



This is EPIC: Extensive Periphery for Impact and Control to study seabird habitat loss in and around offshore wind farms combining a peripheral control area and Bayesian statistics

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ABSTRACT

With the rapidly increasing intensity of human activities in the marine realm, it has become urgent to better understand the impacts of human-induced disturbances on marine species. Marine mammals and birds are often observed to alter their fine-scale spatial distribution patterns in the presence of human at-sea activities, such as ship traffic and offshore wind farms (OWFs). This study presents EPIC (Extensive Periphery for Impact and Control), a novel approach for investigating such displacement in marine megafauna. The approach consists of a survey design that uses the OWFs surroundings in all directions as control space, complemented by a sophisticated statistical approach to quantify the extent and intensity of displacement and habitat loss in and around the area of potential disturbance. The approach is showcased by investigating the effects of an OWF in the Dutch North Sea on the habitat use of razorbills (*Alca torda*) and common guillemots (*Uria aalge*), two seabird species that occur in large numbers across the North Sea. We used an explicit spatial-temporal Bayesian model to predict their spatial distribution patterns based on eight aerial surveys. The model output is used for a simulation study, comparing bird densities in the potential impact area with 1000 similarly sized control areas from the peripheral control space and from these, displacement around the OWF. Strong displacement was found for both razorbills and guillemots, within the OWF footprint but also in its surroundings. Razorbill and guillemot densities inside the OWF were reduced by 0.953 and 1.604 individuals per km², respectively, compared to the remainder of the study area, remaining considerably lower than control densities up to 2 km and > 10 km distance. The presented methodological approach holds great potential for future studies on the effects of local disturbances on displacement of marine megafauna.

1. Introduction

1.1. Changing oceans

Worldwide efforts to increase the production of renewable energy have led to an increasing demand for space in marine habitats. In Europe, the demand for space is mainly due to the development of offshore wind farms (OWFs) with plans to further increase the production's capacity from ca. 120 GW in 2023 to 300 GW by 2050 (European Commission, 2023; Rijksoverheid, 2023). This would require a total number of some 15,000 to 50,000 wind turbines, already taking into account the predicted increase in production capacity of individual

turbines (Li et al., 2023). The North Sea is one of the major offshore energy production areas, with rapidly increasing numbers of OWFs (Garthe et al., 2023). By 2050, roughly 25 % of its surface area may be used for offshore wind production (Jongbloed et al., 2023). Although such plans will aid the global energy transition, negative impacts of wind turbines on marine species, many of those legally protected, have been reported (Dähne et al., 2013; Furness et al., 2013; Garthe et al., 2023; Lindeboom et al., 2011; Peschko et al., 2020, 2021, 2024; Van der Wal et al., 2018). Both collisions and habitat loss have been flagged up as serious risks for marine birds and mammals (Furness et al., 2013; Garthe et al., 2023; Leopold et al., 2013; Marques et al., 2020; Van Kooten et al., 2019).

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Various seabirds and marine mammals have been shown to avoid offshore wind farms, which causes the animals to displace to habitat nearby (Garthe et al., 2023; Heinänen et al., 2020; Leopold et al., 2013; Marques et al., 2020; Mendel et al., 2019; Petersen et al., 2014; Petersen and Fox, 2007; Vilela et al., 2021). Wind farms built within the range of an animal population's spatial range, i.e. habitat, result in habitat loss if the animals avoid using the space in and around the OWF. With increased post-construction monitoring efforts, information about species-specific avoidance behavior is growing (Leopold et al., 2013; Marques et al., 2020; Peschko et al., 2024; Petersen and Fox, 2007; Vanermen et al., 2015). Therefore, it is important to build a proper understanding of how marine species respond to these human-induced disturbances.

1.2. Investigating displacement

Objectively determining displacement in marine environments is difficult, particularly for species that are highly mobile throughout vast areas, but in relatively low densities. Seabirds respond to food sources that are also highly mobile, resulting in temporally variable local “hot-spots” and “coldspots” in their distribution patterns. Moreover, population sizes and their spatial distribution patterns are not stable over time, with seasonal patterns affecting the number of birds present at a single point in time and space. Such factors add stochasticity to species distribution patterns, complicating research into the effects of human-induced activities and pressures (Maclean et al., 2013). Consequently, a single survey cannot provide a complete picture of the spatial distribution, nor does it provide strong indications about habitat (in)suitability. As a result, whilst monitoring the distribution of birds before OWF construction is useful to gain insight into the space-use of the study species in an “undisturbed” environment, solely comparing the OWF area before and after construction does not provide sufficient information to draw conclusions about habitat loss. Similarly, comparing bird densities at an impact site, such as an OWF, with a single reference area in the vicinity may be misleading, given various responses by birds to other factors, such as a shifting prey base that is unrelated to the OWF.

1.3. Impact study designs

Studies on displacement of marine megafauna after the construction of an OWF are commonly done using Before-After-Control-Impact (BACI) studies (Garthe et al., 2023; Peschko et al., 2020; Vanermen et al., 2015). In such studies the OWF (“impact”) area is compared to one or more reference (or “control”) areas with comparable surface area and abiotic characteristics (Smith, 2002). Reference areas are generally located at a similar distance from the coast, have similar water depth and bottom characteristics as does the impact area. Bird densities are monitored and compared between the impact and control area, before and after OWF construction and differences between the two are attributed to the presence of the OWF.

Considering the dynamic spatial behavior of marine megafauna, as well as the rapidly increasing human at-sea activities, the approach of selecting a single presumably representative reference area is questionable. An alternative study design would use a larger study area that encompasses the OWF (Garthe et al., 2023; Peschko et al., 2024; Vallejo et al., 2017; Vilela et al., 2021). In this design, the densities within the contour (so-called “footprint”) of the OWF can be compared to densities in all directions in the proximity of the wind park. This study design is not yet commonly applied but has strong advantages over a BACI approach (Underwood, 1994). By monitoring an extensive periphery of the OWF, spatial and spatiotemporal anomalies or other (unknown) confounding factors (Christensen et al., 2006; Petersen et al., 2014; Petersen and Fox, 2007), can more easily be detected and the dependency on a specific reference site is reduced. Additionally, such a study design enables investigating the densities in the periphery of the OWF to assess the presence of an avoidance effect beyond the OWF

perimeter (Garthe et al., 2023; Peschko et al., 2020; Skov et al., 2016; Vallejo et al., 2017; Walls et al., 2013).

