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Bird Collision Avoidance: Empirical evidence and impact assessments

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Summary

In response to concerns about the risk of collision between seabirds and offshore wind farms, the Offshore Renewables Joint Industry Programme (ORJIP) funded a study to collect data on seabird collision and avoidance rates at an operational wind farm, referred to as the Bird Collision Avoidance (BCA) study. Over the course of this study, it became clear that the data collected in relation to avoidance behaviour, termed empirical avoidance rates, may not be directly comparable to the avoidance rates as presently used by collision risk models, such as the Band model. The aim of this work is to consider how best to use the data collected as part of the ORJIP BCA study in order to inform pre-construction assessments of collision risk at offshore wind farms.

Our analyses demonstrate how assumptions, both in relation to the model itself and, the data used in the model, can affect predicted collision rates. In particular, assumptions about seabird flight height and speed can have important implications for predicted collision rates. Of concern is the fact that reported seabird flight speeds were significantly lower than those typically used in existing guidance. This is important as flight speed is used by the Band model twice. Firstly, in the calculation of the total number of birds that may pass through a wind farm over a given time period and, secondly to estimate the probability that any individual bird may collide with the turbine blades. Flight speed may be estimated from the data collected as part of the ORJIP BCA study in two ways, either as a point estimate or, as an average of the speed at which the birds move through the wind farm. In order to be consistent with how the Band model is implemented, the point estimate of bird speed should be used to calculate the probability of a bird colliding and the average rate at which it moves through the wind farm should be used to estimate the total number of birds likely to move through the wind farm over a given time period.

As suggested by previous studies, meso-avoidance appears to be a key component of overall avoidance behaviour, with most birds within a wind farm taking avoidance action well away from turbines. Recorded micro-avoidance rates were also high, although based on limited data and future studies should consider how best to maximise records of micro-avoidance behaviour. Significantly, the number of birds crossing the turbine rotor-swept area and colliding appeared higher than the predictions made by the Band collision risk model, although this was based on limited data. Given evidence collected by the ORJIP BCA about birds flying in parallel to turbine blades, consideration should be given to taking this into account as part of calculations for the probability of collision.

As may be expected, the empirical avoidance rates recorded as part of the ORJIP BCA study were higher than those collected previously. In part, this is because the avoidance rates used by the Band collision risk model incorporate elements of error, both in relation to the model itself and, in relation to the input parameters. However, by comparing collision rates recorded by the ORJIP BCA study to those that would have been predicted by the Band model in the absence of avoidance behaviour, we are able to recommend avoidance rates for use in the deterministic Band model of 0.995 for northern gannets and large gulls and 0.990 for black-legged kittiwake in relation to option 1 of the Band model and 0.993 for large gulls and 0.980 for black-legged kittiwake in relation to option 3 of the Band model. We were able to undertake further analyses in order to derive avoidance rates suitable for use in the stochastic collision risk model for black-legged kittiwake of 0.994 (95% CIs 0.976 - 0.998) for option 1 and 0.970 (95% CIs 0.871-0.989) for option 3 and, for large gulls 0.997 (95% CIs 0.992 - 0.999) for option 1 and 0.990 (95% CIs 0.974 - 0.995) for option 3. Note that the median values recommended for use in the stochastic collision risk models differ from the values recommended for use in the deterministic model, this relates to differences in the way in which flight height distributions are incorporated into the models. It should be

noted however that the values recommended for use in the deterministic model are within the 95% confidence intervals of those recommended for use in the stochastic model.

Contents

1 Introduction

Offshore wind farms are seen as a key part of efforts to combat climate change (Snyder & Kaiser 2009). However, there are a number of significant concerns about the potential of these wind farms to have a negative impact on wildlife and biodiversity, particularly in relation to birds (Drewitt & Langston 2006; Gibson *et al.* 2017). Of particular concern is the potential for birds to collide with turbines (Thaxter *et al.* 2017; Furness *et al.* 2013; Garthe & Huppop 2004).

To inform the planning process of the potential impacts of the effects associated with wind farms, detailed Environmental Impact Assessments (EIAs) are required. With respect to birds, a key component of these EIAs is a Collision Risk Model (CRM) which is used to predict the number of individuals of any given species at risk of collision. A variety of different CRMs are available (Tucker 1996; Band 2012) but, at their core, most combine an estimate of the number of birds within a collision window with an estimate of the probability of any individual bird colliding in order to forecast the number of likely collision events (Masden & Cook 2016). These models also require an understanding of bird avoidance behaviour, often referred to as the avoidance rate (Cook *et al.* 2014). Whilst some attempts have been made to measure avoidance behaviour empirically (Krijgsveld *et al.* 2011), more commonly, they have been estimated by comparing the number of recorded collisions with the number predicted prior to construction, in the absence of any avoidance behaviour (Cook *et al.* 2014). Consequently, whilst the avoidance rate is often thought to solely reflect the proportion of birds taking action to avoid collision, in reality it also accounts for uncertainty arising as a result of other factors including weather conditions and model error (Band 2012; Cook *et al.* 2014; Masden 2015). This is of concern as the CRM predictions themselves are known to be highly sensitive to assumptions about avoidance behaviour (Chamberlain *et al.* 2006; Masden 2015). This sensitivity may contribute significant uncertainty into the decision-making process, at significant cost to developers, decision-makers and other stakeholders (Masden *et al.* 2015). Furthermore, whilst no detailed comparisons have been made between predictions from CRMs and observed collision rates, some initial studies suggest that key assumptions, such as a linear relationship between abundance and collision risk, may not be realistic (de Lucas *et al.* 2008; Ferrer *et al.* 2012).

As the size and number of offshore wind farms increases, the probability of estimated collision rates which are of a magnitude likely to have significant population level effects also increases. This poses a challenge for decision-makers who must balance the need to invest in renewable energy, in order to mitigate the impacts of climate change, with the need to minimise deleterious impacts on the environment (Green *et al.* 2016; Gibson *et al.* 2017). Consequently, there is a growing interest in exploring how well estimates from CRMs reflect true collision risk and, the extent of collision avoidance behaviour in vulnerable species. This interest culminated in an Offshore Renewables Joint Industry Programme (ORJIP) funded project on bird collision avoidance at an operational wind farm (Davies *et al.* 2013; Skov *et al.* 2018).

In contrast to previous efforts to estimate avoidance behaviour, the ORJIP Bird Collision Avoidance (BCA) project collected data on empirical estimates of bird behaviour (Skov *et al.* 2018). These estimates of bird behaviour can be used to describe the proportion of birds taking action to avoid collision with turbines. However, as they do not incorporate data describing model error or how birds respond in relation to other factors, for example weather conditions, these behaviour-based avoidance rates will not be directly comparable to those used to date. Consequently, it is important to understand how transferable these rates, termed empirical avoidance rates, are to the existing models.

We aim to assess how these empirical avoidance rates can be used to inform renewable energy development impact assessments and support decision making. We aim to achieve this by taking advantage of the data which have been collected by the ORJIP BCA project describing bird movements within an operational wind farm in fine detail. These data included records of both birds that did not collide and those which did. As we have an estimate of the number of birds which have collided over a given time period, we can use these data both to test how well a CRM performs and to understand how much uncertainty remains in collision estimates once empirical avoidance rates have been accounted for.

The key aims of this project were:

- To consider how best to use the information and outputs from the ORJIP funded BCA project to best assess collision risk at offshore wind farms.
- Consideration of how the flux rate estimated as part of Options 1 & 3 of the Band (2012) model relate to the empirical avoidance rates estimated by the ORJIP BCA study.
- Consideration of error introduced into the avoidance rates used by the Band (2012) model and the extent to which this is unaccounted for once empirical avoidance rates are applied.
- To consider how the information collected as part of the ORJIP BCA study could be used to derive avoidance rates suitable for use in the Band (2012) model.

2 Methodology

Uncertainty is introduced into the collision risk modelling process through the use of summarised data, often collected from unconnected sites, and through simplifications and assumptions in the modelling process. At present, this uncertainty is captured by a correction factor, often referred to as the avoidance rate. However, the relative importance of each of the sources of uncertainty which contribute to the avoidance rate is unclear. In order to determine how applicable avoidance rates, such as that derived from the ORJIP BCA study, are to CRMs, it is important to understand the magnitude of the uncertainty remaining once behaviour, and other measurable factors, have been accounted for.

In this study we assess the results of the ORJIP BCA project, using data both from that project and from other surveys of the Thanet Offshore Wind Farm study site, and consider their application to the Band CRM (Band 2012). Specifically, we aim to compare estimates of the number of collisions expected in the absence of avoidance behaviour, based on pre-construction density estimates of bird abundance and generic data describing bird behaviour, to estimates refined through introduction of site-specific data collected as part of the ORJIP BCA project. We use data describing bird density presented in the post-consent monitoring report for Thanet Offshore Wind Farm (Royal Haskoning 2013), data describing bird behaviour collected by observers using laser rangefinders on turbines G01 and G02 in Thanet Offshore Wind Farm and collisions recorded by cameras mounted on turbines D05 and F04 within the Thanet Offshore Wind Farm (Skov *et al.* 2018).

For the purposes of this analysis, we split the Band CRM into its component parts, as follows, to:

1. identify the area in which to estimate collision risk (study area);
2. estimate the flux rate, i.e. the total number of birds which may pass through the study area over the period of interest (study period);
3. estimate the probability of a bird colliding with a turbine (P_{coll} or $Coll_{int}$);
4. estimate the proportion of birds flying at collision risk height (PCH);
5. combine the data above in order to estimate the total number of expected collisions.

We focus analyses on the five, key species covered by the ORJIP BCA study – northern gannet *Morus bassanus*, black-legged kittiwake *Rissa tridactyla*, lesser black-backed gull *Larus fuscus*, herring gull *Larus argentatus* and great black-backed gull *Larus marinus*.

2.1 Defining area in which to estimate collision risk

Data for this project were collected at the Thanet Offshore Wind Farm. Thanet is located on the east coast of the United Kingdom, in the Southern North Sea. It consists of 100 3 MW turbines (Table 1), covering an area of 35 km^2. However, the data describing collisions were collected from cameras located on the northern edge of the wind farm. Collectively, these cameras were able to observe interactions between birds and eight other turbines (Figure 1). Consequently, we restricted our analyses to the area covered by these cameras (Figure 1).

Table 1. Specification of turbines at Thanet Offshore Wind Farm.

Parameter	Value
Capacity	3 MW
Number of Blades	3
Blade Width	3.5 m
Rotor Diameter	90 m
Rotor Speed	16.1 rpm
Pitch	15˚
Hub Height	70

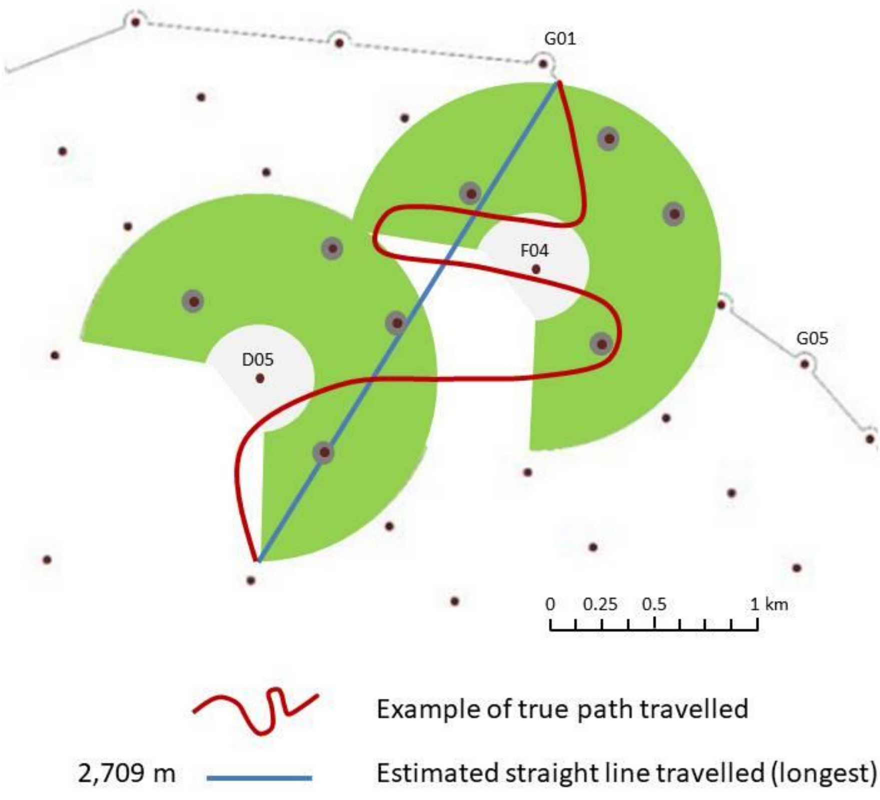


Figure 1. Area covered by two cameras mounted on turbines within the Thanet Offshore Wind Farm (2.983 km^2). Analyses were restricted to the area covered by these cameras, shown in green. Adapted from Figure 4.6 in Skov *et al.* (2018).

2.2 Estimating flux rate

The first step in a CRM is to estimate the flux rate, the total number of birds passing through the study area (figure 1) over the time period of interest. Post-construction density estimates were available only for the period from October – March (Royal Haskoning 2013), consequently, we restricted our analyses to data collected by the ORJIP BCA study in the October-March period. For the purposes of estimating flux, we used the mean of the values for the three post-construction years. The apparent increases in density recorded for lesser black-backed gull, great black-backed gull, black-legged kittiwake and northern gannet between the pre- and post-construction periods must be treated with caution. Pre-construction density estimates are based on a single years' worth of data. The post-construction density data show that there may be substantial annual variation in the estimated density. Monthly surveys from a single year are insufficient to characterise the true usage of a site by the species concerned (Maclean *et al.* 2013) and a recent review has demonstrated that northern gannet in particular shows a strong displacement effect in response to the presence of an offshore wind farm (Dierschke *et al.* 2016). Ideally, density data would have been collected concurrently in relation to the ORJIP BCA study. However, unfortunately this was not possible and the best available density data are those published in the post-construction monitoring report (Royal Haskoning 2013).

Table 2. Density estimates (birds km^{-2}) from within Thanet Offshore Wind Farm (excluding buffer area) used to estimate flux rate for the collision risk model. Taken from table 6 in Royal Haskoning (2013).

	Pre-construction (2004-05)	**Post-construction YR1 (2010-11)**	**Post-construction YR2 (2011-12)**	**Post-construction YR3 (2012-13)**	**Post-construction Mean**
Herring gull	1.95	0.90	0.87	2.30	1.36
Lesser black-backed gull	0.33	0.41	0.62	0.08	0.37
Great black-backed gull	0.02	0.39	1.16	1.53	1.03
Black-legged kittiwake	0.20	1.56	0.92	0.81	1.10
Northern gannet	0.05	0.05	0.17	0.96	0.39

To estimate flux rate, we calculated the total number of birds that would pass through the study area outlined in figure 1 between October and March each year. This followed the methodology set out in Band (2012) combining estimates of bird density with estimates of flight speed, both from generic sources and those recorded as part of the ORJIP BCA and the total duration of the observation period. As only the data collected from the cameras during daylight hours were fully processed, we based our analysis on the number of birds expected to pass through during daylight. We estimated daylight hours between October and March using the suncalc function in the R library RAtmosphere (Gionata *et al.* 2015) to be 1733.55 hours taking an average during the post-construction years (2010/11 to 2012/13 to avoid a leap year).

