Collection of Seabird Flight Height Data at an Operational Offshore Wind Farm Using Aircraft Mounted LiDAR

Final Report

September 2022

Scottish Government
Riaghaltas na h-Alba
gov.scot

Collection of Seabird Flight Height Data at an Operational Offshore Wind Farm Using Aircraft Mounted LiDAR

Final Report

Marine Scotland

APEM Ref: P00005794

Issued September 2022

Anya Wicikowski, Beate Zein, Beth Goddard, Sean Sweeney, Tim Coppack, Steph McGovern

Client:	Marine Scotland
Project reference:	P00005794
Date of issue:	August 2022

Project Director:	Beth Goddard
Project Manager:	Anya Wicikowski
Other:	Beate Zein, Beth Goddard, Amy Williams, Steph McGovern, Tim Coppack, Sean Sweeney, Owain Slater, Sophie Nunn, Mark Wilkins.

APEM Limited, Riverview,
A17 Embankment Business Park.
Stockport,
SK4 3GN, UK

APEM-Marine Scotland (2022): Collection of Seabird Flight Height Data at an Operational Offshore Wind Farm Using Aircraft Mounted LiDAR. Final Report P00005794. 12/09/2022, 66 pp.

Revision and Amendment Register

Version Number	Date	Section(s)	Page(s)	Summary of Changes	Approved by
Draft	24/03/2022	All	All	Creation	AW/AJW
V1.2	12/04/2022	All	All	Internal Review	TC/SS
V1.4	19/05/2022	All	All	Update after external review	BZ/AW
V1.5	20/05/2022	All	All	Internal Review	BG/SMG
V2	05/07/2022	All	All	Update after external review	BZ/AW
V3	24/08/2022	All	All	Formatting edits	CF

Contents

List of Figures

List of Tables

Executive Summary

This technical report presents analysed seabird flight height data collected within and around Beatrice Offshore Wind Farm (OWF) located in the Moray Firth. The aim of the study was to evaluate the impact on the flight height of sea birds in relation to the OWF.

Two aerial surveys were completed in June and July 2021. The first aerial survey took place across two days on the 15th and 16th June 2021 and the second aerial survey took place on the 15th July 2021. Data were collected with a combined still image and aircraft-mounted Light Detection and Ranging (LiDAR) technology. Data were collected along 13 transects spaced two kilometres (km) apart across Survey Area 1 and 9 transects spaced two kilometres (km) apart across Survey Area 2. Additional flight lines were also captured onshore over Wick to validate the accuracy of the LiDAR data. Images were collected continuously (abutting digital still imagery) along the survey lines, at two-centimetre (cm) ground sample distance (GSD). The surveys were completed by one aircraft with approximately eight hours on-task per survey. Data were processed to allow each individual flying bird to be identified in the imagery and then matched with height measurement points collected from the LiDAR system.

These flight height data represent site-specific flight height measurements. For the majority of species, the birds were found flying less than 25 metres (m) above sea surface level, with the exception of herring gull (*Larus argentatus*) which were primarily recorded at flight heights of 50–100 m.

The differences in flight height of seabirds in the wind turbine generator (WTG) area (Survey Area 1) and a control area without WTGs (Survey Area 2) were studied. There was a significant difference in flight height between these areas. The birds recorded in Survey Area 1 were flying significantly lower (11.32m) than the birds in Survey Area 2 (20.03m) which could indicate an effect of the WTGs on the flight height in the study area.

Additionally, flight heights of sea birds were studied in relation to the distance to the nearest WTG, in Survey Area 1 only. There was no significant effect in the results of the linear models for most species. However, gannets and large gulls had significant results for flight height in relation to the distance to the nearest WTGs. The results for gannets show individuals flying lower closer to the WTGs but this result is influenced by one outlier. Large gulls flew significantly higher closer to the WTGs but this is based on a sample of eight individuals. Generally, the sample size of seabirds detected in this area was low which could have affected the statistical power. There were also no birds detected between 0 – 40 m of a WTG. The closest and second closest bird were at 44 m and 189 m, respectively. These could indicate avoidance

behaviour of the detected sea birds and makes the analysis of flight height in close proximity to WTGs difficult.

The outputs of flight heights of seabirds produced from the combined imagery-LiDAR system could be incorporated into collision risk modelling (CRM). The benefits of using LiDAR would be the reduced uncertainty of the CRM. This will allow Environmental Impact Assessments (EIA) to be based on robust models and the impact of WTGs to be better understood.

The main limitation of this study was the low sample size, and therefore one recommendation would be to increase the coverage and number of surveys, as this would not only increase the number of flying birds detected, it can also allow seasonal variation to be investigated if surveys are completed at different times of the year. The survey design can be tailored to maximise detection of a specific species by using historic density for a site and peak abundance months.

In this study the number of birds in flight in Survey Area 1 was low and the linear models were mostly unsuccessful in showing any significant effect of WTGs on flight height. Therefore, to evaluate the effect of OWF on flight heights larger sample sizes are needed and surveys should be undertaken pre- and post-construction to allow any changes in flight heights to be investigated at the same location.

1. Introduction

The Scottish Government have a responsibility to manage the marine environment, including to conserve protected seabird species and designated sites within Scottish territorial waters. To achieve this, risk should be identified, potential impacts investigated, and where necessary appropriate conservation and mitigation actions taken to protect seabird species. The Scottish Government, through The Crown Estate Scotland, released details in February 2022 of multiple potential development areas as part of their 2022 ScotWind leasing round (Scottish Government, 2020). For each of these sites there are likely environmental implications to be considered and investigated as part of individual comprehensive Environmental Impact Assessments (EIAs) and Habitats Regulations Appraisals (HRA ;Scarff, *et al*. 2013).

In order to address the potential impacts and effects that offshore wind farms (OWFs) may have on seabird species within the marine environment, collision risk should be assessed (Masden, *et al*. 2016). In most cases this is achieved through collision risk modelling (CRM). At present, there are a number of tools which are commonly used to model collision risk, these require bird flight heights as an input parameter (Band, 2012, Johnston *et al*. 2014; McGregor, *et al*. 2018). Previously, site specific seabird flight heights have been estimated from individual surveyors performing boat-based surveys or size-based calculations from aerial digital survey imagery (Johnston *et al*. 2014; McGovern *et al*. 2019). These methods can have limitations such as low sample size, boat-based observations having bias, lack of validation and quantification of error and size-based methods relying on published information that leads to large confidence limits (Johnston, *et al*. 2014). Where uncertainly remains within the assessment process, for instance as a result of the input parameters, then this may lead to further uncertainty in the CRM results (Johnston, *et al*. 2014).

To address this uncertainty, flight heights from multiple sources are combined, negating the issues around sample size and reducing random error in results. However, data are lacking in some areas including the northern North Sea (Johnston, *et al*. 2014). Furthermore, these flight heights are not site-specific and do not allow the influence of wind turbines to be investigated once a site is constructed.

An alternate solution is to use Light Detection and Ranging (LiDAR) technology to measure seabird flight heights (Cook, *et al*. 2018). LiDAR uses laser light pulses to measure where objects are in space and when combined with aerial digital still imagery can provide highly accurate site-specific and species-specific bird flight heights. As a new application of this technology, LiDAR's effectiveness is in need of testing and review in order to understand how best it may be utilised in the future to fulfil its potential for use in the marine environment, particularly for reducing uncertainties in seabird flight heights and for OWFs EIAs / HRAs (Cook, *et al*. 2018).

In order to undertake a review of the capabilities of LiDAR for determining seabird flight heights in the marine environment Marine Scotland commissioned APEM Ltd (APEM) to undertake a series of surveys using APEM's bespoke combined high-resolution aerial digital stills and LiDAR system.

1.1.1 Survey Aims

1. Collect measurements of seabird flight heights for individual species to allow production of flight height distributions for use in CRM.
2. Investigate whether LiDAR was suitable for collecting robust species-specific avian flight height data from an operational wind farm.
3. Identify and discuss any methodological issues or challenges which may come from collecting data across these sites.
4. Examine whether seabird flights heights differ between an area with WTGs and a control area without WTGs.

2. Methodology

2.1 Survey Planning

Data were collected within and around three OWFs within the Moray Firth, off the northeast coast of Scotland; Beatrice, Moray East and Moray West (Figure 1). At the time of the survey Beatrice had been operational for two years, Moray East was under construction and partially commissioned with 52 turbines present during survey 1 (June 2021) and 66 during survey 2 (July 2021). Moray West was consented, but no construction was underway at the time of the surveys.

APEM's bespoke combined high-resolution aerial digital stills and LiDAR system (herein referred to as imagery-LiDAR system), was fitted into a twin-engine aircraft and operated alongside a high accuracy positioning Inertial Measurement unit (IMU).

The survey flight plan was designed in advance using specialist flight planning software and included 13 transects spaced two kilometres (km) apart across Survey Area 1 and 9 transects spaced two km apart across Survey Area 2. These lines were flown for each survey to deliver a minimum coverage of approximately 10% (Figure 1). The aircraft collected these data at an altitude of approximately 450 metres (m) whilst travelling at a speed of approximately 120 knots. Flying at this altitude allowed for aerial digital survey data to be collected at an average of two centimetres (cm) ground sampling distance (GSD) allowing a high level of identification of seabirds from the digital still images. A Global Positioning System (GPS)-linked bespoke flight management system was used to ensure the tracks were flown with a high degree of accuracy and image capture points were recorded to allow birds to be accurately located within images. Additional survey lines were captured onshore over Wick where measurements of ground elevations had previously been made. These ground measurements were used to ensure high accuracy LiDAR point clouds were produced across the survey zone.

The first aerial imagery-LiDAR survey took place across two days, on the 15th and 16th June 2021, whilst the second survey took place on 15th July 2021. The surveys were completed by a single aircraft with approximately eight hours on-task for one survey.

No health and safety issues were reported during the surveys.

Figure 1 Location of Survey Area 1 and Survey Area 2 in relation to the Moray East, Moray West and Beatrice OWFs with planed survey flight lines.

2.2 Survey Timings and Conditions

2.2.1 Survey 1

15/6/21

For the first survey 19 of the total 22 transects were completed during the first day of data collection. As unsuitable weather approached before the final three transects were flown, the remainder of the survey was postponed until the 16th of June. The cloud cover during the survey was classed as overcast. Visibility started at 20 km, before reducing to three km at the end of the survey. Winds were recorded at between six–20 knots from a southerly direction, with a sea state of zero–two (calm [glass] – smooth). The outside air temperature was recorded as 10°C.

16/6/21

The remaining three transects of Survey 1 were completed on the 16th June. The cloud cover was classed as overcast, with a visibility of three km. Winds were recorded at 20-23 knots from a southerly direction, with a sea state of two–three (smooth to slightly moderate). The outside air temperature was recorded as 16°C.

2.2.2 Survey 2

15/7/21

All 22 transects were completed. The cloud cover was classed as 20% (scattered), with visibility at >10 km for the duration of the survey. Winds were recorded at 9-20 knots from a westerly direction with a sea state of zero (calm [glass]). The air temperature outside was recorded as between 10-16°C.

2.3 LiDAR Calibration

Prior to each survey technical calibration reviews were carried out to ensure both the high-resolution aerial digital stills system and LiDAR were set up to collect optimal data. This allowed for the most accurate data to be collected, processed and verified. Two main quality control stages were utilised:

1. System calibration: this is carried out when the LiDAR system is installed in an aircraft and is valid for the duration of that installation. APEM use a calibration site in Stoke.
2. System verification: this is carried out during the survey itself, by collecting data over highly accurate, ground control points (GCP's), both on the way out to the survey area and again on the return. APEM used a grid of GCP's in Wick for this survey.

Details of each control measure are outlined below.

1. System Calibration

A system boresight calibration survey was carried out by APEM at a pre-existing site in Stoke-on-Trent, England once the LiDAR system was installed into the survey aircraft.

The pre-existing site consisted of a grid of measured XYZ coordinates of fixed features on the ground. During the calibration set-up, the XYZ coordinates were surveyed using a high-accuracy, real-time kinetic positioning global navigation satellite system (RTK GNSS) 'smart rover' with accuracies better than 2 cm. The onshore data were used to calibrate the system to ensure accurate outputs were produced.

The system calibration computes the final offsets and lever arms between all of the system components to allow for production of high accuracy datasets.

During the flight, the Inertial Measurement Unit (IMU) creates trajectory files which records the position of the aircraft / sensor throughout the duration of the survey. The raw trajectory data from the calibration flight were post-processed using the single base function within Applanix POSPac v8 software which resulted in the position of the sensor to be known to a high degree of accuracy throughout the flight.

2. System Verification

The system verification check uses ground measured elevation data to compare against LiDAR data captured over a pre-existing site. For this project, a Ground Control Area (GCA) was established on a flat area of hardstanding in Wick prior to aerial survey. The GCA involves measurement of the XYZ coordinates of a grid of points spaced 50 cm apart over an area of land 500 cm x 500 cm. The XYZ coordinates were measured using an independent RTK GNSS Smart Rover with accuracies of less than 2 cm. During the flights, survey lines were flown over the verification site at the start and end of the mission. Elevations from the processed LiDAR data from these lines were then compared against the GCAs to assess the accuracy of the LiDAR data. One survey line was flown during the June survey due to inclement weather and yielded an accuracy of 1.8 cm Root Mean Square Error (RMSE). Two lines were captured during the July survey and returned an accuracy of 7.6 cm and 9.3 cm.

2.4 Data Processing

All of the high-resolution aerial digital still images collected were georeferenced using the geographical data derived from the GPS-linked bespoke flight management system. A GPS log was recorded during the survey flights, with GPS positions recorded at the start and end of each line flown and for each image captured throughout the survey. These data were uploaded into GIS to generate flight log shapefiles to represent the flight lines flown and the image nodes captured.

2.5 Image Analysis

The high-resolution aerial digital still images were analysed by trained ornithologists to detect the presence of seabirds. Using APEM's bespoke image analysis software the images were georeferenced, and the spatial locations were accurately determined for any birds in-flight.

Birds detected in the high-resolution aerial digital still imagery were identified to species level, where possible, by experienced ornithologists. Every bird recorded on these surveys was viewed by at least two members of staff as part of our comprehensive quality assurance (QA) process. Blank image QA was performed on at least 10% of the imagery to ensure no birds were missed. Finally, all bird identifications were checked by an experienced QA manager at APEM.

Once the image analysis was complete, APEM's BIRD software automatically generated a tabulated database containing information corresponding to each individual sighting including group / species, geographical position of the individual, timing of the sighting and behaviour (flying, sitting, submerged etc.). The database was exported into Excel format to provide simple raw count-based data. Taking the positional information stamped to each sighting, the sightings were plotted directly into a GIS to create shapefiles, whereby each sighting is represented by a single point. The digital nature of both the outputs (tables and shapefiles) enabled both a statistical and spatial statistical analysis to be performed on these data.

2.6 LiDAR Analysis

The data collected from the LiDAR system was output as a database of the point cloud with each point having a XYZ coordinate. The processed LiDAR point clouds were then loaded into specialist LiDAR analytical GIS software, along with the shapefile of flying bird locations identified and tagged during image analysis.

Analyses were carried out to identify points in the point cloud above the sea surface that correspond to the approximate location of the same bird in flight within the high-resolution aerial digital still imagery. The size and behaviour of the bird (gliding / banking / diving [Appendix VI]) can impact how many hits or returns the LiDAR is receiving from a given individual.

Birds with two or more hits were assumed to be highly accurate. Birds with a single hit were assigned a confidence category of "high" or "low". This is because single hits could also be representative of noise in the point cloud. Noise is a common phenomenon in all aerial LiDAR datasets and is usually attributed to moisture or other significant particulates in the air and can be caused by rain, fog, low clouds, ocean spray, or even large insects. It manifests itself as apparent random points above the normal surface of a point cloud and can be over 100 m high.

2.6.1 Flight Height Less Than Two Metres

The matching process does not change for low flying birds (less than two metres above the water surface). The tagged bird locations are identified in the LiDAR data and all above surface "object" points extracted from the point cloud. The successful mapping of the sea surface means the number of potential false positives was reduced, even close to the surface. Under rougher sea conditions, the amount of noise around the surface is likely to increase. However, under APEM's methodology the imagery is used as the primary source of data for bird identification and the LiDAR matched to the data from the imagery. Therefore, noise from the sea surface was not expected to have a significant impact on the overall results.

When considering these data during the matching process, a single isolated LiDAR point above the surface in close proximity to the tagged bird location can be matched with high confidence.

A single hit close to a bird, but with other single hits (noise) in the vicinity, was assigned to a low confidence score. In general, there may be instances where no match can be made as there are too many noise points to match a bird even to a low degree of accuracy or there are no points in the cloud to match to. This may be caused by the movement of the bird reducing the surface area available for the LiDAR to bounce off or the bird flying too low to the surface to be distinguishable from waves / sea spray during certain conditions. Despite this, no lower cut-off value is enforced for flight heights when birds are close to the sea surface, as success with matching is still made possible by the supporting high-resolution aerial digital still imagery.

2.6.2 Data Set Matching

Once the LiDAR data were matched with birds from the high-resolution aerial digital still imagery, the average flight height for each individual was extracted from the corresponding LiDAR cluster and assigned to a master shapefile. This process then produced a record of each bird species, heading, age, size, geographic coordinates, flying height (metres) relative to base datum and flying height above the sea surface in metres. The number of hits per bird were also recorded in the master shapefile. All species groups with more than one count had a match rate of better than 81% (Appendix II).

2.7 Data Analysis

All data manipulations and analyses were carried out in R (R core team, 2022). GIS software (QGIS) was used to create maps and present spatial data.

The raw counts of birds found in each survey month (survey 1=June 2021, survey 2=July 2021) were collated in tables and distribution maps. The data for the current study was collected by APEM at two different study locations (Survey Area 1, and Survey Area 2, Figure 2). The locations were defined as follows:

Survey Area 1:

- Beatrice, covering birds recorded within the Beatrice OWF boundary.
- Moray East, covering birds recorded within the Moray East OWF boundary.
- Survey Area 1 without OWFs, which covered all areas of Survey 1 that did not overlap with the Moray East and Beatrice OWFs.

Survey Area 2:

- Survey Area 2, covering the control survey area without any WTGs.

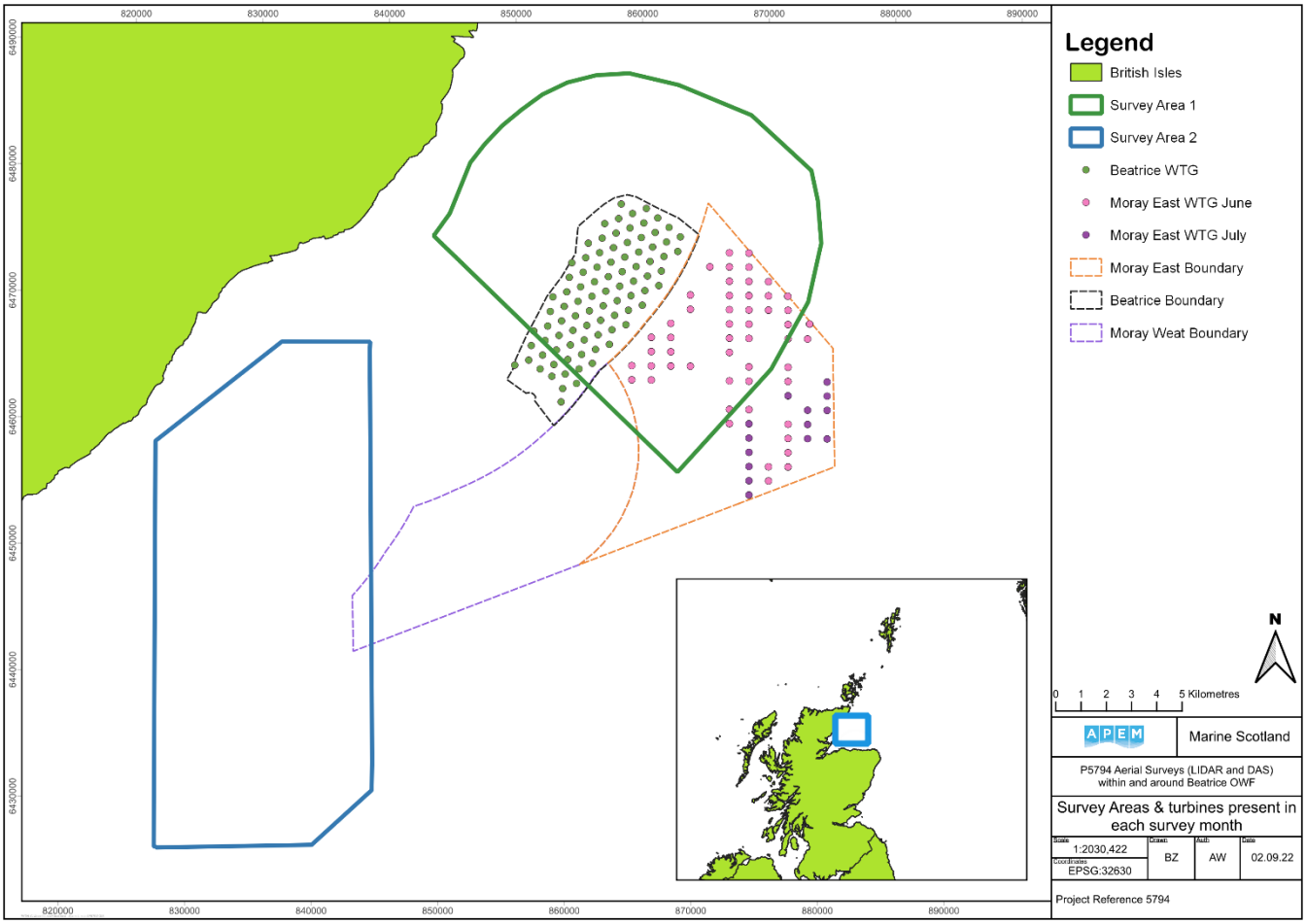


Figure 2 Map demonstrating Survey Area 1 and Survey Area 2 specified in the models, and the turbines present in each survey month.

2.7.1 Comparing flight height in the different study areas

The flight height of birds in areas with WTGs and without WTGs were compared. A visual comparison between Survey Area 1 with WTGs and Survey Area 2 without WTGs is shown in a violin plot for the following species which are of high risk of collision; fulmar (*Fulmarus glacialis)*, gannet (*Morus bassanus*), large gulls (*Larus argentatus* and *Larus marinus*) and kittiwake (*Rissa tridactyla*) for each survey month. Additional statistical analysis was performed to compare the flight height in the different study areas for the species of interest. A non-parametric two-sample Mann Whitney U test or Wilcoxon rank sum test was performed for each species and for the species combined.

Histograms of distance to nearest turbine (m) were created for each species detected in survey 1 and survey 2 (Appendix V), using the ggplot2 package in R. The script used is available in Appendix IV.