1.4. Objectives

The objective of this paper is two-fold. First, we present our EPIC (“Extensive Periphery for Impact and Control”) approach, that uses a survey area covering the OWF and its surroundings in all directions, and applies a robust statistical framework developed for this survey design. This approach is designed to analyze patterns and anomalies in spatial distribution patterns, whilst accounting for the high spatiotemporal variation that is typical in distribution patterns of highly mobile species. Second, we aim to investigate the extent of displacement of two species of *Alcidae* in and around a twin-OWF in the Dutch North Sea, in order to showcase the application of this approach. Using this case-study, we discuss the suitability of our EPIC approach for effect studies on (particularly but not exclusively) OWFs in our rapidly changing oceans.

2. Methods

2.1. Data collection

2.1.1. Study design

The study area covers 1832 km² of the Dutch North Sea, with Gemini Offshore Wind Park located in the centre (Fig. 1). Gemini consists of two turbine fields (ZeeEnergie and Buitengaats) separated by approximately 5 km. The OWF has been fully operational since 2016, five years before the aerial surveys for this impact study were performed. Our study area extends 15 to 25 km around Gemini OWF and does not overlap with other offshore wind farms. The nearest other OWF (DolWin alpha complex, Germany) is located approximately 20 km distance East from Buitengaats, less than 5 km away from the Eastern boundary of the study area. North of Gemini, inside the study area and parallel to the Northern study area edge, is a deep-water shipping lane (Fig. 1). Below the Southern edge of the study area is another shipping lane. Shipping intensity is relatively high in both these lanes, with potential but unknown effects on the spatial distribution of the study species.

2.1.2. Study species

Our study species are the razorbill (*Alca torda*) and common guillemot (*Uria aalge*). These are the most common auks (*Alcidae*) in the North Sea (Skov et al., 2007). Both species are protected under the European Birds Directive and the Nature Conservation Act (SOVON, 2023a, 2023b) and known to be relatively susceptible to human disturbance (Dierschke et al., 2016; Furness et al., 2013; Leopold and Verdaat, 2018).

Several studies have indicated avoidance of offshore wind farms by auks, making these suitable species to study habitat loss from the growing number of OWFs in the North Sea (Dierschke et al., 2016; Furness et al., 2013). Razorbills are food specialists throughout the year, which may make them particularly vulnerable to displacement in response to OWF developments (Ouweland and Leopold, 2004). However, while guillemots have a broader diet in winter, both species have been shown to avoid OWFs. Avoidance is not absolute, as some individuals do enter OWFs, but average densities within OWFs are reduced. However, (partial) habitat loss is not restricted to the footprint of the OWF, as reduced densities have been found around OWFs as well, in some cases up to ca. 10 km from the wind farm (Dierschke et al., 2016; Leopold et al., 2013; Peschko et al., 2020; Petersen and Fox, 2007; Vanermen et al., 2015; Walls et al., 2013).

Both razorbills and guillemots spend most of their time swimming and only fly at low altitudes, hence they are not at risk for collisions with wind turbine rotor blades. They occur in large numbers throughout the North Sea and were the most numerous birds in the Gemini OWF area pre-construction (Van Bemmelen et al., 2015). These birds reach the study area by swimming from breeding colonies in the British Isles (and

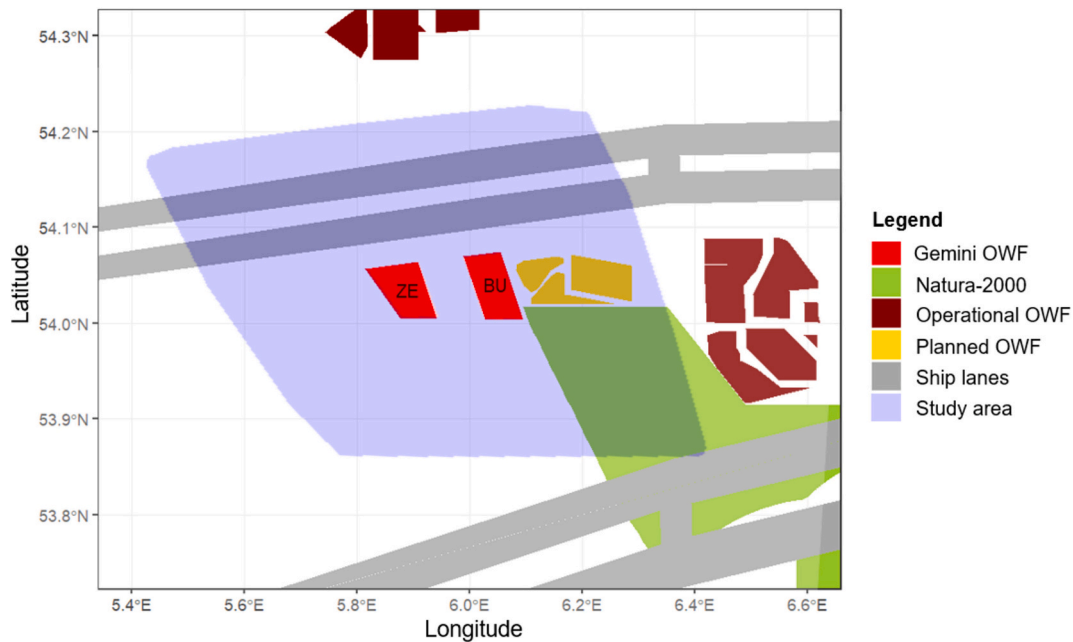


Fig. 1. Study area (semi-transparent purple polygon) around Gemini OWF and its context. Gemini is a “twin” OWF, comprising ZeeEnergie (ZE) and Buitengaats (BU). The Natura-2000 area that is partly inside the study area is Borkum Reef Ground (BRG). This Natura-2000 site has been declared by Germany in 2017, protecting a larger area with reef-like structures at the seafloor. The legal protection does not continue into Dutch waters, but the habitat structure likely extends further West. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

possibly Helgoland, Germany) in summer (from June/July, after breeding). During this seasonal migration they travel singly or in groups across the North Sea, covering large distances (Dunn et al., 2020; Van Katwijk and Camphuysen, 1993). Within the study area they are present in their highest densities in winter (October – March) (Van Bemmelen et al., 2015), hence surveys for the presented study were performed during winter.

2.1.3. Aerial surveys

Line-transect surveys have been performed as digital aerial surveys using the HiDef system (Weiß et al., 2016; Žydelis et al., 2019), which employs four high-resolution cameras looking down. Cameras were mounted below a Partenavia 68 aircraft with no overlap in their field of view. Total length of transects (per survey) was 750 km. With a flight altitude ranging 500 to 550 m, the collected footage had a resolution of approximately 2 cm/pixel, and was annotated manually by experienced ornithologists of BioConsult SH. The transect lines were placed 2500 m apart, a design that is considerably denser than in comparable studies (Heinänen et al., 2020; Vilela et al., 2021). The aerial imagery collected during a single survey covers approximately 22 % of the study area.

