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Investigating avoidance and attraction responses in lesser black-backed gulls *Larus fuscus* to offshore wind farms

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ABSTRACT: Movements through or use of offshore wind farms by seabirds while commuting or foraging may increase the potential for collision with turbine blades. Collision risk models provide a method for estimating potential impacts of wind farms on seabird populations, but are sensitive to input parameters, including avoidance rates (ARs). Refining understanding of avoidance through the use of high-resolution empirical movement data has the potential to inform assessments of the collision impacts of offshore wind farms on seabird populations. We assessed the movements of GPS-tagged lesser black-backed gulls *Larus fuscus* from a breeding colony in northwest England to estimate the species' AR and avoidance/attraction index (AAI) to nearby offshore wind farms. To investigate both macro- (0–4 km) and meso-scale (0–200 m) responses to wind turbines, we used calculations of AR and AAI based on simulated vs. observed tracks. We found that birds exhibited an AR of −0.15 (95% CI: −0.44 to 0.06), indicating a degree of attraction within 4 km of the wind farms. However, AAI values varied with distance from wind farm boundaries, with a degree of avoidance displayed between 3 and 4 km, which weakened as distance bands approach wind farm boundaries. Meso-scale avoidance/attraction was assessed with regard to the nearest individual turbine, and flight height relative to the rotor height range (RHR) of the nearest turbine. We found attraction increased below the RHR at distances <70 m, while avoidance increased within the RHR at distances approaching the turbine. We explore how high-resolution tracking data can be used to improve our knowledge of *L. fuscus* avoidance/attraction behaviour to established wind farms, and so inform assessments of collision impacts.

KEY WORDS: Anthropogenic impact · Collision risks · Seabirds · Tracking · Wind turbines

1. INTRODUCTION

The UK government has pledged to reduce greenhouse gas emissions to net zero by 2050 (Department for Business, Energy & Industrial Strategy 2019). This goal will be achieved in part by producing 40 GW of electricity by 2030 through offshore wind (Department for Business, Energy & Industrial Strategy 2020a). Harnessing energy resource alternatives to fossil fuels is vital to curb CO_2 emissions, and decelerate

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climate warming (Carbon Brief 2015). As of March 2020, a total of 2040 offshore wind turbines were operational within the UK, with 925 under construction, and 843 awaiting construction (Department for Business, Energy & Industrial Strategy 2020b). Additionally, large areas of the coastal waters of England, Scotland, and Wales have been proposed for further development of offshore wind turbines (Crown Estate Scotland 2019, Crown Estate 2020, Scottish Government 2020).

Wind farms may affect seabird populations through several pathways, including: collision (Musters et al. 1996, Desholm & Kahlert 2005, Newton & Little 2009); displacement (Welcker & Nehls 2016, MMO 2018); barriers to movement (Desholm & Kahlert 2005, Masden et al. 2010); and habitat alterations (Inger et al. 2009, Andersson & Öhman 2010). Wind farms may also provide de facto marine protected areas by excluding fisheries (Halouani et al. 2020), and seabird attraction to offshore turbines may arise from potential foraging opportunities created by turbines and other infrastructure acting as epifaunal reefs, fish aggregation devices (Inger et al. 2009, Wilson & Elliott 2009), and/or platforms for resting (Savidge et al. 2014, Dierschke et al. 2016). However, the extent to which seabird collision risk is influenced by the attraction to turbines is currently poorly understood.

Collision risk models (CRMs) (e.g. Band 2012, Kleyheeg-Hartman et al. 2018) are commonly used to estimate the mortality posed by wind farm turbines, and so inform the environmental impact assessment process for proposed developments. CRMs incorporate turbine parameters and aspects of bird flight characteristics and morphology. These models also include a parameter relating to the proportion of birds which actively avoid collision, termed the avoidance rate (AR) (Band 2012). The value assigned to the AR can provide a degree of uncertainty around mortality estimates produced by CRMs (Chamberlain et al. 2006, Cook et al. 2012). Calculation of ARs, as used in CRMs, can be carried out through the comparison of post-construction mortality rates to those predicted pre-construction (Band 2012, Cook et al. 2014, 2018, Cook 2021); however, collection of at-sea mortality data is difficult (Newton & Little 2009). Avoidance responses may be directly observed through a bird's behaviour and manoeuvrability in the presence of turbines (Thaxter et al. 2018) or by comparison of observed versus expected values of presence within defined areas around turbines or wind farm perimeters (Schaub et al. 2019). AR metrics calculated through this approach may represent attraction and avoidance as positive and negative values, respectively (Cook et al. 2014, Schaub et al. 2019). Behavioural responses to wind farms may be measured at hierarchical scales, including: macro-response, which considers attraction to, or displacement from, the entire wind farm on the scale of a few kilometres; meso-response, which occurs on sub-kilometre scales immediately outside or within the wind farm, and regards movement influenced by the presence of turbines; and micro-avoidance, which relates to horizontal and vertical avoidance of collision within a few metres of turbine blades (Cook et al. 2014, May 2015). The total behavioural response to a wind farm can then be calculated by combining estimates of behaviour at macro-, meso-, and micro- scales (Cook et al. 2014, 2018, May 2015). Behavioural traits may cause the rates of avoidance or attraction to vary between species, or individuals, and with distance to the wind farm boundary (Petersen 2005). However, to date, there have been very few empirical studies which have quantified avoidance behaviour at offshore wind farms (Green et al. 2016, Skov et al. 2018a).

Potential impacts of wind farms can lead to development delays; e.g. concern about the potential collision risk to Sandwich terns *Thalasseus sandvicensis* has led to the refusal of planning consent in relation to one offshore wind farm in England (Broadbent & Nixon 2019). This decision was in part influenced by lack of certainty in ARs, which therefore reduced confidence in the CRMs used in the assessment process. This highlights a current lack of data on bird behaviour, which may lead to CRMs relying on generalized assumptions (Cook et al. 2014, 2018, Green et al. 2016). CRMs are sensitive to estimates of a number of behavioural parameters (Chamberlain et al. 2006, Masden & Cook 2016) and there remains uncertainty around these key parameters, which may vary according to internal (e.g. behavioural states) or external factors (e.g. meteorological and diurnal conditions), as outlined in Masden & Cook (2016). Therefore, increased empirical knowledge of these behaviours may increase confidence in model outputs (Green et al. 2016). Knowledge regarding seabird behaviour may be improved through technological advances in telemetry (Thaxter et al. 2015, Garthe et al. 2017), laser range-finders (Cole et al. 2019), radar (Desholm et al. 2006, Fijn et al. 2015), and automated radar-tracking combined with cameras (Skov et al. 2018b), which may provide more accurate observations of flight height, movement patterns, and avoidance/attraction behaviour, to address these areas of uncertainty.

