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ORIGINAL PAPER

Avoidance and attraction responses of kittiwakes to three offshore wind farms in the North Sea

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Abstract
Seabird collision risk is a key concern in relation to the environmental impacts associated with offshore wind farms (OWFs). Understanding how species respond both to the wind farm itself, and individual turbines within the wind farm, is key to enabling better quantification and management of collision risk. Collision risk is of particular concern for the black-legged kittiwake, *Rissa tridactyla*, where modelling predicts unsustainable population level impacts. In this study 20 adult breeding kittiwakes, were tracked with GPS from Whinnyfold, Scotland (57°23′07″N, 001°52′11″W) during the breeding season in 2021. An Avoidance-Attraction Index (AAI) was estimated at several bands within macro- and meso-scales (0–4 km from outer boundary and 0–400 m from turbines, respectively), and the Avoidance Rate (AR; used in environmental impact assessments) at macro-scale to estimate avoidance behaviour to three operational OWFs within their foraging range. One offshore wind farm and its buffer zone (0–4 km from outer boundary) was visited more frequently by the majority of tracked individuals (19/20 birds), despite being twice as far as the closest OWF (17.3 and 31.9 km respectively), whilst 10 or less individuals used the remaining two OWFs. At the most frequented OWF we found macro-scale attraction to the closest band (0–1 km) trending towards avoidance in the furthest band (3–4 km). At the meso-scale we found avoidance of areas below the rotor height range (RHR, a.k.a. rotor swept area/zone) up to 120 m from individual turbines, which decreased to 60 m when within the RHR. Our results indicate that kittiwakes may be slightly attracted to the area around OWFs or aggregate here due to displacement but avoid individual turbines. Increased productivity in the OWF area may potentially be drawing birds into the general area, with aversion to individual turbines being responsible for meso-scale observations.

Keywords Kittiwake · *Rissa tridactyla* · Avoidance · Attraction · Collision-risk modelling · Offshore wind farm

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Introduction

Seabirds are amongst the most threatened groups of birds and may have experienced declines of up to 70% globally between 1950 and 2010 (Paleczny et al. 2015). Populations are subject to a broad range of anthropogenic pressures including climate change, commercial fisheries, and infrastructure developments (Burthe et al. 2014; O'Hanlon et al. 2023). The rapid expansion of the offshore wind industry as part of efforts to reduce reliance of fossil fuels and mitigate the impacts of climate change (Rodrigues et al. 2015) represents another potential pressure on these populations (Furness et al. 2013), which may encounter multiple wind farms over the course of their annual cycles (Busch and Garthe 2018; Thaxter et al. 2019).

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Offshore Wind Farm (OWF) impacts can be grouped into lethal or sublethal. Collision events, occurring when a bird collides with a turbine or associated infrastructure, pose a lethal impact (Desholm and Kahlert 2005; Drewitt and Langston 2006). Sublethal impacts include displacement, attraction, and barrier effects (Masden et al. 2009; Furness et al. 2013; Vanermen et al. 2015b; Cook et al. 2018) which can affect individuals by altering how they interact with their environment. These may have energetic consequences which then impact survival or productivity by influencing body condition and provisioning rates (Masden et al. 2010; Horswill et al. 2017). Collision risk is often a key consenting consideration for OWF projects due to the estimated cumulative impact on populations within protected areas (Brabant et al. 2015; Busch and Garthe 2018; Goodale et al. 2019; Broadbent and Nixon 2019). Consequently, assessing collision risk using a Collision Risk Model (CRM) is an important part of the Environmental Impact Assessments (EIAs) carried out in relation to new OWF developments (Masden and Cook 2016).

CRMs combine a range of parameters covering the properties of the OWF in question (e.g. number of turbines, turbine height, rotor width), the attributes of the species concerned (e.g. wingspan, flight height, flight speed) and the density of that species within a wind farm in order to estimate the flux of birds passing through an OWF and the probability of any individual colliding with a turbine (Masden and Cook 2016). In the final step of a CRM an avoidance rate (AR) is applied, which accounts for the proportion of birds which are likely to avoid collision. The final predicted collision rates are highly sensitive to these avoidance rates (Chamberlain et al. 2006; Masden and Cook 2016), which can be hard to quantify (Green et al. 2016) and are often based on extrapolations from studies at onshore wind farms and/or data from related species (Cook et al. 2018).

Avoidance rates, as used in CRMs, are obtained by combining the behavioural response of birds to the OWF and its turbines with elements of model error within those CRMs arising as a result of uncertainty surrounding input parameters and the simplified set of assumptions on which the models are based (Masden and Cook 2016). By collecting data describing the distance at which birds detect and respond to wind turbines (May 2015), it will be possible to better understand the behavioural elements of avoidance rates, and therefore gain a better understanding of species collision risk.

Avoidance behaviour can be interpreted over three nested scales (May 2015; Cook et al. 2018): (i) macro-scale where OWF footprints are avoided entirely, often considered in km, (ii) meso-scale when single turbines or turbine arrays are avoided, where responses are quantified in metres, and (iii) micro-scale, comprising a last second escape response to avoid a moving rotor. At a macro-scale there is relatively good evidence, from post-construction monitoring (Dierschke et al. 2016), for species to show a propensity to either avoid (e.g., gannets *Morus bassanus* and divers *Gavia* spp.), or be attracted to OWFs (cormorants *Phalacrocorax carbo*, shags *P. aristotelis*, and some large gull *Larus* spp.). Though, recent studies highlight the potential for spatial, seasonal and individual differences in these responses which may be linked to factors such as turbine density, and prey availability (Skov et al. 2018; Peschko et al. 2020, 2021; O'Hanlon et al. 2024; Thaxter et al. 2024). The relatively fine spatial scales associated with meso, and micro avoidance make investigating behaviour at these levels more challenging. However, technology such as high-resolution GPS tracking and combined camera-radar systems are offering promising solutions to these problems (Schaub et al. 2020; Johnston et al. 2022; Tjørnløv et al. 2023).

Black-legged kittiwakes *Rissa tridactyla* (hereafter, kittiwake) are amongst the species most vulnerable to collision risk due to their flight heights overlapping with rotor swept zones (Furness et al. 2013), which range from 21 to 191 m in this study (Table 1). They also make relatively long foraging trips, averaging 24.8 ± 12.1 km (Thaxter et al. 2012), equating to a foraging range of 11.9 km (IQR 2.3–30.9, Wakefield et al. 2017), which could increase OWF encounters. This is an additional threat to a species already exposed to multiple, significant pressures such as climate change, commercial fishing and highly-pathogenic avian influenza (HPAI), which likely contribute to ongoing substantial population declines (O'Hanlon et al. 2023). Evidence for macro-scale response is equivocal, with post-construction monitoring studies suggesting responses ranging from weak avoidance to strong attraction (Trinder and Furness 2023). For meso and macro-scale responses, much of our understanding is

Table 1 Relevant parameters for the three offshore wind farms in the home range of kittiwakes tracked from Whinnyfold during the breeding season in 2021

Name	Number of turbines	Area (km^2)	Turbine density (turbine/km^2)	Minimum distance between turbines (m)	Commenced operation	Rotor height range (metres above mean sea level)	Closest distance from colony (km)
Hywind	5	2.49	2.01	1385	2017	21–175	31.9
EOWDC (Aberdeen Bay)	11	4.26	2.91	814	2018	27–191	17.3
Kincardine	5	5.29	1.60	1000	2021	27–191	40.9

based on data from related species, including lesser-black backed *Larus fuscus* and herring gulls *Larus argentatus* (Cook et al. 2018). This is of significant concern given the projected cumulative impact of collisions on kittiwakes modelled in a North Sea colony imposed potential unsustainable pressure on the population (Busch and Garthe 2018). As a consequence, decision-makers are faced with a conservation dilemma. On the one hand, they may refuse consent for a project on the basis of negative impacts on a threatened and declining species, putting targets to develop renewable energy as a means to reducing reliance on fossil fuels at risk. Alternatively, they may consent that project, despite the projected impacts, but noting that climate change is a significant driver of population declines in that species (Davies et al. 2023). In this context, given the uncertainties surrounding projected collision risk (Searle et al. 2023), data describing kittiwake interactions with OWFs will be of huge value by enabling decision-makers to better understand these risks and balance the need to develop renewable energy with obligations to protect the environment.