Within the data collected using the laser rangefinders two possible distances were measured for each bird – a straight line between the first and last encounters and the true distance travelled between these two. The differences between the values of speed derived from these two measures have potential implications for the final collision rates given the differences in the numbers of birds that may pass through the areas if they take more meandering paths. Table 3 details these differences for each species.

Table 3. Average distances travelled (m) and speed (ms^{-1}) of birds depending on distance measured as part of the ORJIP BCA study (Skov *et al.* 2018) and the generic speed estimate taken from Alerstam *et al.* (2007) and Pennycuick (1997). Note that the values presented here differ to those presented in table 5.13 of the ORJIP BCA final report as we restrict our analyses to the data collected between October and March.

	Average distance (m) straight line	Average distance (m) true length	Average speed - straight line (ms^{-1})	Average speed - true length (ms^{-1})	Generic Speed (ms^{-1})
Herring gull	869.23	1213.24	8.0	9.8	12.8
Lesser black-backed gull	715.70	1012.22	8.4	10.4	13.1
Great black-backed gull	760.85	1053.04	8.5	10.0	13.7
Black-legged kittiwake	614.32	923.60	6.7	8.6	13.1
Northern gannet	1045.45	1251.85	11.7	13.1	14.9

2.3 Probability of collision/collision integral

To estimate the number of expected collisions, the flux of birds passing through the rotor swept area over a given period is multiplied by the probability of an individual bird passing through the rotor and colliding. The ‘probability of collision’ is based on the probability of the bird and the turbine being in the same place at the same time. For Option 1 of the Band CRM – the ‘basic’ model – this is estimated based on the size (Table 1) and speed of the turbine blades and the size (Table 4) and speed (Table 3) of the birds, assuming that the birds have a cruciform shape (Band 2012; Masden & Cook 2016). Option 3 of the Band CRM – the ‘extended’ model –, also considers the flight height distribution of the species concerned, accounting for the fact that birds are less likely to collide further away from the centre of the rotor swept area (Band 2012), in order to estimate the ‘collision integral’.

2.4 Flight height models

In order to determine the proportion of birds at collision risk height, species and site-specific flight height distributions were derived from the data collected using laser rangefinders. Data reflect a sample of the birds present in the study region. Consequently, in deriving distributions of seabird flight heights similar to those of Johnston *et al.* (2014), it was necessary to use a modelling approach that was sufficiently flexible that it could fit to a variety of forms, but not so flexible that it would over-fit to the data. We considered a number of different distributional forms for each species using the fitdistr function in MASS (Venables & Ripley 2002) and the normalmixEM function in Benaglia *et al.* (2009). For each species, we then consider which distribution best fitted the observed data.

2.5 Collision models

Using the information derived from the steps above, we are able to work through the Band CRM (Band 2012), introducing site-specific information at each step in order to understand how estimates of collision change as the parameters used by the model are refined. Initially, we replicate the collision risk model as it would be carried out ‘pre-construction’ as part of an Environmental Impact Assessment (EIA), using pre-construction density estimates, generic bird data and parameters based on the turbines installed (Tables 1-4), but, in contrast to the CRMs carried out as part of EIAs, we assume no avoidance behaviour.

We then refine the predictions by introducing: (i) post-construction density data, (ii) site-specific information on flight speed and (iii), finally, site-specific information on avoidance behaviour (Figure 2). Following this approach, we have eight different pathways leading to estimated collision rates based on the assumptions and data used (Figure 2). As the study area was wholly within the area of the Thanet Offshore Wind Farm, we consider only meso- and micro-avoidance and not, macro-avoidance.

Table 4. Seabird morphometric data, taken from Robinson (2017), flight mode (flapping or gliding flight) and, avoidance rates taken from Skov *et al.* (2018).

	Length	**Wingspan**	**Flight mode**	**Macro-avoidance**	**Meso-avoidance**	**Micro-avoidance**	**Overall avoidance**
Herring gull	0.61	1.44	flap	0.442	0.9614	0.9565	0.999
Lesser Black-backed Gull	0.59	1.45	flap	0.639	0.8937	0.9565	0.998
Great-black-backed Gull	0.71	1.575	flap	0.469	0.8423	0.9565	0.996
Black-legged kittiwake	0.39	1.075	flap	0.575	0.9160	0.9500	0.998
Northern gannet	0.935	1.725	glide	0.816	0.9205	0.9500	0.999

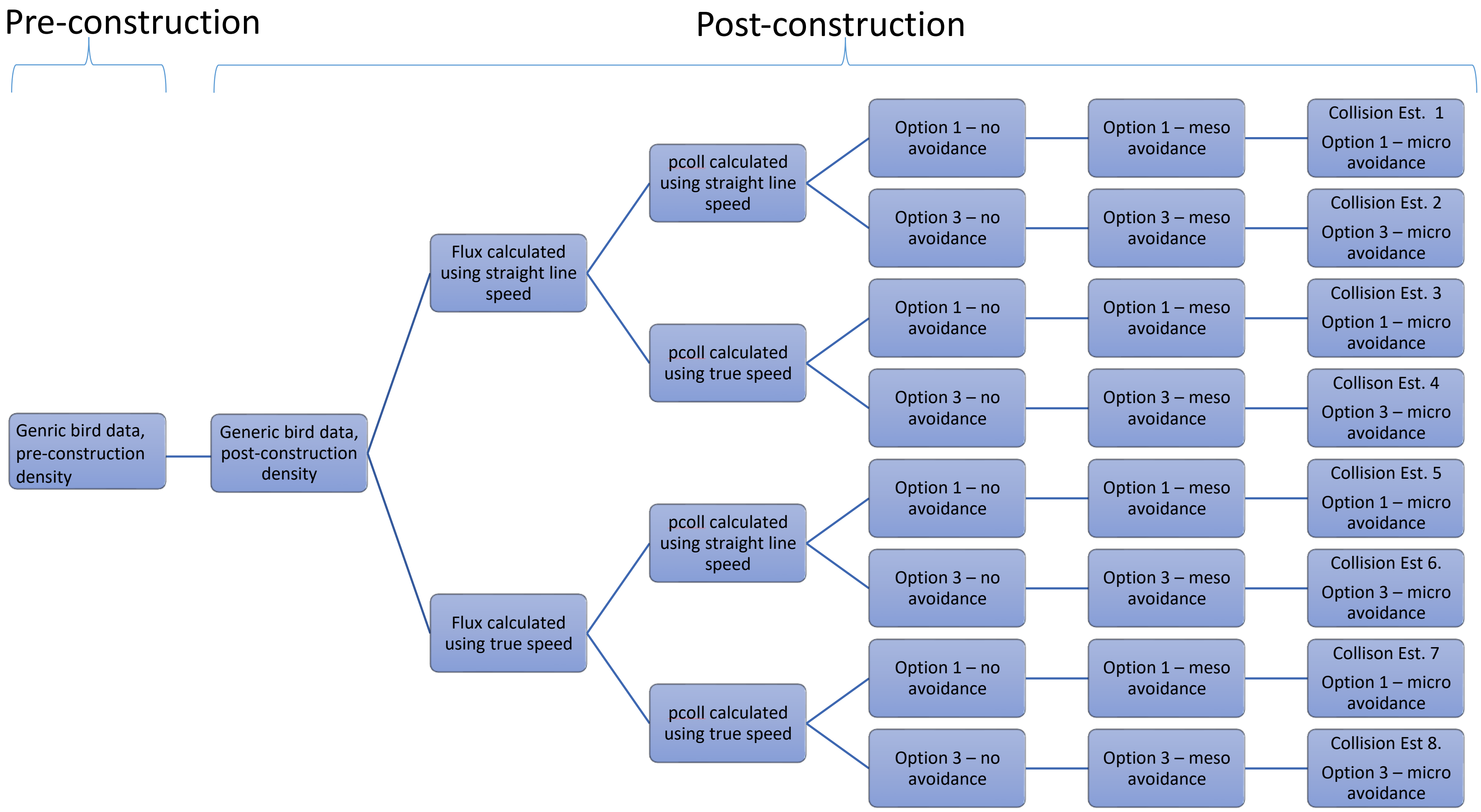


Figure 2. Schematic for producing estimates of collision at the eight turbines monitored during the ORJIP BCA project comparing the generic estimate that might be produced ‘pre-construction’ with more refined estimates produced using ‘post-construction‘ data. At each step, collision rates are refined by introducing more site-specific data. Different pathways reflect the different ways in which flight speed and flight height may be incorporated into the model.

2.6 Recorded collisions

Over the course of the ORJIP study, six birds were recorded colliding with turbines (Table 5). As density data were only available for the period October-March, the collision involving a large gull recorded on 21st August 2015 was not included in our analyses. As, with the exception of the black-legged kittiwake, birds involved in the collisions were not identified to species level, we group them as large gulls and, for the purposes of the analysis, compare these collision rates to the sum of those estimated for herring, lesser black-backed and great black-backed gulls.

Table 5. Birds recorded colliding with turbines during the ORJIP Bird Collision Avoidance Project (Skov *et al.* 2018).

Species/Group	Date
Black-legged kittiwake	1st November 2014
Lesser/Great Black-backed Gull	24th November 2014
Unidentified gull	28th November 2014
Large gull	21st August 2015
Large gull	12th December 2015
Unidentified gull	10th February 2016

2.7 Comparison of avoidance rates derived from ORJIP BCA study with those estimated using traditional approach

The above steps consider only birds within the wind farm and, therefore, do not account for macro-avoidance behaviour or, the avoidance rate as used in the Band CRM at present. The ORJIP BCA estimated an overall empirical avoidance rate, combining macro-, meso- and micro-avoidance. These values (Table 4) were well above those presently recommended (Cook *et al.* 2014). However, the values from the ORJIP BCA study and existing guidance may not be strictly comparable as they were derived in different ways.

The avoidance rates recommended in existing guidance are derived by comparing observed and predicted collision rates (Cook *et al.* 2014). As the predicted collision rates are based on estimates from the Band model, they incorporate elements of model error arising as a result of the assumptions made (Band 2012). The empirical avoidance rates derived from the ORJIP BCA project do not incorporate this model error and, consequently, are likely to be higher than those used at present. Furthermore, macro-avoidance incorporates both barrier effects and displacement (Cook *et al.* 2014). The data collected by the ORJIP BCA project at the macro scale covers birds in flight approaching the operational wind farm but, is not able to compare pre- and post-construction bird densities within the wind farm. Consequently, the ORJIP BCA data only incorporates the barrier effects element of macro-avoidance and not the displacement element. How these elements interact is unclear, however, in the absence of such information, the macro-avoidance rates derived as part of the ORJIP BCA project are not consistent with the assumptions about avoidance behaviour made by the Band model.

In order to facilitate a comparison between the existing guidance and the values obtained from the ORJIP BCA study, we recalculate avoidance rates by the 'traditional' approach of comparing the number of observed collisions to those predicted in the absence of avoidance behaviour (Eq. 1). We do this for each of the pathways set out in Figure 2. As avoidance rates will typically be applied in a pre-construction context, we also estimate a predicted collision rate based on the pre-construction estimates of bird density data and site-specific estimates of flight speed and height measured as part of the ORJIP BCA project. To investigate the impact of site-specific data in this calculation, we also estimate avoidance rates based on pre- and post-construction density data using generic bird data.

$$Avoidance\ Rate\ = 1 - \left(\frac{observed\ collision\ rate}{predicted\ collision\ rate}\right)$$ Equation 1.

3 Results

3.1 Flux calculations under two flight path measurements

Following the protocol described above, pre- and post-construction flux values were calculated for each of the five species under investigation using generic, ‘straight line’ and ‘true length’ estimates of speed (Table 6). The difference between the estimates of flux based on ‘straight line’ and ‘true length’ estimates of speed ranged from 203 great black-backed gulls to 22,892 herring gulls based on pre-construction densities and from 3,781 northern gannets to 15,926 herring gulls based on post-construction densities. Figure 3 visually represents the differences between the measurements based on straight line’ and ‘true length’ estimates of speed, those based on the latter resulting in increases in the numbers of bird likely to pass through the area surrounding the two turbines (Figure 1). Changes in the density of the species between the pre- and post-construction periods (Table 2) also result in changes in estimated flux rates.

Table 6. Values of flux for five seabird species using generic and site-specific estimates of speed and pre- and post-construction density data.

Species/Group	Generic Flux		Straight-line flux		True length flux	
	Pre-construction	Post-construction	Pre-construction	Post-construction	Pre-construction	Post-construction
Herring gull	171525	119334	107823	75015	130715	90942
Lesser black-backed Gull	29707	33308	18954	21251	23682	26553
Great black-backed Gull	1882	96656	1172	60175	1374	70577
Black-legged kittiwake	18004	98725	9184	50363	11779	64592
Northern gannet	5119	40274	4020	31628	4501	35409

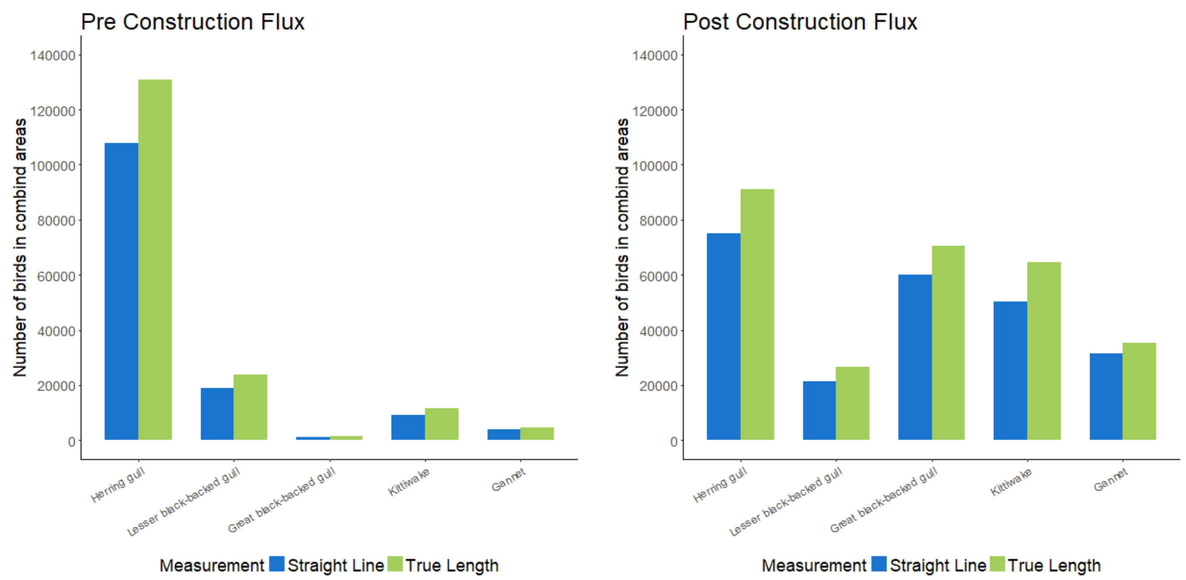


Figure 3. Pre- and post-construction flux values for five species using ‘straight line’ or ‘true length’ estimates of speed.