Telemetry, such as high-resolution GPS tracking, can be used to link seabird populations to development areas, but also provide improved information on the movement and foraging ecology of species of high vulnerability to collision with wind turbine blades. One such species is the lesser black-backed gull *Larus fuscus*, which is Amber-listed under the UK Birds of Conservation Concern (Eaton et al. 2015) and regarded as a species with comparatively high vulnerability to collisions with wind farms (Furness et al. 2013, Spelt et al. 2019, Thaxter et al. 2019). The species' vulnerability to potential collision mortality from wind farms has been highlighted as having the potential to impact Special Protection Area (SPA) populations of lesser black-backed gulls (RSPB 2021). Lesser black-backed gulls can be attracted to turbine arrays for roosting opportunities on turbine pylons (Vanermen et al. 2020). Roosting or foraging opportunities may also influence macro-responses. However, previous reviews of the responses of gull species, including lesser black-backed gulls, to offshore wind farms have reported variable patterns of behaviour, including avoidance, attraction, or an absence of an apparent macro-response (Cook et al. 2014, Dierschke et al. 2016, Welcker & Nehls 2016, Vanermen et al. 2020). Interactions with offshore wind farms by this species have also been recorded to vary between individuals, and temporally between years and within seasons (Thaxter et al. 2015). While Cook et al. (2014), reviewing estimates of avoidance derived from both mortality rates and behavioural observations, found varying macro-scale responses of avoidance and attraction in lesser black-backed gulls to offshore wind farms, within-wind farm (i.e. meso + micro) ARs could not reliably be quantified due to limited data. However, recent assessment of the 3-dimensional vertical and horizontal movements of lesser-black-backed gulls using GPS tracking data has indicated a meso-avoidance signal at wind farms in northwest England (Thaxter et al. 2018), with this result being supported by further observations in the North Sea at other wind farms (Vanermen et al. 2020). Nevertheless, it is evident that when referring to these scales, variation in response distances may further exist within them. To date, few studies have examined the macro-response distances of lesser black-backed gulls to offshore wind farms (Welcker & Nehls 2016, Vanermen et al. 2020). Therefore, a knowledge gap exists with respect to both the extent of meso- and macro-scale avoidance and attraction responses, and response distances.

To enhance the current knowledge of the avoidance/attraction behaviour exhibited by lesser black-backed gulls to offshore wind farms, we investigated the movements of GPS-tagged birds from a breeding colony in the Morecambe Bay and Duddon Estuary SPA. We adapt an approach from Schaub et al. (2019), which calculated the avoidance/attraction index (AAI) in a terrestrial raptor, and further modified the method to be applicable for central-place foraging individuals. By comparing the degree of divergence or alignment between observed locations to simulated/random locations, we aimed to assess variation in avoidance/attraction to nearby offshore wind farms across macro- and meso-scales, while also deriving an estimate of macro-avoidance. Improved knowledge of avoidance and attraction behaviour exhibited at distance or in close proximity to wind turbines is essential to address knowledge gaps in lesser black-backed gull movement ecology and inform CRM estimates.

2. MATERIALS AND METHODS

2.1. Study area and tag deployment

Fieldwork was carried out at the South Walney National Nature Reserve, Cumbria, England (54° 2′ N, 3° 10′ W), within the Morecambe Bay and Duddon Estuary SPA. A total of 49 tags, 44 University of Amsterdam UvA-BiTS 5CDLe GPS tags and 5 Movetech Flyway18 GPS-GSM tags, were deployed on breeding adult lesser black-backed gulls in 2014 and 2016. Birds were caught on the nest, using a walk-in wire mesh trap and, to enable long-term deployment (3–5 yr), GPS tags were attached using wing-loop harnesses made from Teflon ribbon, which have previously been shown to have no measurable impacts on breeding success or over-winter survival (Thaxter et al. 2014, 2016). Deployment of tags was undertaken under licence to the independent Special Methods Technical Panel under the UK Ringing Scheme. All tag and attachment combinations were below 3% of individual body mass.

2.2. Wind farm parameters

The region of the Irish Sea adjacent to South Walney contains 5 offshore wind farms, including Barrow (n = 30 turbines; in an area of 7 km^2; operational 2006), Ormonde (n = 30; 7 km^2; operational 2012), Walney (n = 102; 53 km^2; operational 2012), Walney Extension (n = 20; 14 km^2; operational 2018), and West of Duddon Sands (n = 109; 61 km^2; operational 2014). Wind farm boundaries were defined by forming an outline along the outermost turbine locations.

Collectively, therefore, 291 turbines were considered, covering an area of 161 km^2 (Fig. 1). Distinct rotor height range (RHR) and turbine height were considered for each defined wind farm (Table S1 in the Supplement at www.int-res.com/articles/suppl/m686p187_supp.pdf). Rotors varied from 45 to 77 m in radius (Table S1).

2.3. Data processing

Data were collected between 2014 and 2019 and retrieved from 48 of the 49 tags deployed. Data from the breeding season (May–July) during the nestling and fledgling periods were selected. UvA and Movetech tags collected date-time-stamped GPS locations throughout the breeding season, every 5 min. However, UvA also collected bursts of higher-resolution data at a sampling interval of 10–60 s if the battery had full charge, with sampling intervals reduced to 30 min when birds were at the colony. The GPS data were filtered to investigate avoidance and attraction at both macro- (fix frequency: <5 min) and meso- (fix frequency: <20 s) scales. Selected fixes were intended to represent only the offshore movements undertaken by gulls, and the average trajectories from the colony. To filter GPS locations by these criteria, observed points were selected using the distance and angle from the colony of each GPS point as follows: using the 'trip' grouping (an identifier allocated to each sequence of points exiting and re-entering a 200 m boundary around the colony), trips where the maximum distance from colony overlapped with the sea were selected on the assumption that furthest point was the final intended destination before returning to the colony. In addition, the angle of the location representing the furthest distance per trip in relation to the colony was ascertained. The distribution of these angles was then calculated. Trips falling within the interquartile range of this distribution were then selected to reflect potential direction of journeys made by birds from the colony.