In total, eight surveys were conducted, the first as a pilot in March 2022. This was deemed successful and the other seven were flown between October 2022 and March 2023, following the same procedure. Detailed flight information and a summary of the collected data can be found in the Supporting Information.

2.2. Statistical analysis

2.2.1. Data processing

To facilitate manual annotation of the footage, photographs of each of the four physical cameras were split in half, resulting in eight images that shot synoptically. The numbers of birds on each set of eight images were summed, using the average geographical position (directly under the plane) of these images. Using the surface area covered per image, we calculated the densities of razorbills and guillemots, thereby accounting for survey effort. All data exploration, visualization and statistical models were performed in R Studio (RStudio Version 2022.07.0 + 548

“Spotted Wakerobin”).

2.2.2. Statistical models

We modelled the spatial distributions of razorbills and guillemots using generalized linear models (GLMs). The data were severely zero-inflated and continuous, therefore we applied zero-altered gamma distribution (ZAG) models. These models use a Bernoulli model to handle absence-presence data and a Gamma distribution for presence-only data. We then combined the expected values from both models to estimate the observed bird densities.

Initially tested models included generalized additive models (GAMs) with water depth and distance to the OWF and shipping lanes as covariates, but this did not improve model performance (see Supplementary Information). To manage the spatial-temporal dependency in the data, both components of the ZAG model incorporated a spatial-temporal correlation structure. This structure is referred to as a spatial random field (SRF) in both the Bernoulli and Gamma GLMs. Due to the irregular timing of the surveys, we used a ‘replicate’ correlation structure (spatial-temporal model) instead of the auto-regressive correlation (spatio-temporal model) to model the spatial random field (SRF). This approach allows the SRF to vary between surveys, accommodating shifts in the locations of bird density hotspots over time.

The ZAG-GLM expected values are defined by $\pi_{is} \times \mu_{is}$ where π_{is} results from the Bernoulli model, formulated as:

$$\text{Bird}01_{is} \sim \text{Bernoulli}(\pi_{is})$$

$$E(\text{Bird}01_{is}) = \pi_{is}$$

$$\text{Logit}(\pi_{is}) = \text{Intercept} + \text{Survey}_i + \text{SRF}_{is}$$

And μ_{is} values result from the Gamma model, formulated as:

$$\text{BirdPos}_{is} \sim \text{Gamma}(\mu_{is}, \tau)$$

$$E(\text{BirdPos}_{is}) = \mu_{is}$$

$$\text{Log}(\mu_{is}) = \text{Intercept} + \text{Survey}_i + \text{SRF}_{is}$$

In these formulas, i represents a focal location (point of observation) in the study area and s represents a focal survey.

We used Integrated Nested Laplace Approximation (INLA) via the *R-INLA* package (Lindgren and Rue, 2015) to fit the spatial-temporal Bernoulli and Gamma GLMs. We preferred this approach because of the complex model structures we applied, which were required to appropriately deal with the strong spatial and temporal dependency in our data. Application through *R-INLA* was preferred over its frequentist alternative (e.g. using the *mgcv* package (Wood, 2007)), because of its large flexibility and strength in dealing with complex model structures (i.e. spatial-temporal models and the use of zero-altered Gamma; this is further discussed in section 3.6) (Munoz et al., 2013; Redding et al., 2017). This method requires selection of a specific mesh for the SRF and set priors for parameters associated with spatial correlation. Model selection and validation was performed according to Zuur et al. (2017a, 2017b). Posterior simulation was used to predict 1000 datasets: predicting bird densities in space and time, given randomly sampled locations and surveys, for as many points of observation as our original dataset, repeated 1000 times. These were then analyzed using the *DHARMa* package (Hartig and Hartig, 2022). Details are discussed in the Supplementary Information.

2.2.3. Displacement simulation study

We investigated the presence and strength of displacement, or habitat loss, in and around the OWF, by performing a simulation study based on the model predictions. This was done by comparing the bird density in a focal impact area to the bird densities within a “reference

$$\text{Difference in density [n/km}^2\text{]} = \text{Density in reference [n/km}^2\text{]} - \text{Density impact [n/km}^2\text{]}$$

$$\text{Birds displaced [n]} = \text{Surface area disturbed [km}^2\text{]} * \text{Difference in density [n/km}^2\text{]}$$

area”, being the peripheral control space. We did a simulation study for various potential impact areas: starting with the OWFs themselves (distance to OWF = 0 km), followed by investigating “boundary layers” around the OWF. For these boundary layers, we adhered to steps of 1 km, up to 10 km around the OWF (thus, potential impact area layers around the OWF being >0 to 1 km, >1 to 2 km, ... to >9–10 km). Each of these boundary layers was investigated individually: such that the mean bird density in the boundary layer ranging from X to $X + 1$ km distance around the OWF is not influenced by the density at any smaller distances than X . Any reference to a boundary layer at r km distance from the OWF refers to the boundary where r is the outer edge of the boundary layer (maximum distance) and the inner edge is at $r-1$ km from the OWF. More details in Supporting Information.

For each zone, we assessed bird densities against those in 1000 randomly selected “control” areas that were matched in size and located within the broader study area but beyond the impact zones. Instead of comparing the mean densities in these impact areas with the mean density in the entire reference area, we randomly selected 1000 “control” areas from within the reference area, which is the remaining space within the study area after exclusion of the focal “impact” area. Hence, the reference area becomes smaller with boundary layers at increasing distances. Random selection of the control areas was done for each potential impact area separately. Each of the 1000 control areas had a similar surface area as the focal impact area and was selected by random selection of a single point location within the reference area. Around this point, a square polygon was drawn with a surface area equal to the surface area of the (selected part of the) wind park. By checking for intersections with the OWF and study area contours, we ensured that the square was entirely within the study area and entirely out of the OWF and focal impact area. For all 1000 control areas, we calculated the

mean bird density as well as the variance around the mean and the 99 % confidence interval (CI) and used these values to compare the density inside the potential impact area to the reference area.

Based on the output of the simulation study, we estimated the distance from the OWF up to where the bird density is still lower than expected, i.e., there is habitat loss. We define this “disturbance distance” as the distance of the outer edge of the boundary layer wherein the mean density is equal or greater than the lower limit of the 99 % CI around the mean density in the reference area. If this is not reached within the most distant boundary layer (at 10 km from the OWF), we adhere to a disturbance distance of 10 km for further calculations.