2.7.2 Modelling fight height in relation to WTG distance

The flight heights of the birds were modelled in relation to the distance to the closet WTG in Survey Area 1 using linear and mixed models in R.

The distance for each recorded bird to the nearest WTG was calculated in QGIS. WTG data were altered to only include those that were in situ at the time of each survey in June and July 2021.

Histograms of the flight height relative to sea surface level showed that these data were not normally distributed. To account for these data distribution, we used Box-Cox transformation for the mixed models. The R script used is available in Appendix IV.

For the statistical modelling the lme4 package was used (Bates, *et al*. 2015). The height relative to sea level measured by the LiDAR system (BirdZ_SeaL) was analysed, using ‘distance to the nearest WTG (m)’ as a continuous variable with a fixed effect. The different survey months were included as a random effect. Additionally, the main species were analysed together, and common name included as a random effect.

3. Results

The raw species count results and the distribution maps were calculated (Appendix III).

3.1 Comparing Flight Height in the Different Study Areas

The flight height of each of the core bird species were identified in the imagery-LiDAR system (Figure 3; Figure 4). Data were presented in the lowest species or group level the individual was identified to except for large gull which were grouped because of low sample sizes. In June only two groups (kittiwake, large gull) were detected in the survey, whereas all species of interest were recorded in July.

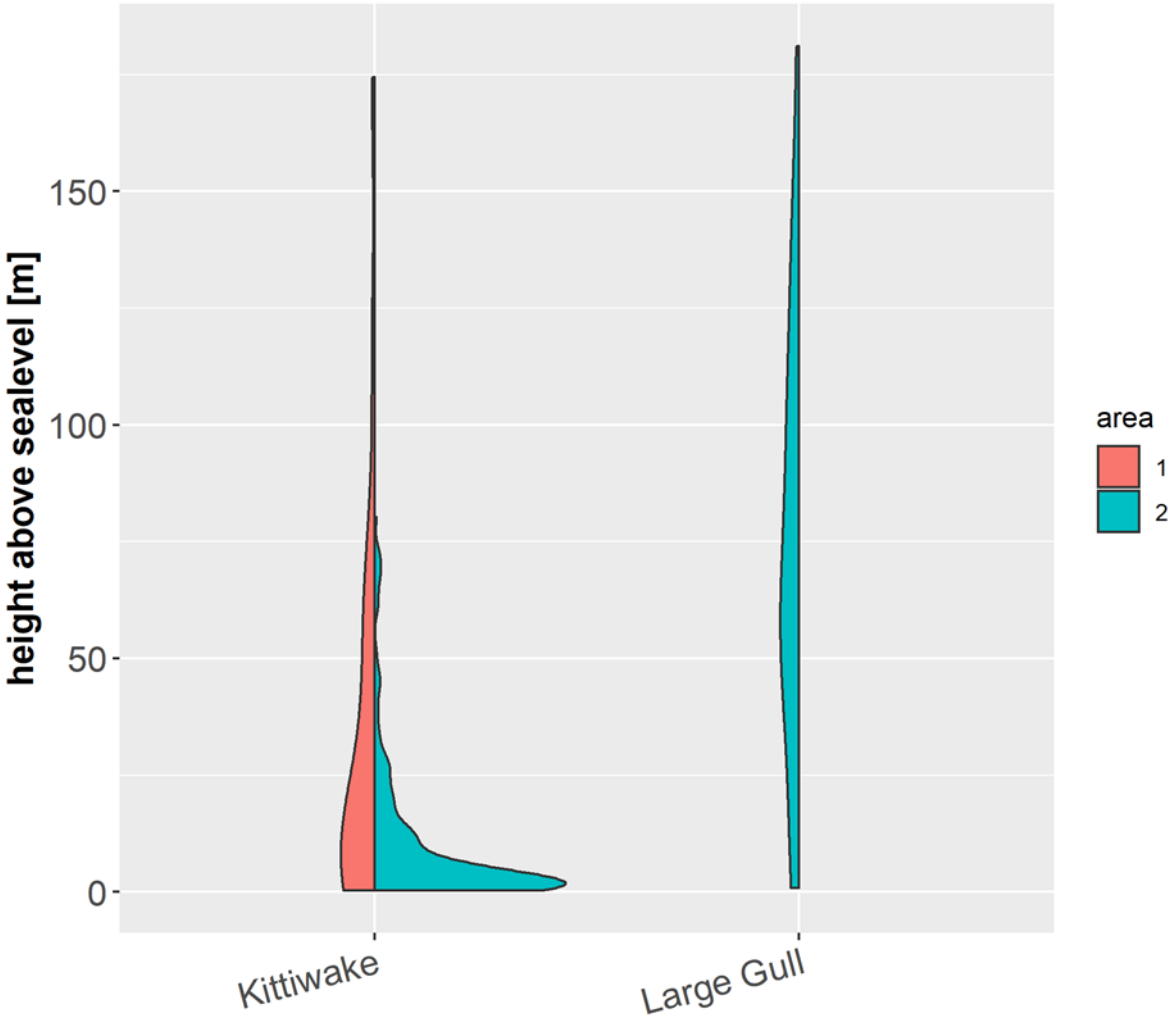


Figure 3 Bird flight height (m) above the sea surface measured from LiDAR in June. The plot is split into the two survey areas (Survey Area 1 with WTGs and Survey Area 2 the control area without WTGs).

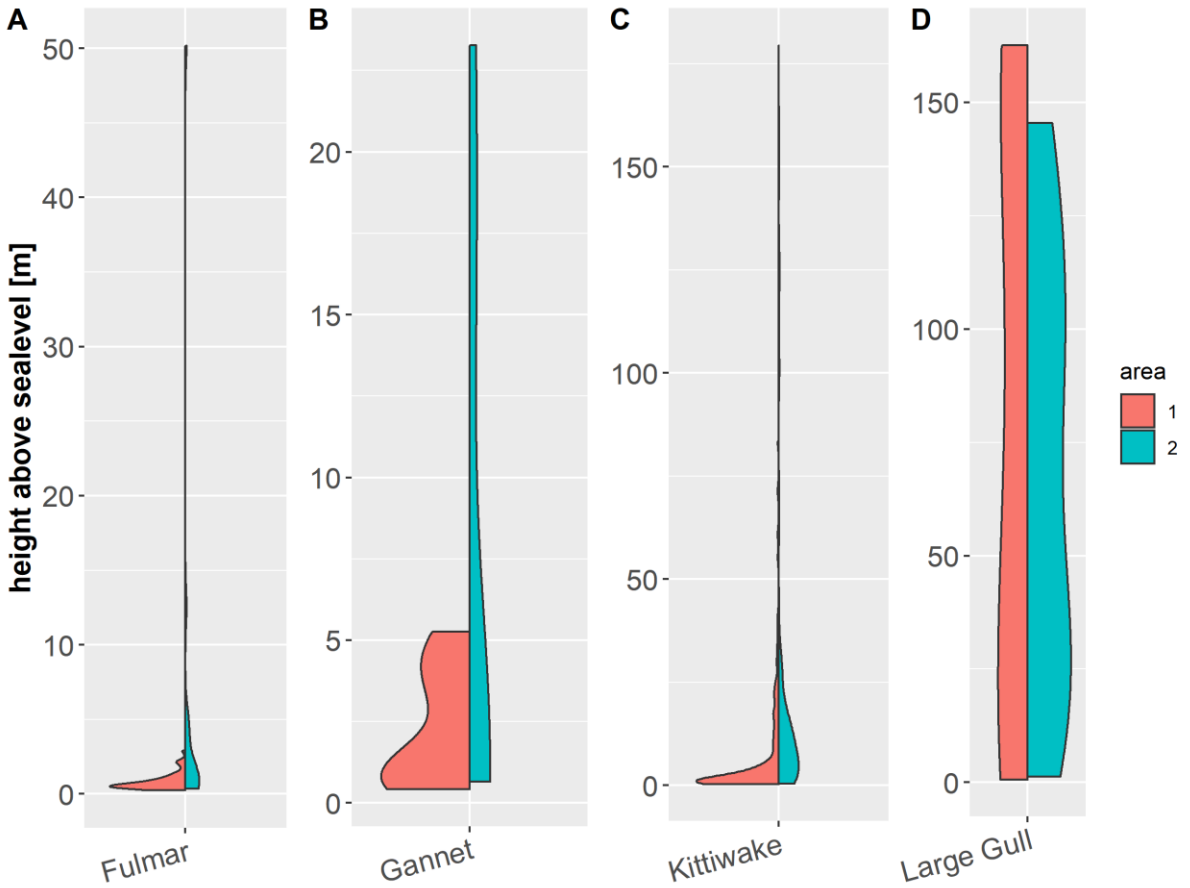


Figure 4 Bird flight height (m) above the sea surface measured from LiDAR in July. The plot is split into the two survey areas (Survey Area 1 with WTGs and Survey Area 2 the control area without WTGs). The four plots here are in different scales; plot A and B with low flying birds fulmar and gannet and plot C and D with birds flying at a larger range of heights (kittiwake and large gulls). The x-axis scales are different in each plot.

Statistical tests were performed to study the difference in flight height between Survey Area 1 and Survey Area 2 for all four core species combined (fulmar, kittiwake, gannets and large gulls) and for each species separately. For all species the mean height above sea surface level was 11.32 m (SD= 26.61) in Survey Area 1 and 20.03 m (SD= 33.73) in Survey Area 2. The Wilcoxon rank sum test with continuity correction showed highly significant results between the flight height of Survey Area 1 and Survey Area 2 for all four species (p=<0.001).

For the four species analysed separately significant and highly significant differences were found in the flight height of kittiwakes and gannets. There was no difference for fulmars and large gulls. The number of detected species were low in both areas for some areas (kittiwakes (Survey Area 1 = 220, Survey Area 2 = 413), fulmars (Survey Area 1 = 70, Survey Area 2 = 45, gannet (Survey Area 1 = 17, Survey Area 2 = 41) and large gull (Survey Area 1 = 8, Survey Area 2 = 37).

Table 1 Fight height analysis for the different study sites (Survey Area 1 with WTGs, Survey Area 2 without WTGs) for the four study species using Wilcoxon rank sum test with continuity correction.

	Total detected Area 1	Total detected Area 2	Mean height Survey Area 1(m)	SD	Mean height Survey Area 2 (m)	SD	P value
Kittiwake	220	413	12.49	24.87	17.84	30.83	**<0.001**
Fulmar	70	45	1.72	5.34	3.53	7.89	0.053
Gannet	17	41	2.45	2.96	12.89	18.44	**0.004**
Large gull	8	37	81.92	72.49	72.40	48.05	0.870

3.2 Modelling fight height in relation to WTG distance

3.2.1 All species combined

The results of the flight height of each species relative to the distance to the nearest WTG in Survey Area 1 are shown in Figure 5. There was a slight tendency for birds flying higher closer to the WTG. However, the closest bird recorded to a WTG was at a distance of 44 m and the second closest bird was at a distance of 189 m, furthermore, the sample of birds of interest in Survey Area 1 in the two survey months was low (n= 315).

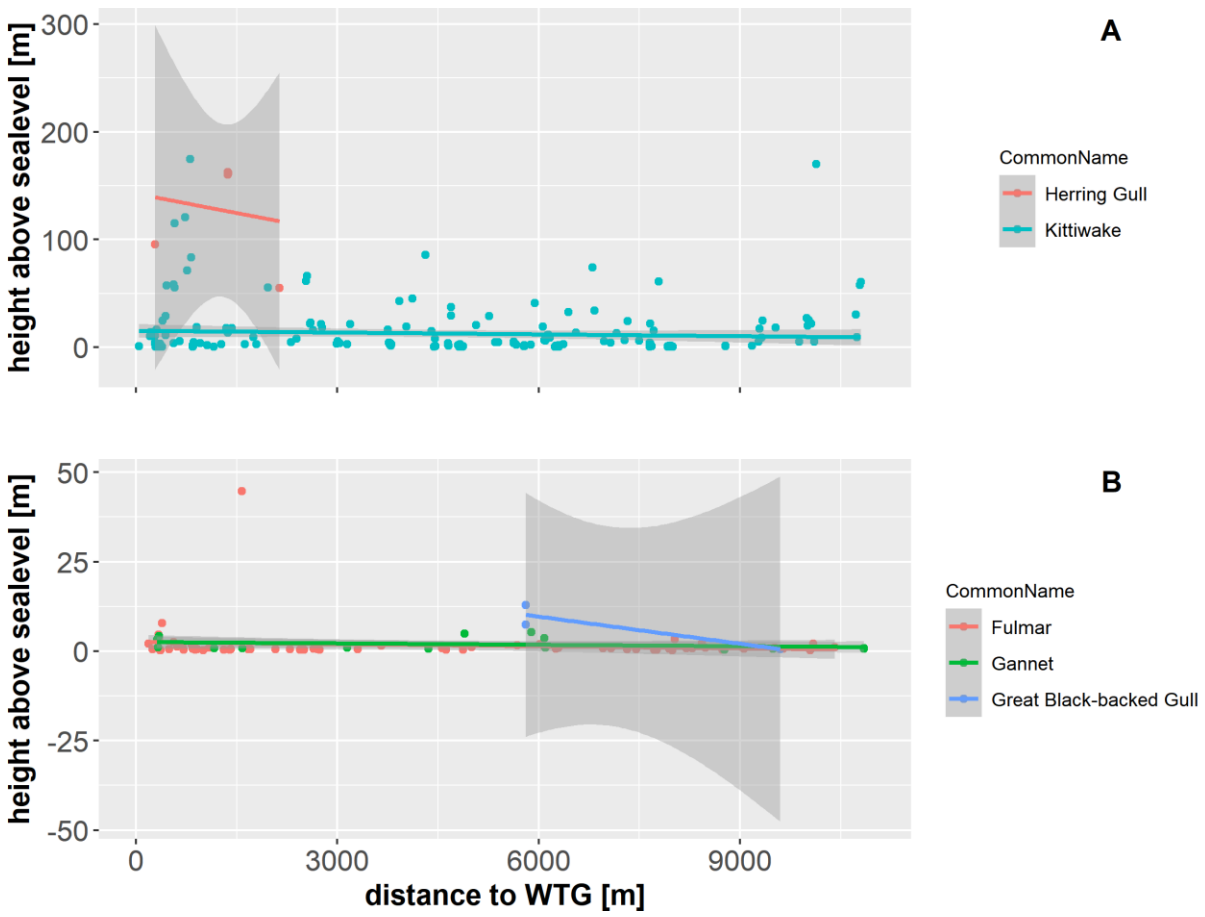


Figure 5 Split scatterplot demonstrating bird flight height relative to distance to the nearest WTG in Survey Area 1.

For the combined species a linear mixed model (LMM) was conducted for the LiDAR flight heights with distance to nearest WTG and random effects were included for species type and survey month. A plot of the model shows that height does not vary with distance to WTG, demonstrated by the straight line through the plot.

The model output suggests there was no relationship between the fixed variable of distance from WTGs (DistanceScaled) and the height relative to sea surface level (BirdZ_SeaL), with a p-value of 0.427.

The model fit is evaluated with a residual and a Q-Q plot (Appendix IV). Residual plots show the difference between predicted and actual data and therefore the error in the predicted values. Visually this should represent a random cloud of points around zero with no general pattern in the data. This is similar to our data showing a reasonable error for our models. The Q-Q plot gives an indication of the distribution of residuals of the model (i.e., if they are normally distributed). In the best case, the points of a model would match a diagonal straight 45degree line. If the pattern of the data is deviating from this line, then the model is not presenting the data in full, however, it is important to evaluate the amount of this deviation and a low deviation is generally expected. For this data the model fit is generally good as the points are

fitting the lines well for most of the data. However, the data is lightly tailed to the right and left sides indicating that the model doesn't predict extreme values equally well. However, the overall fit of the model is good.

The model output can be explained by the fact that the different species are behaving differently, and separate models are needed at species level. Additionally, the results can be explained by the low sample size and the lack of birds recorded in the close proximity of the WTGs.

3.2.2 Kittiwake

A generalized linear mixed model (GLMM) was used to analyse the flight height against the distance to the closest WTG for kittiwakes. A random effect for month was included in the model and residual and Q-Q line plots were reported (Appendix IV). There is no significant effect of the distance to WTGs ($p = 0.540$).

In the residual plot for kittiwakes, two clouds can be observed indicating a lack of observed data in some parts. However, the spread of data for lower fitted values could indicate heteroscedasticity, which is not clear as there are two disconnected clouds. The Q-Q plot is showing a good fit for medium values, however a slightly worse fit for large values and the worst fit for very small values. These results could be driven by the fact there were likely two types of behaviours recorded. A large number of kittiwakes were recorded very close to the surface and a smaller amount of birds in flight at higher altitudes and few birds were recorded in between. For future analysis this difference in bird behaviour should potentially be considered.

3.2.3 Fulmar

Fulmars were detected in June and July and a LMM was performed to study the effect of flight height to the distance of the nearest turbine (Appendix IV). There was no correlation between the flight height and the distance to the nearest turbine ($p = 0.399$). The residual plot for fulmars is generally centred as a random cloud around zero with one outlier. Model fit in the Q-Q plot is good for medium values with a slightly worse fit for the extreme values. There is no large effect of the outlier and the model should be a good representation of the data. However, birds were detected too far away from the WTGs to study the relationship of distance to the flight height of the birds. The closest fulmar was detected 189.4 m away from the WTGs.

3.2.4 Gannet

A LMM was performed for gannets to study the effect of flight height to the distance of the nearest turbine (Appendix IV). There was a significant correlation between the flight height and the distance to the nearest turbine ($p < 0.001$) with Gannets flying lower closer to the WTGs. The residual plot is showing a clear pattern and one outlier and Q-Q plots are heavy-tailed. The low sample size and lack of birds recorded close to OWF is limiting the conclusions which can be drawn from this model. Comparing flight height against the distance to nearest WTGs shows that a larger sample size is needed for more robust results.

3.2.5 Large Gull

Large gulls were only detected in July and a LM was performed to study the effect of flight height to the distance of the nearest turbine (Appendix IV). There was a significant correlation between the flight height and the distance to the nearest turbine ($p = 0.002$). Large gulls are showing the opposite effect than the other species with higher flight height closer to the WTGs. However, the sample size is very low ($n=8$) and the Q-Q plot shows a heavy-tailed fitted line. Visual examination of Figure 5 for large gulls shows that there is an indication that there could be an underlying effect. However, a higher sample size is needed for a more robust evaluation.

4. Discussion

In the surveys in June and July (survey 1 and 2) a wide variety of species were detected in the images. In both surveys the most common species detected were guillemots. The detected species assemblage is in line with previous findings in the east of Scotland during the summer months (APEM, 2018).

The imagery-LiDAR system performed well, with a match rate of greater than 81% for all species groups with more than one count (Appendix III). The imagery-LiDAR system appeared to be capable of measuring flight heights of small seabird species such as puffin. Although, not included in the results of this study the imagery-LiDAR system was also able to measure flight heights for tern species when on transit to the study site. This suggests the combined system is suitable for collecting species specific seabird flight heights both over the open sea and within an operational wind farm.

Flight heights for the four species of interest were plotted with violin plots for each survey area. Generally, flight heights were recorded below 25 m above sea surface level for most species in both survey areas (Survey Area 1 = 89% and Survey Area 2 = 80% below 25m). Additionally, large gulls, kittiwakes and fulmars were recorded at flight heights of up to 50-150 m. The results of flight heights in the current study are in line with previous research of those seabird species, suggesting that they are commonly found in flight just above the sea surface (Johnston, *et al*. 2014).

The methodology for this survey programme used the imagery collected to inform the LiDAR analysis and subsequent data matching. Thus, birds below two metres were not under-recorded, an issue that had been highlighted in earlier studies (Cook *et al*. 2018).

There was a significant difference for flight heights of all four species in a combined analysis between the two areas. In Survey Area 1, the site with WTGs, birds flew lower (11.32 m (SD= 26.61)) than those recorded in Survey Area 2 (20.03 m (SD= 33.73)), the area without WTGs. This could be driven by species with a higher sample size. However, this also suggests different flight height patterns in the different areas, which could be related to the presence of WTGs. Studies on seabird flight behaviour have also indicated that seabirds may change flight altitudes when approaching wind turbines, this is known as macro avoidance (Cook, *et al*. 2012). By detecting this change in flight height, it can be assumed that this combined imagery-LiDAR system could potentially be used as a tool to detect the macro avoidance rates within and around wind farms, allowing the potential impact of the wind farm to be detected (Furness, *et al*. 2013).

Species-specific analysis showed highly significant differences for flight heights between survey areas for kittiwake and gannet and close to significant differences for fulmar. Kittiwake and fulmar had the highest sample size of individuals and a subjectively similar sample size over both survey areas. However, gannet and large gulls had a comparatively large difference in sample size between survey areas which impacts the statistical power of the species-specific analysis.

Histograms plotting the distribution of distance to nearest turbine for each species (Appendix V) demonstrated some discreet differences between species. Guillemots demonstrated some evidence of avoidance, with most individuals recorded 20-30 km away from turbines in both survey months; however, in June a high number were also recorded closer to turbines at 200-5,000 m. The distribution of kittiwakes, gannets, guillemot / razorbills, and great skuas was not consistent between the two survey months, and no behavioural patterns could be concluded from the histograms. A few species appeared to show consistent distributions in both survey months; fulmars were recorded closer to turbines (min 189 m) with numbers decreasing as distance from turbine increased. Herring gulls were mostly recorded >20,000 m away from turbines, suggesting avoidance of turbines. Razorbills, only recorded in June, were mostly distributed 625-15,000 m away from turbines, and fewer recorded outside this distance. Overall, the histograms did not provide evidence of any conclusive trend in respect to the number of birds recorded at different distances to the nearest WTG of the different species. This can partially be explained by the low number of individuals recorded in Survey Area 1. However, no bird was recorded closer than 189 m which suggests avoidance behaviour. Previous studies in this location were specifically designed to investigate seabird displacement from OWF area, meaning they would be more suitable to inform investigations (MacArthur Green, 2019) as the results in this study are based only on flying birds. Avoidance of the area does have implications for collision risk modelling however, as the lower number of individuals in the area reduces the number likely to collide with the WTG. Furthermore, it makes assessing the impact of WTGs on flight heights at this scale difficult. Surveys should be planned, assuming a reduction in densities recorded pre-construction, so that a precautionary approach to survey effort can be planned to ensure a suitable sample size can be achieved.

Flight height in relation to the nearest WTG was studied using different linear models. There were significant results for gannets and gulls. The results of the gannets indicate the birds are flying lower closer to the WTGs. However, the results were largely influenced by one bird being detected far away from the WTGs. Only eight large gulls were detected in Survey Area 1, however a significant effect of those birds flying higher closer to the WTGs was found. There was no significant effect of flight height in relation to the distance of WTGs for the other species.