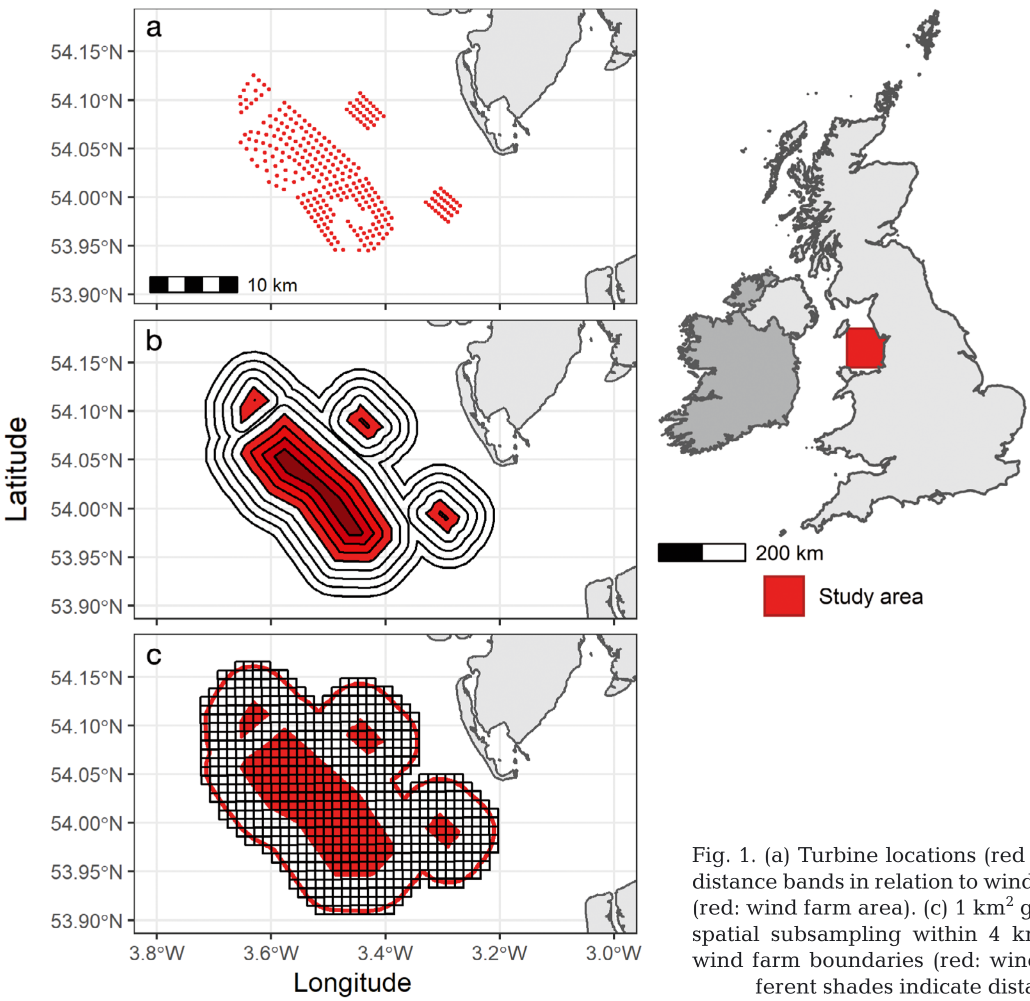

Fig. 1. (a) Turbine locations (red points). (b) 1 km distance bands in relation to wind farm perimeters (red: wind farm area). (c) 1 km^2 grid cells used for spatial subsampling within 4 km buffer around wind farm boundaries (red: wind farm area; different shades indicate distance band)

Use of the interquartile range of trajectories from individual trips where the maximum distances from the colony was reached while offshore, rather than use the full distribution of tracks, was intended to reflect trips that were truly marine in destination. While use of interquartile range was subjective, it is underpinned by the rationale to exclude trips which hugged the shore and subsequently went inland, potentially with no intention of travelling offshore and exhibiting no response to the offshore wind farms.

2.4. Analysis

Avoidance behaviour was assessed through comparison of simulated and observed tracks in order to examine if observed responses to wind farms and turbines exhibited by birds were a consequence of chance alone. Analyses were conducted on data pooled across years, because within-year sample sizes proved insufficient for robust year-specific analyses. To create simulated tracks, the observed tracks were altered in their orientation by rotating the observed trajectories from the colony by a random angle derived from a normal distribution based on observed angles within the original trip trajectory (Fig. 2). A total of 300 simulated tracks were produced for each observed trip. This method was modified from Schaub et al. (2019), however with differences in the method of rotation and the scales of analysis. Similar to Schaub et al. (2019), we opted to maintain the internal structure of the original tracks when producing random simulations (Richard et al. 2013). In contrast to Schaub et al. (2019), who randomly rotated tracks around a centroid of the track itself when within a wind farm, we rotated entire 'trips' (see Section 2.3) around a centroid based on the location of a central place, in this instance an individual's breeding colony. Our analysis rotated entire trips from a central place of departure and return to examine a birds avoidance/attraction response when outside of a wind farm as well as when within. All analysis was carried out using R (Version 4.1.1) (R Development Core Team 2021), with data filtering facilitated through the R package BTOTrackingTools (Version 1.0) (Thaxter 2020).

2.4.1. AAI and AR

AAI (Schaub et al. 2019) was calculated within defined distance bands from the wind farm and from individual turbines in order to investigate macro- and meso-scale responses respectively (and explained further in Sections 2.4.2 and 2.4.3). This was calculated for each distance band by subtracting the expected proportion of location fixes (produced by the simulated tracks) from the observed proportion (corresponding to the original tracks), and dividing by the average between the observed and mean expected proportion (see Eq. 1). Positive values of AAI indicate attraction, and negative values indicate avoidance (Schaub et al. 2019). We assessed the statistical significance of AAI values based on 95 % confidence intervals (CIs) based on quantiles of the simulations. When the 95 % interval did not contain 0, the result was deemed statistically significant.

$$\mathrm{AAI} = (\mathrm{Prop_{obs}} - \mathrm{Prop_{exp}}) \div \overline{\mathrm{Prop_{obs/exp}}} \qquad (1)$$

A macro-AR was calculated for distances varying between 1 and 6 km from the wind farm boundary. Using the method described in Schaub et al. (2019), the mean expected proportion of location fixes in the area minus the observed proportion is divided by the mean of expected proportion (our Eq. 2). As in Schaub et al. (2019), negative values of AR indicate attraction, and positive values indicated avoidance.