3.2 Probability of collision/collision integral

By refining the data used for the Band CRM, for each species, we obtained three estimates (based on generic, ‘straight line’ or ‘true length’ estimates of speed) for the probability of collision and two estimates (based on ‘straight line’ or ‘true length’ estimates of speed) for the collision integral (Table 7).

The probability of a bird colliding with a turbine is based on the length of time it takes for the bird to cross the rotor-swept area (Band 2012). Consequently, utilising the slower site-specific flight speeds obtained using the laser rangefinders results in an increased probability of collision. These differences are most noticeable for species such as black-legged kittiwake and herring gull, for which there is the greatest difference between the generic and straight line or true speeds. Similarly, as the straight-line speeds are slower than the true speeds, both the probability of collision and collision integral are higher when estimated using the straight-line speed.

Table 7. Estimates of probability of collision and collision integral obtained using generic and site-specific estimates of speed.

	Probability of Collision			Collision Integral	
	Generic Speed	**Straight line Speed**	**True Speed**	**Straight line Speed**	**True Speed**
Herring gull	0.092286	0.123504	0.107849	0.080257	0.069501
Lesser black-backed gull	0.090344	0.118373	0.101968	0.065471	0.056400
Great black-backed gull	0.095414	0.127808	0.114204	0.092973	0.080208
Black-legged kittiwake	0.077145	0.116359	0.096935	0.045394	0.038025
Northern gannet	0.103378	0.118540	0.110711	0.021401	0.017663

3.3 Flight heights

For lesser black-backed gull, great black-backed gull and herring gull, flight height data most closely fitted a gamma distribution (Figure 4). For black-legged kittiwake, flight height data most closely matched a normal distribution while flight height data for northern gannet most closely matched a normal-mixture distribution. It should be noted that these data indicated a higher proportion of birds at collision risk height than was observed in the generic flight height distributions (Johnston *et al.* 2014). There are several potential explanations for differences between the observed flight height distributions and the generic data:

1. The laser rangefinder data may be biased against birds flying closer to the sea surface. Birds close to the sea surface may be harder for observers to detect if flying between the troughs of waves and/or less conspicuous against the background. A previous study using laser rangefinders (Borkenhagen *et al.* 2018) suggested that birds at lower altitudes may be under-represented in estimates of flight height.

2. There is also the possibility that the generic data may be biased as a result of birds being attracted to survey vessels or due to observers detecting birds as they were flushed from the sea surface by the survey vessels (Johnston *et al.* 2014; Camphuysen *et al.* 2004).

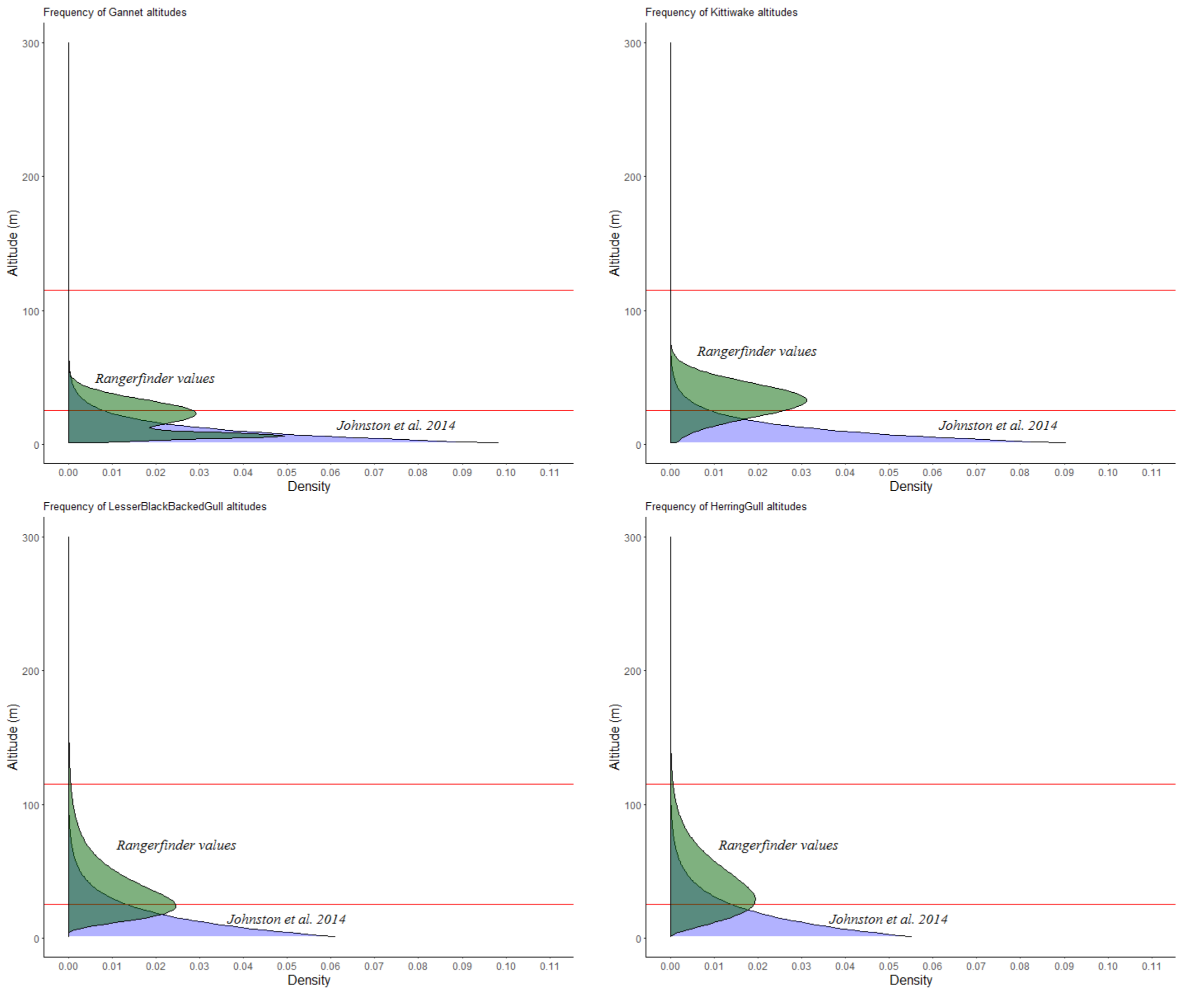
3. The flight heights of birds differed inside and outside the wind farm. There is some evidence that gulls may fly higher inside a wind farm than outside from both the

ORJIP BCA study and previous studies (Cook *et al.* 2014; Thaxter *et al.* 2017; Skov *et al.* 2012), although this difference may potentially reflect the locations of wind farm sites relative to the coast (see below). The data underpinning the generic distributions in Johnston *et al.* (2014) were all derived from pre-construction estimates of seabird flight height.

4. There are site-specific differences in seabird flight heights. Previous studies have shown that seabird flight heights may vary on a site-specific basis (Johnston & Cook 2016; Ross-Smith *et al.* 2016). Such differences may relate to behavioural characteristics such as whether birds are using an area for foraging or commuting flights. In contrast, data from Johnston *et al.* (2014) averaged flight heights across a broad range of habitats.

5. Wind speed and direction are likely to influence seabird flight altitudes. The laser rangefinder data available to the ORJIP BCA study analyses were constrained by the limited range of weather conditions during which observers were able to safely access turbines to collect these data, i.e. during relatively calm weather conditions. Consequently, the laser rangefinder data may be biased towards behavioural flight height responses to calm weather.

With the data available, it is not possible to determine which, if any, of these explanations is the key reason for the differences between the distributions reported here and those reported by Johnston *et al.* (2014). In practice, all five are likely to have had some impact.



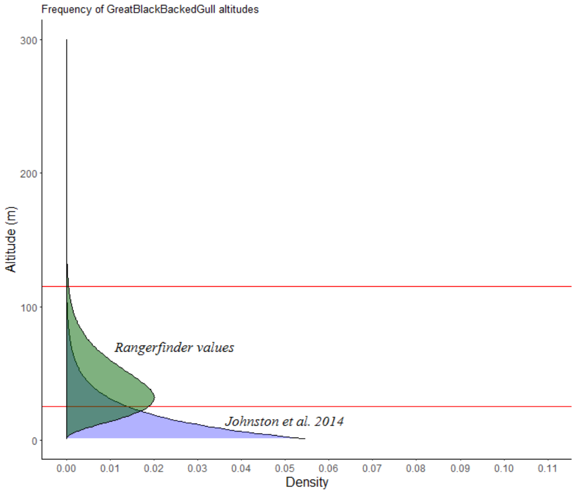


Figure 4. Comparison of flight height distributions derived from laser rangefinder data (green) collected as part of the ORJIP BCA project and generic flight height distributions (purple) derived from data collected as part of boat surveys and presented in Johnston *et al.* (2014). Red lines indicate the upper and lower limits of the turbine rotor swept areas of turbines installed at Thanet.

Table 8. Proportion of birds at collision risk height in relation to turbines installed at Thanet (25-115m) recorded using laser rangefinders as part of the ORJIP BCA project and predicted from generic data (Johnston *et al.* 2014).

	ORJIP BCA	(Johnston *et al.* 2014)
Herring gull	0.768	0.239
Lesser black-backed Gull	0.725	0.205
Great black-backed Gull	0.826	0.245
Black-legged Kittiwake	0.744	0.090
Northern gannet	0.285	0.075

3.4 Collision models

We combine the revised estimates of flux, the probability of collision and flight heights presented above in order to investigate how estimated collision risk varies in relation to the assumptions made during the modelling process and the incorporation of site-specific data. For each species, we are able to estimate a collision rate at each point along the eight pathways identified in Figure 2. Full details of the calculations underpinning the following table are available in Appendix 1.

Table 9. Change in predicted collision rates for the non-breeding season from Option 1 and Option 3 of the Band CRM (Band 2012) as density data are changed from pre-construction (pre) to post-construction (post) estimates, generic bird data (gen) are replaced with site-specific bird data (SSp), flux rates and probability of collision are calculated using either straight line (SL) or true (TD) speed and meso- (Me) and micro- (Mi) avoidance are introduced.

Density Estimate			Pre	Post													
Flight height			Gen	Gen	SSp	SSp		SSp		SSp		SSp		SSp		SSp	
Flight speed			Gen	Gen	Gen	SSp		SSp		SSp		SSp		SSp		SSp	
Distance measure			Gen	Gen	Gen	SL	TD	SL	TD	SL	TD	SL	TD	SL	TD	SL	TD
Pcoll/CollInt			Gen	Gen	Gen	SL	TD	TD	SL	SL	TD	TD	SL	SL	TD	TD	SL
Avoidance			No	No	No	No		No		Me		Me		Me/Mi		Me/Mi	
Band CRM Option	1	Herring gull	618.94	430.61	1381.01	1161.79	1229.92	1014.53	1408.45	44.85	47.47	39.16	54.37	1.95	2.07	1.70	2.36
	3		408.74	284.37	284.37	983.54	1032.55	851.73	1192.36	37.96	39.86	32.88	46.03	1.65	1.73	1.43	2.00
	1	Lesser black-backed gull	89.86	100.75	356.41	297.95	320.69	256.66	372.28	31.67	34.09	27.28	39.57	1.38	1.48	1.19	1.72
	3		56.01	62.80	62.80	227.30	244.66	195.81	284.01	24.16	26.01	20.81	30.19	1.05	1.13	0.91	1.31
	1	Great black-backed gull	7.19	368.95	1244.60	1037.92	1087.75	927.44	1217.33	163.68	171.54	146.26	191.97	7.12	7.46	6.36	8.35
	3		5.06	259.95	259.95	913.98	924.79	788.49	1071.97	144.14	145.84	124.35	169.05	6.27	6.34	5.41	7.35
	1	Kittiwake	21.07	115.52	926.04	712.54	761.30	593.60	913.85	59.85	63.95	49.86	76.76	2.99	3.20	2.49	3.84
	3		9.17	50.28	50.28	373.49	401.25	312.86	479.00	31.37	33.70	26.28	40.24	1.57	1.69	1.31	2.01
	1	Northern gannet	6.46	50.84	193.52	174.27	182.21	162.76	195.10	13.85	14.49	12.94	15.51	0.69	0.72	0.65	0.78
	3		3.26	25.65	25.65	110.58	102.17	91.26	123.80	8.79	8.12	7.26	9.84	0.44	0.41	0.36	0.49

3.4.1 Herring gull

Based on the pre-construction density data and generic bird data, 618 herring gulls were predicted to collide during daylight hours between October and March each year (Figure 5). Following construction of the wind farm, the density of birds, and therefore number of expected collisions, decreased. However, site-specific flight height data suggests a far higher proportion of birds at risk height than is assumed by the generic data, reflected in an increase in the predicted collision rate at the third step of the analysis. Introducing site-specific flight speed information results in further changes to the predicted collision rates, although the extent of changes is dependent on whether these estimates are based on straight line or true speed. Incorporating different measures of speed affects both the estimated flux rate and estimations of the probability of birds colliding. However, in relation to the predicted collision rate, the selection of the appropriate measure of speed appears to be most important when calculating the probability of collision (Table 9). As may be expected, the selection of Option 1 or Option 3 of the Band CRM (Band 2012) also results in a significant change in the predicted collision rate. However, as avoidance behaviour is incorporated, predicted collision rates begin to coalesce. When only meso-avoidance is incorporated, differences are still evident and, the lowest collision rates are observed when flux rate is estimated using straight line speed and the probability of collision is estimated using true speed. When micro-avoidance is incorporated, collision estimates following each of the eight pathways all fall to around 1-2 birds per winter. The most noticeable changes in the number of predicted collisions occur in relation to the introduction of site-specific flight height data and the introduction of micro-avoidance behaviour.

