(Intercept)    -5.06     156.51  -0.032    0.974
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 

Theta = 0.0837 
Number of iterations in BFGS optimization: 34 
Log-likelihood: -110.8 on 8 Df
```

```
> summary(LBB_gull <- NB.KLM2.imp)

Call:
glm.nb(formula = KLM ~ offset(log(KM2)) + BA + CI + BA:CI, data = BB_DD, 
    link = log, init.theta = 0.1785599767)

Deviance Residuals: 
    Min       1Q   Median       3Q      Max  
-1.1672  -0.9123  -0.5927  -0.3368   2.0809  

Coefficients:
              Estimate Std. Error z value Pr(>|z|)    
(Intercept)    -1.0783     0.3180  -3.391 0.000697 ***
BATRUE          0.4061     0.5621   0.723 0.469924    
CITRUE         -1.1099     0.5059  -2.194 0.028253 *  
BATRUE:CITRUE   1.5745     0.8335   1.889 0.058892 .  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for Negative Binomial(0.1786) family taken to be 1)

    Null deviance: 125.66  on 179  degrees of freedom
Residual deviance: 113.02  on 176  degrees of freedom
AIC: 487.05

Number of Fisher Scoring iterations: 1


              Theta:  0.1786 
          Std. Err.:  0.0325 

 2 x log-likelihood:  -477.0530 
```

```
> summary(herring_gull  <- zeroinfl.ZM3.imp)

Call:
zeroinfl(formula = ZM ~ offset(log(KM2)) + sin(2 * pi * (MONTH/12)) + cos(2 * pi * (MONTH/12))
+ BA + Turbines | 1, data = BB_DD, dist = "negbin")

Pearson residuals:
    Min      1Q  Median      3Q     Max 
-0.3583 -0.3059 -0.1573 -0.0586 20.2468 

Count model coefficients (negbin with log link):
                         Estimate Std. Error z value Pr(>|z|)    
(Intercept)               -4.4674     0.6871  -6.502 7.95e-11 ***
sin(2 * pi * (MONTH/12))   2.0661     0.7150   2.890 0.003858 ** 
cos(2 * pi * (MONTH/12))   2.0896     0.6488   3.220 0.001280 ** 
BATRUE                    -0.9255     0.9205  -1.005 0.314667    
TurbinesTRUE               3.9735     1.0515   3.779 0.000158 ***
Log(theta)                -2.0456     0.3086  -6.628 3.39e-11 ***

Zero-inflation model coefficients (binomial with logit link):
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   -9.794    151.730  -0.065    0.949
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 

Theta = 0.1293 
Number of iterations in BFGS optimization: 35 
Log-likelihood: -95.14 on 7 Df
```

```
> summary(GBB_gull  <- NB.GM3.imp)

Call:
glm.nb(formula = GM ~ offset(log(KM2)) + sin(2 * pi * (MONTH/12)) + 
    cos(2 * pi * (MONTH/12)) + BA + Turbines, data = BB_DD, link = log, 
    init.theta = 0.2086673375)

Deviance Residuals: 
    Min       1Q   Median       3Q      Max  
-1.2595  -0.8275  -0.4313  -0.2104   3.2992  

Coefficients:
                         Estimate Std. Error z value Pr(>|z|)    
(Intercept)               -2.1572     0.2797  -7.711 1.24e-14 ***
sin(2 * pi * (MONTH/12))   0.5451     0.2844   1.916   0.0553 .  
cos(2 * pi * (MONTH/12))   2.2612     0.3542   6.384 1.72e-10 ***
BATRUE                    -0.7581     0.5554  -1.365   0.1723    
TurbinesTRUE               1.0808     0.7074   1.528   0.1266    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for Negative Binomial(0.2087) family taken to be 1)

    Null deviance: 149.83  on 179  degrees of freedom
Residual deviance:  99.27  on 175  degrees of freedom
AIC: 394.6

Number of Fisher Scoring iterations: 1


              Theta:  0.2087 
          Std. Err.:  0.0421 

 2 x log-likelihood:  -382.5960 
```

```
> summary(BL_kittiwake <- NB.DTM3.imp)

Call:
glm.nb(formula = DTM ~ offset(log(KM2)) + sin(2 * pi * (MONTH/12)) +
    cos(2 * pi * (MONTH/12)) + BA + Turbines, data = BB_DD, link = log,
    init.theta = 0.3714972114)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.7772  -0.8910  -0.4521  -0.1973   2.6346

Coefficients:
                         Estimate Std. Error z value Pr(>|z|)
(Intercept)               -1.8960     0.2299  -8.248  < 2e-16 ***
sin(2 * pi * (MONTH/12))   0.9017     0.2168   4.160 3.18e-05 ***
cos(2 * pi * (MONTH/12))   2.6216     0.2666   9.833  < 2e-16 ***
BATRUE                     1.4075     0.3898   3.610 0.000306 ***
TurbinesTRUE               0.2519     0.4868   0.517 0.604840
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for Negative Binomial(0.3715) family taken to be 1)