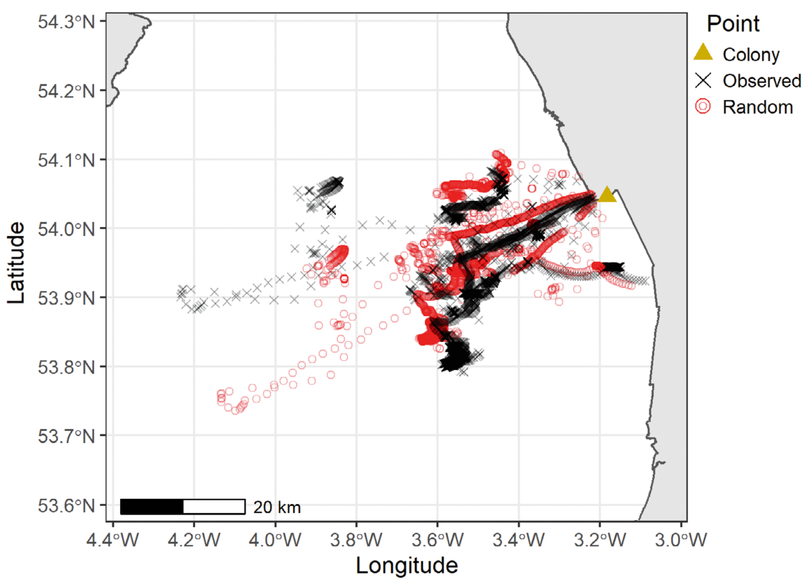

Fig. 2. Example of observed GPS fixes from *Larus fuscus* foraging trips (black), and corresponding randomized trajectories (red), with altered trajectory departure angles from the colony

Statistical significance of AR values was assessed using 95% CIs based on quantiles of the 300 simulations. For intervals which did not contain 0, the result was deemed to be statistically significant.

$$AR = (\overline{Prop_{exp}} - Prop_{obs}) \div \overline{Prop_{exp}} \qquad (2)$$

2.4.2. Macro-response

Macro-avoidance/attraction was calculated for a maximum of 8 × 1 km distance bands from the wind farm boundaries, including up to 4 km inside and outside of the boundary (Fig. 1b). The value of 4 km from wind farm boundaries was chosen based on current industry standards (Petersen 2005). Within the 4 km boundary, random and observed GPS fixes were grouped into 1 km^2 grid cells (Fig. 1c). Cells which overlapped with distance bands were allocated to the band nearest the centroid of the cell. AAI values were calculated by randomly selecting 21 contiguous grid cells per each distance band (21 grid cells were equivalent to the area of the smallest distance band [−3 to −4 km, within wind farm]); this was to ensure that the spatial structure is comparable for each distance band and that the bands with a greater number of grids cells did not have a greater weighting in the analyses. To maintain a degree of spatial similarity between the selected cells, nearest-neighbour analysis was used in the selection of the cells within each distance band, by selecting 1 random grid cell within each distance band, and subsequently selecting the nearest 20 grid cells around the randomly selected grid cell. Random selection of differing combinations of grid cells was carried out 300 times. Each selection of random grid cells sampled all simulated tracks combined. An overall mean AAI value was calculated from AAI values from the 300 iterations of random sampling of 21 grid cells.

2.4.3. Meso-response

To investigate finer-scale meso-responses, GPS fixes of a higher resolution with sampling intervals <20 s were used. The distance of each point from the nearest turbine was calculated (Fig. 1a). Using GPS-derived altitude, fixes were allocated as 'above', 'within', or 'below' RHR, or 'loafing' (Table S1). Trajectory speeds, calculated using time and distance between fixes, were used to characterize loafing points, defined as points with trajectory speeds <4 km h^{-1}, a value based on perceived minimum flight speeds (Shamoun-Baranes et al. 2011, Thaxter et al. 2018). Points 200 m from the nearest turbines were selected, and grouped into 10 m distance bands from turbines. AAI values were calculated separately for each distance band.

2.4.4. Individual sensitivity analysis

To investigate the potential for individual bias in the calculation of AAI, we performed a jack-knife analysis of macro- and meso-scale responses by systematically excluding each individual from assessments. The degree of similarity or variation between each modified assessment was investigated through visual analysis of plots depicting trends in AAI values across macro-/meso-distance scales.

3. RESULTS

3.1. Filtered data

Following the filtering process, 23 out of 48 individuals provided data applicable for investigating macro-responses to wind farms, and 18 individuals provided data suitable for investigating meso-responses (Fig. 3). Remaining data covered all years, excluding 2019. For the datasets suitable to investigate macro- and meso-scale responses, the mean ± SD offshore trip distances were 20.82 ± 11.94 km and 20.24 ± 12.17 km respectively, and mean ± SD trajectories from the colony were respectively 63.28 ± 30.23° and 51.42 ± 33.24°.

3.2. Macro-response

The AR within 4 km of the wind farm boundaries was found to be −0.15 (95% CI: −0.44 to 0.06), the minus indicating a slight degree of attraction. Values of AR increased with the reduction of distance bands outside of the wind farm examined, from −0.19 (95% CI: −0.53 to 0.05) at 6 km to −0.03 (95% CI: −0.19 to 0.08) at 1 km (Table 1). While this may suggest a reduction in attraction, it is more likely an artefact of the changing relative proportions of total observed/simulated fixes versus fixes within the wind farm. There was also a propensity for bird tracks to primarily overlap with the southeast areas of the study area (Figs. 3a & 4).

AAI values at the majority of distance bands examined indicated no significant avoidance or attraction based on 95% CI, as the intervals contained 0. AAI

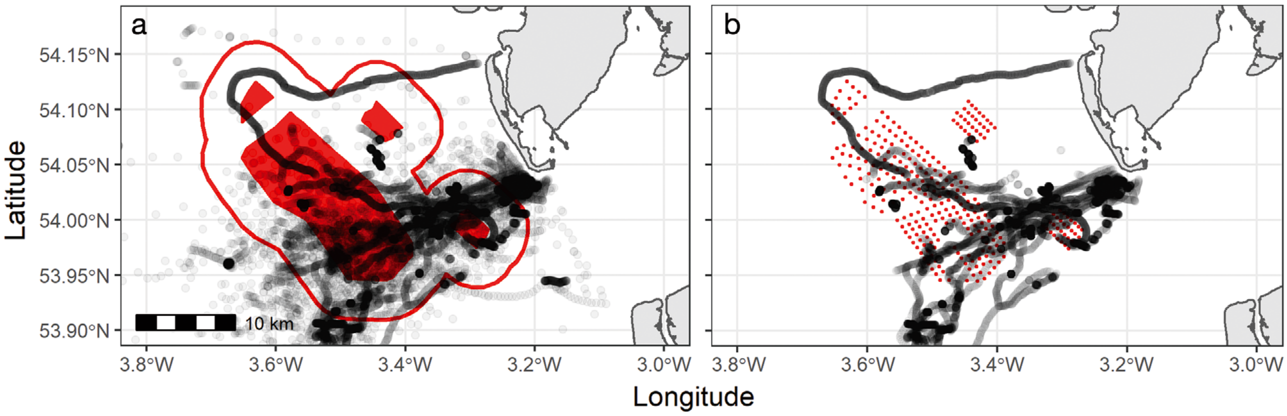

Fig. 3. Available *Larus fuscus* GPS fixes: (a) with a sampling interval <5 min (black) in relation to wind farm perimeters and associated 4 km buffer (red); (b) with a sampling interval <20 s (black) in relation to wind turbines (red)