We use GPS tracking to investigate the interactions of kittiwakes with OWFs, with data collected from a colony at which individuals may interact with at least three operational OWFs during the breeding season (O'Hanlon et al. 2024). We estimate the Avoidance Rate (AR), and an Avoidance-Attraction Index (AAI) using the approach developed by (Schaub et al. 2020) and adapted by Johnston et al. (2022), at the macro-scale for each wind farm individually and collectively. We then pool data from within the wind farms to estimate an AAI describing how birds respond to individual turbines at a meso-scale. We discuss our results in relation to kittiwake collision risk and the potential implications for the OWF industry.

Methods

Study area and tag deployment

Fieldwork was carried out at Whinnyfold, UK (57°23′07″N, 001°52′11″W) located within the Buchan Ness to Collieston Coast SPA, which holds c. 11,000 apparently occupied nests of kittiwakes (Seabird Monitoring Programme database, 2021). A total of 21 breeding adults were tagged across two days in June/July 2021 during late incubation/early chick-rearing with UvA-BiTS (University of Amsterdam Bird Tracking System) GPS trackers (Bouten et al. 2013). For further details see O'Hanlon et al. (2024). Trackers were set to collect a 3D position, speed, and direction every 10 min when birds were outside the colony and every 30 min when inside the colony to conserve battery power. When birds entered a pre-defined area of interest around the OWFs (Figure S1), tags recorded data every 10 s. In addition, when the battery was full, and birds were outside the colony measurements were taken every 10 s.

The combined mass of the GPS device and attachment materials was 10.03 ± 0.06 g, which represented 2.25–2.74% of the tagged kittiwakes' body mass. We monitored the productivity of tagged individuals ($N=21$), alongside marked control individuals that were caught but not tagged ($N=21$), and control individuals that were not caught ($N=21$) to check for potential adverse effects of device deployment. There were no significant differences in the rate of nest failures between tagged, control marked and control unmarked individuals (Pearson's Chi-squared test: $\chi^2=3.231$, $P=0.199$), nor in the minimum number of fledglings (Kruskal-Wallis chi-squared test: $\chi^2=1.66$, $P=0.436$). For a more detailed account of tagging and monitoring procedures, see O'Hanlon et al. (2024).

Wind farm parameters

There are three operational OWFs with a total of 21 turbines in the typical foraging range of the kittiwake colony at Whinnyfold (Fig. 1); Hywind (57°29′12″N, 001°21′24″W), the European Offshore Wind Development Centre (EOWDC, also referred to as "Aberdeen Bay"; 57°13′24″N, 001°59′41″W), and Kincardine (57°0′18″N, 001°51′50″W; Fig. 1; Table 1). The areas covered by these OWFs are relatively small in comparison to some of the larger developments in the North Sea, and respectively small numbers of turbines are likely to lead to contrasting scenery effects. Therefore, we primarily address avoidance behaviour in the vicinity of the OWFs relating to collision risk as opposed to large-scale redistribution and habitat loss. The boundaries of these wind farms were defined using the outer-most turbine locations (Fig. 1), as opposed to lease areas, to more accurately reflect how they would be perceived by birds.

Data processing

All data processing and analysis was conducted in R (version 4.2.0, R Development Core Team 2022). Initially, we ascertained if fixes were located in the marine environment using a low-tide shapefile (Ordnance Survey 2023) and bathymetry contour of 2 m (GEBCO 2009. The GEBCO_08 Grid, version 20091120, General Bathymetry Chart of the Oceans. https://www.gebco.net/). A perimeter of 1000 m was defined around the breeding colony to indicate the start and end of foraging 'trips' of consecutive GPS fixes to exclude preening and comfort behaviour.

Data processing diverged for subsequent macro- and meso-scale analyses. For macro-scale analysis data were interpolated to the lower fix rate of 10 min using the

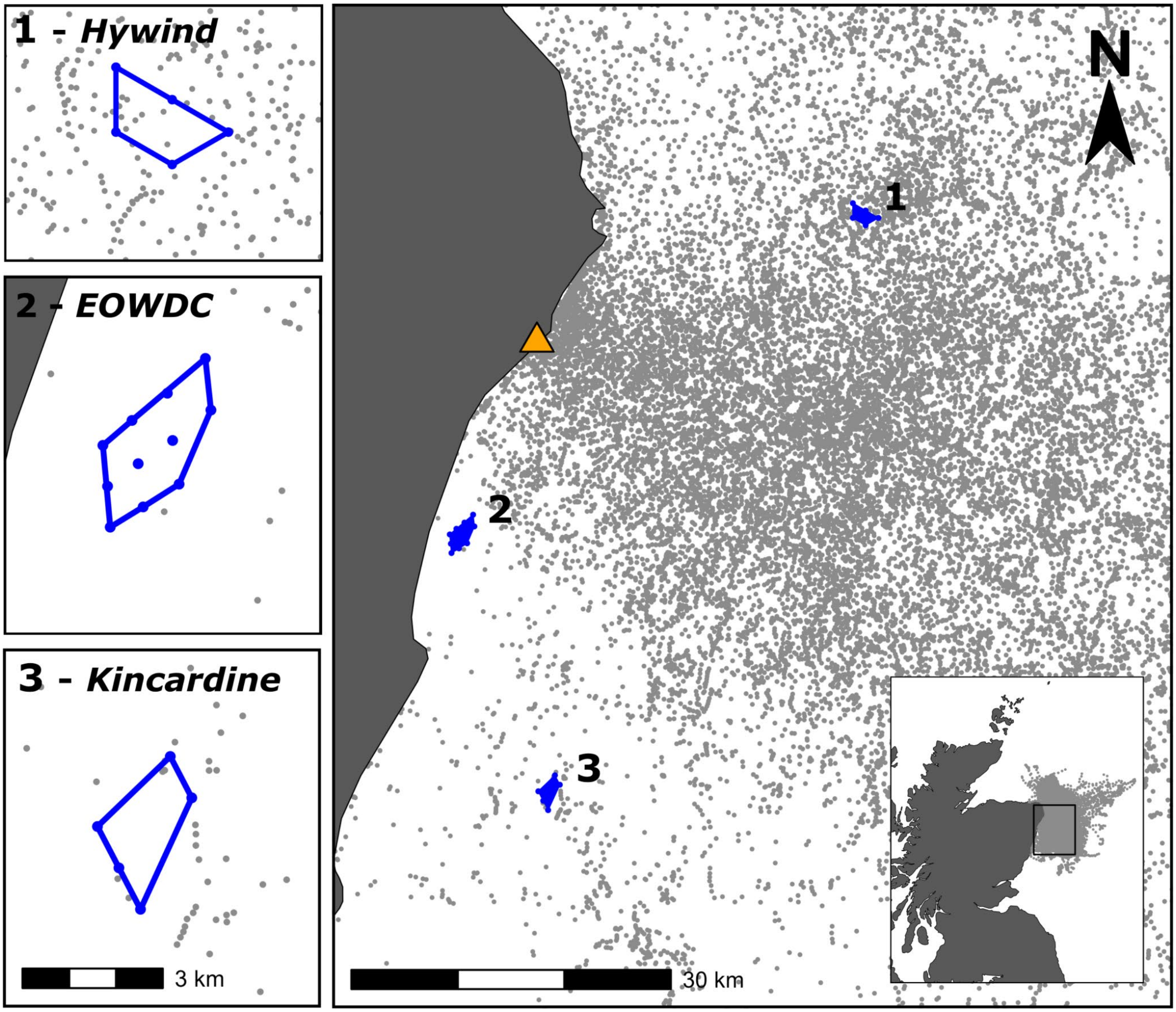


Fig. 1 Map showing fixes interpolated to 10 min intervals ($n=28{,}104$) from 20 kittiwakes breeding at Whinnyfold (orange triangle) on the east coast of Scotland. Numbers refer to offshore wind farms (1-Hywind, 2-EOWDC, 3-Kincardine) with all observed fixes in grey. Blue line shows the outline of the wind farm used for investigating macro-response, with the blue points representing individual turbines used to investigate meso-response

'momentuHMM' package (McClintock and Michelot 2018) in order to account for spatially uneven sampling introduced as result of the geofence boundaries not encompassing the 4 km buffer for macro-scale analyses (Figure S1) and battery level. Data was not interpolated to retain the high-resolution data for the meso-scale analysis, but the data were filtered so any fixes which were over 11 min apart were excluded for further analysis, as such fixes are often much less accurate.