    Null deviance: 305.36  on 179  degrees of freedom
Residual deviance: 137.89  on 175  degrees of freedom
AIC: 661.27

Number of Fisher Scoring iterations: 1


              Theta:  0.3715
          Std. Err.:  0.0608

 2 x log-likelihood:  -649.2660
```

```
> summary(common_guillemot  <- NB.ZK3.imp)

Call:
glm.nb(formula = ZK ~ offset(log(KM2)) + sin(2 * pi * (MONTH/12)) +
    cos(2 * pi * (MONTH/12)) + BA + Turbines, data = BB_DD, link = "log",
    init.theta = 0.8218936395)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.9395  -0.7508  -0.3503  -0.1178   3.1204

Coefficients:
                         Estimate Std. Error z value Pr(>|z|)
(Intercept)               -1.9593     0.2122  -9.233  < 2e-16 ***
sin(2 * pi * (MONTH/12))   1.3764     0.1861   7.398 1.38e-13 ***
cos(2 * pi * (MONTH/12))   3.0495     0.2582  11.809  < 2e-16 ***
BATRUE                     0.3175     0.2948   1.077  0.28149
TurbinesTRUE              -1.2552     0.4249  -2.954  0.00314 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for Negative Binomial(0.8219) family taken to be 1)

    Null deviance: 405.17  on 179  degrees of freedom
Residual deviance: 138.69  on 175  degrees of freedom
AIC: 604.74

Number of Fisher Scoring iterations: 1


              Theta:  0.822
          Std. Err.:  0.156

 2 x log-likelihood:  -592.743
```

```
> summary(razorbill <- NB.ALK3.imp)

Call:
glm.nb(formula = ALK ~ offset(log(KM2)) + sin(2 * pi * (MONTH/12)) +
    cos(2 * pi * (MONTH/12)) + BA + Turbines, data = BB_DD, link = "log",
    init.theta = 0.3245836595)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-1.88721  -0.68272  -0.26738  -0.07238   2.68811

Coefficients:
                         Estimate Std. Error z value Pr(>|z|)
(Intercept)               -4.1265     0.4244  -9.723  < 2e-16 ***
sin(2 * pi * (MONTH/12))   1.8319     0.3397   5.392 6.96e-08 ***
cos(2 * pi * (MONTH/12))   3.1035     0.4331   7.166 7.71e-13 ***
BATRUE                     2.7988     0.4902   5.710 1.13e-08 ***
TurbinesTRUE              -1.1048     0.5932  -1.862   0.0625 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for Negative Binomial(0.3246) family taken to be 1)

    Null deviance: 212.380  on 179  degrees of freedom
Residual deviance:  87.307  on 175  degrees of freedom
AIC: 391.55

Number of Fisher Scoring iterations: 1


              Theta:  0.3246
          Std. Err.:  0.0703

 2 x log-likelihood:  -379.5490
```

```
> summary(harbour_porpoise <- NB.BV0.imp)

Call:
glm.nb(formula = BV ~ offset(log(KM2)) + BA + Turbines, data = BB_DD,
    link = "log", init.theta = 0.1169593186)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.8026  -0.5531  -0.3918  -0.2518   1.7030

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -3.7235     0.3999  -9.310   <2e-16 ***
BATRUE        1.5068     0.7144   2.109   0.0349 *
TurbinesTRUE  0.7883     0.8499   0.928   0.3537
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for Negative Binomial(0.117) family taken to be 1)

    Null deviance: 67.609  on 179  degrees of freedom
Residual deviance: 54.002  on 177  degrees of freedom
AIC: 201.92

Number of Fisher Scoring iterations: 1


              Theta:  0.1170
          Std. Err.:  0.0387

 2 x log-likelihood:  -193.9170
```

Wind farm + 3 km buffer

```
> summary(northern_fulmar <- NB.NSV3.imp)

Call:
glm.nb(formula = NSV ~ offset(log(KM2)) + sin(2 * pi * (MONTH/12)) +
    cos(2 * pi * (MONTH/12)) + BA + Turbines, data = BB_DD, link = "log",
    init.theta = 0.1726057739)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.0475  -0.6815  -0.4751   0.0000   2.2134

Coefficients:
                           Estimate Std. Error z value Pr(>|z|)
(Intercept)              -2.000e+00  2.620e-01  -7.633 2.29e-14 ***
sin(2 * pi * (MONTH/12))  3.397e-01  3.268e-01   1.039  0.29860
cos(2 * pi * (MONTH/12))  6.676e-01  3.608e-01   1.850  0.06432 .
BATRUE                   -2.091e+00  6.696e-01  -3.123  0.00179 **
TurbinesTRUE             -3.308e+01  4.479e+06   0.000  0.99999
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for Negative Binomial(0.1726) family taken to be 1)