In addition, we calculated a Bayesian test statistical (BTS) value. This value represents the fraction of the control areas with a mean density larger than the impact area. It was calculated as:

$$\text{BTS} = \frac{\text{Number of control areas with a larger bird density than impact area}}{\text{Number of control areas}}$$

A BTS value of 0.5 indicates that, across the study area, the density within the impact area was similar to that in the surrounding waters. We considered that values above 0.7 are a strong indication for habitat loss, and, conversely, that value <0.3 would indicate attraction to the OWF.

After determining the disturbance distance, we calculated the total disturbed surface area as the space within the disturbance distance) and the total number of birds displaced. This was done using the average bird densities within and outside the disturbed area, and the surface area of the disturbed area:

The mean density within the reference area is the mean density within the entire reference area. The upper and lower limit of the number of displaced birds were determined from the upper (U) and lower (L) limits of the 99 % CIs of the mean densities in both the impact (I) and reference (R) area:

$$\text{Maximum [n]} = (\text{CI}_{\text{RU}}[\text{n/km}^2] - \text{CI}_{\text{IL}}[\text{n/km}^2]) * \text{Disturbed area [km}^2\text{]}$$

$$\text{Minimum [n]} = (\text{CI}_{\text{RL}}[\text{n/km}^2] - \text{CI}_{\text{IU}}[\text{n/km}^2]) * \text{Disturbed area [km}^2\text{]}$$

Important to note is that we do not draw any conclusions about the effect of the OWP based on the significance or strength of the covariate “minimum distance to the OWP” in the models, which is a standard approach in most studies on habitat loss due to OWPs that apply frequentist-style GLMs/GAMs. Instead, we base our conclusions on the results of the simulation study (Details in the Supporting Information).

3. Results & discussion

3.1. Data coverage

The data has a zero-inflation percentage of 96.7 % for razorbill and 96.0 % for guillemot observations. The mean density of razorbills and guillemots across the entire study area, given all surveys, is 2.31 n/km² and 2.10 n/km² respectively, but there is large variation between surveys (details in Supporting Information). In individual surveys, average razorbill densities ranged from 1.58 to 4.97 individuals/km², with relatively stable densities apart from two highs during two surveys in February 2023. Average guillemot densities varied more strongly,

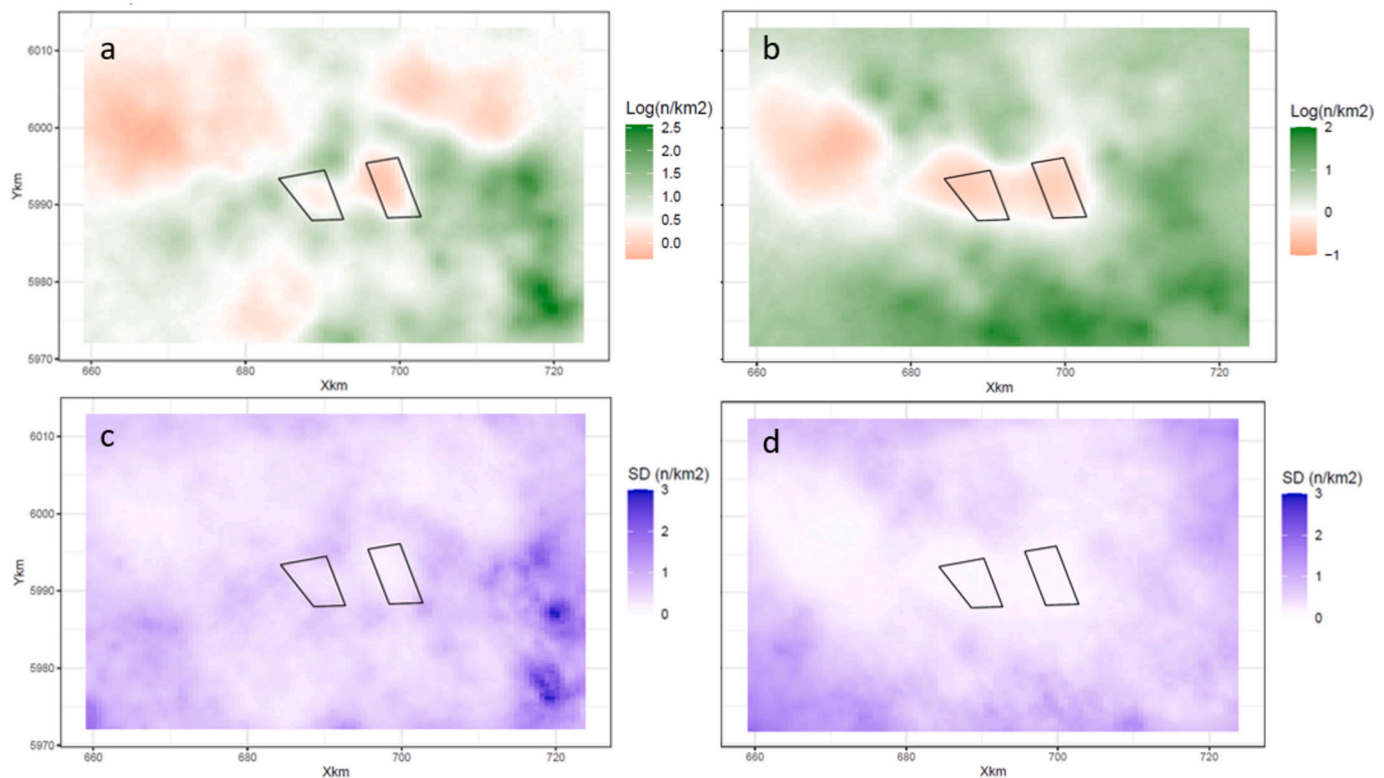


Fig. 2. Predicted densities^a (a-b) and standard deviations (c-d) for razorbills (left, a;c) and guillemots (right, b;d) within the study area. Black polygons represent the twin OWF. Visualized densities and standard deviations represent the mean value per grid cell^b, from the predicted spatial densities per survey that resulted from 1000 datasets simulated using the ZAG-GLMs. Mean spatial densities per survey provided in Supporting Information. Note that as a result of the study area shape, the right top and left bottom corners have high standard deviation as these corners were not covered by transects.

a) Densities are visualized on a natural-logarithmic scale (^cLog).

b) Mean values have been calculated on a spatial grid of 200×200 cells, distributed over a geographical space of 60 km horizontally (Xkm) and 40 km vertically (Ykm). The resolution of the grid cells is $0.3 \text{ km} \times 0.2 \text{ km}$: one grid cell has a surface area of 60 m^2 . For making predictions on a spatial grid, INLA requires equal numbers of grid cells in the x- and y-dimension.

between 0.09 and $8.60 \text{ individuals/km}^2$, with no clear temporal pattern: major peaks were observed in December 2022 and February 2023, and extreme lows in October 2022 and January 2023.