values were found to be lowest in the 4 km distance band outside the wind farm perimeter (mean AAI: −0.52; 95% CI: −1.12 to −0.03), displaying significant avoidance. Significant attraction was indicated −1 to −2 km inside the wind farm (mean AAI: 0.38; 95% CI: 0.19 to 0.58) (Fig. 4, Table 2). Inclination towards either avoidance or attraction was reduced at distances closer to the wind farm perimeters (between 0 and 3 km). Visual analysis suggests little sensitivity of macro-scale AAI values to individual variation (Fig. S1).

3.3. Meso-response

Fig. 3b displays the tracks considered in the assessment of meso-scale responses (those with a time step <20 s) and Fig. 5 shows all fixes within the boundaries of the wind farms, relative to distance from nearest turbine and altitude. Through visual inspection of Fig. 6, it is apparent there was an increase in avoidance behaviour within the RHR, with AAI values reducing to −2 in distances nearer than 60 m to turbines (Table 3). By contrast, below the RHR, there was an apparent increase in attraction at distances from 40 to 10 m. There were no observed points above the RHR closer to turbines than 60 m (Table 3), but no apparent trend in distances >60 m from the turbine. Visual analysis of Fig. S2 suggests little sensitivity of meso-scale AAI values to individual variation.

4. DISCUSSION

4.1. Avoidance behaviour

Through the comparison of observed vs. expected tracks, we estimated an AR which indicated that lesser black-backed gulls from the study colony

Table 1. *Larus fuscus* avoidance rate (AR) values across 1 km bands from wind farm boundary. 95% CIs based on quantiles of simulations

Distance band (km)	AR	SD	95% CI Lower	95% CI Upper
1	−0.03	0.08	−0.19	0.08
2	−0.05	0.13	−0.27	0.13
3	−0.08	0.14	−0.34	0.09
4	−0.15	0.16	−0.44	0.06
5	−0.17	0.18	−0.50	0.06
6	−0.19	0.19	−0.53	0.05

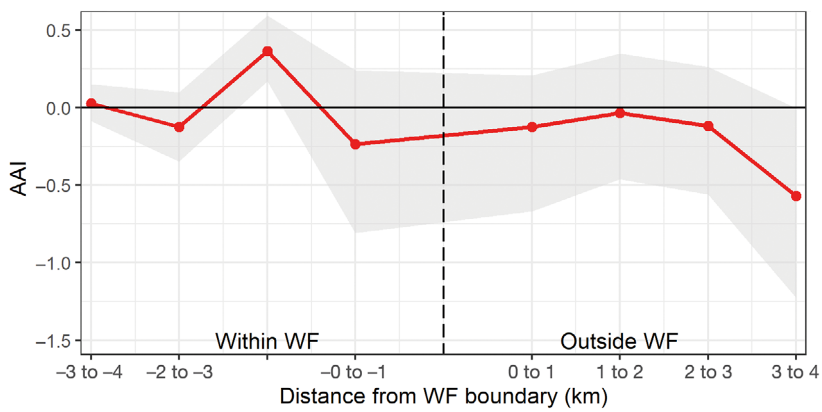

Fig. 4. *Larus fuscus* mean avoidance/attraction index (AAI) values for each 1 km band from wind farm (WF) boundaries (dashed line). Grey shading: 95% CI

Table 2. *Larus fuscus* mean avoidance/attraction index (AAI) values across 1 km bands from wind farm boundaries. 95% CIs based on quantiles of simulations. Also shown are the number of observed points, and mean number of expected points per distance band (taken from 300 random iterations)

In relation to wind farm boundaries	Distance (km)	n (observed)	n (expected)	Proportion (observed)	Proportion (expected)	Mean AAI	SD	95% CI Lower	95% CI Upper
Outside	3–4	309.67	363.90	0.07	0.10	−0.52	0.36	−1.12	−0.03
	2–3	493.81	469.70	0.11	0.12	−0.16	0.32	−0.65	0.32
	1–2	626.63	524.28	0.14	0.14	−0.07	0.30	−0.59	0.35
	0–1	561.82	481.22	0.12	0.13	−0.11	0.26	−0.62	0.18
Inside	0 to −1	520.06	475.00	0.12	0.13	−0.24	0.34	−0.80	0.19
	−1 to −2	815.13	478.13	0.19	0.13	0.38	0.12	0.19	0.58
	−2 to −3	549.03	497.15	0.13	0.14	−0.09	0.15	−0.33	0.15
	−3 to −4	495.40	400.93	0.12	0.11	0.05	0.08	−0.06	0.18

exhibited an overall degree of attraction to wind farms within a 4 km boundary. However, we found that examining the AR for a total area surrounding the wind farm masked variation in responses at differing distances outside and within the wind farm. Comparing avoidance/attraction behaviour within various distances bands within the 4 km boundary, we found evidence of significant macro-avoidance at a distance of 3–4 km outside the wind farm, and attraction −1 to −2 km within the wind farm. However, the apparent macro-response was weak at other distance bands outside the wind farm and indicated that the majority of birds did not alter flight routes to avoid wind farms. Rather, birds may enter wind farms and avoid turbines on a meso-scale, as observed in lesser black-backed gulls at a wind farm in the southern North Sea, off the Belgian coast (Vanermen et al. 2020). While inside the boundaries of wind farms, birds may exhibit meso-scale responses of avoidance or attraction by remaining outside the rotor swept area of turbines, or altering their flight height (our Figs. 5 & 6) (Thaxter et al. 2018). Turbine blades exist on a vertical plane, and wind direction will alter their orientation. Blade orientation may have a strong influence on micro-scale avoidance behaviour (Skov et al. 2018b); however, information on the orientation of turbine blades was unavailable for this study, and thus we considered the rotor swept area as a sphere.