    Null deviance: 106.544  on 185  degrees of freedom
Residual deviance:  75.734  on 181  degrees of freedom
AIC: 260.62

Number of Fisher Scoring iterations: 1


              Theta:  0.1726
          Std. Err.:  0.0471

 2 x log-likelihood:  -248.6210


> summary(northern_gannet <- NB.JVG3.imp)

Call:
glm.nb(formula = JVG ~ offset(log(KM2)) + sin(2 * pi * (MONTH/12)) +
    cos(2 * pi * (MONTH/12)) + sin(2 * pi * (MONTH/6)) + cos(2 *
    pi * (MONTH/6)) + BA + Turbines, data = BB_DD, link = log,
    init.theta = 0.4856030804)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.7504  -0.9815  -0.5409   0.1056   2.2738

Coefficients:
                         Estimate Std. Error z value Pr(>|z|)
(Intercept)              -1.60731    0.18198  -8.832  < 2e-16 ***
sin(2 * pi * (MONTH/12)) -0.06577    0.18500  -0.356 0.722204
cos(2 * pi * (MONTH/12))  1.30050    0.22622   5.749 8.98e-09 ***
sin(2 * pi * (MONTH/6))  -0.07317    0.19341  -0.378 0.705198
cos(2 * pi * (MONTH/6))  -0.51617    0.20271  -2.546 0.010887 *
BATRUE                    0.97546    0.32727   2.981 0.002877 **
TurbinesTRUE             -1.52350    0.43132  -3.532 0.000412 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for Negative Binomial(0.4856) family taken to be 1)

    Null deviance: 204.94  on 185  degrees of freedom
Residual deviance: 150.23  on 179  degrees of freedom
AIC: 592.59

Number of Fisher Scoring iterations: 1


              Theta:  0.4856
          Std. Err.:  0.0887

 2 x log-likelihood:  -576.5930
```

```
> summary(great_skua <-  zeroinfl.GJ0.imp)

Call:
zeroinfl(formula = GJ ~ offset(log(KM2)) + BA + Turbines | 1, data = BB_DD, dist = "negbin")

Pearson residuals:
       Min         1Q     Median         3Q        Max 
-0.4399487 -0.3519842 -0.2682172 -0.0001365  5.3955832 

Count model coefficients (negbin with log link):
             Estimate Std. Error z value Pr(>|z|)    
(Intercept)   -1.6931     0.4018  -4.214 2.51e-05 ***
BATRUE        -0.9276     0.6269  -1.480    0.139    
TurbinesTRUE -15.9426  1599.7443  -0.010    0.992    
Log(theta)     2.3071     4.6580   0.495    0.620    

Zero-inflation model coefficients (binomial with logit link):
            Estimate Std. Error z value Pr(>|z|)  
(Intercept)   1.1871     0.4872   2.437   0.0148 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 

Theta = 10.0449 
Number of iterations in BFGS optimization: 21 
Log-likelihood: -73.14 on 5 Df
```

```
> summary(little_gull <- NB.DWM3.imp)

Call:
glm.nb(formula = DWM ~ offset(log(KM2)) + sin(2 * pi * (MONTH/12)) + 
    cos(2 * pi * (MONTH/12)) + BA + Turbines, data = BB_DD, link = log, 
    init.theta = 0.05920453935)

Deviance Residuals: 
     Min        1Q    Median        3Q       Max  
-0.85158  -0.51907  -0.23715  -0.06085   2.22388  

Coefficients:
                         Estimate Std. Error z value Pr(>|z|)    
(Intercept)               -5.0785     0.8533  -5.951 2.66e-09 ***
sin(2 * pi * (MONTH/12))   3.1713     0.8126   3.902 9.52e-05 ***
cos(2 * pi * (MONTH/12))   2.1590     0.7601   2.841   0.0045 ** 
BATRUE                     1.9721     1.0495   1.879   0.0602 .  
TurbinesTRUE              -0.3196     1.2185  -0.262   0.7931    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for Negative Binomial(0.0592) family taken to be 1)

    Null deviance: 60.659  on 185  degrees of freedom
Residual deviance: 37.788  on 181  degrees of freedom
AIC: 193.1

Number of Fisher Scoring iterations: 1


              Theta:  0.0592 
          Std. Err.:  0.0184 
Warning while fitting theta: alternation limit reached 

 2 x log-likelihood:  -181.1040 
```

```
> summary(common_gull <- zeroinfl.STM4.imp)

Call:
zeroinfl(formula  =  STM  ~  offset(log(KM2))  +  sin(2  *  pi  *  (MONTH/12))  +  cos(2  *  pi  *
(MONTH/12)) + BA + CI + BA:CI | 1, data = BB_DD, 
    dist = "negbin")