Analysis

To assess avoidance/attraction behaviour we simulated trips to compare against observed tracks to detect if there was any divergence in locations with respect to the location of several OWFs within the range of the colony. Initially, we simulated trips by taking each individual trip (c. 50 trips per bird) and rotated it around the colony (Johnston et al. 2022) by drawing a random angle from a normal distribution characterised by the angle of all observed fixes from the colony, and then reprojecting this trip at that angle while retaining its original shape (Fig. 2). This simulated trip was then overlayed on a polygon of UK land cover, obtained from R package 'rnaturalearth' (South 2017), and if less than 10% of locations intersected with land then this trip was added to the simulated dataset. If over 10% of locations intersected with land, this trip was discarded on the basis that kittiwake

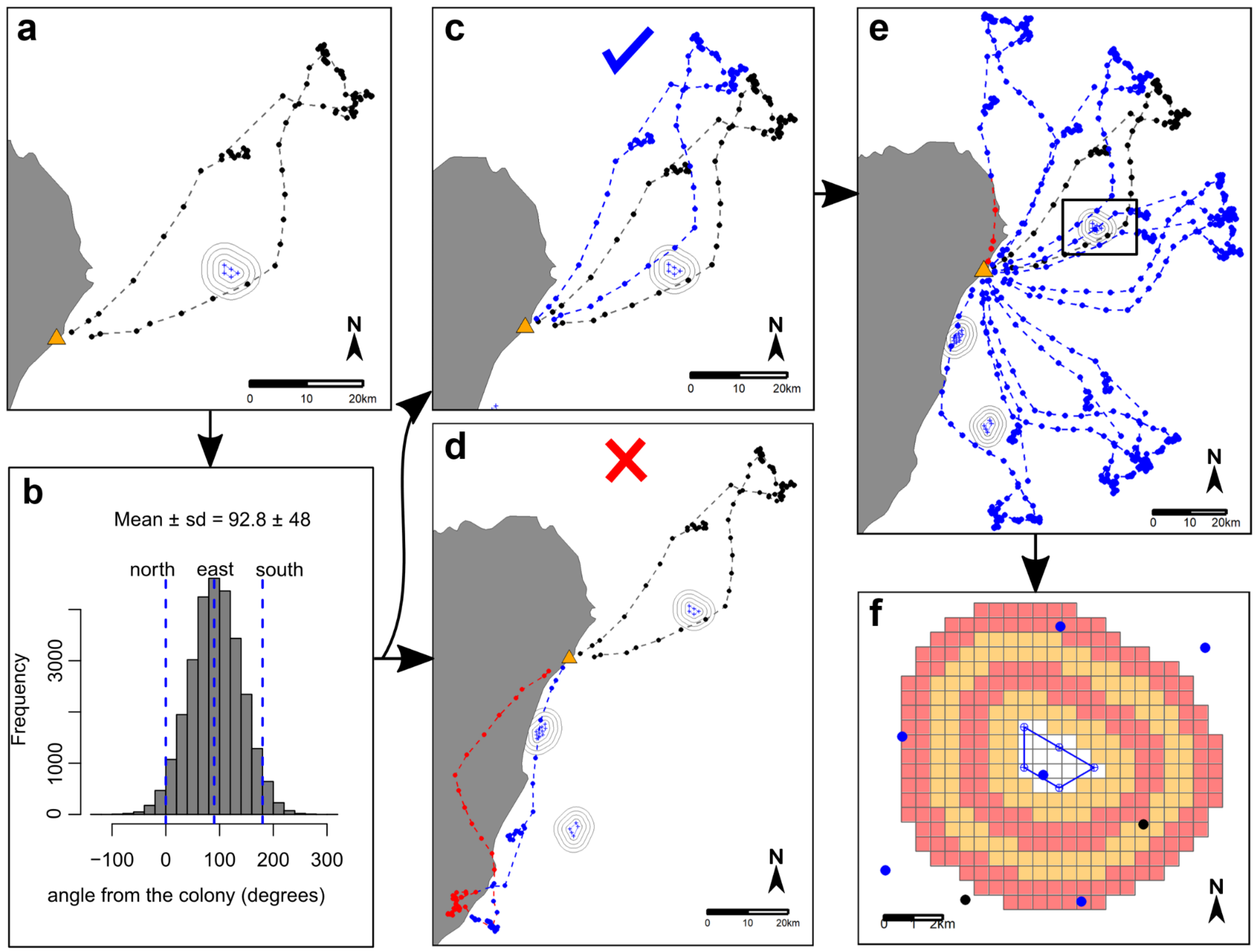


Fig. 2 Schematic of simulating tracks: (**a**) An observed track, with black points indicating fixes interpolated to 10 min intervals and the grey dashed line linking consecutive fixes. Wind farms are shown as blue polygons and turbines are blue crosses. The colony is indicated by an orange triangle. To simulate a track a new angle is drawn from the observed angle from the colony distribution (**b**), which is then reprojected along this angle - simulated tracks are indicated by blue (**c**). If more than 10% of the track is on land it is rejected, as in panel d which has ~45% of its locations on land and is rejected due to not being biologically plausible. Panel e displays seven simulated tracks in blue. For subsequent AAI analysis each 1 km band in the 0–4 km buffer outside the wind farm was composed of 0.5 km^2 grid cells, as seen in panel f which displays Hywind with distance bands in alternating red and orange

foraging trips are overwhelmingly marine owing to their diet. This process was repeated until there were 150 simulated trips for each observed trip. The described method was conducted separately on the interpolated and full datasets, with resulting simulated datasets used for macro- or meso-scale analyses, respectively.

To assess avoidance and attraction, the avoidance/attraction index (AAI) (Schaub et al. 2020; Johnston et al. 2022) was calculated in defined distance bands from; (i) the wind-farm boundary for macro-scale, and (ii) turbines for meso-scale analysis. This was calculated for each distance band by scaling the difference in expected proportion of location fixes (simulated tracks) from the observed proportion (original tracks), with the average between the observed and mean expected proportion of fixes:

$$AAI = (Prop_{obs} - Prop_{exp}) \div \overline{Prop_{obs}/Prop_{exp}}$$

Where $Prop_{obs}$ and $Prop_{exp}$ are the observed and expected proportion of fixes within a distance band, respectively. Positive AAI values indicate attraction, and negative values indicate avoidance. At both macro- and meso-scale, values of AAI values were deemed statistically significant if 95% confidence intervals (CIs, based on quantiles of the simulations) did not contain zero, as in previous applications of this method (Schaub et al. 2020; Johnston et al. 2022).

Macro-scale

Avoidance-attraction index (AAI) Macro-scale AAI was calculated in each of four, approximately one-kilometrewide distance bands (i.e., 0–1, 1–2, 2–3, 3–4 km) extending away from the boundary of each OWF. As OWFs were relatively small, we did not investigate any attraction/avoidance responses within the OWF footprint itself. Each distance band was divided into 0.25 km^2 cells (Fig. 2F). Simulated and observed GPS fixes were grouped into each 0.25 km^2 cell. For EOWDC which was within 4 km of the coast, we discarded any cells which had any intersection with land (Figure S1). AAI values were calculated by randomly selecting 48 (n) contiguous grid cells (equivalent to the area of the smallest distance band for a single wind farm) for each distance band by picking a grid cell at random in each distance band, and then selecting the 47 (n-1) nearest cells. This was carried out so that spatial structure was comparable for each distance band, ensuring that with increasing distance from the boundary, bands did not get a greater weighting owing to their greater number of grid cells (Johnston et al. 2022). This process was repeated 200 times for all OWFs combined, and then each separately. When this process was carried out for all OWFs combined, the random cell for each distance band could be chosen in any of the three OWFs, but the 47 contiguous cells would all be within that OWF's distance band. When this was conducted for each separate OWF, the two remaining OWFs and surrounding boundaries were effectively ignored. Therefore, we obtained mean AAI values for all OWFs analysed simultaneously, and for each OWF separately by running four sets of 200 iterations of random sampling of 48 grid cells.