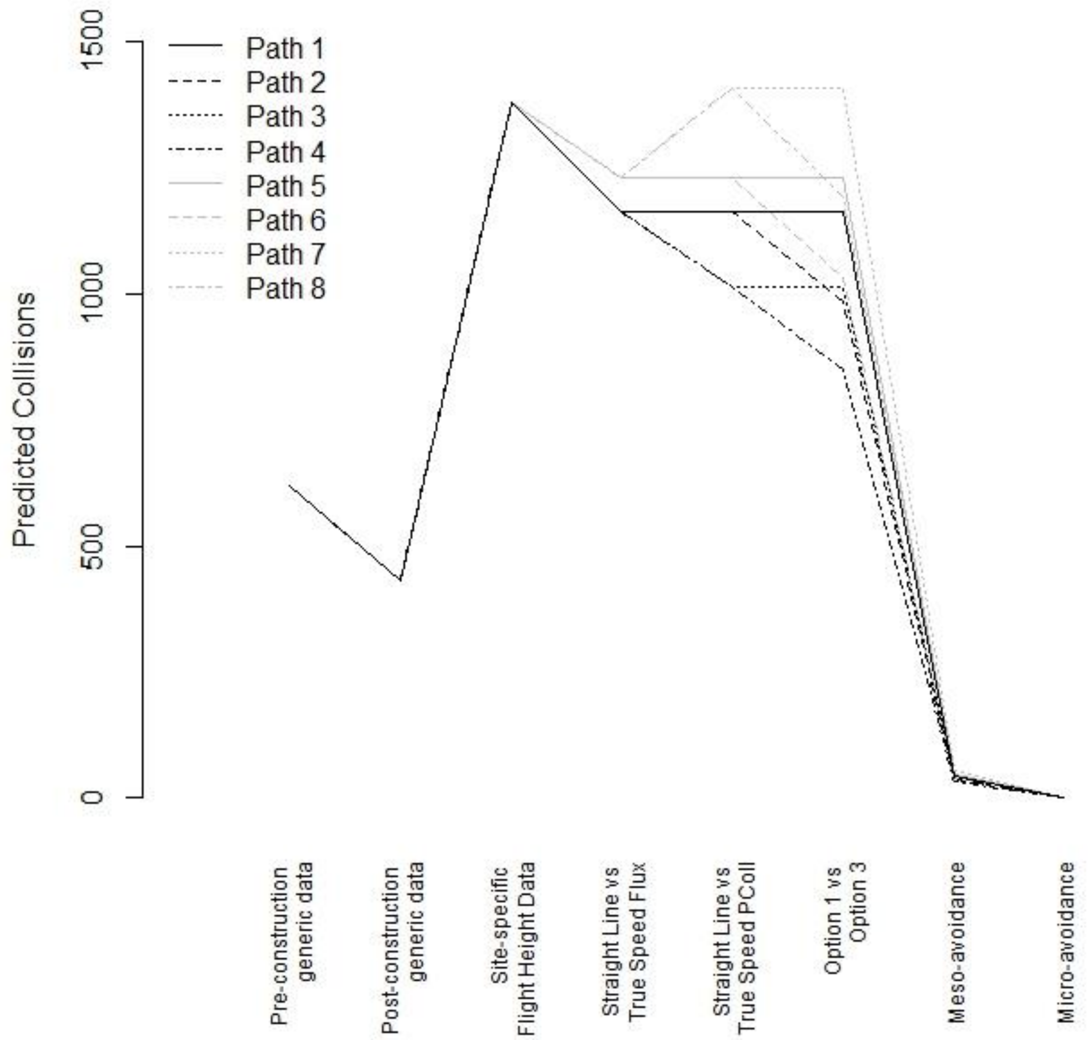


Figure 5. Change in predicted collision rate for herring gull as model assumptions and parameters are refined.

3.4.2 Lesser black-backed gull

The density of lesser black-backed gulls in the study area over winter was much lower than for herring gulls. In contrast to herring gull, there was a slight increase in the density of lesser black-backed gulls recorded during the post-construction monitoring. Aside from this difference, the changes in the predicted collision rates of lesser black-backed gulls as model assumptions and parameters were refined were broadly similar to those recorded for herring gulls (Figure 6).

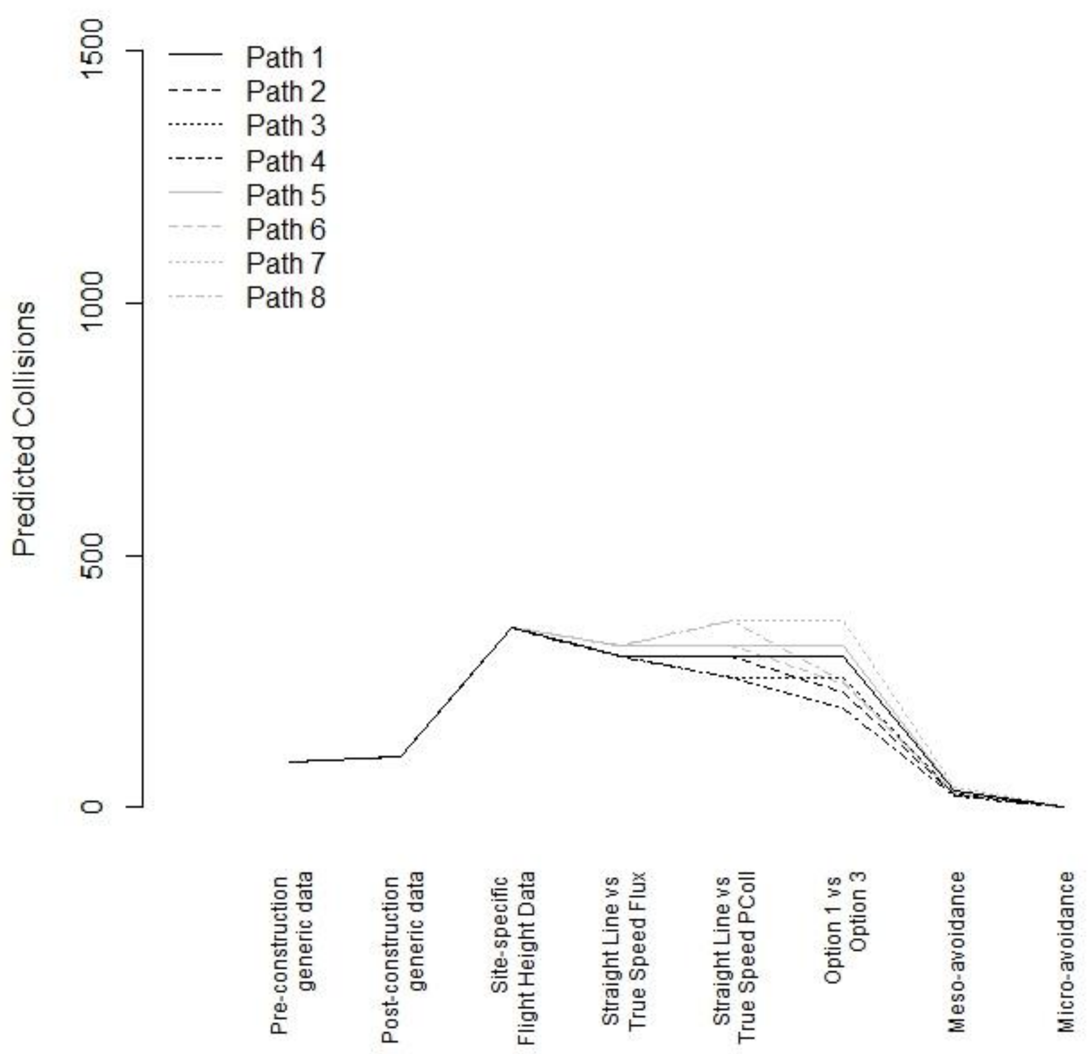


Figure 6. Change in predicted collision rate for lesser black-backed Gull as model assumptions and parameters are refined.

3.4.3 Great black-backed Gull

Great black-backed gulls were the most numerous species recorded in the study area. As with lesser black-backed gull, they increased in density during the post-construction period. Other changes in the predicted collision rates of great black-backed gulls as model assumptions and parameters were refined were broadly similar to those recorded for the other study species.

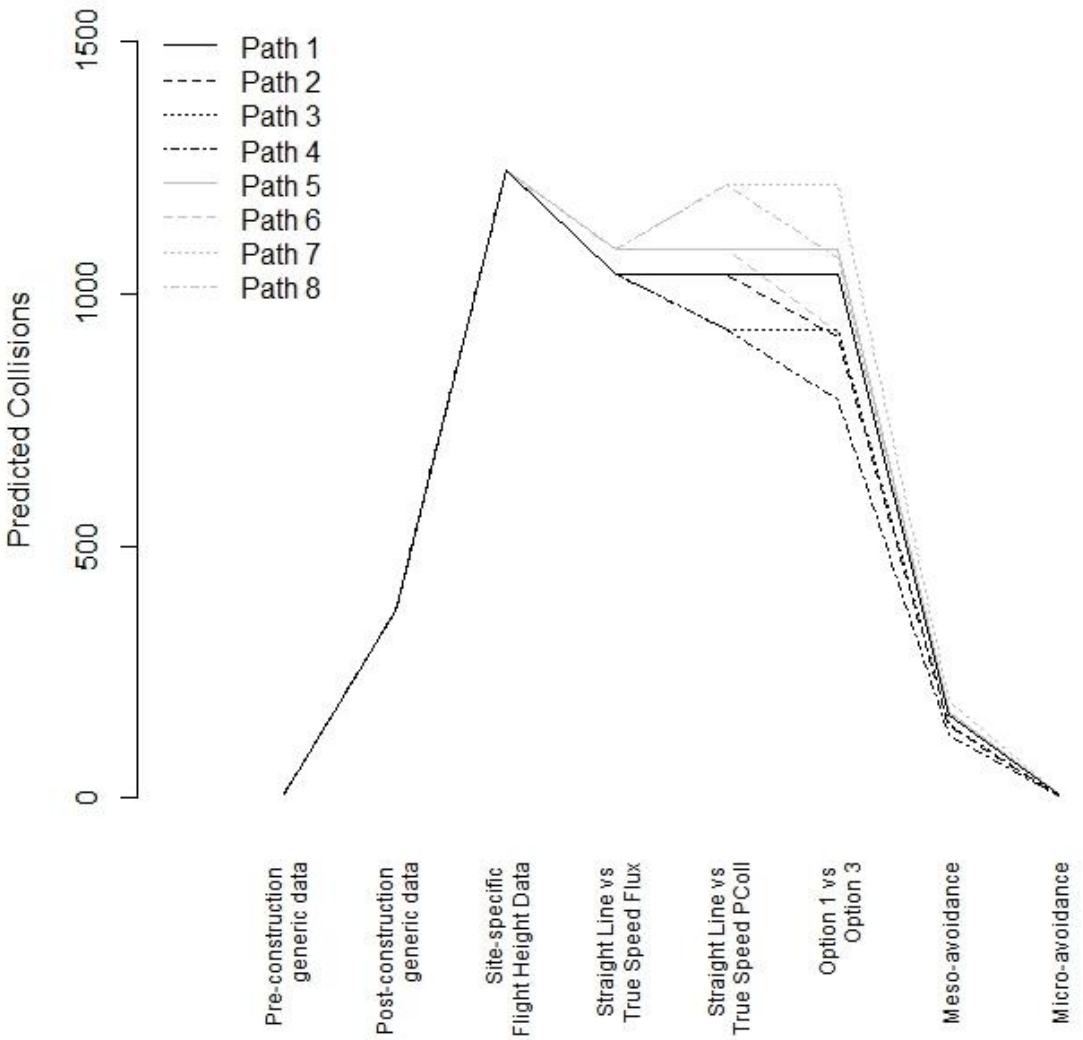


Figure 7. Change in predicted collision rate for great black-backed Gull as model assumptions and parameters are refined.

3.4.4 Black-legged kittiwake

As with the black-backed gull species, black-legged kittiwake increased in density during the post-construction period. Other changes in predicted collision rates as model assumptions and parameters were refined were broadly similar to those recorded for the other study species.

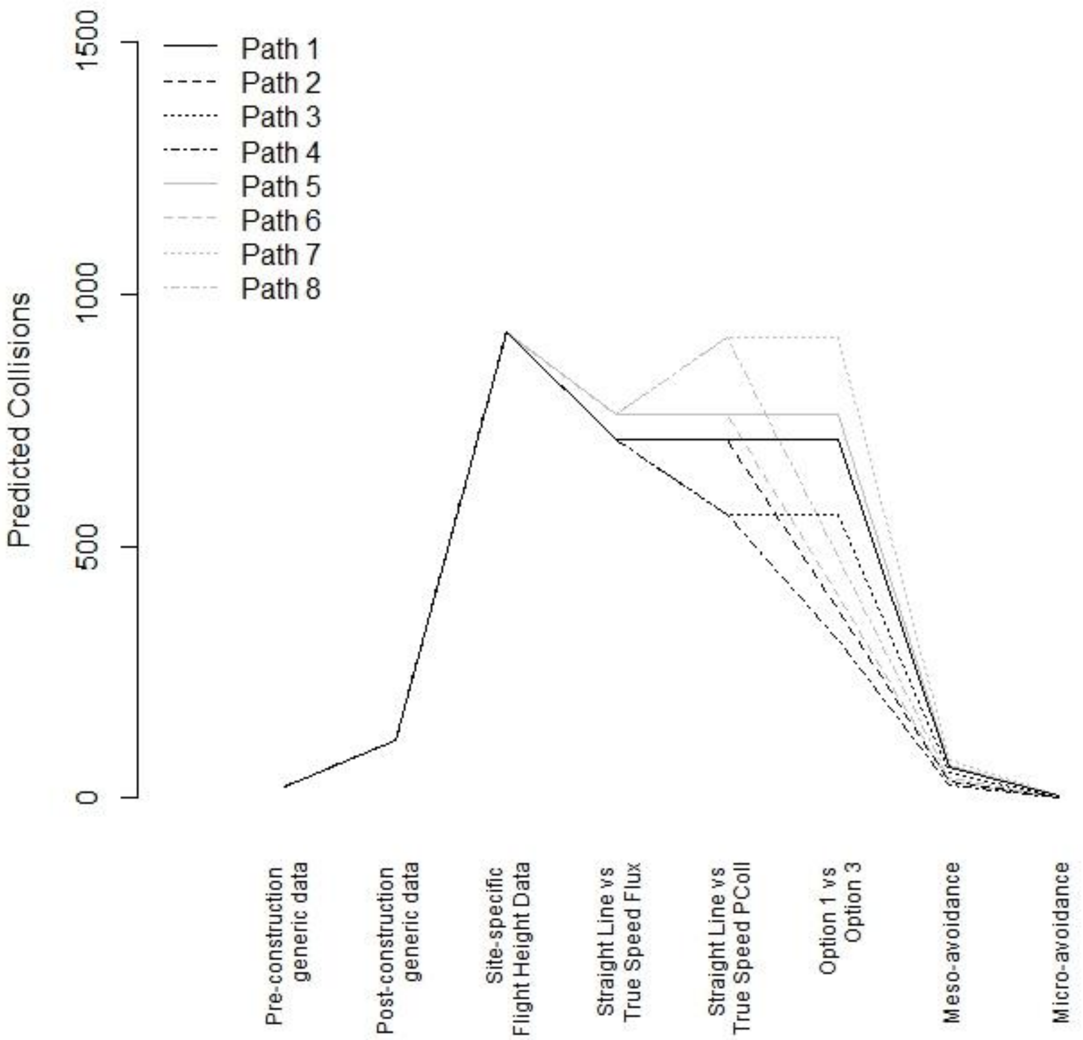


Figure 8. Change in predicted collision rate for Black-legged kittiwake as model assumptions and parameters are refined.

3.4.5 Northern gannet

Northern gannets were the least abundant of the study species in the study area. Densities increased between the pre- and post-construction periods. Other changes in predicted collision rates as model assumptions and parameters were refined were broadly similar to those recorded for the other study species.