Pearson residuals:
     Min       1Q   Median       3Q      Max 
-0.32225 -0.29674 -0.17963 -0.03897  7.48894 

Count model coefficients (negbin with log link):
                         Estimate Std. Error z value Pr(>|z|)    
(Intercept)               -4.9842     0.7843  -6.355 2.09e-10 ***
sin(2 * pi * (MONTH/12))   1.7799     0.5344   3.331 0.000866 ***
cos(2 * pi * (MONTH/12))   3.3944     0.8664   3.918 8.94e-05 ***
BATRUE                     1.4551     0.9328   1.560 0.118768    
CITRUE                     0.1994     0.9508   0.210 0.833927    
BATRUE:CITRUE              1.7996     1.3890   1.296 0.195099    
Log(theta)                -2.2637     0.2512  -9.010  < 2e-16 ***

Zero-inflation model coefficients (binomial with logit link):
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   -11.85     423.83  -0.028    0.978
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 

Theta = 0.104 
Number of iterations in BFGS optimization: 31 
Log-likelihood: -127.6 on 8 Df
```

```
> summary(LBB_gull <- NB.KLM2.imp)

Call:
glm.nb(formula = KLM ~ offset(log(KM2)) + BA + CI + BA:CI, data = BB_DD, 
    link = log, init.theta = 0.1619062963)

Deviance Residuals: 
    Min       1Q   Median       3Q      Max  
-1.2670  -0.8894  -0.6109  -0.3406   1.9956  

Coefficients:
              Estimate Std. Error z value Pr(>|z|)   
(Intercept)    -1.0771     0.3322  -3.242  0.00119 **
BATRUE          0.7366     0.5683   1.296  0.19487   
CITRUE         -1.1188     0.5250  -2.131  0.03309 * 
BATRUE:CITRUE   2.3865     0.8347   2.859  0.00425 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1 

(Dispersion parameter for Negative Binomial(0.1619) family taken to be 1)

    Null deviance: 153.53  on 185  degrees of freedom
Residual deviance: 121.29  on 182  degrees of freedom
AIC: 569.33

Number of Fisher Scoring iterations: 1


              Theta:  0.1619 
          Std. Err.:  0.0267 

 2 x log-likelihood:  -559.3250 
```

```
> summary(herring_gull  <- NB.ZM3.imp)

Call:
glm.nb(formula = ZM ~ offset(log(KM2)) + sin(2 * pi * (MONTH/12)) + 
    cos(2 * pi * (MONTH/12)) + BA + Turbines, data = BB_DD, link = log, 
    init.theta = 0.1512015971)

Deviance Residuals: 
     Min        1Q    Median        3Q       Max  
-1.23224  -0.60499  -0.28657  -0.07296   2.88796  

Coefficients:
                         Estimate Std. Error z value Pr(>|z|)    
(Intercept)               -4.6746     0.5944  -7.864 3.72e-15 ***
sin(2 * pi * (MONTH/12))   1.9601     0.4923   3.982 6.84e-05 ***
cos(2 * pi * (MONTH/12))   2.7719     0.5971   4.642 3.44e-06 ***
BATRUE                     0.8889     0.7058   1.259    0.208    
TurbinesTRUE               1.2637     0.7939   1.592    0.111    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for Negative Binomial(0.1512) family taken to be 1)

    Null deviance: 138.411  on 185  degrees of freedom
Residual deviance:  69.968  on 181  degrees of freedom
AIC: 257.24

Number of Fisher Scoring iterations: 1


              Theta:  0.1512 
          Std. Err.:  0.0392 

 2 x log-likelihood:  -245.2360 


> summary(GBB_gull  <- NB.GM3.imp)

Call:
glm.nb(formula = GM ~ offset(log(KM2)) + sin(2 * pi * (MONTH/12)) + 
    cos(2 * pi * (MONTH/12)) + BA + Turbines, data = BB_DD, link = log, 
    init.theta = 0.2180415366)

Deviance Residuals: 
    Min       1Q   Median       3Q      Max  
-1.3397  -0.8348  -0.4362  -0.2081   3.4579  

Coefficients:
                         Estimate Std. Error z value Pr(>|z|)    
(Intercept)               -2.1758     0.2769  -7.858 3.91e-15 ***
sin(2 * pi * (MONTH/12))   0.6924     0.2716   2.549   0.0108 *  
cos(2 * pi * (MONTH/12))   2.2874     0.3330   6.869 6.48e-12 ***
BATRUE                    -0.1690     0.5050  -0.335   0.7379    
TurbinesTRUE               0.4718     0.6209   0.760   0.4473    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for Negative Binomial(0.218) family taken to be 1)

    Null deviance: 161.85  on 185  degrees of freedom
Residual deviance: 111.04  on 181  degrees of freedom
AIC: 454.59