Avoidance rate (AR) In addition to AAI, we calculated AR, due to it being the standard metric calculated for collision risk models in the UK, at the macro-scale for distance bands between 1 and 4 km from boundaries of all wind farms together, and each separately, as for AAI above. Here the mean expected proportion of location fixes minus the observed proportion was divided by the mean of the expected proportion, in each of the respective bands:

$$AR = (\overline{Prop_{exp}} - Prop_{obs}) \div \overline{Prob_{exp}}$$

Interpretation of AR uses the opposite sign as that of AAI, i.e., positive values indicate avoidance, and negative values indicate attraction. As for AAI, significance of AR values was assessed using 95% CIs based on quantiles of the 150 simulations, where intervals not containing zero were deemed to be statistically significant. Given the low observation rates for some of these calculations, particularly in EOWDC (Table 3), we conducted sensitivity testing to assess the reliability of AR values obtained in such instances. We generated new AR values in each of the four distance bands by resampling observed fixes at Hywind 100 times. Sensitivity was assessed by quantifying the percentage of times the resampled AR rates fell within the full sample's confidence intervals. We conducted this for four sample resolutions ($n = 5/10/25/50$) which dictated how the observed data were resampled to a lower resolution for the smallest distance band, 0–1 km. As Avoidance Rate is calculated for bands of increasing size, resampling for subsequent bands was scaled by the relative area of the different bands around Hywind (Table S1). The corresponding fixes removed from the observed data sets were removed from the simulated data set according to their original fix location (i.e., prior to reprojection) before recalculation of AR for each iteration.

Meso-scale

Meso-scale AAI was calculated in each of twenty 200 m distance bands extending away from individual turbines, as opposed to OWF boundary in the macro-scale analysis, and irrespective of which OWF the turbine was located in. Following previous studies on similar species only fixes with a flight speed (ground speed; calculated between fixes) greater than 4 km h^{-1} were classified as being in flight and included in analyses (Shamoun-Baranes et al. 2011; Thaxter et al. 2018). Distance from the nearest turbine was determined for each fix and meso-response was investigated by grouping fixes by this distance into 20 m^2 cells, thus extending to 400 m distance from all investigated turbines ($n = 21$). This ensured we could maximise samples while excluding fixes overlapping into the radii of other turbines being investigated within the same footprint as the minimum distance between any two turbines being considered was 814 m in EOWDC (Table 1). Given that most fixes were recorded in and around Hywind, in which the minimum distance between turbines is 1385 m, any influence of surrounding turbines should be minimal.

Observed and simulated fixes were pooled into two different height layers using GPS derived altitude above mean sea level: (i) below and (ii) within rotor height range (RHR), which is also known as the rotor swept area/zone. As there were no observed fixes with flight heights above the RHR within the considered sample, this height layer was not considered. Inaccurate flight height data obtained from GPS may be a result of atmospheric effects and satellite geometry (Karaim et al. 2018). Davies et al. (2024) investigated this in greater depth using a GPS altitude error model with the same dataset (Ross-Smith et al. 2016; Péron et al. 2020) and found an estimated altitude observation error SD between 18.987 and 0.232 m depending on the number of satellites being used. It is possible that error is reflected in our data, with evidence seen in negative altitudes in Fig.4B, but due to the majority of fixes having a high temporal resolution this should be minimised (Thaxter et al. 2018). Given the small sample which was imbalanced across OWFs (relatively few fixes for turbines in EOWDC and Kincardine) we calculated meso-scale AAI for the pooled sample of all OWFs and not for separate OWFs, where fixes were analysed according to the wind farm parameters of the turbine that they were closest to (Table 1). To ensure that the interpretation of the pattern at Hywind was not distorted by pooling with fixes from other OWFs, we also conducted meso-scale analysis on Hywind data alone.

Results

All but one of 21 tagged breeding adults returned viable data ($n=20$), totalling 210,109 fixes after initial processing, with one tag being unsuccessful in transmitting data. Further processing to interpolate to a resolution of fixes every 10 min resulted in a dataset of 28,104 fixes (~13% of full dataset) to be used for macro-scale analysis. Interpolation wasn't required for meso-scale analysis as the location of geofences (Figure S1) don't intersect the spatial scale being investigated (up to 400 m away from individual turbines).

Each tagged individual flew within at least one of the OWF footprints and the buffer (0–4 km) used for investigation of attraction/avoidance at the macro-scale with a total of 592 fixes (Table 2). Hywind and its buffer had a substantially higher proportion of fixes (83% of total OWF fixes, $n=492$, Table 2) than Kincardine or EOWDC. This was reflected in the number of individuals recorded at each OWF, with Hywind and its buffer extending to 4 km having fixes from almost all individuals ($n=19$), whereas EOWDC had half of the total individuals ($n=10$), and Kincardine had less than a quarter ($n=4$).

Regarding meso-scale analysis there were 294 fixes in total that were within 400 m distance from considered turbines. Of these fixes, 91% ($n=269$) were for turbines within Hywind OWF, with 16 for EOWDC turbines and 9 for Kincardine turbines (Fig. 4A). There was a total of 12 individuals within 400 m of Hywind's turbines, with two individuals moving within 400 m of EOWDC and Kincardine's turbines.

Table 2 Number of interpolated fixes within each offshore wind farm and their buffer zones used for assessing macro-scale response to respective offshore wind farms using AAI

	Hywind	Kincardine	EOWDC	All OWFs
Within OWF footprint	10	3	0	13
0–1 km	101	17	0	118
1–2 km	115	10	9	134
2–3 km	127	11	15	153
3–4 km	139	20	15	174
Total	492	61	39	592
Individuals	19	4	10	20

Macro-response

Avoidance rate (AR)

When all OWFs were analysed together there was significant attraction in two narrower distance bands indicated by negative mean AR values (Table 3). When a distance band of up to 4 km from the OWF boundaries was analysed, mean AR values increased to zero, indicating no avoidance or attraction with a similar pattern being observed for Hywind when analysed individually (Table 3). Mean AR values at Kincardine indicated significant attraction in the narrowest distance band (1 km, AR = -1.07, 95% CI: -2.59 to -0.01), whereas results at the widest distance band indicated significant avoidance (4 km, AR = 0.12, 95% CI: 0.05 to 0.17). At EOWDC it was not possible to calculate AR for the 1 km band as there were no observed fixes after the data was interpolated. There was significant avoidance in the 2 km distance band (AR = 0.33, 95% CI: 0.03 to 0.52), however this result must be interpreted with caution given the low observation rates ($n=9$; Table 3) around this OWF. Sensitivity testing indicated that an equivalent observation rate at Hywind in this distance band would have led to an AR that fell within the confidence intervals of the AR derived from the full dataset only 57% of the time (0–2 km, mean fixes resampled 11.3 ± 2.5, Table S1), with a roughly five-fold increase in sampling rate required to reach 90% (Table S1, Figure S2).

Avoidance-attraction index (AAI)

Patterns observed from AR values for different OWFs were similar to those shown by AAI (Table S2). For all OWFs there was a trend for increasing avoidance with distance from the OWFs, but it was not significant (Fig. 3). There was significant attraction to the 0–1 km band of both Hywind (AAI = 0.33, 95% CI: 0.22 to 0.33) and Kincardine (AAI = 0.61, 95% CI: 0.35 to 0.89). At Hywind, attraction decreased with distance (Fig. 3), with the furthest distance band analysed (3–4 km) indicating a significant avoidance response (AAI = -0.29, 95% CI: -0.48 to -0.04). As for AR, we could not calculate an AAI value for the 0–1 km distance band at EOWDC, and other distance bands did not indicate any significant attraction or avoidance response.

Meso-response

Meso-scale AAI figures (Table S3) indicate avoidance close to the turbines, with significant avoidance in the 20–40 m

Table 3 Avoidance rate (values) across increasing one km bands from offshore wind farm boundaries with 95% CIs derived from quantiles of simulations and bold CI values indicating a significant result. As in Schaub et al. (2019), negative values of AR indicate attraction, and positive values indicated avoidance

Wind farm	Distance band (km)	N observed	Mean N expected	AR	sd	95% CI	
						Lower	**Upper**
All	1	120	101.4	-0.36	0.19	**-0.71**	**-0.10**
	2	254	242.5	-0.19	0.11	**-0.39**	**-0.05**
	3	407	433	-0.06	0.05	-0.14	0.01
	4	582	655.1	0.00	0.01	-0.02	0.02
Hywind	1	103	72.53	-0.44	0.22	**-0.82**	**-0.14**
	2	218	175.9	-0.24	0.12	**-0.45**	**-0.08**
	3	345	314.4	-0.09	0.06	**-0.20**	**-0.01**
	4	484	474.4	-0.01	0.02	-0.04	0.02
Kincardine	1	17	17.2	-1.07	1.80	**-2.59**	**-0.01**
	2	27	40.8	-0.19	0.30	-0.80	0.14
	3	38	73	0.10	0.11	-0.11	0.25
	4	58	111.6	0.12	0.04	**0.05**	**0.17**
EOWDC	1	0	11.2	–	–	–	–
	2	9	25.8	0.33	0.16	**0.03**	**0.52**
	3	24	45.6	0.04	0.11	-0.16	0.19
	4	40	69.1	-0.04	0.05	-0.14	0.03