The sample size of the flying birds detected in Survey Area 1 was low (n = 315) particularly in the area containing WTGs which is likely affecting the statistical power

of the analysis. Additionally, the detected birds were far away from the WTG, with the closest bird 44 m away and the second closest 189 m. This could suggest avoidance behaviour of the detected sea birds around the WTG. A larger sample size is needed for achieving meaningful results of the study of flight height in relation to WTGs. This could be achieved by repeating the study in an area with a higher abundance of sea birds or conducting more surveys. However, if seabirds are avoiding WTGs the effect of height on their flight pattern might be difficult to study in close proximity of 0-200 m.

The outputs produced from the combined imagery-LiDAR system could be incorporated into collision risk modelling for use within either Band Option 1 by specifying the proportion of birds recorded at collision risk height (CRH) or within Band Option 2 as the proportion of individuals recorded in one metre flight height bands (Band, 2012, Johnston *et al*. 2014; McGregor, *et al*. 2018). The implication of using these values would need to be determined and clear guidance on best practice given, as it may be advisable to undertake linear modelling of the dataset first in order to interpolate between flight bands where there were no individuals recorded flying at those heights. If a representative dataset is collected with a large sample size it can be argued that the raw data could be suitable for use within the CRM.

In order to safely collect data over the wind farm, the aircraft must be at least 305 m above the highest object. Therefore, with the combined imagery-LiDAR system the aircraft altitude was approximately 500 m. There is potential that collecting data at this height could lead to a cone effect whereby higher-flying birds have a lower probability of being included within the imagery, causing a bias in the data. This is not restricted to the imagery-LiDAR system. Provided that an accurate IMU is integrated on the camera system, analysis for actual area sampled at each altitude can be calculated. The effect is likely to be minimal however, as during this survey no birds were found above 200 m suggesting that they may not utilise the airspace at the point where the cone effect may be more relevant. Further study could be undertaken collecting flight height data at differing altitudes to see if there are any impacts on results. There would however be a trade-off in resolution and species identification with differing flight altitudes.

During this study low sample sizes were encountered, therefore it can be recommended that when planning combined imagery-LiDAR surveys previous data on species densities should be analysed to infer predicted encounter rate. Key species for collision risk should be selected to ensure accurate CRM can be undertaken. Furthermore, if future studies are undertaken power analysis can be undertaken to identify the minimum sample size required to detect an effect size and the survey planned accordingly (Cohen, 1988; Maclean *et al*., 2016).

Overall, the combined imagery-LiDAR system successfully allowed a large sample of different species flight heights outside and within an active wind farm to be measured. Potential macro avoidance of wind turbines was found; however, there was only a minimal statistical difference. A combined imagery-LiDAR flight height dataset has the capability to be used in CRM for EIA, with the advantage of greatly reducing associated error and potential risk.

5. Acknowledgements

Many thanks to the European Maritime Fisheries Fund for the funding for this project.

Many thanks to Marine Scotland Science for commissioning the piece of work, and NatureScot and RSPB for their guidance and comments throughout planning, analysis and reporting as part of the Steering Group, with special thanks to Dr Tom Evans, Anna Kebke, Dr Helen Wade and Dr Aly McCluskie.

6. References

APEM, 2018. Pre-construction Aerial Survey Report 2018. *APEM Scientific Report for Moray Offshore Windfarm (East) Limited*, November 2018.

Band B., 2012. Using a collision risk model to assess bird collision risks for offshore windfarms. *British Trust for Ornithology*.

Bates D., Mächler M., Bolker B., Walker S., 2015. "Fitting Linear Mixed-Effects Models Using lme4." *Journal of Statistical Software*, 67(1), 1–48. doi: 10.18637/jss.v067.i01.

[BTO] The British Trust for Ornithology, 2015. The BTO at Sea. *Annual Review 2015*. September–October 2015 316: 10–1.1.

Canty, A. and Ripley, B., 2010. boot: bootstrap R (S-Plus) functions. R package version 1.2-42.

Cook, A.S.C.P., Ward, R.M., Hansen, W.S. and Larsen, L., 2018. Estimating seabird flight height using LiDAR. *Scottish Marine and Freshwater Science*, 9(14), pp.1-52.

Cohen, J., 1988. Statistical Power Analysis for Behavioural Sciences. 2nd Edition. Lawrance Erblaum Associates, Hillsdale, New Jersey.

Efron, B. & Tibshirani, R.J. 1993. An introduction to the bootstrap. Chapman & Hall, London.

Forewind, 2013. Dogger Bank Creyke Beck Environmental Statement Chapter 11 Appendix A - *Ornithology Technical Report*. F-ONC-CH-011 Appendix A, Issue 1.

Furness, R.W., Wade, H.M. and Masden, E.A., 2013. Assessing vulnerability of marine bird populations to offshore wind farms. *Journal of environmental management*, 119, pp.56-66.

Johnston, A., Cook, A.S., Wright, L.J., Humphreys, E.M. and Burton, N.H., 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.

MacArthur Green, 2019. Beatrice Offshore Wind Farm Year 1 Post construction Ornithological Monitoring Report 2019. MacArthur Green *Scientific Report for Beatrice Offshore Windfarm.* April 2019.

Maclean, I.M., Skov, H., Rehfisch, M.M. and Piper, W., 2006. Use of aerial surveys to detect bird displacement by offshore windfarms. *BTO Research Report*, 446.

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

McGovern, S., Wilmott, J.R., Lampman, G., Pembroke, A., Warford, S., Rehfisch, M. and Clough, S., 2019. The First Large-Scale Offshore Aerial Survey Using a High-

Resolution Camera System. In Wind Energy and Wildlife Impacts (pp. 115-123). *Springer*, Cham.

McGregor, R.M., King, S., Donovan, C.R., Caneco, B., Webb, A. 2018. A Stochastic Collision Risk Model for Seabirds in Flight. *HiDef BioConsult Scientific Report to Marine Scotland*, 06/04/2018, Issue I, 59 pp.

QGIS.org, 2021. QGIS 3.16. Geographic Information System User Guide. QGIS Association. Electronic document: https://docs.qgis.org/3.16/en/docs/user_manual/index.html

R Core Team (2020). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/.

Scarff, G., Fitzsimmons, C. and Gray, T., 2015. The new mode of marine planning in the UK: Aspirations and challenges. *Marine Policy*, *51*, pp.96-102.

Scottish Government, 2020. Sectoral marine plan for offshore wind energy. Available at:https://www.gov.scot/publications/sectoral-marine-plan-offshore-wind-energy/documents/ (2022).

Appendix I. JNCC Bird Groups

Table I.1 JNCC Bird Groups

JNCC Code	Grouping	Species Code	Species
220	Fulmar	220	Fulmar
95006	Shearwater	460	Manx Shearwater
710	Gannet	710	Gannet
95032	Skua species	5690	Great skua
94003	Small gull species	6020	Kittiwake
95034	Large gull species	5920	Herring gull
		6000	Great black-backed gull
95040	Auk species	6340	Guillemot
		6360	Razorbill
		6540	Puffin

Appendix II. Digital Still Imagery to LiDAR Match Rates

Table II.1 Survey 1 Imagery to LiDAR Match Rate.

Common Name	Unable to match	Matched	Grand Total	Match Rate
Auk species	0	1	1	100%
Auk / Shearwater species	1	0	1	0%
Fulmar	5	48	53	91%
Gannet	6	39	45	87%
Great Black-backed Gull	0	2	2	100%
Great Skua		3	3	100%
Guillemot	101	662	763	87%
Guillemot / Razorbill	1	7	8	88%
Herring Gull	5	21	26	81%
Kittiwake	21	239	260	92%
Razorbill	5	27	32	84%
Total	145	1049	1194	88%

Table II.2 Survey 2 Imagery to LiDAR Match Rate

Common Name	Unable to match	Matched	Grand Total	Match Rate
Fulmar	5	66	71	93%
Gannet	0	18	18	100%
Great Black-backed Gull	0	3	3	100%
Great Skua	0	6	6	100%
Guillemot	68	526	594	89%
Guillemot / Razorbill	4	17	21	81%
Herring Gull	2	19	21	90%
Kittiwake	41	396	437	91%
Manx Shearwater	1	0	1	0%
Puffin	0	1	1	100%
Unidentified Bird species	1	0	1	0%
Grand Total	122	1052	1174	90%

Appendix III. Raw species counts and distribution

Survey 1

A total of 1,194 birds were recorded in flight in the combined Survey Area 1 and Survey Area 2 during the June survey. The most abundant species recorded was guillemot (n=763), followed by kittiwake (n=260), fulmar (n=53), gannet (n=45), herring gull (n=26), razorbill (n=32), guillemot / razorbill (n=8), great black-backed gull (n=2), great skua (n=3), auk species (n=1), auk / shearwater species (n=1) and small gull species (n=1). Figure III.1 shows the distribution of all birds recorded in flight in June 2021.

Table III.1 Raw counts of bird species recorded in flight during the June 2021 survey.

Species	Total
Fulmar	53
Gannet	46
Great Skua	3
Kittiwake	260
Small Gull Species	1
Herring Gull	26
Great Black-backed Gull	2
Guillemot	763
Guillemot / Razorbill	8
Razorbill	32
Auk / Shearwater species	1
Auk Species	1
Total Birds	***1,194***

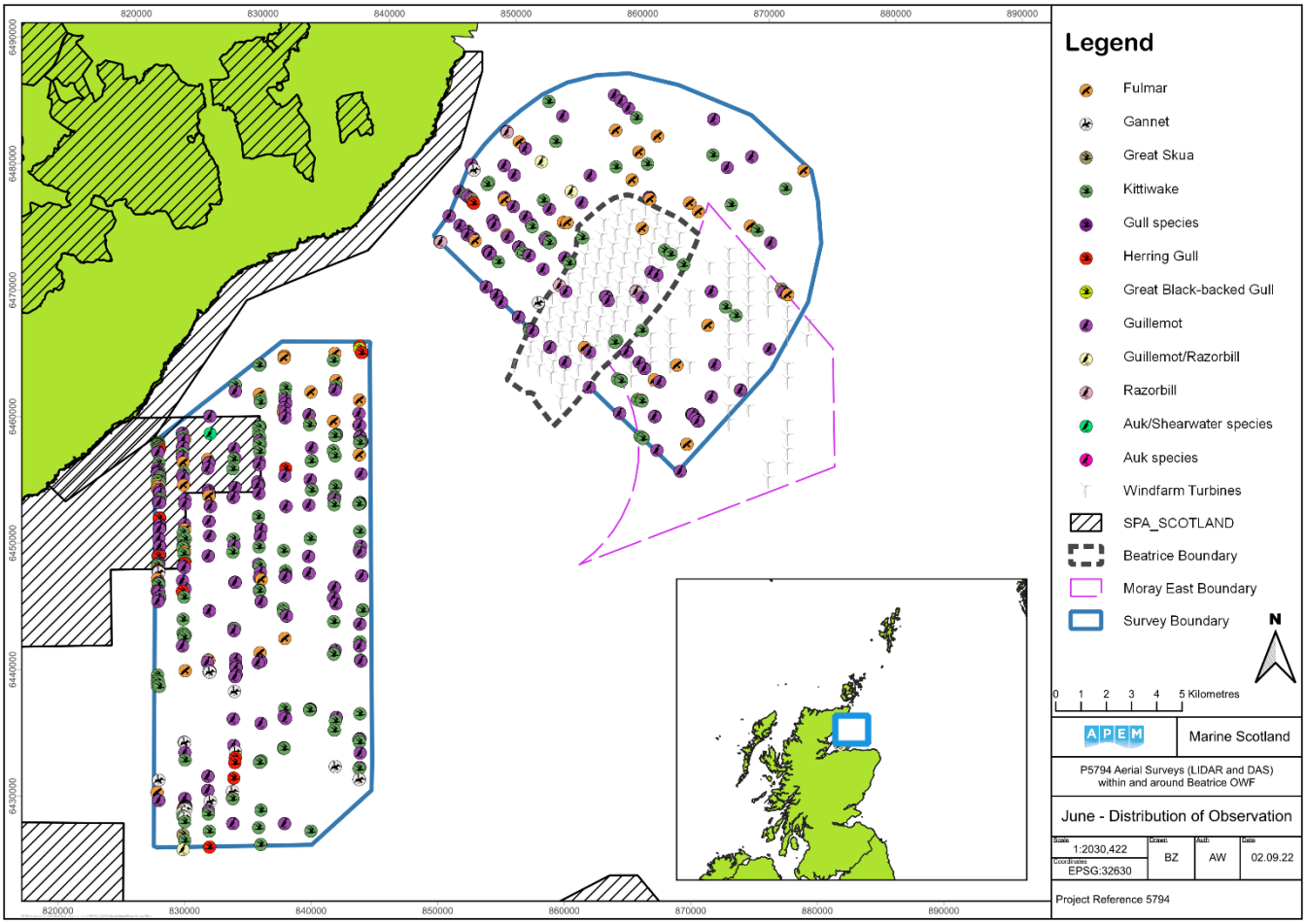


Figure III.1 Distribution of flying bird observations in the June 2021 survey.

Survey 2

A total of 1,175 birds were recorded in flight in the combined Survey Area 1 and Survey Area 2 during the July survey. The most abundant species recorded was guillemot (n=594), followed by kittiwake (n=437), fulmar (n=71), guillemot / razorbill (n=21), herring gull (n=21), gannet (n=18), great skua (n=6), great black-backed gull (n=3), Manx shearwater (n=1), puffin (n=1) and unidentified bird species (n=1). Figure III.2Figure III.2 Distribution of flying bird observations in the July 2021 survey. shows the distribution of all birds recorded in flight in July 2021.

Table III - 2 Raw counts of bird species recorded in flight during the July 2021 survey.

Species	Total
Fulmar	71
Manx shearwater	1
Gannet	18
Great Skua	6
Kittiwake	437
Herring Gull	21
Great Black-backed Gull	3
Guillemot	594
Guillemot / Razorbill	21
Puffin	1
Unidentified bird species	1
Total Birds	***1,175***

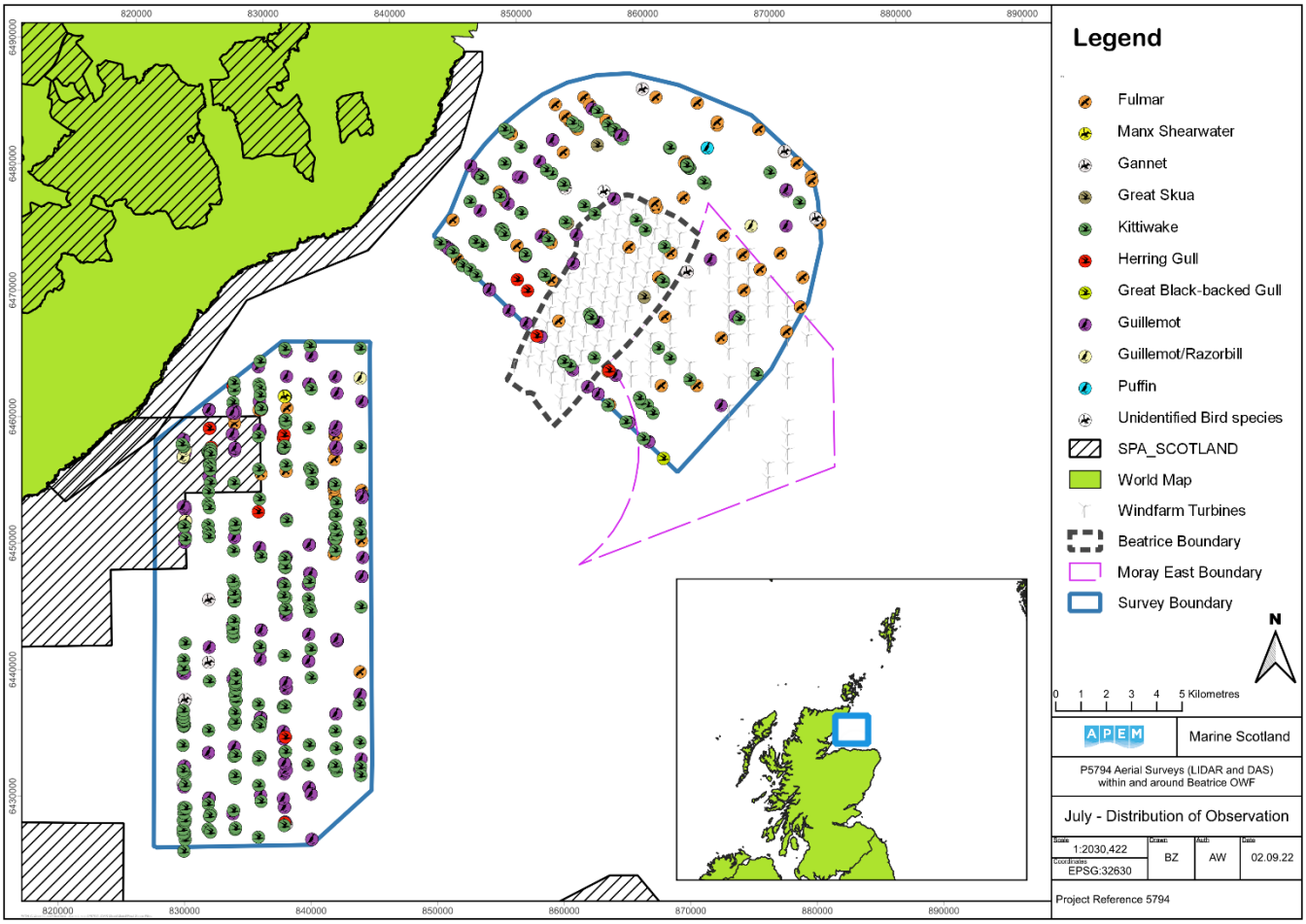


Figure III.2 Distribution of flying bird observations in the July 2021 survey.

Appendix IV. Model diagnostic plots and full model outputs

Modelling fight height in relation to WTG distance (all species combined)

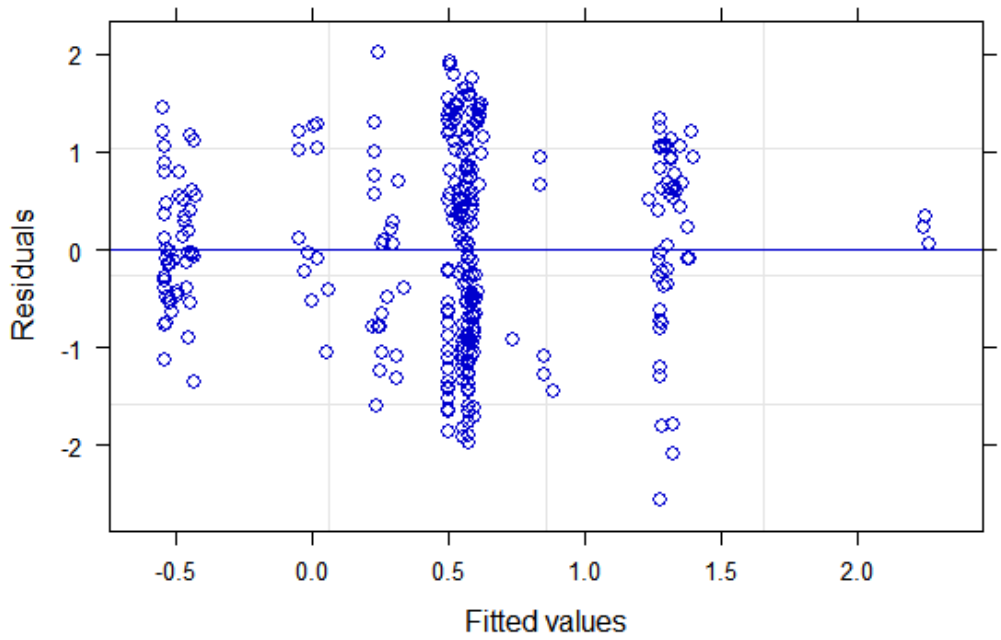


Figure IV.1 Plot of the LMM for both survey months in Survey Area 1.

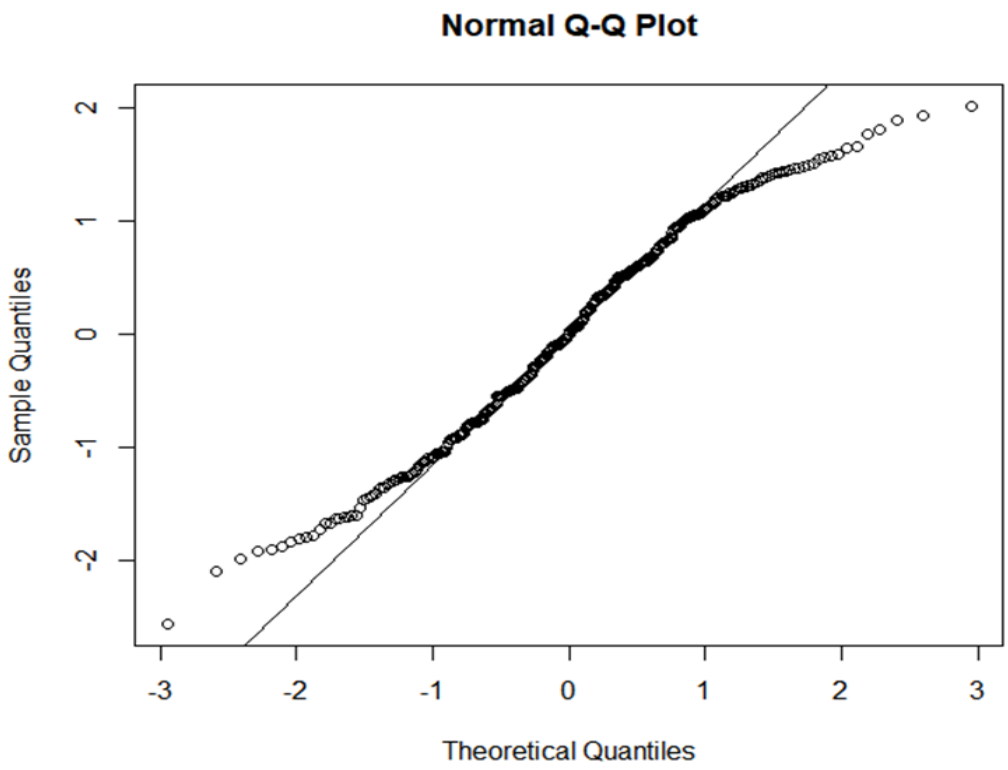


Figure IV.2 Q-Q line plot of the LMM of flight height against distance to the nearest turbine.