The results show that the detection and estimation of macro-response are sensitive to the distance considered around a wind farm. Values of AR were found to decrease when the total area examined outside of the wind farm increased. This was attributed to proportions of the total observed/simulated fixes versus fixes within the wind farm becoming skewed as the total area decreased, while the wind farm area remained static. Careful consideration is therefore needed in selecting an appropriate area surrounding a wind farm to calculate macro-response. This was accounted for when examining AAI by calculating values for each distance band sep-

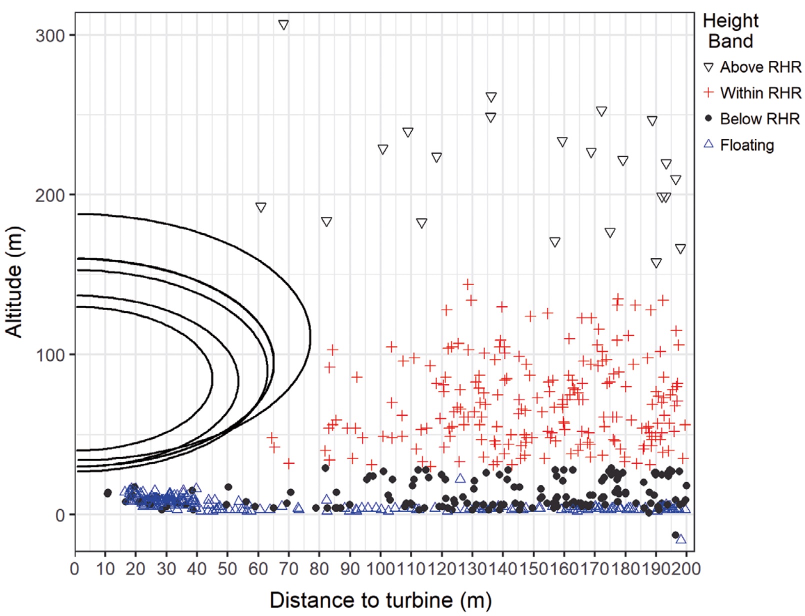

Fig. 5. Observed *Larus fuscus* GPS points within boundaries of wind farms plotted in relation to distance from nearest turbine and altitude. Black curves: turbine rotor-swept area of the 6 wind farms in this study (2 are of identical height and blade radius). RHR: rotor height range

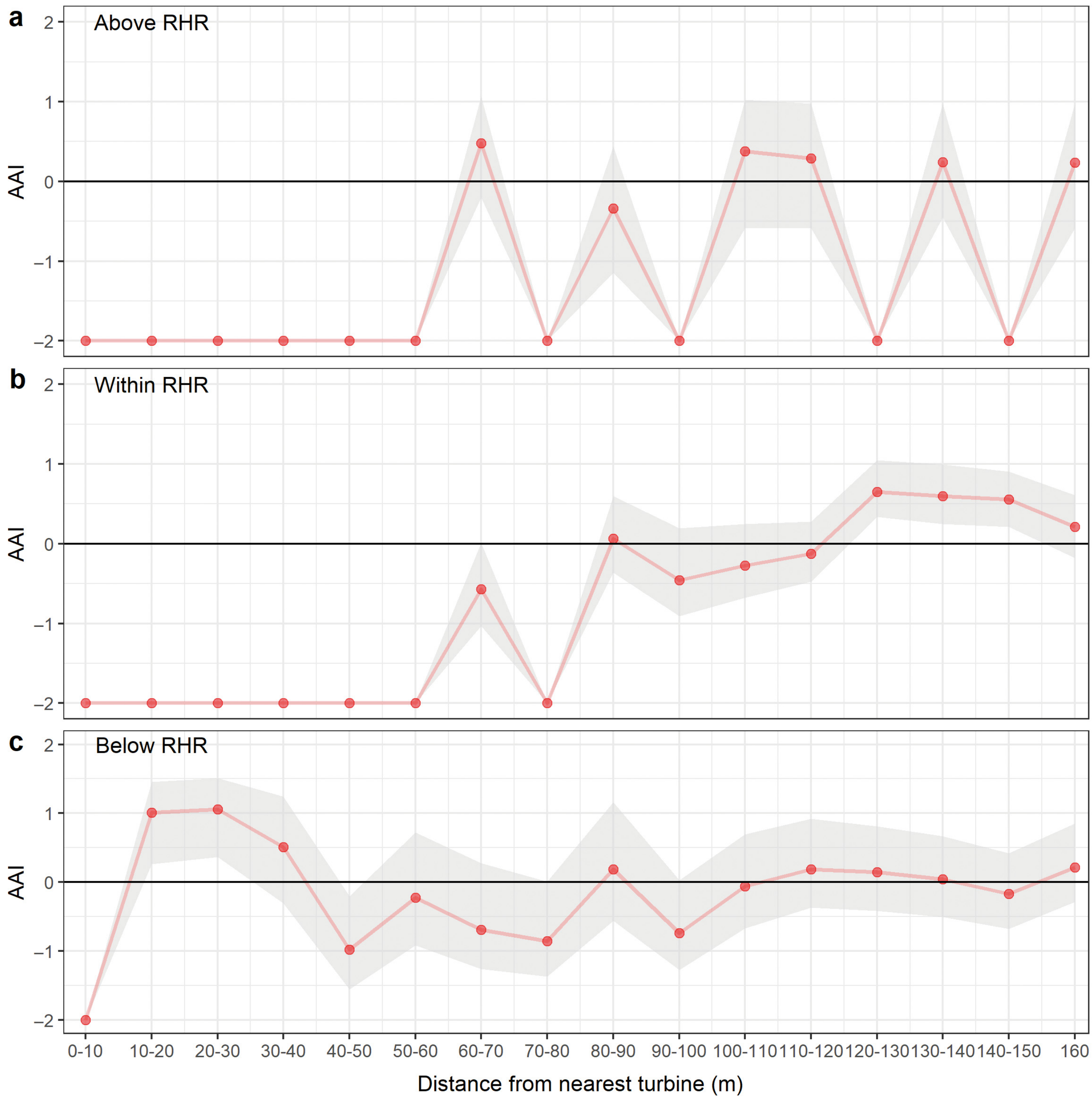

Fig. 6. *Larus fuscus* mean avoidance/attraction index (AAI) values calculated for 10 m distance bands from nearest turbine, for points (a) above, (b) within, and (c) below rotor height range (RHR) of nearest turbine. Red points: mean AAI values; grey shading: 95% CI. AAI values calculated for each random iteration (n = 300). Positive values relate to attraction, and negative values relate to avoidance

arately, and using random sampling to account for spatial bias between bands.