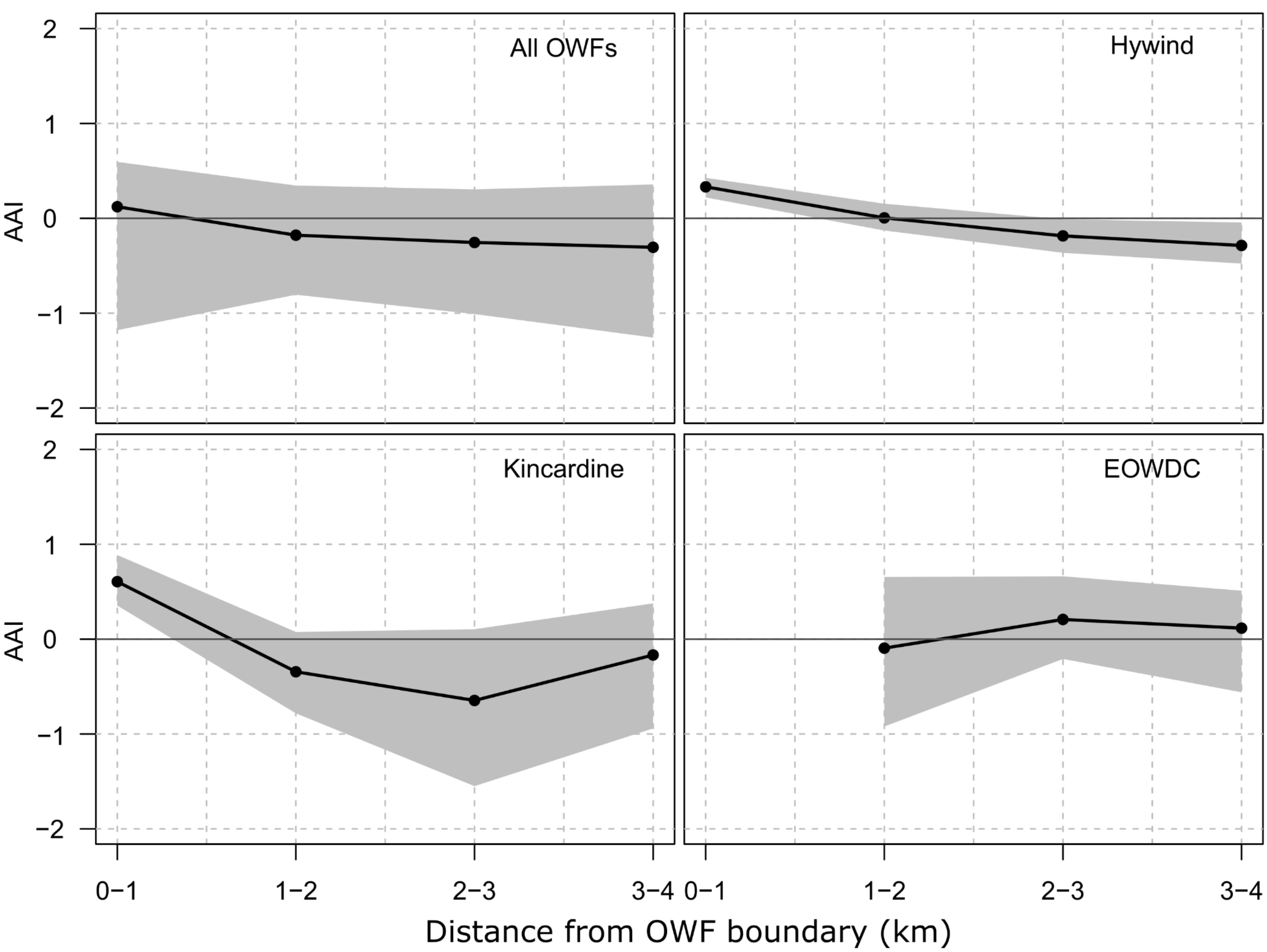


Fig. 3 Avoidance-attraction index (AAI) results for macro-response for all OWFs together (top-left) and each OWF separately. Grey shading indicates 95% CI. Positive values of AAI indicate attraction, and negative values indicate avoidance with the horizontal grey line intercepting zero indicating the boundary between the two, which if not overlapped by CIs indicates a significant response

(AAI = -2.00, 95% CI: −2.00 to -2.00), and 40–60 m (AAI = -2.00, 95% CI: −2.00 to -2.00) distance bands within RHR (Fig. 4). Below RHR there was largely significant avoidance from the 0–20 m band up to the 120–140 m band (AAI range = -2.00 to -0.94, Table S3). In both height layers (within and below RHR) there is no significant avoidance or attraction response beyond the 140–160 m band extending to 400 m distance from the turbines, bar some apparent attraction to the 360–380 m band below the RHR (Fig. 4, Table S3). Although there were some positive mean AAI values, indicating attraction, the majority of these were not significant (all CIs contained zero) throughout the entire 0–400 m distance for both height layers. When considering only Hywind fixes, meso-scale AAI figures varied slightly (Figure S3), but the interpretation of the pattern remains the same.