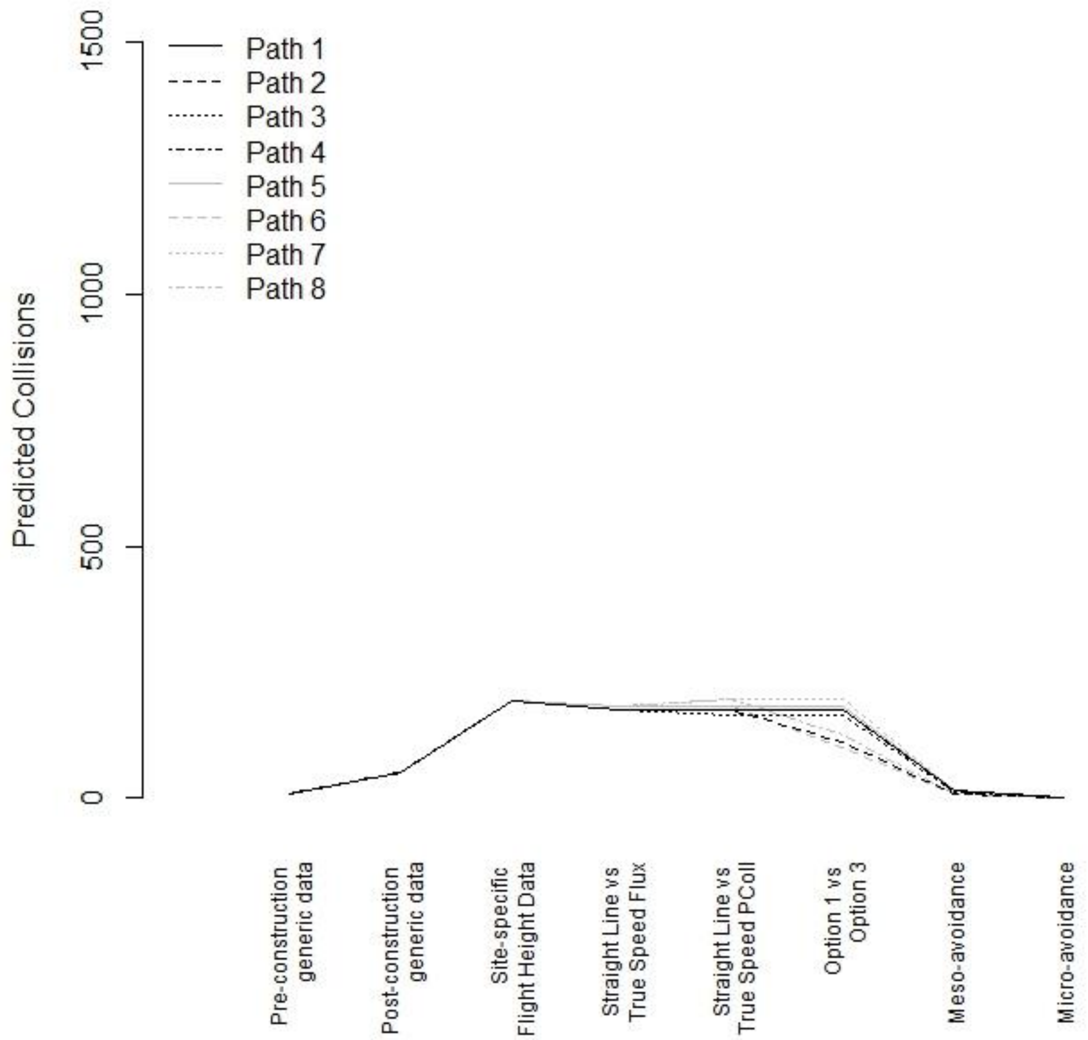


Figure 9. Change in predicted collision rate for northern gannet as model assumptions and parameters are refined.

3.5 Predicted vs. observed collision rates

The final predicted collision rates broadly follow the pattern of species abundance within the study area. Great black-backed gull, the most abundant species, is predicted to have the greatest number of collision while northern gannet, the least abundant species, is predicted to have the fewest (Figure 10a). However, the use of generic or site-specific data and the assumptions made about the data in the Band CRM also have an impact on the final conclusions that are reached (Figure 10b). The relative importance of the use of generic or site-specific data and these assumptions appears to vary by species. For example, the relative change in predicted collision rate according the assumptions made was greatest for black-legged kittiwake (figure 10b). For black-legged kittiwake, collision estimate 5 was 60% greater than the mean collision rate across all eight of the pathways highlighted in figure 2. In contrast, for great black-backed gull, this figure was only 22% (figure 10b).

Having accounted for avoidance behaviour, predicted collision rates were still higher than observed collision rates (Figure 10). For Black-legged kittiwake a single collision was recorded in November 2014, compared to predictions of between 1 and 4 collisions per winter, depending on the data and assumptions used in the model. It was not possible to identify the large gulls that were recorded colliding to species level. Consequently, we compare the observed collision rate for large gulls to the combined predicted collision rate for herring, lesser black-backed and great black-backed gull. Two large gulls were recorded colliding in winter 2014/15 and winter 2015/16. This compares to predicted collision rates of 7-13 birds per year.

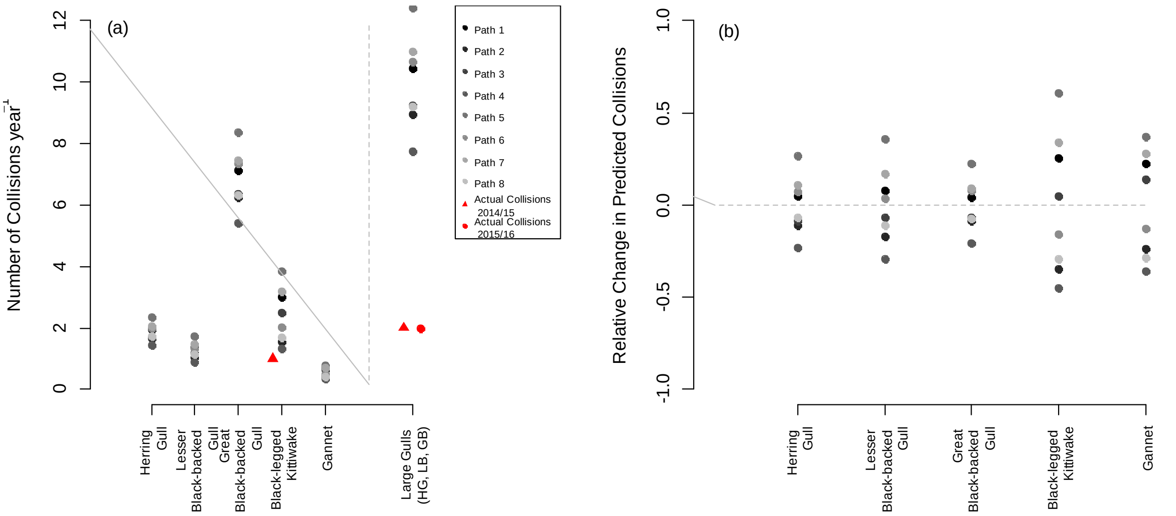


Figure 10. (a) Comparison between predicted and observed collision rates in relation to the data and assumptions incorporated into the Band collision risk model (Band 2012) and whether Option 1 or Option 3 of the Band CRM is used. For actual recorded collisions, it was not possible to distinguish between the large gull species; consequently, the final column includes the total number of predicted collisions for herring, lesser black-backed and great black-backed gulls. (b) Relative change in predicted collision rates in relation to the data and assumptions incorporated into the Band collision risk model (Band 2012) and whether Option 1 or Option 3 of the Band CRM is used.

3.6 Comparison of avoidance rates derived from ORJIP BCA study and those estimated using traditional approach

Avoidance rates estimated using the traditional approach for the Option 3 of the Band CRM were lower than for Option 1 of the Band CRM (Table 10). The reason for this is that avoidance rates estimated in this way incorporate elements of model error. By accounting for the uneven vertical distribution of birds, Option 3 of the Band CRM accounts for some (but not all) of this model error, reducing the predicted collision rate and, following equation 1, the estimated avoidance rate.

For large gulls and black-legged kittiwake it was possible to estimate avoidance rates for the pre- and post-construction periods using generic data. Higher avoidance rates estimated for the post-construction period reflect changes in the density estimates. However, for the reasons explained above (section 2.2), such changes may not reflect macro-responses to the wind farm. Density estimates, and consequently, predicted collision rates for the post-construction period were higher than for the pre-construction period. These differences are most notable for the black-legged kittiwake (Table 10). Avoidance rates estimated in this way based on the post-construction density estimates may be thought of as equivalent to the within-wind farm avoidance rates presented in Cook *et al.* (2014).

Table 10. Avoidance rates calculated from pre- and post-construction density estimates using generic estimates of flight height and flight speed. Avoidance rates based on pre-construction data reflect total avoidance whilst those based on post-construction data reflect within wind farm avoidance only.

	Pre-construction		Post-construction	
	Option 1	Option 3	Option 1	Option 3
Black-legged Kittiwake	0.952	0.891	0.991	0.980
Large gulls (HG, LB, GB)	0.994	0.991	0.995	0.993

The avoidance rates estimated in this way can be further refined by incorporating site-specific data into the calculations of predicted collision rates (Table 11). Incorporating this site-specific information resulted in higher estimated avoidance rates. Again, we see that the change in avoidance rates estimated using pre- and post-construction data was greater for black-legged kittiwakes than it was for large gulls. However, a key reason for the differences in the avoidance rates relates to the substantial differences between the generic and site-specific flight height distributions (Figure 4). The site-specific data includes a far greater proportion of birds at collision risk height. Consequently, following equation 1, this results in a greater predicted collision rate which, when compared to the observed collision rate, results in a higher avoidance rate as the model predicts that a greater number of birds must have taken action to avoid a collision.

Table 11. Avoidance rates calculated from a comparison of predicted and observed collision rates based on **pre-** and *post*-construction density estimates and post-construction site-specific estimates of flight speed and flight height following the collision estimate pathways shown in Figure 2. Avoidance rates based on pre-construction data reflect total avoidance whilst those based on post-construction data reflect within wind farm avoidance only. Clear cells indicate rates calculated based on Option 1 of the Band model, grey cells indicate rates calculated based on Option 3 of the Band model.

	Collision Estimate 1	Collision Estimate 2	Collision Estimate 3	Collision Estimate 4	Collision Estimate 5	Collision Estimate 6	Collision Estimate 7	Collision Estimate 8	ORJIP BCA
Black-legged kittiwake	**0.992** / *0.998*	**0.985** / *0.997*	**0.990** / *0.998*	**0.982** / *0.996*	**0.993** / *0.999*	**0.988** / *0.998*	**0.992** / *0.999*	**0.986** / *0.998*	0.998
Large gulls (HG, LG, GB)	**0.998** / *0.999*	**0.997** / *0.999*	**0.997** / *0.999*	**0.997** / *0.999*	**0.998** / *0.999*	**0.998** / *0.999*	**0.998** / *0.999*	**0.997** / *0.999*	0.998

4 Discussion

4.1 Importance of site-specific data

Much of the focus of uncertainty in relation to collision risk models has focussed on avoidance rates (Chamberlain *et al.* 2006). However, recent analysis suggests that this focus may partly reflect a misunderstanding of how the avoidance rate is used by collision risk models and, that other factors including flight heights and speeds may be similarly important (Masden 2015). The analysis presented above demonstrates the substantial impact that the use of site-specific data can have on estimated collision rates (Figures 5-10). However, it should be emphasised that the estimates of parameters such as flight speed and height presented in Skov *et al.* (2018) come from a single site during the non-breeding season. Given the influence of site-specific data on the estimated collision rates, such data may not be directly transferable to other sites or, to the breeding season.

The estimate of the proportion of birds at collision risk height has a substantial effect on the predicted collision rates (Figures 5-9). This is the case for both the basic and extended models. There are substantial differences between the flight height distribution estimated using laser range finders as part of this study and the generic distributions presented in Johnston *et al.* (2014). Such differences must be treated with caution as it is unclear the extent to which they reflect genuine differences between the two approaches and the extent to which they reflect bias in the data collection methodologies. However, the results do highlight the importance of using a robust and, ideally site-specific, flight height estimate in predicting collision risk.

The Band CRM makes use of bird speed twice: firstly, in order to estimate the flux rate of birds through the wind farm and; secondly, to estimate the probability of a bird colliding with a turbine rotor. Furthermore, flight speed may be estimated at different resolutions, with implications for the model outputs. For the purposes of our analyses, we used two different estimates of flight speeds. The first of these was simply the straight-line distance between the first and last laser range finder points and the time taken to travel between them (referred to above as straight-line speed). However, the birds may not have been travelling in straight lines (as assumed in the calculations of flux rate). Consequently, we estimated a second speed based on the point estimate of speed as measured using the laser range finders (referred to above as True Speed). It is important to note that both of these speeds were markedly lower than the generic speeds typically recommended in guidance (Alerstam *et al.* 2007). Consequently, the flux rates estimated from these data were lower than those estimated using the generic data and the probabilities of collision estimated were greater than those estimated using generic data. There are four possible combinations for how these flight speeds could be incorporated into the collision risk model with respect to their use in estimating the flux rate and probability of collision (straight line-straight line, straight line-true speed, true speed-true speed, true speed-straight line). Which of these combinations is selected has implications for the final estimated collision rate (Figures 5-9). In agreement with Skov *et al.* (2018), we feel that the combination which is most consistent with how the Band CRM is implemented is likely to be the use of the straight line speed estimate of the flux rate and the true speed estimate of the probability of collision. This is because the straight-line speed will reflect the average rate at which birds move through the wind farm while the true speed will be a point estimate of the speed of the bird as it passes the turbine blades.

4.2 Macro-avoidance

Macro-avoidance relates to the change in bird numbers within a wind farm site arising as a result of processes including, but not limited to, displacement, attraction and barrier effects (Cook *et al.* 2014). These responses may reflect either a functional change in habitat use (i.e. displacement or attraction) or anticipatory evasion of the wind farm due to perceived collision risk (i.e. barrier effects) (May 2015). The analyses described above concerned birds already present within the wind farm and, consequently, did not consider macro-avoidance.

The ORJIP BCA study estimated macro-avoidance by comparing the density of bird tracks within the wind farm to the density of bird tracks in a 3 km buffer around the wind farm (Skov *et al.* 2018). In common with previous findings (Cook *et al.* 2014), Skov *et al.* (2018) suggested significant inter-specific variation in the estimated macro-avoidance rates ranging from 0.797 (SD 0.026) for northern gannet to 0.566 (SD 0.058) for black- legged kittiwake and 0.481 (SD 0.038) for large gulls.

The macro-avoidance rates reported for gulls are much higher than those reported elsewhere (Cook *et al.* 2014; Vanermen *et al.* 2015; Krijgsveld *et al.* 2011). This is likely to be because the ORJIP BCA study focuses on the movements of birds in and around the wind farms and does not account for any displacement or attraction effects. Analysis of post-construction data collected from operational wind farms suggests that large gulls may be attracted to the wind farm and that black-legged kittiwakes may show little or no difference in area usage (Dierschke *et al.* 2016; Vanermen *et al.* 2015). The apparent high rate of macro-avoidance evident in gulls as part of this study may relate to the presence of fishing vessels on the edge of the wind farm. Fishing vessels cannot operate within the wind farm and, a previous study (Krijgsveld *et al.* 2011) noted gulls being attracted to fishing vessels on the edge of a wind farm. Seabird observers noted a similar effect as part of the ORJIP BCA study. In such circumstances, birds will be responding to the fishing vessels rather than the turbines. This may result in the number of birds outside the wind farm being inflated and the number within the wind farm being artificially reduced. This effect may hold for black-legged kittiwakes and large gulls. Consequently, the macro-avoidance rates estimated for large gulls and black-legged kittiwake as part of the ORJIP BCA study should be used with caution in relation to collision risk modelling based on pre-construction bird density estimates.