Kittiwake

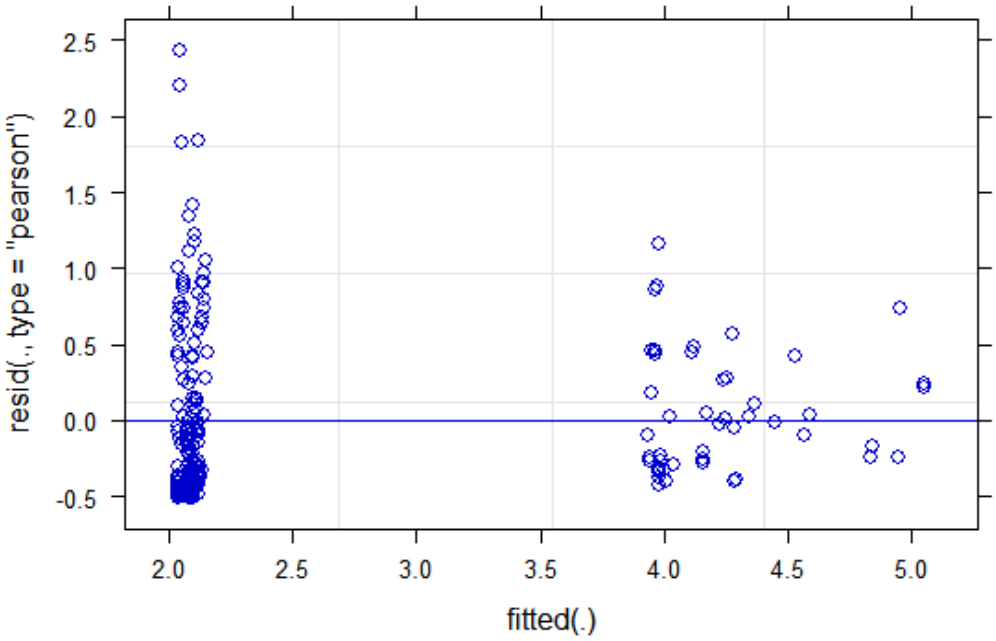


Figure IV.3 Plot of the GLMM for kittiwake for both survey months in Survey Area 1.

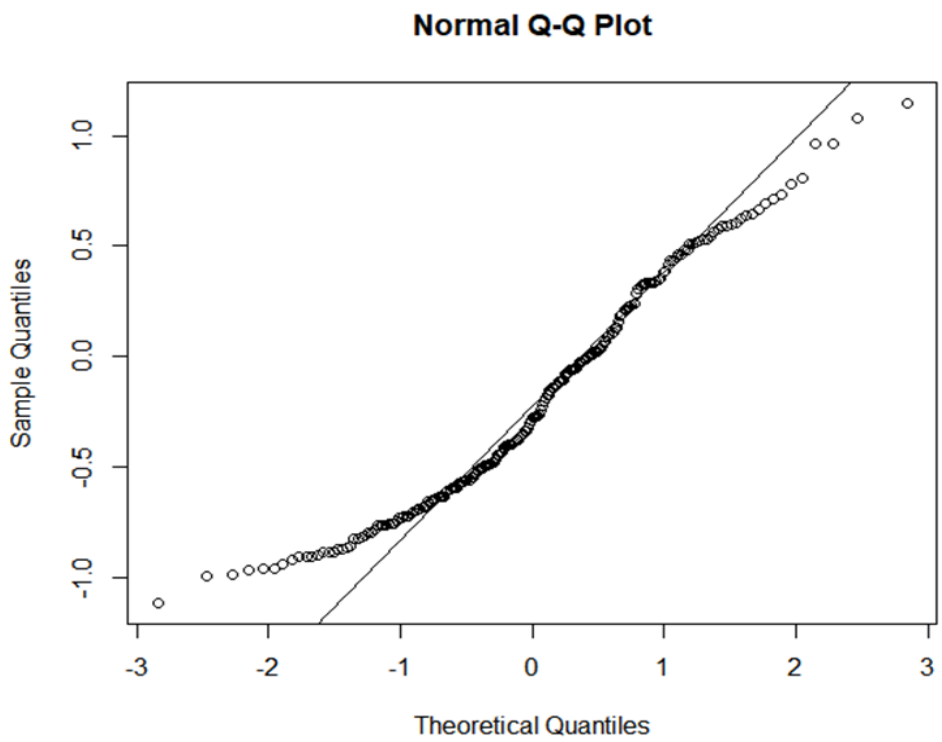


Figure IV.4 Q-Q line plot of the GLMM of flight height of kittiwakes against the distance to the nearest turbine.

Fulmar

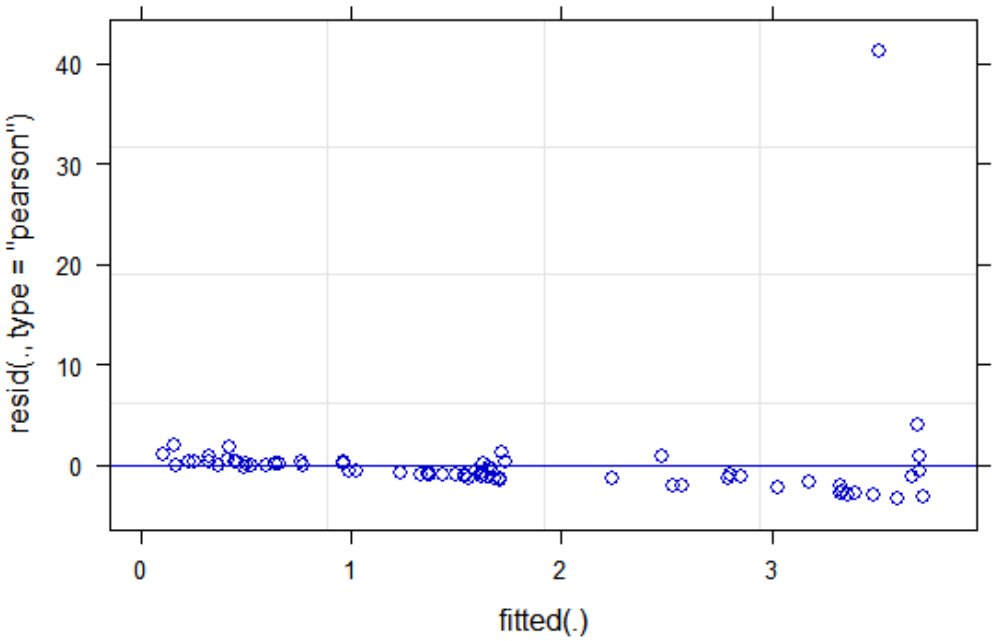


Figure IV.5 Plot of the LMM for fulmar for both survey months in Survey Area 1.

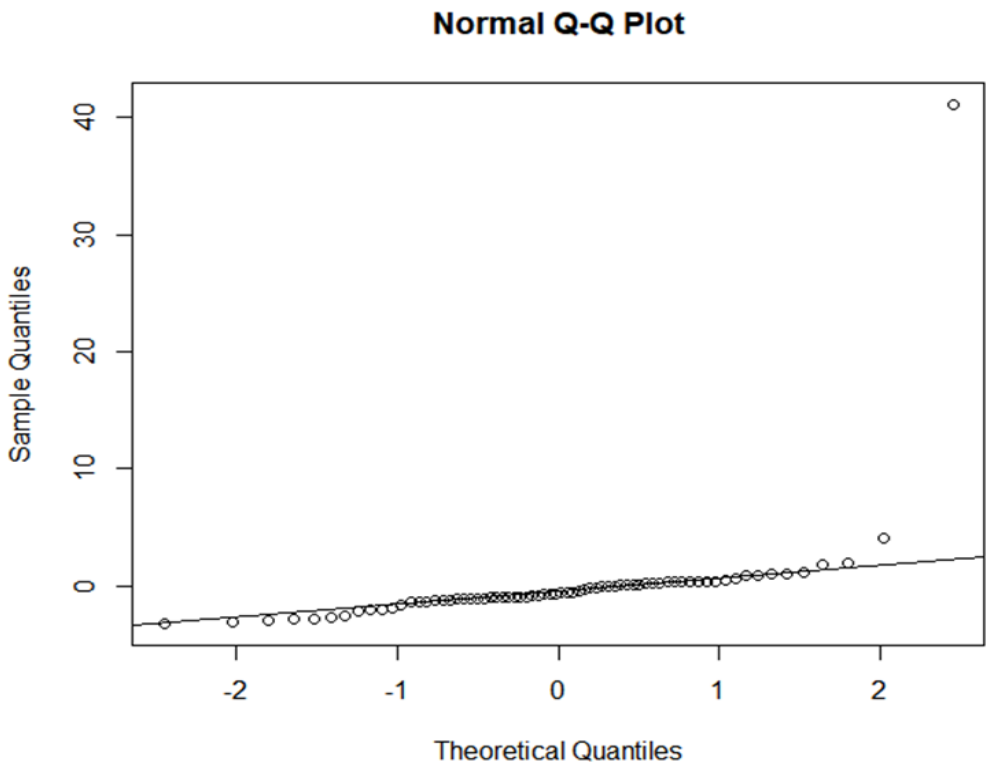


Figure IV.6 Q-Q line plot of the LM of flight height of fulmars against the distance to the nearest turbine.

Gannet

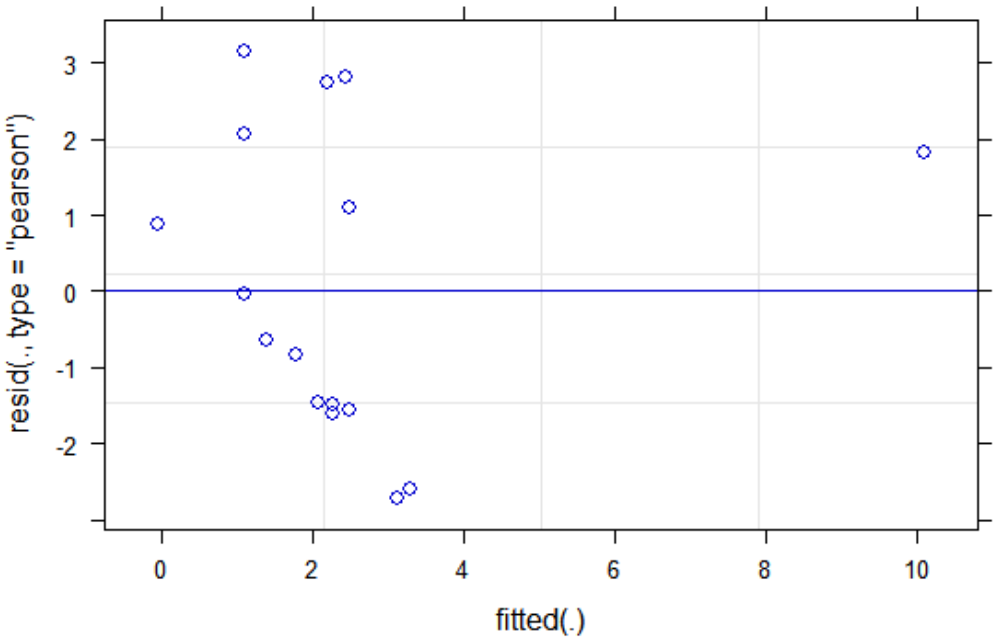


Figure IV.7 Plot of the LMM for gannets for both survey months in Survey Area 1.

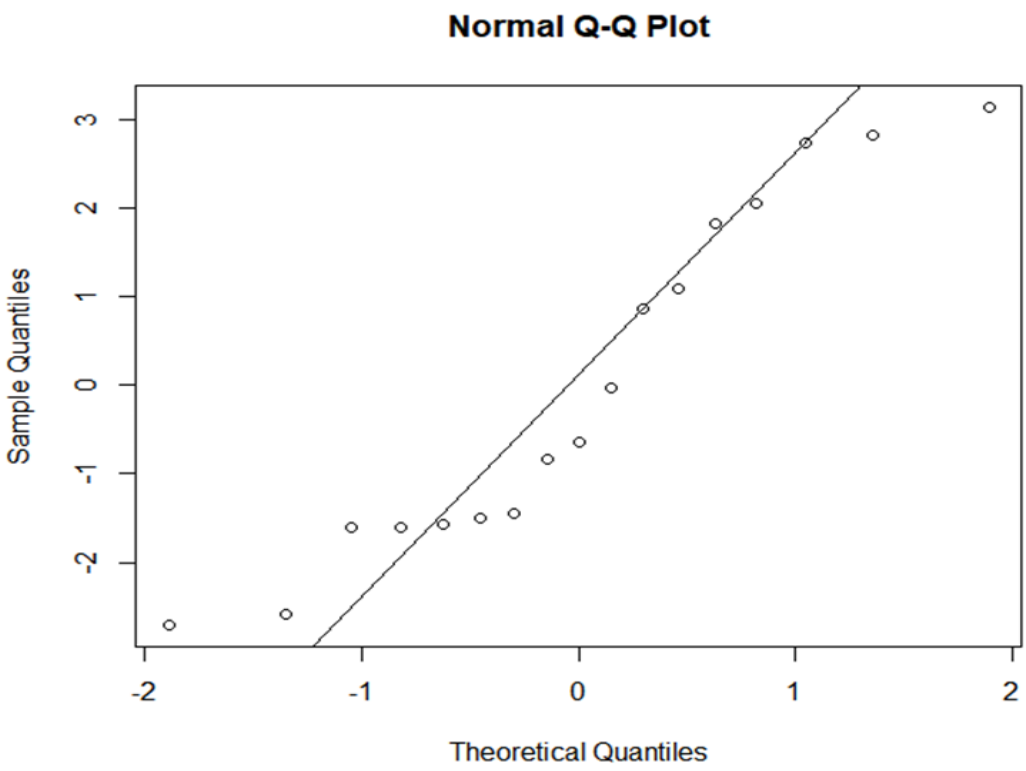


Figure IV.8 Q-Q line plot of the LMM of flight height of gannets against the distance to the nearest turbine

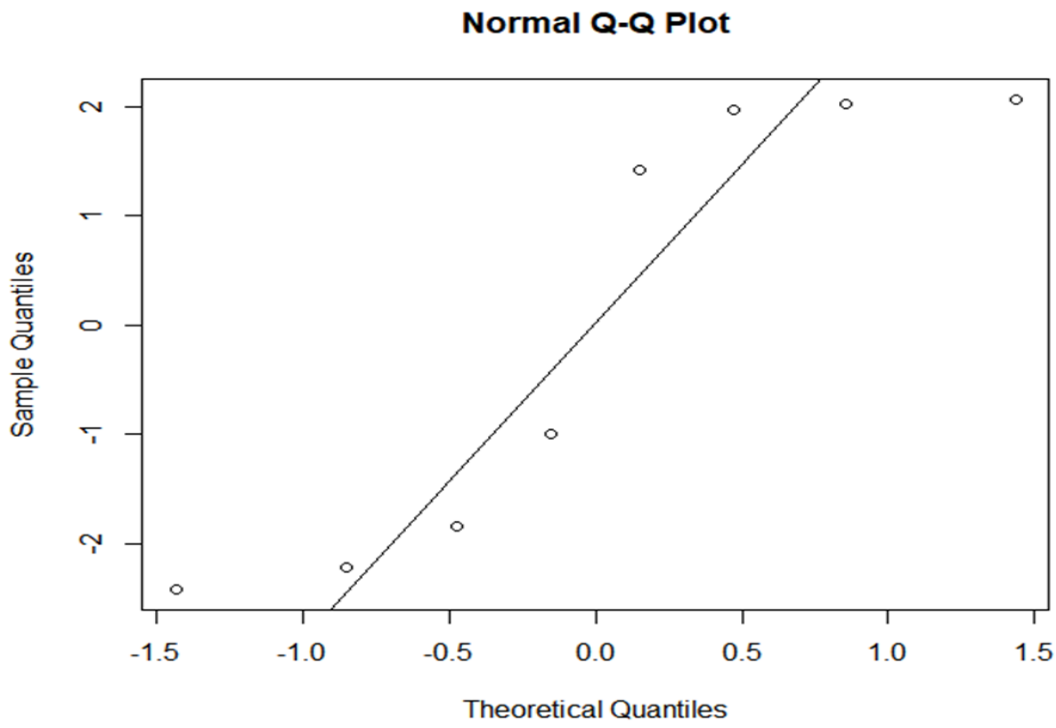


Figure IV.9 Q-Q line plot of the LM of flight height of large gulls against the distance to the nearest turbine.

Comparing flight height in different area with and without WGTs

Core species (large gulls, kittiwake, fulmar, gannet)
Wilcoxon rank sum test with continuity correction
data: corspec$BirdZ_SeaL by corspec$area
W = 56813, p-value = 0.000000000000001543
alternative hypothesis: true location shift is not equal to 0
95 percent confidence interval:
 -3.980004 -1.520024
sample estimates:
difference in location
-2.719962
Area1 Mean height seaL= 11.32 m s.d= 26.61
Area2 Mean height seaL 20.03 = s.d= 33.73

Kittiwake
Wilcoxon rank sum test with continuity correction
data: kittiwake$BirdZ_SeaL by kittiwake$area
W = 34715, p-value = 0.000001006

alternative hypothesis: true location shift is not equal to 0
95 percent confidence interval:
-3.3299740 -0.7600427
sample estimates:
difference in location
-1.839956
Area1 Mean height seaL= 12.49 s.d= 24.87
Area2 Mean height seaL= 17.84 s.d= 30.83

Fulmar
Wilcoxon rank sum test with continuity correction
data: fulmar$BirdZ_SeaL by fulmar$area
W = 1237.5, p-value = 0.05343
alternative hypothesis: true location shift is not equal to 0
95 percent confidence interval:
-0.78999810008 0.00003286683
sample estimates:
difference in location
-0.299965
Area1 Mean height seaL= 1.72 s.d= 5.34
Area2 Mean height seaL= 3.53 s.d= 7.89

Gannet
Wilcoxon rank sum test with continuity correction
data: gannet$BirdZ_SeaL by gannet$area
W = 181.5, p-value = 0.004449
alternative hypothesis: true location shift is not equal to 0
95 percent confidence interval:
-9.6579730 -0.4699419
sample estimates:
difference in location
-5.960084

Area1 Mean height seaL= 2.45 s.d= 2.96
Area2 Mean height seaL= 12.89 s.d= 18.44

Gull
Wilcoxon rank sum test with continuity correction
data: gull$BirdZ_SeaL by gull$area
W = 154, p-value = 0.8703
alternative hypothesis: true location shift is not equal to 0
95 percent confidence interval:
-47.63005 61.76006
sample estimates:
difference in location
4.263862
Area1 Mean height seaL= 81.92 s.d= 72.49
Area2 Mean height seaL= 72.40 s.d= 48.05

Comparing flight height in relation to distance to nearest WGT

Core species (large gulls, kittiwake, fulmar, gannet)

```
Linear mixed model fit by REML. t-tests use Satterthwaite's method
['lmerModLmerTest']
Formula: ((BirdZ_SeaL^lambda - 1)/lambda) ~ Turbine_Distance_M_scaled *      (1 |
CommonName) + (1 | month)
   Data: area1
REML criterion at convergence: 898.8
Scaled residuals:
     Min       1Q   Median       3Q      Max
-2.61097 -0.79216 -0.00487  0.79954  2.05542
Random effects:
 Groups     Name        Variance Std.Dev.
 CommonName (Intercept) 1.2132   1.1015
 month      (Intercept) 0.3051   0.5523
 Residual               0.9589   0.9792
Number of obs: 315, groups:  CommonName, 5; month, 2
Fixed effects:
                      Estimate Std. Error       df t value Pr(>|t|)
(Intercept)             0.9688     0.6506   4.1117   1.489    0.209
Turbine_Distance_M_scaled   0.2832     0.3564 310.0732   0.795    0.427

Correlation of Fixed Effects:
          (Intr)
Trbn_Dst_M_ -0.108
```

Kittiwake

```
Generalized linear mixed model fit by maximum likelihood (Laplace Approximation)
['glmerMod']
 Family: inverse.gaussian  ( 1/mu^2 )
Formula: BirdZ_SeaL_sqrt ~ Turbine_Distance_M_scaled + (1 | month)
   Data: kittiwake
     AIC      BIC   logLik deviance df.resid
   763.8    777.4   -377.9    755.8      216
Scaled residuals:
    Min      1Q  Median      3Q     Max
-0.9350 -0.7283 -0.4153  0.4196  4.4823
Random effects:
 Groups   Name        Variance Std.Dev.
 month    (Intercept) 0.003769 0.06139
 Residual             0.294173 0.54238
Number of obs: 220, groups:  month, 2
Fixed effects:
                      Estimate Std. Error t value Pr(>|z|)
(Intercept)             0.16771    0.07766   2.160   0.0308 *
Turbine_Distance_M_scaled -0.05798    0.09470  -0.612   0.5404
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Correlation of Fixed Effects:
          (Intr)
Trbn_Dst_M_ -0.261
```

Fulmar

```
Linear mixed model fit by REML. t-tests use Satterthwaite's method
['lmerModLmerTest']
Formula: BirdZ_SeaL ~ Turbine_Distance_M_scaled + (1 | month)
   Data: fulmar
REML criterion at convergence: 423.7
Scaled residuals:
    Min      1Q  Median      3Q     Max
-0.6277 -0.2298 -0.1253  0.0502  7.8833
Random effects:
 Groups   Name        Variance Std.Dev.
 month    (Intercept)  2.676   1.636
 Residual             27.290   5.224
Number of obs: 70, groups:  month, 2
Fixed effects:
                      Estimate Std. Error     df t value Pr(>|t|)
(Intercept)              2.761      1.536  1.708   1.798    0.235
Turbine_Distance_M_scaled   -3.841      4.525 67.554  -0.849    0.399
Correlation of Fixed Effects:
           (Intr)
Trbn_Dst_M_ -0.498
```

Gannet

```
Linear mixed model fit by REML. t-tests use Satterthwaite's method
['lmerModLmerTest']
Formula: BirdZ_SeaL ~ Turbine_Distance_M_scaled + (1 | month)
   Data: gannet
REML criterion at convergence: 69.3
Scaled residuals:
    Min      1Q  Median      3Q     Max
-1.3060 -0.7526 -0.3054  0.8807  1.5152
Random effects:
 Groups   Name        Variance Std.Dev.
 month    (Intercept) 1.431    1.196
 Residual             4.304    2.075
Number of obs: 17, groups:  month, 2
Fixed effects:
                      Estimate Std. Error      df t value Pr(>|t|)
(Intercept)              0.3622     1.1329  1.0882   0.320 0.799591
Turbine_Distance_M_scaled   5.7669     1.3873 14.5092   4.157 0.000901 ***
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Correlation of Fixed Effects:
           (Intr)
Trbn_Dst_M_ -0.466
```

Gull (only July)

```
Call:
lm(formula = gull$BirdZ_SeaL_sqrt ~ gull$Turbine_Distance_M_scaled)
Residuals:
    Min      1Q  Median      3Q     Max
-2.4172 -1.9338  0.2128  1.9764  2.0664

Coefficients:
                              Estimate Std. Error t value  Pr(>|t|)
(Intercept)                     12.574      1.187  10.591 0.0000417 ***
gull$Turbine_Distance_M_scaled  -33.238      6.217  -5.346   0.00175 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Residual standard error: 2.211 on 6 degrees of freedom
Multiple R-squared:  0.8265,	Adjusted R-squared:  0.7976
F-statistic: 28.58 on 1 and 6 DF,  p-value: 0.001751
```