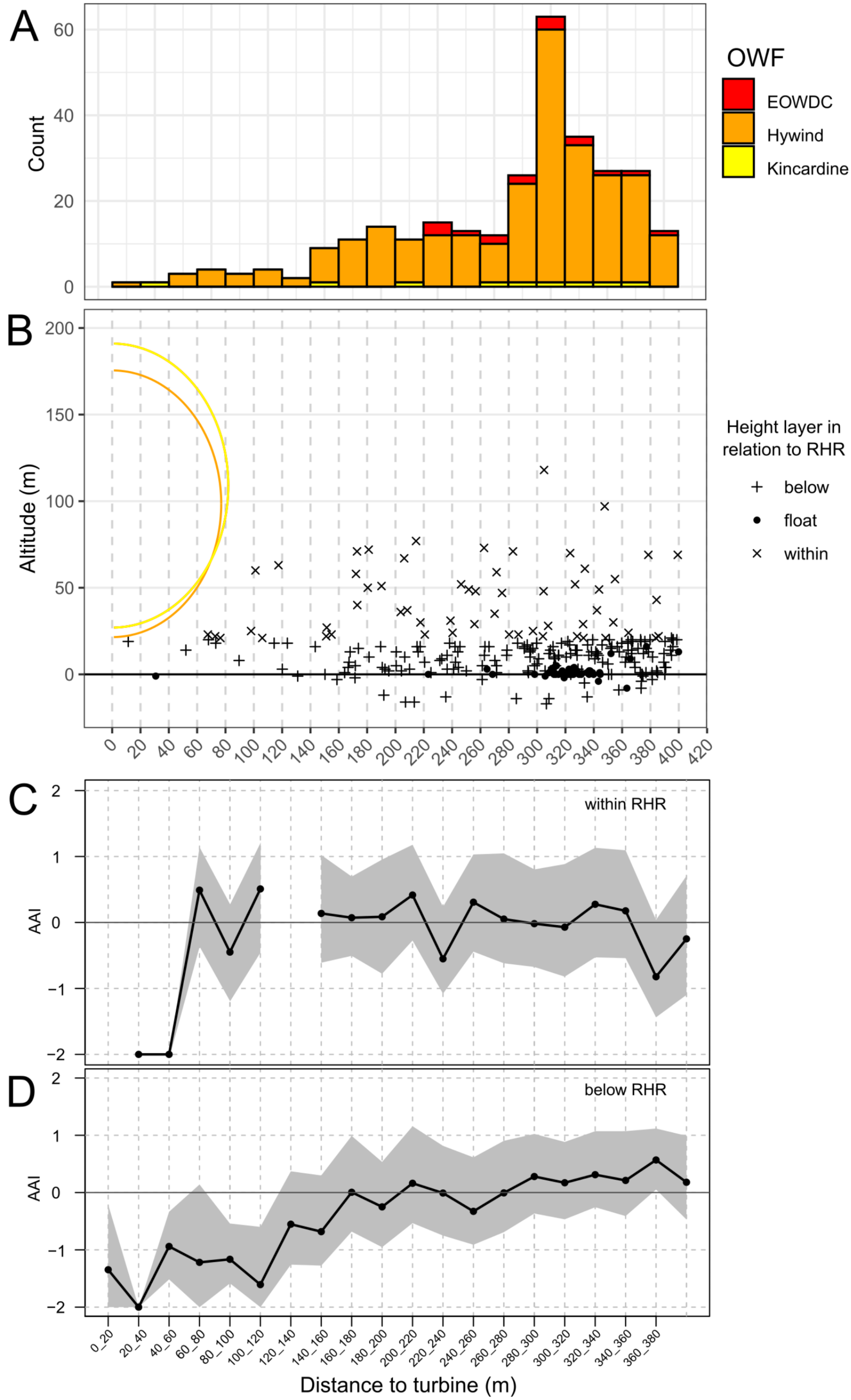
Discussion

Our results highlight that the interactions of birds with OWFs are likely to be more complex than a binary avoidance/attraction response. In common with previous studies which found inconsistent responses in kittiwakes (Dierschke et al. 2016), we also found evidence indicating attraction and avoidance. The fundamental difference being that these responses herein were determined by the spatial scale of investigation within the same sample. At the macro-scale we found attraction to the 1 km band around the boundary of OWFs. Upon closer inspection at the meso-scale, no attraction response was detected within 400 m of the respective turbines, with a strong avoidance detected at both height layers analysed (within and below RHR). We discuss these results and their potential implications for statutory impact assessments, which struggle to capture the complexity of such responses, as this study contributes to a growing list of bird species which exhibit nuanced spatial responses to OWFs in the marine environment (Peschko et al. 2021; Johnston et al. 2022; van Bemmelen et al. 2024).

At a population level, the effect sizes of macro-responses we detected were marginal and required a relatively high number of data points to elucidate, with sensitivity testing indicating that lower observation rates may result in unreliable avoidance rates. Consequently, to obtain sufficient data to quantify meso-responses we had to pool data across all three OWFs in our study area. Furthermore, as with Johnston et al. (2022), broad confidence intervals, overlapping with zero, for both macro- and meso-responses suggest that responses at greater distances may have gone undetected due to low statistical power.

The majority of our understanding of species responses to OWFs is based on aerial and/or ship-based survey data collection, typically as part of year-round pre- and post-construction monitoring. However, the statistical power to detect potential patterns from these data can be weak (Maclean et al. 2013; Vanermen et al. 2015a) which is likely to have contributed to the ambiguity in reports on kittiwake attraction/avoidance responses from such studies (Dierschke et al. 2016; Trinder et al. 2023). However, there are alternative methods to investigate species interactions with OWFs, such as GPS and the products of developing technology (Largey et al. 2021). In common with studies of lesser black-backed gulls using GPS tracking, we found evidence indicating attraction to the edge of OWFs at a macro-scale (Vanermen et al. 2020; Johnston et al. 2022). Similar results have also been reported using methods such as radar and visual observations (Krijgsveld et al. 2011; Skov et al. 2018) which can make use of finer scale movement data, as opposed to the broad-scale distribution data available from standard survey methodologies. Hypotheses to explain this include an increase in productivity around the wind farms (Floeter et al. 2017) and an aggregation of fishing vessels on the edge of the wind farm (Krijgsveld et al. 2011). An alternative explanation could be that our results are detecting an aggregation of birds immediately outside the OWF which have been displaced from inside the wind farm. A recent tracking study of Sandwich terns *Thalasseus sandvicensis* (Thaxter et al. 2024) found that birds enter the OWF when foraging but appear to avoid them when commuting. Similar behaviour could be exhibited by birds in our study, with birds congregating around the wind farm before/after foraging within the OWF footprint. Ideally, we would have extended macro-scale analysis to within the OWF footprint (Johnston et al. 2022), but the small size of the wind farms in this study prevented this. Thus, we recommend repeating similar analyses for kittiwakes interacting with larger OWFs and studies of individual-level responses, such as using individual step selection functions (e.g. van Bemmelen et al. 2024) to aid understanding.

At rotor height, and at the meso-scale, our results showed similarities to those of Johnston et al. (2022) for lesser black-backed gull, which found evidence of significant avoidance of the area around 60–80 m from the turbine rotor swept areas, but contrasted in that there was no evidence of attraction to the area around the turbine bases. Data were also consistent with a camera-radar study carried out at EOWDC concurrent with the GPS data collection, which found evidence of kittiwake avoiding turbines to a distance of up to 150 m (Tjørnløv et al. 2023). These studies suggest that there may be a consistent response to turbines at a species, and potentially family, level. This would align with previous analyses of avian collision rates with wind turbines, which suggested a strong phylogenetic component to risk (Thaxter et al. 2017). These findings may also have implications


A
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Height layer in relation to RHR
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Distance to turbine (m)

Fig. 4 (**A**) Histogram of observed fixes in each 20 m horizontal distance band from the turbine with bars split into colours to indicate different wind farms. (**B**) Observed GPS fixes within 400 m of turbines (i.e., meso-scale) plotted in relation to distance and altitude from nearest turbine (m). Shapes of points indicate the height layer in relation to the rotor heigh range (RHR), indicating fixes that are either within the RHR, or below, which includes fixes defined as floating on the water. The colour of the hollow semi-circles display the different RHR for respective wind farms, according to the legend for panel A, noting that EOWDC and Kincardine are very similar and overlap considerably. Mean AAI values for 20 m distance bands from the nearest turbine for fixes within (panel **C**) and below (panel **D**) rotor height range, where breaks in the band indicate absence of observed fixes. Grey shading indicates 95% CI and the horizontal grey line intercepting zero indicates the boundary between the two, which if not overlapped by CIs indicates a non-significant response. AAI values calculated for each of 200 random iterations. Positive values of AAI indicate attraction, and negative values indicate avoidance

for proposed mitigation measures. Painting blades has been suggested as a means to reduce collision rates by increasing the visibility of the turbine rotor sweep by breaking up motion-smear but note that efficacy will likely vary across species (May et al. 2020). It has been suggested that painting blades to make them visible at distances of up to 1 km in the offshore environment may be an effective means to reducing seabird collision risk (Martin and Banks 2023). However, our results suggest that visibility may not be a key limiting factor as birds are safely approaching, and responding to, turbines at far shorter distances.

While the investigation of population-level responses, as in our study, is directly related to predicting the impacts of OWFs on seabird population through metrics such as the Avoidance Rate (AR), it is also necessary to understand responses at the level of the individual. A study conducted on the same kittiwake dataset highlighted that 15 out of 20 individuals overlapped with one of the three OWFs at one point, and time spent in OWFs varied from between 10 min up to 4 h across all individuals (O'Hanlon et al. 2024), highlighting the discrepancy of potential impacts facing individuals across the population. Empirical studies into other seabird species interacting with OWFs within their foraging range displayed similar patterns between gannets and guillemots, where a small proportion of the population interacted with OWFs considerably, while the larger proportion avoided them entirely (Peschko et al. 2020, 2021). We must consider the potential consequences of varying responses of individuals to OWFs as those that are more attracted to the area around OWFs may experience any potential impacts, particularly collision mortality, at a greater magnitude. Although this doesn't fit well into the current paradigm for environmental impact assessments, from which predictions are largely performed and withdrawn at the population-level, the increasing use of individual-based models provide the opportunity to account for such between individual variance, from which population level impacts will emerge from upon scaling up (Warwick-Evans et al. 2018).

With the wealth of studies employing similar approaches and relevant data sets across a wide range of seabirds, there is the potential to employ a meta-analytic approach to overcome the previously mentioned issues associated with smaller data sets (Stewart et al. 2007). Alongside further insights into how different species respond to OWFs at different scales, this approach may allow us to investigate the drivers of such responses, which may include the properties of the OWFs themselves, as well as potential habitat-related effects. These include the potential for higher productivity and the concentration of fishing vessels on the edge to OWFs to attract birds (Floeter et al. 2017; Skov et al. 2018), and for higher densities of turbines to elicit a stronger avoidance response as they offer a stronger visual deterrent. Of the three wind farms considered in our study, EOWDC was the least frequented, which could be related to the higher relative turbine density but could equally be a reflection of this colony's standard foraging distribution. Avoidance rate of Sandwich terns increased with turbine density at OWFs in the UK and the Netherlands (van Bemmelen et al. 2024), and similar patterns have been suggested for a range of species, including kittiwake (Leopold et al. 2012). However, disentangling these relationships from other potentially confounding factors (e.g., distance from coast, habitat) can be challenging. In addition, our study was conducted in the breeding season and may not represent avoidance responses throughout the annual cycle, when birds from this colony may encounter much larger OWFs. Pooling results using meta-analytic type approaches is likely to be valuable in addressing these factors.