The results for northern gannet are consistent with previous studies, which suggested high macro-avoidance rates for this species, ranging from 0.64 (Krijgsveld *et al.* 2011) to 0.85 (Vanermen *et al.* 2015) and possibly as high as 0.92 (Welcker & Nehls 2016), although it should be noted the latter study was based on a limited sample size. It should also be noted that the rate estimated as part of the ORJIP BCA project may be an underestimate for two reasons. Firstly, without comparison to pre-construction estimates of bird density, these data do not capture any impact of displacement on the number of birds recorded. Secondly, collecting data on the movements of birds outside the wind farm using radar requires a trade-off between the distance over which a radar system can operate and resolution at which data can be collected. For the systems used in this study, the optimum distance over which to collect data was judged to be 3 km. However, past studies have noted that northern gannets may take action to avoid entering a wind farm at distances far greater than 3 km (Petersen *et al.* 2006). However, like gulls, northern gannets are known to be attracted to fishing vessels (Votier *et al.* 2010). The extent to which displacement from the wind farm, attraction to fishing vessels and the presence of the wind farm as a barrier to flying birds may interact with one another is unclear. Consequently, it is difficult to assess the extent to which the estimate of 0.79 may be precautionary.

It should be noted that comparison of pre- and post-construction density estimates suggested an increase in density post-construction for four of the five species (Table 2).

However, the pre-construction density estimates were based on survey effort from a single year, it is questionable this effort is sufficient to characterise the baseline conditions of the wind farm site (Maclean *et al.* 2013). Consequently, it is difficult to assess the extent to which the reported changes were "genuine", particularly in the case of northern gannet, a species for which a strong displacement effect has previously been reported (Dierschke *et al.* 2016).

4.3 Meso-avoidance

To our knowledge, the ORJIP BCA study is the first that systematically set out to measure the meso-avoidance rates of seabirds within an operational wind farm. Data presented in a previous review (Cook *et al.* 2014) suggested that meso-avoidance rates were likely to be high, with few birds passing in close proximity to turbines.

In the ORJIP BCA study, meso-avoidance rates appear to be calculated in a logical way, comparing the track length per unit area within the rotor-swept zone and a 10 m buffer (as defined in Cook *et al.* (2014) to a theoretical density assuming birds were spread evenly throughout the wind farm. The resulting rates support previous hypotheses that meso-avoidance rates are likely to be very high and that birds within wind farms show strong avoidance of turbines.

4.4 Micro-avoidance

Micro-avoidance rates collected as part of the ORJIP BCA study were based on extremely limited sample sizes. It is important to highlight that this is likely to reflect the fact that most birds take action to avoid collisions at distances that do not necessitate the "last-second" avoidance behaviour reflected by micro-avoidance, rather than a short-coming in the study design. In total, only 299 birds were recorded approaching turbines closely enough to necessitate "last-second" collision avoidance behaviour. Consequently, it was not possible to consider species-specific micro-avoidance behaviour.

The results from the ORJIP BCA study are consistent with those from past studies that have shown that very few birds approach turbines closely enough to necessitate micro-avoidance behaviour (Krijgsveld *et al.* 2011; Thaxter *et al.* 2017; Mendel *et al.* 2014; Desholm *et al.* 2006). Data from across these studies suggested that micro-avoidance rates were likely to be >0.93, although, it should be noted that there were significant limitations in the derivation of this rate (Cook *et al.* 2014). However, the estimate from the ORJIP BCA study of 0.9500 (SD 0.0128) for all seabirds was consistent with this previous estimate. In terms of the number of records of birds interacting with turbines, the sample size from the ORJIP BCA study is substantially higher than any previous attempt. Consequently, whilst there is clearly a need for additional data collection to support this, the estimate of 0.9500 (SD 0.0128) for micro-avoidance from the ORJIP BCA study is, at this time, the best available data with which to quantify micro-avoidance behaviour in seabirds.

4.5 Use of avoidance rates from ORJIP BCA study

It is important to note that there is a difference between the empirical avoidance rate derived in the ORJIP BCA study and the avoidance rate as used by the Band CRM. The empirical avoidance rate, as derived by the ORJIP BCA study, incorporates detailed information about the distribution and movements of birds within a wind farm and their interactions with turbines. The avoidance rate as used by the Band CRM is based on a comparison of predicted and observed collision rates. The predicted collision rates will incorporate elements of error in relation to both the data used and the model itself (Band 2012). The incorporation of this error is likely to mean that the avoidance rates used by the Band CRM are likely to be lower than those measured empirically.

The total empirical avoidance rates estimated as part of the ORJIP BCA study include avoidance behaviour at the macro-, meso- and micro-scales. However, for the reasons set out above (section 4.2), we feel that the estimates of macro-avoidance from this study are not applicable in the context of how the Band CRM is used in the pre-construction assessment of collision risk. Empirical avoidance rates combining the remaining meso- and micro-avoidance correspond to the within-wind farm avoidance rates presented in Cook *et al.* (2014). The resulting empirical within-wind farm avoidance rates are 0.9956 for large gulls, 0.9958 for black-legged kittiwake and 0.9960 for northern gannet. However, as these rates do not incorporate model error in the same way that those recommended by existing guidance do (Cook *et al.* 2014), they are not directly applicable to the Band collision risk model.

Based on the data collected as part of the ORJIP BCA study and analysed above (section 3.6), we suggest that a total avoidance rate of 0.995 is suitable for use in the basic Band CRM for large gulls (Table 12). Given previous evidence of strong macro-avoidance in the northern gannet (Dierschke *et al.* 2016), we suggest that 0.995 is also a suitable minimum value to use for this species in relation to the basic Band CRM (table 12). Analyses of collision rates presented above (Tables 10 & 11) suggest that black-legged kittiwake may be more prone to collisions than large gulls. Consequently, we suggest that an avoidance rate of 0.990 is suitable for this species (Table 12). It is acknowledged that this is lower than in previous guidance (Cook *et al.* 2014). However, we feel this is justified as, in the previous guidance black-legged kittiwake was grouped with other small gull species (Cook *et al.* 2014). In the density data used in the above analysis (Royal Haskoning 2013) to estimate the predicted collision rate, the number of black-legged kittiwakes not identified to species level is likely to be negligible. As no other small gulls, whether identified to species level or not, were recorded colliding, we feel the estimate of 0.990 for black-legged kittiwake is robust. These avoidance rates are considered to include macro-avoidance (Table 12).

We were able to undertake further analyses (described in Appendix 1) in order to derive avoidance rates suitable for use in the stochastic collision risk model for black-legged kittiwake of 0.994 (95% CIs 0.976 - 0.998) for option 1 and 0.970 (95% CIs 0.871-0.989) for option 3 and, for large gulls 0.997 (95% CIs 0.992 - 0.999) for option 1 and 0.990 (95% CIs 0.974 - 0.995) for option 3. Note that the median values recommended for use in the stochastic collision risk models differ from the values recommended for use in the deterministic model, this relates to differences in the way in which flight height distributions are incorporated into the models. However, it should also be noted that the values recommended for use in the deterministic model are within the 95% confidence intervals of those recommended for use in the stochastic model.

In relation to the extended Band CRM, we note the sizeable difference between the observed and recorded flight height distributions, and the potential for bias associated with the collection of flight height data using laser range finders (Borkenhagen *et al.* 2018) to contribute to this difference. This difference has a noticeable effect on the avoidance rates estimated using generic and site-specific data. Given the precautionary principle in assessing collision risk, we suggest that the estimates of avoidance rate made using generic flight height data (Table 10) should be used for the extended Band CRM. Ideally site-specific estimates of flight height would be used to estimate avoidance rates. However, given uncertainty in the flight height data recorded as part of the ORJIP BCA project and, the discrepancy with previous estimates of seabird flight height (figure 4), we believe this reflects a realistic, precautionary approach. If the number of birds at risk of collision is over-estimated, then, following equation 1, the overall avoidance rate is also likely to be overestimated. Consequently, for the extended Band CRM, we recommend using avoidance rates of 0.993 for large gulls and 0.980 for black-legged kittiwake (Table 12). It should be noted that this reflects an increase in the rate recommend for large gulls in previous guidance (Cook *et al.* 2014) and is the first time it has been possible to calculate a total avoidance rate for black-legged kittiwake for Option 3 of the Band CRM based on empirical data. However, based on the data collected as part of the ORJIP BCA project, it has not been possible to calculate an avoidance rate suitable for use in Option 3 of the Band CRM for northern gannet as no collisions were recorded (Table 12).

It is important to highlight some key limitations in how the avoidance rates presented in table 12 were derived. Data were collected from a single site, during the non-breeding season in daylight hours. As the avoidance rates derived from these data are higher than those presented elsewhere (Cook *et al.* 2014), care must be taken before applying them to other sites and to breeding season estimates of collision rates. Consequently, with the exception of black-legged kittiwake, the avoidance rates we recommend are based on generic flight speed and height data as we feel these retain a sufficient level of precaution whilst also being applicable to a broader range of sites and, to the breeding season. In relation to black-legged kittiwake, the recommended rate of 0.990 is derived using site-specific flight height and speed data as this was lower than the rate derived using generic data (tables 10,11 and 12).

Table 12. Recommended avoidance rates for use in the deterministic Band Collision Risk Model, derivation of these avoidance rates and rationale for recommendations.

	Band Model Option	Recommended Avoidance Rate	Derivation of Avoidance Rate	Rationale
Northern gannet	1	0.995	It was not possible to estimate an avoidance rate by comparing predicted and observed collision rates. However, given clear evidence of strong macro-avoidance at Thanet from Skov *et al.* (2018), and at other sites (Dierschke *et al.* 2016), it was felt appropriate to use the same value as recommended for large gulls.	Following the logic of Cook *et al.* (2014), given strong evidence of high macro-avoidance in northern gannets from a variety of sites (Dierschke *et al.* 2016), we feel that it is unlikely that the total avoidance rate for northern gannet would be less than that for large gulls.
	3	NA		As no collisions involving northern gannets were recorded as part of the ORJIP BCA study, it was not possible to compare predicted and expected collision rates. Furthermore, given clear differences in the flight height distributions of northern gannet and large gulls (Johnston *et al.* 2014) it is unlikely to be appropriate to base any value on that for large gulls, as we have done for Option 1 of the Band model. Consequently, in the absence of other data, it is still not possible to recommend a suitable avoidance rate for Option 3 of the Band CRM for northern gannet.
Black-legged kittiwake	1	0.990	Calculated using equation 1 by comparing the observed collision rate to predicted collision estimate 3 (figure 2). The predicted collision rate in the absence of avoidance behaviour was estimated using site-specific estimates of flight height and speed and pre-construction density	Avoidance rates for black-legged kittiwake which were suitable for use with Option 1 of the Band model ranged from 0.952 – 0.998 (tables 10 & 11). Based on the observed collision rate, a rate of 0.952, derived using generic bird flight data and pre-construction density estimates was felt to be overly-precautionary.

			estimates. The flux rate was estimated using straight line speed and the probability of a bird colliding was estimated using the true speed.	The most appropriate approach for deriving avoidance rates using the data collected by the ORJIP BCA project was felt to be the use of straight line speed to estimate flux rate and true speed to estimate the probability of collision. This resulted in estimated avoidance rates of 0.990 based on the pre-construction density estimates and 0.998 based on the post-construction density estimates (table 11). This compared to a rate of 0.991 derived using post-construction density estimates and generic bird data (table 10). Consequently, 0.990 was selected as the most precautionary of the realistic estimated values. Furthermore, as black-legged kittiwake are believed to show little change in numbers in response to the presence of a wind farm (Dierschke *et al.* 2016), this was considered a realistic value for total avoidance.
	3	0.980	Calculated using equation 1 to compare the observed collision rate to the collision rate estimated using generic bird flight data and post-construction density estimates.	Avoidance rates for black-legged kittiwake which were suitable for use with Option 3 of the Band model ranged from 0.891 – 0.998 (tables 10 & 11). Based on the observed collision rate, a rate of 0.891, derived using generic bird flight data and pre-construction density estimates was felt to be overly-precautionary. The most appropriate approach for deriving avoidance rates using the data collected by the ORJIP BCA project was felt to be the use of straight line speed to estimate flux rate and true speed to estimate the probability of collision. This resulted in estimated

				avoidance rates of 0.982 based on the pre-construction density estimates and 0.996 based on the post-construction density estimates (table 11). This compared to a rate of 0.980 derived using post-construction density estimates and generic bird data (table 10). As a consequence of the notable differences between the observed and generic flight height distributions, the rate of 0.980 was felt to be the most precautionary of the realistic values. Whilst this is based on post-construction density estimates, as black-legged kittiwakes do not appear to show a noticeable change in density in response to the presence of an offshore wind farm (Dierschke *et al.* 2016), this is felt to be a realistic value for total avoidance.
Lesser black-backed gull	1	0.995	The large gulls recorded colliding with turbines during the ORJIP BCA project could not be identified to species level. Consequently, a large gull avoidance rates was estimated by comparing the observed large gull collision rate to the sum of the lesser black-backed, herring and great black-backed collision rates predicted in the absence of avoidance behaviour using equation 1. Predicted collision rates were estimated using post-construction density estimates and generic bird flight data for each species.	Avoidance rates for large gulls which were suitable for use with Option 1 of the Band model ranged from 0.994 – 0.999 (tables 10 & 11). Those based on site specific data were felt to be insufficiently precautionary (table 11). This is likely to reflect the high proportion of birds reported at collision risk height by Skov *et al.* (2018) in comparison to previous studies (Johnston *et al.* 2014; Johnston & Cook 2016; Corman & Garthe 2014; Borkenhagen *et al.* 2018; Ross-Smith *et al.* 2016). Given the uncertainty this introduces, it was felt that for large gulls, the avoidance rates derived using generic data were most appropriate (table 10). Using the generic data avoidance rates of 0.994 using the pre-construction density estimates and 0.995 using the post-construction density estimates

				were calculated. Of these, the estimate of 0.995 derived using post construction density estimates was felt to be most appropriate because density estimates were based on multiple years' data and, gulls may be attracted to wind farms following construction (Dierschke *et al.* 2016).
	3	0.993	The large gulls recorded colliding with turbines during the ORJIP BCA project could not be identified to species level. Consequently, a large gull avoidance rates was estimated by comparing the observed large gull collision rate to the sum of the lesser black-backed, herring and great black-backed collision rates predicted in the absence of avoidance behaviour using equation 1. Predicted collision rates were estimated using post-construction density estimates and generic bird flight data for each species.	Avoidance rates for large gulls which were suitable for use with Option 3 of the Band model ranged from 0.991 – 0.999 (tables 10 & 11). Those based on site specific data were felt to be insufficiently precautionary (table 11). This is likely to reflect the high proportion of birds reported at collision risk height by Skov *et al.* (2018) in comparison to previous studies (Johnston *et al.* 2014; Johnston & Cook 2016; Corman & Garthe 2014; Borkenhagen *et al.* 2018; Ross-Smith *et al.* 2016). Given the uncertainty this introduces, it was felt that for large gulls, the avoidance rates derived using generic data were most appropriate (table 10). Using the generic data avoidance rates of 0.991 using the pre-construction density estimates and 0.993 using the post-construction density estimates were calculated. Of these, the estimate of 0.993 derived using post construction density estimates was felt to be most appropriate because density estimates were based on multiple years' data and, gulls may be attracted to wind farms following construction (Dierschke *et al.* 2016).
Herring gull	1	0.995	The large gulls recorded colliding with turbines during the ORJIP BCA project could not be identified to species level.	Avoidance rates for large gulls which were suitable for use with Option 1 of the Band model ranged from 0.994 – 0.999 (tables 10