R Script for Linear Mixed Modelling and Distance to Turbine Histograms

```
#### R code for Models and Distance to Turbines (m) ####

#### Created by Alexandra McCubbin and Beate Zein for APEM Ltd


#### Section below created by Beate Zein for APEM Ltd
rm(list = ls())
#### Install packages... ####
library(nlme)
library(lme4)
library(tidyverse)
library(ggeffects)
library(stargazer)
library(arsenal)

#set working directory and select data
path_out = "C:"
options(scipen = 999)   # prevents small/large numbers being shown in e format

#June data
setwd("C:/")
testfiles <-list.files("C:/")  ### assign files in the directory as 'testfiles'
testfiles

#### Read in Data for each site ####
June_Beatrice <- read.csv(paste0(getwd(), "/", testfiles[1]))
June_MorayEast <- read.csv(paste0(getwd(), "/", testfiles[2]))
June_Outwith <- read.csv(paste0(getwd(), "/", testfiles[3]))
June_Survey2 <- read.csv(paste0(getwd(), "/", testfiles[4]))

#### Add Location Column ####
```

```
June_Beatrice$Location="Beatrice"
June_MorayEast$Location="Moray East"
June_Outwith$Location="S1Outwith"
June_Survey2$Location="Survey2"

#### Combine into one DataFrame ####
CombinedJune <-rbind(June_Beatrice, June_MorayEast, June_Outwith,
June_Survey2)

#### JULY  Set WD####
setwd("C:/")
testfilesJul <-list.files("C:/")   ### assign files in the directory as 'testfiles'
testfilesJul

#### Read in Data for each site ####
July_Beatrice <- read.csv(paste0(getwd(), "/", testfilesJul[1]))
July_MorayEast <- read.csv(paste0(getwd(), "/", testfilesJul[2]))
July_Outwith <- read.csv(paste0(getwd(), "/", testfilesJul[3]))
July_Survey2 <- read.csv(paste0(getwd(), "/", testfilesJul[4]))

#### Add Location Column ####
July_Beatrice$Location="Beatrice"
July_MorayEast$Location="Moray East"
July_Outwith$Location="S1Outwith"
July_Survey2$Location="Survey2"

#### Combine into one DataFrame ####
CombinedJuly <-rbind(July_Beatrice, July_MorayEast, July_Outwith, July_Survey2)
rm(July_Beatrice,July_MorayEast, July_Outwith,
July_Survey2,June_Beatrice,June_MorayEast, June_Outwith, June_Survey2)

#### Drop Extra Column From July ####
CombinedJuly <- CombinedJuly[-c(30)]
#add month running number
CombinedJune$month<-6
CombinedJuly$month<-7

colnames(CombinedJuly)
colnames(CombinedJune) ### check June and July Column Names Match

#### Combine All Data ####
JuneJulyCombine <- rbind(CombinedJune, CombinedJuly)

#### Summaries ####
summary(CombinedJuly)
summary(CombinedJune)
summary(JuneJulyCombine)

#add survey area 1 and 2
JuneJulyCombine$area<-1
```

```
JuneJulyCombine$area[JuneJulyCombine$Location=="Survey2"]<- 2

#remove NA in height data
JuneJulyCombine<-JuneJulyCombine[!is.na(JuneJulyCombine$BirdZ_SeaL),]

#split up by species
unique(JuneJulyCombine$CommonName)
fulmar<-JuneJulyCombine[JuneJulyCombine$CommonName == "Fulmar",]
kittiwake<-JuneJulyCombine[JuneJulyCombine$CommonName == "Kittiwake",]
gannet<-JuneJulyCombine[JuneJulyCombine$CommonName == "Gannet",]
gull<-JuneJulyCombine[JuneJulyCombine$CommonName == "Herring
Gull"|JuneJulyCombine$CommonName == "Great Black-backed Gull",]

#select core species of interest
corspec<-rbind(fulmar,kittiwake,gannet,gull)

#compare flight height of different study sides
#Mann Whithey U test /Wilcoxon rank sum test
#not measured randomly, left skewed distribution, none equal variance
#non-parametric
#Ho median if flight height is the same in the two areas

#all core species
var(corspec$BirdZ_SeaL[corspec$area=="1"])
var(corspec$BirdZ_SeaL[corspec$area=="2"])
#none equal variances
hist(corspec$BirdZ_SeaL[corspec$area=="1"],breaks=50)
boxplot(corspec$BirdZ_SeaL~corspec$area)
mean(corspec$BirdZ_SeaL[corspec$area=="1"])
sd(corspec$BirdZ_SeaL[corspec$area=="1"])
sd(corspec$BirdZ_SeaL[corspec$area=="2"])
mean(corspec$BirdZ_SeaL[corspec$area=="2"])
#test
wilcox.test(corspec$BirdZ_SeaL~corspec$area,mu=0,alt="two.sided",conf.int=T,conf
.level=0.95,paired=FALSE,exact=F,correct=T) # where y1 and y2 are numeric

#kittiwake
var(kittiwake$BirdZ_SeaL[kittiwake$area=="1"])
var(kittiwake$BirdZ_SeaL[kittiwake$area=="2"])
#none equal variances
hist(kittiwake$BirdZ_SeaL[kittiwake$area=="1"],breaks=50)
hist(kittiwake$BirdZ_SeaL[kittiwake$area=="2"],breaks=50)
boxplot(kittiwake$BirdZ_SeaL~kittiwake$area)
mean(kittiwake$BirdZ_SeaL[kittiwake$area=="1"])
mean(kittiwake$BirdZ_SeaL[kittiwake$area=="2"])
sd(kittiwake$BirdZ_SeaL[kittiwake$area=="1"])
sd(kittiwake$BirdZ_SeaL[kittiwake$area=="2"])
#test
wilcox.test(kittiwake$BirdZ_SeaL~kittiwake$area,mu=0,alt="two.sided",conf.int=T,co
nf.level=0.95,paired=FALSE,exact=F,correct=T) # where y1 and y2 are numeric
```

```
#fulmar
var(fulmar$BirdZ_SeaL[fulmar$area=="1"])
var(fulmar$BirdZ_SeaL[fulmar$area=="2"])
#none equal variances
hist(fulmar$BirdZ_SeaL[fulmar$area=="1"],breaks=50)
hist(fulmar$BirdZ_SeaL[fulmar$area=="2"],breaks=50)
boxplot(fulmar$BirdZ_SeaL~fulmar$area)
mean(fulmar$BirdZ_SeaL[fulmar$area=="1"])
mean(fulmar$BirdZ_SeaL[fulmar$area=="2"])
sd(fulmar$BirdZ_SeaL[fulmar$area=="1"])
sd(fulmar$BirdZ_SeaL[fulmar$area=="2"])
#test
wilcox.test(fulmar$BirdZ_SeaL~fulmar$area,mu=0,alt="two.sided",conf.int=T,conf.lev
el=0.95,paired=FALSE,exact=F,correct=T) # where y1 and y2 are numeric

#gannet
var(gannet$BirdZ_SeaL[gannet$area=="1"])
var(gannet$BirdZ_SeaL[gannet$area=="2"])
#none equal variances
hist(kittiwake$BirdZ_SeaL[kittiwake$area=="1"],breaks=50)
hist(kittiwake$BirdZ_SeaL[kittiwake$area=="2"],breaks=50)
boxplot(gannet$BirdZ_SeaL~gannet$area)
mean(gannet$BirdZ_SeaL[gannet$area=="1"])
mean(gannet$BirdZ_SeaL[gannet$area=="2"])
sd(gannet$BirdZ_SeaL[gannet$area=="1"])
sd(gannet$BirdZ_SeaL[gannet$area=="2"])
#test
wilcox.test(gannet$BirdZ_SeaL~gannet$area,mu=0,alt="two.sided",conf.int=T,conf.l
evel=0.95,paired=FALSE,exact=F,correct=T) # where y1 and y2 are numeric

#gull
var(gull$BirdZ_SeaL[gull$area=="1"])
var(gull$BirdZ_SeaL[gull$area=="2"])
#none equal variances
hist(kittiwake$BirdZ_SeaL[kittiwake$area=="1"],breaks=50)
hist(kittiwake$BirdZ_SeaL[kittiwake$area=="2"],breaks=50)
boxplot(gull$BirdZ_SeaL~gull$area)
mean(gull$BirdZ_SeaL[gull$area=="1"])
mean(gull$BirdZ_SeaL[gull$area=="2"])
sd(gull$BirdZ_SeaL[gull$area=="1"])
sd(gull$BirdZ_SeaL[gull$area=="2"])
#test
wilcox.test(gull$BirdZ_SeaL~gull$area,mu=0,alt="two.sided",conf.int=T,conf.level=0.
95,paired=FALSE,exact=F,correct=T) # where y1 and y2 are numeric

#make violin plot for all core species
corspec$area<-as.factor(corspec$area)

library(ggplot2)
```

```
GeomSplitViolin <- ggproto("GeomSplitViolin", GeomViolin,
                        draw_group = function(self, data, ..., draw_quantiles = NULL) {
                          data <- transform(data, xminv = x - violinwidth * (x - xmin), xmaxv
= x + violinwidth * (xmax - x))
                          grp <- data[1, "group"]
                          newdata <- plyr::arrange(transform(data, x = if (grp %% 2 == 1)
xminv else xmaxv), if (grp %% 2 == 1) y else -y)
                          newdata <- rbind(newdata[1, ], newdata, newdata[nrow(newdata),
], newdata[1, ])
                          newdata[c(1, nrow(newdata) - 1, nrow(newdata)), "x"] <-
round(newdata[1, "x"])

                          if (length(draw_quantiles) > 0 &
!scales::zero_range(range(data$y))) {
                            stopifnot(all(draw_quantiles >= 0), all(draw_quantiles <=
                                                                    1))
                            quantiles <- ggplot2:::create_quantile_segment_frame(data,
draw_quantiles)
                            aesthetics <- data[rep(1, nrow(quantiles)), setdiff(names(data),
c("x", "y")), drop = FALSE]
                            aesthetics$alpha <- rep(1, nrow(quantiles))
                            both <- cbind(quantiles, aesthetics)
                            quantile_grob <- GeomPath$draw_panel(both, ...)
                            ggplot2:::ggname("geom_split_violin",
grid::grobTree(GeomPolygon$draw_panel(newdata, ...), quantile_grob))
                          }
                          else {
                            ggplot2:::ggname("geom_split_violin",
GeomPolygon$draw_panel(newdata, ...))
                          }
                        })

geom_split_violin <- function(mapping = NULL, data = NULL, stat = "ydensity",
position = "identity", ...,
                          draw_quantiles = NULL, trim = TRUE, scale = "area", na.rm =
FALSE,
                          show.legend = NA, inherit.aes = TRUE) {
  layer(data = data, mapping = mapping, stat = stat, geom = GeomSplitViolin,
        position = position, show.legend = show.legend, inherit.aes = inherit.aes,
        params = list(trim = trim, scale = scale, draw_quantiles = draw_quantiles, na.rm
= na.rm, ...))
}

#scale and log data for check
corspec$BirdZ_SeaL_scales<-scale(corspec$BirdZ_SeaL, center = TRUE, scale =
TRUE)
hist(corspec$BirdZ_SeaL_scales)
corspec$BirdZ_SeaL_log<-log(corspec$BirdZ_SeaL)

#rename Great Black-backed gull and herring gull
```

```
corspec_plot<-corspec
corspec_plot$CommonName<-gsub("Great Black-backed Gull" , "Large
Gull",corspec_plot$CommonName)
corspec_plot$CommonName<-gsub("Herring Gull" , "Large
Gull",corspec_plot$CommonName)
#split data by scale of distance
fulgan<-
corspec_plot[corspec_plot$CommonName=="Fulmar"|corspec_plot$CommonName
=="Gannet",]
kitgul<-
corspec_plot[corspec_plot$CommonName=="Kittiwake"|corspec_plot$CommonNam
e=="Large Gull",]

#make the plots
library(cowplot)

#June
#no fulmar and gannet in june
kitgul_June<-kitgul[kitgul$month==6,]
plot2<-ggplot(kitgul_June, aes(x=CommonName, y=BirdZ_SeaL, fill = area)) +
geom_split_violin()+
  labs(y = "height above sealevel [m]") +
  theme(axis.title.x = element_blank(),axis.text=element_text(size=14),
        axis.title=element_text(size=14,face="bold"),axis.text.x = element_text(angle =
15, hjust=1))

ggsave("cor_species_flightheight_JUNE_seperatescale.png",path = "C:/",
device='png', dpi=300,plot2)

#July
fulgan_July<-fulgan[fulgan$month==7,]
kitgul_July<-kitgul[kitgul$month==7,]
plot1<-ggplot(fulgan_July, aes(x=CommonName, y=BirdZ_SeaL, fill = area)) +
geom_split_violin()+
  labs(y = "height above sealevel [m]") +
  theme(axis.title.x =
element_blank(),legend.position="none",axis.text=element_text(size=14),
        axis.title=element_text(size=14,face="bold"),axis.text.x = element_text(angle =
15, hjust=1))
plot2<-ggplot(kitgul_July, aes(x=CommonName, y=BirdZ_SeaL, fill = area)) +
geom_split_violin()+
  theme(axis.title.x = element_blank(),axis.title.y =
element_blank(),axis.text=element_text(size=14),
        axis.title=element_text(size=14,face="bold"),axis.text.x = element_text(angle =
15, hjust=1))

plot_grid(plot1, plot2, labels = "AUTO")

p<-plot_grid(plot1, plot2, labels = "AUTO")
```

```
ggsave("cor_species_flightheight_JULY_seperatescale.png",path = "C:/",
device='png', dpi=300,p)

# analyse flight height in relation to distance to turbines
#check different distributions
library(fitdistrplus)
#y
fw <- fitdist(corspec$BirdZ_SeaL, "weibull")
fg <- fitdist(corspec$BirdZ_SeaL, "gamma")
fln <- fitdist(corspec$BirdZ_SeaL, "lnorm")
fn <- fitdist(corspec$BirdZ_SeaL, "norm")
fpoi <- fitdist(corspec$BirdZ_SeaL, "pois")

### plot it
par(mfrow = c(2, 2))
plot.legend <- c("Weibull", "lognormal", "gamma", "normal")
denscomp(list(fw, fln, fg, fn), legendtext = plot.legend)
qqcomp(list(fw, fln, fg, fn), legendtext = plot.legend)
cdfcomp(list(fw, fln, fg, fn), legendtext = plot.legend)
ppcomp(list(fw, fln, fg, fn), legendtext = plot.legend)

###
#models
library(lme4)
library(car)
corspec$CommonName<-as.factor(corspec$CommonName)
corspec$Turbine_Distance_M_scaled <- scale(corspec$Turbine_Distance_M, center
= FALSE, scale = TRUE)
area1<-corspec[corspec$area == 1,]
area2<-corspec[corspec$area == 2,]

#area 1 test for normal and others
hist(area1$BirdZ_SeaL,breaks = 100)
area1$BirdZ_SeaL_log<-log(area1$BirdZ_SeaL)

fw <- fitdist(area1$BirdZ_SeaL, "weibull")
fg <- fitdist(area1$BirdZ_SeaL, "gamma")
fln <- fitdist(area1$BirdZ_SeaL, "lnorm")
fn <- fitdist(area1$BirdZ_SeaL, "norm")
fpoi <- fitdist(area1$BirdZ_SeaL, "pois")

### plot it
par(mfrow = c(2, 2))
plot.legend <- c("Weibull", "lognormal", "gamma", "normal")
denscomp(list(fw, fln, fg, fn), legendtext = plot.legend)
qqcomp(list(fw, fln, fg, fn), legendtext = plot.legend)
cdfcomp(list(fw, fln, fg, fn), legendtext = plot.legend)
ppcomp(list(fw, fln, fg, fn), legendtext = plot.legend)

plot(area1$Turbine_Distance_M,area1$BirdZ_SeaL)
```

```
#kittiwake
hist(kittiwake$BirdZ_SeaL,breaks = 50)
hist(kittiwake$Turbine_Distance_M,breaks = 50)
hist(kittiwake$Turbine_Distance_M_log,breaks = 50)
hist(sqrt(kittiwake$Turbine_Distance_M),breaks = 50)

#Fulmar
hist(fulmar$BirdZ_SeaL,breaks = 50)
hist(fulmar$Turbine_Distance_M,breaks = 50)

#gannet
hist(gannet$BirdZ_SeaL,breaks = 50)
hist(gannet$Turbine_Distance_M,breaks = 50)

#guills
hist(gull$BirdZ_SeaL,breaks = 50)
hist(gull$Turbine_Distance_M,breaks = 50)

#Fulamr
plot(fulmar$Turbine_Distance_M_log,log(fulmar$BirdZ_SeaL))
plot(fulmar$Turbine_Distance_M,fulmar$BirdZ_SeaL)

#load the libraries
library(glmm)
library(lme4)

JuneJulyCombine$month<-as.factor(JuneJulyCombine$month)
kittiwake$month<-as.factor(kittiwake$month)
kittiwake$Turbine_Distance_M<-as.integer(kittiwake$Turbine_Distance_M)
kittiwake$BirdZ_SeaL<-as.integer(kittiwake$BirdZ_SeaL)
kittiwake$BirdZ_SeaL_log<-log(kittiwake$BirdZ_SeaL)
corspec$Turbine_Distance_M_scaled_log<-
log(corspec$Turbine_Distance_M_scaled)
corspec$BirdZ_SeaL_log<-log(corspec$BirdZ_SeaL)
corspec$BirdZ_SeaL_sqrt<-sqrt(corspec$BirdZ_SeaL)

area1<-corspec[corspec$area == 1,]

##### Models ####
# Core species in area 1
hist(area1$BirdZ_SeaL,breaks = 50)
#find optimal lambda for Box-Cox transformation
bc <- boxcox(area1$BirdZ_SeaL ~ area1$Turbine_Distance_M_scaled)
lambda <- bc$x[which.max(bc$y)]
lambda
library(lmerTest)
#fit new linear regression model using the Box-Cox transformation
mixedmodelarea1 <- lmer(((BirdZ_SeaL^lambda-1)/lambda) ~
Turbine_Distance_M_scaled * (1|CommonName) + (1|month), data = area1)
```

```
summary(mixedmodelarea1)
plot(mixedmodelarea1,xlab="Fitted values", ylab="Residuals", which = 2)
qqnorm(resid(mixedmodelarea1))
qqline(resid(mixedmodelarea1))


# #### Turbine Distance raw  plot ####
testplot <- ggplot (area1, aes(x = Turbine_Distance_M_scaled, y =
BirdZ_SeaL,color=CommonName)) +
  geom_point()+
  labs(x= "Distance to WTG [m]", y = "height above sealevel [m]") +

theme(axis.text=element_text(size=14),axis.title=element_text(size=14,face="bold"))
+
  geom_smooth (method="lm")
ggsave("cor_species_flightheight_distanceturbine.png",path =
"C:/Users/b.zein/OneDrive - Apem Limited/P5794/LiDAR Mixed
Model/outputs_new/", device='png', dpi=300,testplot)


#take common names from area 1 only for distance to turbine as no turbines in
area2
fulmar<-area1[area1$CommonName == "Fulmar",]
kittiwake<-area1[area1$CommonName == "Kittiwake",]
gannet<-area1[area1$CommonName == "Gannet",]
gull<-area1[area1$CommonName == "Herring Gull"|area1$CommonName == "Great
Black-backed Gull",]
hist(area1$Turbine_Distance_M, breaks = 109)

#kittiwake
hist(kittiwake$BirdZ_SeaL,breaks=500)
length(kittiwake$Bird_No)
#glmm
 require(lme4)
combo <- glmer(BirdZ_SeaL_sqrt ~ Turbine_Distance_M_scaled + (1|month)  , data
= kittiwake,family=inverse.gaussian(link = "1/mu^2"))
summary(combo )
plot(combo , which = 2)
qqnorm(resid(combo ))
qqline(resid(combo ))

#fulmar
hist(fulmar$BirdZ_SeaL_sqrt,breaks=66)
#LM
combof <-lm(BirdZ_SeaL ~ Turbine_Distance_M_scaled, data = fulmar)
summary(combof )
plot(combof , which = 2)
qqnorm(resid(combof ))
qqline(resid(combof ))
```

```
#gannet
hist(gannet$BirdZ_SeaL,breaks=500)
#LM
combog <-lm(BirdZ_SeaL~ Turbine_Distance_M_scaled, data = gannet)
summary(combog )
plot(combog , which = 2)
qqnorm(resid(combog ))
qqline(resid(combog ))

#gull #only sample 1 in june and 8 in july
#remove June for modelling
gull<-gull[-1,]
hist(gull$BirdZ_SeaL_sqrt,breaks=500)
#LM
combog <-lm(BirdZ_SeaL_sqrt ~ Turbine_Distance_M_scaled, data = gull)
summary(combog )
plot(combog , which = 2)
qqnorm(resid(combog ))
qqline(resid(combog ))



#### Section below created by created by Alexandra McCubbin for APEM Ltd
### Histogram distance to WTG for each species
#### Dist to Turbine by spp June ####
setwd("C:/ ")

colnames(CombinedJune)
unique(CombinedJune$CommonName)

JuneFulmar <- subset(CombinedJune, CommonName =="Fulmar")
JuneKittiwake <- subset(CombinedJune, CommonName=="Kittiwake")
JuneGuillemot <- subset(CombinedJune, CommonName == "Guillemot")
JuneRazorbill <- subset(CombinedJune, CommonName == "Razorbill")
JuneGuillRaz <- subset(CombinedJune, CommonName == "Guillemot/Razorbill")
JuneGannet <- subset(CombinedJune, CommonName == "Gannet")
JuneSkua <- subset(CombinedJune, CommonName == "Great Skua")
JuneHerrGu <- subset(CombinedJune, CommonName == "Herring Gull")
JuneGBbg <- subset(CombinedJune, CommonName == "Great Black-backed Gull")
JuneAukSh <- subset(CombinedJune, CommonName == "Auk/Shearwater species")
JuneAukspp <- subset(CombinedJune, CommonName == "Auk species")

ggplot(JuneFulmar, aes(x=Turbine_Distance_M)) +
geom_histogram(fill='#317FA0', color="black", binwidth = 5000)+
#facet_grid(alltog2$Survey)+
labs(x = "Fulmar Distance to Turbine (m)", y = "Frequency")+
theme_classic()+
theme(axis.text.x = element_text(angle = 30, hjust = 1))+
theme(text = element_text(size=16))
filenameFulmarJune<-"June_Fulmar_Hist.png"
```

```
ggsave(filenameFulmarJune, width = 11, height =7)

ggplot(JuneKittiwake, aes(x=Turbine_Distance_M)) +
geom_histogram(fill='#317FA0', color="black", binwidth = 5000)+
#facet_grid(alltog2$Survey)+
labs(x = "Kittiwake Distance to Turbine (m)", y = "Frequency")+
theme_classic()+
theme(axis.text.x = element_text(angle = 30, hjust = 1))+
theme(text = element_text(size=16))
filenameKittiwakeJune<-"June_Kittiwake_Hist.png"
ggsave(filenameKittiwakeJune, width = 11, height =7)

ggplot(JuneGuillemot, aes(x=Turbine_Distance_M)) +
geom_histogram(fill='#317FA0', color="black", binwidth = 5000)+
#facet_grid(alltog2$Survey)+
labs(x = "Guillemot Distance to Turbine (m)", y = "Frequency")+
theme_classic()+
theme(axis.text.x = element_text(angle = 30, hjust = 1))+
theme(text = element_text(size=16))
filenameGuillemotJune<-"June_Guillemot_Hist.png"
ggsave(filenameGuillemotJune, width = 11, height =7)

ggplot(JuneRazorbill, aes(x=Turbine_Distance_M)) +
geom_histogram(fill='#317FA0', color="black", binwidth = 5000)+
#facet_grid(alltog2$Survey)+
labs(x = "Razorbill Distance to Turbine (m)", y = "Frequency")+
theme_classic()+
theme(axis.text.x = element_text(angle = 30, hjust = 1))+
theme(text = element_text(size=16))
filenameRazorbillJune<-"June_Razorbill_Hist.png"
ggsave(filenameRazorbillJune, width =11, height =7)

ggplot(JuneGuillRaz, aes(x=Turbine_Distance_M)) +
geom_histogram(fill='#317FA0', color="black", binwidth = 5000)+
#facet_grid(alltog2$Survey)+
labs(x = "Guillemont/Razorbill Distance to Turbine (m)", y = "Frequency")+
theme_classic()+
theme(axis.text.x = element_text(angle = 30, hjust = 1))+
theme(text = element_text(size=16))
filenameGuillRazJune<-"June_GuillRaz_Hist.png"
ggsave(filenameGuillRazJune, width = 11, height =7)

ggplot(JuneGannet, aes(x=Turbine_Distance_M)) +
geom_histogram(fill='#317FA0', color="black", binwidth = 5000)+
#facet_grid(alltog2$Survey)+
labs(x = "Gannet Distance to Turbine (m)", y = "Frequency")+
theme_classic()+
theme(axis.text.x = element_text(angle = 30, hjust = 1))+
theme(text = element_text(size=16))
filenameGannetJune<-"June_Gannet_Hist.png"
```

```
ggsave(filenameGannetJune, width = 11, height =7)

ggplot(JuneSkua, aes(x=Turbine_Distance_M)) +
geom_histogram(fill='#317FA0', color="black", binwidth = 5000)+
#facet_grid(alltog2$Survey)+
labs(x = "Great Skua Distance to Turbine (m)", y = "Frequency")+
theme_classic()+
theme(axis.text.x = element_text(angle = 30, hjust = 1))+
theme(text = element_text(size=16))
filenameSkuaJune<-"June_Skua_Hist.png"
ggsave(filenameSkuaJune, width = 11, height =7)

ggplot(JuneHerrGu, aes(x=Turbine_Distance_M)) +
geom_histogram(fill='#317FA0', color="black", binwidth = 5000)+
#facet_grid(alltog2$Survey)+
labs(x = "Herring Gull Distance to Turbine (m)", y = "Frequency")+
theme_classic()+
theme(axis.text.x = element_text(angle = 30, hjust = 1))+
theme(text = element_text(size=16))
filenameHerrGuJune<-"June_HerrGu_Hist.png"
ggsave(filenameHerrGuJune, width = 11, height =7)

ggplot(JuneGBbg, aes(x=Turbine_Distance_M)) +
geom_histogram(fill='#317FA0', color="black", binwidth = 5000)+
#facet_grid(alltog2$Survey)+
labs(x = "Great Black-backed Gull Distance to Turbine (m)", y = "Frequency")+
theme_classic()+
theme(axis.text.x = element_text(angle = 30, hjust = 1))+
theme(text = element_text(size=16))
filenameGBbgJune<-"June_GBbg_Hist.png"
ggsave(filenameGBbgJune, width = 11, height =7)

ggplot(JuneAukSh, aes(x=Turbine_Distance_M)) +
geom_histogram(fill='#317FA0', color="black", binwidth = 5000)+
#facet_grid(alltog2$Survey)+
labs(x = "Auk/shearwater Distance to Turbine (m)", y = "Frequency")+
theme_classic()+
theme(axis.text.x = element_text(angle = 30, hjust = 1))+
theme(text = element_text(size=16))
filenameAukShJune<-"June_AukSh_Hist.png"
ggsave(filenameAukShJune, width = 11, height =7)

ggplot(JuneAukspp, aes(x=Turbine_Distance_M)) +
geom_histogram(fill='#317FA0', color="black", binwidth = 5000)+
#facet_grid(alltog2$Survey)+
labs(x = "Auk Species Distance to Turbine (m)", y = "Frequency")+
theme_classic()+
theme(axis.text.x = element_text(angle = 30, hjust = 1))+
theme(text = element_text(size=16))
filenameAuksppJune<-"June_Aukspp_Hist.png"
```

```
ggsave(filenameAuksppJune, width = 11, height =7)

#### Dist to Turbine by spp July ####

colnames(CombinedJuly)
unique(CombinedJuly$CommonName)
setwd("C:/ ")

JulyFulmar <- subset(CombinedJuly, CommonName =="Fulmar")
JulyGannet <- subset(CombinedJuly, CommonName == "Gannet")
JulySkua <- subset(CombinedJuly, CommonName == "Great Skua")
JulyGuillemot <- subset(CombinedJuly, CommonName == "Guillemot")
JulyHerrGu <- subset(CombinedJuly, CommonName == "Herring Gull")
JulyKittiwake <- subset(CombinedJuly, CommonName=="Kittiwake")
JulyGBbg <- subset(CombinedJuly, CommonName == "Great Black-backed Gull")
JulyGuillRaz <- subset(CombinedJuly, CommonName == "Guillemot/Razorbill")
JulyPuffin <- subset(CombinedJuly, CommonName == "Puffin")
JulyUnIDBirSpp <- subset(CombinedJuly, CommonName == "Unidentified Bird
species")
JulyManx <- subset(CombinedJuly, CommonName == "Manx Shearwater")

ggplot(JulyFulmar, aes(x=Turbine_Distance_M)) +
geom_histogram(fill='#317FA0', color="black", binwidth = 5000)+
#facet_grid(alltog2$Survey)+
labs(x = "Fulmar Distance to Turbine (m)", y = "Frequency")+
theme_classic()+
theme(axis.text.x = element_text(angle = 30, hjust = 1))+
theme(text = element_text(size=16))
filenameFulmarJuly<-"July_Fulmar_Hist.png"
ggsave(filenameFulmarJuly, width = 11, height =7)

ggplot(JulyGannet, aes(x=Turbine_Distance_M)) +
geom_histogram(fill='#317FA0', color="black", binwidth = 5000)+
#facet_grid(alltog2$Survey)+
labs(x = "Gannet Distance to Turbine (m)", y = "Frequency")+
theme_classic()+
theme(axis.text.x = element_text(angle = 30, hjust = 1))+
theme(text = element_text(size=16))
filenameGannetJuly<-"July_Gannet_Hist.png"
ggsave(filenameGannetJuly, width = 11, height =7)

ggplot(JulySkua, aes(x=Turbine_Distance_M)) +
geom_histogram(fill='#317FA0', color="black", binwidth = 1000)+
#facet_grid(alltog2$Survey)+
labs(x = "Great Skua Distance to Turbine (m)", y = "Frequency")+
theme_classic()+
theme(axis.text.x = element_text(angle = 30, hjust = 1))+
theme(text = element_text(size=16))
filenameSkuaJuly<-"July_Skua_Hist.png"
ggsave(filenameSkuaJuly, width = 11, height =7)
```

```
ggplot(JulyGuillemot, aes(x=Turbine_Distance_M)) +
geom_histogram(fill='#317FA0', color="black", binwidth = 5000)+
#facet_grid(alltog2$Survey)+
labs(x = "Guillemot Distance to Turbine (m)", y = "Frequency")+
theme_classic()+
theme(axis.text.x = element_text(angle = 30, hjust = 1))+
theme(text = element_text(size=16))
filenameGuillemotJuly<-"July_Guillemot_Hist.png"
ggsave(filenameGuillemotJuly, width = 11, height =7)

ggplot(JulyHerrGu, aes(x=Turbine_Distance_M)) +
geom_histogram(fill='#317FA0', color="black", binwidth = 5000)+
#facet_grid(alltog2$Survey)+
labs(x = "Herring Gull Distance to Turbine (m)", y = "Frequency")+
theme_classic()+
theme(axis.text.x = element_text(angle = 30, hjust = 1))+
theme(text = element_text(size=16))
filenameHerrGuJuly<-"July_HerrGu_Hist.png"
ggsave(filenameHerrGuJuly, width = 11, height =7)

ggplot(JulyKittiwake, aes(x=Turbine_Distance_M)) +
geom_histogram(fill='#317FA0', color="black", binwidth = 5000)+
#facet_grid(alltog2$Survey)+
labs(x = "Kittiwake Distance to Turbine (m)", y = "Frequency")+
theme_classic()+
theme(axis.text.x = element_text(angle = 30, hjust = 1))+
theme(text = element_text(size=16))
filenameKittiwakeJuly<-"July_Kittiwake_Hist.png"
ggsave(filenameKittiwakeJuly, width = 11, height =7)

ggplot(JulyGBbg, aes(x=Turbine_Distance_M)) +
geom_histogram(fill='#317FA0', color="black", binwidth = 5000)+
#facet_grid(alltog2$Survey)+
labs(x = "Great Black-backed Gull Distance to Turbine (m)", y = "Frequency")+
theme_classic()+
theme(axis.text.x = element_text(angle = 30, hjust = 1))+
theme(text = element_text(size=16))
filenameGBbgJuly<-"July_GBbg_Hist.png"
ggsave(filenameGBbgJuly, width = 11, height =7)

ggplot(JulyGuillRaz, aes(x=Turbine_Distance_M)) +
geom_histogram(fill='#317FA0', color="black", binwidth = 5000)+
#facet_grid(alltog2$Survey)+
labs(x = "Guillemont/Razorbill Distance to Turbine (m)", y = "Frequency")+
theme_classic()+
theme(axis.text.x = element_text(angle = 30, hjust = 1))+
theme(text = element_text(size=16))
filenameGuillRazJuly<-"July_GuillRaz_Hist.png"
ggsave(filenameGuillRazJuly, width = 11, height =7)
```

```
ggplot(JulyUnIDBirSpp, aes(x=Turbine_Distance_M)) +
geom_histogram(fill='#317FA0', color="black", binwidth = 1000)+
#facet_grid(alltog2$Survey)+
labs(x = "Unidentified Bird Species Distance to Turbine (m)", y = "Frequency")+
theme_classic()+
theme(axis.text.x = element_text(angle = 30, hjust = 1))+
theme(text = element_text(size=16))
filenameUnIDBirSppJuly<-"July_UnIDBirSpp_Hist.png"
ggsave(filenameUnIDBirSppJuly, width = 11, height =7)

ggplot(JulyManx, aes(x=Turbine_Distance_M)) +
geom_histogram(fill='#317FA0', color="black", binwidth = 5000)+
#facet_grid(alltog2$Survey)+
labs(x = "Manx Shearwater Distance to Turbine (m)", y = "Frequency")+
theme_classic()+
theme(axis.text.x = element_text(angle = 30, hjust = 1))+
theme(text = element_text(size=16))
filenameManxJuly<-"July_Manx_Hist.png"
ggsave(filenameManxJuly, width = 11, height =7)

ggplot(JulyPuffin, aes(x=Turbine_Distance_M)) +
geom_histogram(fill='#317FA0', color="black", binwidth = 5000)+
#facet_grid(alltog2$Survey)+
labs(x = "Puffin Distance to Turbine (m)", y = "Frequency")+
theme_classic()+
theme(axis.text.x = element_text(angle = 30, hjust = 1))+
theme(text = element_text(size=16))
filenamePuffinJuly<-"July_Puffin_Hist.png"
ggsave(filenamePuffinJuly, width = 11, height =7)
```