3.2. Spatial distributions

The spatial distribution of bird densities as predicted by the models based on the data (Fig. 2) is remarkable in three ways. First, we observed consistently low densities for both razorbills and guillemots inside the OWFs, indicating that both species avoid Gemini OWF. Second, we observed a persistent low densities anomaly for both species in the North-West of the study area. The Northern deep-water shipping lane may provide an explanation for the low razorbill densities in the entire Northern part of the study area. However, for guillemots this coldspot is limited to the North-West corner: hence, the presence of this shipping lane does not provide a full explanation. Potentially influential factors for this coldspot may be the distribution of food or disturbing activities around oil platforms further West, but additional studies are required to draw reliable conclusions. Another anomaly was found in the Southern and South-Eastern parts of the study area, where both species showed relatively high predicted mean densities (Fig. 2). Together with the relatively high densities in the Southern part of the study area, this indicates an attractive habitat, potentially linked to the protected habitat of the German Natura-2000 area Borkum Reef Ground (Fig. 1). However, as habitat information is limited, this hypothesis remains speculative. Moreover, given the higher densities of birds (guillemots in particular) across the Southern part of the study area, this “presumably attractive” habitat would have to extend into Dutch waters (Fig. 2b),

which is presently unknown and needs future research. Generally, the variation in densities of both species tended to be relatively high at the periphery of the study area, as shown by the higher standard deviations here (Fig. 2c+d).

3.3. Habitat loss in and around Gemini

The simulation study (see section 2.2.3) reveals habitat loss in both species, with strong differences between razorbill and guillemot densities inside and outside the OWFs (Fig. 3). For razorbills we observed a reduction of 40.2 % inside the OWFs, compared to the simulated control areas outside the OWFs, with mean densities of 1.29 and 2.24 n/km^2 respectively. For guillemots this difference was even larger: we observed a mean density of 0.65 n/km^2 inside the OWF and 2.25 n/km^2 in the 1000 control areas, a reduction of 70.1 %. The BTS values within the OWF area were 0.83 for razorbills and 0.98 for guillemots, revealing that larger densities than in the OWF are found in the majority of the remaining study area (see section 2.2.3). Hence, both species show strong (negative) displacement, or habitat loss, inside and around the OWF, this effect being strongest in guillemots.

The bird densities in boundary layers up to 10 km around the OWF, show that this displacement occurs beyond the OWFs perimeter (Fig. 3). In the boundary layer at 1–2 km distance from the OWF, the mean razorbill density is approximately equal to the lower limit of the 99 % confidence interval around the mean density of the 1000 control area located at further distances from the OWFs (Fig. 3), which shows that there is no displacement beyond this distance. However, in this boundary layer, we still found a BTS value of 0.84, hence although the

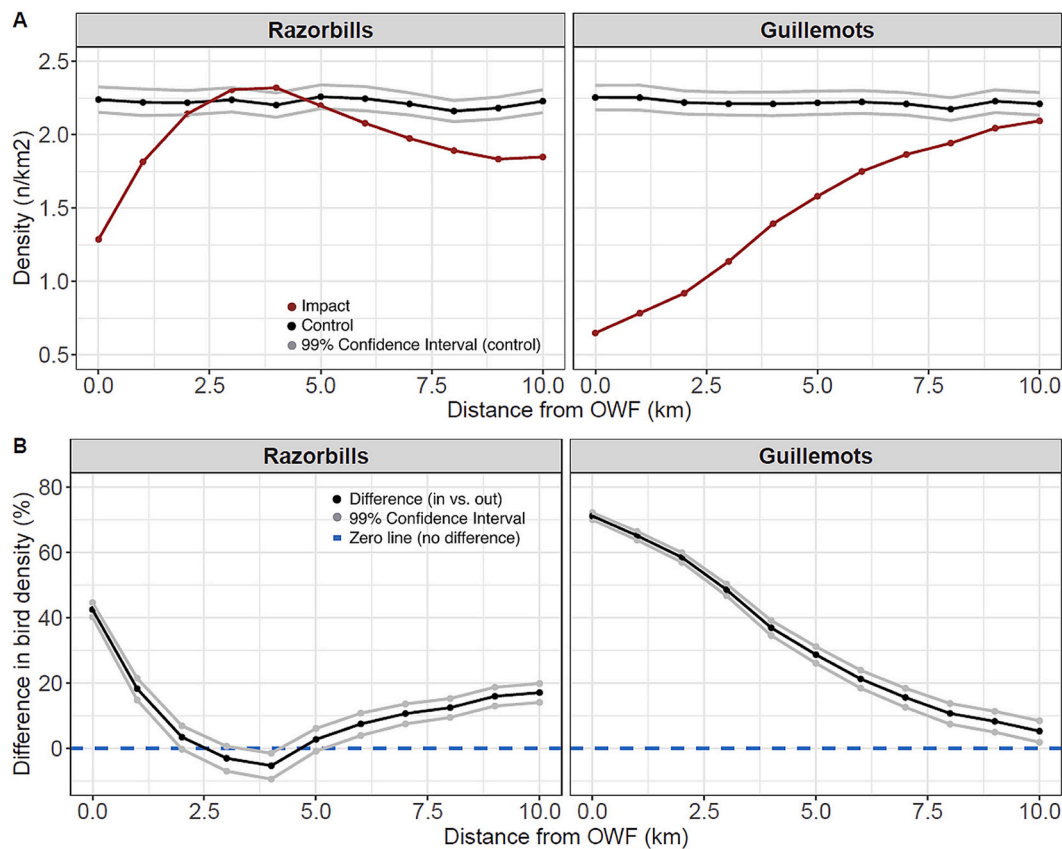


Fig. 3. Comparison of bird densities in potential impact areas and control areas^a, expressed as (A) mean densities inside the impact (red) and control areas (black) and (B) percentual reduction (difference) between the impact and control area^b. Grey lines represent 99 % confidence intervals around the predicted mean densities within the reference area.