Given that kittiwakes are of primary concern to the UKs offshore wind economy owing to predicted impacts on populations of prospective OWFs being above previously defined thresholds, our study into this species avoidance behaviour is timely. However, our results cannot be interpreted in a succinct manner to feed directly into to the way current impacts are assessed, due to their behaviours being more nuanced than such assessments allow for. Such complexity has now been displayed across many seabird species which share their foraging ranges with an increasing number of OWF developments, and as such the tools used for impact assessment will not represent this adequately, and methods should be updated to take advantage of the wealth of data we now have available to us.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s00227-024-04542-y.

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Author contributions This study was conceived and designed by ASCPC, CJP, CBT, EMH. Data collection was performed by DTJ, NJO, GDC and EDW. Data preparation and processing were performed by CJP, PHBS, CBT, ASCPC and DTJ. Statistical analysis and modelling were performed by CJP. The first draft of the manuscript was written by CJP and ASCPC, and all authors contributed to subsequent versions of the manuscript.

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Data availability The kittiwake tracking dataset analysed in this study is available at Movebank (http://www.movebank.org) in the study "BTO - Whinnyfold 2021 - Kittiwake" (Movebank Study ID 4447816442).

Declarations

Compliance with ethical standards All handling of birds was conducted following the direction and legislation from NatureScot and The British Trust for Ornithology, where specific special methods licences were issued for GPS trackers.

Conflict of interest The authors declare that they have no conflict of interest.

References

Bouten W, Baaij EW, Shamoun-Baranes J, Camphuysen KCJ (2013) A flexible GPS tracking system for studying bird behaviour at multiple scales. J Ornithol 154:571–580. https://doi.org/10.1007/s10336-012-0908-1

Brabant R, Vanermen N, Stienen EWM, Degraer S (2015) Towards a cumulative collision risk assessment of local and migrating birds in North Sea offshore wind farms. Hydrobiologia 756:63–74. https://doi.org/10.1007/s10750-015-2224-2

Broadbent ID, Nixon CLB (2019) Refusal of planning consent for the Docking Shoal offshore wind farm: stakeholder perspectives and lessons learned. Mar Policy 110:103529. https://doi.org/10.1016/j.marpol.2019.103529

Burthe SJ, Wanless S, Newell MA, Butler A, Daunt F (2014) Assessing the vulnerability of the marine bird community in the western North Sea to climate change and other anthropogenic impacts. Mar Ecol Prog Ser 507:277–295. https://doi.org/10.3354/meps10849

Busch M, Garthe S (2018) Looking at the bigger picture: the importance of considering annual cycles in impact assessments illustrated in a migratory seabird species. ICES J Mar Sci 75:690–700. https://doi.org/10.1093/icesjms/fsx170

Chamberlain DE, Rehfisch MR, Fox AD, Desholm M, Anthony SJ (2006) The effect of avoidance rates on bird mortality predictions made by wind turbine collision risk models. Ibis 148:198–202. https://doi.org/10.1111/j.1474-919X.2006.00507.x

Cook ASCP, Humphreys EM, Bennet F, Masden EA, Burton NHK (2018) Quantifying avian avoidance of offshore wind turbines: current evidence and key knowledge gaps. Mar Environ Res Doi. https://doi.org/10.1016/j.marenvres.2018.06.017

Davies JG, Humphreys EM, Evans T, Howells RJ, O'Hara-Murray R, Pearce-Higgins JW (2023) Seabird abundances projected to decline in response to climate change in Britain and Ireland. Mar Ecol Prog Ser 725:121–140. https://doi.org/10.3354/meps14462

Davies JG, Boersch-Supan PH, Clewley GD, Humphreys EM, O'Hanlon NJ, Shamoun-Baranes J, Thaxter CB, Weston E, Cook ASCP (2024) Influence of wind on kittiwake Rissa tridactyla flight and offshore wind turbine collision risk. Mar Biol 171:191. https://doi.org/10.1007/s00227-024-04508-0

Desholm M, Kahlert J (2005) Avian collision risk at an offshore wind farm. Biol Lett 1:296–298. https://doi.org/10.1098/rsbl.2005.0336

Dierschke V, Furness RW, Garthe S (2016) Seabirds and offshore wind farms in European waters: avoidance and attraction. Biol Conserv 202:59–68. https://doi.org/10.1016/j.biocon.2016.08.016

Drewitt AL, Langston RHW (2006) Assessing the impacts of wind farms on birds. Ibis 148:29–42. https://doi.org/10.1111/j.1474-919X.2006.00516.x

Floeter J, van Beusekom JEE, Auch D, Callies U, Carpenter J, Dudeck T, Eberle S, Eckhardt A, Gloe D, Hänselmann K, Hufnagl M, Janßen S, Lenhart H, Möller KO, North RP, Pohlmann T, Riethmüller R, Schulz S, Spreizenbarth S, Temming A, Walter B, Zielinski O, Möllmann C (2017) Pelagic effects of offshore wind farm foundations in the stratified North Sea. Prog Oceanogr 156:154–173. https://doi.org/10.1016/j.pocean.2017.07.003

Furness RW, Wade HM, Masden EA (2013) Assessing vulnerability of marine bird populations to offshore wind farms. J Environ Manage 119:56–66. https://doi.org/10.1016/j.jenvman.2013.01.025

Goodale MW, Milman A, Griffin CR (2019) Assessing the cumulative adverse effects of offshore wind energy development on seabird foraging guilds along the East Coast of the United States. Environ Res Lett 14:074018. https://doi.org/10.1088/1748-9326/ab205b

Green RE, Langsten HW, McCluskie A, McCuskie A, Sutherland R, Wilson JD (2016) Lack of sound science in assessing wind farm impacts on seabirds. J Appl Ecol 53:1635–1641

Horswill C, Trathan PN, Ratcliffe N (2017) Linking extreme interannual changes in prey availability to foraging behaviour and breeding investment in a marine predator, the macaroni penguin. PLoS ONE 12:e0184114. https://doi.org/10.1371/journal.pone.0184114

Johnston DT, Thaxter CB, Boersch-Supan PH, Humphreys EM, Bouten W, Clewley GD, Scragg ES, Masden EA, Barber L, Conway GJ, Clark NA, Burton NHK, Cook A (2022) Investigating avoidance and attraction responses in lesser black-backed gulls Larus fuscus to offshore wind farms. Mar Ecol Prog Ser 686:187–200. https://doi.org/10.3354/meps13964

Karaim M, Elsheikh M, Noureldin A, Rustamov RB (2018) GNSS error sources. Multifunctional Operation Application GPS 32:137–144

Krijgsveld KL, Fijn RC, Heunks C, Van Horssen PW, De Fouw J, Collier M, Poot MJM, Beuker D, Dirksen S (2011) Effect studies offshore wind farm Egmond Aan Zee. Final report on fluxes, flight altitudes and behaviour of flying birds. Noordzeewind Rapport OWEZ R 231 T1 20111110. Bureau Waardenburg, Culemborg.

Largey N, Cook ASCP, Thaxter CB, McCluskie A, Stokke BG, Wilson B, Masden EA (2021) Methods to quantify avian airspace use in relation to wind energy development. Ibis 163:747–764. https://doi.org/10.1111/ibi.12913

Leopold MF, van Bemmelen RSA, Zuur AF (2012) Responses of local birds to the Offshore wind farms PAWP and OWEZ off the Dutch mainland coast. IMARES, Den Burg

Maclean IMD, Rehfisch MM, Skov H, Thaxter CB (2013) Evaluating the statistical power of detecting changes in the abundance of seabirds at sea. Ibis 155:113-126. https://doi.org/10.1111/j.1474-919X.2012.01272.x

Martin GR, Banks AN (2023) Marine birds: vision-based wind turbine collision mitigation. Global Ecol Conserv 42:e02386. https://doi.org/10.1016/j.gecco.2023.e02386

Masden EA, Cook ASCP (2016) Avian collision risk models for wind energy impact assessments. Environ Impact Assess Rev 56:43–49. https://doi.org/10.1016/j.eiar.2015.09.001

Masden EA, Haydon DT, Fox AD, Furness RW, Bullman R, Desholm M (2009) Barriers to movement: impacts of wind farms on migrating birds. ICES J Mar Sci 66:746–753. https://doi.org/10.1093/icesjms/fsp031

Masden EA, Haydon DT, Fox AD, Furness RW (2010) Barriers to movement: modelling energetic costs of avoiding marine wind farms amongst breeding seabirds. Mar Pollut Bull 60:1085–1091. https://doi.org/10.1016/j.marpolbul.2010.01.016