Appendix V. Species Specific Histograms for Distance to Nearest Turbine (m)

Survey 1 Histograms

Histograms demonstrate the distribution of distance to nearest wind turbine (m) for each species recorded as flying during survey 1 (June 2021). In June this included eight species and three species groups, including guillemot (n=757), kittiwake (n=261), fulmar (n=53), gannet (n=45), razorbill (n=32), herring gull (n=26), guillemot / razorbill (n=8), great skua (n=3), great black-backed gull (n=2), auk / shearwater species (n=1), and auk species (n=1). Histograms were not created where less than three individuals of each species were recorded (great black-backed gull, auk / shearwater species and auk species).

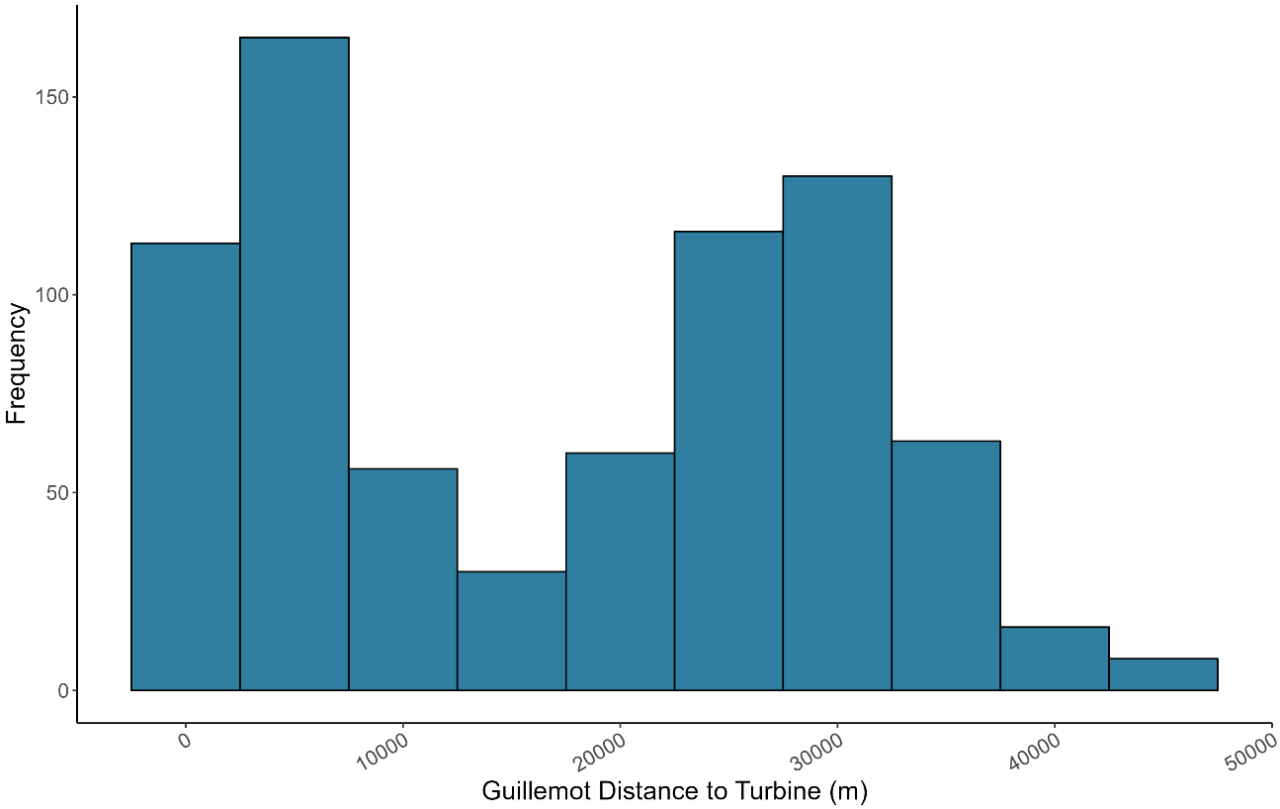


Figure V.1 Histogram of guillemot distance to wind turbine (m) in June 2021.

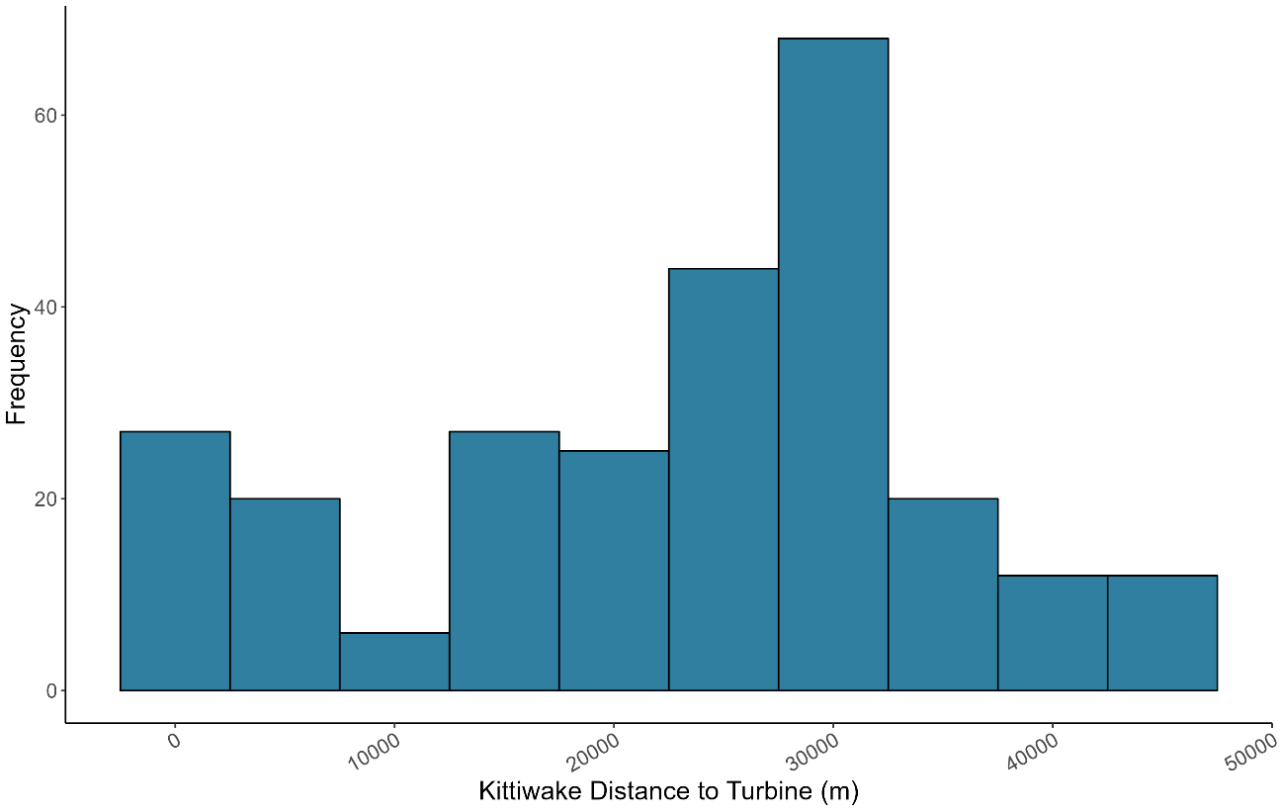


Figure V.3 Histogram of kittiwake distance to wind turbine (m) in June 2021.

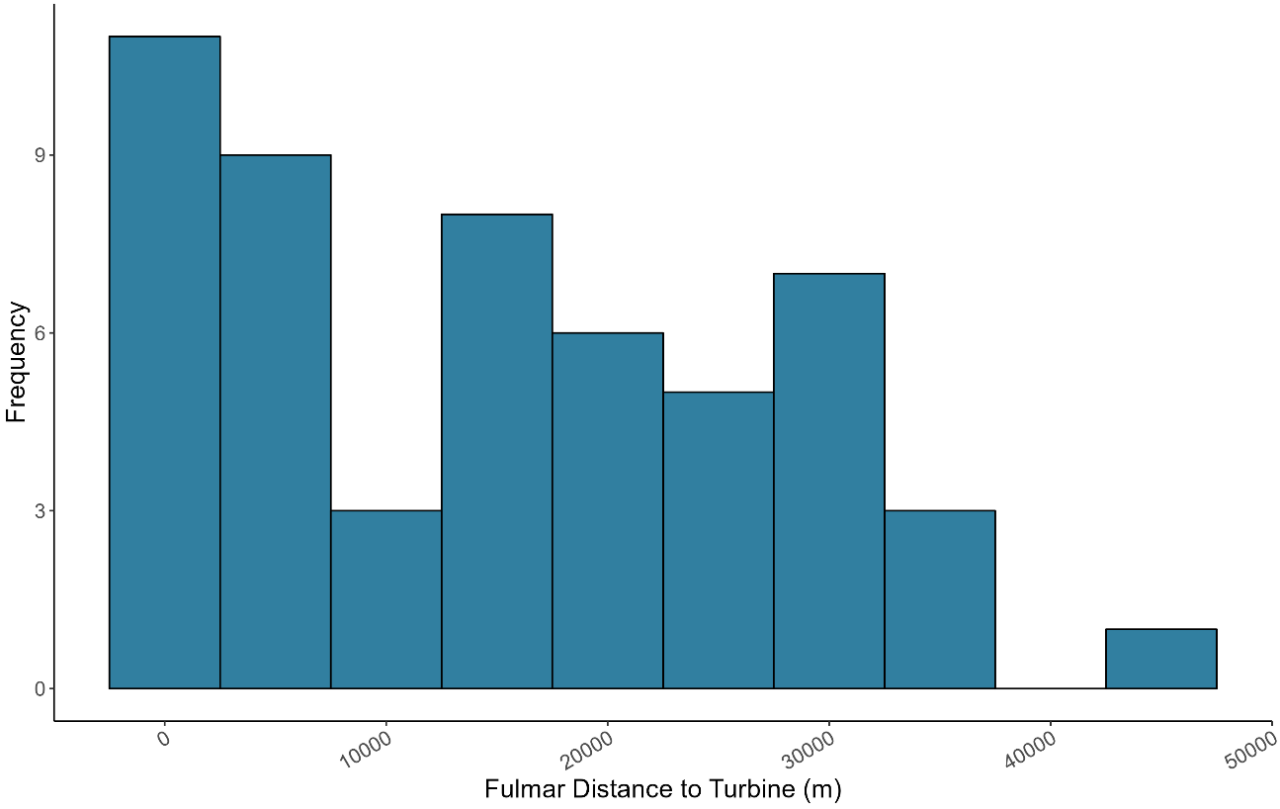


Figure V.2 Histogram of fulmar distance to wind turbine (m) in June 2021.