a) Potential impact areas are the OWFs (Distance from OWF = 0 km), and subsequently increasing boundary layers of 1 km around them (see section 2.2.3).
 b) Percentual difference (reduction) in bird density between impact and control/reference is calculated as $(1 - \text{density impact area} / \text{density in control}) * 100 \%$. The control area consists of 1000 randomly selected control polygons of similar size as the impact area. Distance = 0 represents the OWF. Positive percentual differences indicate a reduction in bird density. Dashed blue line represents no difference (0 %). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

mean densities inside and outside this layer are similar, 84 % of the sampled control areas outside the layer had a larger mean density than the 1–2 km boundary layer. This is more than would be expected if the homogeneity of the distribution of razorbills was similar, suggesting the mean density in the reference area is influenced by some razorbill “coldspots” that lower the mean. Based on our results, we can conclude that there is considerable razorbill displacement up to at least 2 km distance from the OWFs, but we must acknowledge that this displacement effect may extend at larger distances if these “coldspots” or anomalies are caused by some other (unknown) factor. Assuming that razorbills experience habitat loss up to 2 km distance around the Gemini OWF, the impact on this species has an extend of 186 km², including the OWF area.

Razorbill densities show a strong increase from 0 to 2 km distance from the OWFs, peak in the boundary layer 3–4 km distance from the OWFs and appear to slightly decline again further away (Fig. 2). This can also be observed in the spatial densities (Fig. 2a). This pattern suggests that razorbills show a “halo”-effect around the OWFs, as was observed in harbour porpoises (*Phocoena phocoena*) responding to pile driving (Dähne et al., 2013). Such a halo effect has also been reported in divers (*Gaviidae*) (Garthe et al., 2023). Moreover, although not explicitly reported, Welcker & Nehls, (2016; their Fig. 3a) found a similar “halo” pattern for razorbills and guillemots combined (as “alcids”).

A different pattern is observed for guillemots around the OWFs. Guillemot densities show a continuous increase with increasing distance

from the OWFs, up to at least 10 km. Mean predicted guillemot densities do not reach the lower limit of the 99 % confidence interval around the mean predicted densities in the control areas within 10 km from the OWFs (Fig. 1+3). Moreover, the BTS value in the boundary layer of 9–10 km around the OWFs is 0.99, meaning 99 % out of the 1000 control areas outside this layer had a larger mean density. The spatial distribution of predicted guillemot densities (Fig. 2b) supports this: the highest values were clearly observed in the Eastern and Southern edges of the study area. Further East, in German waters, guillemots are likely also displaced by the DolWin OWF complex (Fig. 3). Guillemots may also avoid the Southern shipping lane, located right outside the Southern border of the study area so in the Southeast of the current study area guillemots may face disturbance from three sides.

Based on our results, we can conclude that there is habitat loss for guillemots up to at least 10 km distance from Gemini, which comes down to a total extent of at least 866 km² surface area affected by this OWF. Only very recently, another study found OWF avoidance in guillemots up to distances up to 19.5 km (Peschko et al., 2024). Based on this new information in combination with our results, it can be argued that the spatial extent of our study area does not reach large enough distances from Gemini OWF to define a maximum distance of OWF avoidance for guillemots. These far-reaching effects of OWFs amplify the necessity to consider the space beyond the current study area in order to gain a proper understanding of OWF impacts on species’ spatial distribution patterns, and further supports the necessity of application of the

far-reaching study designs which EPIC enables to investigate.

Earlier studies of spatial distributions and densities of guillemots and razorbills in and around OWFs have drawn varying conclusions (Dierschke et al., 2016; Leopold and Verdaat, 2018). Although in most OWFs both razorbills and guillemots showed reduced densities compared to pre-construction situations (Dierschke et al., 2016; Leopold et al., 2013; Skov et al., 2016; Vanermen et al., 2015), some studies of OWFs near breeding colonies did not find any statistically significant effect (Dierschke et al., 2016; Mendel et al., 2014; Vallejo et al., 2017). Only few studies have studied bird densities beyond 3 km distance from focal OWFs, but the few that did find similar effect distances in razorbills and guillemots as we found around Gemini (Peschko et al., 2024; Vanermen et al., 2015). In similar studies on divers' avoidance was found up to 10 km (Garthe et al., 2023) and 15 km from OWFs (Heinänen et al., 2020). A study on Alpha Ventus OWF (Germany) found that densities of razorbills and guillemots (combined) increased up to 2.5 km from that OWF (Welcker and Nehls, 2016).

There are strong indications that OWF avoidance rates in these seabirds is context dependent. Hence, the avoidance distances and relative differences in density we observed in this study are not simply applicable to other OWFs or seabird species. The presence and strength of relationships between these behavioral responses and OWF characteristics (e.g. size, turbine density, type of foundation), the intensity of e.g., maintenance of the turbines, need to be further investigated. Increasing avoidance rates with increasing turbine density have been observed in Sandwich terns (*Thalasseus sandvicensis*) (Van Bemmelen et al., 2023), and there are also indications that turbine activity affects avoidance in guillemots (Peschko et al., 2020). Intrinsic motivation of birds to enter wind farms may differ seasonally, locally, in relation to activity and individually. Breeding birds may be less inclined to avoid an OWF than wintering birds (Vallejo et al., 2017), while traveling mode may also be related to the motivation to enter a wind farm (Peschko et al., 2021). Finally, whether any level of habituation to OWF presence will occur on a longer term is yet unknown.

3.4. Impacts of habitat loss

Both guillemots and razorbills are not considered to be at risk of collisions, given their low flight altitude that is well below the reach of OWF rotor blades. The impacts of habitat loss are less obvious compared to those of fatal collisions, but its impacts on population level are not necessarily smaller. One collision immediately reduces the number of birds by one, but it does not affect the carrying capacity of the sea for the population: mortality of one individual frees resources that may support the survival of others, while lost birds can be replaced through reproduction and immigration. In contrast, reduced availability of any resource, including suitable habitat, may have a more permanent effect on population sizes (Gill et al., 2001a; Gill et al., 2001b).

In recent years it has become clear that various bird species avoid offshore wind farms (Busch and Garthe, 2016; Garthe et al., 2023; Heinänen et al., 2020; Leopold et al., 2013; Marques et al., 2020; Mendel et al., 2019; Petersen et al., 2014; Petersen and Fox, 2007; Vilela et al., 2021). Displacement is particularly problematic if alternative suitable habitat is only found at larger distances, or if remaining habitats are of poorer quality or in short supply (Dolman and Sutherland, 1995; Fox et al., 2006; Gill et al., 2001a). Moreover, when insufficient alternative habitat is available, bird densities may increase in the remaining available suitable habitat, increasing competition for resources (Dolman and Sutherland, 1995; Furness et al., 2013). In such circumstances, increased energy consumption, reduced energy intake, increased competition, or a combination thereof, may negatively affect fitness: ultimately resulting in population decline (Dolman and Sutherland, 1995; Furness et al., 2013). A reduction of the available space can thus have a permanent negative effects on population size: a new equilibrium has to be established between the number of animals and the remaining "ecological space".