Our work focussed on the breeding season, when movements of lesser black-backed gulls are primarily dedicated to central-place commuting flights for foraging. We did not take into account temporal variables such as time of year and variation between years. Over the course of a breeding season, birds may alter the extent they are at sea, and interactions with wind farms have been shown to vary temporally (Thaxter et al. 2015). To some extent, the attraction of an individual into a wind farm may be underpinned by foraging demands linked to breeding stages, or prey availability. This temporal variation in avoidance/attraction should be taken into account within CRMs, as values of ARs are unlikely to be uniform

Table 3. *Larus fuscus* mean avoidance/attraction index (AAI) values based on 10 m distance bands from nearest turbine and height bands based on rotor height range (RHR) of nearest turbine. 95% CIs based on quantiles of simulations. Also shown are the number of observed points, and mean number of expected points per random iteration (n = 300). (–) SD and 95% CI not applicable

In relation to RHR	Distance (m)	n (observed)	n (expected)	Proportion (observed)	Proportion (expected)	Mean AAI	SD	95% CI Upper	95% CI Lower
Above	0–10	0	1	0	0.1	−2.00	–	–	–
	10–20	0	1	0	0.09	−2.00	–	–	–
	20–30	0	1.06	0	0.09	−2.00	–	–	–
	30–40	0	1.21	0	0.11	−2.00	–	–	–
	40–50	0	1.24	0	0.12	−2.00	–	–	–
	50–60	0	1.29	0	0.13	−2.00	–	–	–
	60–70	2	1.4	0.18	0.12	0.48	0.40	1.06	−0.20
	70–80	0	1.35	0	0.12	−2.00	–	–	–
	80–90	1	1.54	0.09	0.15	−0.34	0.46	0.44	−1.14
	90–100	0	1.43	0	0.13	−2.00	–	–	–
	100–110	2	1.48	0.18	0.14	0.38	0.49	1.02	−0.59
	110–120	2	1.56	0.18	0.15	0.29	0.49	0.98	−0.59
	120–130	0	1.64	0	0.15	−2.00	–	–	–
	130–140	2	1.74	0.18	0.16	0.24	0.47	0.98	−0.45
	140–150	0	1.72	0	0.16	−2.00	–	–	–
Within	0–10	0	1.41	0	0.01	−2.00	–	–	–
	10–20	0	2.34	0	0.01	−2.00	–	–	–
	20–30	0	3.56	0	0.02	−2.00	–	–	–
	30–40	0	4.73	0	0.03	−2.00	–	–	–
	40–50	0	5.72	0	0.03	−2.00	–	–	–
	50–60	0	6.82	0	0.04	−2.00	–	–	–
	60–70	3	8.44	0.03	0.05	−0.57	0.34	0.01	−1.03
	70–80	0	10.11	0	0.06	−2.00	–	–	–
	80–90	8	11.29	0.07	0.07	0.06	0.30	0.59	−0.36
	90–100	5	12.18	0.04	0.07	−0.46	0.32	0.20	−0.91
	100–110	7	13.96	0.06	0.08	−0.27	0.30	0.25	−0.68
	110–120	9	15.22	0.08	0.09	−0.13	0.24	0.28	−0.47
	120–130	22	16.53	0.19	0.1	0.65	0.22	1.05	0.34
	130–140	22	17.42	0.19	0.1	0.60	0.23	1.00	0.25
	140–150	23	19.01	0.2	0.11	0.56	0.22	0.90	0.21
Below	0–10	0	1.17	0	0.02	−2.00	–	–	–
	10–20	6	1.5	0.06	0.02	1.01	0.37	1.45	0.26
	20–30	8	1.88	0.08	0.03	1.06	0.37	1.51	0.36
	30–40	5	2.37	0.05	0.03	0.51	0.49	1.24	−0.31
	40–50	1	2.68	0.01	0.04	−0.98	0.42	−0.20	−1.55
	50–60	3	3.18	0.03	0.04	−0.23	0.50	0.72	−0.92
	60–70	2	3.45	0.02	0.05	−0.69	0.47	0.27	−1.26
	70–80	2	4.16	0.02	0.06	−0.85	0.41	0.01	−1.36
	80–90	7	4.55	0.07	0.07	0.19	0.50	1.16	−0.56
	90–100	3	5.36	0.03	0.08	−0.74	0.41	0.03	−1.27
	100–110	7	5.8	0.07	0.08	−0.06	0.43	0.70	−0.67
	110–120	10	6.32	0.1	0.09	0.19	0.40	0.92	−0.37
	120–130	10	6.46	0.1	0.1	0.15	0.38	0.81	−0.41
	130–140	10	7.27	0.1	0.11	0.04	0.39	0.67	−0.51
	140–150	9	7.98	0.09	0.12	−0.17	0.35	0.42	−0.68

year-round and between years. Similarly, the extent of offshore foraging may vary between colonies, dependent on available food resources and colony size (O'Hanlon & Nager 2018). Placement of the wind farm with respect to foraging areas may dictate the extent of overlap, and the behaviours a species will exhibit while within the wind farm. It is apparent in the case of lesser black-backed gulls that macro-response avoidance to wind farms is slight, and that birds primarily appear to exhibit avoidance on a meso-scale, i.e. within tens of metres of the turbines. The weak attraction to wind farms as exhibited by GPS tracking complement findings based on boat-, platform-, and aerial survey techniques (Dierschke et al. 2016). For this study site, we showed that breeding lesser black-backed gulls changed from exhibiting macro-avoidance at distances >3 km from the wind farm boundary to showing no significant response at closer distances to wind farms. A decision to avoid or enter a wind farm to commute or forage may be made at threshold distance from the wind farm boundary, and lead to a reduction in displacement at decreasing distances from the wind farm. In comparison to other seabirds, the energetic cost of macro-scale displacement from wind farms to lesser black-backed gulls is potentially insignificant; therefore other factors may be contributing to the decision to avoid or enter the wind farm (Masden et al. 2010). Vanermen et al. (2020), studying responses of lesser black-backed gulls to wind farms on the Belgian North Sea coast, similarly reported that birds displayed a degree of macro-avoidance at distances further (>2 km) from the wind farm, while also being attracted to the wind farm edge to roost. The ability of lesser black-backed gulls to avoid turbines on a meso-scale may reduce the exhibition of macro-scale responses to wind farms if the benefit of entering the wind farm to forage, roost, or commute outweighs the cost of turbine avoidance (Vanermen et al. 2015, Dierschke et al. 2016, Welcker & Nehls 2016, Thaxter et al. 2018). This response is in contrast to the high degree of avoidance exhibited by northern gannets *Morus bassanus* (Dierschke et al. 2016), a species which has been similarly observed through GPS tracking (Garthe et al. 2017, Mendel et al. 2019).