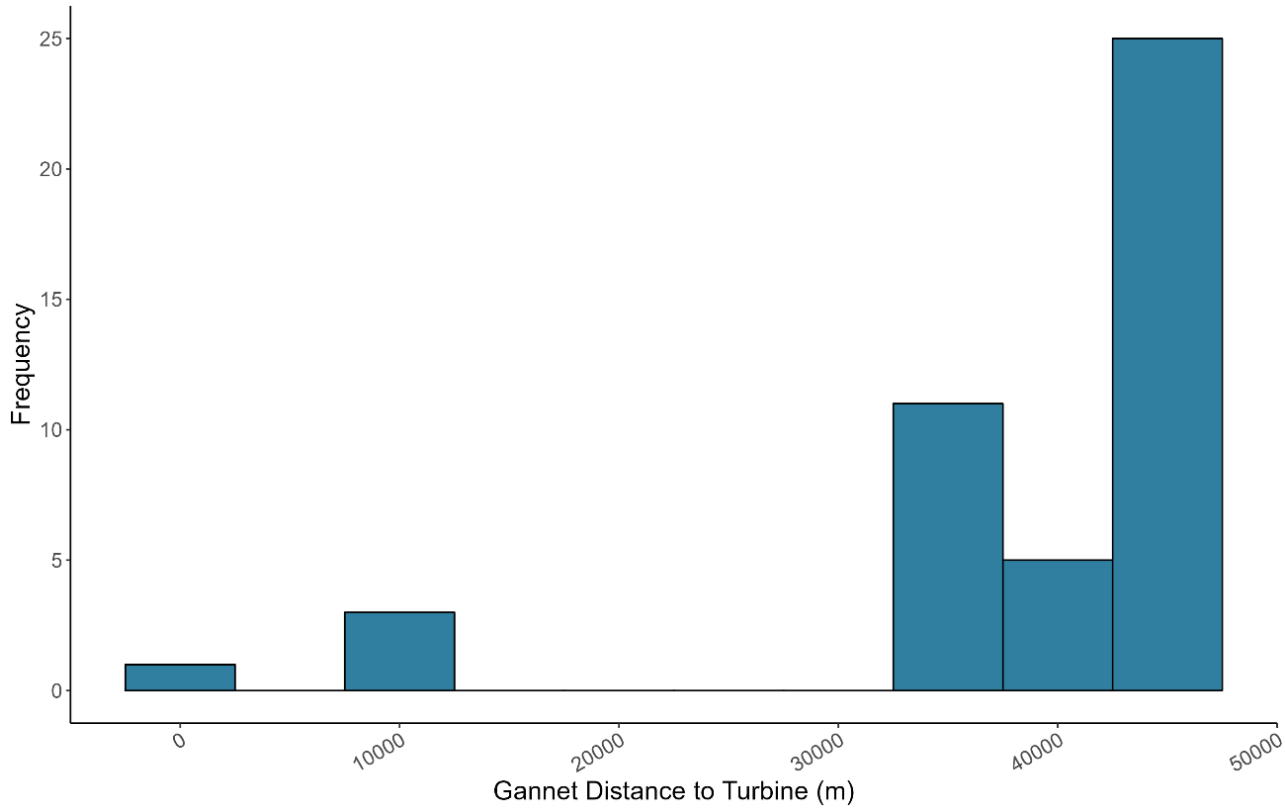


Figure V.5 Histogram of gannet distance to wind turbine (m) in June 2021.

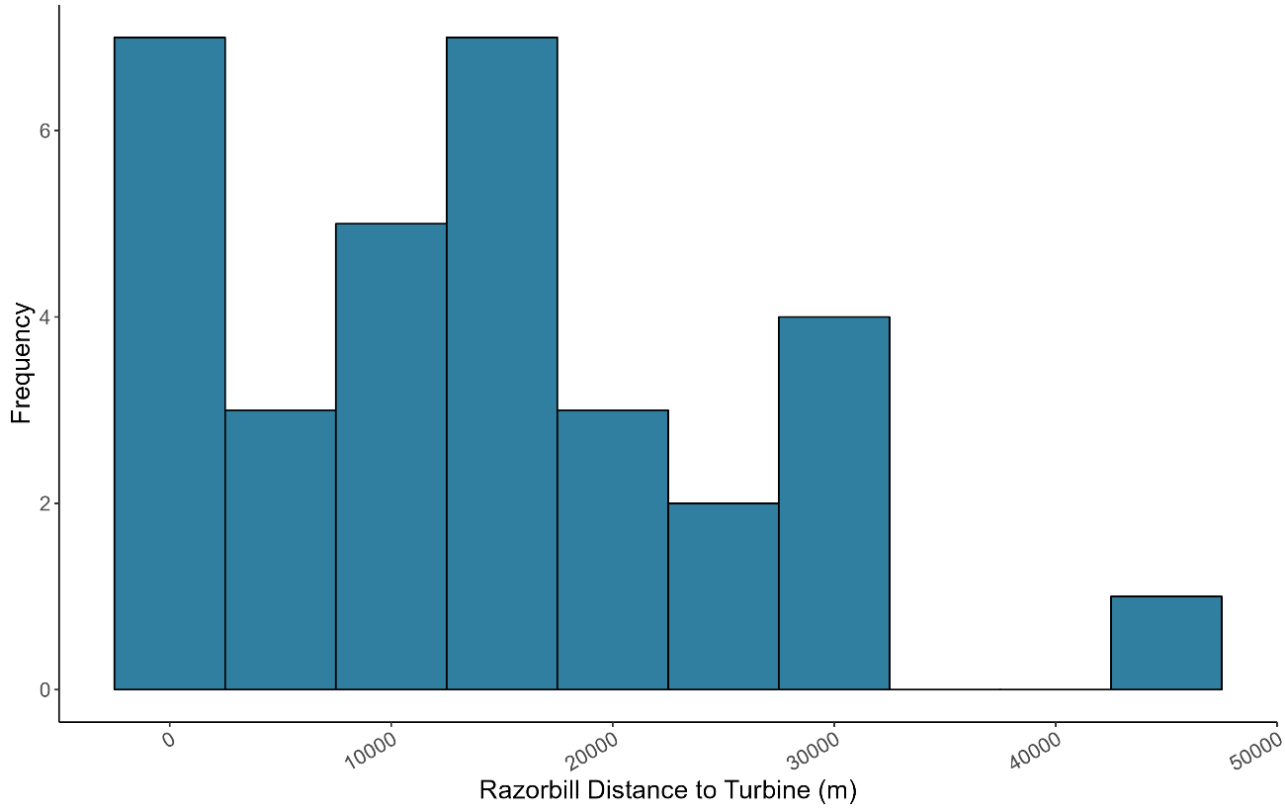


Figure V.4 Histogram of razorbill distance to wind turbine (m) in June 2021

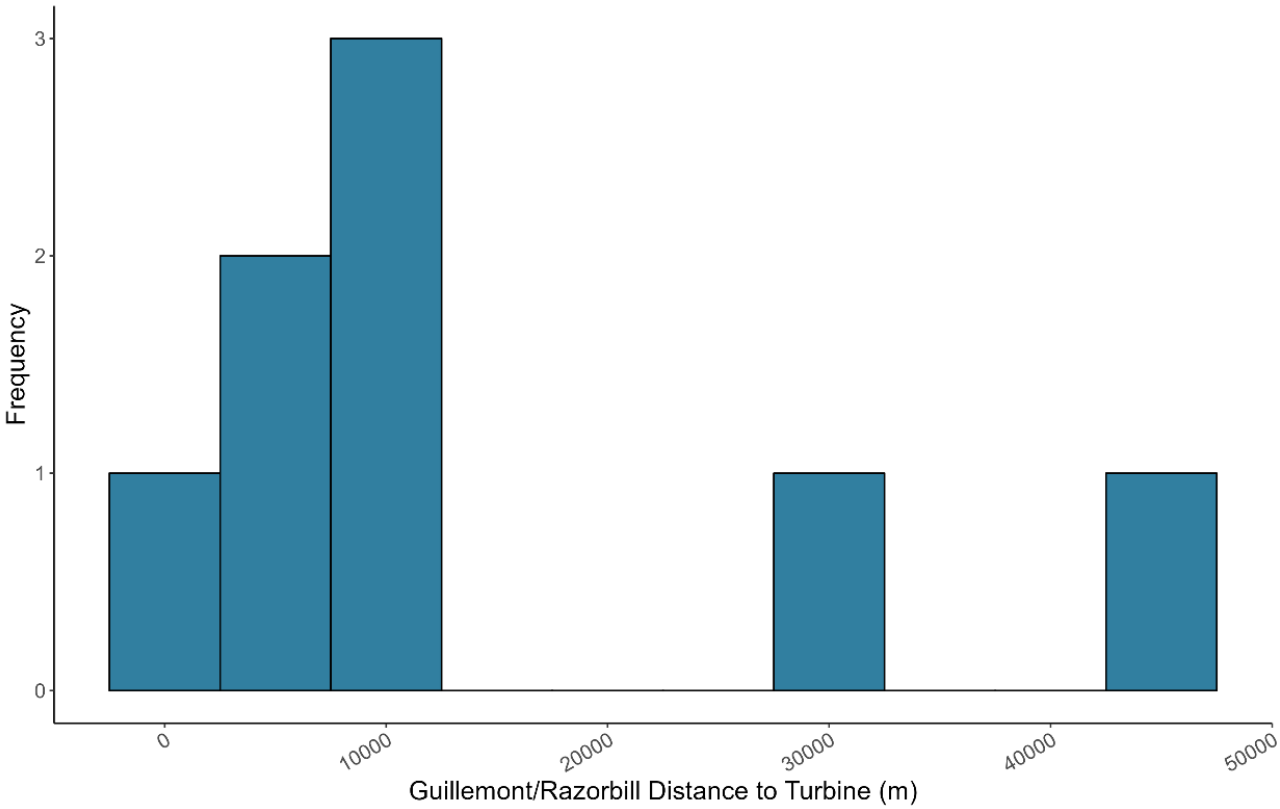


Figure V.7 Histogram of guillemot / razorbill distance to wind turbine (m) in June 2021.

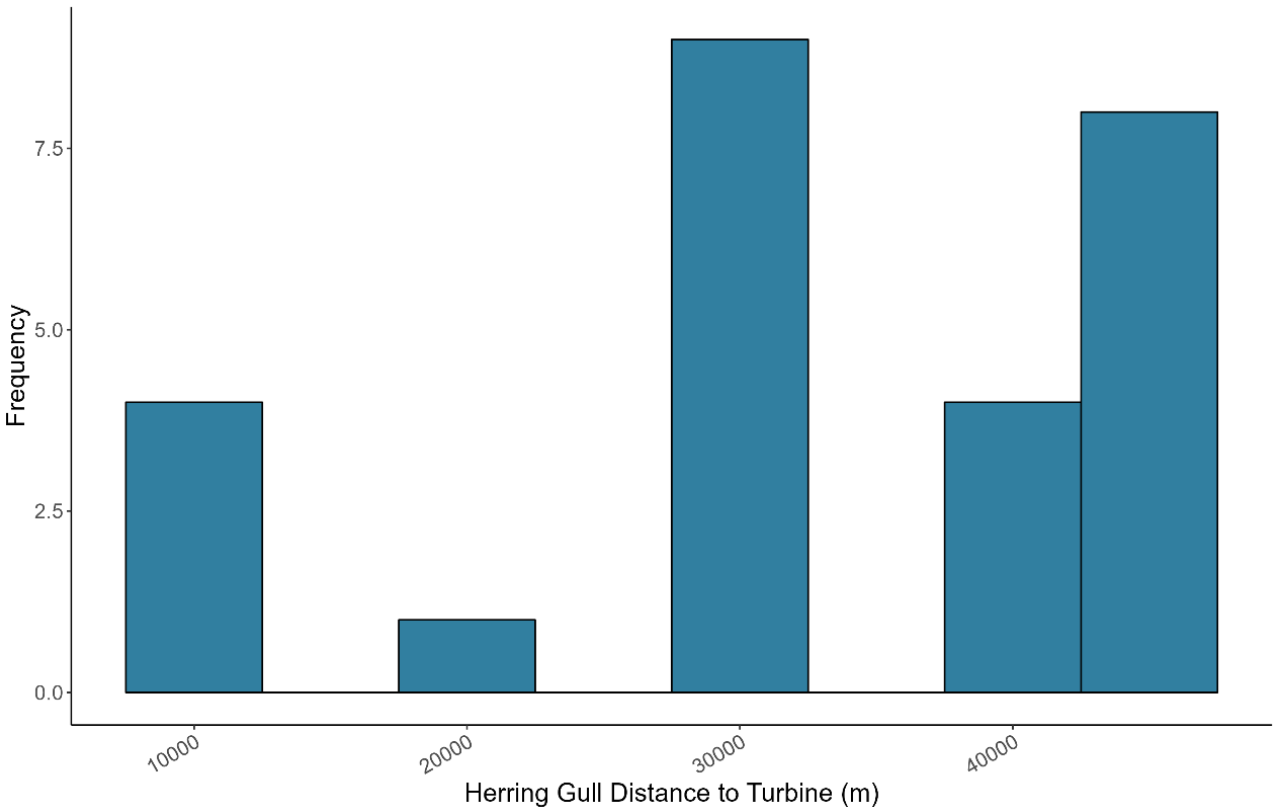


Figure V.6 Histogram of herring gull distance to wind turbine (m) in June 2021.

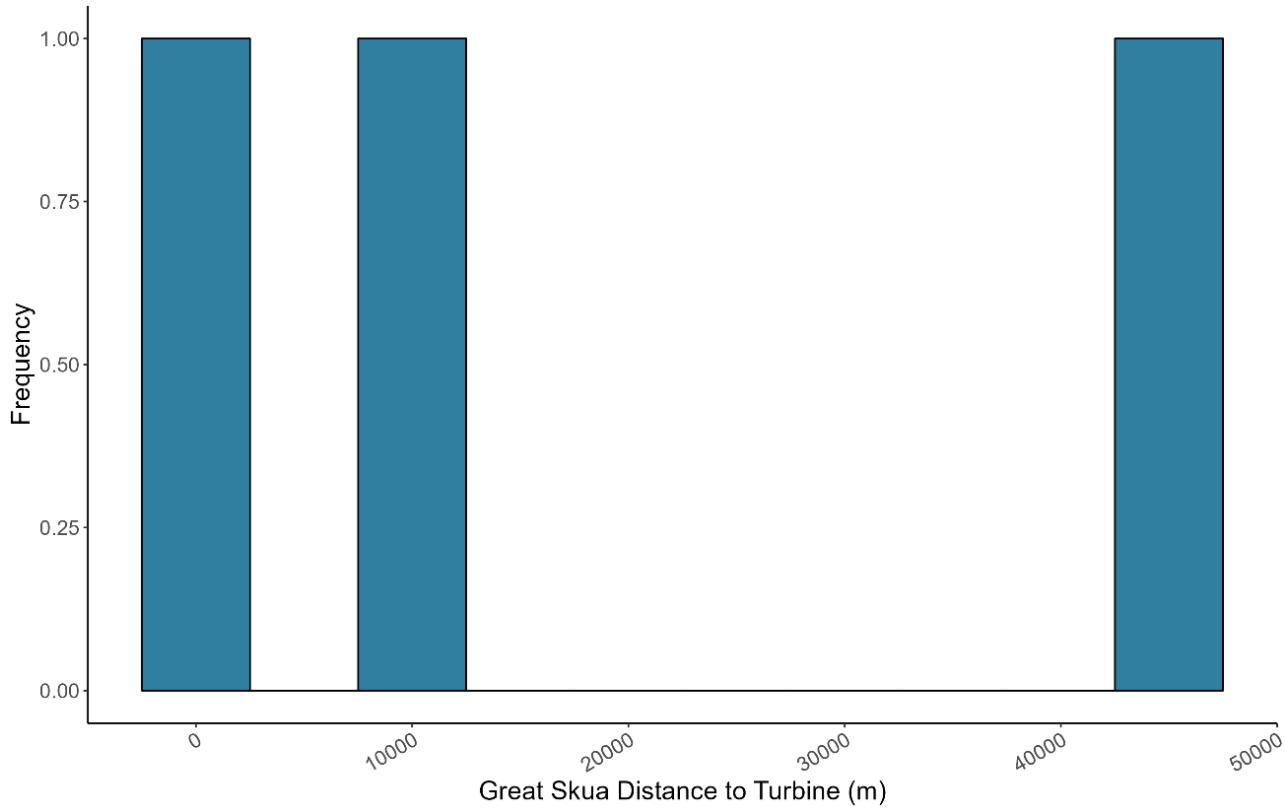


Figure V.8 Histogram of great skua distance to wind turbine (m) in June 2021.

Survey 2 Histograms

Histograms demonstrate the distribution of distance to nearest wind turbine (m) for each species recorded as flying during survey 2 (July 2021). In July this included nine species and two species groups, including guillemot (n=595), kittiwake (n=435), fulmar (n=70), gannet (n=18), herring gull (n=21), guillemot / razorbill (n=21), great skua (n=6), great black-backed gull (n=3), Manx shearwater (n=1), puffin (n=1) and unidentified bird species (n=1). Histograms were not created where less than three individuals of each species were recorded (Manx shearwater, puffin and unidentified bird species).

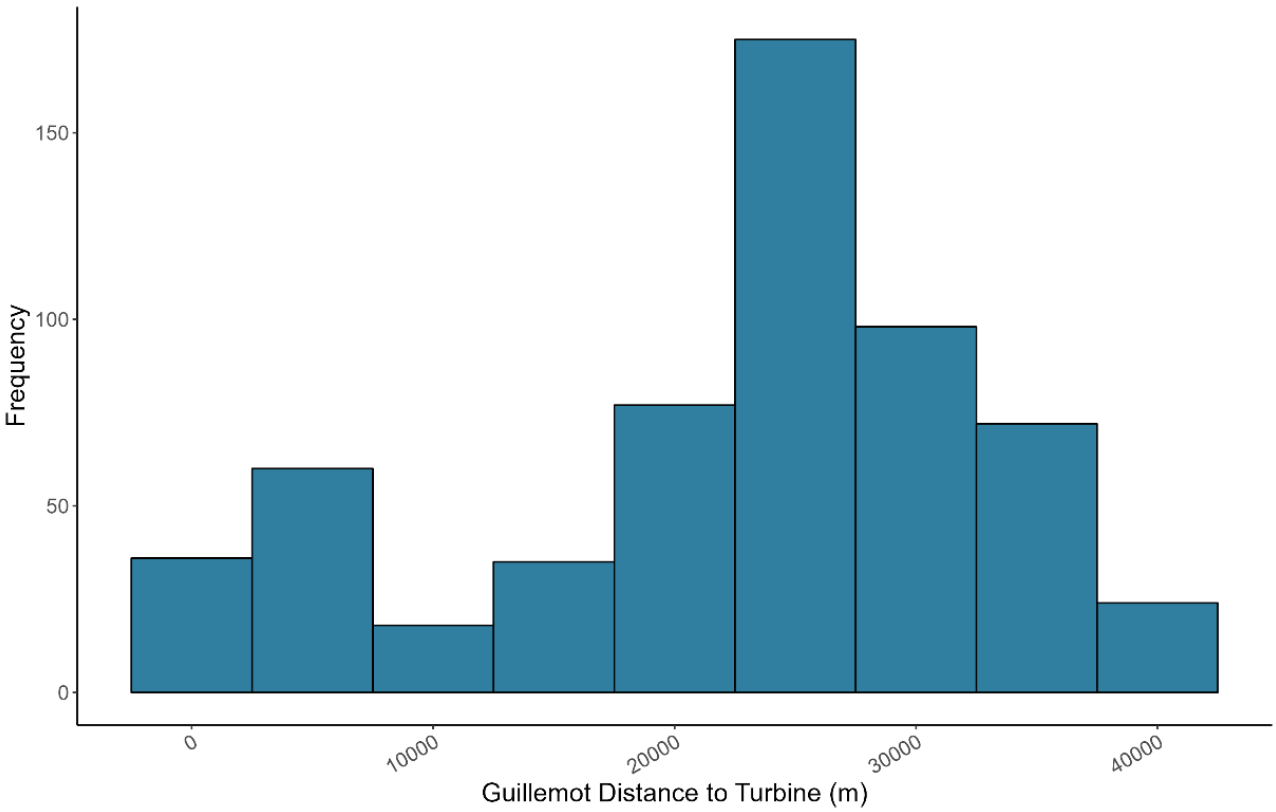


Figure V.9 Histogram of guillemot distance to wind turbine (m) in July 2021.

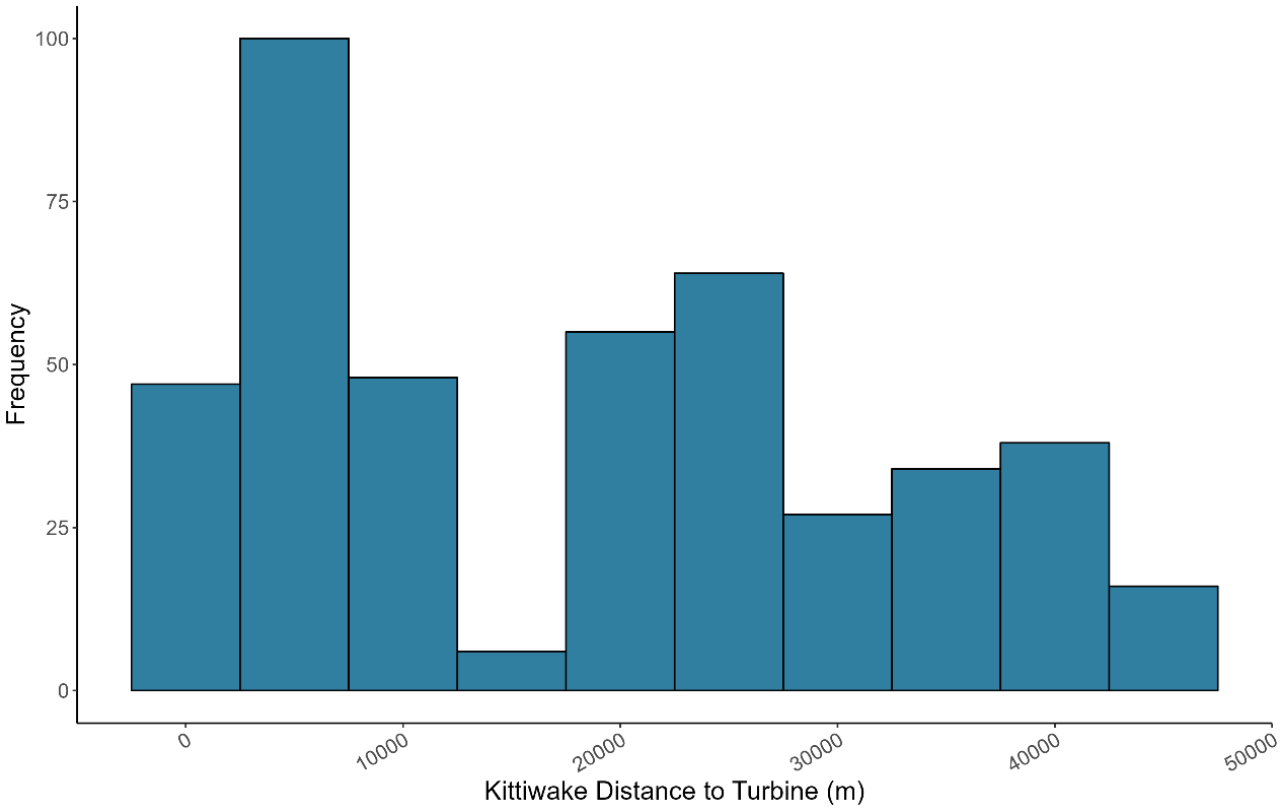


Figure V.11 Histogram of kittiwake distance to wind turbine (m) in July 2021.