The effects of avoidance and habitat loss on individual fitness and whether such effects have significant impacts on population levels, remains to be studied (Vilela et al., 2021). At present, it is unknown whether the amount of available space at sea is limiting population sizes of razorbills and guillemots, nor how many OWFs could be built before space will become a limiting factor. Regarding the ambitious plans of European governments (see Introduction) it is not impossible that this threshold will for some species be reached in upcoming years, supporting the necessity of long-term population monitoring programs. In order to draw conclusions on the impact of Gemini and other OWFs in the North Sea, more information about the factors affecting these seabirds is required, including better insights into their diet and food availability, which is currently limited.

Studying habitat loss from a single offshore wind farms is unlikely to find detrimental effects at the population level of species like guillemots or razorbills, that have vast distributions at sea in the non-breeding season. However, cumulative effects of habitat loss of multiple offshore wind farms are hard to assess. It all comes down to assessing the carrying capacity of the seas at large for the species studied. The study that, to date, probably comes closest to that is the study on red-throated divers in a core winter distribution area in German waters (Heinänen et al., 2020). This study found no reduction in the numbers of wintering birds in this core area, after multiple wind farms became operational here, despite this core area being relatively small (as compared to e.g., the North Sea wintering ranges of razorbills and guillemots), and despite considerable avoidance of the wind farms by the divers: they appeared to just have shifted to the parts of the area without wind farms. However, it is unknown to which point birds can be pushed (displaced) before numbers will drop notably, and if such a point will be a point of no return. Building more and more offshore wind farms, particularly in core-seabird areas, may, or may not push the system to such a point, but if, where and when those points lie, is currently unpredictable.

3.5. EPIC survey design

We have presented the EPIC, that makes use of an extensive periphery in all directions around an OWF as "control" or "reference" space, with strong advantages over alternative impact-control survey designs. The most straightforward advantage of this survey design is that it allows investigation of effects outside the contours of a focal impact area (e.g. a wind farm) (Garthe et al., 2023; Peschko et al., 2020; Skov et al., 2016; Vallejo et al., 2017). When studying the effects of any human activity on marine megafauna, the complex and dynamic nature of their distributions, in particular that of highly mobile species, must be considered in both the survey design and analysis (Heinänen et al., 2020). The EPIC survey design reduces effects of hotspots and coldspots that may temporarily overlap with single reference areas of the same size as the impact area. As the location of hotspots may be different with each survey, the effect of temporary hotspots and coldspots are diluted when multiple surveys are performed, whereas consistently occurring hotspots and coldspots can be identified. Such more permanent anomalies in distribution patterns point at other pressures, positive or negative, unrelated to the effects that are primarily studied, such as the presence of an OWF (Christensen et al., 2006; Petersen et al., 2014; Petersen and Fox, 2007).

Our study shows strong variation in bird densities, both in time (but within a single winter) and in space, within a space with relatively uniform abiotic conditions (e.g. distance to the coast, water depth). This emphasizes the fleeting nature of seabirds' spatial distribution patterns, and the need to conduct multiple surveys over time, to obtain a reliable estimation of whether observed spatial variations are temporary or structural anomalies. Taken together, any study design for spatial effect studies should properly account for this. If a study design fails to do so, it can lead to wrongly defined (Type I error) or undetected (Type II error) effects of the studied potential impact (Heinänen et al., 2020). Therefore, we should be cautious with study designs that make use of a single,

or of a small number of control areas, of similar size and with supposedly similar characteristics as the impact site. Such BACI studies assume that in an undisturbed situation, abundances or spatial density ratios are proportionally consistent over time. For sessile biota this assumption may work, but for highly mobile species that range widely over time and space and that may cluster and disperse at unknown rates, this assumption is likely to be false (Maclean et al., 2013; Vallejo et al., 2017). The results of our study strongly support this. When we look at the predicted bird densities across our study area (Fig. 2, individual surveys provided in Supporting Information S3) and envision the selection of one or several “control” areas that are similar in size as the OWF, it is clear that the outcome of the comparison between impact and control sites would be highly dependent of the location of the latter. The EPIC survey design is designed for investigation of a larger space, aims to focus on what is happening in a focal impact area over a period of time compared to what is happening in all directions around it, removing the necessity of species distributions being near static in space and time in “undisturbed” contexts. This does however not remove the necessity of repeated surveying to obtain reliably results, preferably over a longer time span (e.g. multiple seasons/years), and it can be argued whether eight surveys suffice.

Monitoring a larger space around an OWF enables inclusion of additional environmental variables and other spatial gradients (regardless of whether they are caused by known or unknown factors) in subsequent modelling (Petersen et al., 2014; Petersen and Fox, 2007; Vallejo et al., 2017; Walls et al., 2013). Similarly, complicating factors can be accounted for, such as a situation where the OWF is located in a unique habitat type or close to a seabird colony (Christensen et al., 2006; Dierschke et al., 2016; Harwood et al., 2017; Peschko et al., 2021; Petersen et al., 2014; Vallejo et al., 2017). And finally, a focal OWF is not necessarily the only source of disturbance, especially in intensively used marine region like the North Sea: multiple OWFs (Heinänen et al., 2020), or the presence of shipping lanes or a local fishery may be present in proximity of a focal OWF. In such cases, monitoring a larger area around an OWF is strongly preferred over popular BACI-style designs.

Even so, one may wish the surroundings of the focal offshore wind farm to be uniform, but this will rarely be entirely true. With increasing distances from the wind farm, the environment will be increasingly different, so there is a trade-off between the size of the total study area and the evenness of the reference area. Note that changes in the environment will often go unseen and be unknown, but when examining the results one should always be alert on the possibility that some parts of the study area will be more attractive to certain seabirds than others for reasons unrelated to the wind farm studied. Sudden anomalies in bird densities, at large distances from the wind farm (e.g., as seen in Peschko et al., 2024) are likely unrelated to the wind farm studied and should thus be treated with caution. In our study, higher densities of auks in the southeast corner of our study area may pose such an example of an unknown local phenomenon affecting seabird densities.