4.2. Vertical patterns in avoidance behaviour

We found that AAI values began to show greatest variation at distances approaching 60 m of a turbine, distances which may be within the rotor-swept area of blades of a radius 45–77 m within this study. With approaching distances to turbines, avoidance increased within the RHR, while attraction within the height band below the turbine blades increased. Potential loafing behaviour on the water's surface was increasingly prevalent at distances nearing the turbine base (Fig. 5). These results reflect those of Thaxter et al. (2018), who reported that birds were found within the RHR significantly less than expected by chance. Several factors may influence changes in species flight heights, including behaviour, wind conditions, time of year, and time of day (Corman & Garthe 2014, Ross-Smith et al. 2016). However, these changes in vertical space use while approaching turbines is suggestive of avoidance behaviour. Birds may be drawn towards the space below a turbine for the loafing or foraging opportunities available, but they appear to actively avoid altitudes covered by the turbine rotor sweep when doing so.

4.3. Suggestions for future research

Currently, CRMs use fairly limited models developed for use with survey data, reliant on potentially unrealistic biological assumptions (Masden et al. 2021). Methods trailed in this study are intended to explore how GPS tracking data can be used improve our knowledge of response behaviours in animals and inform assessments of collision risk. To date, few studies have examined the response distances of lesser black-backed gulls to wind farms, with the exception of Vanermen et al. (2020). Both of these studies indicate that macro-responses change with respect to distance from the wind farm and the biological causes, and consequences of this variation in relation to modelling avoidance should be considered in future assessments.

While GPS tracking may improve knowledge of bird response behaviour, the method itself contains error which should be accounted for. The accuracy of GPS fixes can be low (±10 m) (Corman & Garthe 2014), with the addition of error on the vertical plane being larger than horizontal error (Péron et al. 2020). This error in vertical and horizontal positions can be reduced by selecting GPS fixes of a higher resolution (<20 s) (Bouten et al. 2013, Corman & Garthe 2014, Thaxter et al. 2018). Here we selected the fixes of the highest available resolution (<20 s), to investigate meso-scale response incorporating flight height. However, other modelling techniques accounting for observation error separate from behavioural processes (Ross-Smith et al. 2016), or other means of measuring flight height, such as through barometric altimeter sensors, may aid in accounting for vertical error (Cleasby et al. 2015).

Whilst we were able to quantify bird responses to turbines at meso- and macro-scales, the data we present do not allow us to do this at a micro-scale. There are 3 reasons for this. Firstly, to detect micro-scale response, fix rates must be at a higher rate (<1 s) than recorded in this study (<20 s). Secondly, last-second micro-avoidance is likely to be a very rare event (May 2015, Cook et al. 2018); consequently, sample sizes obtainable using GPS data are likely to be insufficient to detect any effect; already our analysis had a limited sample size for investigating meso-scale behaviours within and above the RHR (Fig. 5). Thirdly, using telemetry data, behaviour must be inferred from the recorded tracks through techniques such as hidden Markov models (Dean et al. 2012, Browning et al. 2018). While the combination of GPS tracking with flight height (Cleasby et al. 2015, Thaxter et al. 2018) and depth recorders (Browning et al. 2018) can improve behavioural inferences, uncertainty remains due to the lack of direct observation. Laser-range finders combined with visual observation (Cole et al. 2019), or radar-controlled cameras (Skov et al. 2018b), allow for direct observations of meso- and micro-scale responses to turbines. This may allow the study of behaviours exhibited by birds that may leave them exposed or alert to turbines blades.

4.4. Summary

Through the use of simulated and observed tracks, this study found that there was a degree of attraction displayed by lesser black-backed gulls within 4 km of the wind farms situated offshore from the study colony. However, AAI analysis found there to be variation in avoidance and attraction across distance bands within this boundary, with a degree of avoidance being displayed 3–4 km from the boundary. Therefore, we highlight that ARs may vary spatially, and the boundary selected to investigate avoidance may influence the overall AR. The slight overall degree of attraction to wind farms displayed by lesser black-backed gulls may lead to a greater risk of collision, and highlights the importance of high-resolution information of meso- and micro-scale responses to turbines (Cook et al. 2014, 2018, Skov et al. 2018b, Thaxter et al. 2018). While we only considered offshore foraging birds, individual sensitivity analyses carried out here displays that the individuals largely reacted in a similar manner to the presence of wind farms and turbines. The methodology to calculate AR and AAI used in this study is primarily replicated from Schaub et al. (2019). However, Schaub et al. (2019) investigated avoidance behaviour displayed by a terrestrial raptor, and we have modified the method to be applicable to a central-place foraging seabird. At present, CRMs used in the marine environment make simplified assumptions about the movement and behaviour of seabirds at sea (Masden & Cook 2016). As a consequence, ARs for these models must incorporate both the behavioural aspects of avoidance behaviour, and any error associated with the simplification of these models. The results we present here account for the behavioural element, but not the model error element, meaning that, without further adjustment, they are not directly applicable to widely used CRMs such as the Band (2012) model. However, the results of this study and that of Schaub et al. (2019) are a step towards models based on more realistic assessments of bird behaviour. Therefore, while the indexes of ARs we consider can be used to better understand behaviour, they are not directly applicable to CRMs. Nevertheless, further understanding of behavioural responses to wind farms is valuable in informing assessments.

As the scale of offshore wind farm developments increases, there are significant concerns about the cumulative effects of collision at population scales (Brabant et al. 2015, Busch & Garthe 2016). There is significant uncertainty associated with these cumulative assessments of collision risk, driven by a lack of validation of CRMs and a lack of empirical data on seabird avoidance behaviour. Whilst the ARs we report here are not directly applicable to widely used CRMs, as they lack an element to account for model simplifications and errors (Band 2012), they do provide a valuable assessment of the likely scale of avoidance behaviour in lesser black-backed gulls. Key next steps are validation of existing CRMs so we can understand the relative contribution of behaviour and model error/simplifications to the ARs necessary for CRMs, and development of models that more accurately reflect bird behaviour in the marine environment.

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