Number of Fisher Scoring iterations: 1


              Theta:  0.2180 
          Std. Err.:  0.0407 

 2 x log-likelihood:  -442.5900 
```

```
> summary(BL_kittiwake <- NB.DTM3.imp)

Call:
glm.nb(formula = DTM ~ offset(log(KM2)) + sin(2 * pi * (MONTH/12)) + 
    cos(2 * pi * (MONTH/12)) + BA + Turbines, data = BB_DD, link = log, 
    init.theta = 0.3716096164)

Deviance Residuals: 
    Min       1Q   Median       3Q      Max  
-1.7847  -0.9555  -0.4491  -0.1674   2.7567  

Coefficients:
                         Estimate Std. Error z value Pr(>|z|)    
(Intercept)               -1.9542     0.2337  -8.362  < 2e-16 ***
sin(2 * pi * (MONTH/12))   1.0088     0.2126   4.746 2.08e-06 ***
cos(2 * pi * (MONTH/12))   2.7633     0.2621  10.544  < 2e-16 ***
BATRUE                     1.3603     0.3760   3.618 0.000297 ***
TurbinesTRUE               0.5010     0.4489   1.116 0.264392    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for Negative Binomial(0.3716) family taken to be 1)

    Null deviance: 353.52  on 185  degrees of freedom
Residual deviance: 148.52  on 181  degrees of freedom
AIC: 741.53

Number of Fisher Scoring iterations: 1


              Theta:  0.3716 
          Std. Err.:  0.0567 

 2 x log-likelihood:  -729.5300 
```

```
> summary(common_guillemot  <- NB.ZK3.imp)

Call:
glm.nb(formula = ZK ~ offset(log(KM2)) + sin(2 * pi * (MONTH/12)) + 
    cos(2 * pi * (MONTH/12)) + BA + Turbines, data = BB_DD, link = "log", 
    init.theta = 0.8675478598)

Deviance Residuals: 
    Min       1Q   Median       3Q      Max  
-1.9556  -0.7852  -0.3618  -0.1200   3.2402  

Coefficients:
                         Estimate Std. Error z value Pr(>|z|)    
(Intercept)               -1.9082     0.2012  -9.484  < 2e-16 ***
sin(2 * pi * (MONTH/12))   1.3318     0.1738   7.662 1.82e-14 ***
cos(2 * pi * (MONTH/12))   2.9699     0.2396  12.394  < 2e-16 ***
BATRUE                     0.2081     0.2751   0.757   0.4493    
TurbinesTRUE              -0.8681     0.3562  -2.437   0.0148 *  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for Negative Binomial(0.8675) family taken to be 1)

    Null deviance: 430.84  on 185  degrees of freedom
Residual deviance: 150.05  on 181  degrees of freedom
AIC: 659.73

Number of Fisher Scoring iterations: 1


              Theta:  0.868 
          Std. Err.:  0.156 

 2 x log-likelihood:  -647.727 
```

```
> summary(razorbill <- NB.ALK3.imp)

Call:
glm.nb(formula = ALK ~ offset(log(KM2)) + sin(2 * pi * (MONTH/12)) + 
    cos(2 * pi * (MONTH/12)) + BA + Turbines, data = BB_DD, link = "log", 
    init.theta = 0.2844200863)

Deviance Residuals: 
     Min        1Q    Median        3Q       Max  
-1.77572  -0.75207  -0.29118  -0.07093   2.58616  

Coefficients:
                         Estimate Std. Error z value Pr(>|z|)    
(Intercept)               -4.1500     0.4275  -9.709  < 2e-16 ***
sin(2 * pi * (MONTH/12))   1.8096     0.3353   5.397 6.78e-08 ***
cos(2 * pi * (MONTH/12))   3.1639     0.4295   7.367 1.75e-13 ***
BATRUE                     2.6870     0.4903   5.480 4.26e-08 ***
TurbinesTRUE              -0.9023     0.5591  -1.614    0.107    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for Negative Binomial(0.2844) family taken to be 1)

    Null deviance: 211.554  on 185  degrees of freedom
Residual deviance:  91.892  on 181  degrees of freedom
AIC: 435.64

Number of Fisher Scoring iterations: 1


              Theta:  0.2844 
          Std. Err.:  0.0588 

 2 x log-likelihood:  -423.6400 


> summary(harbour_porpoise <- NB.BV0.imp)

Call:
glm.nb(formula = BV ~ offset(log(KM2)) + BA + Turbines, data = BB_DD, 
    link = "log", init.theta = 0.1310806939)

Deviance Residuals: 
    Min       1Q   Median       3Q      Max  
-0.8367  -0.5652  -0.3991  -0.2401   1.7549  

Coefficients:
             Estimate Std. Error z value Pr(>|z|)    
(Intercept)   -3.7136     0.3877  -9.578   <2e-16 ***
BATRUE         1.4250     0.6685   2.132    0.033 *  
TurbinesTRUE   0.6528     0.7631   0.856    0.392    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for Negative Binomial(0.1311) family taken to be 1)