May RF (2015) A unifying framework for the underlying mechanisms of avian avoidance of wind turbines. Biol Conserv 190:179–187. https://doi.org/10.1016/j.biocon.2015.06.004

May RF, Nygård T, Falkdalen U, Åström J, Hamre Ø, Stokke BG (2020) Paint it black: efficacy of increased wind turbine rotor blade visibility to reduce avian fatalities. Ecol Evol 10:8927–8935. https://doi.org/10.1002/ece3.6592

McClintock BT, Michelot T (2018) momentuHMM: R package for generalized hidden Markov models of animal movement

O'Hanlon NJ, Johnston DT, Cook ASCP, Robinson RA, Humphreys EM (2023) A crowded ocean: the need for demographic and movement data in seabird conservation. Ocean Coast Manag 244:106833. https://doi.org/10.1016/j.ocecoaman.2023.106833

O'Hanlon NJ, Thaxter CB, Clewley GD, Davies JG, Humphreys EM, Miller PI, Pollock CJ, Shamoun-Baranes J, Weston E, Cook ASCP (2024) Challenges in quantifying the responses of black-legged Kittiwakes Rissa tridactyla to habitat variables and local stressors due to individual variation. Bird Study 71:48–64. https://doi.org/10.1080/00063657.2024.2305169

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Paleczny M, Hammill E, Karpouzi V, Pauly D (2015) Population Trend of the World's monitored Seabirds, 1950–2010. PLoS ONE 10:e0129342. https://doi.org/10.1371/journal.pone.0129342

Péron G, Calabrese JM, Duriez O, Fleming CH, García-Jiménez R, Johnston A, Lambertucci SA, Safi K, Shepard ELC (2020) The challenges of estimating the distribution of flight heights from telemetry or altimetry data. Anim Biotelem 8:1–13. https://doi.org/10.1186/s40317-020-00194-z

Peschko V, Mercker M, Garthe S (2020) Telemetry reveals strong effects of offshore wind farms on behaviour and habitat use of common guillemots (Uria aalge) during the breeding season. Mar Biol 167:118. https://doi.org/10.1007/s00227-020-03735-5

Peschko V, Mendel B, Mercker M, Dierschke J, Garthe S (2021) Northern gannets (Morus bassanus) are strongly affected by operating offshore wind farms during the breeding season. J Environ Manage 279:111509. https://doi.org/10.1016/j.jenvman.2020.111509

Rodrigues S, Restrepo C, Kontos E, Teixeira Pinto R, Bauer P (2015) Trends of offshore wind projects. Renew Sustainable Energy Rev 49:1114–1135. https://doi.org/10.1016/j.rser.2015.04.092

Ross-Smith VH, Thaxter CB, Masden EA, Shamoun-Baranes J, Burton NHK, Wright LJ, Rehfisch MM, Johnston A (2016) Modelling flight heights of lesser black-backed gulls and great skuas from GPS: a bayesian approach. J Appl Ecol 53:1676–1685. https://doi.org/10.1111/1365-2664.12760

Schaub T, Klaassen RHG, Bouten W, Schlaich AE, Koks BJ (2020) Collision risk of Montagu's harriers Circus pygargus with wind turbines derived from high-resolution GPS tracking. Ibis 162:520–534. https://doi.org/10.1111/ibi.12788

Searle KR, O'Brien SH, Jones EL, Cook ASCP, Trinder MN, McGregor RM, Donovan C, McCluskie A, Daunt F, Butler A (2023) A framework for improving treatment of uncertainty in offshore wind assessments for protected marine birds. ICES J Mar Sci fsad025. https://doi.org/10.1093/icesjms/fsad025

Shamoun-Baranes J, Bouten W, Camphuysen CJ, Baaij E (2011) Riding the tide: intriguing observations of gulls resting at sea during breeding. Ibis 153:411–415. https://doi.org/10.1111/j.1474-919X.2010.01096.x

Skov H, Heinänen S, Norman T, Ward R, Méndez-Roldán S, Ellis I (2018) ORJIP bird collision avoidance study. Carbon Trust & Discretionary Project Steering Committee

South A (2017) Rnaturalearth: world map data from natural earth

Stewart GB, Pullin AS, Coles CF (2007) Poor evidence-base for assessment of windfarm impacts on birds. Environ Conserv 34:1–11. https://doi.org/10.1017/S0376892907003554

Thaxter CB, Lascelles B, Sugar K, Cook ASCP, Roos S, Bolton M, Langston RHW, Burton NHK (2012) Seabird foraging ranges as a preliminary tool for identifying candidate Marine protected areas. Biol Conserv 156:53–61. https://doi.org/10.1016/j.biocon.2011.12.009

Thaxter CB, Buchanan GM, Carr J, Butchart SHM, Newbold T, Green RE, Tobias JA, Foden WB, O'Brien S, Pearce-Higgins JW (2017) Bird and bat species' global vulnerability to collision mortality at wind farms revealed through a trait-based assessment. Proc Biol Sci. https://doi.org/10.1098/rspb.2017.0829

Thaxter CB, Ross-Smith VH, Bouten W, Masden EA, Clark NA, Conway GJ, Barber L, Clewley GD, Burton N (2018) Dodging the blades: new insights into three-dimensional space use of offshore wind farms by lesser black-backed gulls Larus fuscus. Mar Ecol Prog Ser 587:247–253. https://doi.org/10.3354/meps12415

Thaxter CB, Ross-Smith VH, Bouten W, Clark NA, Conway GJ, Masden EA, Clewley GD, Barber LJ, Burton NHK (2019) Avian vulnerability to wind farm collision through the year: insights from lesser black-backed gulls (Larus fuscus) tracked from multiple breeding colonies. J Appl Ecol 56:2410–2422. https://doi.org/10.1111/1365-2664.13488

Thaxter CB, Green RMW, Collier MP, Taylor RC, Middelveld RP, Scragg ES, Wright LJ, Cook ASCP, Fijn RC (2024) Behavioural responses of Sandwich terns following the construction of offshore wind farms. Mar Biol. https://doi.org/10.1007/s00227-023-04353-7

Tjørnløv RS, Skov H, Armitage M, Barker M, Jørgensen JB, Mortensen LO, Thomas K, Uhrenholdt T (2023) Resolving key uncertainties of seabird flight and avoidance behaviours at offshore wind farms. Policy Commons.

Trinder M, Furness RW (2023) MFRAG - ornithology - beatrice Offshore Windfarm - Post-construction Ornithological Monitoring Report (Year 2). MacArthur Green

van Bemmelen RSA, Leemans JJ, Collier MP, Green RMW, Middelveld RP, Thaxter CB, Fijn RC (2024) Avoidance of offshore wind farms by Sandwich terns increases with turbine density. Ornithological Appl. https://doi.org/10.1093/ornithapp/duad055

Vanermen N, Onkelinx T, Verschelde P, Van de Courtens W, Verstraete H, Stienen EWM (2015a) Assessing seabird displacement at offshore wind farms: power ranges of a monitoring and data handling protocol. Hydrobiologia 756:155–167. https://doi.org/10.1007/s10750-014-2156-2

Vanermen N, Onkelinx T, Van de Courtens W, Verstraete H, Stienen EWM (2015b) Seabird avoidance and attraction at an offshore wind farm in the Belgian part of the North Sea. Hydrobiologia 756:51–61. https://doi.org/10.1007/s10750-014-2088-x

Vanermen N, Courtens W, Daelemans R, Lens L, Van de Müller W, Verstraete H, Stienen EWM (2020) Attracted to the outside: a meso-scale response pattern of lesser black-backed gulls at an offshore wind farm revealed by GPS telemetry. ICES J Mar Sci 77:701–710. https://doi.org/10.1093/icesjms/fsz199

Wakefield ED, Owen E, Baer J, Carroll MJ, Daunt F, Dodd SG, Green JA, Guilford T, Mavor RA, Miller PI, Newell MA, Newton SF, Robertson GS, Shoji A, Soanes LM, Votier SC, Wanless S, Bolton M (2017) Breeding density, fine-scale tracking, and large-scale modeling reveal the regional distribution of four seabird species. Ecol Appl 27:2074–2091. https://doi.org/10.1002/eap.1591

Warwick-Evans V, Atkinson PW, Walkington I, Green JA (2018) Predicting the impacts of wind farms on seabirds: an individual-based model. J Appl Ecol 55:503–515. https://doi.org/10.1111/1365-2664.12996