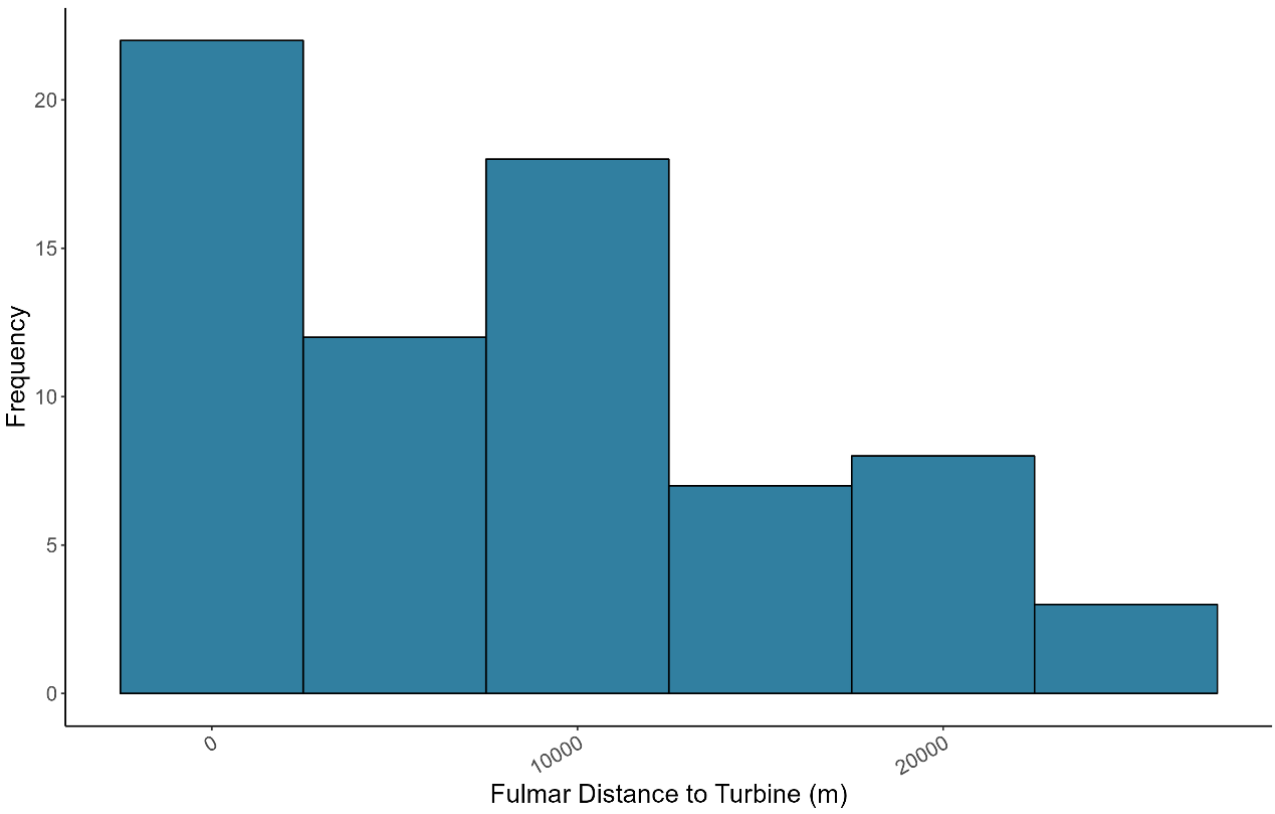


Figure V.10 Histogram of fulmar distance to wind turbine (m) in July 2021.

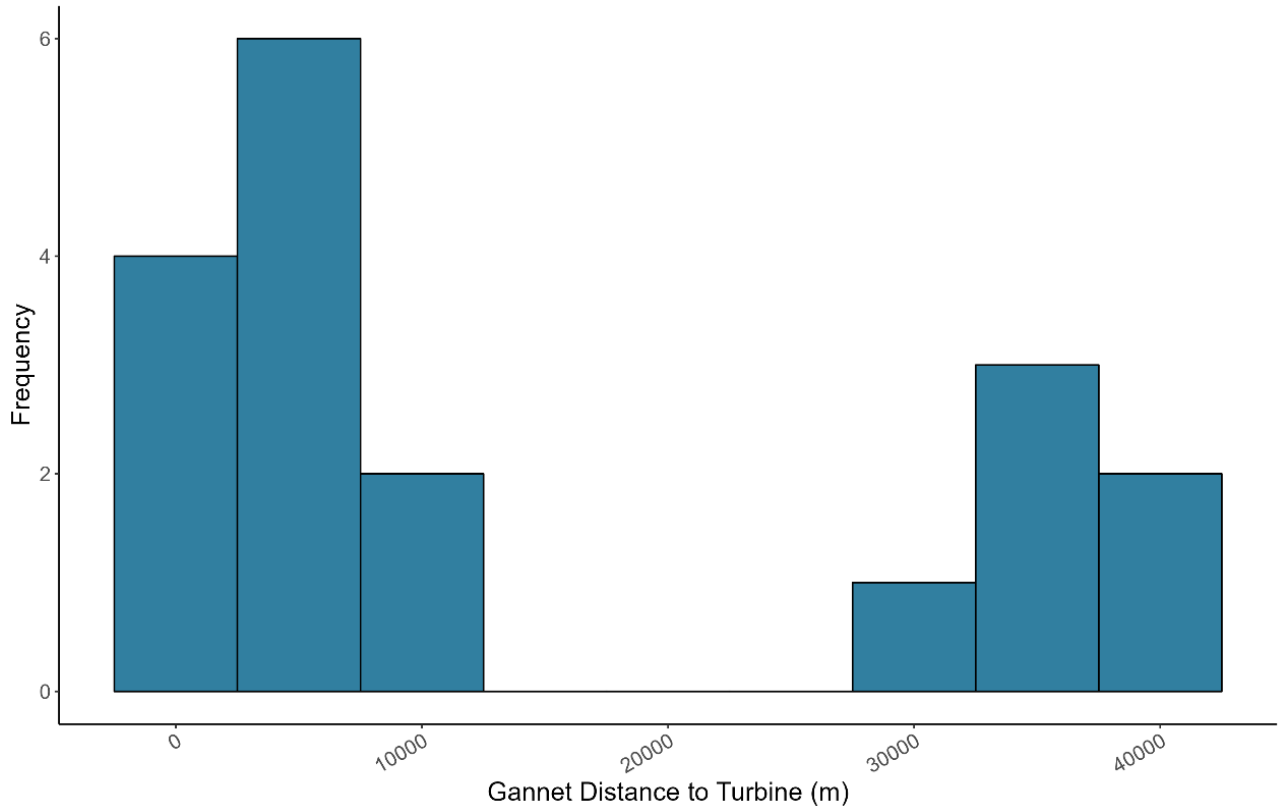


Figure V.13 Histogram of gannet distance to wind turbine (m) in July 2021.

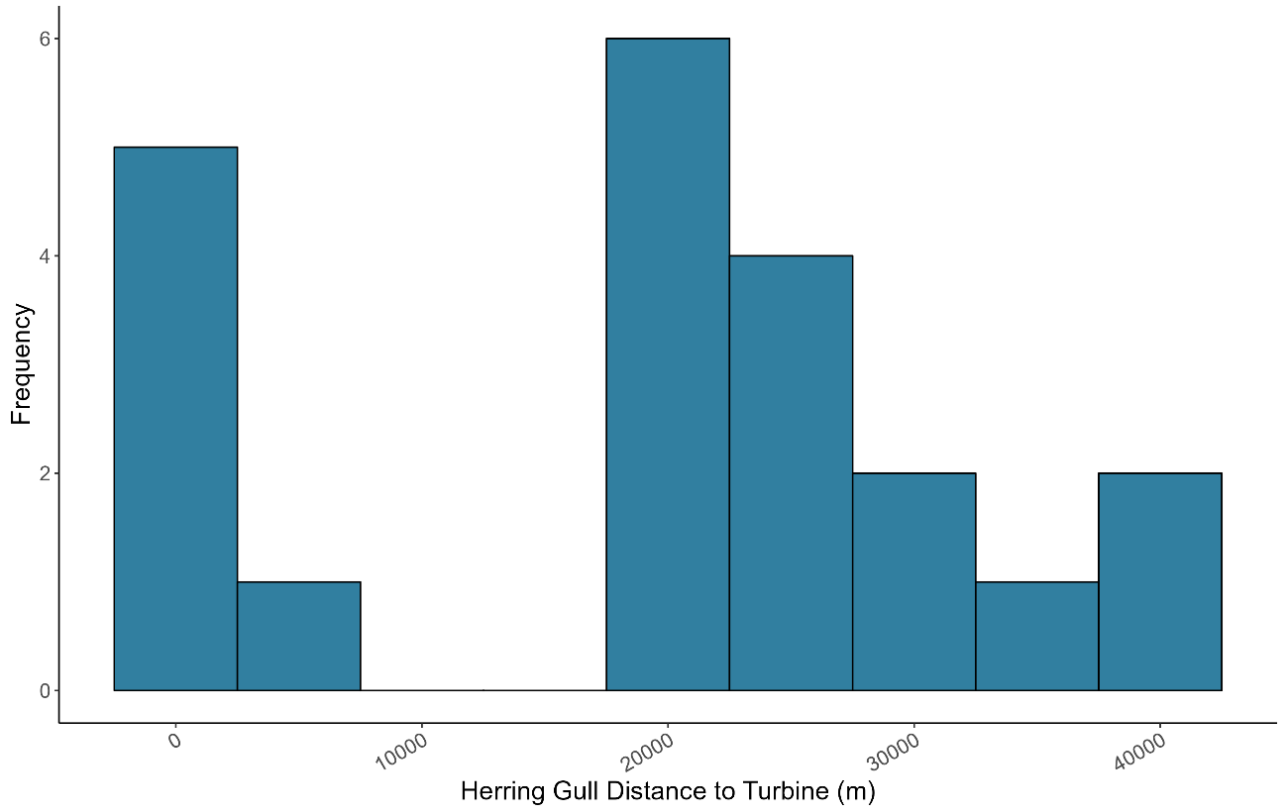


Figure V.12 Histogram of herring gull distance to wind turbine (m) in July 2021.

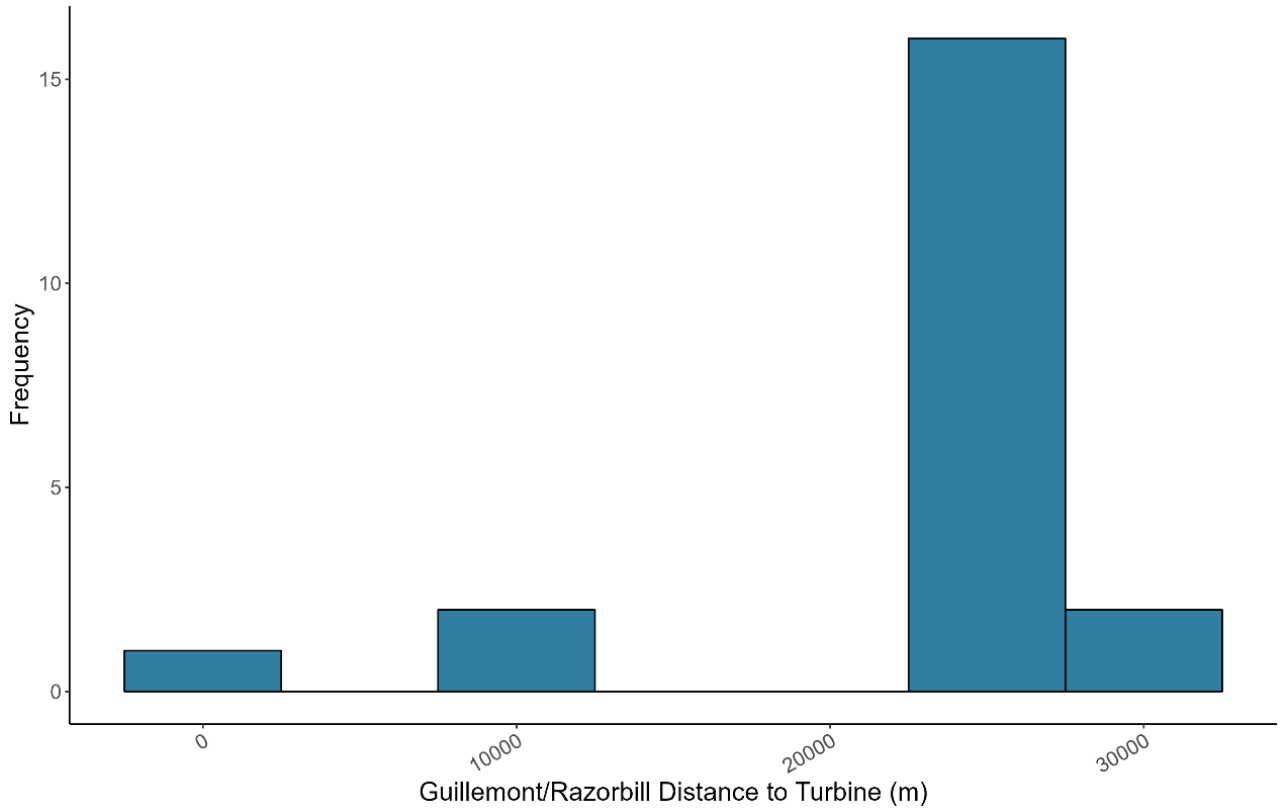


Figure V.15 Histogram of guillemot / razorbill distance to wind turbine (m) in July 2021.

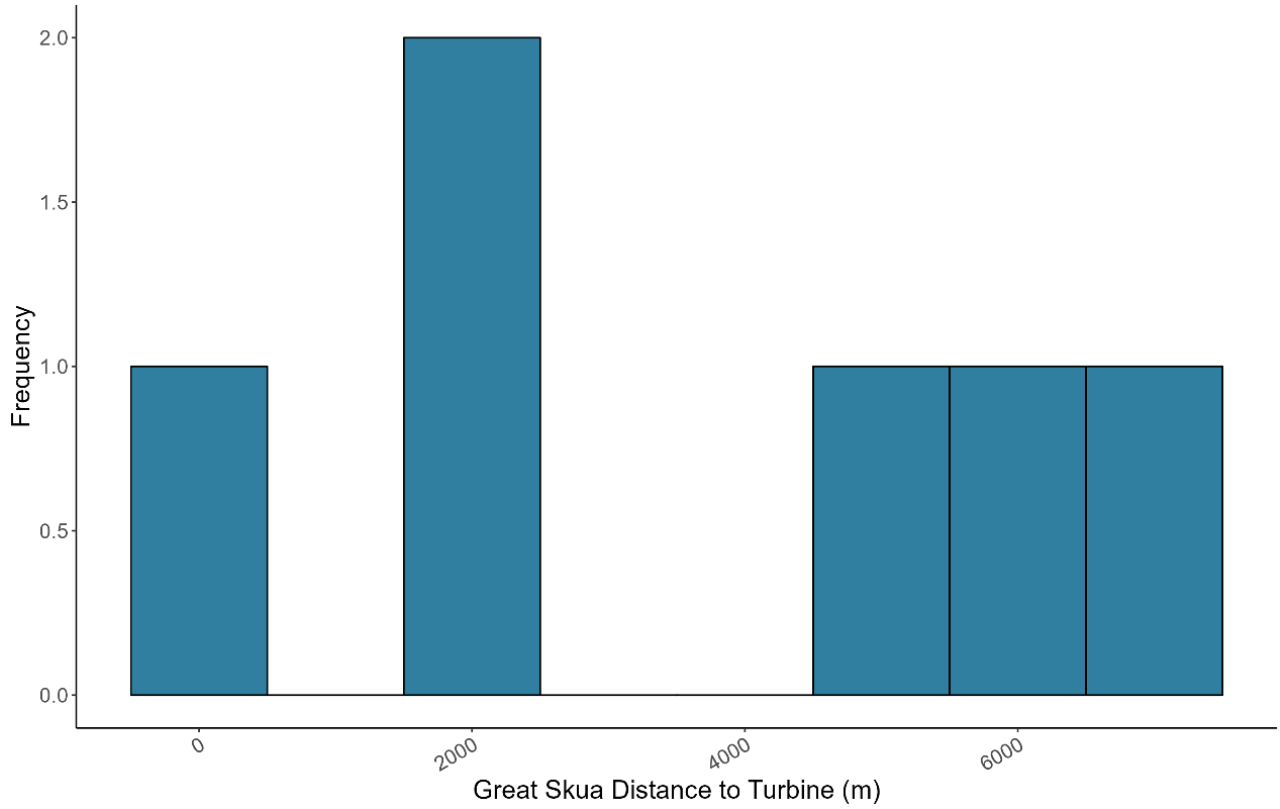


Figure V.14 Histogram of great skua distance to wind turbine (m) in July 2021.

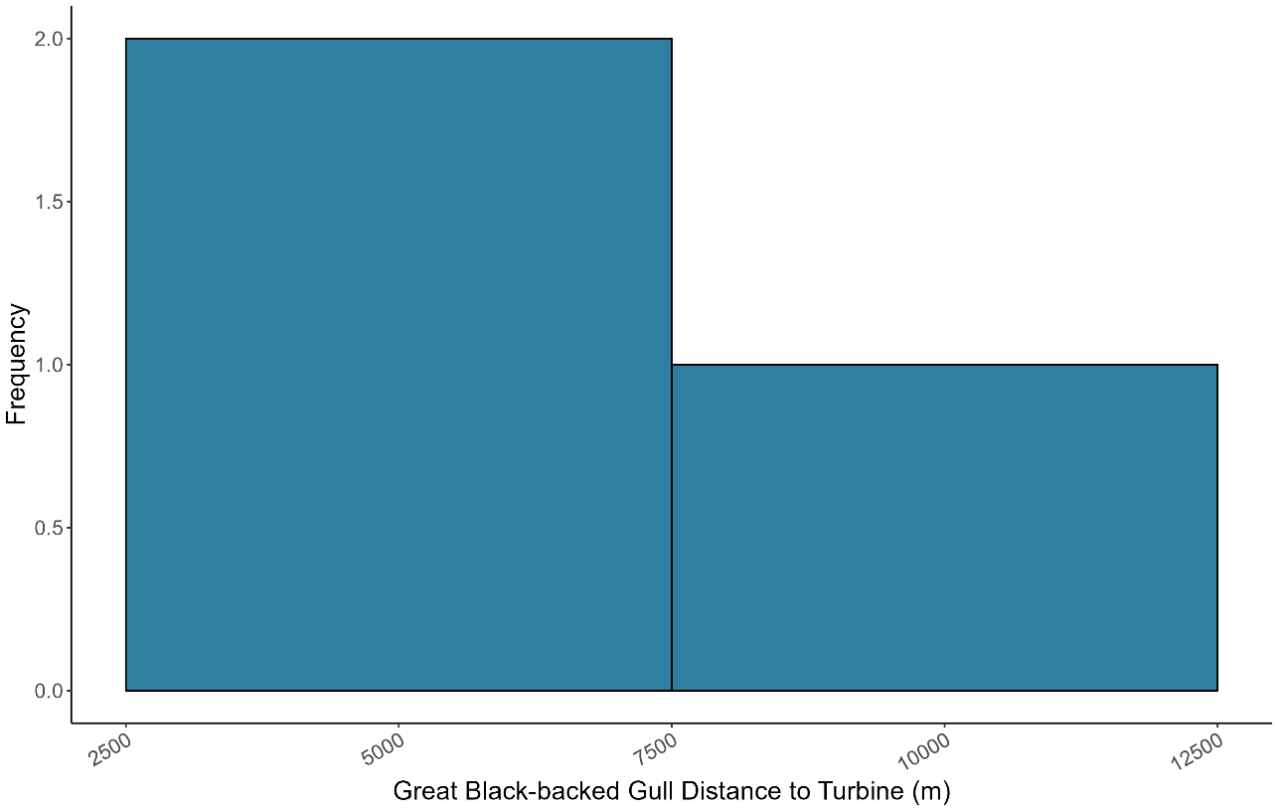
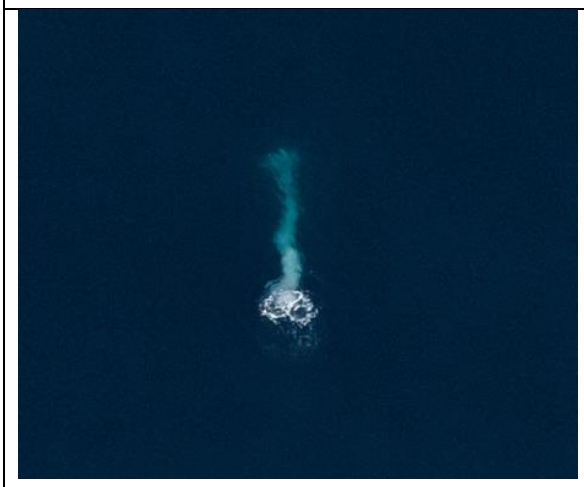


Figure V.16 Histogram of great black-backed gull distance to wind turbine (m) in July 2021.

Appendix VI. Examples of bird flight behaviour

	
Wings bent in flight	Banking in flight
	
Diving	Wings outstretched in flight

Scottish Government
Riaghaltas na h-Alba
gov.scot

This publication is available at **www.gov.scot**

Any enquiries regarding this publication should be sent to us at
The Scottish Government
St Andrew's House
Edinburgh
EH1 3DG

ISBN: 978-1-80435-877-1 (web only)

Published by The Scottish Government, September 2022

Produced for The Scottish Government by APS Group Scotland, 21 Tennant Street, Edinburgh EH6 5NA
PPDAS1146582 (09/22)