    Null deviance: 73.936  on 185  degrees of freedom
Residual deviance: 60.778  on 183  degrees of freedom
AIC: 227.82

Number of Fisher Scoring iterations: 1


              Theta:  0.1311 
          Std. Err.:  0.0403 

 2 x log-likelihood:  -219.8240 
```

Annex V. Seabird survey participants

Following is a list of all volunteers and colleagues who participated in the seabird counting in the course of 2001-2012, with a star (*) for those who joined at least 5 surveys:

Yves Adams
Peter Adriaens
Franky Bauwens*
Olivier Beck
Geert Beckers
Wendy Bonne
Ann Braarup Cuykens*
Robin Brabant*
Wouter Courtens*
Peggy Criel
Luc De Bruyn
Christiaan De Buyzer*
Davy De Groote
Brecht De Meulenaer
Daphnis De Pooter
Nico De Regge
Koen De Witte*
Klaas Debusschere
Misjel Decleer
Wim Declercq
Gerdy Dejonckheere
Jochen Depestele
Maarten Dermout
David Deruytter
Diederik D'Hert
Olivier Dochy
Joris Everaert
Simon Feys*
Nico Geiregat*
Franky Ghyselen
Valerie Goethals
Stijn Hantson
Doreen Heald
David 'Billy' Herman*
Stefaan Herman
Kenny Hessel
Jeroen Huyghe*
Indra Jacobs
Johannes Janssen
Kevin Lambeets*
Jacky Launoy
Valérie Lehouck
Koen Lepla
Iwan Lewylle
Joost Mertens*
Tom Moens
Guido Orbie
An Pauwels
Bert Peccue
Geert Raeymaekers
Karen Rappé
Bob Rumes
Bert Saveyn
Jan Seys*
Bart Slabbinck
Jan Soors
Toon Spanhove
Geert Spanoghe*
Eric Stienen*
Veerle Stuer
Luc Teugels
Eef Thoen
Marijke Thoonen
Filiep T'jollyn*
Henri Tyteca
Marc Van de walle*
Karl Van Ginderdeuren
Nicolas Van Rossem
Jeroen Van Waeyenberge*
Paul Vandenbulcke*
Bob Vandendriessche*
Koen Vandepitte
Nicolas Vanermen*
Ward Vercruysse*
Freek Verdonckt
Glenn Vermeersch
An Versteele*
Hilbran Verstraete*
Annemie Volckaert
Walter Wackenier*
Godfried Warreyn*
Bert Willaert
Tomas Willems

Errata for the report “Bird monitoring at offshore wind farms in the Belgian part of the North Sea - assessing seabird displacement effects”

Nicolas Vanermen, Eric W.M. Stienen, Wouter Courtens, Thierry Onkelinx, Marc Van de walle & Hilbran Verstraete

Tables 2, 3 & 21, Figure 8

Some 1% thresholds given in Tables 2, 3 & 21 are incorrect, and should be the following:

- Northern fulmar - 108,000
- Northern gannet - 9,150
- Great skua - 480
- Common guillemot - 70,500
- Razorbill - 18,000

These figures are based on the number of breeding pairs in the European region as reported by Birdlife International (2004), multiplied by a factor 3 to estimate the number of individuals in the population (Wetlands International 2014). Applying these updated figures shows that – opposed to what is stated in the text and suggested by the graphs in Figure 8 – neither northern gannet nor great skua exceed their 1% threshold in autumn. The updated tables are shown underneath, with the corrected values indicated in red.