			Consequently, a large gull avoidance rates was estimated by comparing the observed large gull collision rate to the sum of the lesser black-backed, herring and great black-backed collision rates predicted in the absence of avoidance behaviour using equation 1. Predicted collision rates were estimated using post-construction density estimates and generic bird flight data for each species.	& 11). Those based on site specific data were felt to be insufficiently precautionary (table 11). This is likely to reflect the high proportion of birds reported at collision risk height by Skov *et al.* (2018) in comparison to previous studies (Johnston *et al.* 2014; Johnston & Cook 2016; Corman & Garthe 2014; Borkenhagen *et al.* 2018; Ross-Smith *et al.* 2016). Given the uncertainty this introduces, it was felt that for large gulls, the avoidance rates derived using generic data were most appropriate (table 10). Using the generic data avoidance rates of 0.994 using the pre-construction density estimates and 0.995 using the post-construction density estimates were calculated. Of these, the estimate of 0.995 derived using post construction density estimates was felt to be most appropriate because density estimates were based on multiple years' data and, gulls may be attracted to wind farms following construction (Dierschke *et al.* 2016).
	3	0.993	The large gulls recorded colliding with turbines during the ORJIP BCA project could not be identified to species level. Consequently, a large gull avoidance rates was estimated by comparing the observed large gull collision rate to the sum of the lesser black-backed, herring and great black-backed collision rates predicted in the absence of avoidance behaviour using equation 1.	Avoidance rates for large gulls which were suitable for use with Option 3 of the Band model ranged from 0.991 – 0.999 (tables 10 & 11). Those based on site specific data were felt to be insufficiently precautionary (table 11). This is likely to reflect the high proportion of birds reported at collision risk height by Skov *et al.* (2018) in comparison to previous studies (Johnston *et al.* 2014; Johnston & Cook 2016; Corman & Garthe 2014; Borkenhagen *et al.* 2018; Ross-Smith *et al.* 2016). Given the uncertainty this introduces, it was felt that for large gulls, the avoidance

			Predicted collision rates were estimated using post-construction density estimates and generic bird flight data for each species.	rates derived using generic data were most appropriate (table 10). Using the generic data avoidance rates of 0.991 using the pre-construction density estimates and 0.993 using the post-construction density estimates were calculated. Of these, the estimate of 0.993 derived using post construction density estimates was felt to be most appropriate because density estimates were based on multiple years' data and, gulls may be attracted to wind farms following construction (Dierschke *et al.* 2016).
Great black-backed gull	1	0.995	The large gulls recorded colliding with turbines during the ORJIP BCA project could not be identified to species level. Consequently, a large gull avoidance rates was estimated by comparing the observed large gull collision rate to the sum of the lesser black-backed, herring and great black-backed collision rates predicted in the absence of avoidance behaviour using equation 1. Predicted collision rates were estimated using post-construction density estimates and generic bird flight data for each species.	Avoidance rates for large gulls which were suitable for use with Option 1 of the Band model ranged from 0.994 – 0.999 (tables 10 & 11). Those based on site specific data were felt to be insufficiently precautionary (table 11). This is likely to reflect the high proportion of birds reported at collision risk height by Skov *et al.* (2018) in comparison to previous studies (Johnston *et al.* 2014; Johnston & Cook 2016; Corman & Garthe 2014; Borkenhagen *et al.* 2018; Ross-Smith *et al.* 2016). Given the uncertainty this introduces, it was felt that for large gulls, the avoidance rates derived using generic data were most appropriate (table 10). Using the generic data avoidance rates of 0.994 using the pre-construction density estimates and 0.995 using the post-construction density estimates were calculated. Of these, the estimate of 0.995 derived using post construction density estimates was felt to be most appropriate because density estimates were based on multiple years' data and, gulls may be

				attracted to wind farms following construction (Dierschke *et al.* 2016).
	3	0.993	The large gulls recorded colliding with turbines during the ORJIP BCA project could not be identified to species level. Consequently, a large gull avoidance rates was estimated by comparing the observed large gull collision rate to the sum of the lesser black-backed, herring and great black-backed collision rates predicted in the absence of avoidance behaviour using equation 1. Predicted collision rates were estimated using post-construction density estimates and generic bird flight data for each species.	Avoidance rates for large gulls which were suitable for use with Option 3 of the Band model ranged from 0.991 – 0.999 (tables 10 & 11). Those based on site specific data were felt to be insufficiently precautionary (table 11). This is likely to reflect the high proportion of birds reported at collision risk height by Skov *et al.* (2018) in comparison to previous studies (Johnston *et al.* 2014; Johnston & Cook 2016; Corman & Garthe 2014; Borkenhagen *et al.* 2018; Ross-Smith *et al.* 2016). Given the uncertainty this introduces, it was felt that for large gulls, the avoidance rates derived using generic data were most appropriate (table 10). Using the generic data avoidance rates of 0.991 using the pre-construction density estimates and 0.993 using the post-construction density estimates were calculated. Of these, the estimate of 0.993 derived using post construction density estimates was felt to be most appropriate because density estimates were based on multiple years' data and, gulls may be attracted to wind farms following construction (Dierschke *et al.* 2016).

4.6 Recommendations for future work

The ORJIP BCA study has collected detailed data on the movements and behaviour of birds within an operational offshore wind farm at a scale never previously attempted. Whilst it has answered many questions about the movements of birds within a wind farm and how they avoid collisions, it has raised many more. In particular, by attempting to derive seabird avoidance rates based on observed behaviour, it has highlighted the potential consequences for the consenting process of the discrepancy between model assumptions and how birds utilise wind farms. The lack of validation for collision risk models has been a key problem for some time (Masden & Cook 2016), with some evidence that modelled predictions may be a poor match for observed collision rates (Ferrer *et al.* 2012; de Lucas *et al.* 2008).

Recommendations for future work fall into two categories – how lessons learned from the ORJIP BCA study can be incorporated into similar studies in the future and how the data can be used to improve and develop models of collision risk.

4.6.1 Lessons learned

Deriving total macro-avoidance rates from the ORJIP BCA study proved challenging. There are two reasons for this. Firstly, it was not possible to collect seabird density data as part of this project. This meant that it was not possible to assess changes in the numbers of birds present between the pre- and post-construction periods, which may be expected in response to displacement effects. Ideally, future studies should seek to collect information about seabird density in parallel to fine-scale behavioural data in order to better understand any displacement effects. Secondly, whilst the study was well set up to look at the impact of barrier effects, attempts to estimate these may have been confounded by the presence of fishing vessels on the edge of the wind farm. Species like gulls and northern gannets may be attracted to fishing vessels over significant distances (Votier *et al.* 2010). Consequently, there is a risk that some birds may have been responding to the presence of fishing vessels on the edge of the wind farm, as reported by observers in both the ORJIP BCA study (Skov *et al.* 2018) and elsewhere (Krijgsveld *et al.* 2011). In order to fully account for macro-avoidance behaviour, it would be valuable if future studies were able to develop spatial modelling approaches which could account for changes in the density of birds between the pre- and post-construction periods. Ideally, such approaches would also account for the movement of fishing vessels, which may attract birds and, thus, give a misleading impression of the impact of barrier effects. Combining digital aerial survey data with radar data may prove a useful approach for this with digital aerial survey data able to offer information on distribution and radar able to offer information on flight paths and speeds.

In the estimation of macro-avoidance behaviour, Skov *et al.* (2018), highlight the different components of uncertainty that may contribute to the total uncertainty surrounding the final macro-avoidance rates. However, in common with the suggested approach for estimating uncertainty set out by Band (2012), these are largely based on expert judgement. Future studies should consider how the need for expert judgement in relation to the estimation of uncertainty can be overcome. For example, spatial and/or temporal modelling approaches could be used in order to determine the level of uncertainty introduced as a result of factors such as the presence of fishing vessels and weather conditions.

The ORJIP BCA study has supported previous suggestions that a significant proportion of avoidance behaviour may take place at the meso-scale (Cook *et al.* 2014). Gathering additional data at this scale is likely to be extremely valuable. However, as such a high proportion of avoidance behaviour occurs at the meso-scale, collecting data on avoidance behaviour at a micro-scale is much more challenging. Whilst the ORJIP BCA study has collected the most comprehensive dataset on micro-avoidance to date, it is clear that much more data are required in order to fully understand micro-avoidance behaviour, particularly at an inter-specific level. Future studies should consider approaches that will maximise the collection of data at the micro-scale. A key gap relates to our understanding of how avoidance behaviour may differ between day and night. Consequently, future studies should make use of thermal cameras to enable collisions to be recorded during the dark.

Estimates of seabird flight heights were based on measurements collected using laser rangefinders. Such measurements may be biased against low flying birds and, consequently, overestimate the number at risk of collision (Borkenhagen *et al.* 2018). Consequently, it is difficult to ascertain the extent to which the flight height distributions obtained as part of the ORJIP BCA study, which are radically different to generic distributions collected from elsewhere (Figure 4), reflect this bias and/or site-specific factors. Ideally, in order to make the most of these data, future studies should collect flight information both inside and outside wind farms using multiple platforms concurrently in order to better understand any potential biases.

4.6.2 Collision risk model development

The disparity between the number of collisions predicted by the Band CRM relative to those observed (Figure 10) highlights the need to start looking at ways to incorporate realistic assessments of bird behaviour into collision risk models. Ideally, we should be asking how to make the model better fit the data, rather than how to make the data fit the model, e.g. through the use of correction factors. At the same time, there is a need to balance the detailed data collected as part of this study with the more generic data typically available as part of pre-construction impact assessments. Below, we highlight areas where we feel refinements could be made to more accurately assess collision risk.

The Band CRM estimates the number of birds at risk of collision by predicting the number of birds likely to pass through the turbine rotor-swept area per second (Band 2012). This is based on an estimate of bird flight speed, to determine how long it would take a bird to pass through the rotor, and density, in order to estimate the number of birds available to pass through the rotor per unit time. As highlighted above (Table 3 and section 4.1) the generic estimates of flight speed far exceed those measured as part of the ORJIP BCA Study, meaning, the use of generic data results in significantly higher estimated flux rates (Table 6). Furthermore, the Band CRM assumes that birds fly at a constant speed, perpendicular to the rotor. If these assumptions are not met, for example, if the flight path taken by a bird is not perpendicular as it approaches the turbine, this may also have significant implications for the number of birds estimated to be at risk of collision (Table 6). For example, birds engaged in area-restricted search foraging behaviour, may be less likely to be travelling in a straight line than those commuting between foraging areas and breeding colonies (Votier *et al.* 2013). Furthermore, rather than approaching the turbine rotor at a perpendicular angle, as assumed by the Band CRM, the ORJIP BCA study noted a significant number of birds flying in parallel to the turbine blades. Models should be refined in order to account for site specific differences in bird behaviour (e.g. commuting vs. foraging flight) as these differences are likely to have a substantial impact on collision risk.

In contrast, the data collected as part of the ORJIP BCA study suggests that the Band CRM may underestimate the probability of a bird passing through a turbine colliding with the blades. Using site-specific data, the probability of collision was estimated at between 0.07 – 0.12 (Table 7), depending on the species and approach used. However, the data collected as part of the ORJIP BCA showed six of the 15 birds that crossed the rotor swept area colliding, implying a greater probability of collision in the region of 0.4, albeit based on limited data. Again, the ORJIP BCA study is the first, to our knowledge, to offer quantitative data regarding the number of birds crossing the rotor-swept area which collide with the turbine blades. One potential reason for this discrepancy is that birds crossing a rotor swept area at an oblique angle may be more likely to collide than those making a perpendicular approach to the rotor (Band 2012). Band (2012) argues that this effect can be offset by the fact that the elliptical shape of the rotor means that birds are less likely to enter the rotor swept area. Subsequent analyses have shown that accounting for an oblique approach may result in a substantially increased collision risk (Christie & Urquhart 2015). Models should be refined in order to more accurately reflect bird movement patterns and account for an oblique approach to the turbine rotors. This will necessitate data describing bird movement patterns being collected as part of EIAs. This could be achieved either through the use of tracking data or, by examination of images collected by digital aerial surveys.

The analyses presented above suggest that the Band CRM may give a misleading impression of absolute collision risk, with predicted collision rates higher than those observed, even after accounting for avoidance behaviour (Figure 10). However, it should be acknowledged that "*all models are wrong, but some are useful*" (Box *et al.* 2005). In the context of collision risk modelling, at present the Band CRM may reflect our best approach for assessing collision risk. However, ideally the predictions should be treated in relative rather than absolute terms. As more data become available, for example, through radar or tracking studies, these data should be used to refine the models in order to more accurately account for bird movement and behaviour. These model refinements (e.g. accounting for differences in behaviour and oblique approaches to wind turbines) are likely to reduce the error associated model simplifications (Band 2012) meaning that the correction factor referred to as an avoidance rate can be more closely aligned with the empirical avoidance rates calculated by the ORJIP BCA study.

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6 References

Alerstam, T., Rosén, M., Bäckman, J., Ericson, P.G.P. & Hellgren, O., 2007. Flight Speeds among Bird Species: Allometric and Phylogenetic Effects. *PLoS Biology*, 5(8), p.e197.

APEM, 2018. *Thanet Extension Environmental Statement Volume 4, Chapter 4, Annex 4 - Thanet Extension OWF Collision Risk Modelling Report*.

Band, B. (2012). Using a Collision Risk Model to Assess Bird Collision Risks for Offshore Wind Farms. Report by British Trust for Ornithology (BTO), Bureau Waardenburg bv and University of St Andrews.

Benaglia, T., Chauveau, D., Hunter, D.R. & Young, D.S., 2009. mixtools : An *R* Package for Analyzing Finite Mixture Models. *Journal of Statistical Software*, 32(6), pp.1–29.

Borkenhagen, K., Corman, A.-M. & Garthe, S., 2018. Estimating flight heights of seabirds using optical rangefinders and GPS data loggers: a methodological comparison. *Marine Biology*, 165(1), p.17.

Box, G.E.P., Hunter, J.S. & Hunter, W.G., 2005. *Statistics for Experimenters: Design, Innovation and Discovery* 2nd Editio., New Jersey: John Wiley & Sons, Ltd.

Camphuysen, C.J., Fox, A.D., Leopold, M.F. & Petersen, I.K., 2004. *Towards standardised seabirds at sea census techniques in connection with environmental impact assessments for offshore wind farms in the U.K., Royal Netherlands Institute for Sea Research*.

Chamberlain, D.E., Rehfisch, M.R., Fox, A.D., Desholm, M. & Anthony, S.J., 2006. The effect of avoidance rates on bird mortality predictions made by wind turbine collision risk models. *Ibis*, 148(s1), pp.198–202.

Christie, D. & Urquhart, B., 2015. A refinement of the Band spreadsheet for wind turbine collision risk allowing for oblique entry. *New Zealand Journal of Zoology*, 42(4), pp.290–297.