We tentatively suggest a study area more than two times larger than the maximum distance up to which an effect is expected in order to have the minimum required reference space. For example, earlier studies have shown that an offshore wind farm might affect distribution patterns of guillemots up to ca 10 km (Leopold, 2018), so transect lines should preferably extend to distances twice that distance from the periphery of the wind farm when studying this species.

3.6. EPIC models

The presented study design must be combined with a statistical analysis procedure that utilizes the full potential of the data collected. In a context like ours, with data characterized by strong spatial and temporal dependency, a spatially explicit Bayesian modelling approach was preferred over its frequentist alternative (e.g. using the *mgcv* package (Wood, 2007)), because of its large flexibility and strength in dealing with data that has spatial and/or temporal autocorrelation (Munoz

et al., 2013; Redding et al., 2017). In our study, we applied a spatial-temporal (replicate SRF) Bayesian model to examine the distribution of razorbills and guillemots in and around an OWF. This modelling procedure was combined with a simulation study is aimed at comparing bird densities in similarly sized areas, using 1000 “control” areas that can be randomly sampled from the peripheral control space (section 2.2.3). The presented simulation study can similarly be applied to the output from a frequentist model with a spatial component, as well as on a Bayesian model with only a single SRF.

For our case study pre-construction, ship-based surveys were performed, in a smaller area than covered in the present study (van Bemelen et al., 2015). This difference in coverage hampers a reliable comparison between before and after bird densities, and before-after differences in the total numbers and densities of birds in the study area can hence not be presented. Although larger numbers of surveys and multiple comparable pre-construction surveys are preferred, the presented approach enables investigating animal displacement in and around an OWF (or other type of disturbance) and facilitates robust statistical impact assessments. This is possible without having pre-disturbance densities, assuming there were no clear anomalies in the spatial distribution of the animals pre-construction.

Various studies have emphasized the advantage of spatially explicit Bayesian models for modelling spatial distributions, and generally working with spatial data, compared to either frequentist GLMs/GAMs or common species distribution modelling (SDM) tools (Engel et al., 2022; Lezama-Ochoa et al., 2020; Redding et al., 2017; Williamson et al., 2022). Advantages include dealing with (fine-scale) spatial clustering, taking into account random effects and producing outputs that better elucidate the role of covariates in predicting species occurrences, amongst others, all ultimately improving model performance and accuracy. To account for spatial and temporal dependency in our data, we used a replicate spatial correlation structure (or spatial-temporal model, see section 2.2). This approach allows for variation in the values and extent of spatial clustering (formation of hotspots) and was in this study preferred over a spatio-temporal model (e.g. Vilela et al., 2021) because of the number of surveys and strong variation therein. For datasets with a larger number of surveys and/or less spatial variation from survey to survey, a simple spatiotemporal correlation structure may suffice (Vilela et al., 2021).

As mentioned earlier, the distribution of marine wildlife is highly dynamic and characterized by local clustering and large variations in both the abundance and distribution of birds in space and time. Our results show that a spatial-temporal explicit Bayesian model is indeed highly capable of dealing with this type of data and provides accurate and high-resolution model predictions. Hence, we strongly advise the application of this type of models, particularly for future studies of the effects of at-sea human activities, or for creating SDMs for any highly mobile species.

It should be noted, however, that the current study only deals with a short period. Seabirds are generally long-lived and will react to a changing environment, be it by the building up of their marine habitat with multiple offshore wind farms by or changes seawater temperatures, with associated changes in their prey base through, e.g., climate change. Moreover, some species, or at least some individuals may learn, through time, that offshore wind farms pose no real threat as long as they stay low. Over the years, some seabirds may thus learn that avoiding offshore wind farms may be counterproductive and they may learn to exploit new food sources within wind farms at sea. The process of habituation could be followed excellently by using an EPIC approach over the entire time in which the offshore wind farm will be operational.

3.7. EPIC future applicability

The EPIC approach can be readily applied to study other potential sources of local disturbance. Both the survey design and modelling are flexible and can be adjusted depending on the focal type of disturbance

and study species. An optimum number of surveys and study area size will be strongly context- and species-dependent, and will vary between studies.

Finally, in the context of habitat loss in and around OWFs, we advise application of digital aerial surveys over boat-based surveys. Aerial surveys take considerably less time (hours instead of days) and come with much higher precision and accuracy (Collier et al., 2022; Heinänen et al., 2020). Moreover, in contrast to surveys with human observers, the data resulting from aerial imagery can be stored and checked. Aerial imagery holds great potential for future automatization of image processing for object detection and species classification.

4. Conclusion

In this study, we introduced and showcased the EPIC approach to study displacement of seabirds in and around an offshore wind farm. We applied spatial-temporal Bayesian models to model the distribution of razorbills and guillemots in and around the OWF, for data characterized by strong zero-inflation and spatial-temporal dependency. The application of spatially explicit Bayesian models by means of INLA can properly deal with such data, whilst allowing for high model flexibility and ultimately providing accurate and high-resolution model predictions.

The strong survey to survey variation that we observed, both in the numbers of birds and the locations of their aggregations, emphasizes the necessity of a study design that captures a large space extending all around a local disturbance, instead of using small and discrete impact and control areas. We found strong differences in the level and extent of displacement between the two species of interest: razorbills and guillemots. Razorbills avoided the OWFs up to 2 km whereas guillemots showed reduced densities up to at least 10 km.

We discussed the advantages of our novel approach for investigating OWF impacts on marine megafauna, over current state-of-the-art impact study approaches and how EPIC reduces the risk to arrive at false conclusions. The EPIC approach helps to pick up, and account for spatial and temporal variations in species' distribution patterns, that are due to other, known or unknown, sources of disturbance. Hence, EPIC has great potential for impact studies on various types of stressors and megafauna species, and offers a robust method for studying the impacts of human stressors in increasingly filled and complex marine landscapes.

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CRedit authorship contribution statement

Anne Grundlehner: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Mardik F. Leopold:** Writing – review & editing, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Anna Kersten:** Writing – review & editing.

Declaration of competing interest

Financial support was provided by TKI Top Sector AgriFood and Gemini Offshore Wind Park. The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data and R scripts are publicly available via the following link: <https://github.com/GruAnne/Epicauks.git>

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Appendix A. Supplementary data

Supporting information file is available, containing an extended methodology section (S1) covering the aerial surveys and statistical modelling procedure; data summaries and technical information of the surveys (S2); and extended results (S3) containing model output for individual surveys, visualization of the effect distances, as well as quantification of the habitat loss in terms of numbers of individuals. Supplementary data to this article can be found online at <https://doi.org/10.1016/j.ecoinf.2024.102981>.

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