Table 2. Seasonal (distance-corrected) numbers residing at the BPNS based on the results of seabird surveys between 2001 & 2007 (summer population indicated by x^S, migratory and/or wintering population by x^M, figures indicated in yellow exceed the 1%-threshold) (threshold values based on Birdlife International 2004 & Wetlands International 2014).

Species	Subspecies / Population	1%-threshold	Mean numbers BPNS 2001-2007			
			Winter	Spring	Summer	Autumn
Red-throated diver	NW Europe (winter)	2,600	966	86	0	209
Diver sp.	-	-	34	1	0	6
Black-throated diver	N Europe & W Siberia	3,500	6	0	0	56
Great crested grebe	NW & W Europe	3,500	1,458	66	1	186
Northern fulmar	Europe	108,000	2,575	1,405	808	8,098
Northern gannet	Europe	9,150	1,799	737	556	4,990
Great cormorant	N & C Europe	3,900	246	86	209	98
Common scoter	ssp. *nigra*	5,500	1,089	3,656	119	85
Great skua	Europe	480	52	37	109	152
Little gull	C & E Europe	1,100	503	2,128	174	969
Black-headed gull	W Europe	42,100	388	1,289	321	1,442
Common gull	NW & C Europe	16,400	3,599	1,806	19	764
Lesser black-backed gull	ssp. *graellsii* + *intermedius*	$(5{,}500^S + 3{,}800)^M$	418	8,595	6,271	3,076
Herring gull	ssp. *argenteus* + *argentatus*	$(10{,}200^S + 20{,}100)^M$	1,844	3,124	2,621	874
Great black-backed gull	N & W Europe	4,200	5,092	590	90	3,850
Black-legged kittiwake	E Atlantic	66,000	6,310	542	58	5,015
Sandwich tern	W Europe	1,700	0	627	987	113
Common tern	S & W Europe + N & E Europe	$(1{,}800^S + 9{,}800)^M$	0	2,431	2,638	286
Common guillemot	Europe	78,500	16,121	2,174	3	5,044
Unidentified auk	-	-	1,077	216	0	324
Razorbill	Europe	18,000	2,907	481	0	1,205
Total			46,451	30,077	14,985	36,839

Table 3. Monthly (distance-corrected) numbers residing at the BPNS based on the results of seabird surveys between 2001 & 2007 (summer population indicated by x^S, migratory and/or wintering population by x^M, figures indicated in yellow exceed the 1%-threshold) (threshold values based on Birdlife International 2004 & Wetlands International 2014).

Species	Subspecies/Population	1%-threshold	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Red-throated diver	NW Europe (winter)	2,600	1,874	534	206	36	3	0	0	0	0	37	530	638
Diver sp.	-	-	15	24	3	0	0	0	0	0	0	0	16	74
Black-throated diver	N Europe & W Siberia	3,500	16	0	0	0	0	0	0	0	0	3	160	8
Great crested grebe	NW & W Europe	3,500	1,982	1,330	102	0	94	3	0	0	0	23	482	1,095
Northern fulmar	Europe	108,000	4,717	1,176	2,078	1,226	670	1,580	469	476	550	1,516	(21,842)	5,034
Northern gannet	Europe	9,150	2,025	2,046	1,375	264	541	541	585	548	1,263	7,838	3,345	676
Great cormorant	N & C Europe	3,900	435	92	30	115	124	288	239	104	118	72	102	356