Cook, A.S.C.P., Humphreys, E.M., Masden, E.A. & Burton, N.H.K., 2014. *The Avoidance Rates of Collision Between Birds and Offshore Turbines*, Scottish Marine and Freshwater Science 5 (16), Edinburgh.

Corman, A.M. & Garthe, S., 2014. What flight heights tell us about foraging and potential conflicts with wind farms: a case study in Lesser Black-backed Gulls (*Larus fuscus*). *Journal of Ornithology*, pp.1037–1043.

Davies, I., Finlay, A., Cole, E. & Alcock, P. 2013. Avoidance behaviour at offshore wind farms: a new joint industry approach. BOU Proceedings – Marine Renewables and Birds. http://www.bou.org.uk/bouproc-net/marine-renewables/davies-et-al-b.pdf.

Desholm, M., Fox, A.D., Beasley, P.D.L. & Kahlert, J., 2006. Remote techniques for counting and estimating the number of bird-wind turbine collisions at sea: A review. *Ibis*, 148(SUPPL. 1), pp.76–89.

Dierschke, V., Furness, R.W. & Garthe, S., 2016. Seabirds and offshore wind farms in European waters: Avoidance and attraction. *Biological Conservation*, 202, pp.59–68.

Drewitt, A.L. & Langston, R.H.W., 2006. Assessing the impacts of wind farms on birds. *Ibis*, 148(s1), pp.29–42.

Ferrer, M., de Lucas, M., Janss, G.F.E., Casado, E., Muñoz, A.R., Bechard, M.J. & Calabuig, C.P., 2012. Weak relationship between risk assessment studies and recorded mortality in wind farms. *Journal of Applied Ecology*, 49(1), pp.38–46.

Furness, R.W., Wade, H.M. & Masden, E.A., 2013. Assessing vulnerability of marine bird populations to offshore wind farms. *Journal of Environmental Management*, 119, pp.56–66.

Garthe, S. & Huppop, O., 2004. Scaling possible adverse effects of marine wind farms on seabirds: Developing and applying a vulnerability index. *Journal of Applied Ecology*, 41(4), pp.724–734.

Gibson, L., Wilman, E.N. & Laurance, W.F., 2017. How Green is “Green” Energy? *Trends in ecology & evolution*, 32(12), pp.922–935.

Gionata, A., Maintainer, B. & Biavati, G., 2015. RAtmosphere: standard atmospheric profiles. R package version 1.1

Green, R.E., Langston, R.H.W., McCluskie, A., Sutherland, R. & Wilson, J.D., 2016. Lack of sound science in assessing wind-farm impacts on seabirds. *Journal of Applied Ecology,* 53(6), pp.1635-1641.

Johnston, A., Cook, A.S.C.P., Wright, L.J., Humphreys, E.M. & Burton, N.H.K., 2014. Modelling flight heights of marine birds to more accurately assess collision risk with offshore wind turbines. *Journal of Applied Ecology*, 51(1), pp.31–41.

Johnston, A. & Cook, A.S.C.P., 2016. *How high do birds fly? Development of methods and analysis of digital aerial data of seabird flight heights*, Thetford.

Krijgsveld, K.L., Fijn, R.C., Japink, M., van Horssen, P.W., Heunks, C., Collier, M.P., Poot, M.J.M., Beuker, D. & Dirksen, S., 2011. *Effect studies Offshore Wind Farm Egmond aan Zee - Final report on fluxes, flight altitudes and behaviour of flying birds*, report by Bureau Waardenburg bv for NoordzeeWind.

de Lucas, M., Janss, G.F.E., Whitfield, D.P. & Ferrer, M., 2008. Collision fatality of raptors in wind farms does not depend on raptor abundance. *Journal of Applied Ecology*, 45(6), pp.1695–1703.

Maclean, I.M.D., Rehfisch, M.M., Skov, H. & Thaxter, C.B., 2013. Evaluating the statistical power of detecting changes in the abundance of seabirds at sea. *Ibis*, 155(1), pp.113–126.

Masden, E.A., 2015. *Developing an avian collision risk model to incorporate variability and uncertainty*, Edinburgh.

Masden, E.A., McCluskie, A., Owen, E. & Langston, R.H.W., 2015. Renewable energy developments in an uncertain world: The case of offshore wind and birds in the UK. *Marine Policy*, 51, pp.169–172.

Masden, E.A. & Cook, A.S.C.P., 2016. Avian collision risk models for wind energy impact assessments. *Environmental Impact Assessment Review*, 56, pp.43–49.

May, R.F., 2015. A unifying framework for the underlying mechanisms of avian avoidance of wind turbines. *Biological Conservation*, 190, pp.179–187.

McGregor, R.M., King, S., Donovan, C.R., Caneco, B. & Webb, A. 2018. *A Stochastic Collision Risk Model for Seabirds in Flight.* Report for Marine Scotland.

Mendel, B., Sommerfeld, J., Sonntag, N., Kotzerka, J., Schwemmer, H. & Garthe, S., 2014. Effects of the alpha ventus offshore test site on distribution patterns, behaviour and flight heights of seabirds. In Beiersdorf, A. & Radecke, A. (Eds.), 2014, *Ecological Research at the Offshore Wind Farm Alpha Ventus: Challenges, Results and Perspectives*. Springer Spektrum pp. 95-110.

Pennycuick, C., 1997. Actual and “optimum” flight speeds: field data reassessed. *Journal of Experimental Biology*, 200(17).

Petersen, I.K., Christensen, T.K., Kahlert, J., Desholm, M. & Fox, A.D., 2006. *Final results of bird studies at the offshore wind farms at Nysted and Horns Rev, Denmark*, National Environmental Research Institute, Denmark.

Robinson, R.A., 2017. *Birdfacts: profiles of birds occurring in Britain & Ireland*,

Ross-Smith, V.H., Thaxter, C.B., Masden, E.A., Shamoun-Baranes, J., Burton, N.H.K., Wright, L.J., Rehfisch, M.M. & Johnston, A., 2016. Modelling flight heights of lesser black-backed gulls and great skuas from GPS: a Bayesian approach. *Journal of Applied Ecology*, 53(6), pp.1676–1685.

Royal Haskoning, 2013. *Thanet Offshore Wind Farm Ornithological Monitoring 2012-2013*,

Skov, H., Leonhard, S.B., Heinänen, S., Zydelis, R., Jensen, N.E., Durinck, J., Johansen, T.W., Jensen, B.P., Hansen, B.L., Piper, W. & Grøn, P.N., 2012. *Horns Rev 2 Monitoring 2010-2012. Migrating Birds.* Horns Rev II A/S, Denmark.

Skov, H., Heinänen, S., Norman, T., Ward, R.M., Méndez-Roldán, S. & Ellis, I. 2018. ORJIP Bird Collision and Avoidance Study. Final report – April 2018. The Carbon Trust. 247 pp.

Snyder, B. & Kaiser, M.J., 2009. A comparison of offshore wind power development in europe and the U.S.: Patterns and drivers of development. *Applied Energy*, 86(10), pp.1845–1856.

Thaxter, C.B., Buchanan, G.M., Carr, J., Butchart, S.H.M., Newbold, T., Green, R.E., Tobias, J.A., Foden, W.B., O'Brien, S. & Pearce-Higgins, J.W., 2017. Bird and bat species' global vulnerability to collision mortality at wind farms revealed through a trait-based assessment. *Proceedings. Biological sciences*, 284(1862), p.20170829.

Thaxter, C.B., Ross-Smith, V.H., Bouten, W., Masden, E.A., Clark, N.A., Conway, G.J., Barber, L., Clewley, G.D. & Burton, N.H.K., 2017. Dodging the blades: new insights into three-dimensional area use of offshore wind farms by lesser black-backed gulls *Larus fuscus*. *Marine Ecology Progress Series*.

Tucker, V.A., 1996. A Mathematical Model of Bird Collisions With Wind Turbine Rotors. *Journal of Solar Energy Engineering*, 118(4), p.253.

Vanermen, N., Onkelinx, T., Courtens, W., Van de walle, M., Verstraete, H. & Stienen, E.W.M., 2015. Seabird avoidance and attraction at an offshore wind farm in the Belgian part of the North Sea. *Hydrobiologia*, 756(1), pp.51–61.

Venables, W.N. & Ripley, B.D., 2002. *Modern Applied Statistics with S.* Fourth Edi., New York: Springer US.

Votier, S.C., Bicknell, A., Cox, S.L., Scales, K.L. & Patrick, S.C., 2013. A Bird's Eye View of Discard Reforms: Bird-Borne Cameras Reveal Seabird/Fishery Interactions. *PLoS ONE*, 8(3), p.e57376.

Votier, S.C., Bearhop, S., Witt. M.J., Inger, R., Thompson, D. & Newton, J., 2010. Individual responses of seabirds to commercial fisheries revealed using GPS tracking, stable isotopes and vessel monitoring systems. *Journal of Applied Ecology*, 47(2), pp.487–497.

Welcker, J. & Nehls, G., 2016. Displacement of seabirds by an offshore wind farm in the North Sea. *Marine Ecology Progress Series*, 554, pp.173–182.

7 Appendix 1 Estimating Avoidance Rates with Confidence Intervals

In light of the development of stochastic collision risk models (Masden 2015; McGregor *et al.* 2018) the project steering group requested BTO to provide estimates of avoidance rates with associated confidence intervals. Following the logic set out in Table 12, we estimate avoidance rates and their associated confidence intervals for black-legged kittiwake and large gulls using post-construction bird density estimates, generic flight height information and estimates of flux rates derived using straight line speed and estimates of the probability of collision and collision integral derived using true speed.

Following the methodology set out in Masden (2015) and McGregor *et al.* (2018) we use a Monte Carlo simulation approach in order to estimate the number of collisions expected in the absence of avoidance behaviour. Following the sensitivity analyses set out in Masden (2015), bird density, bird flight speed and bird flight height distribution were identified as the parameters most likely to affect estimates of collision in the absence of avoidance behaviour. Accordingly, these were randomly sampled, as set out below, and the model was run for 1000 iterations. For each of these 1000 iterations an avoidance rate was calculated using equation 1. The median avoidance rate and 95% confidence intervals were then calculated from these values for black-legged kittiwake and large gulls.

7.1 Bird Density

Estimates of the number of birds likely to collide in the absence of avoidance behaviour can be very sensitive to the estimate of bird density (Masden 2015). Consequently, it is important that simulated density estimates fall within a distribution which is a realistic representation of the birds present at a site. If this distribution is positively biased (i.e. high densities are over-represented in the data) then the avoidance rates that are derived will be over-estimated because the predicted collision rate in the absence of avoidance will have been over-estimated. Conversely, for the same reason, if the distribution used is negatively biased (i.e. low densities are over-represented in the data) the derived avoidance rates will be under-estimated.

The densities presented in Royal Haskoning (2013) do not include estimates of uncertainty. Consequently, it is necessary to make assumptions about the distributional form of the data. We converted the mean post-construction density estimates in table 2 into estimates of the total number of birds within the area covered by the cameras shown in figure 1. For each iteration of the analysis, we then randomly sampled the number of birds within the area covered by the cameras from a Poisson distribution and converted this back into a density estimate for the remaining steps of the analysis. Distributions of density estimates generated in this way appeared a reasonable approximation for the distributions of density estimates obtained from an adjacent site (APEM 2018).

7.2 Bird Speed

As described above, bird speed can be estimated based on the straight-line distance travelled by a bird or, by based on point estimates of speed. Speed is incorporated in the Band model twice – firstly in order to estimate the flux rate and, secondly to estimate the probability of a bird crossing a turbine rotor swept area and colliding. As described above, the straight line speed is used in order to estimate the flux rate and the point estimates of speed are used to estimate the probability of a bird crossing a rotor swept area and colliding.

Masden (2015) and McGregor *et al.* (2018) both use a normal distribution in order to estimate species flight speeds. However, this may generate estimates of flight speed of less than 0 m/s. Following Ross-Smith *et al.* (2016), we assume that birds in flight are travelling at a speed of 4 km/h, approximately 1.1 m/s. Consequently, we use a truncated normal distribution with a minimum value of 1.1 m/s in order to generate estimates of flight speed in each iteration of our analysis. Mean and standard deviations of straight line and point estimates of species flight speeds are generated from the data collected as part of the ORJIP BCA study and presented in table A1.

Table A1. Mean and standard deviation of species true and straight-line speeds.

	True Flight Speed	Straight Line Flight Speed
Black-legged Kittiwake	8.57 (SD 3.47)	6.68 (SD 3.49)
Lesser Black-backed Gull	10.44 (SD 4.25)	8.35 (SD 4.90)
Herring Gull	9.75 (SD 3.44)	8.04 (SD 3.84)
Great Black-backed Gull	10.00 (SD 4.39)	8.52 (SD 5.10)

7.3 Bird Flight Height

Species flight heights are treated differently by the basic and extended Band models (Band 2012). In the case of the basic Band model a single value, the proportion of birds at collision risk height is used. In the case of the extended Band model, a continuous distribution of the proportion of birds at different heights is used. Such distributions can be derived from the survey data collected to support offshore wind farm EIAs (Johnston *et al.* 2014). In order to estimate avoidance rates suitable for use in the basic and extended Band models, we used the generic flight height distributions derived by Johnston *et al.* (2014). The analyses of Johnston *et al.* (2014) used a bootstrapping procedure in order to generate a median flight height distribution and associated confidence intervals for each species. Each bootstrap represented a modelled distribution for random sample of the data for each species. For each iteration of the analysis used to predict the number of birds colliding in the absence of avoidance behaviour we randomly selected one of these bootstrap flight height distributions. In the case of the basic Band model, we used this distribution to estimate the proportion of birds at collision risk height. In the case of the extended Band model this random selection was used as the flight height distribution when calculating the collision integral.

7.4 Avoidance Rates with Confidence Intervals

Following the Monte Carlo simulation exercise described above, the avoidance rates derived were in broad agreement with those outlined in table 12. Whilst there was some discrepancy between the values reported in table 12 and the median values derived using Monte Carlo simulations, the values in table 12 were within the 95% confidence intervals of the new values (Table A2). This discrepancy relates to how the flight height distributions were used when deriving the avoidance rates.

Flight height distributions are estimated following the methodology set out in Johnston *et al.* (2014). The best fit distribution is estimated from the complete flight height dataset and is that which best fits the available data. Confidence intervals were calculated around this distribution using a bootstrapping approach, randomly sampling from the original dataset each time. As a result, each individual bootstrap reflects the shape the distribution would be if some of the data were excluded. It is not meaningful to compare the mean values obtained from the bootstraps to the best-fit distribution because they are a series of sub-samples (Johnston *et al.* 2014; Masden 2015). The values from table 12 are derived using the best fit distribution and the median values in table A2 are derived using bootstrapped values.

We recommend the values in table A2 for use in stochastic collision risk models.

Table A2. Avoidance rates and 95% Confidence intervals derived using a Monte Carlo simulation approach for Black-legged Kittiwake and Large Gulls.

	Basic Band Model	**Extended Band Model**
Black-legged Kittiwake	0.994 (0.976 – 0.998)	0.970 (0.871 – 0.989)
Large Gulls (Lesser Black-backed Gull, Herring Gull, Great Black-backed Gull)	0.997 (0.992 – 0.999)	0.990 (0.974 – 0.995)