Common scoter	ssp. *nigra*	5,500	236	1,801	4,970	130	(5,742)	144	71	138	41	64	140	555
Great skua	Europe	480	151	13	68	31	0	0	135	155	147	194	112	76
Little gull	C & E Europe	1,100	260	747	3,365	2,756	28	0	152	374	1,523	1,081	423	224
Black-headed gull	W Europe	42,100	646	334	3,069	89	642	570	138	242	3,279	341	1,010	186
Common gull	NW & C Europe	16,400	6,611	2,530	3,167	2,199	10	17	24	17	181	1,010	1,002	2,235
Lesser black-backed gull	ssp. *graellsii* + *intermedius*	$(5{,}500^{S} + 3{,}800)^{M}$	86	638	6,532	8,086	11,758	9,262	6,390	3,495	5,500	3,597	513	168
Herring gull	ssp. *argenteus* + *argentatus*	$(10{,}200^{S} + 20{,}100)^{M}$	2,106	1,873	4,743	2,406	2,105	3,715	2,753	1,424	1,069	411	1,155	1,371
Great black-backed gull	N & W Europe	4,200	(18,739)	1,674	823	710	57	138	20	107	717	2,713	7,855	2,276
Black-legged kittiwake	E Atlantic	66,000	12,390	3,478	1,155	288	91	35	107	33	168	5,105	8,428	6,964
Sandwich tern	W Europe	1,700	0	0	170	966	638	1,522	912	522	383	3	0	0
Common tern	S & W Europe + N & E Europe	$(1{,}800^{S} + 9{,}800)^{M}$	0	0	6	2,005	5,294	2,869	2,150	2,776	963	24	0	0
Common guillemot	Europe	78,500	15,067	17,416	5,312	679	24	9	0	0	37	3,773	9,809	13,192
Auk sp.	-	-	702	1,025	465	122	0	0	0	0	0	342	494	1,541
Razorbill	Europe	18,000	2,400	3,303	1,097	220	0	0	0	0	8	1,163	2,211	2,130

Table 21. Estimation of the additional mortality per 10,000 offshore turbines and a micro-avoidance of 97.6%, based on an extrapolation of the CRM results for the Blighbank study area (Birdlife International 2004 [a], Wetlands International 2013 [b]; BTO 2013 [c] and Poot *et al*. 2011 [d]).

Species	Biogeographical population	Population level	Yearly mortality	Number of collisions	Additional mortality
Northern gannet	NE Atlantic	915,000 [a]	8.1% [c]	182	0.2%
Common gull	NW & C Europe	1,640,000 [b]	14.0% [c]	545	0.2%
LBB gull	ssp. *graellsii* + *intermedius*	930,000 [b]	8.7% [c]	11,818	14.6%
Herring gull	ssp*. argenteus* + *argentatus*	3,030,000 [b]	12.0% [c]	1,091	0.3%
GBB gull	N & W Europe	420,000 [b]	16.5% [d]	5,091	7.3%
BL kittiwake	NE Atlantic	6,600,000 [b]	5.9% [c]	5,818	1.5%

Figure 37

The legend of Figure 37 was lacking, impeding interpretation:

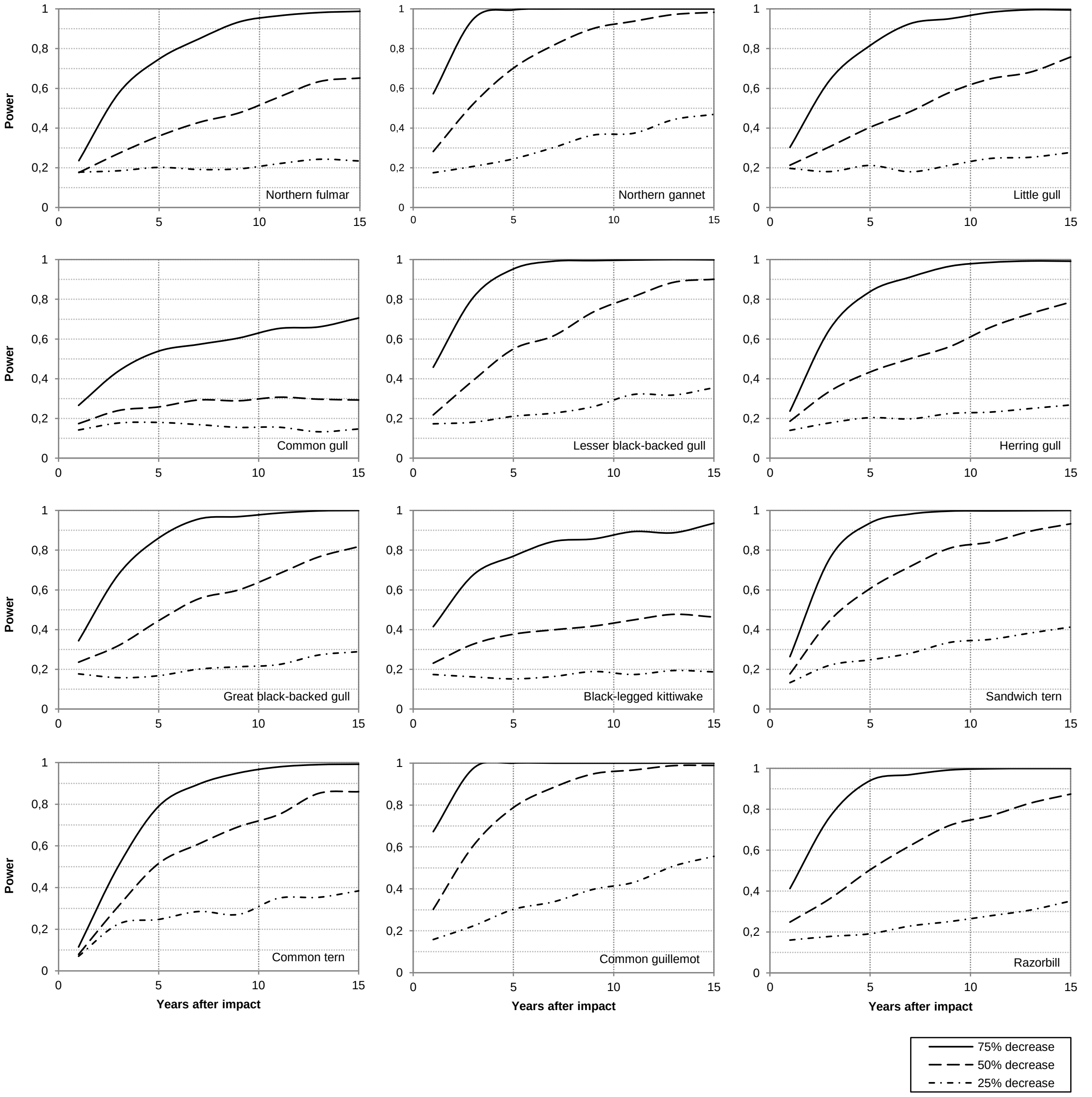

Figure 37. Power results for 12 seabird species for an impact study with a monitoring intensity of one survey of 10 km² per month per area, and 5 years of reference monitoring (significance level = 0.10).

References

BirdLife International 2004. Birds in Europe: population estimates, trends and conservation status. BirdLife International, Cambridge, UK.

Wetlands International 2014. Waterbird Population Estimates. [online] Available at: <wpe.wetlands.org> [Accessed at 10 October 2014]